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RICE CROP DISEASE DETECTION USING YOLO ALGORITHM

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***Abstract*—There are many hurdles in trying to produce a successful yield from the crops. Crops are eventually infested by pests or infected by diseases which destroys a significant amount of the crop if not detected in the early stages.Rice is one of the major food crops of India. The majority of the population consume rice as their daily meal. But every year, a significant part of the crop is destroyed by diseases. Therefore, detection and prevention of such diseases in advance will help us have a greater yield and healthy crop. According to the statistics given by International Rice Research Institute, about 37% of the crop is lost to diseases annually. Modern technology has advanced enough where farmers are able to make out the diseases from the symptoms shown by the crop and searching for them in the internet through smartphones. So here, we propose a method to detect the diseases with the help of YOLO object detection algorithm. A thorough research was conducted into the mechanisms of farming and the type of conditions the crops were grown in, along with the prevention methods of diseases. With the help of image processing and supervised learning, our system detects the diseases so that necessary steps can be taken towards the cure. A number of images were taken and pre-processed before giving them to the model for training. We were able to achieve an accuracy of 98.92 percent. This model can be used to help the farmers to detect the diseases and curb the disease in its early stages so that the yield is maximized at the end of the year.**

Keywords*—deep learning, AI, supervised learning, classification, cnn, yolo

I. INTRODUCTION

Rice is cultivated in more than 100 countries with varying environmental conditions [1]. It is a major food crop in majority of the Asian countries [2]. Unfortunately, there are a number of diseases which can weaken the crop and damage the yield if not treated on time. Thus, it is important that these diseases are cured in time [3]. Rice crop is destroyed not only by diseases but several pests as well [4]. Of the 266 species of insects found in the rice fields, more than 40 of them are pests [5]. Therefore, the need for the timely detection of the disease or pest becomes the utmost priority[6].

Countries that grow rice, have developed their own programs to increase development of rice crops. For example, in Bangladesh, they promised to increase the production of rice significantly by the introduction of green revolution package [7]. A training program that provides science-based information to farmers about integrated pest and disease management was founded by Farmer Schools in Thailand. This helps the farmers to maximize the yield while reducing the diseases [8]. Due to the public policy, some of the developed countries have neglected the farmers and their need for education of the evolving agricultural science [9]. Though chemicals play a key role in abstaining the diseases [10], they are also likely polluting the environment. The chemicals should only be used when there are really needed so that the drawbacks of their usage can be reduced [12]. IPM (Integrated Pest Management) is a framework that helps the agriculture practitioners to detect the diseases and pests and to make tough decisions by providing them with the scientific knowledgeand technology [11]. The in-time detection of lethal diseases can be made possible to the farmers with the help of technology [13]. Advance computing technologies can help farmers make decisions on many aspects of growing crops. Proper diagnosis of the crop in fields is a key point in maximizing the yield [14]. [13]. Unfortunately, the amount of applications of technology is by far less in the field of agriculture compared to other fields like engineering, medicine etc.Due to this, it is still a big problem for the agricultural society to develop a system for the detection of diseases and calculating the percentage of loss in yield in a timely manner [15]. For most cases human visually conducts the treatment of diseases. Trained examiners may be effective in identifying plant diseases, but some related drawbacks may be detrimental to disease recognition efforts [3]. Application of advanced technological tools in the field of agriculture can greatly help the farmers to detect and prevent diseases without waiting for an expert's aid [16]. Computer vision along with deep learning and image processing has been applied in various fields of science which have proven to have applications even in the field of the today's evolving agriculture [17]. Machine vision techniques are used in addition to the computer vision techniques which are playing a key role in the protection of crops [18]. Further addition of digital image processing has led to the idea of crop-field management [19]. The use of modern computer vision and machine vision techniques helps us to implement a disease detection system which not only reduces the amount of time and energy but also performs with higher accuracy[20].

Many object detection and classification models have been used for the timely detection and control of the diseases [21]. In Kawasaki et Research. Al., a CNN based disease classification system was implemented which achieved high classification efficiency by training images alone [22]. Sladojevic et. in research. Al., a deep convolutional network was used to build a plant disease recognition model based on the classification of the leaf image. In the field of image classification [23], Convolutional neural networks (CNN) achieved amazing result. Yao and. In their research, Al. suggested a model for the detection and recognition of White-backedplanthoppers using a three-layered approach. This approach has been proven to be successful in identifying various planthoppers developmental stages at rice plants [24].

As we can see, many researches have conducted by various authors on the problem statement. Next, we go through the basic architectures and the steps involved at each step and usefulness of these architectures in different fields and their applications. In the next chapter we go through the methodology opted by us and the design details i.e., our methodology and the implementation of our method into a working prototype. In the next chapter we discuss about the reliability and usefulness of our model, the results both in simulation and in real-time and the comparison of our design with the other existing models.

II. Literature Survey

The backend or the main architecture behind the YOLO algorithm is CNN (convolutional neural network). CNNs are specialized in the detection and classification of image data. Similar to other neural networks, CNNs have three types of layers- input layer, hidden layer(s) and an output layer.

The layers of the network consist of a number of neurons each connected to neurons in the successive layer. These connections between neurons are known as synapse and each synapse is associated with a particular weight(wgt). The CNN extracts the main features of the given image with the help of feature extractors(f_{ext}). With the help of zero padding(padd), the input image is padded with additional zeros to overcome the shrinkage of the image which occurs during convolution. These feature extractors(kernels) make up a feature map with all the features of the given input image. All these operations are performed in the form of matrices. A ReLu activation function is used for convolution. A pooling layer, conventionally a max pooling layer is used to extract the distinguishing features of the image. This is for a single operation with convolution layer, and max-pooling layer. The final layers of a conventional CNN involve a flattening layer (to reduce the higher dimension data to a single dimension) and a fully connected layer. Normally a SoftMax activation function is used at the output layer which classifies the objects based on the class probabilities. A loss function($loss_{func}$) is also associated with the network to calculate the loss/error(err_{calc}) during training. Generally, categorical_crossentropy function is used to calculate the loss associated with the training of CNN classification models.

Let's say there is an image(img) of dimensions v×v (v_i), which is being given to the CNN network. A kernel(kern) of dimensions p×p (p_i) is being used with valid-padding (no padding). A max pooling layer of size c x c is being used with a stride (str) of 1. The output of the given convolution layer($conv_{out}$) will be a feature map of the order (v-p+1, v-p+1). This is again sent to a max pooling layer to extract the more distinguished features which gives an output with the dimensions ((v-p+1)/c, (v-p+1/c)). These are again given to a convolution layer and the process is repeated for as many convolution layers in the network. In this way each convolution layer extracts a specific feature of the image. As the number of convolution layers increases so does the feature extracting ability of the network. The output of the CNN(Cnn_{out}) is the class probabilities and the class with highest probability is predicted as the output.

$$Cnn_{out} = img * f_{ext} = \sum_{i=0}^{N} wgt_i * img_i * f_{ext_i} \quad (1)$$

$$conv_{out} = ((v_i - 2padd + p_i)/str) + 1 \quad (2)$$

$$err_{calc} = \left(\frac{1}{N}\right) \sum_{i=0}^{N} \nabla_i \times loss_{func}\left(img_i, Cnn_{out_i}, wgt_i\right) \quad (3)$$

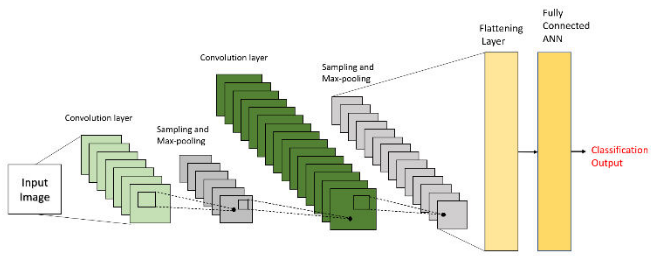

Fig. 1: Basic CNN architecture

YOLO is structured in the same way but the output layer of the YOLO consists of a fully connected convolutional layer. Where a CNN implements the sliding window technique for the detection of objects, the YOLO algorithm directly predicts the class probabilities and bounding boxes of the object based on the position of midpoint (center) of the object in a given grid of the input image. [25]

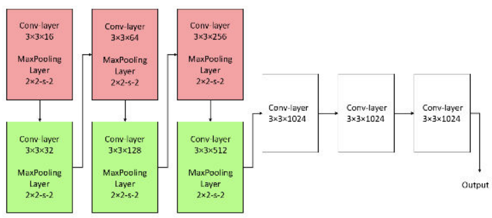

Fig.2: Tiny_Yolov3 architecture

Tiny_yolov3 is proved to be the fastest of all the yolo versions developed so far. The working of tiny_yolov3 is similar to that of a conventional yolo model. The YOLO algorithm divides the image into a grid of dimensions T×T. The prediction or output (yolo_out) of the yolo algorithm is a function of the probability(p_{obj}) or confidence that an object exists in a given grid square, the position of midpoint (center) of the object (mid_x, mid_y) in the grid square, the height (box_h) and width (box_w) of the bounding box and the class probabilities (class1, class2, class3……classN). The prediction of the object depends upon the probability of an object existing(p_{obj}) in a given square of a grid. If there is no object, then pobj becomes zero and all other quantities become don't cares (?).

$$yolo\_out = f(p_{obj}, mid_x, mid_y, box_h, box_w, class1, class2, class3, \ldots., classN) \quad (4)$$

Each square of the grid evaluates only one set of class probabilities at a time so the number of objects detected by a single grid is one. To detect more objects, we use the help of anchors. Anchors are useful when more than a single object is present or assigned to a given square of the grid. Based on the shape of the object, the model can classify and detect the objects in the given input.

A number of predictions are made for the same object from which only one is very close to the ground truth. To select an accurate prediction, we use a method called non max suppression (NMS). Let us assume N predictions have been made, each with an individual confidence of C_{nd} and a threshold value of Th. Let the output of NMS method be $final_{out}$. Firstly, a prediction with a high value of C_{nd} is selected and assumed to be $final_{out.}$ This prediction is then compared with another prediction i.e., IOU (intersection over union) of these two predictions is calculated.IOU is a method used to calculate the overlapping area between two predictions. This process is repeated for all the predictions. If the value is greater than the threshold value 'Th', then that prediction is removed. Normally, a threshold of 0.5 is selected. This is repeated until only one prediction remains which is $final_{out.}$ In this way, an object is detected only once by the model.

$$IOU = Area\ of\ intersection / Area\ of\ union \quad (5)$$

Yolo is extremely fast, since, unlike other classification models, it uses only one evaluation layer. Therefore, it is used in various real time applications such as traffic monitoring and pedestrian detection. A Yolo_v2 network is used. Here the number of layers of Yolo_v2 is changes from 16 to 12 layers in the route layer of the passthrough layer which results in an improvised network YOLO-R. This network is then trained to detect the pedestrians [26].

Yolo is also used in real time face detection. The algorithms mainly used for this application are YOLO and R-CNN (regional CNN).The differences in the architecture between these two networks is that in the yolo model, the training, extraction of details and classification are all done in a single network. Yolo considers the detection process as a regression problemIt is very fast as the classification and prediction of the object is all done by a single evaluating layer. RCNN on the other hand classifies the objects in two stages i.e., the classification of the object (category)and the location of the object and bounding boxes (regression). Since it's a two-stage detection, it is very much slower than YOLO. An improved version of R-CNN known as Fast R-CNN is also developed which is faster than a regular R-CNN but still slower than YOLO[27]

In UAV (Unmanned aerial Vehicle) network, there is a large background noise from the recorded or collected video images and also the dimensions of the vehicle are scaled so much that it is harder to detect a vehicle from the video footage.This problem can be solved by the yolo algorithm as it not only detects the smaller objects through clustering the estimated sizes but also helps the system to extract the smaller features of the vehicle through optimal pooling strategy and dense topology.[28]

III. PROPOSED METHOD

In our proposed method we use the varied version of the yolo algorithm which is tiny_yolov3. This algorithm has only nine convolutional layers as opposed to the basic yolo algorithm which has twenty-one convolutional layers. We take in the disease's physical characteristics as the input. These are processed and given to our model which in turn is trained to detect and classify the disease. The output of our proposed method is a disease detection and classification system.

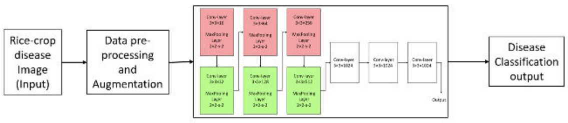

Fig. 3: Our proposed method

We prepared our dataset from the Kaggle dataset repository, UCI machine learning repository and the dataset provided to us by the SmartBridge organization. The dataset consists of 2 classes (False Smut and Leaf Blast) of images with 500 images per each class. These images are again augmented to make a total of 2000 images out of which 1600 images are used as training set; 200 images are used as test set and the remaining are used as validation set.

We divided the training set into a batch-size of 64. We set the learning rate to 0.001. A decay of 0.0005 is employed so the weights don't take on large values. The random parameter is set to one so as to resize the input images to various sizes and generalize the objects thus augmenting data. The parameters jitter, angle, hue and saturation are also employed for the data augmentation. The thresh parameter is the IOU value which is set to 0.5 and the ignore_thresh to 0.7. This ensures that a valid prediction is selected from the various other predictions during non-max suppression. Six anchors are initialized to detect the different diseases occurring in different sizes. Since the diseases may occur in many forms, it is always a good practice to initialize a decent number of anchor boxes such that the detection (bounding box) is always accurate. Note that initialization of a lot of bounding boxes may also cause to predict false positives where in the model confuses one object (disease) with another. So, the number of anchor boxes should not be less as it may neglect few objects and not too high as to predict false positives.

We used the 'leaky' activation function for the initial convolution layers. We also perform zero padding of size (1,1) to avoid the loss in resolution. For the last convolutional layer, we use the 'linear' activation function. In this way, the prediction of the disease becomes a regression problem as is viewed by our tiny_yolov3 model.

We used a remote Linux server for developing our model along with DarkNet. DarkNet framework is helpful in running faster computations with support of GPU. Computations run a lot faster on GPUs than conventional CPUs. It is written in CUDA and C and supports all CUDA supported GPUs. In order to train the model, we used Jetson nano (CUDA supported) as our GPU platform, so as to reduce the training time. We take the help of CUDA and OpenCV and compile the darknet to start our training. It's 128 CUDA cores significantly increase the speed of computing.After the training, the weights are frozen and stored for further testing and classification.

IV. Results and Discussions

The model is thoroughly designed to detect even the tiniest of the details. We up-sample the given input thus profoundly extracting the features. This is done because the image loses its resolution after successive convolutions and thus some of the important features might be lost. Up-sampling makes sure that the model covers the depth of the image and each and every minute detail is extracted. We achieved an accuracy of 98.92% which is by far the highest for any state-of-the-art object detection algorithm. The detection can be done onboard the Jetson nano board with the help of raspberry-pi camera.

The detection can also be performed from a PC or laptop with the help of python and OpenCV. The webcam can be used to detect the disease in real time. With the help of libraries such as Tkinter, we can detect the disease from an image of the diseased plant. In this way, it's very flexible to detect the disease. Though the mode of detection is changing, the accuracy of the model remains the same thus making it a reliable object detection model.

Fig. 5 (a) Detection of False Smut disease in Rice crop using YOLO algorithm-1

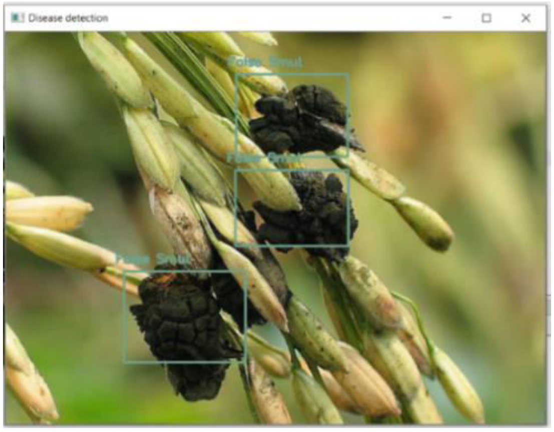

Fig. 5 (b)Detection of False Smut disease in Rice crop using YOLO algorithm-2

Fig. 6 (a)Detection of Leaf Blast disease in rice crop using Yolo algorithm-1

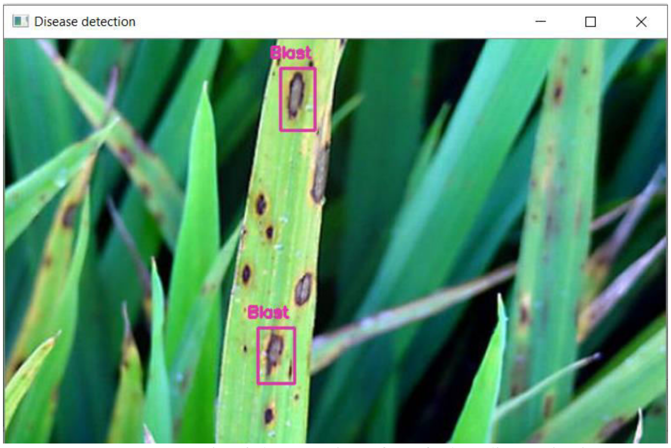

Fig. 6 (b)Detection of Leaf Blast disease in rice crop using Yolo algorithm-2

TABLE I. COMPARISON WITH OTHER EXISTING METHODS[29]

Model	Accuracy
VGG16	97.12
MobileNetv2	96.12
NasNet Mobile	96.95
Inception V3	96.37
Tiny_YoloV3*	98.92

We can see that our model has the highest accuracy compared to other existing models. Also, our model is faster with a refresh rate of about 45 fps whereas the refresh rate for other models is restricted around 15-20fps. Though the localization errors are more in yolo model, it is faster than the other models which makes it the most reliable algorithm suited for the problem.

V. CONCLUSION

In this paper, we proposed a deep learning model based on tiny_yolov3 algorithm to detect the rice crop diseases. The model is very fast and hence it can be applied in real time for the detection and classification of the rice disease. This is helpful in detecting the diseases in the early stages so the farmers can take preventive measures and protect the crop from destruction, thus maximizing the annual yield. The resolution of the camera doesn't matter as the model is designed to detect even the smallest of the features and thus obsoleting the need for high resolution cameras. Future works include a model with more classes of diseases. Adding extra classes to the model results in a fully operational rice crop disease classifier where it can detect and classify all the diseases.The algorithm achieved an accuracy of 98.92%. Since we designed our model based on tiny_yolov3, it can be further applied to detect pests as well making it flexible for development of new models.

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