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REAL-TIME DETECTION AND CLASSIFICATION IN TOMATO FARMING USING THE YOLO MODEL

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,**Abstract**:*There are numerous challenges that the global tomato crop faces, such as pests and diseases that can cause big losses. These problems need early detection to facilitate their management and prevention. Rain is the most important season for spreading disease in a tomato farm compared to other seasons. Diagnosing and classifying tomato diseases and pests are addressed through deep learning, machine learning, and Convolutional Neural Networks (CNNs). In this proposed work, a deep learning technique model called you only look once (YOLO) object detection is used for detecting pest and tomato ripping stages. The Darknet53 pre-trained network was used for feature extraction. In contrast, the YOLO model was used for disease detection and fruit ripening stages. Labels were added by using an image label on the images. The network used ground truth images as the dataset to train the proposed method. The finetuning is done for the proposed network, and obtained the hyperparameters. Now, the proposed model detects images of tomato leaves and tomato ripeness. This proposed model allows real-time object detection with classification, leading to agricultural technology advancement and increased production efficiency.*

Keywords: **YOLO Model, Real-Time Object Detection, Agricultural Technology, Deep Learning, Disease Classification.**

1.INTRODUCTION

Tomato production is essential in the world's agriculture as it is grown extensively and has economic value. Tomato (Solanum lycopersicum L.) is a significant vegetable crop worldwide for fresh consumption and processing [1]. The tomato is widely consumed and processed into concentrated pulp for yearly preservation, giving it economic importance [2]. This economic implication of tomato cultivation was further stressed by studies that analyzed the cost and return structure of tomato farming in West Bengal, India [3]. The survey identified several significant constraints on tomato production, such as the non-availability of institutional support, high costs of seed pesticides, labor during peak seasons, disease infestation, and pest attacks [4].Tomato plants are vulnerable to different pests, such as Tuta absolute, which can cause considerable losses in production and financial implications for the farmer [5]. Moreover, some diseases like late blight caused by Phytophthora infestans are a great menace to tomato farming [6]. The gravity of pest and disease concerns also increases with increased acreage under tomato cultivation [7]. Quickly detecting these problems will allow accurate characterization of growth disorders in tomato plants, enabling producers to apply specific crop protection measures. This results in a higher yield and quality while reducing the dependence on excessive use of pesticides [8]. Early detection of these pests by using advanced technologies like deep learning, Convolutional Neural Networks (CNNs), and machine learning can improve the detection and classification of tomato diseases and pests that could facilitate effective management strategies in the early stages of tomato growth [9, 10]. Toward improved disease management since even this happens before severe symptoms appear [11]. Additionally, using refined algorithms for disease detection in tomato plants can enhance accuracy, particularly under challenging conditions such as occlusion and overlapping leaves [12].

2.RELATED WORKS

Convolutional neural networks (CNNs) have demonstrated potential as practical tools in automating tomato disease and pest detection. Studies are proving how CNNs effectively perform tomato disease detection using just leaf images, giving very high rates of overall accuracy [13, 14]. In addition, the use of revised YOLO algorithms has improved the recognition of tomato pests, leading to practical avenues for pest identification in tomato planting fields [15]. Also, crop pests and diseases can be detected in real-time using deep learning models that enhance agricultural production efficiency and raise crop yield and quality [16]. These technologies make it possible to create mobile applications and online platforms for the quick and reliable detection of diseases and pests, providing farmers with the necessary tools for managing them [17]. Addressing these problems has been made possible through the use of Convolutional Neural Networks (CNNs) and Artificial Intelligence efforts in developing robust deep-learning-based detectors for real-time recognition of tomato plant diseases and pests [18, 19]. Furthermore, economic evaluation of tomato intercropping systems and examination of the Nexus between climate change and pest-disease incidence are also under study to underscore economic risks in tomato farming [20].

Consequently, deep learning models like YOLO (You Only Look Once) have attracted noteworthy interest and adoption in agriculture. Deep Learning techniques are used successfully in various agricultural fields, such as plant disease detection, fruit counting, yield estimation, crop recognition, and classification [21]. They modified the feature layer of the YOLO V3 model to detect tomato diseases and pests by increasing its accuracy and speed [22]. Correspondingly, they developed Maize-YOLO for maize pest detection, outperforming most existing algorithms [23]. Grape bunch detection was done by implementing YOLOv3 [24], while Tian et al. [25] employed YOLOv3-Dense to detect apple lesions on farms. The hybrid models that combine CNNs with Recurrent Neural Networks (RNNs) [26].

YOLO (You Live Only Once) algorithms are more accurate and faster in detecting tomato pests and diseases than other algorithms, such as SSD and Faster R-CNN [24]. With new algorithms, YOLOv5 was specifically tailored to detect tomato pests as a mature single-stage target detection model [27]. Furthermore, early real-time detection of tomato diseases and pests in their natural environments can be significantly improved using object detection algorithms based on YOLOv3 while emphasizing the capability of the model for complex backgrounds [28]. Agriculture is one of the fields where AI is used to enable advancements in farming practices, food security improvement, mitigation of labor challenges, and increasing productivity. The agricultural sectors can improve decision-making processes, resource optimization, and sustainable practices by incorporating AI technologies such as deep learning for plant disease early detection and classification, fruit recognition, and quality inspection in farm products. The role of AI in agriculture is expected to play an essential part in shaping future farming practices globally by ensuring food security through its continued development [29, 30].

METHODS

A. *Data Preparation and Preprocessing*

The dataset has been split into two sets: training images and testing images. In addition, the training set is used to train the YOLOv2 network, while the testing set is employed to assess how well the trained network performs. The training images from the dataset are manually labeled the data using bounding boxes. From the image labeler app, the Groundtruth data (i.e., labels and bounding boxes for objects in images) is extracted as a .mat file. Image Datastore and Box Label Datastore create datastores to load images and label data into the proposed network. Function image Datastore creates a datastore for the image filenames, while function box Label Datastore creates a datastore for labels. Images and labels are then merged, leading to a combined datastore with images and their corresponding label, which are included with their label names. We have used our dataset to train the proposed model. The dataset images have been collected in tomato farms.

B. *Network Configuration*

In the YOLOv2, Darknet-53 serves as the backbone network. In this case, we are looking at a network that extracts features from the input image. The connection between Darknet-53 and YOLOv2 is key to the functionality of the YOLOv2 object detection system. More so, Darknet-53 feature extraction power weights more on YOLOv2 than other variables. It has many more layers and residual connections than its predecessor, Darknet-19. These advancements help increase the accuracy of the YOLOv2 detector while maintaining its processing speed at a high level, enabling it to be used for real-time object detection. Sometimes deep neural networks suffer from vanishing gradient problems, and this necessitates some solutions like those of residual connections within darknet 53. Herein comes a shortcut allowing gradients to be directly backpropagated into earlier layers, bypassing the vanishing gradient problem in most deep neural networks. Through increased depth, this network will learn highly non- linear features through DeepNet-53 instead of its older version; therefore, its ability to detect different objects with increased precision becomes much higher since it understands patterns inclusion than predecessors. These are attributes used by the YOLOv2 object detection system when leveraging Darknet-53. During training, the input images and related bounding boxes are passed through the Darknet-53 network. The network then learns to extract features from the input images to predict object bounding boxes.

Finally, the remaining layers in the YOLOv2 system take the output from the darknet53 network to predict final bounding boxes and class labels. In this case, we set the Feature Layer to 'leakyrelu50,' the layer from which features emanate. The network Input Size is [224 224 3], implying that the image needs to have a size of 224x224 pixels with three colored channels (RGB). The number of Classes was set at 4, meaning that this system was trained on four different classes of objects: Healthy leaf, Diseased leaf, Unripe tomato, and tomato fruit. Estimated sizes of anchor boxes are given based on training data. The number of anchor boxes is seven. Yolo layers were attached to the feature extraction layer for darknet53

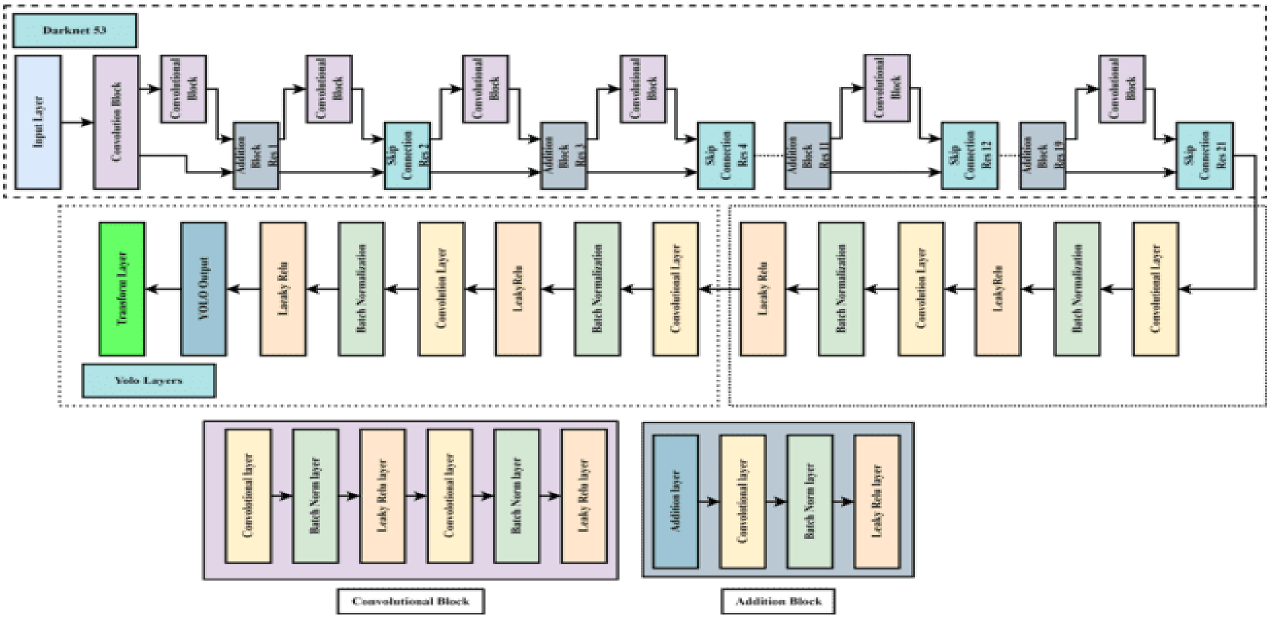


Fig.1. Proposed Network

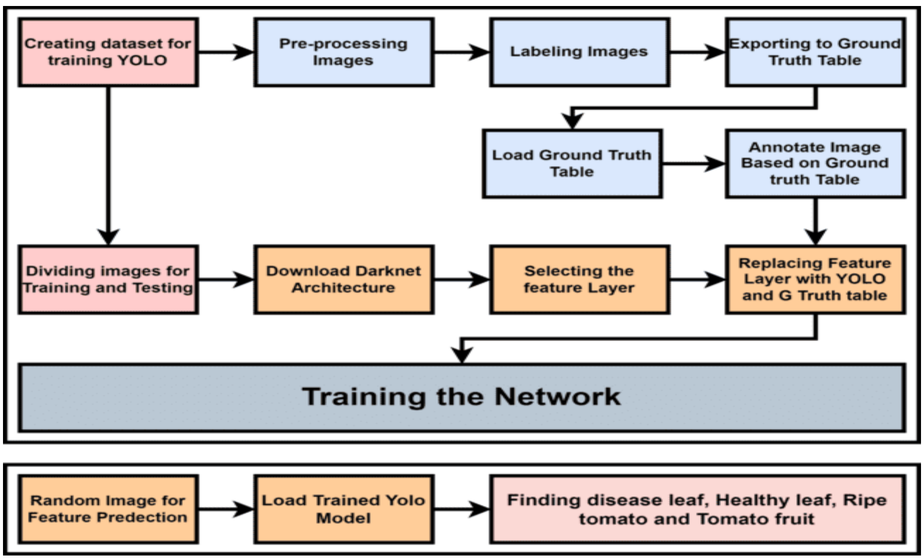


Fig. 2. Block Diagram of the proposed work

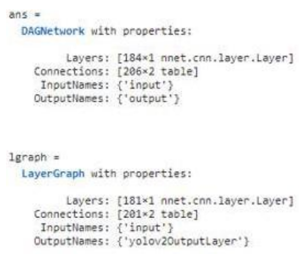
C.Blocks of network

Firstly, the input image is processed to be used for object detection. The image is passed through many blocks of convolution (1-11), and each block includes a layer of convolutional, batch normalization, and leaky ReLU activation functions to get the features from the image. Include residual blocks (11-21) with more convolutional layers to learn complex patterns and reduce training errors. More convolutional blocks (12-19) are then used on the processed data to refine the extracted features further. For effective training and prevention of overfitting, batch normalizations, and leaky ReLU layers are applied after these blocks. The proposed network is shown in Fig 1.

The Block diagram of the proposed network, shown in Fig 2, Darknet 53 feature extractor, is replaced with yolov2. When new images come into the network, they first go through a feature extractor whose features will come out at three different stages but will happen at three different scales. Meanwhile, being passed in those feature extractor layers, these images will be down-sampled in their dimensions to 52 X 52, 26X26, and 13X13, respectively. After extracting the features, it is sent to the classification layer. It has an average pooling layer and softmax layer, which helps the network classify the specified category, whether healthy, diseased, unripe tomato, or tomato fruit

D.Network Training

SGDM Stochastic Gradient Descent with Momentum trains our network over here—the optimized mini-batch size of six with an initial learning rate 1e-3 and maximum epochs of 120. During training, preprocessed data is used for validation. The trained model will be saved for further usage if the proposed network is deployed in hardware and real-time monitoring applications. After being trained, the YOLOv2 detector detects objects in Training images. The detected objects are annotated on images: Healthy leaf, Diseased leaf, Unripe tomato, and tomato fruit.



```
ans =
  DAGNetwork with properties:

         Layers: [184×1 nnet.cnn.layer.Layer]
    Connections: [206×2 table]
     InputNames: {'input'}
    OutputNames: {'output'}


lgraph =
  LayerGraph with properties:

         Layers: [181×1 nnet.cnn.layer.Layer]
    Connections: [201×2 table]
     InputNames: {'input'}
    OutputNames: {'yolov2OutputLayer'}
```

Fig. 3. Dataset is split into different subsets

Fig. 4. Trained Annotated Images

RESULTS AND DISCUSSION

The Fig 3 is the ground truth table made for the image classification task, which identifies some kinds of tomato plants as healthy, fruits, unripe, and diseased leaves. Each label is associated with specific types and label colors. These four classes can be identified and classified among images of tomato plants in real-time processing mode. The YOLO's potential utility in agricultural settings for monitoring plant

Fig. 5. Classification Results Of Proposed Model

distinguish between healthy and diseased leaves and ripe and unripe tomatoes.

The Fig 4 shows how well YOLO works when recognizing things within complex backgrounds. Each sub- image has several colored boxes around it, indicating that YOLO can identify multiple objects at once with a very high level of accuracy. This diversity in coloration, as well as shape, indicates that YOLO can handle different scenarios flexibly. The model instantly detects objects' presence without compromising accuracy, making it useful for any real-time application.

The YOLO (You Only Look Once) model is employed in the image to identify and classify elements within images of tomato plants is shown in Fig 5. It effectively separates unripened tomatoes from fully ripened ones and healthy and diseased leaves. In this case, the labeled output annotates these elements so clearly that we can see how accurate the model is. Score output quantifies this accuracy, with numerical figures representing confidence levels for different labels on various parts of the plant: this represents a potential use-case for such a model in agriculture for crop monitoring and management.

These results indicate that YOLO can be used in real-time object detection and classification tasks like those common in precision agriculture. Given these findings, discussions about the YOLO model will revolve around its possible applications, including areas where it could be improved upon concerning detecting and classifying objects accurately at any given time. The efficiency of the technology may facilitate more refined agricultural systems, thereby increasing productivity levels. To put it differently, accurately identifying various stages of maturity among tomatoes or diseases found on leaves by a model may significantly affect crop health.

CONCLUSION

The study shows how effective the YOLO model is in object detection and real-time classification when applied to tomato farming. The ability of this model to accurately detect and classify different levels of ripeness in tomatoes as well as diseases that can affect leaves is very important for monitoring the health of crops and preventing diseases in precision agriculture. Hence, the YOLO model could be a powerful real-time object detection and classification tool, such as precision agriculture. Moreover, it reflects on possible improvements to the YOLO model. Some challenges experienced during accurately identifying and classifying objects in real time are also identified. Finally, the model is effective here and provides a basis for enhancing agricultural technology, making it more efficient and productive. It remains crucial that future global farming practices rely on AI's role in agriculture, which secures food through development.

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