2581-4575
International Journal For Recent Developments in Science & Technology
Crossref
A Peer Reviewed Research Journal

IMPROVEMENT OF IMAGE QUALITY FOR WHEAT RUST DISEAESED LEAF IMAGE HISTOGRAM EQUALIZATION AND CLAHE

[1]Ch.Varshitha, [2]O.V.Sai Kiran, [3]B.Amaravani, [4]Ch.Rajyalakshmi, [5]M.Rajyalakshmi

[2]Asst.Prof, ECE Dept, RISE Krishna Sai Prakasam Group of Institution, Ongole-523001, AP

[1,3,4,5]B.Tech final year students, ECE Dept, RISE Krishna Sai Prakasam Group of Institution, Ongole-523001, AP

([1]chundivarshitha24@gmail.com;[2]saikiranogirala@gmail.com;[3]amaravani404@gmail.com; [4]mondeddurajyalakshmi@gmail.com; [5]rajyalakshmi245@gmail.com)

ABSTRACT

Wheat is one of the few crops that are significant in the field of agriculture. It is among the most significant in the world. It is a winter cereal crop that contributes around 15% of global food production and is a staple food. Improving the wheat crop's image in the agricultural area is the true problem. It might be difficult to identify the kind of crop illness that it is experiencing because some of these were recorded in actual space conditions. In order to make the illness judgment process easier, we use a few known techniques to enhance the collected photos using image histograms. From these enhanced images, additional features are recovered. By using the histogram equalization technique and investigating different models that deal with CLAHE (Contrast Limited Adaptive Histogram Equalization), we attempt to increase the image's pixel intensity. Finally, we compare the results of the enhanced image with the original photos, which contain fine-grained details about the crop's rust.

Keywords: Wheat crop, Image Enhancement, Histogram Equalization Technique, CLAHE, Disease Prediction.

INTRODUCTION

Any type of image is essentially represented by its dimensions, such as its height and width, which are derived indirectly from the image's pixel count. One way to describe the pixel is as the smallest component that holds the image's information. It is recognized that every single pixel in a picture is a sample in and of itself, and that these samples show the true representations of the image. Images are used to draw attention to the aspects we need to emphasize. One of the most crucial and challenging methods in image research is picture enhancement. Enhancing an image's visual appeal or offering a "better transform representation for future automated image processing" are the goals of image enhancement. A lot of images, including those from medical procedures, satellites, airplanes, and even actual photos, have noise and low contrast. To improve image quality, contrast must be increased and noise must be eliminated. Image enhancement techniques, which increase the quality (clarity) of images for human viewing by reducing noise and blurring, boosting contrast, and exposing details, are among the most crucial steps in the identification and interpretation of medical images.

2581-4575

International Journal For Recent Developments in Science & Technology

Crossref

A Peer Reviewed Research Journal

LITERATURE SURVEY

Image noise can often be accurately fitted to a Poisson Gaussian distribution. However, estimating the distribution parameters from a noisy image only is a challenging task. Here, we study the case when paired noisy and noise-free samples are accessible. No method is currently available to exploit the noise-free information, which may help to achieve more accurate estimations. To fill this gap, we derive a novel, cumulant-based, approach for Poisson-Gaussian noise modeling from paired image samples. We show its improved performance over different baselines, with special emphasis on MSE, effect of outliers, image dependence, and bias. We additionally derive the log-likelihood function for further insights and discuss real-world applicability.

Accurate knowledge of wind directions plays a critical role in ocean surface wind retrieval and tropical cyclone (TC) research. Under TC conditions, apparent wind streaks induced by marine atmospheric boundary layer rolls can be detected in VV- and VH-polarized synthetic aperture radar (SAR) images. It suggests that though relatively noisy, VH signals may help enhance wind streak orientation magnitudes contained in VV signals and thus to achieve a more accurate wind direction estimation. The study proposes a new method for wind direction retrieval from TC SAR images. Unlike conventional approaches, which calculate wind directions from single-polarization imagery, the method combines VV and VH signals to obtain continuous wind direction maps across moderate and extreme wind speed regimes. The technique is developed based on the histogram of oriented gradient descriptor and Hann window function, accounting for the contribution of neighboring wind streak information (weighted by separation distances).

Non-uniform illumination image is often generated owing to various factors, such as an improper setting in the image acquisition device and absorption or reflectance of the objects that results in the existence of different exposure regions in the image. Although Histogram Equalization (HE) is well known and widely used in image enhancement, existing HE-based methods often generate washed-out effects and show unnatural appearance due to the over-enhancement phenomenon, which limits the capabilities of achieving illumination uniformity of an image. Therefore, this study proposes a modified HE method for non-uniform illumination image, namely Nonlinear Exposure Intensity-Based Modification Histogram Equalization (NEIMHE). The proposed NEIMHE method divides the non-uniform illumination image into five sub-regions and modifies the histogram of each sub-region by setting a nonlinear weight into their cumulative density function (CDF) of histogram in each sub-region. Each modified histogram is then equalized using modified HE equations that provide the intensity expansion and different intensity mapping directions for under-exposed and over-exposed sub-regions. A total of 354 non-uniform illuminated sample images were

2581-4575
International Journal For Recent Developments in Science & Technology
Crossref
A Peer Reviewed Research Journal

used to evaluate the performance of the proposed NEIMHE method, qualitatively and quantitatively.

Multiple Sclerosis (MS) is an autoimmune and demyelinating disease that leads to lesions in the central nervous system. This disease can be tracked and diagnosed using Magnetic Resonance Imaging (MRI). A multitude of multimodality automatic biomedical approaches are used to segment lesions that are not beneficial for patients in terms of cost, time, and usability. The authors of the present paper propose a method employing just one modality (FLAIR image) to segment MS lesions accurately. Methods:A patch-based Convolutional Neural Network (CNN) is designed, inspired by 3D-ResNet and spatial-channel attention module, to segment MS lesions. The proposed method consists of three stages: (1) the ContrastLimited Adaptive Histogram Equalization (CLAHE) is applied to the original images and concatenated to the extracted edges to create 4D images; (2) the patches of size $80 \times 80 \times 80 \times 2$ are randomly selected from the 4D images; and (3) the extracted patches are passed into an attention-based CNN which is used to segment the lesions. Finally, the proposed method was compared to previous studies of the same dataset.

Outdoor images in sand-dust environments play an adverse role in various remote-based computer vision tasks because captured sand-dust images have severe color casts, low contrast, and poor visibility. However, although sand-dust image restoration is as important as haze removal and underwater image enhancement, it has not been sufficiently studied. In this paper, we present a novel color balance algorithm for sand-dust image enhancement. The aim of the proposed enhancement method is to obtain a coincident chromatic histogram. First, we introduce a pixel-adaptive color correction method using the mean and standard deviation of chromatic histograms. Pixels of each color component are adjusted based on the statistical characteristics of the green component. Second, a green-mean-preserving color normalization technique is presented. However, using the mean of red and blue components as the mean of the green can result in an undesirable output because the red or blue components of many sand-dust images have a narrow histogram with a high peak. To address this problem, we propose a histogram shifting algorithm that makes the red and blue histograms overlap the green histogram as much as possible. Based on this algorithm, bluish or reddish artifacts of the enhanced image can be reduced. Finally, image adjustment is exploited to improve the brightness of the sand-dust image.

EXISTING SYSTEM

Histogram Equalization follows filtering, the images are treated using the Histogram Equalization approach, which modifies the image's contrast, brightness, and other attributes, which are the grey level intensities of its pixels. There is no loss of image information throughout this procedure. Since the histogram only records the grey level intensities and not

2581-4575

International Journal For Recent Developments in Science & Technology

Crossref

A Peer Reviewed Research Journal

the location of each pixel in the image, we flatten the original histogram of the image in order to extract the hidden feature that is not visible in the image.

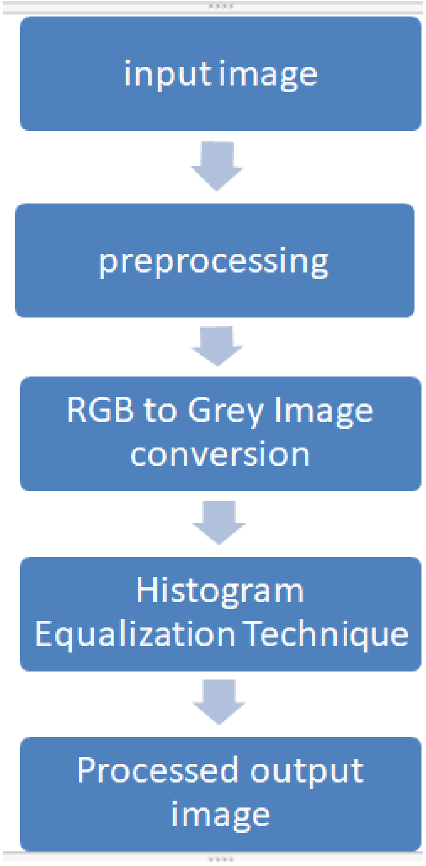

Fig 1: Existing system flow chart

The probability of occurrence of intensity level rk in a digital image Histogram equalization is a technique for adjusting image intensities to enhance contrast. Histogram equalization is used to enhance contrast. It is not necessary that contrast will always be increase.

$$p(r, k) = nk/ MN \quad \textbf{...(Eq.7)}$$

Where k=0, 1, 2 ...L-1

MN = Total number of pixels in the image

nk = number of pixels that have intensity

Normally, the histogram is a graph showing the number of pixels in an image at each different intensity value found in that image. For an 8-bit gray-scale image there are 256 different possible intensities, and so the histogram will graphically display 256 numbers showing the distribution of pixels amongst those gray-scale values. Histogram equalization is the technique by which the dynamic range of the histogram of an image is increased. Through this adjustment, the intensities can be better distributed on the histogram.

2581-4575
International Journal For Recent Developments in Science & Technology
Crossref
A Peer Reviewed Research Journal

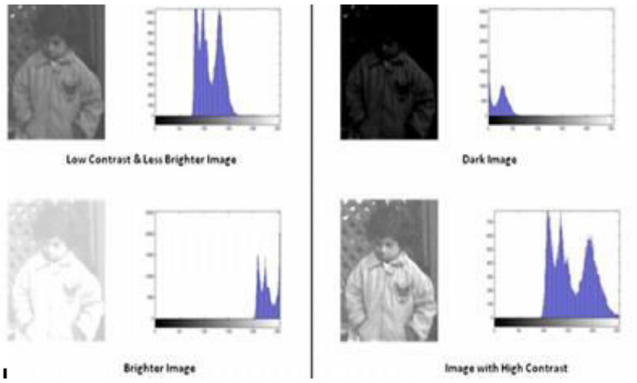

Fig 2:Different Types of Histogram Images with Different Contrasts

PROPOSED SYSTEM

Contrast Limited Adaptive Histogram Equalization (CLAHE) improves image contrast while avoiding noise over amplification in wheat rust detection. CLAHE preserves delicate features like rust spots on wheat leaves by applying localized contrast enhancement to certain areas of the image. This localized improvement makes it easier to differentiate between healthy and rust-affected parts, particularly under different lighting circumstances. CLAHE is a useful preprocessing step for automated wheat rust detection systems, enabling more precise analysis and early diagnosis by enhancing the visibility of subtle signals.

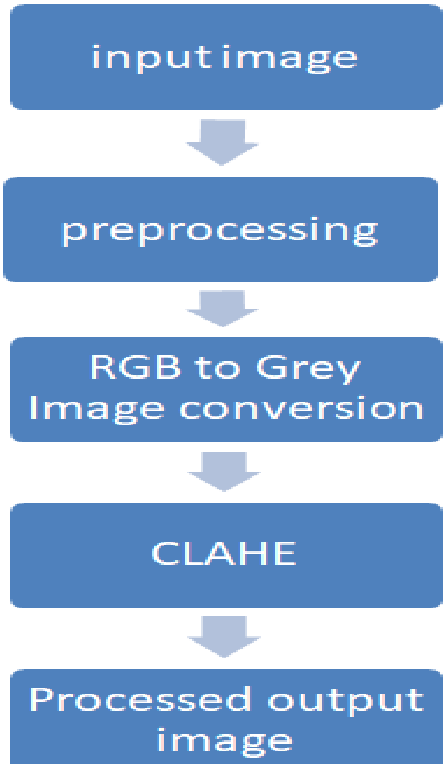

Fig 3: Proposed system flow chart

2581-4575
International Journal For Recent Developments in Science & Technology
Crossref
A Peer Reviewed Research Journal

CLAHE Illustrations: Following the equalization of the image's histogram, we proceed to the CLAHE method, which allows us to obtain a contrast-enhanced image that we may compare to the original image to determine whether a leaf or crop is rusting. The data set comparison of the photos that were taken and then improved using the CLAHE approach to detect crop rust is shown in the table below. The position of the pixels in the image is not stored; just the information about the grey level intensities is.

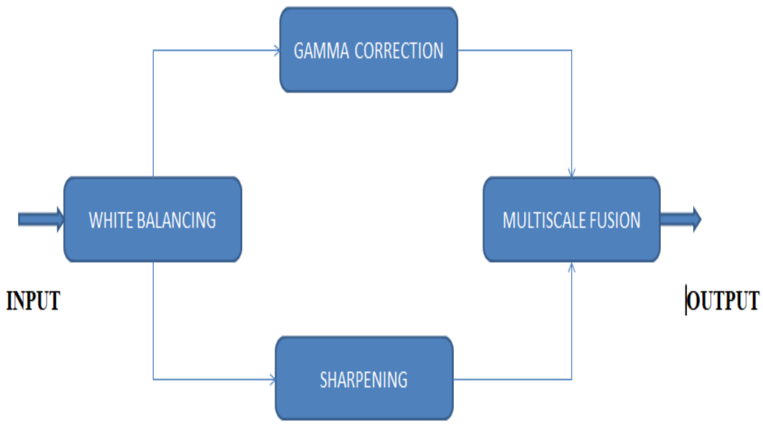

Fig 4: CLAHE Block Diagram

White Level Balancing:

This method are used to remove the overlapping of the colours and to gain the loss of the colour due to underlying scattering. Most of these methods are used for to estimate the colour of the light source to increase corresponding normalized light source intensity.

Loss of Red Channel: using only the information of the green channel allows to better recover the entire color spectrum while maintaining a natural appearance of the background. The compensation should be proportional to the difference between the mean green and the mean red values.The enhancement of red should primarily affect the pixels with small red channel values, and should not change pixels that already include a significant red component.

$$Irc(x) = Ir(x) + a.(\bar{Ig} - \bar{Ir}).(1 - Ir(x)).Ig(x)$$

Loss of Blue Channel: The blue channel may be significantly attenuated due to absorption by organic matter. To address those cases, when blue is strongly attenuated and the compensation of the red channel appears to be insufficient, we propose to also compensate for the blue channel attenuation

$$Ibc(x) = Ib(x) + a.(\bar{Ig} - \bar{Ib}).(1 - Ib(x)).Ig(x)$$

Where I_r , I_g represent the red and green color channels of image I, each channel being in the interval [0, 1], after normalization by the upper limit of their dynamic range; while I_r and I_g denote the mean value of I_r and I_g .each factor in the second term directly results from one of the above observations, and α denotes a constant parameter. In practice, our tests have

International Journal For Recent Developments in Science & Technology
2581-4575
Crossref
A Peer Reviewed Research Journal

revealed that a value of $\alpha = 1$ is appropriate for various illumination conditions and acquisition settings.

Sharpening:

Sharpening is used to improve the image quality. In this step we are using morphological operation. Morphological operation is a general operator. Morphological operation contains:

- **Erosion:** Erosion is used for to find out unwanted information or to open the black spots by using imerode.
- **Dilation:** Dilation are used for to close the unwanted or black spots by using imdilate.

Gamma Correction:

This process adjusts the luminance of an image by applying a non-linear transformation to the pixel values. It's particularly useful for correcting images that are too dark or too bright.

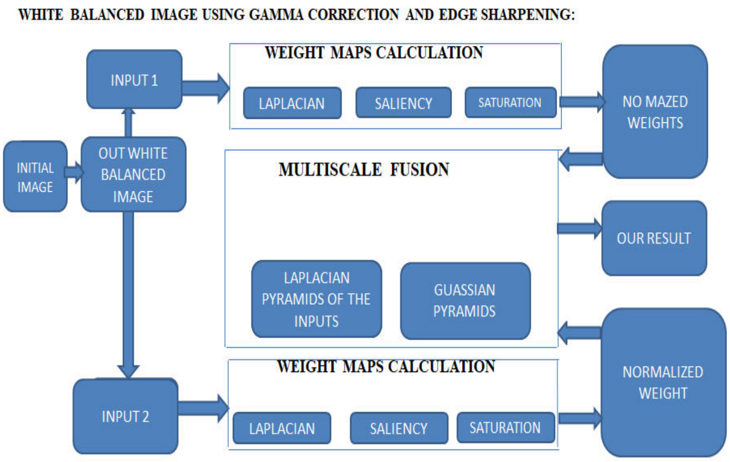

Fig 5: White balanced image using Gamma Correction & Edge sharpening

Multi-Scale Fusion Process:

The pyramid representation decomposes an image into a sum of band pass images. In practice, each level of the pyramid does filter the input image using a low-pass Gaussian kernel G, and decimates the filtered image by a factor of 2 in both directions. It then subtracts from the input an up-sampled version of the low-pass image, thereby approximating the (inverse of the) Laplacian, and uses the decimated low- pass image as the input for the subsequent level of the pyramid. In this equation, Ll and Gl represent the l^{th} level of the Laplacian and Gaussian pyramid, respectively. To write the equation, all those images have been up-sampled to the original image dimension. However, in an efficient implementation, each level l of the pyramid is manipulated at native sub sampled resolution. Following the traditional multi-scale fusion strategy, each source input Ik is decomposed into a Laplacian pyramid while the normalized weight maps Wk are decomposed using a Gaussian pyramid. Both pyramids have the same number of levels, and the mixing of the Laplacian inputs with the Gaussian normalized weights is performed independently at each level.

BENEFITS

Since computerized picture preparation has a very broad range of applications and DIP affects almost all specialist industries, we will only discuss a few of the important applications of DIP. Advanced image preparation goes beyond only altering the spatial objectives of the standard images that the camera captures. Enhancing the photograph's brilliance, etc., isn't the only limitation. Perhaps it is unquestionably getting over it. Waves of electricity can be Imagine that every molecule is traveling at the speed of light in a stream of particles. There is an abundance of vitality in every molecule. We call this pile of energy a photon. The following illustrates the electromagnetic range as shown by the photon's liveliness. We are merely waiting to observe the discernible range in this electromagnetic range.

Seven different hues that are commonly referred to as VIBGOYR are mostly included in the main spectrum. Violet, indigo, blue, green, orange, yellow, and red are all represented by the acronym VIBGOYR. That does not, however, negate the existence of other items within the range. Only the unmistakable portion, where we saw every item, is visible to the human eye. Nevertheless, a camera can see things that the human eye cannot. For example, gamma beams, x beams, etc. As a result, computerized picture handling also examines everything that is difficult. Given that other materials, like X-beam, have been widely used in the medical area, the proper answer can be found in reality. Because gamma beams are widely used in atomic medicine, their analysis is essential.

RESULTS

Fig6.1: INPUT IMAGE

Fig6.2 RED CHANNEL IMAGE

Fig6.3:BLUE CHANNEL IMAGE

Fig6.4: SHARPEN IMAGE

Fig6.5: FUSED IMAGE

Fig 6: Results of CLAHE Technique

International Journal For Recent Developments in Science & Technology
2581-4575
Crossref
A Peer Reviewed Research Journal

We gathered and assembled the visual data of many types of wheat rust damaged leaves. The disease's name appears in a conversation box along with its category. Mean Squared Error and Peak Signal to Noise Ratio are displayed in the output. Using Histogram Equalization & CLAHE, the entire procedure for Image Quality Enhancement for Wheat Rust Diseased Leaf Image greatly increased the contrast and visibility of disease symptoms, enabling precise diagnosis and categorization.

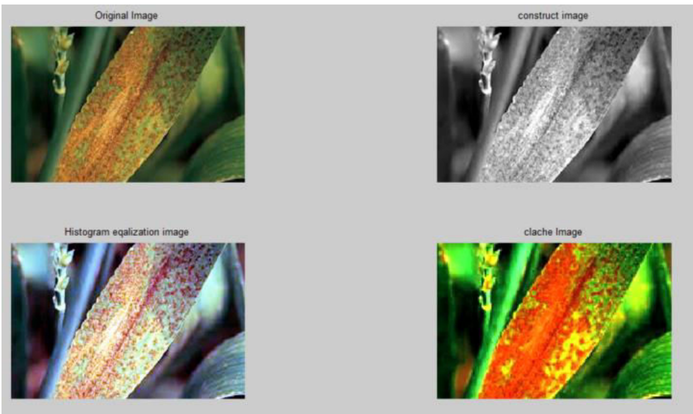

Fig 7: Image Enhancement Techniques

Four distinct variations of a wheat leaf are displayed in the picture. The original image is shown in its original hues in the upper left corner. The grayscale version at the upper right is called "construct image." A "Histogram equalization image," which increases the contrast of the leaf and highlights its intricacies, can be seen in the lower left. The leaf is shown with heightened hues in the lower right corner, titled "clache Image," emphasizing several aspects. This set of pictures shows how different image processing methods can improve or change an image's appearance for a variety of uses.

CONCLUSION:

Different kinds of image enhancement techniques are covered in this project. There are three main steps in the current study: First, it has been discussed how the histogram, histogram equalization, and CLAHE approach can improve the image quality. The photos are transformed to RGB and HSV color spaces in the second stage, and channel-based histograms are employed to distinguish between the various classes. As a result, we represented the color values using 3D graphs. The 3D graphs make it very evident which hue appears most frequently in the image. It is simple to determine which color appears most frequently in an image based on color. After that, picture quality improvement measurements like MSE and PSNR are used to compare the histogram and histogram equalization. Therefore, we can conclude that histogram equalization techniques are an effective means of improving image quality. These techniques are highly beneficial for image segmentation and additional analysis. These techniques can also be applied to the extraction of texture-based features for wheat rust disease identification.

REFERENCES

[1] M. Sunaryo and M. Hariadi, “Preprocessing on digital image 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 visionbased 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. Gonzalez-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.