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Research Article

A Deep Learning Model for Identification of Yellow Wheat Rust

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ABSTRACT

Wheat (Triticum aestivum L.) is a vital staple food in many cropping systems worldwide. It is grown in various nations, including Pakistan. Wheat is subject to different biotic and abiotic challenges. Rust is one of the most significant biotic constraints that appears almost every year in our country. Among the rusts, yellow wheat rust is caused by Puccinia striiformis f.sp. tritici and is geographically widespread. It damages all the major wheat-producing areas, causing significant losses to wheat crop quality and yield. Disease symptom detection needs to be performed at an early stage in order to improve wheat productivity. In the last few years, deep learning has provided significant breakthroughs in image processing. This research aims to develop a deep learning approach-based model for the automatic detection and classification of yellow wheat rust. The model harnessed the power of Convolutional Neural Networks (CNNs), which enables the system to learn various features from pictures of wheat rust without exhaustive programming.

Keywords: INDEX TERMS CNNs, Deep Learning, Disease Detection, Image Processing, Wheat, Yellow Rust.

INTRODUCTION

Wheat is one of the top food crops in 89 developing countries, accounting for 20% of the calories consumed. Primarily, it is considered the chief food in Pakistan and is cultivated in all the provinces(Tadesse et al., 2017). All successive governments have strived towards achieving and maintaining self-sufficiency with wheat. Wheat is the crop that is grown in the largest farming area in the world. It belongs to the family *Poaceae*. Wheat is one of the three dominant crops in the world. With population growth, the demand for food resources increases, but in many places, there is insufficient arable land available for cultivation (Yamini et al., 2025). This places a burden on developed nations to find methods to produce more from established farms and other resources with fewer inputs. Utilizing robotics in place of basic agricultural labor is one of the most effective solutions. Robots are best known for their exploration and harvesting work, detection of problem locations, gathering of imaging data for analytical purposes, and organizing data from agricultural facilities. These robots can be classified as unmanned ground vehicles (UGVs) and unmanned aerial vehicles (UAVs) (Neupane and Baysal-Gurel, 2021).

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Progress made in recent years has seen the Unmanned aerial vehicle (UAV) originally used by armed forces for combat purposes pivot into an entertainment option. UAVs are now employed for numerous civilian applications, including, but not limited to, agriculture, forestry, and other pertinent fields. They are utilized for almost all agricultural activities. For example, drones can facilitate crop monitoring and range estimation, ailment detection, soil and field analysis, and pesticide spraying. These unmanned aerial vehicles have been automated to the point where they can operate independently and effectively, thanks to rapid advancements in robotic engineering (Ivaniuk et al., 2025).

Wheat cultivation is vital for human development and sustainability; however, the crop's yield is limited by three primary diseases: stem rust, leaf rust, and stripe rust (Patil, 2024; Yousafzai et al., 2025) . Each of these has a single fungus responsible for it. Black rust fungus stems from a specific strain called Puccinia graminis f. sp. Tritici, which attacks the stem. Brown rust, on the other hand, is caused by Puccinia recondita f. sp. Tritici, which infects the leaves of wheat. Meanwhile, yellow wheat rust is caused by Puccinia striiformis. As its name suggests, this disease manifests as yellowish stripes on the plant. If left unmanaged, yellow wheat rust is one of the most detrimental diseases affecting wheat in terms of yield loss. It is known that the causal fungal species attack the plant's green tissues, which profoundly impact the plant's photosynthetic activity, its health, and its ability to produce and yield grains (Worku et al., 2020).

Yellow wheat rust is particularly harmful due to its short life cycle and its ability to spread rapidly in some favorable environmental conditions. It is prevalent in areas with relatively cool and humid conditions. It is even more destructive due to its rapid evolution and ability to adapt to a new, changing environment. The impact of yellow wheat rust on yield varies depending on the factors responsible for its causation. The combination of different causative factors may result in a 70 percent yield loss, which is particularly detrimental for farmers, the regional economy, and the food supply for the people (Megahed et al., 2022). These factors include the crop cultivation region, wheat sowing period, the general state of the surroundings, the protective measures taken, and the controlling and medicinal actions that have been executed. The severity level of the disease also plays a significant role in a normal yearly yield assessment.

Literature Review

Several convolutional neural network (CNN) models have been developed and trained to detect plant diseases, exploiting their specific advantages and features. Some of the most popular CNN models for detecting plant diseases include AlexNet, a veteran of CNN-based image classification models (Balasubramanian, 2024). He won several competitions due to his architecture, which consisted of numerous convolutional layers and, subsequently, many fully connected layers. Later, Alex-Net was modified for plant disease detection by training on plant disease datasets. VGG-Net: VGG-Net is distinguished by its extreme depth, having 16-19 weight layers. This model is simple and homogeneous in design, making it very straightforward to implement. VGG-Net has been widely applied to plant disease diagnosis, often modified through transfer learning, which enables fine-tuning of the network (Hassan et al., 2021). Inception-Net (Google-Net): Inception-Net, also known as Google-Net, was the first to utilize inception modules, enabling optimal parallel processing with various-sized convolution filters (Alramli and Tekerek, 2025). Such architecture has not only been successfully applied in the detection of plant diseases but has also proven effective in terms of computational resources. Res-Net: Res-Net (Residual Neural Network) is a deep Convolutional Neural Network (CNN) model known to perform best in image recognition tasks due to the use of residual connections to overcome the vanishing gradient problem (Subramanian and Lakshmi, 2024). Due to its exceptional performance in image recognition tasks, ResNet has been extensively utilized for plant disease detection with varying degrees of transfer learning (Nigam et al., 2023).

Dense-Net: Dense-Net is a CNN model that connects every layer to its adjacent layers, enabling feature and information flow. Such a topology promotes gradient flow, reduces the number of parameters, and enhances the utilization of features. CCVD has shown the usefulness of Dense-Net in plant disease detection (Nagpal and Goel, 2025). MobileNet: MobileNet is a lightweight CNN model designed for mobile devices with limited resources. The use of depth-wise separable convolution features enables a high level of accuracy with minimal computational resource usage. Plant disease detection using MobileNet has been shown to significantly improve the speed of diagnosis (Jesupriya et al., 2025).

Efficient-Net: A family of CNN models that utilize image recognition. Efficient-Net is and has achieved industry-leading results across a range of image recognition tasks. These models employ a compound scaling technique that balances depth, width, and resolution, achieving high accuracy while utilizing relatively few parameters. Efficient-Net has also proven useful in detecting plant diseases (Islam et al., 2024). It is worth mentioning that the selection of the CNN model is influenced by several factors, including the dataset's complexity and size, computational resources, and the demands of the plant disease detection task. Commonly, researchers use transfer learning, where CNN models trained on other datasets, such as ImageNet, are adjusted to focus on the plant disease dataset. This technique allows for taking advantage of known representations, which helps minimize training on restricted plant disease data and enhances model performance. The goal of this project is to analyze the feasibility and effectiveness of a deep-learning-based model for identifying yellow wheat rust. It will cover all major processes required to build the model, from data collection and preprocessing to model architecture design and training methods. Moreover, the application of deep learning in identifying yellow wheat rust will be analyzed for its benefits and drawbacks, while also suggesting other possible avenues for future development and research (Mandava et al., 2024). The goal is to elevate the deep learning capabilities for the automatic recognition of the yellow wheat rust. This work utilized a labeled image dataset of healthy wheat leaves and those of wheat plants affected by yellow wheat rust. The results showed that the illness has a significant impact on the spectra of the infected plants. Identification of the range from 450 nm to 1000 nm can be used as a spectral signature. A direct relationship was established between the primary subordinate variety and illness severity. It is hypothesized that with greater disease severity, a greater range of spectral variations will be collected at a certain disease severity level. It is expected that for a specific disease, the greater the number of disease symptoms, the more complex the spectra become at a certain disease severity level.

An automated recognition of symptoms from the selected image will be performed, and the infected specimen will be classified using a trained Convolutional Neural Network (CNN) model (Hossen et al., 2022). To ensure a high level of accuracy when the model is analyzing disease symptoms, the training objectives are set accordingly. Furthermore, the deep learning model will be optimized to perform and be robust as it is systematically tested during the training, validation, and evaluation phases. Since CNN-based models exhibit a multitude of structural variations for detection problems across various domains, different CNN architectures and deep learning frameworks will be explored. Also, methods for hyperparameter optimization, along with other tuning strategies, will be studied to determine the optimal framework for detecting and classifying yellow wheat rust. Moreover, the accuracy and generalization capability of the model will be improved by integrating transfer learning with pre-trained models built on large datasets.

The assessment will focus on the accuracy of the model after it has been trained using different datasets from various domains and geographical locations. The performance of the model will be assessed based on the following parameters: accuracy, recall, precision, and the provision of insights into various field datasets. The results of this research are expected to enhance the automation of systems for detecting problems such as yellow wheat rust. Constructing a dependable deep learning model could transform the way diseases are addressed by enabling early, accurate, and swift recognition, as well as effective intervention. Accurate and efficient disease diagnosis could positively help mitigate the adverse impact of yellow wheat rust on the economy and the environment for farmers and other stakeholders (Bouvet et al., 2022).

Problem Statement

For agriculturists and farmers, identifying yellow wheat rust, a fungal disease caused by Puccinia striiformis f. sp. tritici, remains one of their toughest battles. Its yields ought to be controlled through the application of effective disease management strategies; thus, the identification of yellow wheat rust must be accurate and swift due to its high potential for the degradation of crop yields and economic returns. Unfortunately, the manual inspections employed in current practices for identifying yellow wheat rust are slow, expensive, and inaccurate. What is needed is a viable and robust solution based on deep learning techniques that can accurately identify yellow wheat rust on wheat crops. The objective of the proposed research is to develop a deep learning model for automating the processes of harvest inspection and enhancing disease detection in agriculture. This is a matter of high relevance as its solution wagers on global food security and agricultural sustainability. Recognizing yellow wheat rust promptly can help farmers develop effective disease management interventions, such as fungicide application or crop rotation, thereby curtailing the disease's progression and impact. When the deep learning model can accurately identify yellow wheat rust, it can increase yield, reduce harmful agricultural practices, and make agriculture more environmentally sustainable.

Tackling these issues involves several roadblocks, such as the creation of a comprehensive and representative dataset containing labeled images of different stages and severities of yellow wheat rust. Moreover, the deep learning model must undergo sufficient training using the correct approaches so that it can be applied to various types of wheat, cultivation environments, and regions. It is also necessary that the model performs in real-time, enabling farmers to take immediate action based on the information detected.

The development of a deep learning solution for identifying yellow wheat rust enables farmers to utilize an accurate and reliable tool for effective disease management. Farmers would greatly benefit if the detection of yellow wheat rust and potentially other related plant diseases were automated, as this would increase agricultural productivity efficiency.

Objectives

To build a deep learning model that detects and categorizes the Yellow Wheat Rust.

The aim is to construct a deep learning model that will be used to detect the yellow wheat rust by employing image processing techniques. The model will require different algorithms and approaches to analyze the given image, detect regions with the disease, and classify the disease's features for advanced processing or analysis. Achieving the goal requires the application of deep learning with image processing. Preparing the system for the automatic identification of diseases in wheat starts with enhancing the captured images to remove unwanted artifacts. Some of the enhancement methods include image re-sizing, contrast enhancement, and noise filtering. These techniques enhance image quality, enabling the model to yield reliable and useful results. The subsequent step is to check the images for the disease's abnormal symptoms and then process them for detection. Regarding name recognition, CNN models are the best option. CNN models can take an image as input and identify features to recognize yellow wheat rust. These features capture the unique observable behaviors and traits of a particular disease. While the features themselves are not explicitly defined within the CNN model, the model learns to automatically distinguish relevant features during the training phase.

Convolutional Neural Network (CNN)

A convolutional brain structure may have tens or hundreds of superimposed layers, each performing the task of recognizing features of a different spatial scale. Each preparatory image is assigned channels at varying levels of intensity, and each convoluted image serves as input for the following layer. A CNN consists of an input layer, many hidden layers, and an output layer. In the provided illustration, the whole structure of CNNs is described.

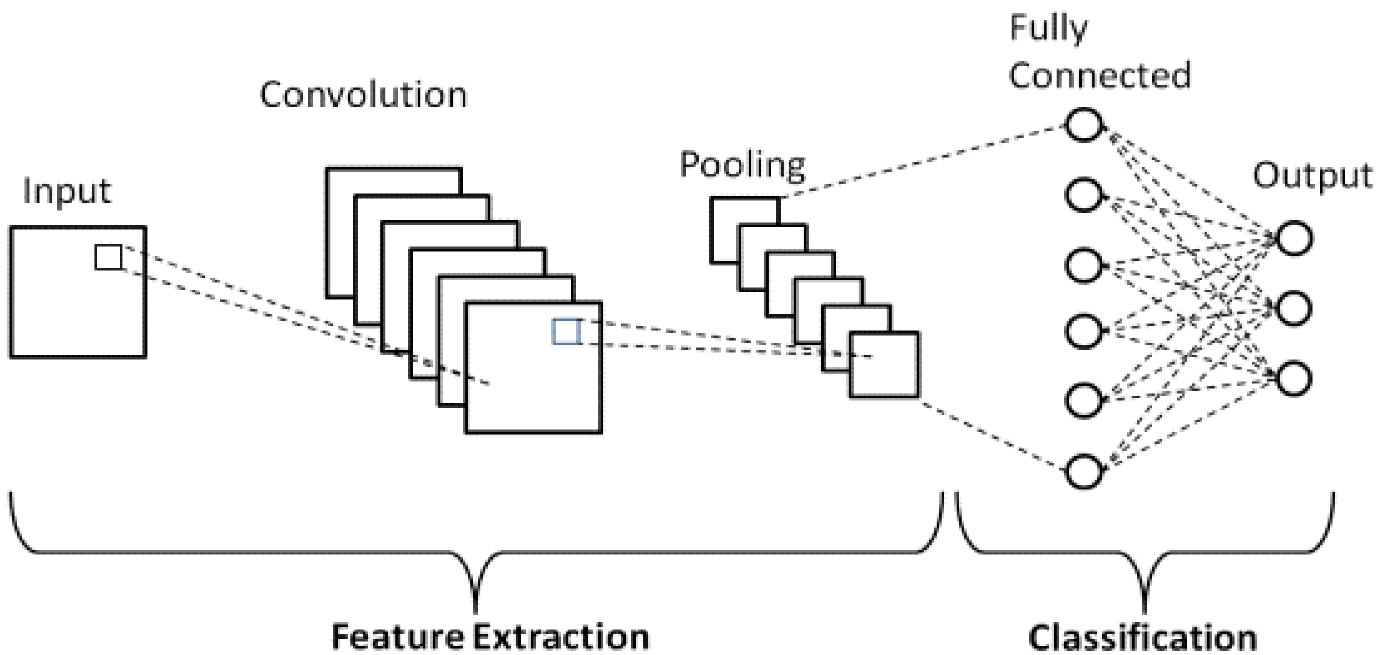

Figure 1. Convolutional Neural Networks (CNNs)

To recognize features characteristic of the information, these layers have to perform the procedure on the information. The three most commonly used layers are pooling, activation (also known as ReLU), and convolution. Convolution operates on images with the aid of convolutional filters, each of which features a different attribute from the input images. ReLU offers highly positive results while nullifying undesirable characteristics; thus, faster and more effective training is possible. Because only the activated features continue to the next layer, this is known as a thrust in some cases. By performing non-linear down-sampling, pooling reduces the number of variables that the network must learn and improves performance. These processes are repeated multiple times in tens or hundreds of layers, where each layer can learn to recognize increasingly sophisticated patterns or features.

Unlike conventional neural networks, a CNN possesses features such as Shared Loads and Inclimitives, wherein all biases and weights of a given layer are the same across all hidden neurons. This implies that all secret neurons identify similar components, such as an edge or a mass, in different regions of the image. This makes the network robust to the pose variation of objects in an image.

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Characterization Layers

After learning patterns in multiple layers, a CNN architecture transitions to the last step — classification. The penultimate layer is a fully connected layer that receives a vector of dimension K (K is the number of classes to be predicted) and contains the likelihood of each class in the image being classified. The last layer of a CNN employs a dense layer for the final classification output.

MATERIAL AND METHODS

Dataset Collection

As far as this study is concerned, a subset of images exists that depict both healthy and unhealthy leaves of a plant. For training a wheat disease detection model, a detailed dataset comprising approximately 5,421 images was compiled. The pictures are in RGB format with a resolution of 162 x 1026 pixels. The methodology for collecting data involves capturing and downloading photographs from trusted online sources. This dataset helps build an accurate classification model that can distinguish between healthy and unhealthy plants. A few sample images from the dataset are displayed in Figure 2. These images have been illustrated with features necessary for the detection and classification of images using algorithms.

Figure 2. Sample image data of Infected, less infected, and Healthy wheat leaves.

Pre-processing

Every single image in the dataset is crude and thus requires specific image processing steps to build a robust Conv-Net model. The sequence of actions is as follows: splitting, Morphological Operations, Foreground (leaf area) masking, and creating an alpha channel image in which the wheat leaf is saved. In the pre-processing dialog, I documented the steps involved in image annotation, augmentation, and splitting the data into training, testing, and validation sets. These steps are extremely important in the data preparation stage.

Data Annotation

As long as relevant data are provided, any data could be used after applying annotations to make them ready for machine learning algorithms. It involves entering contextual data or ground truth labels as an illustration – annotations of data, such as images, text, audio, and videos.

Machine learning models require annotations for training and evaluation purposes because they aid the algorithm in learning how to recognize patterns, make predictions, or accurately execute defined functions. The created patterns, referred to as annotations, enable the model to perform a complex task that involves generalizing to latent data. Different types of data annotation techniques exist, and they largely depend on the classification of the data and the intended objective of the classification.

Image Annotation: In image annotation, objects or regions within an image are labeled and annotated. Bounding boxes and pixel-level segmentation are examples of this type of precise annotation, in which a rectangular box is drawn around an object.

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Text Annotation: There is a process called annotation, where specific sections of the document are tagged with relevant words or phrases. For example, sentiment analysis is a type of tagging where the emotion corresponding to a portion of text is noted. Entity recognition is a more complex annotation method that involves tagging names of individuals, organizations, and places. Other methods include sentiment analysis and part-of-speech tagging.

Audio Annotation: Segments within an audio recording can also be tagged with relevant words or phrases. For example, one person conversing with another, marking them as different speakers, is an example of speaker diarization. It can also be defined as the process of transcribing recorded words and labeling them.

Video Annotation: Video annotations refer to the process of tagging objects, actions, or events within a video. For instance, a tag can be placed on a moving object within a video frame, a process known as object tracking. Tags can also be placed on specific movements within the aforementioned time window, a process known as activity recognition.

Human beings generally understand the guidelines and marking criteria, thereby allowing trained human annotators to interpret data annotations. Depending on the scale of complexity in marking, machine learning technologies can significantly ease these tasks through automation. The learning processes of a machine model depend on its data and the quality of annotation. Quality-annotated data ensure a model works on a well-defined and representative sample, allowing it to perform better during real-life usage.

Yolov5

It contains three fragments:

Spine: YOLOv5 integrated Deep Learning Models into Darknet and transformed it into CSP-Darknet, which serves as the backbone that helps extract key parts of an image. DarkNet is used for object detection. The base layer's part map is divided into two parts using a CSPNet method, where these two regions are joined in a cross-stage order.

Neck: Yolov5 uses a path aggregation network (PANet) as a neck, which serves to build up a feature pyramid network. FPN propagates a single-scale image of any size with a few feature maps at certain levels in a convolutional style. The principal design of the logic of convolution has little influence on this system. It helps the model recognize the same objects that vary in scale and size.

Conclusion: The ' who cares about anything else' layer, headed by the head of Yolov5, oversees the final step in assembling the pieces, so to speak. It does a bulky guess. Utilizing anchor boxes, it creates the final output vector, which contains the class, confidence scores, and bounding boxes. The architecture diagram of YOLOv5 is shown in Figure 3

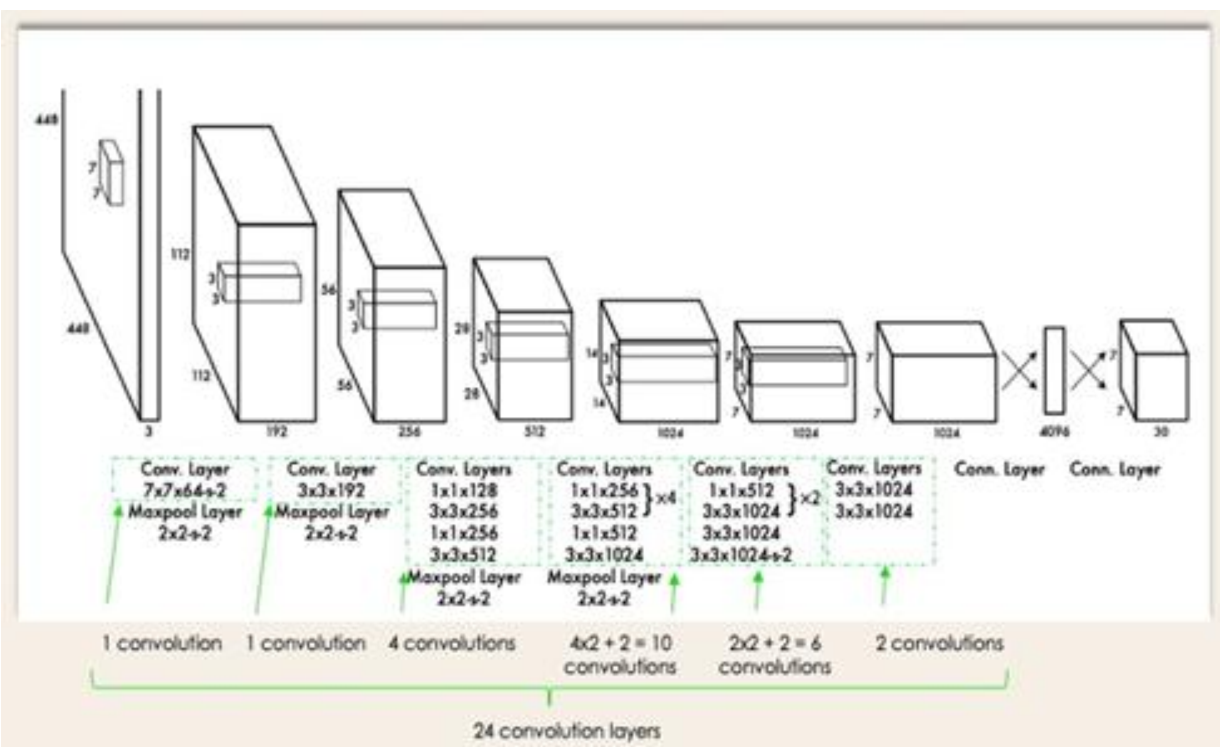

Figure 3. YOLO architecture.

Just Go for It v5 was developed in 2020 by the same team that created the first Only Take the Plunge estimation as an open-source project, sponsored by Ultralytics. Just Go for It v5 builds upon earlier versions, adding several enhancements and modifications.

In contrast to Only Pull Out All the Stops, Go for It v5 utilizes a more complex design, known as EfficientDet (as illustrated below), which is based on the EfficientNet backbone. Adding a more complex architecture in Go for It v5 enables the model to achieve higher accuracy and greater generalization of object classes.

There is also another difference between Only Pull Out All the Stops with Go for It v5 in the type of training data used to train the object recognition model. Only Go for It was trained on the PASCAL VOC dataset, which has 20 object categories. Just Go for It v5, on the other hand, was trained on a larger and more diverse dataset, which contains 600 object categories. Who cares about anything else? v5 includes one more procedure for making the anchor boxes, called "dynamic anchor boxes." Figure 4 provides a comprehensive overview of the entire procedure, from data sourcing to model deployment. In pixel and image analysis, convolutional layers are fundamental, as they perform the convolution operation on the input images, for instance, the parrot image shown. Convolutional layers are composed of filters, also known as kernels, which are used to perform a specific and essential task: feature extraction, typically achieved using a sliding window approach. Pooling layers are particularly crucial in deep learning for image processing. These layers downscale the spatial size of the features and keep the important data. The model utilizes a stacking of convolution and pooling layers to capture and learn sophisticated interactions between features, thereby computing accurate predictions. Fully connected layers rest on top of these learned features and predict the output. These layers connect each neuron from the previous layer to every neuron in the next layer. This enables the model to learn complex feature interactions and make predictions. The model can be deployed for actual use after training and testing the evaluation set. In this section, input data is fed into the trained model to derive predictions or outputs based on the learned patterns and relationships within the data.

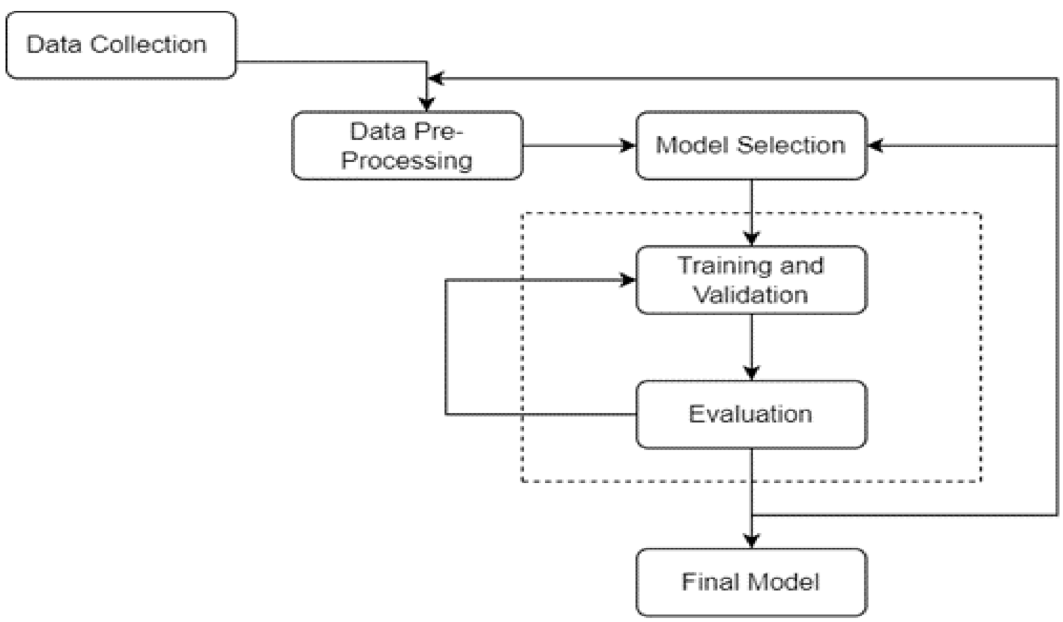

Figure 4. Block diagram of the proposed model.

The figure provides an overview of the model, beginning with data gathering and culminating in model deployment. It illustrates the training process and how the input data is processed through various layers and steps of the training phase, where the data is trained, and features are extracted. Figure 5 depicts a block diagram that covers all the processes in the complete workflow, which includes data collection, data prepossessing, cloning the repository, importing the necessary libraries, training the model, testing it, and saving the trained model. This diagram serves as a guide through the processes required for the YOLOv5 model, which includes an outline of all twelve primary processes and fifty-seven ancillary actions, encompassing the collection of data to the storage of the trained model. The diagram highlights the importance of collecting data that is relevant to the evaluation and training processes. Hence, the acquired data undergoes a cleansing process, where various forms of cleaning, augmentation, and normalization are performed to ensure that it is suitable for training the model.

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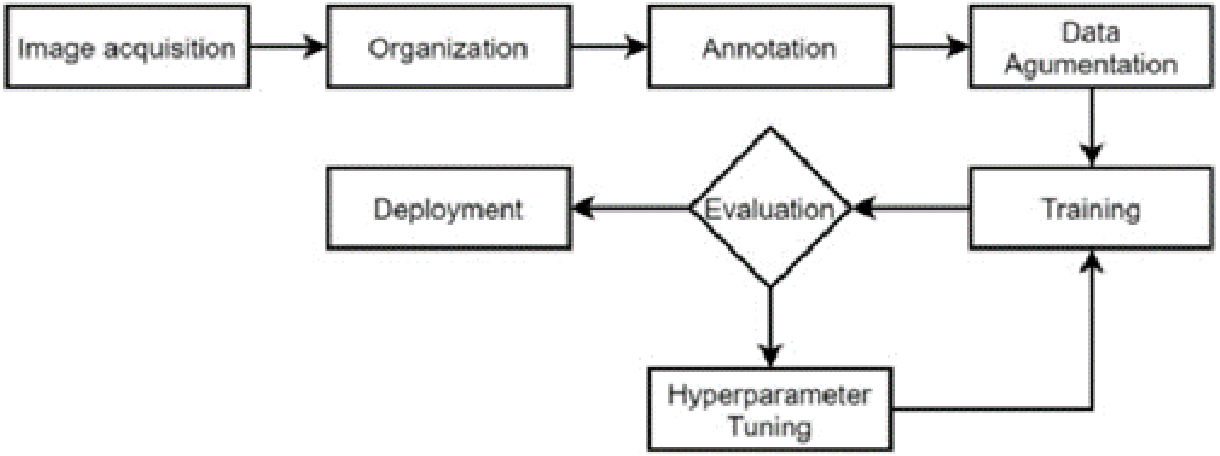

Figure 5. Block Diagram of Current Research Work.

RESULTS

The model's performance is summarized in Table 1, which includes the precision and recall measures for each class, as well as the overall average precision (mAP). The model's mAP is 93%. The model's mAP, along with the mAP for each class, is given for 509 valid images, which contain a total of 662 instances. The instances refer to the total number of species of parrot in the 509 images. FLOPs quantify the computational workload associated with a single instance of a particular model. An instance of the YOLOv5 model has a FLOP count of 29.8.

Table 1. YOLOv5 Performance Summary

Class	Test Images	Instances	Precision	Recall	mAP 50%	mAP 50-95%
"0"	509	51	0.98	0.954	0.982	0.718
"R"		53	0.967	0.755	0.833	0.61
"MR"		85	0.911	0.671	0.872	0.528
"MRMS"		107	0.934	0.935	0.965	0.654
"RS"		87	0.903	0.857	0.919	0.574
"S"		54	0.856	0.815	0.883	0.601
"0S"		59	0.886	0.921	0.942	0.64
OverAll		662	0.93	0.871	0.93	0.674

YOLOv5 is one of the most recent advancements in object detection. YOLOv5 considers the image as a grid and predicts bounding boxes and class probabilities for each grid square. This is what enables the model to detect and classify multiple instances of yellow wheat rust in a single image at the same time. Unlike traditional classification approaches, YOLOv5 performs a bit better when the accuracy of location and context information required in disease detection is needed. The ability to use YOLOv5 for classifying yellow wheat rust allows for accurate and efficient disease detection. With its ability to detect numerous instances of rust and accurately classify and localize them simultaneously, we can take quick and effective actions to prevent the spread of the disease. However, its effectiveness in practice is contingent upon continuous validation and refinement of the model against real-world data, which must be done persistently.

CONCLUSION

Through this article, we propose a deep learning model that employs precise and automated detection of yellow wheat rust in different wheat crops using YOLOv5. The deep learning model is one of the most advanced object detection architectures, which segments an image into several parts and then forecasts bounding boxes along with class probabilities for each part. As a result, the model can detect and classify more than yellow wheat rust in a single image. YOLOv5 excels over regular classification models in providing localization and context and is, therefore, much more appropriate for disease-detection-based applications. Employing YOLOv5 for the detection of yellow wheat rust assures effective and efficient detection of the disease. The model's ability to detect and recognize multiple instances of rust at the same time and its accurate localization corresponds to a well-timed and accurate response towards the containment of the disease. The evidence shows that deep learning techniques proved to be very beneficial in increasing the effectiveness of the disease diagnosis. Still, additional proof and adjustment through actual data need to be performed to make sure that it works and is useful in practical scenarios. Agricultural scientists and practitioners can use the developed models for the formulation and operationalization of effective and timely disease control measures. In addition, the detection accuracy can be improved by combining hyperspectral images with multimodal data.

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AUTHOR CONTRIBUTIONS

All authors contributed equally to this research work

COMPETING OF INTEREST

There are no conflicts of interest declared by the authors.

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