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Assessing the Impact of Segmentation on Wheat Stripe Rust Disease Classification Using Computer Vision and Deep Learning

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ABSTRACT Wheat is a staple crop that is grown across the world due to its substantial contribution to human nutrition. Its significance is evident as it provides almost 20% of calories and protein required for daily human consumption. However, wheat yield is affected by rust disease that can reduce 30% of wheat production which is a serious threat to food security. In order to minimize the loss, it is crucial to identify precisely and localize the wheat rust disease and its infection types. For this purpose, several classification and segmentation techniques are used which are based on machine/deep learning models. This paper provides a realistic analysis and evaluation of various segmentation techniques including Watershed, Grab Cut, and U2-Net. These techniques are applied to the wheat stripe rust data to generate multiple datasets such as Watershed segmented data, GrabCut segmented data, and U2-Net segmented data. Subsequently, a pre-trained deep learning model, ResNet-18 is applied to these datasets to assess the impact of segmentation on classification accuracy. The highest classification accuracy (96.196%) is achieved on the dataset segmented by U2-Net. This research collates several state-of-the-art segmentation techniques in terms of correctness and their direct impact on classification accuracy which gives a pragmatic analysis for researchers to choose optimal segmentation technique. The research primarily focuses on the direct impact of segmentation on classification accuracy of wheat stripe rust, which has not been given sufficient focus in earlier researches.

INDEX TERMS Machine learning, deep learning, segmentation, cropping, classification, wheat stripe rust disease.

I. INTRODUCTION

Wheat plays a vital role in the world economy regarding food security, cultivated land, and commerce [1]. In 2019, wheat production is estimated at 766 million tonnes cultivated on 240 million hectares globally, which makes it the second most-produced cereal [2]. Although this production is huge, there is still a need to increase wheat yield to feed the increasing population. Several factors can decrease wheat yield such as soil fertility, climatic conditions, fertilizer usage, disease attacks, irrigation plan, and others. Among these factors, wheat stripe rust disease can adversely damage the crop which results in 30-40% loss in wheat production as discussed in [3].

Stripe rust is caused by an airborne fungus named *Puccinia striiformis* that rapidly prevails within the field its surroundings [4]. This disease mainly occurs on leaves but also affects glumes and awns which give rise to information of infection hot spots in the crop. The cool and moist weather is suitable for its attack and prevalence where new lesions inside the leaf are produced which contain new spores. In a very humid atmosphere, these spores are usually present in small clumps

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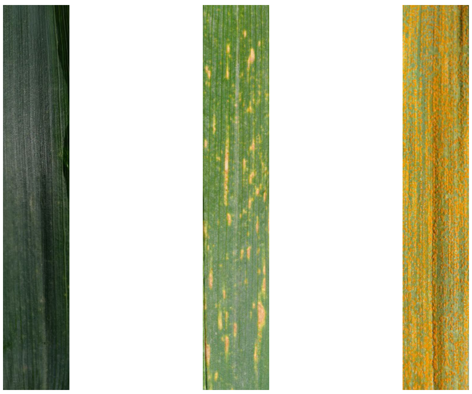
and travel by the air resulting in a uniform pattern of disease. Normally, it attacks the wheat crop at any stage and disrupts the sugar supply to the seeds. Consequently, wheat yield loss is faced in terms of quality and quantity by reducing the weight, number, and size of grains. The stripe rust can cause a 100 percent yield loss if attacks the wheat crop in early stages with constant humid conditions [5].

The stripe rust disease is classified into three main infection types i.e. (i) Healthy, where the wheat leaves are completely green with no spores, (ii) Resistant, where the wheat leaves have small spores but they have the capacity to resist the rust attack, (iii) Susceptible, where the wheat leaves are adversely affected by the rust disease. Figure 1 shows different infection types of stripe rust on wheat crops.



(a) Healthy Leaf (b) Resistant Leaf (c) Susceptible Leaf

FIGURE 1. Infection Types of Wheat Rust.

1) MOTIVATION

Wheat stripe rust is considered as one of the conspicuous factors which contribute greatly to the reduction of wheat yield, especially in the province of Khyber Pakhtunkhwa and northern Punjab, Pakistan. 70% of the wheat production area in Pakistan is vulnerable to stripe rust, which totals to 5.8 million hectares [6]. Several studies show that the disease had left a serious impact on the country's economy. [7] reported a loss of US$8 million due to wheat stripe rust in only three districts in the province of Balochistan. A loss of 2 billion Pakistani rupees was encountered due to stripe rust between 1997 to 1998 [8]. The Inqilab-91(Yr25) wheat variety was the one which was hugely destroyed during 2004, which resulted in affecting 80% of the country's wheat-growing area [9].

To control rust disease attacks and their spread, timely detection is crucial. The traditional means of rust detection and control are very time-consuming as they require experts to do field visits and then suggest remedial measures to the farmers. One of the highly used traditional approaches includes using molecular methods for disease detection in plants which require specialized skill sets to performs as discussed in [10]. This process can be optimized significantly using the latest technology-based solutions that can detect the wheat rust disease and map it into infection types so that farmers can take immediate remedial actions. These systems are not only time & cost-efficient but also increase wheat production by resource optimization.

In the last few years, researchers have used several sophisticated techniques for wheat disease detection such as remote sensing, machine & deep learning, and the Internet of Things (IoT) as discussed in [11], [12]. In remote sensing, multi-spectral, and hyper-spectral data is used to compute various Vegetation Indices (VIs) which provide significant information related to crop disease [13]. In [14], ZY-3 satellite is used to capture multi-spectral data with a spatial resolution of 5.8 meters. Different VIs are computed to identify the healthy and rust-affected areas of wheat. The satellite platforms provide low spatio-temporal data which makes it challenging to identify the accurate area under rust attack and its infection types. Moreover, high processing is required prior to use the satellite data such as radiometric calibration, orthorectification, etc.

To overcome this limitation, Unmanned Aerial Vehicles (UAV) are getting popular in the agriculture domain to perform several tasks including crop disease detection. UAV mounted with multi-spectral or hyper-spectral camera offer images provide high-resolution data which provide considerably better results. In [15], drone data is used to detect different types of rice diseases including leaf blast, sheath blight, brown spot, and bacterial blight. Though UAV platforms provide high-resolution data as compared to satellite data with no time constraints, this data cannot be used to accurately identify the stressed areas and to map different infection types of crop diseases.

A lot of research has been done since the last decade where IoT-based technology is used for crop disease detection [16], [17]. In [17], an IoT-based system for leaf disease detection is presented, where, optical images are used along with other sensors data. The developed system is unable to localize the areas under stress, and it can only classify healthy leaves and damaged leaves. The IoT-based systems require a wide range of sensors along with other electronic equipment, which makes them unsuitable for large agricultural land due to high development and deployment costs. In [18], an IoT-based system is presented to predict diseases in Pearl Millet, where, different deep learning models are used. The images are collected by this system and sent to the cloud automatically. A deep learning model 'Custom-Net' is proposed which achieved the highest accuracy of 98.78% as compared to the other models such as VGG-19, VGG-16, Inception, Inception-V3, ResNet-V2, and ResNet-50.

To perform a more detailed analysis of crop diseases, image processing, machine, and deep learning techniques are used, which normally require high-resolution optical imagery [19], [20]. For this purpose, image segmentation plays a key role and greatly impacts the performance of any disease detection and classification model. It is a process of partitioning an image into different categories, where every pixel in the image is assigned to one of the specific categories [21].

Later, machine or deep learning models are applied to the segmented data to classify the disease into its different types. In [22], a detailed survey of CNN-based deep learning models is presented which are used to detect plant leaf diseases. The most popular deep learning models are LeNet5, GoogLeNet, ResNet, VGGNet, ResNeXt, DenseNet, LeafNet, and M-bCNN.

Towards this end, we have proposed a systematic and intelligent approach for wheat stripe rust classification that employs advanced segmentation techniques. The high-resolution optical data is collected using mobile cameras with a resolution of 48 mega-pixels. The collected images are first segmented using several segmentation techniques (Watershed, GrabCut, and U2-Net) to generate datasets corresponding to each of these techniques. After segmentation, the resultant images are cropped to remove the irrelevant area in the images. Subsequently, a pre-trained deep learning model, 'ResNet-18' is applied on all types of segmented datasets to assess the effect of segmentation techniques on classification accuracy. The key contributions of this paper are given below:

- Acquisition of wheat stripe rust dataset indigenously through field surveys of National Agriculture Centre (NARC), Islamabad, Pakistan. This entire activity is challenging pertaining to the short life span of the subject disease requiring frequent visits to capture the disease data at all stages amply.
- Generation of multiple datasets by applying several segmentation techniques to the raw dataset.
- Evaluating the impact of several segmentation techniques on classification accuracy

The previous work done in this domain does not include a comparison of segmentation techniques on the wheat leaf dataset. This paper focuses on wheat leaves as this crop is a major contributor to the country's economy and its yield can be considerably lowered when infected with stripe rust disease. The segmentation techniques used in this paper give different segmentation results depending on the nature of the leaf; i.e., a healthy leaf, or a disease-infected leaf. The difference in segmentation results is due to differences in texture, color, and shape. It is observed that some techniques perform worst on a disease-infected leaf, while some yield good segmentation results irrespective of the leaf nature. The segmented data is then fed into a pre-trained classification model and the impact of segmentation on the classification accuracy is observed.

The rest of the paper is organized as follows: the Related work is discussed in Section-II, Methodology is presented in Section III, Section-IV contains the Results and Discussion and Section-V presents the Conclusion & Future work.

II. RELATED WORK

A lot of research has been done in the agriculture sector where several Machine and Deep Learning based techniques are considered for crop disease detection. Segmentation is a prerequisite to perform disease detection which helps to extract the region of interest. In [23], a technique for wheat leaf lesion color segmentation is proposed which provides improved multi-channel selection based on the Chan–Vese (C-V) model. Specifically for wheat disease detection, an image segmentation algorithm is proposed in [24]. The proposed segmentation approach has fewer iterations and higher accuracy compared to traditional C-V and gradient descent CV (g-CV) models.

Similarly, hybrid techniques are also considered for improving image segmentation for similar domain [25]. In [26], particle swarm optimization based SVM (Support Vector Machines) P-SVM is used for segmentation and classification of plants. The proposed P-SVM model achieves better results compared to other models providing a sensitivity of 0.9581, accuracy of 0.9759, specificity of 0.9676, and segmentation and classification accuracy of 95.23. A new segmentation technique based on feature diversity is presented in [27] in which Watershed algorithm is used to extract image feature eigenvectors; the model efficiency and accuracy are good which are verified by experimental results. The image is converted to grayscale, which is followed by creating a histogram and clusters where FCM (Fuzzy c-means) is applied on each cluster, which results in segmented regions.

In [28], a new segmentation technique is proposed which is based on Artificial Neural Networks (ANNs). This method is used to segment RGBSV(RGB and HSV) cluster spaces. The method starts by removing noise from the color space, which is followed by converting the pixels to RBGSV. Finally, the method separates pixels of the same color and calculates neighborhood size. The proposed algorithm is a faster color image segmentation algorithm that can benefit computer vision applications. Similarly, in [29], a segmentation technique is presented which is based on the C-means-based neural network. They presented an Objective function which calculates the distance between image pixels and cluster centroids. This method segments the image much faster than other ANN-based segmentation techniques. Another image segmentation technique is presented in [30] which is based on fuzzy connectedness. The method uses dynamic weights(DyW) to adjust the linear weights in fuzzy correctness, which achieves an accuracy of 99.15% on different ranges of images.

To segment the colored images, several new techniques have been proposed. In [31], a new segmentation technique is proposed which uses Support Vector Machines. This technique is applied to colored medical images to segment different regions in the image. The technique segments 768×576 color images in 1 second. In [32], Otsu segmentation is used to segment outdoor images with vein detection and a protrusion-notch removal to refine the extracted image. The system segments the images with average precision and recall scores of 0.92 and 0.90, respectively. Another segmentation technique is presented in [33] which combines scale-space filter and Markov random field to segment the colored images. The scale-space filter provides effective results on color image segmentation, but sometimes valleys and peaks are misclassified. The misclassified peaks are then compensated using Markov random field.

In [34], an unsupervised image segmentation technique is presented that uses texture statistics and level set methods. The proposed method is different from other segmentation techniques which use independent variables. Similarly, in [35], a region-based segmentation technique is proposed in which a mean shifting algorithm is used. The method starts by extracting the color, textures, and location of each pixel, then makes clusters using mean-shift clustering. Experimentation results have confirmed that the proposed model can provide good and fast segmentation results. Another framework for color image segmentation is presented which is based on Markov Random field [36]. They use a line process that is implemented using an edge detection algorithm. Using the line process has the advantage that it has an explicit edge representation rather than an implicit edge representation. One disadvantage is that it has inaccuracies in the edge detection algorithm. In [37],an edge-based image segmentation technique that is based on feature phase symmetry and path cost minimization is introduced for segmenting ultrasound images. The edge detection is performed on the ultrasonic images using plane symmetry which achieves an accuracy of 87%.

Crop disease detection poses great importance due to its impact on food production and quality. Different feature extraction, cropping, and segmentation techniques are used to detect different crop diseases as discussed in [38]. An advantage of using this method is that plant diseases are identified at an early stage. In [39], automatic cropping techniques are used to obtain the clean regions of interest for better classification performance by preserving the most visually important region. The benefit of using this technique is that, if the aspect ratio of the cropping rectangle is known in advance, then the problem can be optimized and solved in a linear complexity (to the number of pixels).

There are several machines and deep learning techniques which are applied to the imagery dataset to segment and identify crop diseases. In [22], a detailed survey of CNN-based deep learning models is presented which are used to detect plant leaf diseases. The most popular deep learning models are LeNet5, GoogLeNet, ResNet, VGGNet, ResNeXt, DenseNet, LeafNet, and M-bCNN. In [40], deep learning segmentation approach and optimized image registration techniques are also used to do vine disease detection using UAV multi-spectral images. The proposed model provides 87% accuracy on leaf level and 92% accuracy on grapevine level. In [41], fruit crop diseases are also being recognized using automated segmentation techniques based on correlation coefficient and deep CNN features. This method achieved a classification accuracy of 98.6%. Similarly, an empirical analysis of olive leave spot disease is carried out using auto-cropping segmentation and fuzzy C-Means classification [42]. The results obtained by FCM are comparable to that of manual scoring providing an accuracy of 86%.

In [43], LeNet architecture is used to classify banana leaves diseases where the results are evaluated under challenging conditions such as complicated background, varying image resolution, and illumination. The proposed method achieves an accuracy of 92.88% on train and test datasets of 80% and 20% respectively. In [44], Deep Residual Neural Network-based algorithm is used for detecting multiple plant diseases which achieved a balanced accuracy of 0.87 under challenging testing. In [45], faster region-based convolutional neural network is used to classify images within images within 0.2 seconds. In [46], a Convolutional Neural Network based approach is proposed for mapping crop types. CNN's are used to clean the dataset where the Sentinel time series are extracted from each pixel. These are further used to train another CNN model which classifies the image into different classes. The proposed method achieves an accuracy of 74%. In [47], Sahu et al performed a comparison of pre-trained model and training from scratch for classifying leaf images of the bean crop. The results are then compared where the pre-trained model performs best with an accuracy of 97.06% and the model from scratch performs worst with an accuracy of 70%.

In [48], an AI-driven framework is proposed to detect guava diseases where HSV and RGB histograms are used along with Local Binary Patterns (LBP) texture features. In order to perform disease recognition, four types of advanced classification techniques are applied including Fine Complex Tree, Bagged Tree, KNN, Boosted Tree, and Cubic SVM. The Boosted tree achieved the highest accuracy of 99% on LBP, RGB, and HSV features. In [49], cassava mosaic disease detection is performed by applying a deep residual convolutional neural network which outperformed the plain convolutional neural network with the margin of 9.25%. In [50], cassava disease detection is performed where a novel technique to generate synthetic data is presented which is based on color histogram transformation. The modified MobileNetV2 neural network achieved satisfactory accuracy on the low-quality augmented dataset as compared to the baseline model. Similarly, an apple disease detection technique is presented in [51], where MASK RCNN is applied on the PlantVillage dataset to identify the affected regions. The results indicated that an ensemble subspace discriminant analysis (ESDA) classifier obtained an accuracy of 96.6%.

The deep learning segmentation technique 'U2-Net' is proved to be very effective for segmentation in several applications such as medical image segmentation [52], Segmentation of Pathological OCT Scans [53] and many more. Several techniques have been used for segmentation, cropping, and crop disease detection which are based on machine learning, deep learning, and others. In this research work, we applied different segmentation techniques such as Watershed, GrabCut, and U2-net to the wheat stripe rust dataset. A deep learning model ResNet-18 is applied on the three types of segmented datasets along with the raw dataset and results are compared to find the best segmentation technique which enables the classifier to classify the infection types of wheat stripe rust. The major motivation behind choosing the proposed research is that research in the past has provided very successful results, thus, benefiting in maximizing the yield of several crops. On thorough study, it is found that there is scope for further investigation and discussion on the impact of segmentation techniques for the specific problem of wheat stripe rust detection. The work can be further extended to cover other crops as well. The choice of this specific problem is done because Pakistan, being an agricultural country, relies greatly on wheat and stripe rust is one of the factors limiting its yield.

A. STUDY AREA

The study area for the proposed research is National Agriculture Research Center (NARC), Islamabad, located at 33.67°N latitude, and 73.13°E longitude. Wheat, mustard, and maize are the most important crops harvested in this region. The dataset is collected between March and April 2021. The wheat used for this research is sown in the first week of November 2020. The varieties of the wheat crop used for capturing images of wheat stripe rust disease for this research are 'Pak-13', 'Borl-16', 'Zincol-16', and 'Markaz-19'. The map of the study area is shown in Figure 2

III. METHODOLOGY

A segmentation framework to classify wheat stripe rust into three infection types including healthy, resistant, and susceptible, is proposed. The collected dataset is segmented by three segmentation techniques including Watershed, GrabCut, and U2-Net (deep learning based technique). The segmented images are cropped later to extract the region of interest and exclude the unwanted regions. After cropping the images, the deep learning model, ResNet-18 is applied to generated segmented data. The overall architecture of the proposed framework is shown in Figure 3 which is discussed below:

A. DATA ACQUISITION AND DATA PRE-PROCESSING

The wheat stripe rust dataset has been collected from wheat fields located at the National Agriculture Research Center (NARC), Islamabad, Pakistan. A mobile camera (specifically Samsung Galaxy A31 device rear camera) is used to capture optical images at different stages of wheat growth. Typically, rust disease appears at the end of February and lasts until April. The wheat leaves are placed on a screen and the mobile camera is kept at a height of around 4-6 inches above the screen and the image is captured such that the camera is vertically above the screen facing downwards.

Initially, the data is collected without creating any uniform background behind the leaves; then the process is optimized by placing a white/blackboard behind the leaves before capturing images. This enables us to reduce background noise and take focused images of wheat stripe rust disease. Additionally, this will assist in optimizing the segmentation process. The images are captured in both CR2 and PNG format, but later the images are converted into a single format (PNG) for data processing. Subsequently, the total number of collected images are 1924 which are labeled by the agricultural expert into three categories including healthy, resistant, and susceptible. The images are pre-processed by applying histogram equalization to improve contrast. These pre-processed images are resized to 224×224 pixels to optimize processing speed and to ensure compatibility with pre-trained models. Augmentation techniques like random horizontal flip and random vertical flip, etc, are also applied during the training phase.

The code and dataset used for the work is available on Github[1]

B. SEGMENTATION

Segmentation is the process of assigning each pixel of the image into one specific class or category based on some criteria. The segmentation techniques used in this research are discussed below:

1) WATERSHED METHOD

In the Watershed Method, an image is considered as a landscape with elevation and depth defined by the gray values of the gradient magnitude. This method finds catchment basins by considering bright pixels as elevation and dark pixels as depth in the image [54]. This technique is applied to segment the wheat leaf image to extract stripe rust disease patterns from the background by creating background markers and leaf markers. The background markers are recreated by removing non-green backgrounds using a color histogram threshold followed by computing color indices for red and green colors.

Afterward, Otsu thresholding is applied to segment these indices into two groups which is a technique, that returns a single intensity threshold that separates the foreground from the background. This method iterates on a set of all possible threshold values and calculates the spread of pixels on each side of the threshold i.e., the pixels either belong to foreground or background [55]. In the collected dataset, some leaf images contain green regions that are not of interest such as grass. These regions are removed by using the local entropy of grayscale values which measures statistical randomness such as if the entropy exceeds the specified threshold, the region is considered as a background.

In contrast to the background markers, the leaf markers are created to find the location of the target leaf in the image using gray-scale morphology, which takes the inverse of the background marker as an input. The Watershed technique is applied to extract the leaf, which is followed by applying leaf structure refinement to obtain the final output as shown in Figure 4.

2) GrabCut SEGMENTATION

GrabCut segmentation is another image segmentation technique that makes use of the GraphCut method. The GraphCut

[1]Github Repository: https://github.com/eruditehassan/segmentation-classification-wheat-rust

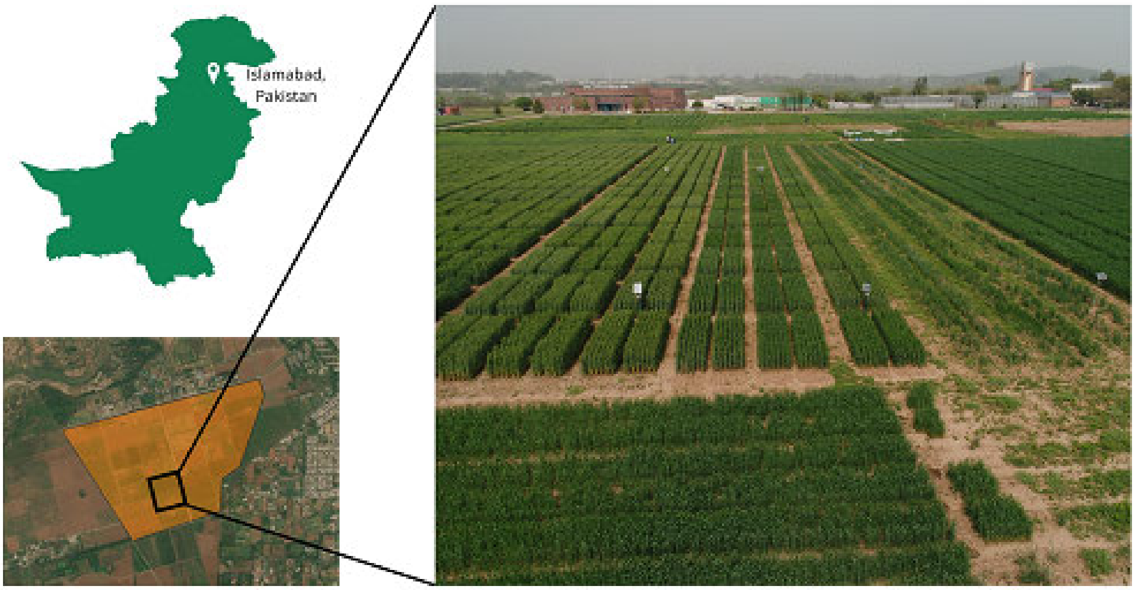


FIGURE 2. Study Area - National Agriculture Research Center (NARC), Islamabad.

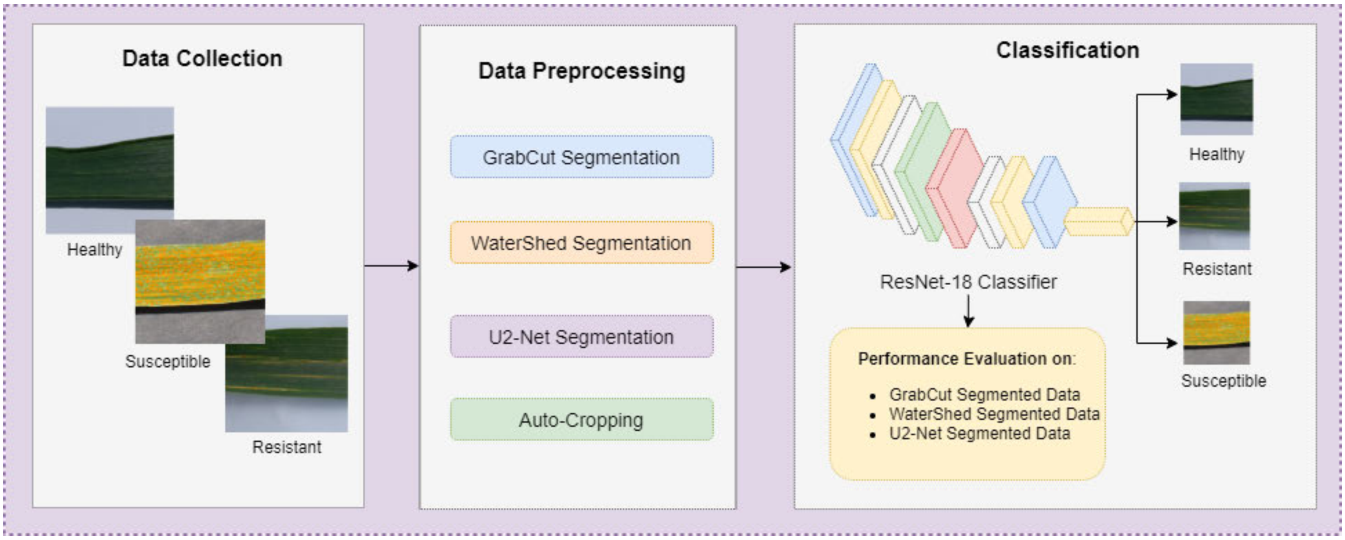


FIGURE 3. System Architecture.

method is a segmentation technique in which each image is considered as a graph of interconnected nodes where each node is a pixel and lines connecting these nodes are called edges. A path is generated which connects all the nodes to traverse across the graph. The pixels are assigned higher weights if they have a high probability of relating to each other where the edges having low weights are removed from the graph which results in segmentation of the image. To segment an image with the GrabCut method, initially a rectangle is drawn on the image including the foreground followed by border-matting which calculates alpha-matte around the rectangle and pixels of the foreground region as discussed in [56]. Subsequently, a graph is created where two special nodes namely source and sink nodes are created. Each pixel in the image is connected to the source and sink node where the foreground of the image is represented by source nodes, while the background is represented by sink nodes.

The region information calculates the weights by determining the probability that the pixel belongs to either the foreground or background where these weights are used to create a Markov random field. A Min-cut/Max-Flow algorithm is used to segment the graph which separates the source node

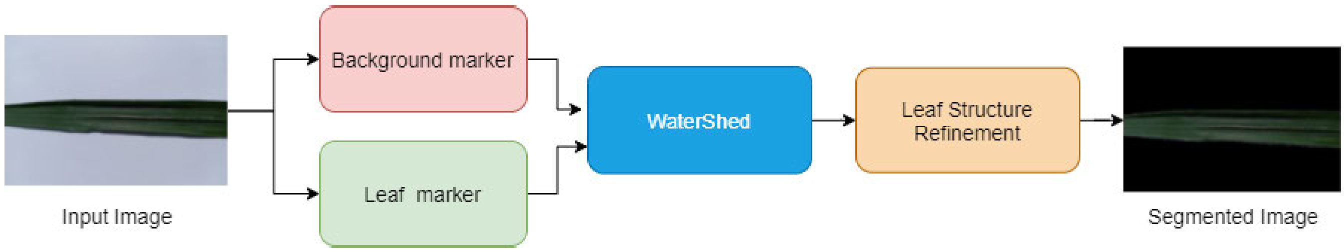


FIGURE 4. Segmentation Pipeline using Watershed Technique.

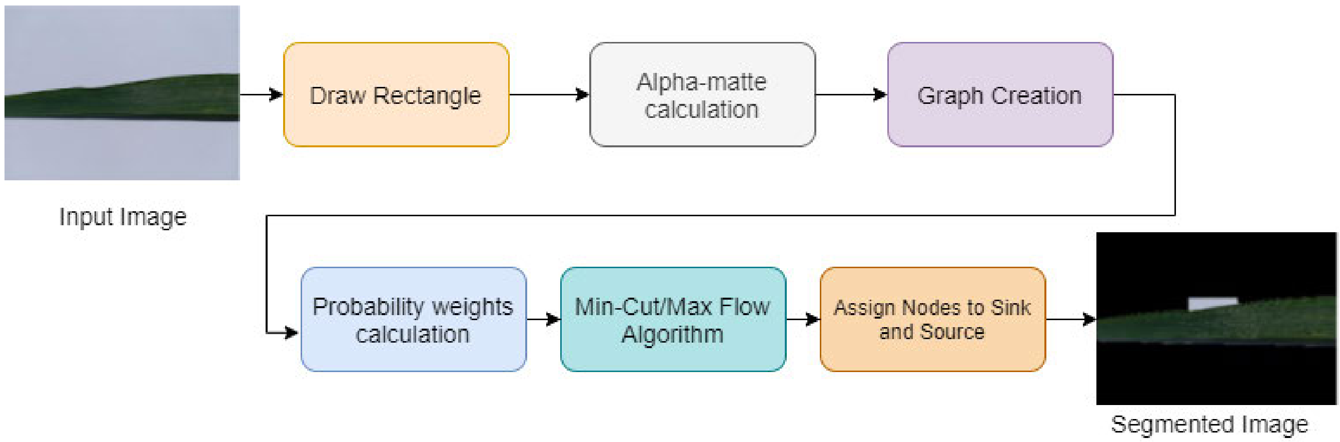


FIGURE 5. Segmentation Pipeline using GrabCut Technique.

from the sink node. After separation of the source and sink nodes, all connected nodes to the source node are assigned the foreground region, and nodes connected to sink nodes are assigned the background region [57].

3) U2-NET

U2-Net is an advanced deep learning model for background removal which generates the mask that is further used to segment the image by utilizing image processing functionality of OpenCV and Pillow libraries as discussed in [58], [59], and [60]. The image with some background is fed into the U2-Net model, which generates a mask for the image. The mask is used to extract the region of interest from the original image by excluding the background. Figure 6 shows the flow of leaf image segmentation using the U2-Net model where the white area in the mask is the object of interest and the black area in the background.

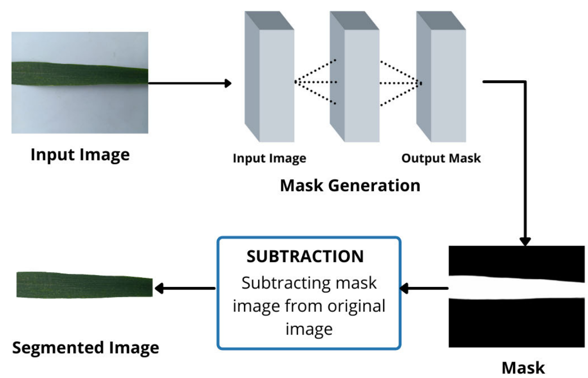


FIGURE 6. Segmentation Pipeline using U2-Net workflow.

C. CROPPING

The cropping is used to exclude unwanted regions in the segmented image. There are two main types of cropping, namely manual, and automated, as discussed below:

a: MANUAL CROPPING

In manual cropping, the image is cut manually to extract the relevant portion of the image. It gives perfect results as the images are carefully cut by visual inspection. One big downside of this approach is that it consumes a substantial amount of time. Moreover, as the data keeps increasing, every time, this manual approach would have to be followed.

b: AUTOMATED CROPPING

Automated cropping uses image processing techniques to crop an image based on pixels. For example, if there is a dark background, then the region of interest containing colored pictures would be cropped by omitting the black background.

This approach is efficient in terms of processing time as it automates the entire cropping process.

All segmented images are cropped, where the regions with only dark or transparent pixels are removed and the regions with colored pixels are retained. The process is applied to all the images to obtain the cropped dataset.

D. CLASSIFICATION

Classification is a process in which a given set of data is categorized into different classes. In this paper, a supervised classification is performed, where a labeled dataset is used to classify the images into three classes such as healthy, resistant, and susceptible. For this purpose, a pre-trained deep learning model ResNet-18 is applied to three types of datasets created by the segmentation techniques.

While training the ResNet-18 model, the Cross-Entropy Loss is used as the loss, and Adam optimizer is used with a fixed learning rate of 3e-5 for all the datasets. The end goal of the research is to assess the effect of segmentation and its different types on classification accuracy. For this purpose, ResNet-18 is trained on 4 different datasets listed below:

1) Raw Dataset with no segmentation
2) Watershed Segmentation Dataset
3) GrabCut Segmentation Dataset
4) U2-Net Segmentation Dataset

The overall flow of classification is shown in Figure 7, where cropped images are fed into the classifier which assigns each image to one of the leaf classes (healthy, resistant, and susceptible).

IV. RESULTS AND DISCUSSION

In this section, the performance of different segmentation techniques in terms of classification accuracy is discussed in detail. Additionally, cropping results and the performance of the classifier (ResNet-18) on different datasets are also discussed.

A. EVALUATION OF SEGMENTATION TECHNIQUES

To remove the background and extract only the damaged areas, three types of segmentation techniques are applied including Watershed, GrabCut, and deep learning based U2-Net method. The performance of these segmentation techniques is discussed below:

1) WATERSHED METHOD

This segmentation method is applied to the wheat stripe rust data which is labeled into three classes including healthy, resistant, and susceptible. This segmentation technique produced some sharply segmented images when tested on healthy and resistant images. However, when the script is tested on a susceptible images dataset, results are not satisfactory i.e. 285 out of 735 images are incorrectly segmented (See Table 1).

The segmentation of different classes of leaves with Watershed techniques is shown in Figure 8.

The results obtained by the Watershed segmentation method are shown in Table 1.

TABLE 1. Segmentation Results obtained after applying Watershed Segmentation Technique.

Class	Total	Correctly Segmented	Incorrectly Segmented
Healthy	673	655	18
Resistant	516	507	09
Susceptible	735	450	285

2) GrabCut METHOD

The segmentation results of the GrabCut method on different classes of leaf images is shown in Figure 9. This method performed relatively poorly compared to the Watershed method, and a large percentage of images belonging to resistant (32.9%) and susceptible (31.9%) classes are incorrectly segmented.

It is observed from Figure 9 that the GrabCut method removes the finger but does not remove the background completely. The method is applied to all images of the three classes and segmentation results are given in Table 2.

TABLE 2. Segmentation Results obtained after applying GrabCut Technique.

Class	Total	Correctly Segmented	Incorrectly Segmented
Healthy	673	576	97
Resistant	516	346	170
Susceptible	735	471	235

Most of the incorrectly segmented images are those where the background is not removed correctly, for instance, as shown in Figure 10.

3) U2-NET

U2-Net is a deep learning based segmentation technique that generates a mask from the original image, and this mask is further used to segment the image as shown in Figure 11. There are a small number of incorrectly segmented images which shows that the method performed better as compared to the Watershed and GrabCut methods. Table 3 shows that 99%, 91%, and 96% images are correctly segmented as Healthy, Resistant, and Susceptible respectively.

The segmentation results on different classes of images by U2-net are shown in Figure 12. The results obtained by U2-Net on different classes are shown in Table 3. The main reason for a small number of incorrect segmentation is images with a poor focus on the leaf. Moreover, some images have

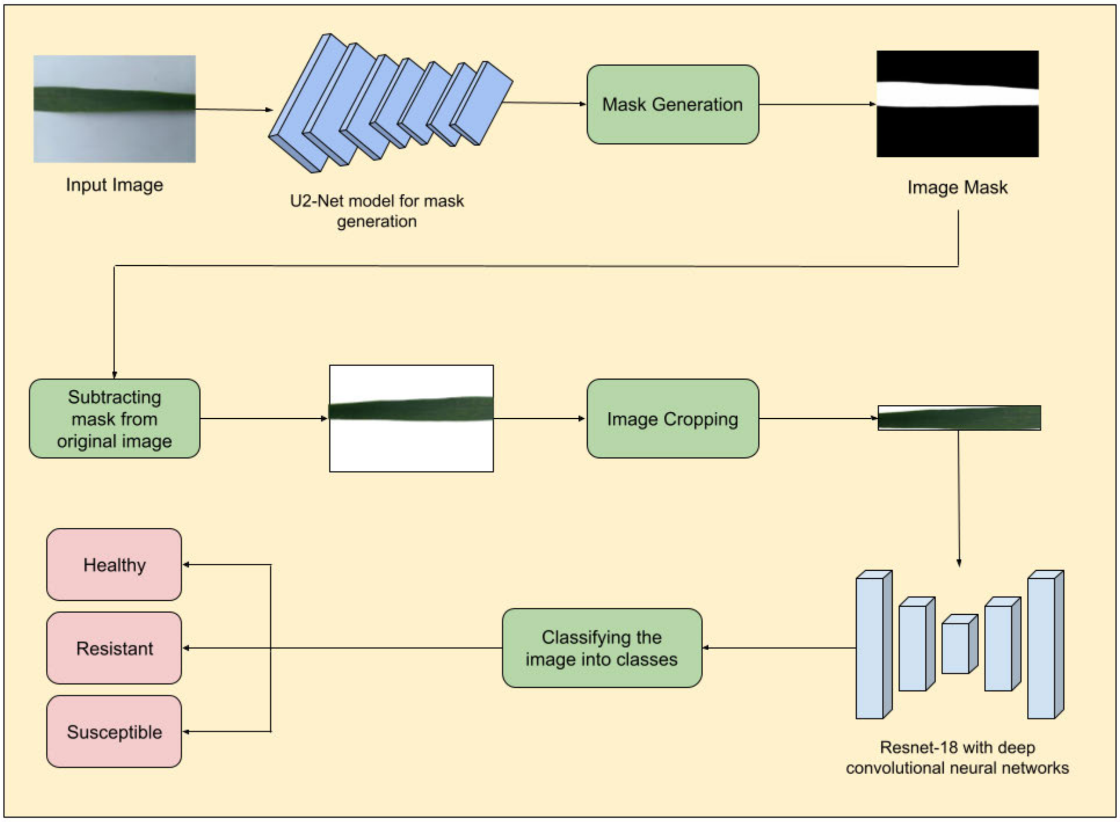


FIGURE 7. Image Classification Workflow.

content other than leaf such as human hand which makes the segmentation model difficult to segment.

TABLE 3. Segmentation Results obtained after applying U2-Net Technique.

Class	Total	Correctly Segmented	Incorrectly Segmented
Healthy	673	667	6
Resistant	516	468	48
Susceptible	735	707	28

4) COMPARISON OF TECHNIQUES

The results of all the segmentation techniques are compared in terms of correctness, where the same set of images are used to evaluate their performance. Table 4 shows the performance comparison of all segmentation techniques on the entire dataset. It is observed from Table 4 that the deep learning based segmentation method (U2-Net) outperformed other techniques with 95.738%, whereas GrabCut showed the lowest performance with 72.4%. The performance of the Watershed method lies between the U2-Net and the GrabCut method with 83.7%.

TABLE 4. Comparison of Different Segmentation Techniques.

Technique	Total	Correctly Segmented	Correct %
Watershed Segmentation	1924	1612	83.783%
GrabCut Method	1924	1393	72.401%
U2-Net	1924	1842	95.738%

To evaluate the performance the metrics used are accuracy, precision, recall, F1 score, and AUC.

The main reason for the optimal performance of U2 Net is that it is a pre-trained model and generalizes well on segmentation tasks. Moreover, it is based on an architecture that is an end-to-end Fully Convolutional Network (FCN), which means that it does not contain any dense layers and only contains convolutional layers making it suitable for images of any size.

On the other hand, the key reason for the poor performance of the GrabCut method is owing to some image fragment noise after segmentation. The GrabCut technique produces

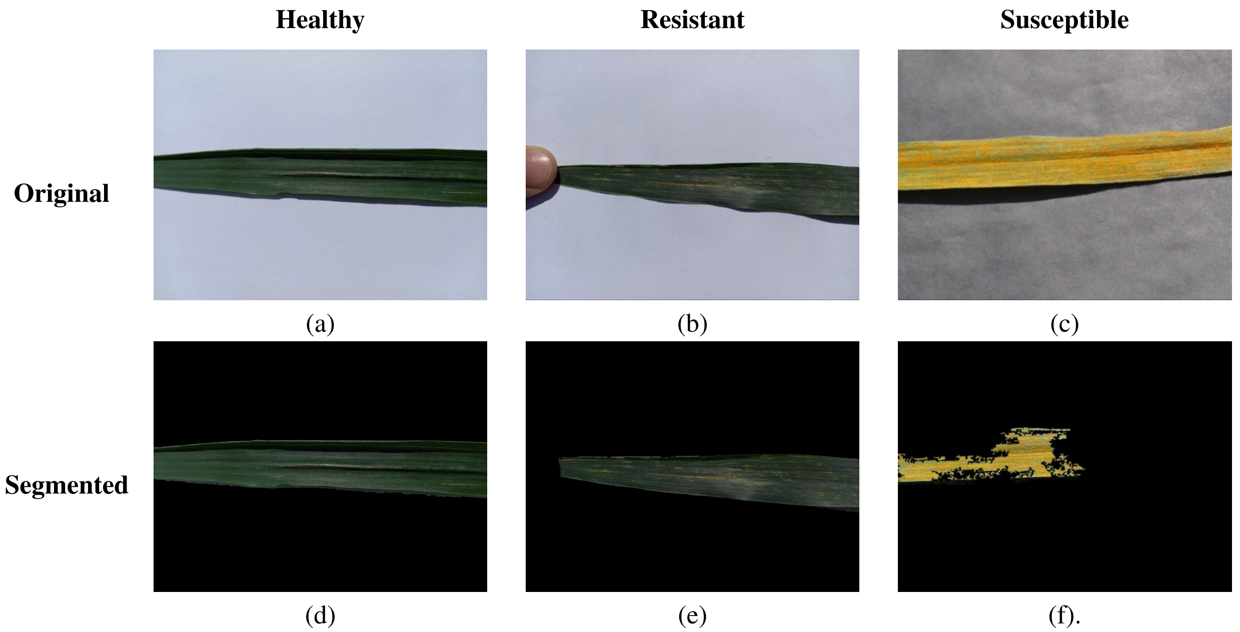


FIGURE 8. **Wheat Leaf Segmentation using Watershed Method (a) A healthy leaf image to be segmented, (b) A resistant leaf image to be segmented, (c) A susceptible leaf image to be segmented, (d) Accurately segmented healthy leaf image with dark background, (e) Accurately segmented resistant leaf image with removal of other objects, (f) Poorly segmented susceptible leaf image due to Watershed's inability to segment non-green regions.**

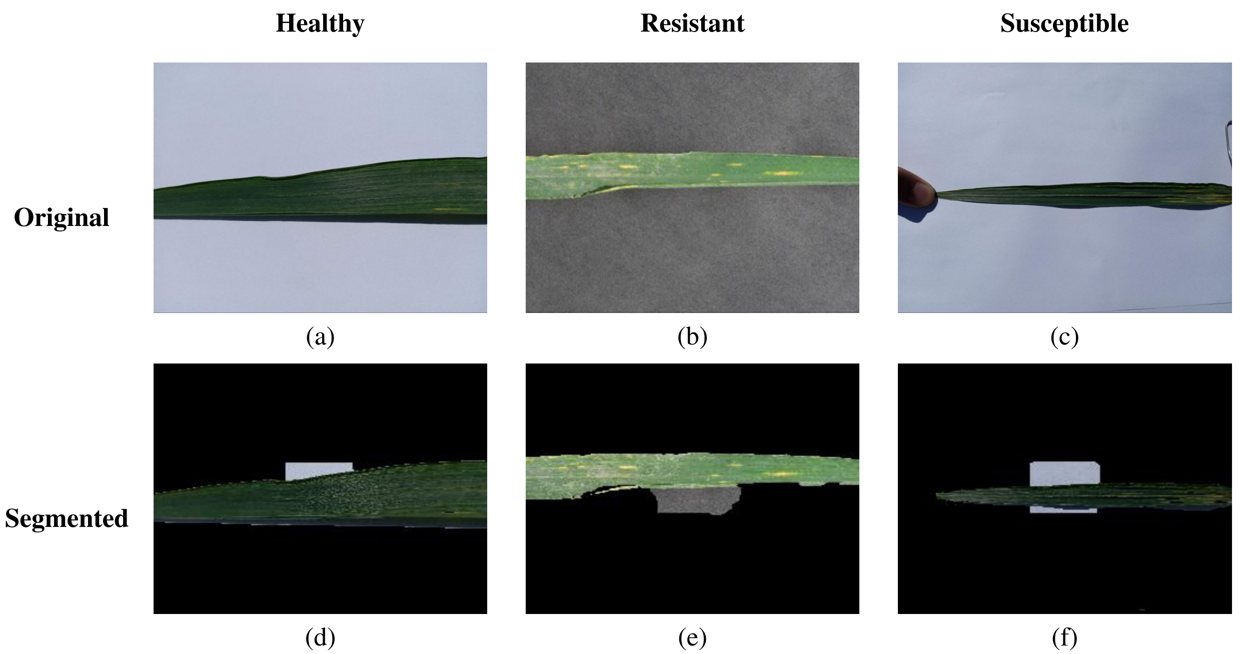


FIGURE 9. **Wheat Leaf Segmentation using GrabCut Method (a) A healthy leaf image to be segmented, (b) A resistant leaf image to be segmeted, (c) A susceptible leaf image to be segmented, (d) Inaccurately segmented healthy leaf image with some noise, (e) Inaccurately segmented resistant leaf image with partial leaf and noise, (f) Inaccurately segmented susceptible leaf image with noise.**

unacceptable segmentation results because the foreground is not clearly separated from the background, which makes it difficult for GrabCut to segment the image as the method uses a pixel color distribution. The moderate performance of the Watershed method is pertaining to the fact that it makes use of background markers that remove the non-green background and extract the green leaf. This works well in the case of healthy leaves; however, susceptible leaf images are having shades of yellow along with green, leading to compromised segmentation of leaves.

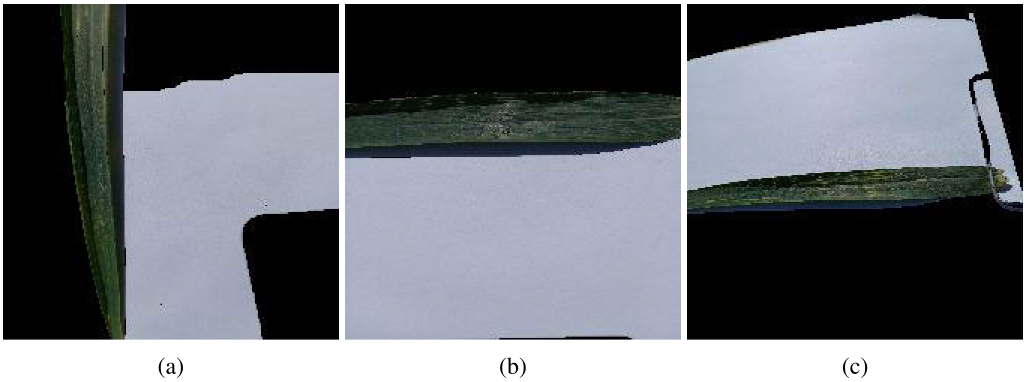


FIGURE 10. Incorrectly Segmented Images by GrabCut This method performs relatively poor on the image dataset as the segmented images contains noise due to the fact that GrabCut is unable to segment the image having unclear distinction between the foreground and background as shown in (a), (b) and (c).

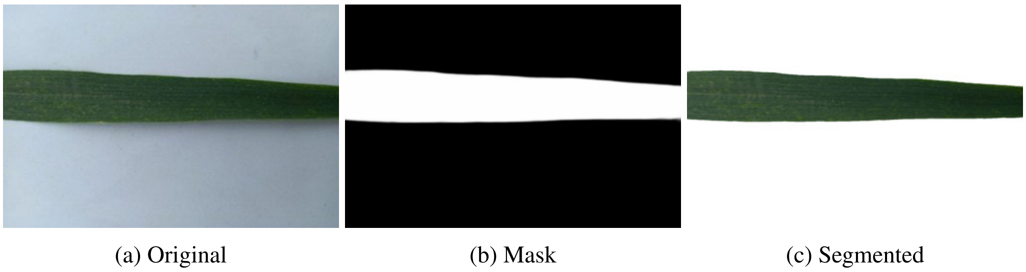


FIGURE 11. Wheat Leaf Segmentation using U2-Net. (a) An original leaf image given to U2-Net, (b) U2-Net generates a mask of the image, (c) The mask is subtracted from original image resulting in segmentation of the original image.

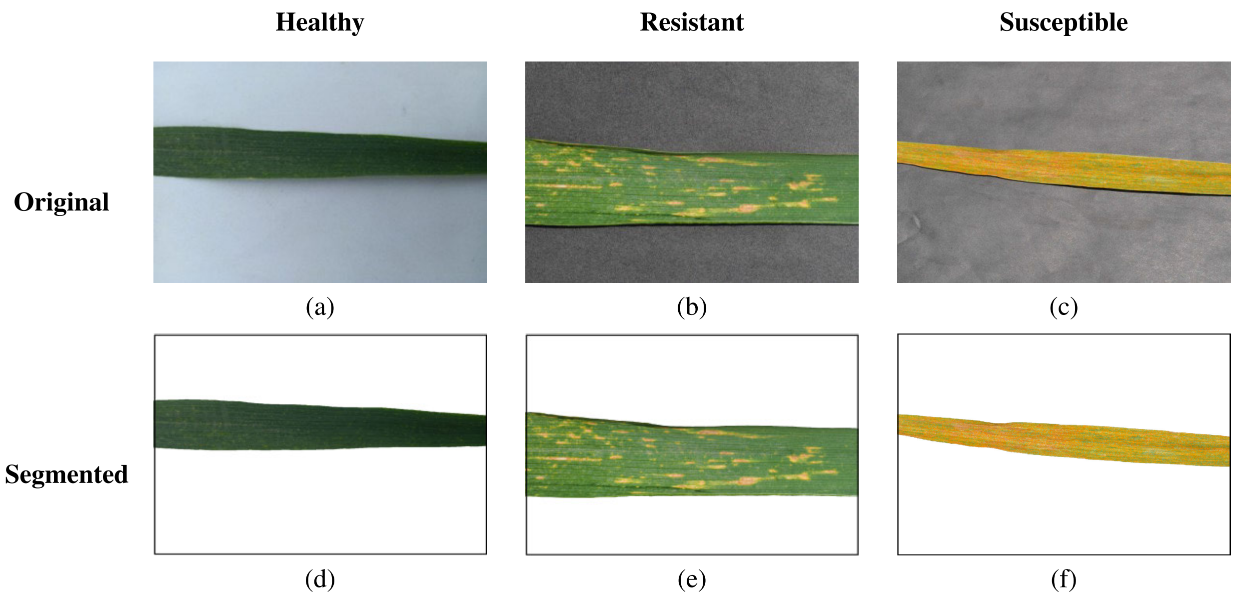


FIGURE 12. Wheat Leaf Segmentation using U2-Net Method (a) A healthy leaf image to be segmented, (b) A resistant leaf image to be segmented, (c) A susceptible leaf image to be segmented, (d) Perfectly segmented healthy leaf image with a transparent background, (e) Perfectly segmented resistant leaf image with a transparent background, (f) Perfectly segmented susceptible leaf image, U2-Net can address the problem of watershed with yellow leaves.

a: TIME COMPLEXITY

The segmentation techniques are further analyzed by feeding images of varying sizes to understand the increase in time with the increase in image size, thus estimating the time complexity of the segmentation techniques. The computing machine used has Core i5-8500H CPU and GTX 1050Ti GPU

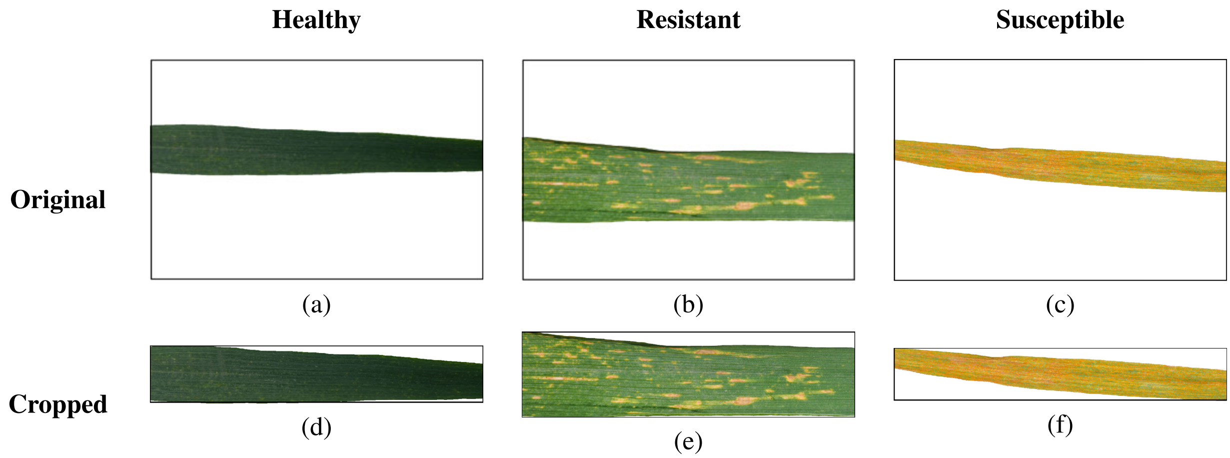


FIGURE 13. Wheat Leaf Cropping (a) A healthy segmented image to be cropped, (b) A resistant segmented image to be cropped, (c) A susceptible segmented image to be cropped, (d) Cropped healthy leaf image (e) Cropped resistant leaf image (f) Cropped susceptible leaf image.

for processing. The computing machine is the same for all the segmentation techniques.

After feeding each of the methods with images of varying sizes, the corresponding processing times are recorded. To consider all the factors influencing time, the time includes the duration for loading dependencies, models, and inputs, and the time for actual processing.

Figure 14 shows the time it takes for various techniques used to segment images of varying sizes. It can be understood from the figure that both Watershed, and U2-Net are growing linearly with the input size (size of the image), while Grabcut is growing nearly exponentially as the size of the input increases. In terms of computation time and complexity, Watershed exhibited the optimal performance.

B. RESULTS OF CROPPING TECHNIQUES

To minimize processing time, cropping is used to exclude unwanted areas from the segmented images. For this purpose, auto-cropping is applied to the dataset and a boundary is added to the images to define their area clearly, highlighting the white or blank region, as can be seen in Figure 13. The performance of the cropping technique can be quantified in terms of the proportion of blank pixels that are present before cropping and the proportion of blank pixels that are present after cropping has been done. The blank pixels are not completely removed because the cropping technique crops a rectangle and the area of interest is not always a perfect rectangle particularly in the case of leaf images, as can be seen in Figures 13. The percentage of blank pixels are calculated for the entire dataset. Firstly, the percentage of blank pixels for all images is calculated, and then, mean percentage of blank pixels for a specific class of the entire dataset is considered. These percentages of blank pixels before and after cropping are shown in Table 5.

TABLE 5. Percentage of Blank Pixels Before and After Cropping.

Class	Before Cropping	After Cropping
Healthy	84.20%	27.50%
Resistant	83.54%	38.06%
Susceptible	83.68%	38.95%

C. EVALUATION OF CLASSIFICATION

There are three types of datasets obtained after applying the segmentation techniques i.e. Watershed, GrabCut, and U2-Net. The deep learning model ResNet-18 is applied on these three datasets along with the raw dataset which contains original images, where no segmentation technique is applied. To evaluate the performance, the metrics used are accuracy, precision, recall, F1 score, and AUC. Accuracy shows the number of correct predictions made by the model. Precision tells us about the quality of positive predictions. It is obtained by dividing true positives by the total number of positives. Recall is another metric used for the correct identification of false positives, it is obtained by dividing true positives by the sum of true positives and false negatives. F1 score is the weighted average of precision and recall. AUC (Area Under the Curve of ROC plot) gives the ability of a classifier to identify the classes correctly. The performance of ResNet-18 classifier on all datasets is discussed below:

1) CLASSIFICATION RESULTS USING RAW DATASET

The classifier is trained and tested on the raw dataset without running any segmentation techniques to observe the effects of segmentation on classification accuracy. The results show that the ResNet-18 achieved an accuracy of 77.901%, where the confusion matrix is shown in Figure 15. The confusion

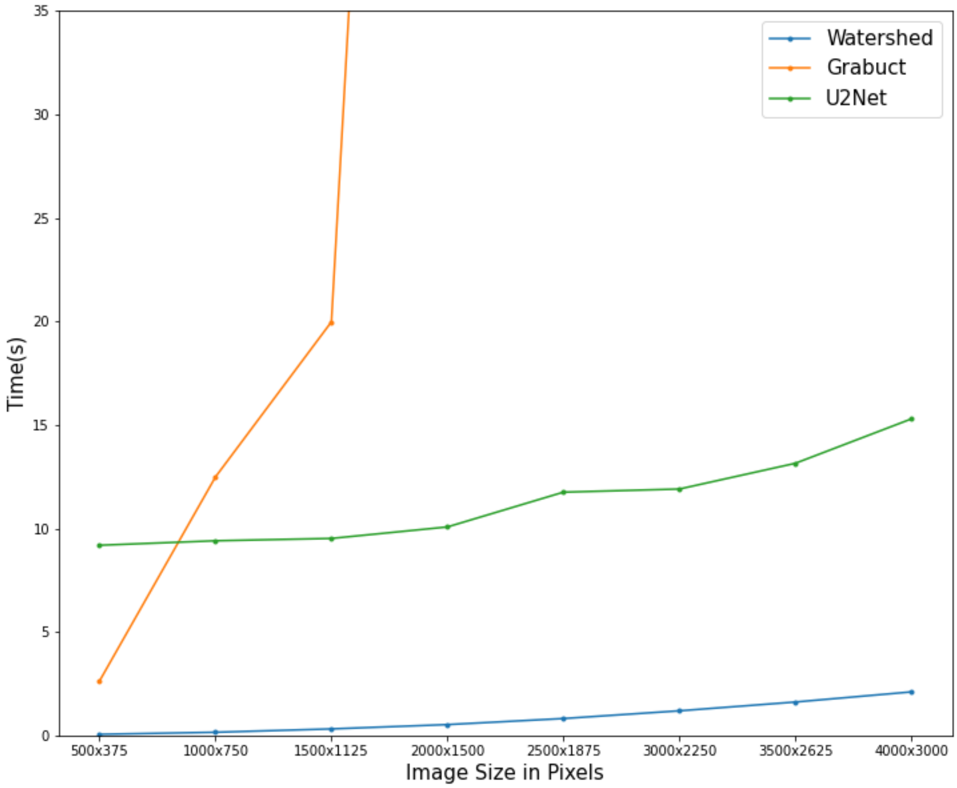


FIGURE 14. Time for Segmentation with Varying Image Sizes.

matrix is used to describe the performance of a machine learning algorithm by displaying side by side comparison of actual labels and predicted labels.

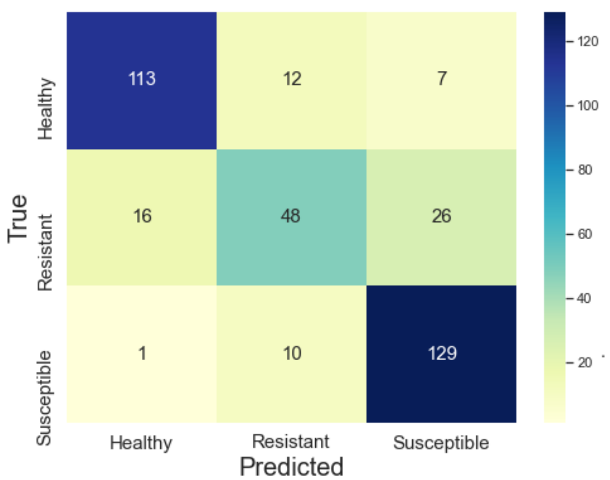


FIGURE 15. Confusion Matrix for Raw Dataset.

It is clear from Figure 15 that the classifier performed well on healthy and susceptible images as there are a small number of incorrectly classified images. However, there are a total of 42 images of resistant class that are incorrectly classified as susceptible and healthy.

The ROC plot obtained for the Raw dataset is shown in Figure 16

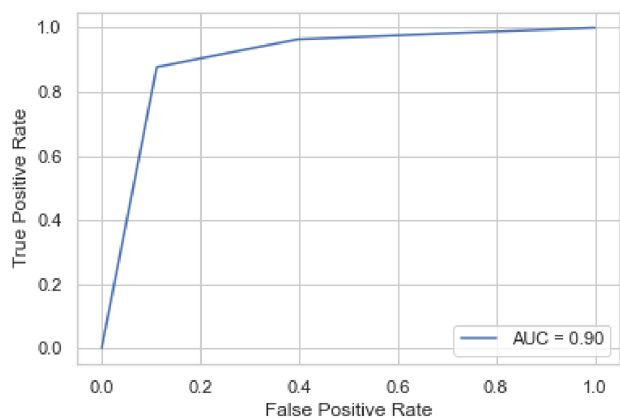


FIGURE 16. ROC Plot for Raw Dataset.

2) CLASSIFICATION RESULTS USING WATERSHED DATASET

The dataset generated by the Watershed Segmentation technique is fed to the classifier training purposes and the results are evaluated on a test dataset. Watershed dataset provided an accuracy of 88.122%, where the confusion matrix is shown in Figure 17. The number of misclassified images corresponding to healthy, resistant, and susceptible classes are 1, 19, and 24 respectively. This shows that the majority of the images are correctly classified by the ResNet-18 on the Watershed dataset.

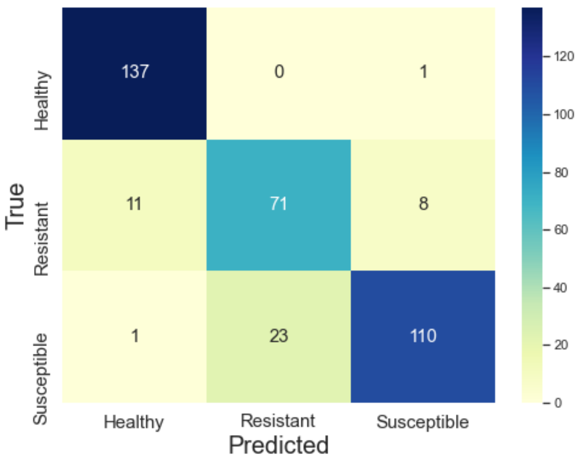


FIGURE 17. Confusion Matrix for Watershed Dataset.

The ROC plot obtained for this dataset is shown in Figure 18

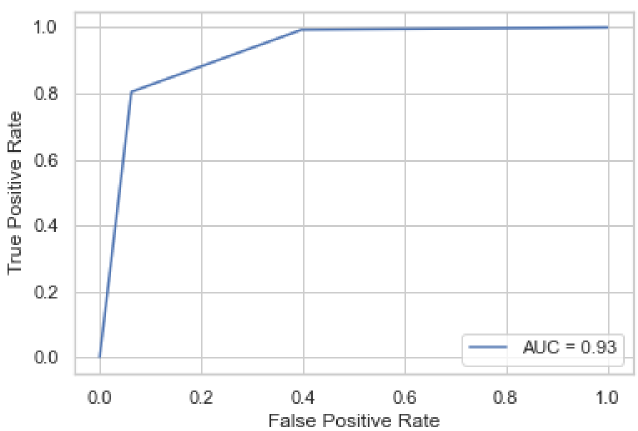


FIGURE 18. ROC Plot for Watershed Dataset.

3) CLASSIFICATION RESULTS USING GrabCut DATASET

The ResNet-18 is applied on the dataset generated by the GrabCut segmentation method, which achieved an accuracy of 84.697%, where the confusion matrix is shown in Figure 21. The performance of the ResNet-18 model on segmented data by the GrabCut method is better as compared to the model performance on the raw dataset and relatively a small number of images are misclassified pertaining to healthy, resistant, and susceptible classes, i.e 5, 14, and 25 images respectively.

The ROC plot obtained for this dataset is shown in Figure 20

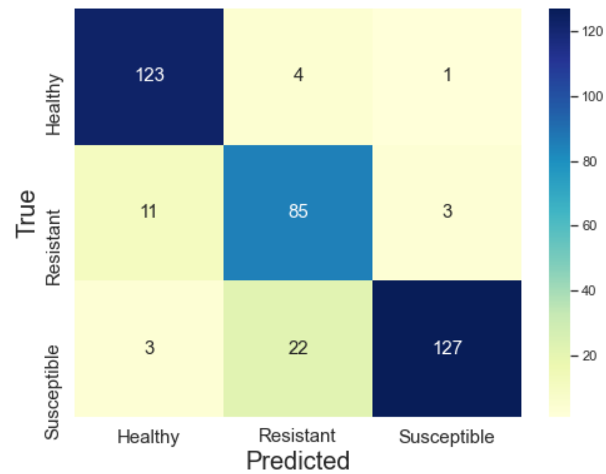


FIGURE 19. Confusion Matrix for GrabCut Dataset.

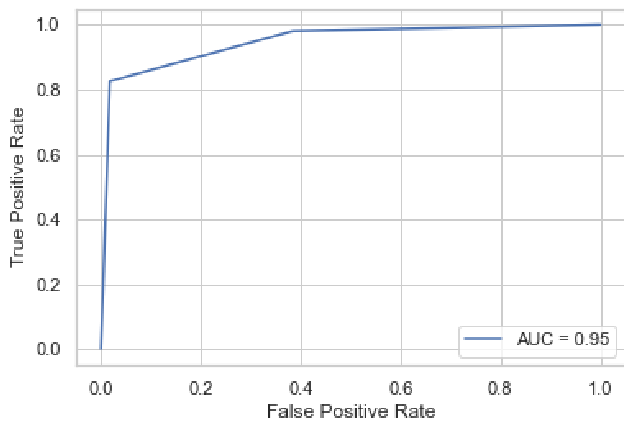


FIGURE 20. ROC Plot for Grabcut Dataset.

4) CLASSIFICATION RESULTS ON U2-NET DATASET

The deep learning based U2-net model provided the best results in terms of both classification accuracy and segmentation correctness. Most of the images are very sharply segmented, thus providing improved results for classification. The classification accuracy achieved on the U2-Net dataset is 96.196%, which is higher than the other techniques used. The confusion matrix of the U2-Net dataset can be seen in Figure 21. There is a smaller number of misclassified images related to healthy, resistant, and susceptible classes, i.e., 3, 8, and 11 images, respectively, which indicate the optimal performance of the U2-Net dataset compared to other datasets used. The comparison of the performance metrics of the ResNet-18 classifier on the datasets obtained using different segmentation techniques is shown in Table 6.

The ROC plot obtained for this dataset is shown in Figure 22

Table 6 shows that ResNet-18 performance is much higher on the dataset segmented by U2-Net with the highest accuracy, precision, recall, F1-Score and AUC. The classifier

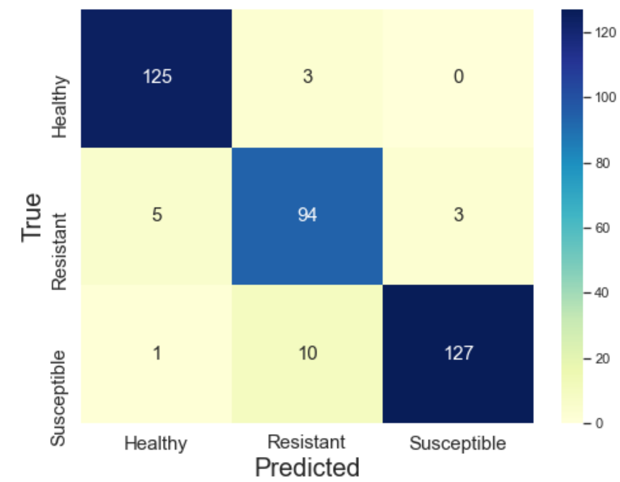


FIGURE 21. Confusion Matrix for U2-Net Dataset.

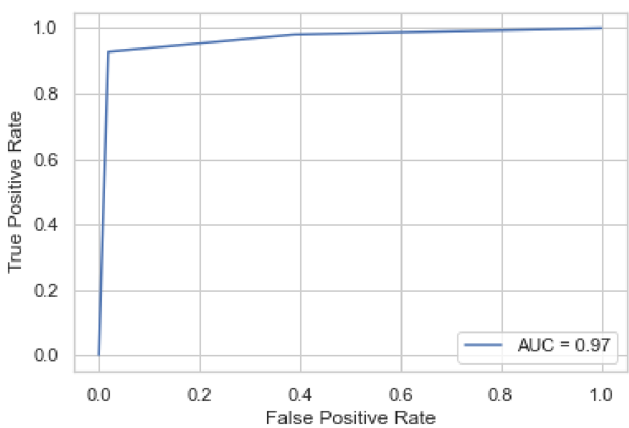


FIGURE 22. ROC Plot for U2-Net Dataset.

TABLE 6. Comparison of Performance Metrics of ResNet-18 Classification on Multiple Datasets.

Dataset	Accuracy	Precision	Recall	F1	AUC
Raw	77.901%	0.78	0.77	0.77	0.90
Watershed	88.122%	0.87	0.87	0.87	0.93
GrabCut	84.697%	0.84	0.85	0.84	0.95
U2-Net	**96.196%**	**0.94**	**0.94**	**0.94**	**0.97**

performs poorly on a raw dataset with the lowest accuracy of 77.9%. The reason for this difference is that these images have a lot of noise with a cluttered background, which makes it difficult for the model to classify such images. The accuracy of the classifier on the Watershed & GrabCut segmented dataset is relatively moderate owing to segmentation performance.

The classification results on the different types of segmented and raw datasets highlight the importance of segmentation on the performance of a classifier. Watershed provided impressive results for Healthy and Resistant classes but provided poor results for yellow-colored susceptible leaf images. However, the deep learning based segmentation model, U2-Net, produced the optimal results as it has segmented up to 95.738% (See Table 4) of the images correctly in the entire dataset.

D. VALIDATION ON OPEN SOURCE DATASET

To validate and consolidate the work, the same process has been applied to an open-source wheat rust dataset.

1) DATASET

The dataset has been obtained from Kaggle[2] and labeled into 3 classes but only two (healthy and stripe_rust) are relevant to the proposed work. The strip_rust class has been renamed to susceptible to match with the work. There are 102 healthy and 208 stripe rust images with varying resolutions. The dataset is split into 80% train images and 20% test images.

2) PROCESSING

The same pre-processing and processing steps are applied to this dataset as described earlier in Data Acquisition and Preprocessing section, Segmentation section, and Classification section.

E. RESULTS

The results obtained are consistent with those obtained earlier and thus validate the work.

1) RESULTS ON ORIGINAL VALIDATION DATASET

The original dataset, without segmentation is passed through the same pipeline as shown in Figure 3 to observe the results.

It is observed that the classifier achieved an accuracy of 87.097%. The confusion matrix for the classification is shown in Figure 23

2) RESULTS ON SEGMENTED VALIDATION DATASET

The validation dataset is passed through the segmentation pipeline discussed earlier in Figure 6 to get segmented images. A very few images with very inconsistent results due to poor capturing are omitted from the dataset to avoid problems. The classifier achieved an accuracy of 92.308%, having an improvement of 5% over the original dataset. The corresponding confusion matrix is shown in Figure 24

Accuracy, Precision, Recall, F1 score and AUC are shown in the Table 7

These results show that the proposed work is applicable in general and not biased towards a single dataset.

[2]Wheat Leaf dataset: https://www.kaggle.com/olyadgetch/wheat-leaf-dataset

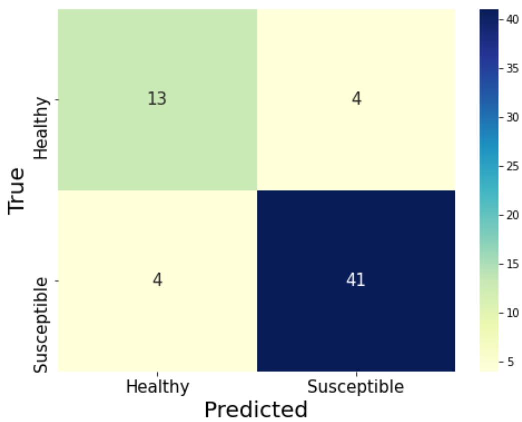


FIGURE 23. Confusion Matrix for Raw Validation Dataset.

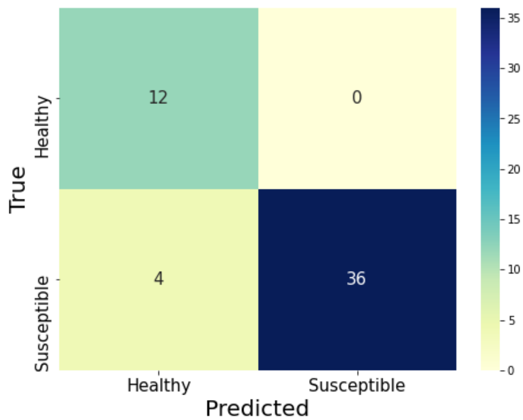


FIGURE 24. Confusion Matrix for Segmented Validation Dataset.

TABLE 7. Comparison of Performance Metrics of ResNet-18 Classification on Validation Datasets.

Dataset	Accuracy	Precision	Recall	F1	AUC
Raw	87.096%	0.87	0.87	0.87	0.84
Segment-ed	**92.3%**	**0.923**	**0.923**	**0.923**	**0.95**

V. DISCUSSION

The proposed work utilizes various segmentation techniques on the wheat stripe dataset to assess the impact of segmentation on classification accuracy. Positive results are obtained through experimentation and it is found that proper segmentation increases the accuracy during classification. Initially, only a single dataset is used for the work, and the potential problem could be the results being biased to the specific dataset. To address this issue, the results are reproduced on a separate open-source wheat stripe rust dataset. Higher accuracy is obtained during classification when the leaf images in the open-source dataset are segmented, thus, consolidating the work.

The limitations of this research are that it has only been validated on the wheat stripe rust dataset and it is unknown whether the same results will be obtained for other agriculture applications. Moreover, for the accuracy to actually improve after segmentation, the dataset must be captured properly so that automated segmentation can be applied to it. A poorly captured dataset can lead to poor segmentation results, thus reducing the accuracy rather than increasing it. The hardware implementation of this work is yet to be done; therefore, the challenges associated with it are not known at this moment.

VI. FUTURE WORK

In this paper, the impact of segmentation on the performance of a classification algorithm has been discussed. For this purpose, a framework for wheat stripe rust classification is proposed, where different segmentation techniques are applied to the dataset. Auto cropping technique is applied to the segmented images to remove the extra area other than the region of interest further. Subsequently, ResNet-18 is applied on three types of segmented datasets along with the raw dataset. The results show that the ResNet-18 classifier outperformed on the dataset segmented by the deep learning segmentation model i.e. U2-Net, with the highest accuracy of 96.19%. The classification results on the GrabCut segmented dataset provided unsatisfactory results, while the Watershed segmentation technique provided competitive results for healthy leaves but failed to accurately segment the images belonging to the susceptible class. On the other hand, U2-Net proved to be very effective for this dataset because it provides accurate segmentation which enables the classifier to classify the stripe rust into its infection types (healthy, resistant, and susceptible).

It is evident from the results that classification accuracy is greatly influenced by segmentation techniques. The raw dataset without segmentation provided a classification accuracy of 75% and the GrabCut & Watershed segmentation improved the classification accuracy up to 88.12%. However, the highest accuracy of 96.19% is observed on the dataset obtained after segmentation by the U2-Net deep learning method.

In the future, more advanced and sophisticated segmentation techniques can be explored and applied to wheat leaf datasets. The idea could be further extended to develop a generic system capable of processing data of different crop types. In addition, the hardware implementation of the proposed system can be explored to realize the concept of embedded AI on devices such as NVIDIA Jetson Nano or Raspberry Pi. Further, the capabilities of AWS Greengrass and IoT Core can be utilized to periodically update the deep learning model based on the acquisition of new images.

The dataset collection process can be enhanced by using a systematic approach that may not only decrease the noise in the acquired images but also help to reduce the pre-processing steps required to make the images suitable for segmentation.

In addition, the higher resolution images may be obtained using a DSLR camera, which can enhance the segmentation and classification accuracy. Additionally, the existing dataset used in this research work will be further increased by capturing more images to test the robustness of the selected segmentation and classification algorithm on a large dataset.

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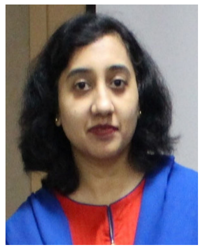

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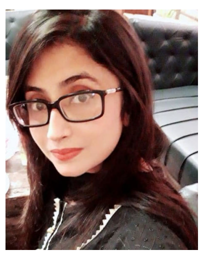

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