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Image quality enhancement for Wheat rust diseased images using Histogram equalization technique

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***Abstract*—In the agriculture domain, wheat is the most important crop across the world. It is a winter cereal crop that provides 14% food production worldwide. Wheat is an essential food for everyone. The motivation behind this work is to enhance the quality of wheat crop images in the agricultural area. Sometimes, the pictures captured in a real-time environment may not be clear for detecting the disease from the crop. So, there is a need to enhance the images. In this paper, histogram features (statistical feature) are extracted for further recognition of wheat rust diseased images. The histogram equalization is a good approach to enhance the pixel intensity of an image. Moreover, various challenges to enhance the quality of an image have also been explored, such as the effect of the histogram, histogram equalization, and Contrast Limited Adaptive Histogram Equalization (CLAHE). Also, it is observed that instead of plotting a simple histogram, histogram equalization is the best way to equalize all pixel values at the same level. In addition to that, various color spaces models such as RGB and HSV have been utilized for analysis. Thereafter, the importance of a 3D plot for color distribution is also discussed. It is concluded that histogram equalization really helps in enhancing the quality of the image and also using 3D plots one can get fine information to estimate the majority of different colors present in the image for performing segmentation and feature extraction.**

***Index Terms*—Wheat crop disease, Feature extraction, Histogram equalization, Image enhancement, RGB and HSV Color space.**

I. Introduction

Wheat rust is one of the diseases that occurred on the wheat crop. This disease adversely affects the yield of the wheat crop that may lead to food insecurity. It is very difficult to inspect these diseases manually due to labor-intensive and prone to human errors. Therefore, an attempt to recognize the disease using computer vision techniques has been carried out in this article. Three different types of features can be extracted from the image such as size, texture, and color. Further, these features help in recognize or classifying the diseased image. In this study, experiments are performed to extract the texture and color features. The texture is a complex visual pattern, composed of spatially organized entities that have characteristics of brightness, color, shape, and size. If there is a larger variation of intensity values of the image then it can be directly said that texture is rough whereas if there is less variation in the intensity values then it is called as texture smooth. Texture features help in image segmentation, texture synthesis, and also image classification. The texture information can be extracted using statistical-, structural-, model-, and filter-approach. In the statistical approach, there are three methods as First-order, Second-order, and third/higher-order measure methods are present as represented in Fig. 1. To find the statistical feature, texture gray level histogram plays a very important role. The statistical approach is further divided into three types. In the first-order measure, all the statistical operations used as a feature extraction method such as mean, variance, standard deviation, skewness, Kurtosis. Moreover, the histogram-based methods do not give information about the location of the pixel values. To extract the position of pixels, Grey Level Co-occurrence Matrices (GLCM) are used which is comes under a second-order measure. The third/higher-order methods provide multi-scale features. There are various techniques used for extracting the multi-scale feature such as Gabor filter, Fourier transforms *etc*, where higher-order features are extracted which are used for image segmentation.

A. Wheat rust

Wheat rust is the most common fungal disease which can cause even 100% damage to the wheat crop. There are mainly three types of rust disease that occurred on a wheat plant called Stem rust, Leaf rust, and Strip rust. All the different types of disease can be differentiated by their colors. The stem rust has a black color which is caused by Puccinia graminis f. sp. tritici. Leaf rust is also called brown rust. The causal agent for brown

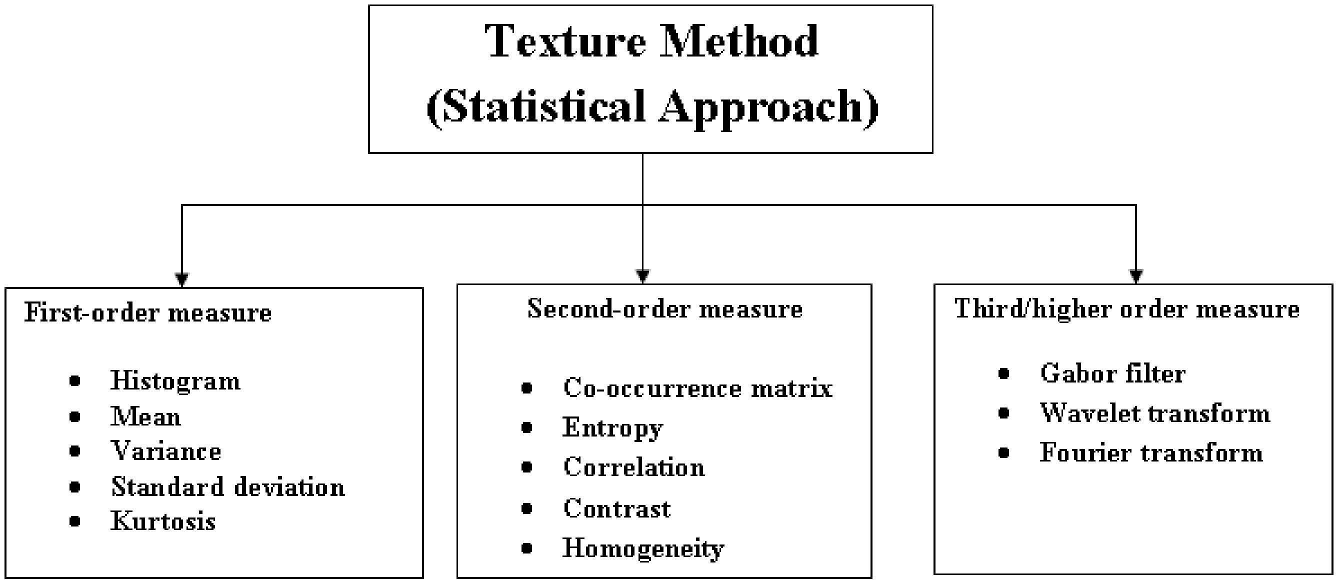

Fig. 1. Feature extraction techniques based on texture approaches

rust is Puccinia triticinia Eriks. The strip rust or yellow rust is found in the northern area and it is caused by Puccinia striiformis f. Tritici Eriks. Therefore, based on the color author can easily classify them. In this study, among these three diseases, only two diseased classes are considered such as leaf rust and stem rust. The third class taken for the study is healthy wheat plants. The motive of the current study is that "Can we classify the disease class from healthy using image processing techniques?".

B. Histogram and Histogram equalization

The histogram is a plot of the frequency of occurrence of an event. A histogram of an image represents the relative frequency of occurrence of various gray levels. Histogram of images provides a global description of their appearance. The global nature of the image displays several pixels in each gray level but not their spatial location. The histogram of two different images can be the same but the distribution can be different. We can generate different images from the same histogram as pixel location is not maintained in the histogram, it only counts the pixel in each gray or RGB (Red Green Blue) level. In term of mathematics, a histogram is the function m_i which counts several pixel values that lies into each category that is known as bins. Let n be the total number of pixels and a total number of bins are k. Then, histogram m_i may have the following conditions as given below:

$$n = \sum_{i=1}^{k} m_i$$

Histogram equalization is the distribution of pixels where all gray levels have an equal number of pixels. It is an image enhancement technique where the adjustment of pixels performed by increasing the contrast and brightness of the image without loss of information. Histogram equalization reallocates the pixel intensity values evenly by using the cumulative histogram as a transfer function. The main objective of histogram equalization is not only to spread the dynamic range but also to have equal pixels at all gray levels. It is not possible to get an exactly equalized image in a digital image. In histogram equalization, the decision is taken based on the density (number of pixels) of the image. Let us consider an image denoted by F and the range of gray level values are between [0, G-1]. Then, the Probability Density Function (PDF) of the image can be represented as:

$$PDF(r_i) = n_i/N, i = 0, 1, 2, 3..., G-1$$

where, r_i denotes the i^{th} gray levels and n_i denotes the number of pixels in the image. After that, the Cumulative Distribution Function (CDF) function can be calculated the help of PDF as given below:

$$CDF(r_i) = \sum_{a=0}^{k} PDF(r_i)$$

Thereafter, histogram equalization technique use the CDF to equally distribute the pixel values. It can be calculated as:

$$S_i = CDF(r_i) \times (G-1)$$

Finally, All the calculated values are obtained from S_i are to rounded off, and all the pixel values are placed accordingly. Sometimes, the issue of quantization occurred may occur which may lead to degrading the quality of the image. Histogram equalization gives good results, not in the agricultural domain but also in other domains such as medical imaging [1]–[3]. This may lead to enhance the quality of images for further diagnosis of disease. Contrast Limited Adaptive Histogram Equalization (CLAHE) is the advanced method to equalize the histogram. In which the whole image is divided into tiles and the size of each tile can be 8×8, 4×4, and so on. If the image has a lot of noise then it will be amplified during this time and to limit each tile contrast limited is used. It limits the contrast below a specific limit on each tile. The problem may occur due to these tiles because the image is further divided into parts so to match the border of each edge bi-linear interpolation is used. CLAHE is an advanced method of histogram equalization used to removes the problem of over-brightness from histogram equalized images.

C. RGB vs. HSV color space

As we know that photosynthesis is a process, where plants can manage their oxygen and carbon dioxide in the atmosphere. However, due to unbalancing these plants may suffer from the disease. The disease on plants/crops can directly decrease the quantity and quality of food [4]. Therefore, by using image pre-processing, leaf disease can be recognized. From the distribution of color, we can also identify the disease. The color can be represented using three channels, a mathematical model called color space used in computer vision, computer graphics, and also image processing techniques can be utilized to represent these colors [5]. The color model is a specification of the coordinate system and a subspace within that system where each color is represented by a single point. Image segmentation is an active research area where the image is divided into a different region of interest-based on the texture of the image [6]. It is an efficient method of classifying the images. RGB (Red Green Blue) color space is the combination of three channels and can be depicted in 3-Dimensional space. In image processing, RGB can be represented into three coordinate values. The image can be plotted only in red, green, and blue channels by varying the last co-ordinate value of image *i.e.,* 1 for red, 2 for green, and 3 for blue. In the RGB model, each color appears in its primary spectral component of red, green, and blue. This model is based on the Cartesian coordinate system. This module is based on the rectangular coordinate system. There is a need to normalize the color value of images into unit cube *i.e.,* all values of RGB are assumed to be in the range from [0, 1]. On the other hand, Hue Saturation Value (HSV) is also a color space model used for extracting histogram-based features. HSV color space is more suitable for segmenting rough and dull images. In the HSV, H (Hue) is represented as the angle between 0 to 2π. S (Saturation) is the authenticity of hue angle for white pixel value and V(Value) represents the percentage which lies between 0 to 100. Hue makes the angle with vertical axis, Saturation defines how pure hue is *i.e.,* it defines the ratio of purity of hue between 0 to 1. Value range from 0 to 1 *i.e.,* V=0 means black color and V=1 means white color.

In this study, a comprehensive study of the histogram has been discussed. To extract the features both from color and texture has been explored using histogram equalization and colored 3D plots. Moreover, there is also discussion of the effect of the histogram on RGB and HSV color mode. Section II comprises a literature survey, Section III contained the dataset information and also the experimental setup for the research work. Thereafter, Section IV contained the proposed approach. Section V and Section VI represents the result and analysis with comparative analysis. In the last section conclusion and future work has been presented.

II. Literature

Plant disease detection is in great progress in recent years. Many researchers are working in this area, some of them are using the PlantVillage dataset which is openly available on the internet and some of them are working on the real-time image-based dataset. PlantVillage is the dataset, where 14 different crops image dataset is available. In [7] author proposed the segmentation technique for wheat disease detection. For the experiments, they used images that were collected from the internet. They transform the images to LAB Color space from RGB space and apply *k*-means clustering to segment the diseased portion from healthy part and they achieved the accuracy of 90%. In [8] authors used annotated images and apply marker controlled watershed transform method for extracting the features. The result obtained that SVM-based methods produced the best results for the diagnosis of disease. In [9] authors reported the contrast enhancement technique for measuring the performance of image data. They analyze the performance of images on Histogram equalization (HE), Adaptive Histogram Equalization (AHE), and Contrast Limited Adaptive Equalization (CLAHE). The performance of the image was measured using Mean Square Error (MSE), Root Mean Square Error (RMSE), Peak Signal-to-Noise ratio, *etc*. As a result, they found that histogram equalization performs well to enhance the quality of the image. Dixit et al. reviewed wheat leaf disease detection using machine learning methods and also explored the various method for feature detection. Histogram equalization is the best way to enhance the images for segmentation of yellow wheat rust disease occurred on wheat crop [10]. Zhang et al. proposed the Deep Convolutional Neural Network (DCNN) for automatic disease detection and achieved a good accuracy of 0.85 on Hyperspectral images collected from UAV (Unmanned Aerial Vehicles) [11]. Mi et al. proposed the model CNN-based model called C-DenseNet which is the enhanced version of DenseNet in which authors achieved the accuracy of 97.99% for grading the wheat stripe rust [12]. Chouhan et al. presented the survey on plant pathology are reviewed that image pre-processing techniques are efficient to see the variability effect on images [13]. They found that Histogram equalization is the best way to enhance the quality of the image and also transforms the image in HSV and RGB color space to increase the segmentation accuracy. In recent years, Convolutional Neural Networks (CNNs) based architectures [14] are very helpful to detect disease. There is the concept of transfer learning models that provides the pre-trained models which are already trained. One has to just call them for building their model [15]. In [16] reported the technique for vegetable disease detection on real-time images. They applied the histogram equalization for pre-processing the images and used the *k*-means clustering for segmentation of disease. The best results were reported by the SVM classifier. Additionally, in [17] they also implemented histogram equalization and wavelet filtering to best deal with the lighting conditions. Gray Level Co-occurrences Matrix (GLCM) was used to find the second-order features. The classification was done by a Neuro-fuzzy classifier with an accuracy of 90%. Abbas et al. also reported that histogram equalization is the better way to recognize the wheat leaf disease images [18]. In [19] authors proposed that soybean leaf disease detection from image processing based techniques that are helpful for Histogram, RGB, HSI color space for image segmentation. Zheng et al. proposed the model for detecting the yellow rust of wheat crops. They used different classification methods such as linear discriminant analysis, support vector machine, and artificial neural network and found that SVM performed best for yellow rust monitoring [20].

III. Dataset and Experimental setup

In the current study author considered the three sample images from a dataset of wheat rust disease which is open source and collected in Ethiopia and Tanzania by CIMMYT partners available on *www.kaggle.com*. This dataset has three classes of wheat such as leaf rust, stem rust, and healthy leaf. We considered one-one image from each class. Most of the images in this dataset were collected from Google which is noisy. Therefore, there is a need to enhance the images for future research. The experiment for the current study performed on Python using image library such as open cv2, scikit, numpy and also for plotting graphs matplotlib library has been used. Google Colab is used for performing an experiment that is open source for running python stuff which automatically downloads all the libraries from the internet. There is no need to externally install the libraries on colab. The experimental set used for the current experiment is given below:

Operating System: Windows10

Graphic card: Tesla K80 with 12 GB of GDDR5 VRAM, Intel Xeon Processor with two core @ 2.20 GHz

RAM: 13 GB RAM

IV. Proposed approach

The proposed approach is based on image enhancement for further segmentation of disease on wheat plants. The following steps are followed to enhance the image:

Step 1: The sample of images considered for the experiment are taken from the wheat rust disease dataset. It has three classes, therefore from each class one-one image is selected for further experiment.

Step 2: In the second step, image enhancement techniques have been used. Histogram equalization, CLAHE, and color space models are used to enhance the image.

Step 3: Before checking the intensity value on the histogram equalization. First, we plot the simple histogram and then compare with equalized graph and found that most of the pixel intensity values are at the same level using simple histogram equalization and CLAHE.

Step 4: After analyzing the images from the histogram, we use color space models such as RGB and HSV for producing the best results. Thereafter, three-dimensional plots are utilized for normalizing the pixel values.

Step 5: Results obtained from the three plots shows that the healthy leaf has the highest occurrence of green color whereas in the diseased leaf there is the distribution of other colors such as red, brown, dark brown *etc*.

V. Result and Analysis

This section describes the results of the experiments performed on various classes of wheat rust disease. The input sample of leaf images are represented in Fig. 2. In which, three images (healthy leaf, leaf rust, and stem rust) are considered for the current study. In the study the results are represented in three subsections such as results of histogram equalization, RGB vs. HSV color space, and three dimensional plots. First two subsections results are based on the histogram and third subsection is the depiction of the color model of RGB and HSV images of the given input image.

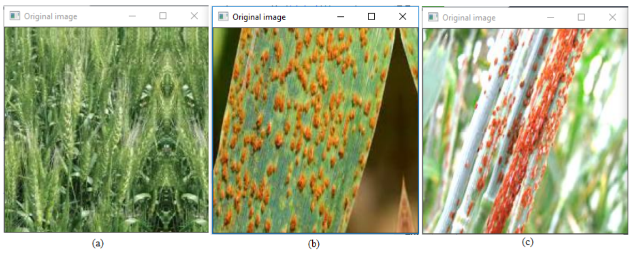

Fig. 2. A sample of input wheat image (a) Healthy leaf (b) Leaf Rust (c) Stem Rust

A. Histogram Equalization

The histogram is the representation of pixel values in a graphical way. From the histogram of the image, we can directly find the range of pixel values which lies between 0 to 255. The x-axis represents the gray level values and the y-axis represents the frequency of gray level present in the image. The Fig. 3, Fig. 4, and Fig. 5 are further divided into two parts: Subfigure (a) and Subfigure (b). Subfigure (a) represents the histogram of the input image and Subfigure (b) is the representation of histogram image equalization. In the subfigures (a) of Fig. 3, Fig. 4, and Fig. 5 initially maximum pixel values are lie on 150, 50 to 150, and 100 to 250 for healthy leaf, leaf rust, and stem rust respectively. Therefore, there is a need to enhance the quality of the image. The quality of the image can be enhanced by applying any transfer function. In the current study, we used histogram equalization to enhance the quality of the image where all the pixel's values will be approximately at an equal level. Histogram equalization can be obtained by applying the transfer function *i.e.,* probability density function and cumulative distribution function that will provide the new arrangement for pixel values. Therefore, we can directly say that the graph is somewhat equalized *i.e.,* most of the pixel values are at the same level as in Subfigures (b) of Fig. 3, Fig. 4, and Fig. 5 *i.e.,* all are normalized in the graph.

B. RGB vs HSV Color space

A color image consists of three colors: Red, Green, and Blue. These are called channels of the image. In this study, we used two-color models (RGB, HSV). In RGB color space all the pixels values lie between 0 to 255 whereas in HSV color space model pixel values lie between 0 to 1. We build three separate histograms of Red, Green, and Blue channels in RGB and HSV color space. As a result, it is very difficult to identify the healthy and disease leaf both from RGB and HSV

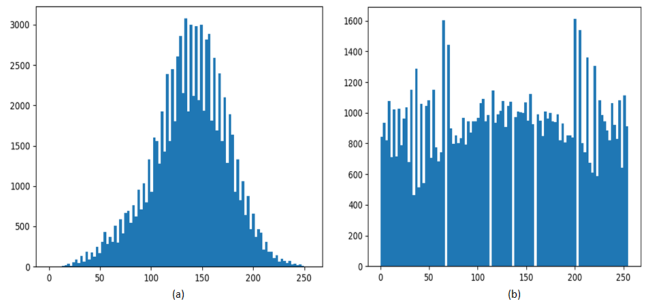

Fig. 3. Results of the histogram on Healthy Leaf (a) Histogram of input image (b) Histogram Equalization of input image

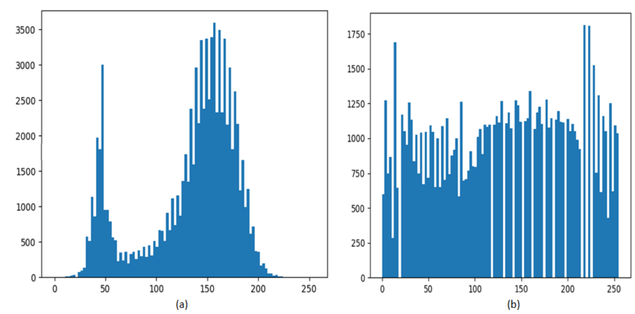

Fig. 4. Results of the histogram on Leaf Rust (a) Histogram of input image (b) Histogram Equalization of input image

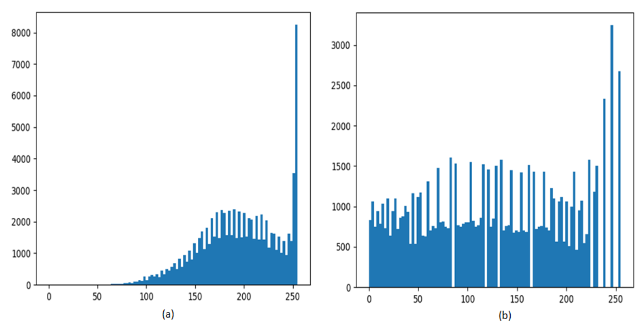

Fig. 5. Results of the histogram on Stem Rust (a) Histogram of input image (b) Histogram Equalization of input image

models. Therefore, to resolve this problem we used three-dimensional plots to recognize healthy and disease images.

C. Results of 3D Color plots

Three-dimensional plots are used to represents all the data points in the 3D space. Using these plots one can easily see the distribution of pixel values according to their color or intensity values. In this study, we first normalize all the pixel values by dividing them by the value of 255. Therefore, it is very easy to categorize the image according to their category. The Fig. 6, Fig. 7, and Fig. 8 shows the three-dimensional scatter plot for RGB and HSV models. In these Figures, there are further two

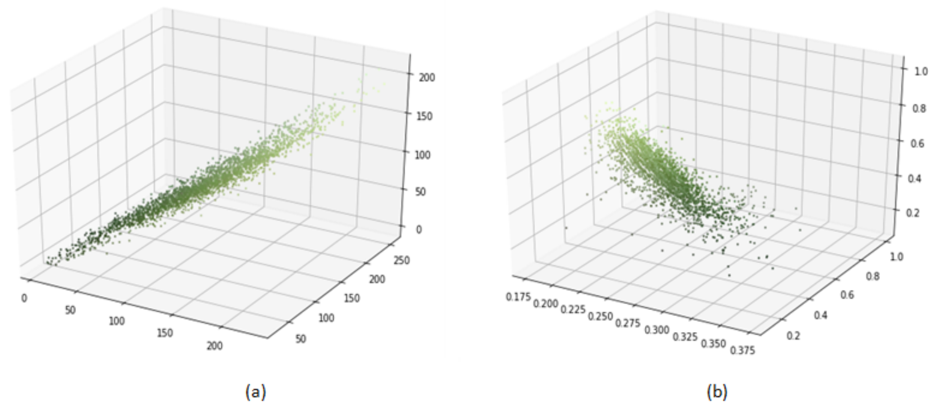

Fig. 6. The 3D graph representation of Healthy Leaf (a) Image in RGB color space (b) Image in HSV color space

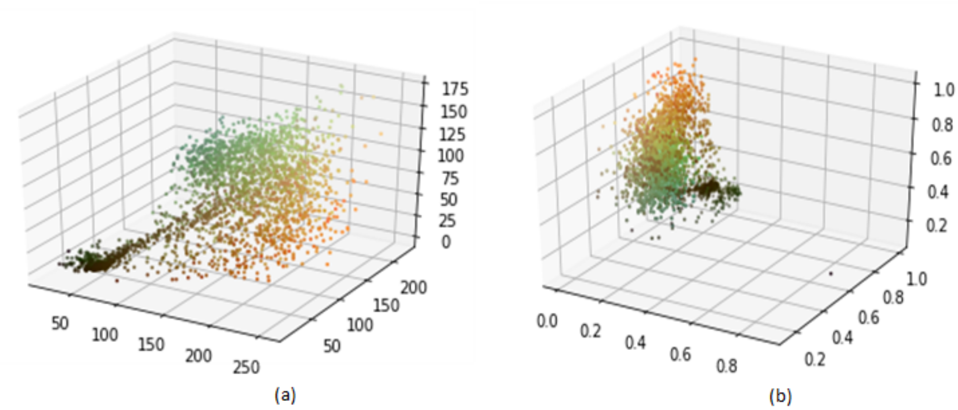

Fig. 7. The 3D graph representation of Leaf Rust (a) Image in RGB color space (b) Image in HSV color space

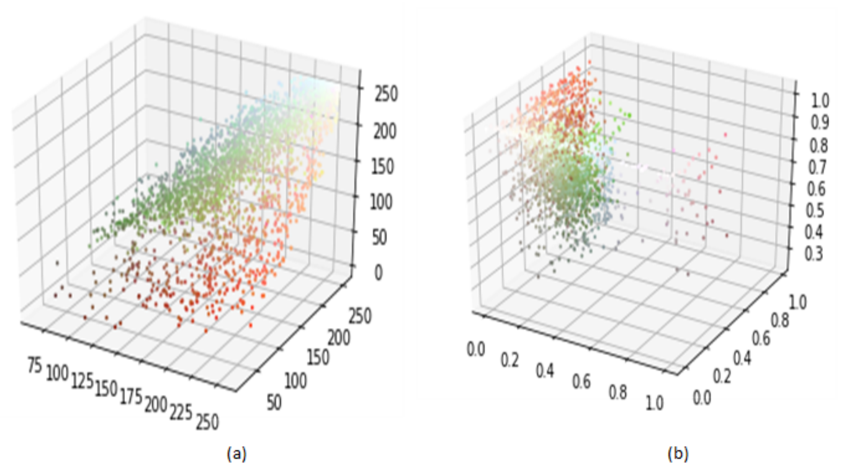

Fig. 8. The 3D graph representation of Stem Rust (a) Image in RGB color space (b) Image in HSV color space

categories: subfigure (a) and subfigure (b) are the 3D plots for RGB and HSV models respectively.

Fig. 6 shows that green color has the highest probability both in RGB as well as in the HSV model. Consequently, one can easily identify that the image of the leaf is a healthy leaf because all the healthy plants have a green color. Simultaneously, In Fig. 7 the brown color has the highest occurrence values, after that green color, and then black color. Therefore, we can say that leaf is defective by the disease because the green color shows that the leaf is healthy but in the graph brown color has a maximum value. So, it is stated that the leaf has leaf rust disease which means brown color teliospores are present on the leaf whereas Fig. 8 depicts the three-dimensional scatter plot of intensity values both for RGB and HSV models. From the graph, it is clear that red color has the highest probability, and then green color and other colors. The color of stem rust is black, initially, it is brown as its level is increased then brown color changed to black color. Therefore, we can say that the leaf is somewhat infected by disease but we cannot categorize the type of disease. To identify the diseased area region of interest can be calculated using modern state-of-art techniques.

VI. Comparative Analysis

The section illustrates the comparative analysis of considered images and it is further divided into three subsections. To compare the results author used two metrics one is Mean Square Error (MSE) and another is Peak Signal-to-Noise Ratio (PSNR). These metrics are used to restore the image quality and also both metrics require at least two images. One image is the input image and another is the output image after image equalization. The MSE can be defined as the mean of the square of the difference between the actual image and the predicted image. Suppose f(x,y) is the original image and $\hat{f}$(x,y) is the enhanced image. The value for MSE and PSNR is as given below:

$$MSE = 1/nm \sum_{i=j=1}^{nm} (f(x,y) - f(\hat{x},y))^2$$

The Peak Signal-to-Noise ratio (PSNR) is then used for scaling the MSE according to the image range. It can be calculated by the logarithm of the ratio of the square of maximum intensity value to the MSE. For example, the maximum intensity value of the 8-bit image is 255.

$$PSNR = 10 \log_{10}({Max_I}^2/MSE)$$

Table I depicts the image quality measurement using the image metrics such as MSE and PSNR. The image quality is either degrades or improved can be checked by using these comparison metrics. The significance of MSE and PSNR is that MSE should be decreased and PSNR should be increased for the improved images. In this experiment, we considered three different types of input images (Healthy leaf, Leaf rust, and Stem rust) and further applied histogram equalization and CLAHE transformation to produce the images with improved quality. We compared MSE and PSNR values for these three types of images. We found an improvement in terms of MSE and PSNR when the histogram equalized image (generated from the original image) is compared with the CLAHE image (generated from original image). The same improvement has been achieved for the same leaf and stem rust input images. Thereafter, the CLAHE equalization technique is used to further enhance the quality of the image. CLAHE is a good way to remove the over brightness from the image and also helps to decrease the error and increase the PSNR as shown in Fig. 9, Fig. 10, and Fig. 11 for healthy leaf, leaf rust, and stem rust images, respectively. There is an increase in the contrast of the image while applying the transformation function on the input image. In the current study, to get fine information besides improvement of the image is up to some extent. Further, the improvements can be done using modern techniques of image processing and computer vision.

Fig. 9. Results of the Histogram Equalized and CLAHE image on Healthy Leaf (a) Input image (b) Enhanced image (c) Enhanced CLAHE image

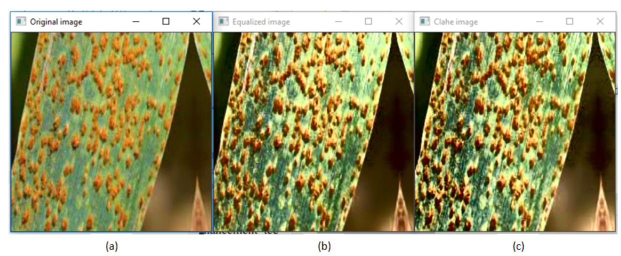

Fig. 10. Results of the Histogram Equalized and CLAHE image on Leaf Rust (a) Input image (b) Enhanced image (c) Enhanced CLAHE image

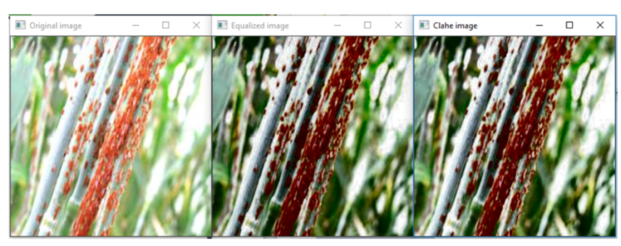

Fig. 11. Results of the Histogram Equalized and CLAHE image on Stem Rust (a) Input image (b) Enhanced image (c) Enhanced CLAHE image

TABLE I
ILLUSTRATES THE COMPARISON OF MSE AND PSNR FOR MEASURING THE IMAGE QUALITY COMPARISON OF INPUT, HISTOGRAM, AND CLAHE IMAGE

Comparison Study	Healthy Leaf		Leaf Rust		Stem Rust	
	MSE	PSNR	MSE	PSNR	MSE	PSNR
Original vs. Histogram Equalized image	1379.81	16.73	1143.31	17.55	5234.12	10.94
Original vs. CLAHE image	1411.71	16.63	1259.26	17.13	4713.97	11.39
Histogram Equalized vs. CLAHE image	191.41	25.31	451.77	21.58	138.24	26.72

VII. CONCLUSION AND FUTURE WORK

In this study, different types of techniques of image enhancement techniques are discussed. The current study consists of three major steps: Firstly, the role of the histogram, histogram equalization, CLAHE technique to enhance the quality of the image has been discussed. In the second step, the images are converted to RGB and HSV color space, and also channel-based histograms are being used to differentiate the different classes. Therefore, we used 3D plots to represents the color values. It is very clear from the 3D plots which color has the highest occurrence in the image. Based on color, one can easily get to know which color has the highest frequency in the image. Thereafter, the comparison of histogram and histogram equalization is done using image quality improvement metrics such as MSE and PSNR. As a result that, we can say that histogram equalization techniques are a good way to enhance the quality of the image. These methods are very helpful in further analysis and segmenting the images. Also, these methods can be utilized to extracting texture-based features for the detection of wheat rust disease. In the future, this work can be extended by applying the segmentation for detecting the area where actually disease is occurring on wheat plants and also for improving the quality of images, advanced methods of state-of-art technologies can be utilized.

REFERENCES

[1] M. Sunaryo and M. Hariadi, "Preprocessing on digital itmage using histogram equalization: An experiment study on mri brain image," *International Journal of Computer Science and Information Technologies*, vol. 7, no. 4, pp. 1723–1727, 2016.

[2] Z. Ullah, S.-H. Lee, and D. An, "Histogram equalization based enhancement and mr brain image skull stripping using mathematical morphology," *Authorea Preprints*, 2020.

[3] A. M. Pour, H. Seyedarabi, S. H. A. Jahromi, and A. Javadzadeh, "Automatic detection and monitoring of diabetic retinopathy using efficient convolutional neural networks and contrast limited adaptive histogram equalization," *IEEE Access*, vol. 8, pp. 136668–136673, 2020.

[4] S. Zhang, Y. Shang, L. Wang, *et al.*, "Plant disease recognition based on plant leaf image," *J. Anim. Plant Sci*, vol. 25, no. 3, pp. 42–45, 2015.

[5] P. Ganesan and V. Rajini, "Assessment of satellite image segmentation in rgb and hsv color space using image quality measures," in *2014 International conference on advances in electrical engineering (ICAEE)*, pp. 1–5, IEEE, 2014.

[6] M. R. Hassan, R. R. Ema, and T. Islam, "Color image segmentation using automated k-means clustering with rgb and hsv color spaces," *Global Journal of Computer Science and Technology*, 2017.

[7] X. Niu, M. Wang, X. Chen, S. Guo, H. Zhang, and D. He, "Image segmentation algorithm for disease detection of wheat leaves," in *Proceedings of the 2014 International Conference on Advanced Mechatronic Systems*, pp. 270–273, IEEE, 2014.

[8] L. Han, M. S. Haleem, and M. Taylor, "A novel computer vision-based approach to automatic detection and severity assessment of crop diseases," in *2015 Science and Information Conference (SAI)*, pp. 638–644, IEEE, 2015.

[9] D. Asamoah, E. Ofori, S. Opoku, and J. Danso, "Measuring the performance of image contrast enhancement technique," *International Journal of Computer Applications*, vol. 181, no. 22, pp. 6–13, 2018.

[10] A. Dixit and S. Nema, "Wheat leaf disease detection using machine learning method-a review," *International Journal of Computer Science and Mobile Computing*, vol. 7, no. 5, pp. 124–129, 2018.

[11] X. Zhang, L. Han, Y. Dong, Y. Shi, W. Huang, L. Han, P. González-Moreno, H. Ma, H. Ye, and T. Sobeih, "A deep learning-based approach for automated yellow rust disease detection from high-resolution hyperspectral uav images," *Remote Sensing*, vol. 11, no. 13, p. 1554, 2019.

[12] Z. Mi, X. Zhang, J. Su, D. Han, and B. Su, "Wheat stripe rust grading by deep learning with attention mechanism and images from mobile devices," *Frontiers in Plant Science*, vol. 11, 2020.

[13] S. S. Chouhan, U. P. Singh, and S. Jain, "Applications of computer vision in plant pathology: a survey," *Archives of computational methods in engineering*, vol. 27, no. 2, pp. 611–632, 2020.

[14] R. Budhouliya, R. K. Sharma, and H. Singh, "Recognition of online handwritten gurmukhi strokes using convolutional neural networks.," in *ICAART (2)*, pp. 578–586, 2020.

[15] S. Sood and H. Singh, "An implementation and analysis of deep learning models for the detection of wheat rust disease," in *2020 3rd International Conference on Intelligent Sustainable Systems (ICISS)*, pp. 341–347, IEEE, 2020.

[16] U. Rahamathunnisa, M. Nallakaruppan, A. Anith, and K. S. Kumar, "Vegetable disease detection using k-means clustering and svm," in *2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS)*, pp. 1308–1311, IEEE, 2020.

[17] A. Rao and S. Kulkarni, "A hybrid approach for plant leaf disease detection and classification using digital image processing methods," *The International Journal of Electrical Engineering & Education*, p. 0020720920953126, 2020.

[18] F. I. Abbas, N. M. Mirza, A. H. Abbas, and L. H. Abbas, "Enhancement of wheat leaf images using fuzzy-logic based histogram equalization to recognize diseases," *Iraqi Journal of Science*, pp. 2408–2417, 2020.

[19] A. S. Rajput, S. Shukla, and S. Thakur, "Soybean leaf diseases detection and classification using recent image processing techniques,"

[20] Q. Zheng, H. Ye, W. Huang, Y. Dong, H. Jiang, C. Wang, D. Li, L. Wang, and S. Chen, "Integrating spectral information and meteorological data to monitor wheat yellow rust at a regional scale: A case study," *Remote Sensing*, vol. 13, no. 2, p. 278, 2021.