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COMPARISON OF CONVENTIONAL AND COMPUTER-BASED DETECTION OF SEVERITY SCALES OF STALK ROT DISEASE IN MAIZE

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SUMMARY

Various diseases harm the maize crop, but stalk rot has significantly reduced crop yield. The susceptible stalk requires identification by pathologists to apply the precise dose of fungicide to the crop. Farmers in developing nations faced challenges for their timely hiring. Furthermore, differences in pathologists' professional competencies result in inaccurate diagnoses. In this paper, the convolutional neural network (CNN) utilization helped classify the severity levels of stalk rot as elaborated in Hooker's scale. The field experiment commenced at the Maize and Millet Research Institute Yousafwala, Sahiwal, using a smartphone to get images of resistant and susceptible lines fed to the proposed model for evaluation into six severity scales. The model's overall accuracy was 83.58%. Recording of the recall ratio of highly susceptible, susceptible, moderately susceptible, highly resistant, resistant, and moderately resistant had scores of 1.000, 0.766, 0.966, 0.800, 0.733, and 1.000, respectively, with an average of 0.877. Precision for highly resistant was 1.000, resistant was 0.785, moderately resistant was 0.789, moderately susceptible was 0.805, susceptible was 0.958, and highly susceptible was 1.000, with an average of 0.889. Highly significant ($P < 0.01$) results from the chi-square test exhibited significant differences between traditional and deep learning approaches. The results of the proposed model showed less confusion than the visual-based method. The proposed approach is a vital source of detection of resistant lines against stalk rot disease by developing country farmers. The suggested model eliminates the need for pathologists, making it a valuable tool for identifying stalk rot resistant lines. It aids farmers in finding resistant lines for breeding projects and estimating the fungicide dose against stalk rot. It also helps minimize the production cost and environmental pollution.

Keywords: CNN, deep learning, severity classes

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Key findings: The proposed model identified the Hooker's severity scales more accurately than farmers' assessments. It can be an essential tool for resistant line identifications. The study results will help to minimize the cost of production and environmental pollution.

INTRODUCTION

Among cereal crops, maize (*Zea mays*) has immense significance in Pakistan due to its consumption as food and feed. However, disease incidents limit a crop's ability to reach its full potential. Among the diseases, stalk rot has a detrimental impact on grain yield and quality (Jim, 1999; Yang *et al.,* 2002). Small-scale farmers are particularly vulnerable to severe plant diseases as they solely depend on the supply of high-yielding crops to exist. Although plant diseases threaten food security continually, new technologies have significantly addressed the global food demands (Albahri *et al.,* 2023). Early disease identification and severity classification are the main preemptive to reach the corn's full potential.

Many conventional-based methods for stalk rot severity identification include phenotypic selection, while a genotypic-based identification method includes PCR techniques, which are human-dependable activities (Qureshi *et al.,* 2015a, b). A human judgment-based disease categorization and identification are prone to inaccuracy (Reddy *et al.,* 2023). Also, visual identification is a meticulous and time-consuming task (Petchiammal *et al.,* 2023). In consulting an expert, farmers have to travel great distances, raising further the cost of production. However, recent developments in computer and mobile technology have completely changed the situation and minimized the role of humans in disease severity identification. The precision and speed of computer-aided results have shown remarkable improvements in agriculture (Owomugisha *et al.*, 2014). Computer-aided approaches have become frequent techniques for fruit sorting, grading, and defect determination (Gomes and Leta, 2012). Identifying diseases of sugar cane based on lesion-area images began proliferating (Upadhye *et al.,* 2022). Maize leaf disease studies also run with the help of computer-aided models using textural features (Kaur *et al.,* 2019). A model can gain training via supervised learning using labeled data to address severity issues (Mehta *et al.,* 2023). Although many different supervised learning methods exist, convolutional neural networks have become extremely important, resulting from their image identification success (Ding *et al.,* 2023). CNN is the best alternative for plant phenotyping due to its automatic extraction of desirable areas for detecting diseases (Dechant *et al.,* 2017).

Problem statement

Pathologists, experienced farmers, or extension workers can visually identify maize stalk rot. Small-scale farmers lack the information necessary to identify the disease assessing its severity. Visual inspection is time-consuming and offers a possibility for human mistakes when diagnosing the disease in its early stages. Image processing models can easily identify the disease and its severity level quickly. A correctly trained CNN will produce results quite similar to the precise values. In this regard, the project sought to determine if CNN can replace human detection for plant disease identification, test the viability of identifying maize stalk rot based on severity scales using convolutional neural networks, and compare traditional and deep learning techniques in severity scale identification.

MATERIALS AND METHODS

The research goal was to create a neural network model for identifying severity scales and compare them against farmer findings with the CNN model, using pathologist findings as a standard. For the presented study, the field experiment continued at the Maize and Millet Research Institute (MMRI) Yousufwala, Sahiwal, at 175 masl (latitude of 31°41 north and longitude of 73°12 east). Adopting an augmented experimental design had seed

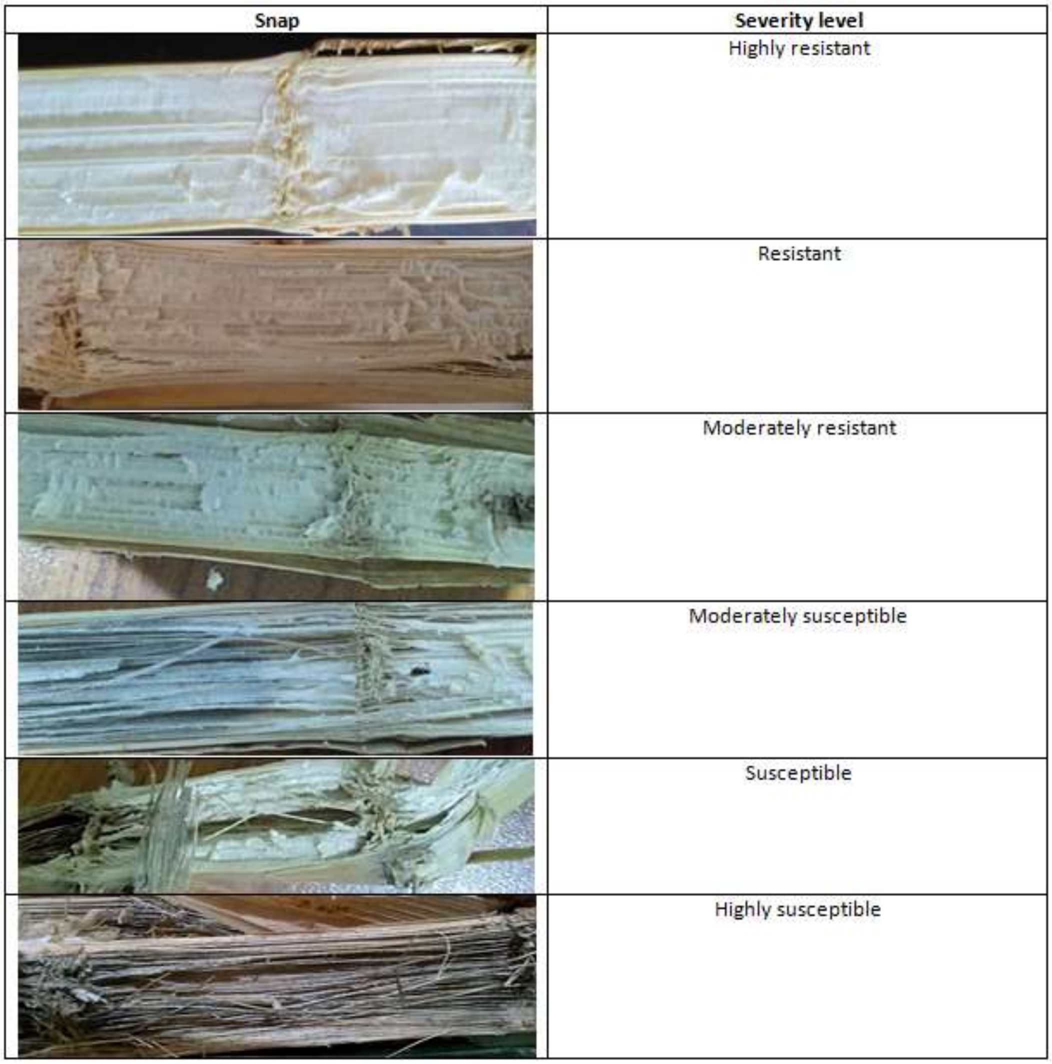

Figure 1. Stalk rot severity levels.

planting by hand in a 10-meter-long row. Planting transpired during spring and autumn, maintaining a plant-to-plant distance of 20 cm and a row-to-row distance of 75 cm. Standard agronomic practices adoption helped protect the crop. Plants' artificial inoculation ensued at the tasseling/silking stage. Recording the resistance/susceptibility of lines progressed after 28 days of injection using Hooker's severity scale (1956) (Figure 1).

Image processing techniques require the dataset for model training. Dataset preparation about severity levels materialized in the mentioned field experiment. Collected images incurred three divisions, i.e., train, validation, and test datasets. Image preprocessing and labeling were necessary before feeding them to the proposed model. Cropping images also minimized the computational time of the model. The CNN model consisted of a convolutional layer and hidden and output layers. The convolutional layer was responsible for parameter reduction (Figure 2). The hidden layers performed different operations on pixel values to draw the feature of interest. The output layer is also a classifying layer responsible for categorizing images into their respective severity classes. Probing the reliability of the model used accuracy, precision, and recall ratio.

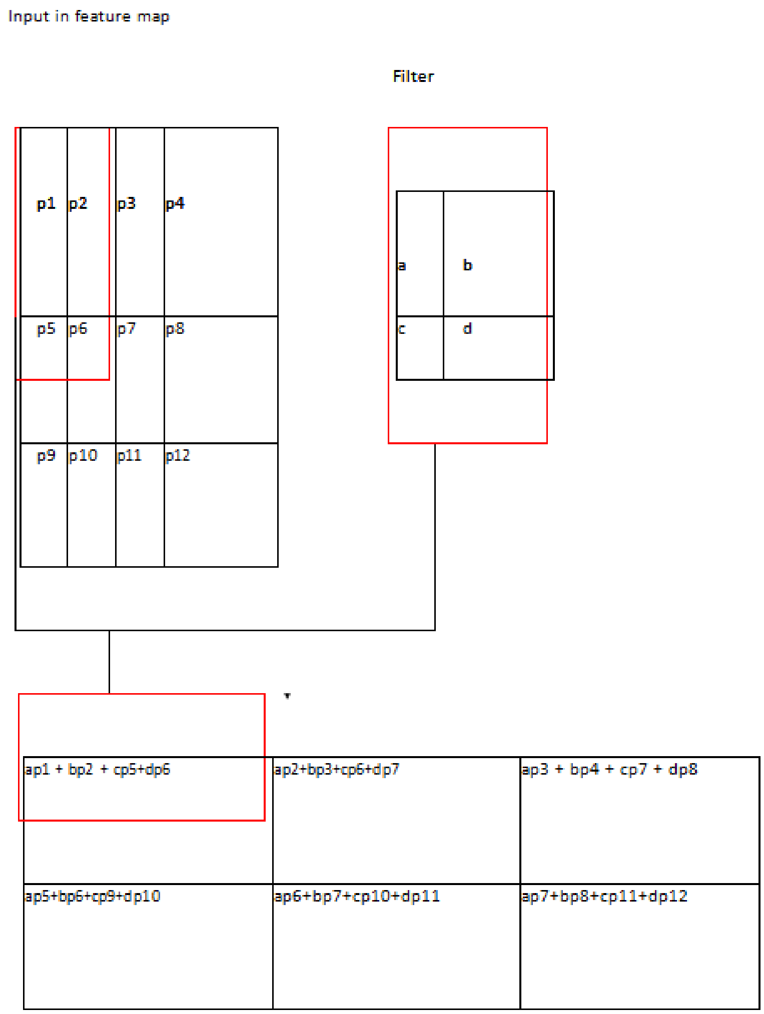

Figure 2. Parameter reduction by Convolutional operation.

RESULTS

In Pakistan, visual inspection was the primary technique to classify plant diseases. A neural network algorithm can categorize diseases more accurately than human judgment. The model was able to run more quickly, providing the severity level of stalk rot at the farmer's doorsteps. The parameters used to determine the model's performance were accuracy, precision, and recall ratio. The average accuracy of the model was 83.58% at six severity scales during validation (Figure 3). Figure 4 has an explanation of the loss function.

The accuracy of the model during training and validation appears in Figure 3. Fifty was the number of iterations the model performed to achieve accuracy. The training accuracy was 95%, while the validation accuracy was 85% when iterations were 10. Training accuracy became 100%, while validation accuracy was 85% when iterations were 20. The model's further training remained stable up to 50 iterations, but validation accuracy fluctuated and became constant at 83.58%. Figure 4 represents the loss function exhibited by the model. Up to 10 iterations, the training loss was 0.100, reducing to 0.050 at iteration 50. Similarly, validation was 0.395 at iteration 10, which increased to 0.410 at iteration 50.

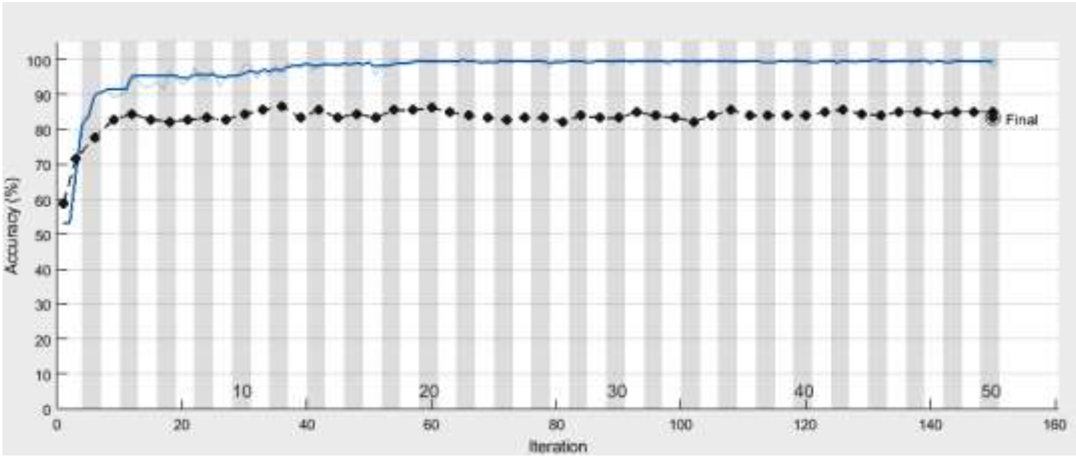

Figure 3. Accuracy of the classification model for six severity scales.

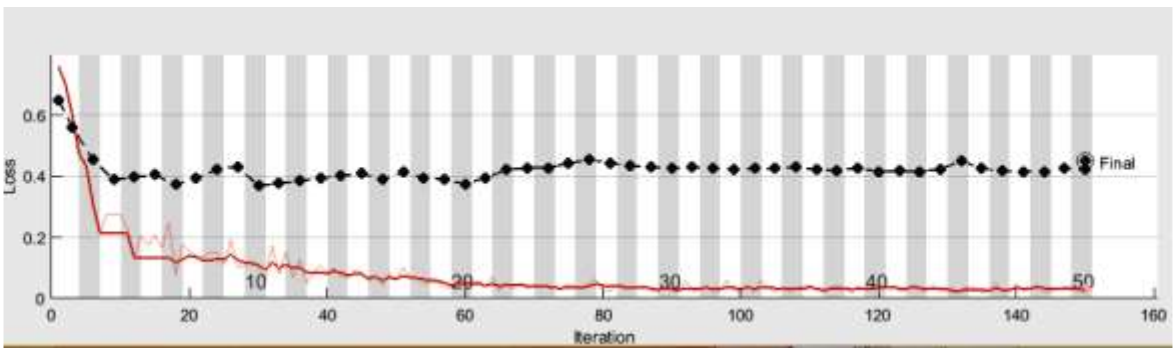

Figure 4. Loss function of the classification model for six severity scales.

Recall ratios emerged at 0.800, 0.733, 1.000, 0.966, 0.766, and 0.760 for the highly resistant, resistant, moderately resistant, moderately susceptible, susceptible, and highly susceptible, respectively, with an average of 0.877. Precision for highly resistant was 1.000, resistant was 0.785, moderately resistant was 0.789, moderately susceptible was 0.805, susceptible was 0.958, and highly susceptible was 1.000, with an average of 0.889 (Table 1). The mean absolute error was 0.80. The confusion matrix provides details on the recognized and anticipated categories. Four hundred twenty (420) out of 600 images became the first to be used to train the model.

The training and validation datasets had 70 and 30 images for each severity class, respectively. Twenty-four images received accurate classification as highly resistant, with six pictures misclassified as resistant. Eight images acquired incorrect categories as moderate resistance, while 22 attained the correct classification as resistant. Nine images received incorrect categorization by the model, and 21 images gained proper detection with moderate resistance. One image incurred an improper category, whereas 29 images of moderately susceptible subjects bore the correct classification. Seven images sustained an inaccurate label as moderately susceptible, and 23 images of the susceptible class reached appropriate detection. All images of a highly susceptible class gained suitable perception (Table 2).

The study further analyzed the differences between the traditional and deep learning approaches. The findings of pathologists served as the standard. First,

Table 1. Classification accuracy of stalk rot severity into six classes

Severity levels	Total	Classification		Recall Ratio	Precision	Accuracy (%)
		Correctly	Incorrectly			
Highly Resistant	30	24	6	0.80	1	83.58
Resistant	30	22	8	0.733	0.625	
Moderately Resistant	30	21	9	0.75	0.724	
Moderately Susceptible	30	29	1	0.966	0.805	
Susceptible	30	23	7	0.766	0.958	
Highly Susceptible	30	30	0	1	1	
Average				0.835	0.852	
Mean Absolute Error	0.80					

Table 2. Confusion Matrix of six severity classes.

Input	HR	R	MR	MS	S	HS
HR	24(80%)	6	0	0	0	0
R	0	22(73.33%)	8	0	0	0
MR	0	9	21(70%)	0	0	0
MS	0	0	0	29 (96.66%)	1	0
S	0	0	0	7	23 (76.66%)	0
HS	0	0	0	0	0	30 (100%)

Table 3. Severity level evaluation of stalk rot by pathologist, farmer, and deep learning model.

Treatment	Severity level evaluation		
	Pathologist (check)	Farmer	Deep learning model
DR39	HS	HS	HS
DR42	HS	HS	HS
DR57	HS	HS	HS
DR58	MS	S	MS
DR59	S	HS	S
DR60	S	HS	S
DR62	S	HS	S
DR68	MS	S	S
DR69	S	HS	S
DR74	HS	S	HS
DR79	HS	HS	HS
DR80	MS	S	MS
DR81	MS	MR	MS
DR85	S	MR	MS
Y02	R	MR	R
Y05	MR	S	MR
Y06	R	HR	R
Y12	HR	HR	HR
Y13	HR	R	R
Y14	R	R	R
Y18	R	MR	R
Y19	R	MR	R
Y22	MR	MS	MR
Y24	MR	S	MR
Y25	MR	MS	R
Y27	R	HR	R
Y30	HR	R	HR
Y32	HR	HR	R
Y35	R	MR	R
Y36	R	R	R

HR= highly resistant, R= resistant, MR= moderately resistant, MS= moderately susceptible, S= susceptible, HS= highly susceptible.

Table 4. Comparison of conventional and deep learning techniques in stalk rot severity classification.

Techniques	Severity level identification		Chi-square Value	P Value
	correct	incorrect		
Pathologist	30	0		
Farmer	08	22	38.67	0.00001**
CNN model	25	05		

CNN= Convolutional Neural Network, ** Highly Significant at $P < 0.01$.

providing stalks infected with stalk rot continued to the farmer for the severity evaluation, recording his results. Later on, feeding the same stalk to the proposed model received scrutiny. The results are available in Table 3. The pathologist marked treatments (DR59, DR60, and DR62) as susceptible, while the farmer incorrectly identified them as highly susceptible. The deep learning model correctly identified these treatments.

The treatments, DR81, DR85, and Y02, attained inappropriate assessments from the farmers as moderately resistant, while the model incorrectly marked DR85 as moderately susceptible. The farmer and model mistakenly judged Y13, with the Y25 incorrectly identified by the farmer as moderately susceptible and the model as resistant. Performing a chi-square test to determine the model's significance showed highly significant (0.00001) results (Table 4).

DISCUSSION

Feeding stalk image attributes in a computer-aided model helps categorize the severity of the stalk rot disease affecting the maize crop. The accuracy, precision, and recall ratio received by the convolutional neural network verified the model. In Pakistan, farmers often use visual examination to determine whether the disease is afflicting the stalk. Visual approaches have never accurately identified stalk rot disease or accurately assessed its severity.

Compared with the human screening procedure, the computer-aided model presented in the study produced more reliable and steady outputs. In the current age of technology, real-time categorization of stalk rot severity into various degrees yields the most precise and quick findings. Crop stress identification and categorization often use traditional machine and deep learning approaches (Singh *et al.,* 2018; Baer *et al*. 2022; Qureshi *et al*., 2023). The feature extraction approach distinguishes these methods from each other. Preprocessing and labeling ensure model correctness (Panshul *et al.,* 2023).

Unlike DCNN, which uses convolutional layers to automatically extract image features, traditional machine learning must segment the target images and manually isolate the necessary characteristics (Ubbens and Stavness, 2017). A CNN detection and characterization of biotic and abiotic stress has increased significantly in recent years (Singh *et al.,* 2018). Compared with conventional machine learning techniques, the study of Ma *et al.* (2018) on four cucumber leaf diseases revealed that DCNN had a high detection accuracy. The significance of the deep learning technique, which bases categorization on color, texture, and shape, also came from Veeramani *et al.* (2018). In the manuscript, the study used a CNN learning-from-scratch technique to categorize the stress caused by maize stalk rot.

The accuracy of the model for categorizing severity into six scales was 83.58. These outcomes agree with other deep-learning-based stress studies reported by Ferentinos (2018). The number of images required to train a CNN model to get the best results is challenging to quantify (Kamilaris and Prenafeta-Boldú, 2018). Moreover, dataset preparation under field and laboratory conditions produces different results when evaluated under the same CNN model. According to Ferentinos (2018), when applying a CNN model to laboratory images after being trained on photos taken in the field, its accuracy level dropped from 99% to 68%. Moshou *et al.* (2004) studied rust disease in wheat using deep-learning model. They got an accuracy of 99% in their results. Abdulridha *et al.* (2016) explored the role of CNN in wilt disease identification in avocados. They reported an accuracy of 98% using a deep learning model.

Lawrence *et al.* (2004) studied the nematodes of cotton crops using a deep-learning technique. They claimed 97% model accuracy. Li *et al.* (2009) studied the leaf roller disease of rice using an image-processing technique. They showed significant improvement in the model performance using massive preprocessed datasets. They claimed the accuracy of 95% of their proposed model. Sladojevic *et al.* (2016) studied different crop diseases using a deep-learning technique. They reported a model accuracy of 96.3%. Oppenheim and Shani (2017) studied the potato silver scurf, black dot, common scab, and black scurf. They reported accuracy from 83% to 96% by changing the model's number of iterations.

Atole and Park (2018) reported the golden apple snail in rice using a deep-learning technique and got an accuracy of 91.23%. Liang *et al.* (2019) performed an experiment to estimate the severity levels of diseases. They got 91% accuracy from their proposed model. Their findings are in accordance with this study's findings. Highly significant results from the chi-square test showed a significant difference among the techniques for the evaluation of stalk rot severity. The confusion matrix created from the findings of the CNN model also endorsed the same results. Our findings align with those of Fuentes *et al.* (2017), who noted a significant degree of class confusion.

CONCLUSIONS

The yield of maize crops in Pakistan is lower than in other progressive countries due to a late assessment of stalk rot severity in the field conditions. Farmers lack expertise in correctly identifying and classifying diseases using a traditional approach. Compared with the visual inspection approach, the proposed model offered an automated solution to the issue of farmers' difficulties in diagnosing and classifying maize stalk rot. Farmers now have better tools for more accurate vulnerability assessment using the neural network model. It minimizes the need for pathologists, extension workers, and experienced farmers and increases maize productivity. It also helps apply accurate fungicides to the field, ensuring low production costs and decreasing environmental pollution.

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