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A Novel Approach for Identification of Weeds in Paddy By using Deep Learning Techniques

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ABSTRACT- Weed is an unwanted plant which is grown in agriculture land. The land which is not cultivated will be fully covered by Weeds. Management of weed is the major concern for farmer because the weed will reduce the crop production quantity. There are many methods to control the weeds, one of those methods is manual plucking which is expensive because it takes more time, consumes human work. Second is by applying any chemicals suggested by external experts. This may cause damage to the crop which is cultivated. Identifying weeds in early stage of crop growth and destroying them through proper method is most important for increasing the crop production. We proposed an efficient method for identifying and classifying weed in paddy field by using Deep learning-based computer vision techniques. We applied Semantic Segmentation model for classifying weeds in agriculture land. We trained our model with SegNet with different batch size of 16,32,64 and obtained a highest accuracy of 94.223 for dropout value 0.1 and batch size set to 32.

Keywords: Paddy Crop, Weeds, Segmentation, Computer vision, Deep Learning Model SegNet.

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1. INTRODUCTION

In India nearly 65% of agriculture land is utilized for cultivating Paddy. More than 80% of population consumes Rice as every day routine food. Increasing the production of Paddy growth is the only solution to satisfy the demand and need. Weeds causes damage in Rice production because they are grown unwantedly and occupy the place of Rice which leads to less production. The herbicide, pesticide, manure, fertilizer and water which is necessary for the crop to grow. All these nutritious elements were by default applied to the weeds in crop field, which will grow along with the crop. Proper control of weed is necessary to increase the crop production. Proper management of weed control is necessary for efficient plant growth.

Weeds can be classified into three types namely grasses, sedges and broad leaf.

Grasses-Echinocloa colonum (Jungle rice), Echinocloa crusgalli (Barn yard grass)

Sedges-Cyperus difformis (Common sedge), Cyperus iria (Umbrella sedge)

Broad-Leaf Weed-Commelina benghalensis (Day flower), Monochoria vaginalis (Oval-leafed Pond weed)

(a)

(b)

(c)

Figure 1: Major weeds in paddy (a)-Grasses (b)-Sedges (c)-Broad-Leaf Weed

2. RELATED WORKS

A. Subeesh et al. [1], proposed a model based on Deep Neural Network. They classified Weed and pepper crop leaf by using 1106 images from which 685 were pepper leaves images and 421 were of various weeds. They used Deep learning model namely AlexNet, GoogleNet, InceptionV3 and Xception. Training and testing were done by different batch size and epoch. They achieved accuracy of 97.7% by using Inception-V3 model.

Alex Olsenet al. [2], Collected Weed images from different land in Australia.They classified Eight Deep weeds in land by using e Inceptionv3 and ResNet50 CNN model. Their model achieved and average accuracy of 95.1% and 95.7%.

A S M Mahmudul Hasan et al. [3], made a survey on different Deep learning models used for classifying and detecting weeds from images. They mainly surveyed on how data acquisition is performed on images. Second, How many images were used for classifying weeds. Third what is the different Deep learning techniques used in the model and finally what is the performance metrics for every model. They finally concluded their review by applying supervised algorithm and by using labeled images, highest accuracy is obtained.

Radhika Kamath et al. [4] Proposed a model built on multiple classifier system which uses machine learning algorithm Support Vector machine and Random Forest for classifying weed and paddy crop in images. Their model achieved an accuracy of 91.36% by using multiple classifier system which performs better than single classifier system.

Haichen, Jiang et al. [5], Proposed the model with machine learning algorithms support vector machine. They used the model in the combination of VGG16+SVM for classification. Their model achieved an accuracy of 96.4%. They used 4245 images of both plant and weed images of wheat, corn and sugar beet.

Xu M et al. [6], proposed Fully Convolutional Network for semantic segmentation by using SegNet. They compared the accuracy of SegNet model with FCN and U-Net model. SegNet method achieved an accuracy of 92.7%.

Radhika Kamath et al. [7], proposed Deep learning based semantic segmentation model SegNet, PSPNet, U-Net for classifying two commonly grown weed along with paddy. They divided the dataset into two parts. First dataset consists of only weed plant images. Second dataset consist of weed and paddy images. PSPNet model and U-Net model obtained better result.

3. MATERIALS AND METHODS

The work is proposed on accurately identifying and classifying crop and weed in paddy field. First step is collection of data. We collected images from kaggle and plant village and some from online resources. Our model is mainly designed on focusing three classes of weeds namely grasses, sedges and broad-leaf weed. Data augmentation is applied for increasing the dataset size as the images collected were not sufficient.

3.1 Data Pre-processing

As the data were collected from different resources, normalization of the images is necessary for further processing. Removal of noise and light variation is done to all images.

3.2 Data Augmentation

Increase in the dataset will produce accurate result. More data will help the system for better training performance. Normal augmentation methods like image rotation, Flipping, Image cropping, Zooming were applied for generating new images. The quality of the dataset images were increased which avoids overfitting problem while processing.

We have taken 1239 images in the dataset which consist of 426 paddy,216 of Echinocloa colonum(Jungle rice), 124 of Echinocloa crusgalli (Barn yard grass), 114 of Cyperus difformis (Common sedge),86 of Cyperus iria (Umbrella sedge), 127 of Commelina benghalensis (Day flower) and 146 of Monochoria vaginalis (Oval-leafed pond weed) images. Further we divided our dataset in the ratio of 8:2 which consist of 80% of training data and remaining 20% of data for testing and validation.

4. PROPOSED DEEP LEARNING MODEL

SegNet is the Semantic Segmentation model is used along with deep learning model to obtain better accuracy. Image Segmentation is implemented in this model which uses the concept of encoding-decoding structure. To develop the low resolution feature map, endocder is used for downsampling the spatial resolution of image for classifying output labels.The decoder again upsamples the feature represented in the full resolution image. SegNet is one of the Semantic segmentaion model which we used in this work to obtain better performance and accuracy.

SegNet is the Semantic segmentation model which classifies each pixel of the image to its label class. SegNet has an Encoder network which is followed by decoder network. Encoder is usually pretrained classifier such as VGG or ResNet. The role of decoder is to project the low resolution feature which is learnt by the encoder on to the pixel for dense classification. Encoder used in SegNet model has 13 convolutional layers which is similar to VGG16 model. There is no fully connected layers to

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retain the highest resolution feature map at output. This reduces the parameters from 134M to 14.7M. The decoder also consist of 13 layers. Final output is passed to the Soft-Max Classifier to produce the probabilistic class output for each pixel individually.

The model is trained with different batch size of 16,32,64. Epoch is set to 30 and an early stopping is set to 10 epoch.

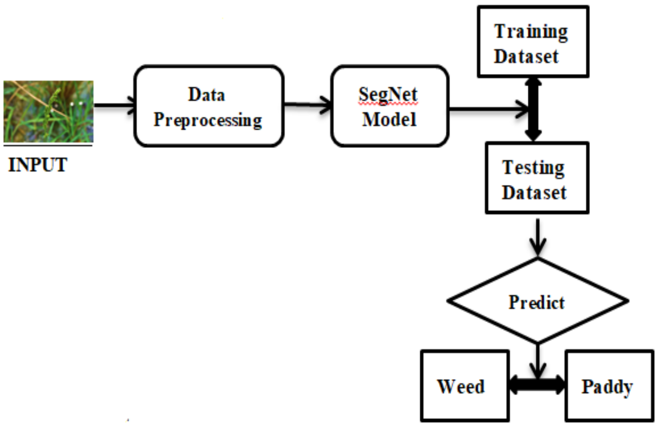

Figure 2: Architecture diagram of the proposed model

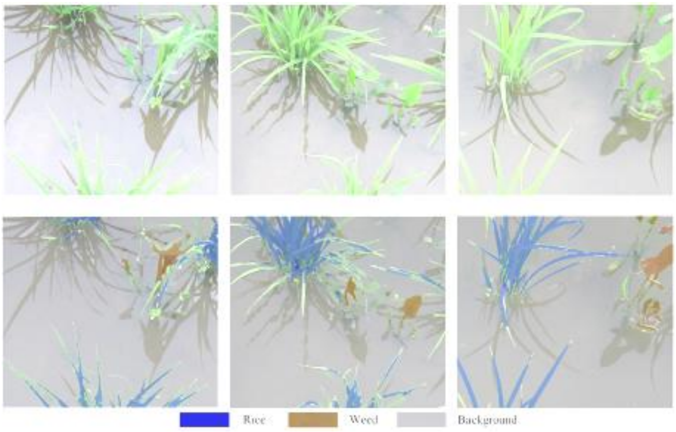

Figure 3: Sample output obtained by our proposed model

5. RESULTS AND DISCUSSION

The collected images were taken as input and all the preprocessing work is done on the input images. The labels for every image were defined and grouped together. Multiclass classification is performed in this model as the system will predict whether weed is present in the tested Image. SegNet model were used for predicting whether weed is present in the image. Two main components specified for classifying image are Convolutional_base and classifier. Convolutinal_base extracts all the features in the images and the classifier model classify the features based on the input image. The pretrained classifier uses fully connected layers followed by the output layer is activation function. In this model we use SoftMax activation function.

During training phase, loss function used in this model for multiclass classification is cross entropy loss. Batch size 32 predicted accurate weed classification for 30 epoch value and the initial rate for learning is set to 0.001.

We used confusion matrix for effective calculation of performance for deep learning classifier models. We have taken multi class classification problem so each image is classified as grass or sedges or broad-leaf weed or the paddy crop. For evaluating the performance of the model few metrics were taken into consideration. Accuracy, Precision, Recall and F1-score were the metrics evaluated.

$$Accuracy\ Metrics = \frac{TP+TN}{TP+TN+FP+FN}$$

$$Precision\ Metrics = \frac{TP}{TP+FP}$$

$$Recall\ Metrics = \frac{TP}{TP+FN}$$

$$F1\ Score\ Metrics = \frac{TP2*Precision*Recall}{Precision*Recall}$$

Where, TP-True Positive, TN-True Negative, FP- False Positive, FN-False Negative.

Classification is done by our deep learning model SegNet for calculating the performance.

TRUE POSITIVE (TP): A Weed which is actually present in field along with paddy and classified as Weed is present (TP).
TRUE NEGATIVE (TN): A Weed is not present in the paddy field image and the system classifies; no weed is present (TN).
FALSE POSITIVE (FP): A Weed is not present in the paddy field image and the system classifies, weed is present (FP).
FALSE NEGATIVE (FN): A Weed which is actually present in field image along with paddy image and the model classified as Weed is not present (FN).

If there is a confusion in classifying whether the Weed is present or not in the image of paddy field, we made a classification of data inside the matrix called as confusion matrix. SegNet model Accuracy can be computed by using Confusion Matrix which classifies data correctly into its label.

SegNet Model accuracy of varying different dropout, batch size and epoch is shown in the following *table.*

Table 1: Accuracy of SegNet model by different batchsize and dropout

Dropout	Batchsize	Epoch	SegNet Accuracy
0.1	16	30	93.624
	32	30	94.223
0.3	16	30	90.264
	32	30	91.133
0.5	16	30	92.164
	32	30	91.352

Dropout is set to 0.1, 0.3,0.5 and tested for the different batch size of 10, 20, 30. When compared with other model Batch size 30 gave the accurate result for SegNet model. Adam optimizer is used which obtains high accuracy in segmentation and

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classification of weed from paddy images. The Proposed model accurately classified different weed classes from paddy images. To check if the model is trained sufficiently, we can visualize in graph. We can calculate Training vs. validation loss or training vs. validation accuracy over number of batch size and Epoch. Either underfitting or Overfitting problem can be easily identified while visualizing the graph and can easily identify our model how it has trained.

The dataset is imported and splitted into three sets: Training, Validation and Testing. To train our Deep learning SegNet model we use Training data which is of 64%. To check whether the model is trained well we need to check the fitness of the model by using 16% of validation data in validation model. Remaining 20% of entire data is used as Test set.

Following graph shows the different dropout and batch size used in SegNet model for calculating accuracy.

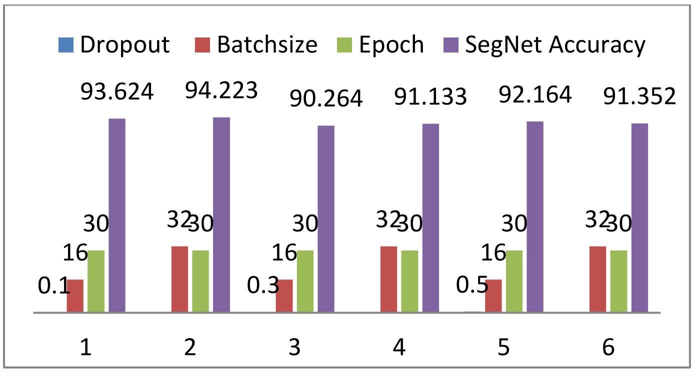

Figure 3: Graph shows the SegNet model accuracy by using different dropout

Loss and accuracy is calculated for every epoch and graph is plotted. Based on the result, optimization is obtained from which we can come to a conclusion whether changes can be done in architecture of the model.

Training Loss is used to calculate how our deep learning model SegNet fits the training data. This specifies how it checks and assesses the error of SegNet model on portion of dataset which is initially used for train the model known as training set. Train loss is calculated by taking sum of errors in each example image of training set. Train loss should be calculated after each batch. Here, we used different batch size as 16 and 32 for measuring batch size. Following graph represent visual view of train loss.

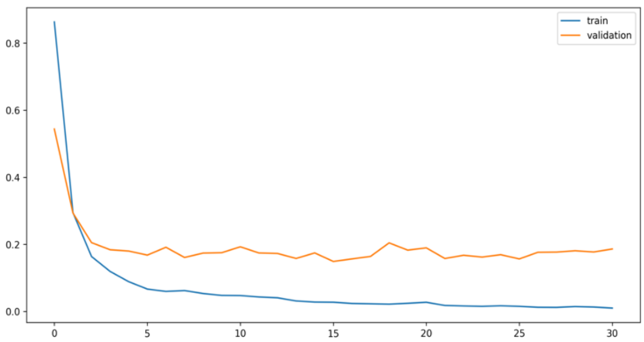

Figure 4: Train and Validation loss of SegNet Model

Validation Loss is used to calculate the performance of our Deep learning model SegNet on Validation Set. To Validate the performance of our SegNet model we use some portion of dataset known as Validation Set. Validation loss is also calculated by taking sum of errors in each example image of validation set. After every epoch validation loss is calculated. In this model we have set the Epoch value as 30. The following learning curve is calculated for training and validation loss of our SegNet model.

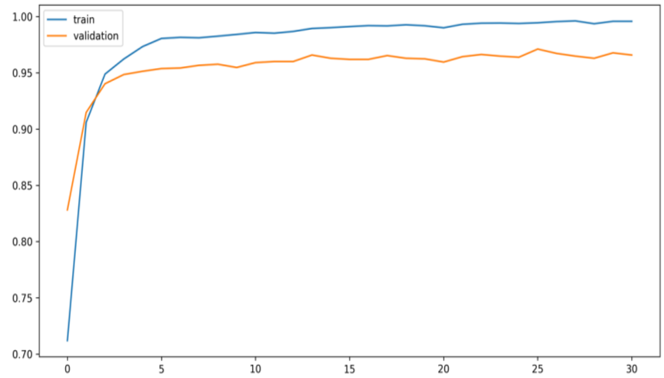

Figure 5: Train and Validation accuracy of SegNet Model

6. CONCLUSION

This proposed model uses SegNet based Semantic Segmentation process for classification. We tried our model with different Dropout, Batchsize and Epoch values. SegNet based semantic segmentation model worked better and achieved a highest accuracy of 94.223 for dropout value 0.1 and batch size set to 32. Our future work will be based on collecting weed land paddy crop images from real time environment and applying different models for predicting and classifying weeds. Since, the data which we collected and used in this model is not sufficient. If the dataset size is increased with more real field images the performance and accuracy of the system will also get increased. Our model will help the farmers for easily identify the weeds in early stage and can take effective measures to control the weed growth in early stage. The economic loss caused by weed can be reduced which results in increase in production of Paddy.

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