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INTELLIGENT RESISTANT SOURCE DETECTION AGAINST STALK ROT DISEASE OF MAIZE USING DEEP LEARNING TECHNIQUE

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SUMMARY

Maize incurs many diseases, but stalk rot has badly influenced the crop yield. A pathologist, extension worker, or experienced farmer can only identify susceptible stalks to determine the accurate application of fungicide to the crop. It is rigorous for the farmers of developing countries to hire them in time. Moreover, a variation in the views of professionals leads to incorrect findings. In this manuscript, pathologists' discoveries have become a standard to compare the farmer's detections with an intelligent-based model. The Convolutional Neural Network (CNN) employment sought to identify the resistant and susceptible stalk against stalk rot. The Maize and Millet Research Institute Yousafwala, Sahiwal, was the chosen field for experimentation. Gathering resistant and vulnerable images from maize germplasm, having local origins, progressed via a smartphone. The CNN architecture's exploration classified the images into two resistant and susceptible classes. The *P* value (0.00001) calculated by the Chi-square method for resistant and predisposed groups showed highly significant results. An 83.88% achieved accuracy came from the CNN, while 49.5% of the accuracy resulted from the farmer. Recording recall ratio and precision of 0.766 and 0.896 occurred for resistant, and 0.911 and 0.796 were the recordings for susceptible classes by deep learning technique, respectively. The proposed approach is an influential source of detection of resistant lines against stalk rot disease by minimizing the need for pathologists, extension workers, or experienced farmers. It will help farmers to identify the quantity of fungicide against stalk rot and explore lines for resistant breeding programs.

Key words: Extension worker, disease, CNN, deep learning

Key findings: The proposed model identified the resistant lines against stalk rot more accurately, benefiting breeding programs for improving existing high-yielding varieties.

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INTRODUCTION

Maize (*Zea mays L*.) ranks third in Pakistan among grain crops. Globally, an estimation reveals that maize farms will increase from 216 to 227 million (5% increase) up to 2030 (Erenstein *et al.,* 2021). Maize has nutritional significance along with food sources, fuel for humans, and feed for animals (Price and Lalonde, 2023). New technologies have played crucial roles in meeting world food requirements, but plant diseases are still alarming to food reserves (Kunyanga *et al.,* 2023). Pakistan produces maize but has yet to reach its high-yield potential. It may be due to the late treatment of diseases. The quantity and quality of grain incur adverse influences from the stalk rot disease (Jim, 1999; Yang *et al.,* 2002). Phenotypic and genetic variations of pure lines against the stalk rot provide helpful information for breeding programs (Qureshi *et al.,* 2015a, b); however, stalk rot still has more drastic impacts among fungal diseases.

The impact of stalk rot infection on grain micronutrients (Fe, Mn, Zn, Ca, Mg, Cu, N, P, and K), macronutrients (starch, fat, and protein), debris, qualities like breadth, hardness, and unit grain weight is also evident (Bandara *et al.,* 2017). Farmers with small land holdings are seriously troubled by plant diseases because their survival depends solely upon available healthy crops. The early-stage disease recognition and classification is highly critical in disease management. It is only possible by the visit of pathologists, extension workers, or experienced farmers, dependent on time that is a specialized activity, adding to the production cost. However, recent mobile advancements and computer technology have revolutionized the circumstances and provided the solution at the farmer's doorstep.

Disease identification and classification dependent upon human judgment always leave errors (Azmi *et al.,* 2023). Moreover, visually observing characteristics is a tedious and time-consuming job (Petchiammal *et al.,* 2023). The computer-aided techniques' role has developed significant importance in agriculture due to their accuracy and speediness (Sekharamantry *et al.,* 2023). Supervised learning uses labeled data to train the model (Rani *et al.,* 2023). It is mainly applicable to solving identification problems. Many supervised-learning algorithm types are available, but the convolutional neural network (CNN) has gained immense prominence due to its remarkable achievement in the image identification fields (Bharadiya*,* 2023). The key idea of a CNN is to elaborate the technique of self-learned characteristics. CNN does not involve the erosion of the plant from the soil compared with previous conventional methods. It only needs the images of diseased plant parts for disease classification, resulting in accurate and timely identifications.

Defects in potatoes, classification of grains based upon apparent features, sorting, and grading of fruits on color quality can now undergo scrutiny through computer-aided techniques to achieve high-quality results in a short time frame (Hasankhani and Navid, 2012; Gomes and Leta, 2012). Sugarcane images' exploration helps detect diseases (Upadhye *et al.,* 2022), and the texture features of inertia, homogeneity, and correlation have played a vital role in image-based plant disease identification (Kaur *et al.,* 2019). Accurate and precise application of pesticides to the crop has become possible due to early and timely detection of diseases (Thorat *et al.,* 2023). The study objectives sought to 1) compare the findings of pathologists, farmers, and the CNN; 2) elaborate the feasibility of convolutional neural networks to classify stalk rot of maize; and 3) propose a model for the recognition of resistant versus susceptible stalks of maize against the stalk rot disease.

MATERIALS AND METHODS

Field experiment

The Maize and Millet Research Institute (MMRI) Yousafwala, Sahiwal, was the chosen site for the productive study. The institution has a distance of 11 km from Sahiwal. It has an elevation of 175 m with a latitude of 31°41 N and a longitude of 73°12 E. The institute's chief purpose is to develop and multiply high-quality sorghum, maize, and pearl millet seeds.

Maize has a higher priority over other cereal crops due to its utilization as a food and the availability to grow in two seasons, i.e., Kharif and spring. The site temperature ranges between 40 °C to 50 °C in summer and 5 °C to 10 °C in winter, with an annual average rainfall of about 349 mm. It is near the edge of the Thar Desert, resulting in the warming of the wet and cooling of the dry seasons. The soil is fertile and favors the short and scrubby vegetation. Sowing of seeds in the field used an augmented experimental design. Seeds, grown manually, ensued in a single-row plot, with a length of 10 m. Growing two seeds per hill had the row-to-row distance adjusted to 75 cm and the plant-to-plant distance to 20 cm. Applying an average dose of fertilizers, 60-200-100 and 60-250-125 of KNP per hectare, transpired during autumn and spring, respectively. Earthed up, normal hoeing, irrigation, and 2–3 foliar insecticidal treatment applications proceeded as per standards to save the crop against sucking insects and maize borer. The experiment included two parts, i.e., natural infection and artificial inoculation. Randomly selected plants for artificial inoculating came from the silking/tasseling stage. The degree of resistance or susceptibility continued to documentation after 28 days of vaccination.

Research design

The research objective was to design a neural network model that would help in classifying resistant and susceptible stalks against the stalk rot stress (Figure 1). Owomugisha *et al.* (2014) developed a model for disease classification and described the ways to measure the classification performance. The conceptual model details appear in Figure 2.

Dataset

Proper datasets are necessary starting from the training phase to the testing phase in an object-recognition research. Different kinds of approaches could be applicable for acquiring the images. In this study, adopting a nonparticipant technique served in obtaining the healthy and susceptible images of the stalk of the maize plant. The needed images came from a camera of an android mobile phone. Resistant and susceptible stalk images compilation continued at the Maize and Millet Research Institute, Yousafwala. Plant categories separated into two groups on visual examination of the stalk by the pathologist and served as a standard for developing the farmer model and CNN. Image pixel values became a source for training and testing of the model.

Image preprocessing and labeling

Images taken through the smartphone had different resolutions and sizes. These characteristics incurred uniform adjustments to get better pattern extraction. This preprocessing was also necessary to get consistent results from the deep neural network. Moreover, the image preprocessing procedure included cropping and marking the stalk to focus the area of interest. Images with higher resolution in the interest area became eligible for the dataset. Image resizing also happened to minimize the training time for the model.

Sample division

The process divided the datasets into training, validation, and test datasets. Training data sets were exploratory for learning the model. Validation datasets served to tune hyperparameters and also measured output errors. Test datasets' utilization helped to check the actual performance. Finally, the database consisted of 600 images, achieved constitution, containing equal quantities of resistant and susceptible images. Images comprising 85% were usable for training the model, while 15% served as exercises to test and validate the model's performance.

Convolutional neural network

The neural network contained an input, a hidden, and an output layer (Figure 3). The convolutional layer was the principal layer of a CNN model. The detail of layers with the

Figure 1. Resistant and susceptible stalks.

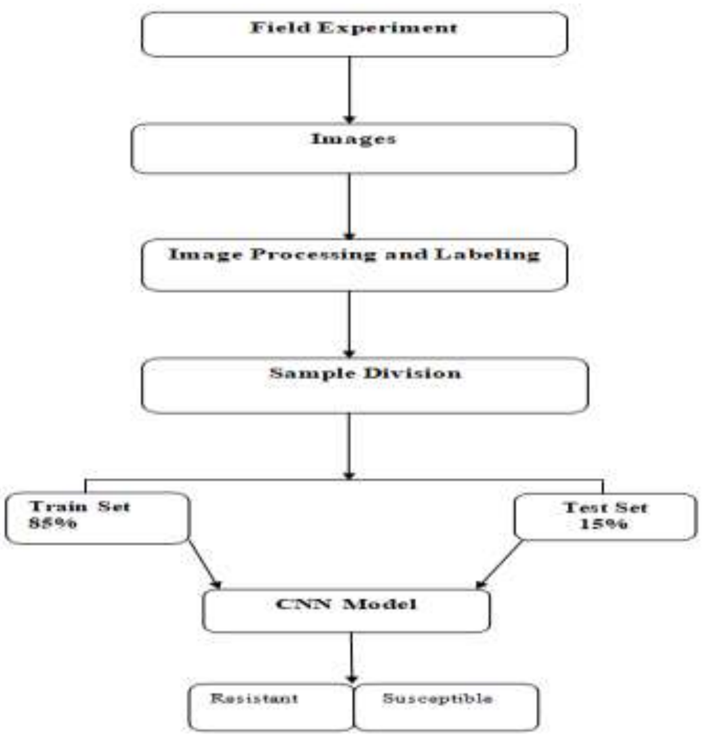

Figure 2. Conceptual Design of the Proposed Model.

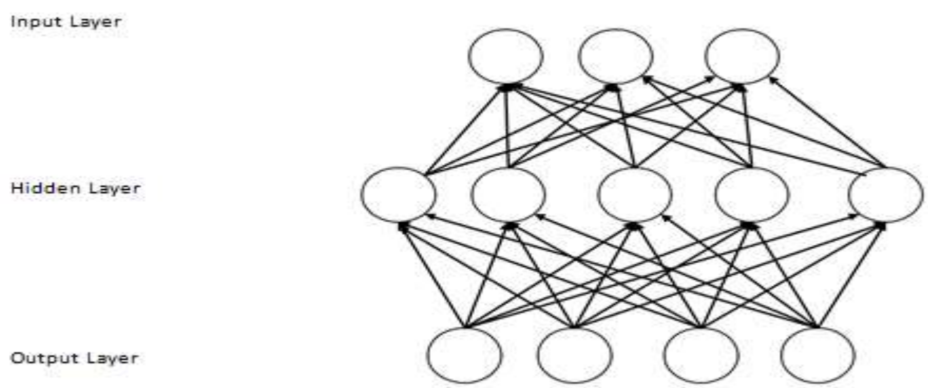

Figure 3. Architecture of neural network.

Table 1. Summary of the CNN layers.

Layer	Size	Other parameters
Input	300x300x3	
Convolution (C1)	3x8	padding=same
Pooling	2	stride = 2
Convolution (C2)	3x16	padding=same
Pooling	2	stride = 2
Convolution (C3)	3x16	padding=same
Pooling	2	stride = 2
Convolution (C4)	3x32	padding=same
Pooling	2	stride = 2
Convolution (C5)	3x32	padding=same
Pooling	2	stride = 2
Convolution (C6)	3x64	padding=same
Fully Connected + Softmax	2	

parameters used in the model has descriptions in Table 1. The algorithms work in the following ways:

1. Input: This consists of N images labeled with K classification tags, named as training set.
2. Learning: This step uses the training set to describe accurately to which each class belongs. This step is often the training or learning of the classifier level.
3. Evaluation: The classifier served mainly to guess the classification labels of images it has not perceived before and estimate the quality of the classifiers. We link the classifier's guessed tags with the actual ones of the images.

Model training

During this process, labeled stalk images get fed into the model to train it. Identified model neurons worked on labeled images to give a desirable output of the training session. The iterations carried out during the training session considered the objective of minimizing the error rate and adjusting the input weights.

Model validation and testing

Training of the model proceeded to check the actual model output with the desired one. Output errors measured during the validation further attain use to adjust the weight of the neurons for fine-tuning, that testing of the model could produce outcomes near to actual results.

Research quality

Muthukannan and Latha (2015) defined the statistical measures to check the performance of the model of disease plants using artificial neural networks. Accuracy, precision, and recall ratio operations aided the model evaluation.

RESULTS

The chief method employed for disease classification in Pakistan depended upon visual inspection. The study progressed to compare the findings of a farmer developed with the CNN and elaborate on the feasibility of convolutional neural networks to classify resistant and susceptible stalks against the stalk rot of maize. Pathologists' findings became a standard for comparing the state-of-the-art method and CNN. Pathologists divided the 600 images into two classes (resistant and susceptible) with an equal image number. Afterward, selected same images' random provision to the developing farmer continued for the accuracy comparison. The architecture explained in the paper delivers a more reliable classification of the facts employed by applying the neural network algorithm. Using the CNN empowered the model to provide more reliable feedback to the farmers in a shorter time frame. The findings of the research are the following:

Validation of the model

Model validity continued by the accuracy, precision, and recall ratio using the confusion matrix. In the validation, dividing the label data into two major classes ensued. The overall accuracy of the model was 83.88% (Figure 4). Recall ratio and precision at 0.766 and 0.896 were notable for the resistant class, while 0.911 and 0.796 emerged for the susceptible, respectively (Table 2). Average calculated values of 0.838 and 0.846 resulted in recall ratio and precision, respectively. The computed Absolute Error for each class represented the error amount in the prediction without considering their direction. The Mean Absolute Error of 0.322 appears in Table 2, elaborating the mean as the trial sample of the absolute differences between estimated and exact values, having all sample variances with equal weight. The loss function during the training is available in Figure 5.

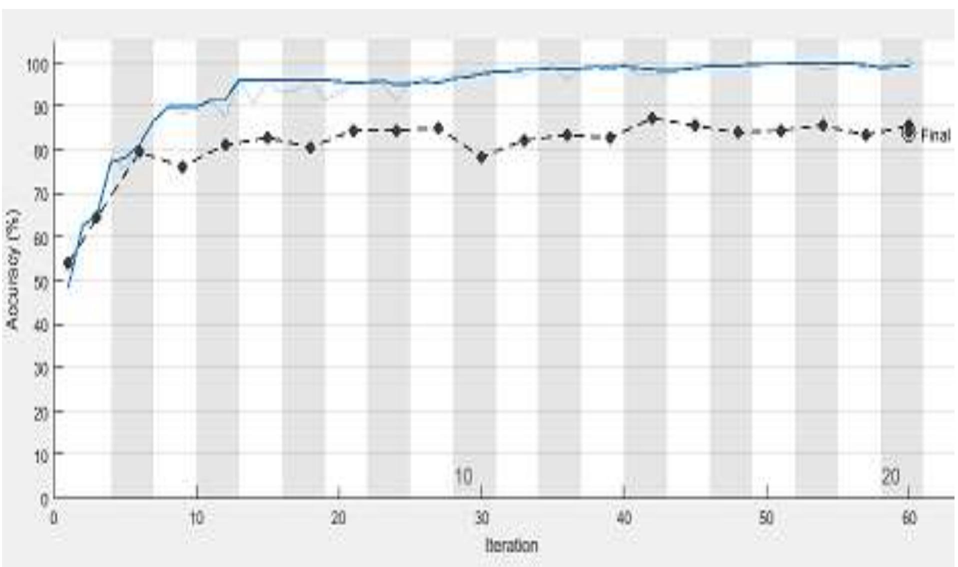

Figure 4. Accuracy of the classification model.

Table 2. Recall ratio, Precision, and Accuracy of stalk rot severity in two classes.

Severity levels	Total	Classification		Recall Ratio	Precision	Accuracy (%)
		Correctly	Incorrectly			
Resistant	90	69	21	0.766	0.896	83.88
Susceptible	90	82	8	0.911	0.796	
Average				.838	0.846	
Mean Absolute Error	0.322					

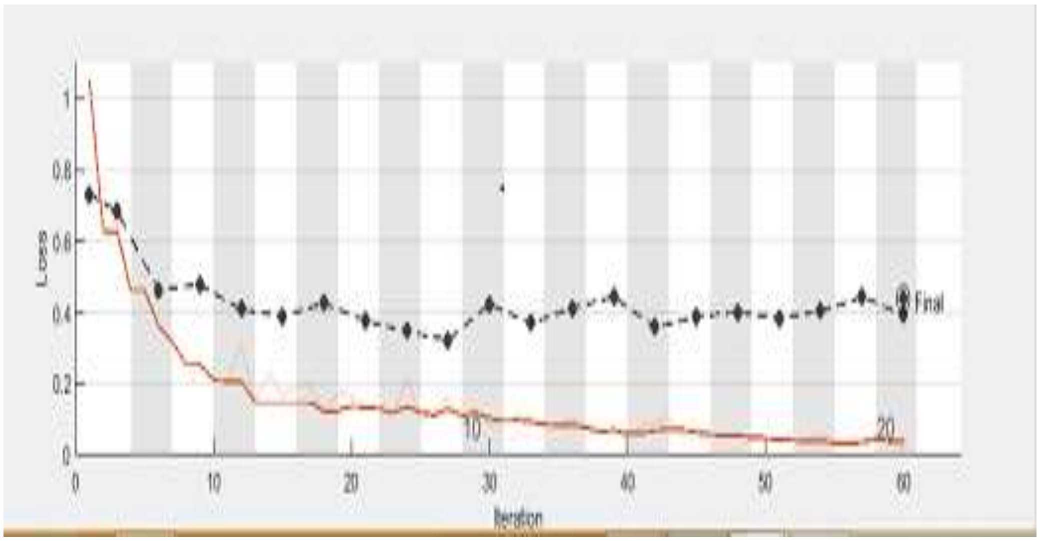

Figure 5. Loss function of the classification model.

Table 3. Confusion Matrix of stalk rot classes.

Input	R	S
R	69 (76.66%)	21
S	8	82 (91.11%)

R = Resistant, S = Susceptible

Confusion matrix

The confusion matrix elaborates information about the defined and expected classes. Initially, 510 images among the 600 labeled images were operative to train the model. The validation process used 180 images. The confusion matrix's description resulting from the classification of stalk rot appears in Table 3. The model correctly classified 69 as resistant and 82 as susceptible. Twenty-one (21) of the resistants and eight of the susceptibles had an incorrect classification by the model.

It was visible that the farmer correctly identified 42 images as resistant and 47 as susceptible, showing 49.44% average accuracy, while CNN showed 83.88% accuracy. The Chi-Square test also checked the independence or homogeneity of the techniques. A highly significant difference was evident among the methods, having a *P* value less than 0.01 (Table 4). The techniques' comparison study showed that CNN results were more appropriate than the farmer findings (Figure 6).

Table 4. Effect of techniques in classifying resistance and susceptible stalk against stalk rot.

Techniques	Resistant		Susceptible		Chi-square Value	*P* Value
	correct	incorrect	correct	incorrect		
Pathologist	90	0	90	0	50.65	0.00001**
Farmer	42	48	47	43		
CNN	69	21	82	8		

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

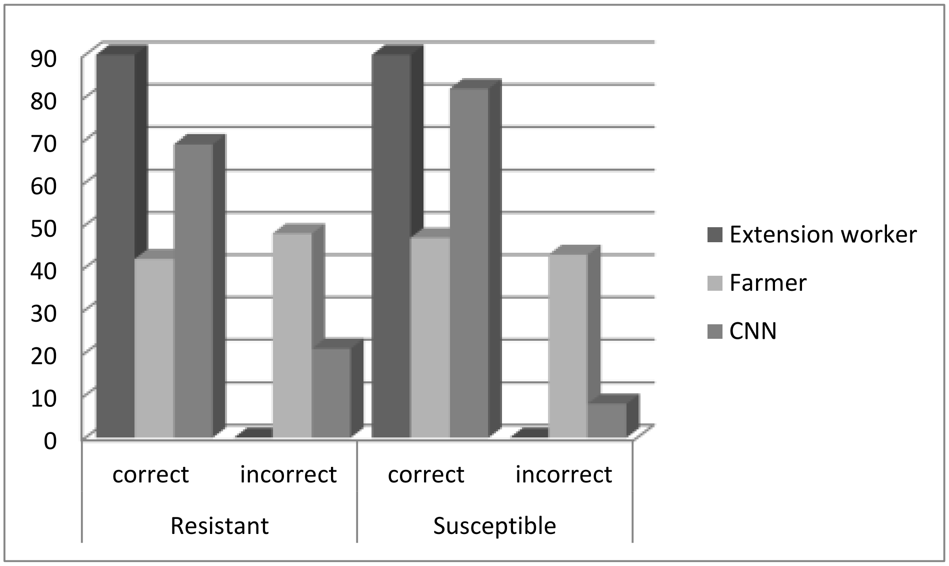

Figure 6. Comparison of techniques in classifying the stalk against stalk rot.

DISCUSSION

The classification of the stalk rot disease employed the computer-aided model. The model's verification for correct classifying used accuracy, precision, and recall ratio achieved through the convolutional neural network. The proposed architecture operated with few convolutional layers (6) to minimize the computational cost and easiness of deployment over mobile phones. Generally, farmers in Pakistan rely upon visual inspection to identify the diseases influencing the stalk. The ocular methods always left errors in the proper identification and severity of stalk rot disease. The computer-aided model offered more concise output than the human inspection method. Farmers in Pakistan also relied on extension workers or pathologists to assist them in recognizing the disease, creating hurdles in achieving the full potential of the maize crop. The availability of extension workers or pathologists is insufficient to attend to all farm areas within a time frame. Late visits led to the drastic impact of disease, resulting in a yield decline. The computation of images visually demands experts with more time. The situation requires an architecture development through computer-aided technology that reduces the need for the expert and provides the solution to the farmers in shorter periods. The use of neural networks by the researchers in plant disease identification and classification is in Table 5. Results collected from the structured interview with the extension worker and pathologists in Pakistan emphasized the need for an architecture that will later be available on a mobile phone for the correct stalk rot disease and its severity determination.

Table 5. Review of accuracy of plant disease identification and classification by neural network.

Author and Title	Crop	Disease/pest	Accuracy percentage (%)
Moshou *et al.* (2004)☐	Wheat	Rust	99
Abdulridha *et al.* (2016)	Avocado	Wilt	98
Lawrence *et al.* (2004)	Cotton	Nematode	97
Liu *et al.* (2009)	Rice	Leaf roller	95
Mohanty *et al.* (2016)	Different crops	Diseases of different crops	99.3
Sladojevic *et al.* (2016)	Different crops	Diseases of different crops	96.3
Oppenheim and Shani (2017)	Potato	Common Scab, Black Scurf, Black Dot, Silver Scurf	83 to 96
Atole and Park (2018)	Rice	Golden Apple Snail	91.23

Plant breeders and pathologists work out the stalk rot severity in the field conditions (Qureshi *et al.,* 2015a), which is laborious and time-consuming. The real-time classification of stalk rot severity into different levels provides the most accurate and rapid results in this technological era. Typically, conventional machine and deep learning methods are operational in recognizing crop stress and classification (Singh *et al.,* 2018). The difference between these methods is the feature of the procedure of the extraction technique. Conventional machine learning demands dividing the studied image and isolating the desired traits by hand, while DCNN automatically isolates image traits by convolutional layers (Ubbens and Stavness, 2017; Baer *et al*., 2022).

A rapid increase in the study of abiotic and biotic stress identification and classification through CNN surfaced in recent years (Singh *et al.,* 2018). Ma *et al.* (2018) studied four cucumber leaf diseases and found that DCNN had a higher identification accuracy than traditional machine learning methods. Veeramani *et al.* (2018) also reported the importance of deep learning methods where classification depended upon color, texture, and morphology. The computational complexity of the neural network showed a vital consideration in its design. A plain architecture with shallow layers was mainly functional. The importance of the simplest model that could be accessible in mobile already has an explanation by Ma *et al.* (2018). The existing study exhibited the pronounced impact of CNN in classifying maize stalk rot severity. The overall accuracy was 83.88% in stalk rot classification. These findings agree with the findings observed in deep learning (Ferentinos, 2018). How many images are necessary for the CNN model training to get the perfect results is yet to be described (Kamilaris and Prenafeta-Boldú, 2018). The reason is that each crop may have many diseases related to some environmental factors (Barbedo, 2018).

Moreover, labeling all these diseases seems challenging (Kamilaris and Prenafeta-Boldú, 2018). Each severity class had a balanced number of images in the training and validation. Buda *et al.* (2018) reported that imbalance classes distressed convergence and the model's generalization ability. Considering accurate classification objectives and the prompt response of the model, the study ran to classify stalk rot disease into two levels. The images of the study came from the experimental fields at the flowering stage, considering all environmental factors. Barbedo (2018) described that it was hard to collect numerous images. Thus, it is necessary to consider the lesion area only. DeChant *et al.* (2017) reported that they handled the impact of dead ground vegetation, illumination variations, background leaves, and insects on their model without success. Ferentinos (2018) stated that his model struggled to cope with where the examined leaf inhabited a small and non-central part of the image.

Considering these limitations led to taking only images of the lesion area. Capturing the photos in the field and laboratory conditions produces different accuracy levels for the same CNN model. Ferentinos (2018) reported that the CNN model trained under the images of field conditions, when used for laboratory, decreased the accuracy level from 99% to 68%. The recall ratio of 0.911 for susceptible in Table 2 is analogous to the findings of Wang *et al.* (2017). Liang *et al.* (2019) experimented to determine the disease severity. They found 91% accuracy. The results of this study endorsed their findings. Our results also align with the study of Fuentes *et al.* (2017), who described the high level of confusion among the classes. Significant differences among the techniques in Table 4 also supported the findings of Qureshi and Qayyum (2014). A comparison of approaches in Figure 6 also showed that CNN results were closer to the standard than the conventional method.

CONCLUSIONS

Extension workers and pathologists reported the stalk rot severity problems faced by the farming communities. It resulted in low yields of maize crops in Pakistan compared with its potential, resulting in more fungicidal applications and environmental pollution. The disease incurs a wrong classification into severity levels due to the farmers' lack of experience. Misjudgment leads to inappropriate actions of the farmers, subsequently increasing the cost of production with low yield. The research focused on the benefits of deep learning algorithms for classifying resistant and susceptible plants. Likewise, early identification and severity of the disease through advanced technology helps in deciding measures for its control with correct timing. The research enhanced the images' pixel values taken by the farmers. The data obtained from the pixel values are conforming to get the minimum in return values. Maize used as food and feed for humans and animals, respectively, requires the urgent need to get the full potential of maize crops by addressing biotic stresses on time using computer-aided technology.

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