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PADDY GRAIN MATURITY ESTIMATION USING DEEP LEARNING APPROACH- YOLOMATURITY

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ABSTRACT

The detection of crop maturity is one of the most crucial parts of precision farming. Crop maturity estimation can support farmers to harvest their crop at a proper time. Crop harvesting in premature/post mature can lead to crop quality degradation. We have proposed an approach using deep learning that can automate the process of paddy grain maturity detection. Our proposed approach YOLOMaturity (YOLOResNet70Combined) has performed well on available dataset. We have compared our approach with the modifications of the YOLO algorithms, and it outperformed other discussed approaches. Proposed approach yield 10.3 %, 9.6 %, 12.4%, 12.1%, 8.4%, 6.5% and 9.3% better mAP(Mean Average Precision) compared to YOLOv4RCombined, YOLOv4FPN, YOLOv5sFPN, YOLOv5sR, YOLOResNet43HardSwish,YOLOResNet43Combined and YOLOResNet70HardSwish respectively. Proposed approach furnished validation accuracy 97.7 %, training accuracy 97%, validation loss 7.6% and training loss 10%. These results indicate that our proposed approach have promising result and can be utilized for automatic real-time paddy grain maturity.

Keywords: *Precision Farming, Deep Learning, Maturity Detection, Paddy Grain, YOLOResNet70*

1. INTRODUCTION

Reliable predictions of crop yields can aid farmers in diagnosing crop conditions and implementing essential production enhancements, as well as assist policymakers to successfully manage local food supplies, assure timely imports and exports, and attain food security [1]. In addition, the recent appearance of crucial issues such as climate change, severe droughts, rising temperatures, and an increase in the frequency of extreme weather events has created substantial obstacles to the accurate prediction of crop output [2]. Consequently, much effort is currently being invested in crop yield forecasting. Particularly, the use of satellite pictures, which is the sole way to anticipate agricultural yields in vast and inaccessible regions, has gained popularity [3]. However, reliable prediction remains difficult due to the need to account for a multitude of environmental elements, cropping systems, management methods, model uncertainties, and unforeseen climate change challenges [4]. Consequently, an efficient method for crop yield prediction is required [5].

Long before the birth of the computer age, forward-thinking farmers engaged in what is now known as precision agriculture. They were able to deduce the origins of field variability and the necessary steps for attempting to increase crop yields. The farmers accomplished this by keeping track of their fields during the growing and harvesting seasons and used their acquired knowledge and experience to determine the best actions for the following year.

According to Wolfert et al. [6], the increase in data-producing devices and sensors has been an ongoing trend in agriculture, allowing farmers to transition to data-driven decision making. This is usually known as smart farming. Kamilaris et al. [7] provide a comprehensive assessment of the various objectives and approaches employed in smart farming.

Crop maturity detection is one of the most important tasks in agriculture sector. Quality of grain majorly depends on crop harvesting at a proper time. If crop harvesting is done pre/post maturity, then it leads to grain quality degradation and hence market value of grain decreases which incurs huge loss to the farmers. At maturity, a crop generates its maximum dry matter yield, after which the grains stop growing and simply lose moisture. When harvested at the optimal time, grain maintains its high quality and retains its market value. If you harvest your crop too soon, you will end up with a higher percentage of unfilled or

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immature grains. This results in a poor yield and increases the amount of grain that is broken when it is milled. Rice that has been harvested too late will have higher breakage and excessive loss because of the late harvest. The germination potential of rice seed is also impacted by the timing of harvesting [8].
Traditional method to detect maturity level of crop for harvesting is completely based on experience and is a manual process and hence chance of wrong prediction is more. Many a time this leads to grain quality degradation.

Some of the basic ways to determine crop maturity are as follows-

Rain moisture content

The optimal moisture content range for grains is between 20 and 25 percent (wet basis). The texture of grains when crushed between the teeth should be solid but not brittle.

Paddy grains per panicle

When between 80 and 85 percent of the grains are straw, the crop should be cut (i.e., yellow-colored).

The number of days after planting the seed

In general, the optimal time to harvest late-maturing varieties is between 130 and 136 days after sowing, while medium-maturing varieties should be harvested between 113 and 125 days, and early maturing varieties should be harvested after 110 days.

Total days following departure

The optimal time for harvesting during the dry season is between 28 and 35 days after heading. 32 to 38 days after heading is the optimal period to harvest during the rainy season.

Other things to consider

To prevent the grain from becoming rewetted and to decrease the amount of broken grain, the harvest must be timed such that threshing can occur as quickly as possible after cutting.
If the crop has a lot of surface moisture (for instance, because it recently rained or because it is early in the morning), it is better to wait until the surface moisture evaporates before harvesting.

When a crop reaches its maximum dry matter yield, the grains stop growing and only start to lose moisture [9]. In California, it was observed that a 10-day harvest delay decreased the head rice yield from 63.8% to 45.8% [10]. Shattering following a delayed harvest was observed to cause a yield loss of wheat of up to 17% in Canada [11]. Delay harvesting leads to rice chalkiness [12].
Nearly half of the world's population relies on rice as their primary food source, making it one of the most important cereal crops [13]. Sixteen percent of the world's total agricultural output is made up of the production of paddy as shown in Figure 1.
Population is increasing at a rapid rate and to satisfy the hunger of the increasing population there is need to enhance the production of rice and to maintain the quality of rice [14]. But relying on visual observation to determine the maturity stage of rice is not efficient. There is need of such an approach which can detect maturity level of rice efficiently. Traditional methods are time consuming and cannot guarantee the accuracy level of maturity detection. There is need of a simple, effective, and less time-consuming method with a high level of accuracy.
During the maturation process, crop maturity can be estimated by measuring the weight of oven-dried samples and developing regression models [15]. In addition, numerous grain crops, including wheat, [16] barley, [17] maize, [18] and rapeseed, have had success with the application of determining the optimal harvest date [19] based on grain moisture content. These methods cannot be used for real-time applications since they are expensive, labor-intensive, and time-consuming. Therefore, the rice's maturity must be determined using a method that is practical, effective, and fair.
For last few years, we have witnessed the relevance of Computer vision, machine learning, and deep learning are delivering promising results in numerous academic disciplines. On the task of yield prediction, multiple classic machine learning approaches have been utilized. However, it can be challenging to identify ideal characteristics, and older approaches have limited data-learning capabilities. With the evolution of computing technology, it is now possible to create and train unique multilayer algorithms. These techniques are typically known as deep learning. Convolutional Neural Networks (CNNs) have shown to be the most effective deep learning paradigm for picture categorization and analysis. In the case of CNNs, no precalculation of features is required, as feature extraction is accomplished by the convolutional layers of the network and optimal features are obtained during training. Due to its structure, CNNs require massive quantities of training data to converge [20]. The advantage of CNNs in agricultural yield prediction over conventional

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machine learning approaches is explored by You et al. [21]. CNNs have been effectively applied to crop categorization [22] and weed identification [23].We have observed the application of deep learning in the diagnosis and categorization of various diseases, image captioning, and the detection of moving objects [24]. Application of deep learning has resolved many real time issues efficiently. We can rely on deep learning approaches to detect the maturity level of plant crops.

Zhu et al. [25] proposed using support vector machines to identify the heading stage of wheat crops. Ji et al. [26] suggested an SVM method for detecting apples with an 89% accuracy rate. In their study, Kausar et al. [27] suggested a Pure CNN model with a low number of parameters for categorising fruits, achieving an accuracy of 98.88%. In their paper, the writers categorise a variety of fruits. Mazen et al. [28] proposed a method that can distinguish between unripe, ripe, and overripe fruits depending on their maturity stage. They have categorised bananas according to (number of brown spots divided by total surface area). More brown spots indicate that bananas are ripe. The maturity of the banana is determined. In addition, they compared their proposed system against other classification algorithms, including SVM [29], KNN [30], decision tree [31], Nave Bayes [32], and discriminant analysis. Guo et al. [33] suggested a method for accurately recognising rice flowering panicles in high-definition RGB images of wild rice fields. They merged the sliding window method with SVM classification. Johnson [34] used regression tree to forecast maize and soybean harvests at the county level in the US.Cie et al. [35] tested three machine learning (ML) approaches, including Support Vector Machine (SVM), random forest (RF), and neural network (NN), with a classical regression method (Least Absolute Shrinkage and Selection Operator-LASSO) for wheat yield prediction in Australia. Results demonstrated that ML approaches are demonstrably superior to conventional regression techniques. Khaki et al. [36] Presented the fact that Deep Learning (DL) contains numerous stacked non-linear layers, each of which can turn the raw input data into a more abstract representation.Consequently, DL has proven a potent and effective tool for a range of high-impact concerns, including image identification [37], disease detection [38], classification [39], and maturity estimate [40].Yang et al. [41] trained a Convolutional Neural Network to estimate field-level rice yield using very high-resolution UAV photos. They asserted that the outcomes were significantly superior to those of the conventional Vegetation index (VI)-based statistical model. Despite this, the use of machine learning and deep learning to yield estimation is still in its development, particularly in India.

Recent advances in deep learning (DL) techniques based on end-to-end training via deep hidden layers have enabled sophisticated and reliable agricultural production prediction. Thus, DL is actively employed for crop yield forecasting. Specifically, comparative studies have demonstrated that DL models are superior to existing regression or ML approaches for predicting crop productivity [42].Chlingaryan et al. [43] conducted a review on the use of machine learning for nitrogen status estimation.The research concludes that rapid advances in sensing technologies and ML approaches will lead to cost-effective agriculture solutions.Elavarasan et al. [44] A literature review was conducted on machine learning algorithms for crop production prediction based on climate factors. The article recommends a comprehensive search for crop yield influencing variables.

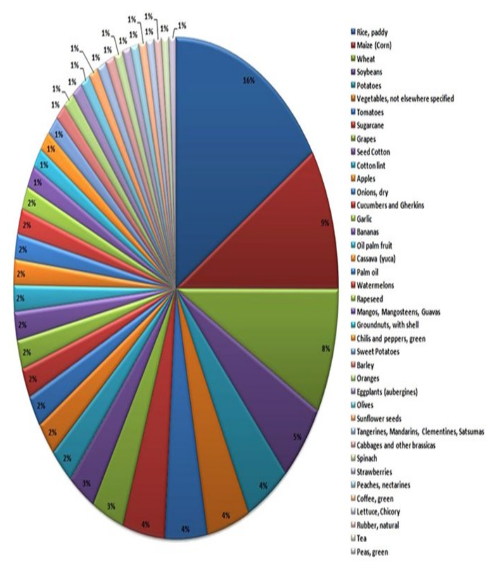

Figure 1. The United Nations' Food And Agriculture Organization's Estimates Of Global Agricultural Output

For a real time, maturity detection of rice grain, we require a model which can furnish promising result with minimum human involvement. Our aim here is to develop a model which can ensure the maturity of the rice grain. To develop a model that can precisely confirm whether rice grain is mature for

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cultivation or require more time to cultivate. If rice grain is harvested in premature stage, then certainly its nutritional value will degrade and may also lead to chalkiness in rice grain [45].Zhang et al. [46] have developed an algorithm based on improved Faster R-CNN for automatic identification of multiple developmental stages of rice spikes. They collected data from greenhouse pots and field during 2019-2021. Following training, the model's accuracy on the training and validation sets reached as high as 97.55% and 96.68%, respectively.

With the emergence of deep learning techniques and to have high quality product there is need to have an approach which can furnish better reliable result. Ablation study is a must to select the best model for the purpose.

After going through the various approaches as suggested by many authors we found that there is potential to improve the existing approaches. Existing approaches lack proper feature extraction and feature selection methods. Ablation study is a must in order to find the suitable parameters that can enhance the accuracy of maturity detection of paddy. Very less work has been done in the domain of paddy maturity detection and with the increasing population and decreasing farm land it is very crucial to develop such an approach which can detect the maturity and hence rice quality and quantity can be enhanced. Ablation study which we have presented can motivate other researchers to work in this domain to propose more advanced and efficient methods to detect paddy maturity.

We propose deep learning approach YOLOMaturity detection algorithm to detect the maturity of rice grain. The remaining sections are organised as follows. Section 2 covers the Materials and Methodology used to detect rice grain maturity. The third section discusses experimental results and analysis, while the fourth section provides concluding remarks and future work.

2. MATERIALS AND METHODOLOGY

2.1 Image Acquisition

Sona Masoori paddy used in this paper for training and testing the proposed model were captured from Salempur Village, Ara, Bihar, India using digital camera (Canon EOS M50) with a resolution of 3648 × 2056 pixels in day light. The samples were captured at distances between 500 mm and 1000 mm, which corresponds to the optimal harvesting operation distance. Figure 2 depicts a sampling of the recorded photos. Total of 400 images of matured paddy and 350 images of pre-matured paddy were captured. The maximum chance of confusion regarding maturity of paddy grain arises during last around 20 days of near maturity period. We have captured continuous 5 days to collect pre-mature data and 3 days continuously captured matured paddy grain with the help of agriculture experts. Agriculture experts suggested that during last 20 days, confusion mainly arises whether paddy is mature enough for harvesting or not. Experts manually examines this by observing moisture level and color of the paddy grain, but this requires high level of expertise. Highly experienced farmers and agriculture experts helped us to collect the data for our research purpose. Using data augmentation, we generated more data from the existing dataset. Data augmentation technique also reduces the chance of over fitting [47]. Using data augmentation 2100 new pre-mature paddy data accounting to total 2450 pre-mature dataset and 2400 new matured paddy data generated accounting to total mature paddy dataset of size 2800. Randomly, 80% of data is separated for training and the remaining 20% for testing. The ground truth bounding boxes for training dataset were manually labelled using the labelImg graphical image annotation tool.

2.2 Image Annotation

Using the labelImg tool, bounding boxes were generated, and annotation files were saved in YOLO format. From a total of 750 pictures, 31,500 bounding boxes were produced. Images were meticulously annotated to prevent mis annotations.

Figure 2a: pre-mature paddy image

Figure 2b: pre-mature paddy image captured after 5 days of first image

Figure 2c: mature paddy image

Figure 2c: mature paddy image captured 2 days after first mature paddy image captured

2.3 Experimental Setup

Training and testing were conducted on 11th Generation Intel(R) Core (TM) i5-1135G7 processors running at 2.40GHz with 16 GB of RAM. Python was used to implement the proposed model on the Google Collaborator platform, enabling the virtual GPU.

2.4 Proposed Approach

The proposed YOLOMaturity approach is presented in Figure 3. We have used backbone with 70 layers of ResNet 70. The ResNet70 residual blocks were arranged as 1,2,8,8,4 to enhance the detection accuracy, speed and to overcome the issue of neuron degradation. The main purpose to integrate ResNet to proposed approach is to improve the network degradation problem and to enhance the speed and accuracy of the network. We have incorporated 1*1 convolution layer with ResNet70, and leaky ReLu activation function was used to the convolution layer to enhance the training speed and performance. FPN was used as neck in the proposed approach to obtain feature pyramids. We have modified original front detection layer (FDL*3) of YOLO3 to FDL*2 as this increased detection speed. We have incorporated IoU loss functions (DIoU and GIoU) for better performance and checking bounding box overlapping.

In our proposed approach, we have used combined activation function. In the same backbone residual block, the ReLu activation function activated the 1*1 convolution layer and the HardSwish activation layer activated the 3*3 convolution layer. Combined activation functions enhance the mapped features expressions and can help to enhance the feature extraction process and thus improves the performance of the proposed network by enabling proper non-linearity. After ResNet70 backbone we introduced SPPNet[48]. The SPP layer pools the features and provides outputs of fixed length, which are subsequently sent to the fully connected layers (or other classifiers).

Input image for both training and testing were fed to the proposed model of the dimension 512*512 pixels, learning rate 0.002, total number of epochs 3500, momentum 0.925, weight decay 0.0005, batch size 64. Auto anchor generation was used to generate anchor boxes.

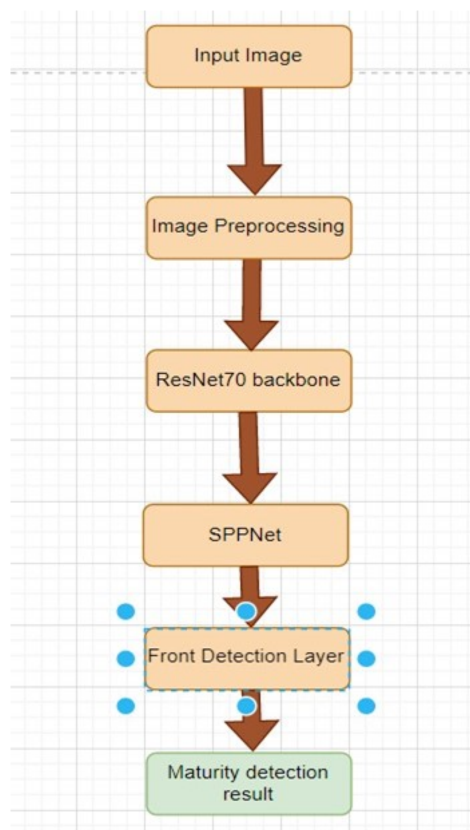

Figure 3: Proposed Approach Architecture

To assess the performance of the proposed model, we employed the performance evaluation criteria

Precision, Recall, F1 Score, and Mean Average Precision (mAP). Precision is the proportion of accurately predicted positive observations relative to the total number of correctly predicted positive observations. Recall is the proportion of accurately anticipated positive observations to all actual observations. The F1 Score is determined by the weighted average of Precision and Recall. Therefore, this score considers both false positives and false negatives. It is not as intuitive to comprehend as precision, but F1 is typically more beneficial than precision, especially if you have an uneven class distribution. When false positives and false negatives have comparable costs, accuracy is maximised. Average precision computes the mean precision value for recall values greater than 0 and less than 1. Formula in mathematics can be defined as:

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (1)$$

$$\text{Recall} = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (2)$$

$$\text{F1} = \frac{2 * Recall + Precision}{Recall + Precision} \quad (3)$$

$$\text{mAP} = \frac{1}{n} \sum_{k=1}^{k=n} AP_k \quad (4)$$

Where AP_k is the AP of class k, n is thenumber of classes.

Apart from the proposed YOLOMaturity (YOLOResNet70Combined) we have also trained and tested other modifications of YOLO model under the similar condition and same experimental setup. These are presented in Table 1.

3. EXPERIMENTAL RESULTS

Table 2 presents the experimental results of improved YOLO models. YOLOv4RCombined model has furnished better precision and F1 Score compared to YOLOv4FPN whereas mAP of YOLOv4FPN is better than YOLOv4RCombined. These were the two modifications of YOLO4 taken into consideration for comparative analysis. Compared to the modifications of YOLO4, YOLO5 modifications have generated poor results. Compared to YOLOResNet43HardSwish, YOLOResNet43Combined have better recall, F1 Score and mAP. Our Proposed Approach YOLOMaturity (YOLOResNet70Combined), has produced greater precision, recall, F1 Score, and mAP than the other YOLO model variants. This indicates that combined activation functions Leaky and HardSwish have better impact on ResNet70.

Table 1: Modified Trained models

Model	Residual Block Arrangement	Backbone	Activation Function	Neck
YOLOv4RCombined	2,3,4,3,2	CSPDarkNet53	Leaky (1*1) and Hardmish(3*3)	FPN
YOLOv4FPN	2,3,4,3,2	CSPDarkNet35	HardMish	FPN
YOLOv5sFPN	1,3,4,3,2	Focus−CSPNet	Leaky (1*1) and HardMish(3*3)	FPN
YOLOv5sR	1,3,9,9,3	Focus−CSPNet	Leaky (1*1) and HardSwish(3*3)	PANet
YOLOResNet43HardSwish	2,3,4,3,2	ResNet43	HardSwish	FPN
YOLOResNet43Combined	2,3,4,3,2	ResNet43	Leaky (1*1) and HardSwish (3*3)	FPN
YOLOResNet70HardSwish	1,2,8,8,4	ResNet70	HardSwish	FPN
YOLOResNet70Combined	1,2,8,8,4	ResNet70	Leaky (1*1) and HardSwish(3*3)	FPN

Table 2: Experimental results of improved YOLO models

Model	Precision %	Recall %	F1 Score %	mAP %
YOLOv4RCombined	81	85	83	85.5
YOLOv4FPN	73	85	78.5	86.2
YOLOv5sFPN	53.8	83.4	65.4	83.4
YOLOv5sR	53.8	85.3	66	83.7
YOLOResNet43HardSwish	82	86.1	84	87.4
YOLOResNet43Combined	79	87.2	83	89.3
YOLOResNet70HardSwish	81	86	83.4	86.5
YOLOResNet70Combined	84	93	88.2	95.8

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Training and validation accuracy of the proposed YOLOMaturityapproach (YOLOResNet70Combined) is presented in Figure 4 and liveloss plot is presented in Figure 5. Training accuracy of the proposed approach was 97% and validation accuracy is 97.7%. Also training loss was 10% and validation loss was 7.6%.

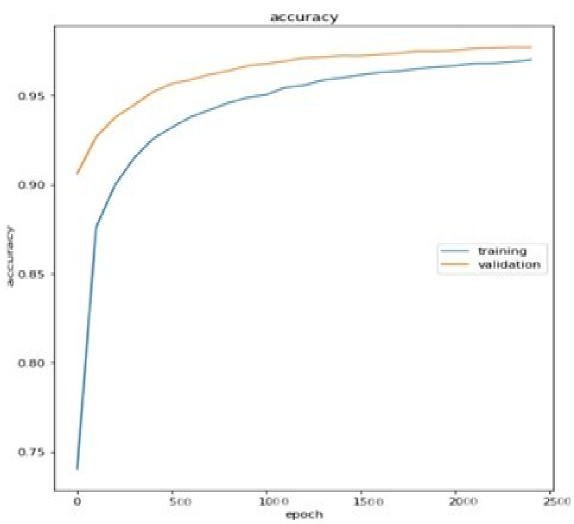

Figure 4: Training and Validation accuracy plot

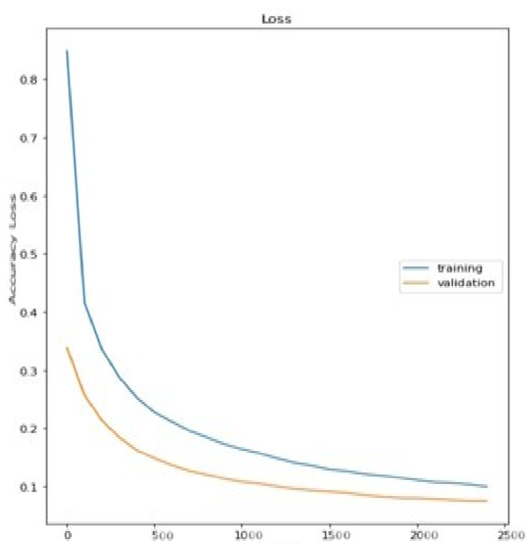

Figure 5: Live loss plot

4. CONCLUSION AND FUTURE WORK

We have presented our proposed approach and compared the proposed approach with different modification so the YOLO algorithms. We focused on optimizing the result. We focused primarily on the backbone, neck, and activation function in order to optimise the performance of YOLOResNet70 in detecting the maturity degree of paddy grains. We found that ResNet70 when combined with activation functions leaky and HardSwish it outperformed the other combinations and approaches presented in the paper.

Our proposed approach furnished better precision, recall, F1 score, and mAP as compared to other discussed approaches. Compared to YOLOResNet70HardSwish our proposed approach performed 9.3% better in respect to mAP. In future work, other backbones can be explored along with other combination of activation functions and different arrangements of residual blocks

In our proposed work we have focused on the role played by the activation function, arrangement of residual blocks, selection of backbone and neck. We have proposed that combined activation function can play an important role in accuracy enhancement for object detection. Arrangement of residual blocks does play an important role. Further work can be done by combining other activation functions.

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