Integrating Fuzzy Based Mask RCNN Model for Accurate FHB Severity Estimation in Wheat

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ABSTRACT

The Fusarium Head Blight (FHB) disease is the most frequent disease among all types of wheat diseases. The FHB disease originates through Fusarium graminearum fungus. Once, the FHB fungus is transferred to the wheat plant, the complete wheat spike kernel is damaged. In this study, the fuzzy-based Mask Region-based Convolutional Neural Network (MRCNN) model has been trained to recognize FHB disease along with their severity in a real-time manner. The main aim of this study is to extract individual wheat spikes from wheat plant images and determine their severity level. The fuzzy-based MRCNN model extracts 13,353 from 953 wheat plant images. Among from total number of extracted individual spikes, a total number of 6842 diseased spikes were used to calculate the FHB disease severity in each spike. Furthermore, several alternative design options namely as number of layers, kernel size, number of threshold values, epochs, and different functions in different layers, and select the best design options of them. The fuzzy-based MRCNN model estimates the severity in low, medium, and high severity levels. The threshold value at 0.9 with different three epochs achieve higher Mean average precision (mAP) (97.9%) than other threshold values with the same number of epochs for individual wheat spikes extraction. For FHB disease severity estimation in each wheat spike, a total of 93.7% average f1-score has been calculated in this study. Various experiments show that the accuracy achieved using a fuzzy-based MRCNN model for FHB severity disease estimation is better than other state-of-the-art previous techniques.

1. INTRODUCTION

Wheat is the second largest food crop in the world [1]. Due to its high yield potential, high nutritional content, and superior adaptability, it is the main crop for human consumption. According to the National Agricultural Research Institute of World [2], a total of 5.63% quality of wheat grain has been lost due to Fusarium head blight (FHB) disease in wheat plants. FHB is often known as scab and it is a destructive disease that is mostly produced from Fusarium asiatica and Fusarium graminearum pathogens. During the flowering stage of wheat, favorable climatic conditions, such as high humidity and warm temperatures, encourage infection. FHB can have an enormous effect on wheat productivity and quality, resulting in yield loss and mycotoxins contamination offers health hazards to farmers and consumers [3]. The detection of FHB [4] disease helps to improve the wheat grain yield quantity. The severity of FHB must be precisely determined, and pesticides must be used effectively for the prevention of FHB spreading in wheat plants. The FHB disease is evaluated either through experienced evaluators or computer vision techniques. The experienced evaluator takes time to identify the FHB infection on wheat ears and this process is time-consuming and too costly [5]. Thus, it is difficult to quantitatively measure and evaluate the occurrence of FHB disease in wheat ears through experienced evaluators. The process of experienced evaluator a creates poor efficiency, and laboriousness problems. Once, the FHB disease has been identified, the fungicides pesticide can be operated on wheat plants on time so that FHB disease can be controlled based on time. Therefore, it is important for accurate diagnosis of FHB disease automatically without human intervention. Through the usage of computer vision techniques [6], the FHB disease is identified automatically. Even, the identification of FHB disease is helpful for small as well as large-scale field farmers. To increase grain yield productivity, machine learning technology (MLT) has been developed. The development of MLT in conjunction with image processing for the diagnosis of FHB disease has been crucial [7]. The authors [8] have made several attempts to use machine learning, image processing, and other technologies for the diagnosis of agricultural diseases. Crop

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disease classification [9] was made possible by manually extracting the color, shape, texture features of the disease and utilizing Fuzzy Logic (FL) classification, Artificial Neural Networks (ANN), AdaBoost, Decision Trees (DT), Naive Bays (NB), and Random Forests (RF). It is required to extract plant disease features that have a significant influence on improving the identification accuracy when utilizing traditional machine learning approaches for plant disease diagnosis [10].

To solve the feature missing issues in traditional machine learning models [11], deep learning techniques have been proposed. In deep learning techniques [12], there is no need for feature extraction techniques. In recent years, researchers [13] have been increasingly interested in deep learning in addition to the methodologies and models to increase the disease identification rate. Deep learning techniques are widely used in image identification. These techniques constitute a breakthrough in the field of computer vision.

1.1 The major contribution of this paper

This study aims to develop an efficient, effective, and more accurate wheat FHB disease detection model that can easily locate the exact location of the disease along with its severity in wheat spikes based on Fuzzy fuzzy-based MRCNN approach.

- For wheat FHB disease detection, a Fuzzy-based MRCNN model is constructed.
- Identify the severity of the wheat FHB disease in individual spikes.
- To compare the results of the Fuzzy fuzzy-based MRCNN model with previous existing models for wheat FHB disease detection.

1.2 Problem definition

One of the most damaging diseases [6] in the world is the FHB, which is widespread and common throughout the entire world. Wheat FHB disease is the biggest problem in the world, but computer vision techniques can easily detect it in the early stage. In the previous studies, wheat diseases [12], [16], [21] were detected manually by a large number of experts in this field and created uniformity problems in prediction. Several researchers [13], [8] face some issues when trying to find wheat FHB disease in wheat kernels which are as follows:

- The wheat FHB disease has been detected in hyperspectral images by various authors [14], [15]. However, the process of hyperspectral imaging for disease detection is too expensive and it creates a lot of difficulties to detect the FHB in wheat plants.
- The traditional machine learning models [3],[16] don't find out the exact location of FHB disease in a wheat plant appropriately.

The structure of this paper is as follows: The literature review has been described in section 2. The materials and methods for FHB disease identification have been defined in section 3. The experimental setup details have been given in section 4. The discussions and result implications have been defined in section 5. Lastly, the conclusion of this paper has been expressed in section 6.

2. RELATED WORK

The researchers [13] used hyperspectral imaging and Principal Component Analysis (PCA) to determine Fusarium infection in wheat. The spectral angle mapper was used in the laboratory to classify the severity. The researchers [2] detect the FHB disease under controlled environmental settings with healthy and disease canopy HSI images. The authors [14] examined the relationships between HSI data and FHB severity to quantify wheat resistance to FHB. Spikes were correctly categorized as healthy or infected using a support vector machine (SVM) and Fisher linear discriminant analysis (79–89%). The diagnosis model's performance was subsequently enhanced by utilizing a support vector machine with particle swarm optimization (PSO-SVM) [6]. The PSO-SVM model based on the fusion of spectral and color features was determined to be the best by the experimental findings. Additionally, the training and prediction sets' accuracy rates were 95% and 92%, respectively. A technological foundation for the prompt and efficient control of FHB and the targeted application of a pesticide is provided by the approach based on the fusion of image and spectral characteristics to identify the severity of FHB. Huang et.al [7] detect the FHB disease at different canopy images through SVM. The FHB disease features have been selected through band features, spectral position features, and vegetation indices. After the selection of features, the SVM model is used for FHB disease classification purposes. The SVM selects the FHB disease features based on correlation analysis. The FHB identification model was built using the SVM algorithm. The leafy model had an overall accuracy of 65% and the leafless model had an accuracy of 81%. The experimental results show that the selected features could be used to identify vertical-angle FHBs with great success. Qiu et al [10] design a method to gather hyperspectral images of wheat spikes in the field. The classification of sick and healthy pixels was performed using a deep neural network (DNN), and the accuracy was as high as 74.3%. The majority of research has chosen several distinct wavebands and has created models or suggested indices for FHB detection using machine learning. DNN has been widely used to analyze hyperspectral images in recent years and has displayed great performance. The researchers [8] use the hyperspectral images to distinguish the FHB disease in wheat heads. The convolutional bidirectional recurrent neural network model achieves higher accuracy (0.846) on the validation dataset. In a large test dataset, the 2D-CNN-BidGRU model showed the best generalization performance with an F1 score and accuracy of 0.75 and 0.743. Although hyperspectral imaging can help identify FHB, several issues restrict its usage. First, hyperspectral imaging is expensive, making it challenging to spread its use. The authors [12] uses a deep convolutional neural network (DCNN) model that can extract the wheat spikes directly from wheat plant image. The authors [3] recognize the FHB disease and find their severity through the Resnet 50 pretrained model of CNN. The experimental results show that the Resnet50 pretrained model achieves high classification accuracy (97.86%) for wheat FHB disease detection with its severity. Detecting wheat spikes and FHB using deep learning (DL) is interesting. However, this field needs further research. CNN, a well-known deep neural network, has evolved into a typical technique for object detection. To accurately assess the FHB disease, a new approach based on Faster RCNN should be developed [9]. Su et al [11] proposed a technique of assessing FHB severity using a Mask-RCNN network that has a 77% accuracy rate for wheat ear evaluations.

Several different applications rely on determining FHB levels in the field [4], [5], [17] such as disease resistance, determining efficacy of disease management methods, and determining crop quality. Therefore, accurate estimation of FHB on wheat plants is essential which helps to reduce the grain yield quantity [18] .

3. MATERIALS AND METHODS

The main purpose of this study is to detect wheat FHB disease along with its severity within its spikes appropriately.

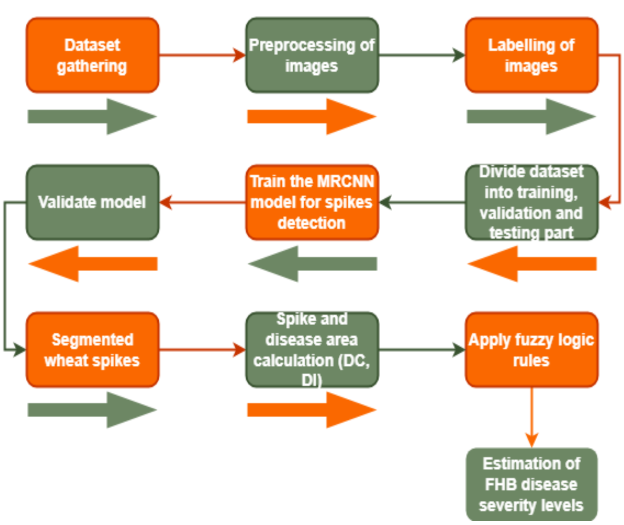

Fig. 1. Strategy for finding FHB disease.

3.1. Dataset Collection and preprocessing

The results of previous studies show that there is an unavailability of the FHB disease dataset. The flow diagram for the wheat FHB disease recognition system has been presented in Figure 1.

In the current study, the FHB disease dataset has been collected from secondary sources. Through the usage of secondary sources, a total number of 953 wheat plant images have been collected [19], [20]. All the images have different resolutions and have a .jpg format. The wheat spike sample images have been shown in Figure 2.

Fig. 2. Dataset collected samples

The size of gathered images is of various dimensions. The next step is to separate the image based on the color code from the infected crop images after sorting out our images by conducting the preprocessing phase by resizing and normalization. After resizing and normalization of images [9], the bad conditions images have been removed from the whole dataset. The preprocessed images have been used for image annotation purposes.

3.2. Image labelling

The wheat spikes and diseased images were manually annotated using the annotation tool, which is useful for training and validation purposes in the fuzzy-based MRCNN model. A total of 953 images were collected from secondary sources. Among this group, 653 and 300 wheat plant images were chosen at random for spike identification purposes. The artificial image annotation software Visual object tagging tool (VOTT) was used to perform all image labeling. Image annotation consists of three steps [13]. First, the original image was labeled with a wheat spike. Once upon a time, in wheat spike labeling, the labeled panicle was supposed to divide the annotated panicle into sub-images and name the third part corresponding to each spike. There are two labels of wheat spike images: one label is a healthy spike and another label is diseased spikes. The labeled images are shown in Figure 3.

Fig. 3. Sample of labeled images corresponding to the original image

3.3. Fuzzy logic system

The fuzzy-based Mask RCNN model extracts the wheat individual spikes with FHB disease along with its severity.

The MRCNN model performs the binary classification on wheat spikes and tells whether the wheat spike is healthy or FHB diseased. If the condition of the wheat spike is identified, then it is easily determined the severity of FHB disease in wheat spikes through the membership functions in the fuzzy logic system. A fuzzy logic system helps to determine the disease intensity (DI) and disease coverage (DC) through membership functions. The DC and DI rely on low, medium, and high ranges. The main aim of DC is to how much wheat spike is affected by FHB disease. While DI tells how much disease is infected in the wheat spikes area. The severity of FHB disease is measured in 0-100. The range of DC and DI values describes the membership function. To specify the fuzzy inference rules that control how the inputs are related to the output. These rules are commonly represented as "IF-THEN" expressions. The fuzzy set rules for FHB disease severity estimation have been defined in Table 1. The value of low (L) lies between 0-30 and values of medium (M) lie between 30-70. Even, the value between 70-100 is considered as high (H). With the usage of fuzzy inference for computing the output fuzzy set for FHB Severity (FS) based on the input values of Disease Coverage (DC) and Disease Intensity (DI) based on membership functions and fuzzy rules. Once, the fuzzy output set has been received, we utilize a defuzzification method (e.g., centroid or weighted average) to transform it into a crisp number expressing the predicted FHB severity with low, medium, and high.

Table 1: Fuzzy Inference System Rules for Assessing FHB Disease Severity

DC	DI	Fuzzy severity
L	L	L
L	M	L
L	H	M
M	L	L
M	M	M
M	H	H
H	L	M
H	M	H
H	H	H

3.4. Architecture of Mask RCNN

During wheat plant images collection, a total number of 953 images have been collected from secondary sources. A total number of 658 and 285 wheat images have been used for training and testing purposes in the MRCNN model respectively. The Mask RCNN extracts and classifies each wheat spike along with its bounding box. The MRCNN is a neural network that consists of feature extraction, region proposal network, ROI alignment, region regression layer, Mask head, and fully connected layers. The description of each layer is defined in the following sub-sections.

- Feature extraction: In the MRCNN model, the features of an image are extracted automatically. The feature extraction model uses a pretrained model of neural networks. The feature extraction layer consists of a convolutional layer, downsampling layer, and feature maps layer [21]. A square kernel function moved over the image that turns one function into another to obtain more information. Convolutional layers combine the kernel value with the values in the image that are now covered by the kernel to produce a convoluted value. Stride is the distance traveled by the window at one moment. In this work, we experimented with several kernel sizes and stride values before settling on a kernel of size 3*3 with stride 1. During training, the kernel's value is changed with different number of epochs. After feature mapping in the convolution layer, the spatial resolution of an image decreases. As the spatial resolution decreases the feature channels increases which contain more semantic information about an image. The combination of feature maps and feature channels creates a feature pyramid network that provides a multi-scale representation of all objects present in an image.
- Region proposal network (RPN): The feature maps extracted by the backbone network are applied as input to the RPN. To generate multiple objects present in the image, the RPN creates bounding boxes of multiple objects present in an image [21].
- Region of interest (ROI) align: After obtaining the region proposals, RoI Align is used to extract fixed-size feature maps from these regions of interest. The RoI Align procedure ensures that the features are correctly aligned, preventing quantization issues caused by RoI pooling [10]. The two most common pooling functions are max pooling and average pooling.
- Region regression: The region regression layer performs an object classification and bounding box regression on each aligned feature. The wheat spike condition within each ROI is predicted in classification. Even, the bounding coordinates of each object present in an image are performed by bounding box regression [22]. The bounding box of each classified object was implemented through proposal height and width coordinates.
- Mask Head: The Mask head consists of a convolutional layer, pixel-wise segmentation, and object instance probability functions. The convolutional layer is responsible for producing the contextual as well as pattern information in each aligned ROI. Once, the pattern information is extracted, the binary mask of each predicted pixel tells the object pixel information. The probability of each object pixel in an ROI is implemented using the sigmoid function.
- Fully connected layer: The fully connected layer is the last layer of the MRCNN model. The SoftMax function is implemented in this layer. The objectness score is calculated in this layer [23].

4. EXPERIMENTAL RESULTS AND DISCUSSION

MRCNN and a fuzzy rules system have been used for the prediction of wheat FHB disease and its severity in wheat spikes. For preprocessing, feature extraction, and classification, Python programming was employed. The experiment has been performed on PyCharm 2.4. A personal computer (Processor: Intel(R) Xeon(R) CPU E3-1225 v3 @ 3.20GHz, Operating System: Windows 10, 64-bit, Memory: 20 GB) was used to perform the full model training and validation process. Optimized training speed in GPU mode (NVIDIA RTX 2070 8 GB). Additionally, several inbuilt Python libraries Keras and TensorFlow have been used to perform the MRCNN model. The experimental setup has considered the following phases:

- The author used the secondary source dataset that contains 953 wheat plant images.
- The wheat plant image contains spikes into FHB diseased and healthy spike classes.

To build and create our model utilizing MRCNN, the authors use three essential phases for wheat head spikes extraction as well as disease recognition. The first stage is called the training phase and it entails a series of layers called convolution, activation, pooling, fully-connected, and dropout. The original image serves as the convolution layer's input. Applying a series of K learnable filters, each of which has square width and height dimensions, a pooling layer is used to minimize the input volume's spatial size, which in turn lowers the network's computational load and several parameters. At the very end of the network, fully linked layers are added before the Softmax classifier is used. Additionally, dropout is used to avoid overfitting by changing the network architecture during training. After the classification and bounding region of FHB disease in each spike, the severity has been determined through fuzzy rules. The fuzzy system designs the severity rules based on the percentage of infection. The fuzzy system determines the FHB disease severity with three levels (low, medium, and high). For experimental work, a total number of 953 wheat plant images contain the FHB disease heads and healthy heads. Among this group, 653 and 300 wheat spike images were chosen at random for training and validation purposes in the fuzzy-based MRCNN model. The MRCNN model uses Resnet-50 for the feature extraction in the MRCNN model. The effectiveness of the MRCNN model is accessed through different threshold values. Each of the threshold values is chosen and tested for the various numbers of epochs. Through the usage of the MRCNN model, a total number of 13,353 wheat individual head spikes have been extracted. Among extracted head spikes, a total number of 6842 spikes are fully FHB diseased. The FHB diseased spikes have been helpful for FHB disease severity calculation in each spike. The mean average precision calculation with different threshold values of 0.9, 0.8, 0.7, 0.6, and 0.5 with different numbers of epochs for individual wheat spikes extraction have been shown in Table 2.

Table 2: Mean average precision (mAP) for wheat spikes extraction

Threshold values	Number of epochs	Precision	Mean average precision (mAP)
0.5	50	0.63	0.75
0.5	60	0.69	0.78
0.5	70	0.71	0.796
0.6	50	0.72	0.78
0.6	60	0.76	0.81
0.6	70	0.78	0.82
0.7	50	0.713	0.79
0.7	60	0.73	0.82
0.7	70	0.75	0.86
0.8	50	0.74	0.89
0.8	60	0.79	0.91
0.8	70	0.81	0.93
0.9	50	0.82	0.946
0.9	60	0.836	0.95
0.9	**70**	**0.849**	**0.979**

The shape of the bounding box of each spike is in a quadrilateral polygon along with height and width coordinates. Even, the mAP for different threshold values achieves high results with different numbers of epochs. The threshold value at 0.9 with different three epochs achieve higher mAP (97.9%) than other threshold values with the same number of epochs. The higher value of mAP shows that MRCNN is an effective model for wheat head spikes extraction.

Once, the individual wheat spikes have been extracted, it is easy to determine the disease coefficient (DC) and disease intensity (DI) for FHB disease estimation. The FHB disease has been estimated through fuzzy rules. The details of fuzzy rules have been already described in Table 1. The severity of FHB disease has been estimated in terms of low, medium, and high. The fuzzy rules are passed before training to the MRCNN model. The severity of FHB disease has been determined through low, medium, and high levels. The performance of the fuzzy-based MRCNN model is evaluated through validation precision, recall, and F1-score parameters. For FHB disease severity estimation, a total of 93.7% average f1-score has been achieved.

4.1. Limitations of MRCNN model for FHB disease recognition

This study is the first to try to fill in the gaps mentioned above by using MRCNN for spike extraction and a Fuzzy rule system for severity assessment to improve the performance of FHB illness identification. In this work, the limitations have been described as:

- Furthermore, FHB disease detection adds another layer of complication. Based on visual symptoms, it identifies and assesses the severity of the disease in the wheat harvest stage. These symptoms might appear in a variety of patterns, such as discoloration, mold growth, or lesions on the wheat heads, making disease identification difficult.

- It is critical to identify the FHB disease at the development stage for severity assessment. Early-stage infections may not have proper symptoms, whereas late-stage infections may have symptoms that are impacted by other factors and give a more complicated severity estimation.

4.2. Comparison with existing work

The performance of the fuzzy-based MRCNN model has been compared with previous existing models for wheat FHB disease recognition. The fuzzy-based MRCNN model has been compared with svm, CNN, and MRCNN models for wheat FHB disease recognition. However, none of the studies fined the severity of FHB disease in each wheat spike. The comparison analysis of the Fuzzy fuzzy-based MRCNN model with existing work has been shown in Table 3.

Table 2: Comparison analysis of fuzzy-based MRCNN model with existing work

References	Name of disease	Classifier	Recognition accuracy(%)
[7]	FHB	SVM	81
[8]	FHB	2D-CNN-BidGRU	74.3
[24]	FHB	MRCNN	77
Proposed model	FHB disease and its severity	Fuzzy based MRCNN	93.7

5. CONCLUSION AND FUTURE SCOPE

A high-performance framework of deep learning-based disease detection algorithms was developed for automated field testing of FHB resistance in wheat. In this study, the wheat FHB disease severity model is built that will calculate the FHB disease in each spike. The severity of FHB disease has been calculated through a fuzzy-based MRCNN model. To extract the individual wheat spikes extraction, a total number of 953 wheat plant images have been used to train fuzzy based MRCNN model. Through the usage of the MRCNN model, a total number of 13,353 wheat individual head spikes have been extracted. Among extracted head spikes, a total number of 6842 spikes are fully FHB diseased. The fuzzy-based MRCNN model has never been used for FHB disease severity. The threshold value at 0.9 with different three epochs achieves higher mAP (97.9%) than other threshold values with the same number of epochs. For FHB disease severity estimation in each wheat spike, a total of 93.7% average f1-score has been achieved. In the future, the FHB disease dataset will be extended and available publically. The findings of this study will have significant implications for the efficient selection of FHB-resistant wheat spikes. The integration of the fuzzy-based MRCNN model is designed to significantly contribute to the development of resilient wheat varieties which reduces FHB losses that significantly impacts global food security. These advances in agricultural technology have the potential to promote sustainable agricultural development and pave the way for more resilient for productive crop management practices.

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