Image Specular Highlight Removal using Generative Adversarial Network and Enhanced Grey Wolf Optimization Technique

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Abstract*—Image highlight plays a major role in different interactive media and computer vision technology such as image fragmentation, recognition and matching. The original data will be unclear if the image contains highlights. Moreover, it may reduce the robustness in non-transparent as well as glassy objects and also it reduces accuracy. Hence, the removal of highlights is an extremely crucial thing in the dome of digital image enhancement. This is to develop the enhancement of the texture in imageries, and video analytics. Several state-of-art methods are used for removing highlights; but they face some difficulties like insufficient efficacy, accuracy and producing less datasets. To overcome this issue, this paper proposes an optimized GAN technology. The Enhanced Grey Wolf Optimization (EGWO) technique is employed for feature selection process. Generative Adversarial Network is a machine learning (ML) algorithm. Here, two neural networks that will compete among themselves to produce better calculations. The algorithm generates realistic data, especially images, with great practical results. The investigational outcome reveals that the future algorithm has the ability to verify and eliminate the illumination spotlight in the image so that real details can be obtained from the image. The effectiveness of the proposed work can be proved by comparing the proposed optimized GAN with other existing models in highlight removal task. The comparison outcome gives better accuracy with 99.91% compared to previous existing methods.

Keywords*—Highlight detection; optimization; specular highlight detection; GAN

I. Introduction

Image spotlight is a mutual factor in this physical biosphere, frequently an illumination is produced when the light contacts the material surface [1]. The highlights can easily damage the quality of the target image owing to the combined effect of the sunlight and the target's surface's physical characteristics. The flow and strength of the illumination will be determined by objective's category and dye, and also the reservation among the external area and the source of light [2]. Due to these highlights, the brightness of the image will be reduced in a sliding window and it frequently causes some unwanted discontinuities in the diffused part of the object [3]. Moreover, it will not provide true details of the image. To overcome this difficulty, a highlight removal method is introduced. The elimination of image spotlight is a major difficulty in supercomputer illustrations, computer visualization, and so on. Meanwhile, it delivers valuable info for some solicitations [4]. Because of two motivations. Firstly, it is necessary to find out the direction from where the light will be reflected. Secondly, eliminating the consequence from high spot will have the ability to improve the execution of various visualization tasks, like object recognition, essential image disintegration, and tracing.

Nevertheless, various methods have been recommended to find and repair specular reflection affected areas that rely on the evaluation of fixed images [5] . Due to this, the specular highlight may use high-level contextual cues to reduce uncertainty in areas with transformer module, thereafter the detection and correction of specular highlights from transmissive materials are more challenging and not forthright, especially when the geometry of the object is unknown. Therefore, the highlighted extracted method includes multi-scale data to identify regions with various level of highlight intensity. The estimated intensity ratio of the previous highlight removal method is used to relate the modifications among the diffused and specular replication modules then it enables the elimination of spotlights from a sole image. Hence, the standardized weighting mechanism is used to reinstate the fringe pattern in the illuminated zone whereas the highlight removal cannot be consistent between images from different viewpoints [6].

The occurrence of high spot drives a thoughtful influence on numerous features of invention. The furthermost mutual influence is that the spotlight will convey sound and intrusion to the new image, thus the specularity on all images will be reduced, and it creates a new region with an aware of highlight image creation model [7]. Once associated with the translation tasks of additional image, the image that containing the spotlight and the dispersed image will display a heavy amount of resemblance. These resemblances in them are equal, and are different only in rare emphasized zones and gives unfortunate outcomes in argumentative workout. Hence, to carry out the issue occurred by the resemblance, an autoencoder is placed in front of the attention component, where the replication intensity of each pixel in the highlighted images is predicted by highlighted concentration cover [8].

The active rank of an image can be obtained from various ideas of image detector and the active rank is defined as the proportion among the minimum and major value that are recorded or depicted on the display [9]. Capturing image sequences with different exposure periods, provides a well-exposure all through the object surface to deal with the issue of consequent saturation. Thus, certain circumstances or expectations have the capability of enabling content analysis-based solutions. The picture element analysis based on later methods can be considered as the shiniest pixels as the high spot, that disposed to untrue recognition of spotlight and the regions with unclear white regions are developed under chromaticity analysis. Hence, the solicitation of vigorous detecting approaches cannot safe the renovated info in the current highlighted regions as the bright illumination is returned in the reflective path instead of sprinkling towards the instrument.

Projecting uniformity image patterns onto the surface underlying featureless objects has traditionally been used as a reconstruction technique to get remote sensing data. But specular reflection creates highlights, projection over these areas could result in saturation of the image through overuse [10]. The features of the estimated design continue to pose multiple problems, which have been discovered to influence the outcomes of the reconstruction. Under photometric calculations, the connection amongst the image illumination and exterior depth are used to enable this renovation. Even so, it is an under-confined difficulty; expectations are computed stronger for the features of the dispersed replications. To handle specular surfaces, a reflectance model is introduced. It describes the bond among the replicated brightness and exterior depth under an orthographic camera estimation hypothesis.

In the field of image synthesis, the Generative Adversarial Network(GAN) already has tremendous success [11]. The GAN's aim is to evaluate a set of training examples to discover the probability distribution. Generative Adversarial Network has the capability to create new examples from the estimated probability distribution. To eliminate the highlights, this paper offers a novel based GAN method for dealing with problems. In other words, the removal of specular highlights is an image-to-image transformation among the diffuse area and the highlighted area.

The key contribution of the paper is briefed as follows:

- At first, images with heavy quantity of highlights are collected and handled in this process.
- Moreover, the impulsive noise that exists in the grey scale image can be filtered by the Wavelet Decomposition Anisotropic Filter (WDAF).
- The segmentation process employed in this paper is K-means clustering and is utilized to find the groups in the unlabelled data.
- The feature selection process is carried out by the Enhanced Grey Wolf Optimization (EGWO) process to improve the hunting strategy of the wolves.
- Feature extraction process is done by Gray-Level Co-Occurrence Matrix (GLCM) algorithm; this will reduce the unwanted data from the dataset.
- The Generative Adversarial Networks (GAN) is used to notice the emphasized area from the image.
- Finally, the highlights in the image can be eliminated by Structure texture layering Algorithm
- The concluded method's success has been recognized and contrasted to other approaches to prove its better in accuracy and efficacy.

The remaining of this study is divided into the resulting sections as follows: Section II exposes the relevant works are done from a thorough analysis. Problem statement is discussed in Section III. The particulars of EGWO-GAN explored in Section IV. Under Section V, the outcomes of the experiment are reviewed and provided exactly. Section VI is the conclusion of the paper.

II. Related Works

Su et al. [6] discussed that the Lightweight optimization technique is employed for eliminating the issues in multi-view digital image. The highlights can be removed by assumptioning the estimation of illumination chromaticity, and it carries out the orthogonal subspace projection. The method provides a practical feature which doesn't requires image reflectance priors. A Ground truth dataset is employed to establish the demonstration of the process. The paper reveals that the accuracy and robustness is more effective when compared to the existing method. The paper doesn't explain that how a single phased image could be taken from multi view facial images.

The removal of specular spotlight in colour images play a title role to enable numerous hypermedia and supercomputer visualization tasks revealed by Wu et al. (2022). Here the details of the Ground truth illuminated images are furnished and the images that photographed are real world objects. The dataset used here is Paired Specular Diffuse (PSD) dataset. Here an organic lattice is used to deteriorate the illumination in the assumed sole image and it uses GAN network Without requiring an explicit assessment the network functions the consideration mechanism to represent the mapping relationship among the diffused area and the illuminated area.

The detection result of the specular highlight will be lesser. High specularity and specularity on metal materials are not explained in this paper.

Under computer vision technology the Non-destructive surveying mechanism strictly improved the investigation of fresh fruit quality revealed by Hao, Zhao, and Peng [12]. During image acquisition specular highlight easily affects the fruit that has soft surface and small texture. The illuminated highlight that appears on the body of fruit will strongly affect the standard inspection. To solve this issue, a specular spotlight removing mechanism is used and it's founded on the basis of multi-band polarization imaging technique. The image at real time is realized first by developing a new multiband polarization imager. Secondly, a combined multi-band-polarization habitual vector is utilized to check whether the illuminated highlight was removed. Then the illuminated highlight was removed by separating ergodic least-squares combined with a Max-Min multi-band-polarization strategy. At last, the missed particulars are retrieved by chromaticity consistency. The suggested method will eliminate the spotlight strongly and gives an improved exchange among precision and complexity when compared to the existing method. The paper doesn't give a brief explanation about strong picture quality and unbiased estimation indexes.

Fu et al. [1] states that the highlight detection is the basic and difficult task in today's image processing field. Recent method provides a clear result by practicing two processes on artificial training facts in a controlled mode for detecting and removing highlights. A novel network is used to remove the illumination spotlight. Then a dataset with 16K real image is introduced first to reject the domain area among artificial preparation prototypes and actual investigation images and also for helping the learning-based methods. Investigation result declares that the future work is faraway enhanced than the previous technique. The study does not explain about the highlight colour evaluation model. ElMasry, Gou, and Al-Rejaie [13] disclosed that the illumination or highlight trouble arose in radiometric images, the reflecting variation will be obtained from its real value, and it hides severe problems in food products or detect heavy negative issues may cause breakdown in the investigation and verification processed. According to a non-repetitive model, the multicolour dispersion type and Principal Component Analysis (PCA) were identified and removed by specular highlight objects. The method gives effective results on hyperspectral and multispectral images; it strongly reduces the oddity and effectively increases the excellency in the illuminated data. The investigational outcomes give that the suggested technique along with PSNR will give better results. The robustness is not explained briefly here.

The specular highlight spotting and elimination are the main difficulties in computer vision technology and image visualization said by Wu et al. [14] . Deep learning model is used as the proposed method here to find and deteriorate the specular spotlight in a sole image. The specular highlight is verified using encoder and decoder web. Unet-Transformer network is used to remove highlights. Spotlight investigation pattern is used as a cloak to train the rejected work. Both the networks can be guided in a powerful mode. The feature texture is poor here. The result should become more effective in public benchmark and real-world images when compared with previous method. The study about dataset is not discussed here. Huang, Hu, and Wang [15] disclosed that a novel uniformity framework method is introduced here to detect and remove highlights in pretended images, facial images, verbal images and organic images. Three main components are used. They are spotlighting characteristic ejected component, spotlight coarse rejected component, and spotlight filter rejection component. The spotlighting characteristic ejected component will divide the highlighted and non-highlighted image from the real image. Then the removed spotlighted image is re-obtained from spotlight coarse rejected component and the spotlight filter rejection component is gained by contextual spotlight attention mechanisms. The proposed work will gain better visual effects. The facts about real textures are not explained clearly here.

The organized bright prediction is broadly employed in 3D outline dimension revealed by [16]. Here the fringe surface is covered completely and huge reflective surfaces are affected by uneven spotlights. A polarization-based algorithm, is introduced to solve uneven illumination. By using this algorithm, the SNR of the polarized image is developed and the spotlights are removed. The centralized weighting algorithm is used to resave the surface knowledge in highlighted domain. The project result proves that the SNR of polarization figure is developed with the help of the proposed algorithm. The result proves that the fringe module is restored. The study does not explain about the saturated components. Modern high spot elimination procedures couldn't semantically distinguish among all-white or near-white resources on the external face of smooth liquor bottles discussed by Guo et al. [17] The latest spotlight elimination processes grounded under deep learning process and it will deficit resistance in system design, ensure issues with complex training, and have inadequate objective relevance. They consequently do some jobs with less efficiency because they are unable to find and delete highlights in some tiny sample highlighted datasets. Hence, this study suggests a quick highlight removal technique that combines U2-Net and LaMa. The U2-Net is applied in the beginning of the process to detect problems. Lama is used as the core. The model is easy, efficient and simple to carry out. This proposed work provides good results than the previous method. The study about flexibility is not explained here.

Xia et al.[18] state that the specular highlights caused by laparoscopes may produces wrong visual observations, audio restoration and image fragmentation in medical and normal images. The removal of illumination from a sole image is more essential because both the normal and medical images are located in amorphous regions. Therefore, a global optimization technique grounded on a dichromatic reflection model is suggested towards controlling these issues from a sole image. The future work comprises two methods for the removal of spotlights from the image. One is for calculating the spreading of pigmentation to precise the shade and congestion in the illuminated areas and the other one uses complex optimization with double generalisation to compute diffused and specular replication coefficients. According to the experimental findings the suggested method eliminates the illuminations from the natural and endoscopic images. A stereo reconstruction application that uses a dataset presents that the highlight reduction method may removes the RMSD of the exterior renovation truthfulness from 1.10mm to 0.69mm.

The highlight removal methods calculate and group the illuminated chromaticity value to extract diffused and specular replication constituents on or after a solitary image established under the dichromatic reproduction model said by Souza et al. in [19]. Whereas these methods can produce results that are visually appealing, their clustering algorithms either have poor setup and are too costly to perform in actual time. In this study, a high-grade of pixel grouping algorithm is proposed to eradicate the high spot from the sole image. In existing methodology, the max and min values of all the pixels are calculated. In order to suggest a successful pixel clustering method, the dissemination arrangement of those standards in a max-min chromaticity universe is examined by pseudo specular free image. In order to differentiate among diffuse and specular components, the intensity ratio is estimated for each cluster. To apply the method on CPU and GPU frameworks an optimization technique is suggested. When using only the CPU, the investigational outcomes shows that the proposed method is not only faster than the state-of-the-art method but also more accurate. Therefore, the existing previous technique can eliminate specular highpoints from a 4K image with a resolution of 3840 by 2160 in just 24 milliseconds when using the GPU.

One of the supreme essential study questions in supercomputer visualization and computer graphics is how to eliminate specular highlights from an image discussed by Fu et al. in [20]. Several techniques have been established but they generally won’t operate fit for actual images because of the attendance of composite resources, solid shades, rich textures, constrictions, and hue enlightenment, among other factors. This paper introduces an original spotlight reduction mechanism to eliminate the highlights. The technique is constructed on two findings: (i) the specular highlights are frequently small and thin in dissemination; and (ii) the enduring turgid images can be characterized by an undeviating amalgamation. An optimization framework is created for the observation of the turgid and illuminated images from a sole image. The diffusion mechanisms are restored by boosting the sparseness of the encrypting factors via the L0 norm. According to the illumination definition, the additive colour mixing theory, the encrypting factors and the illumination that focuses to non-negativity. Extensive researches on a variety of images have proven the efficacy of the future work and its advantage above the earlier approaches.

Facemask spotlight elimination methods object to increase image eminence and simplify responsibilities like surface reconstruction and verification by removing the specular highlight from facial images said by Z. Wang et al [21]. However, earlier learning-based methods frequently fails when applied to images from the real world because their simulations are frequently qualified on combined artificial or test site images owing to the necessity of combined preparation information. As an alternative to these techniques, the spotlight elimination system is suggested, which is pre-formed on an artificial dataset then finetuned on the unpaired rough imageries. To accomplish this, a spotlight cover supervision training method is proposed that allows Generative Adversarial Networks (GANs) to train a highlight removal network utilising real-world image. In spite of the fact, nearly every image is taken in the rough embrace under certain areas, have found that even small areas without highlights can deliver valuable info for the process of removing illumination. This stimulates to create a region-based discriminator that can differentiate between the highs and lows in a facemask image and habit it to improve the originator. According to the experimentations, the approach yields result that are of a higher calibre than those produced by contemporary highlight removal methods.

III. Problem Statement

Lightweight Optimization (LWO) based on machine learning technique that clears the problems in the earlier studies and it is used for identifying and graphing the highlights in the image [6]. It will not provide correct data because the computational complexity is poor here and this will affect the image quality. It will reduce the network parameters and computational complexity. Therefore, for achieving clear and good results machine learning (ML) based Generative Adversarial Network (GAN) is used. For removing the highlights from the image and to provide higher accuracy and better complexity, an Enhanced Grey Wolf Optimization (EGWO) method is utilized here and it will also reproduce the behaviour of grey wolves in a helpful way.

IV. Methodology

The planned technique is charted in Fig. 1. Enhanced Grey Wolf Optimization based Generative Adversarial Networks is utilized for this process. There are many datasets presented and they are used for training and testing purpose and this process uses Kaggle dataset to discuss about the data and to find the accurate coding for the data etc., The images that contain highlights are exposed to pre-processing technique to reduce the noise in the image. Similarly, the recognized EGWO-GAN method is utilized to label the image high spot and its classifications. Moreover, it is utilized to achieve a greater accuracy worth. Henceforth the accepted method considers and then it labels the highlights in the image.

A. Data Collection

The dataset used for the testing and training process is Kaggle dataset. Approximately 10,000 dataset imageries with high spots have remained together and castoff in this research. From that image 50% (5000) of imageries were selected for training data and 50% (5000) of imageries were selected for testing data [22]. It holds 48-by-48-pixel grayscale images. The pixel section comprises a string in each picture. The training group covers 28,709 representations. The test group covers 3,589 representations.

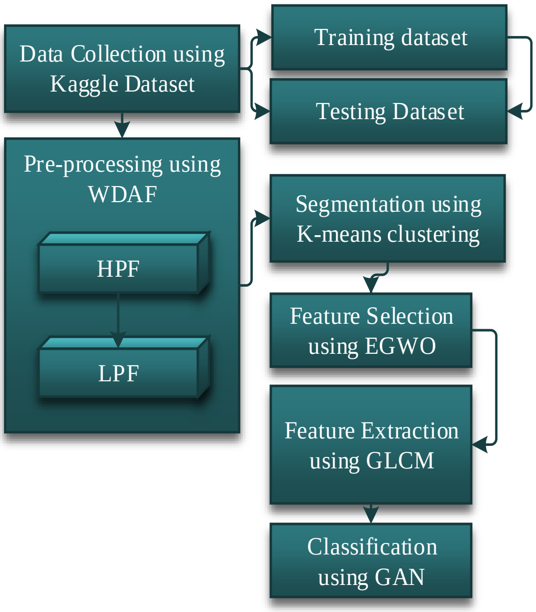

Fig. 1. Proposed EGWO-GAN technique

B. Pre-processing

Lately, filtering by image reinforcements has increased the importance for noise elimination [23]. Though, to verify the reflected region in the image, a pre-processing technique has been introduced. Pre-processing will reduce the noise in the image. Some appearance of accidental symbols and unevenness in radiance and hue of the appearance is titled as noise. It is very important to remove the noise because the noise in the image will affect the quality of the image. So many filters are used to remove noise. Under this study, Wavelet Decomposition Anisotropic Filter (WDAF) is used for decreasing or eliminating the impulsive noise from the grey scale images. The filter is very effective in identifying peak noises from the image. The functionality, time complexity, and relative performance of these filters are compared for better performance. Henceforth, the attained noiseless images are applied in the EGWO-GAN model to eliminate the high spot from the image.

The difficulty in discrete time is given in Eqn. (1),

$$\mathrm{m[k]} \times \mathrm{n[k]} = \sum_{y=-\infty}^{\infty} m[y]n[k-y] \quad (1)$$

where, m[k] and n[y] are denoted as the illustrations of the intake image, while n[k] and n [k − y] is denoted as the illustrations of compulsion reaction.

Alteration of wavelet breakdown to high and low pass indications is assumed in Eqn. (2) and Eqn. (3),

$$\mathrm{jhigh}[\mathrm{y}] = \sum_{\mathrm{k}} \mathrm{m}[\mathrm{k}]\,\mathrm{h}[2\mathrm{y}-\mathrm{k}] \quad (2)$$

$$\mathrm{jlow}[\mathrm{y}] = \sum_{\mathrm{k}} \mathrm{m}[\mathrm{k}]\,\mathrm{n}[2\mathrm{y}-\mathrm{k}] \quad (3)$$

where, j high[y] and j low[y] are the illustrations of the outlet gestures, h is represented as the half band high pass filter and n is represented as the half band low pass filter.

The divergence function is given in Eqn. (4) and the anisotropic function is given in Eqn. (5),

$$\partial gi(x,y;k)\partial h = div[f(x,y;k)\nabla \mathrm{gi}(\mathrm{x},\mathrm{y};\mathrm{k}), \quad (4)$$

$$\mathrm{n(k)} = \frac{1}{1+(\mathrm{f}/\lambda)^2}, \quad (5)$$

div is denoted as the divergence operator, gi is represented as the diffusion coefficient, $\mathrm{g}(\mathrm{x},\mathrm{y})$ is noted as the image with coordinates (x, y) at period k, ∇ is a inclined operator, k= |∇g| and λ is the inception of inclination magnitude.

The conservative anisotropic filter presents a stairway result to strained images, so, the dispersion constant to the conservative anisotropic dissemination filter has been introduced in Eqn. (6),

$$EAD = div[f(x,y;k)\nabla \mathrm{gi}(\mathrm{x},\mathrm{y};\mathrm{k}) \times \left[1 - \frac{1}{1+exp\left(-g\,(P^2 * P_0^2) - \alpha\left(\frac{P_0^2}{P^2}\right)\right)}\right] \quad (6)$$

Finally, WDAF is given in Eqn. (7),

$$\mathrm{W_{WDAF}} = \mathrm{jhigh}[\mathrm{y}] + \mathrm{jlow}[\mathrm{y}] + \mathrm{EAD} \quad (7)$$

C. Segmentation using K-means Clustering

A segmentation mask is formed for all samples, it structures the similar ellipse with white colour on a black background [24]. Numerous investigation instructions consume advanced segmentation methods under the basis of grey scale image. The present work will utilize the potential of colour image segmentation approach using K-means (KMC) clustering algorithm. This procedure is used for removing the entirely highlight affected areas.

The process of converting unidentified dataset information into various cluster particles is the main aim of the K-means clustering procedure [25]. This will solve the problems that coming under clustering or data science. The main importance of this clustering is that it will give a guarantee to convergence. It will give a smooth starting to the directions of the centroids. This algorithm figures the centroids and repeats till finding the correct centroid. It will simplify the clusters with different shapes and sizes.

The highlighted image that contains the spatial co-ordinates to resolve i*j, then the images should be assembled to form the k-clusters. Consider h (i, j) as the information pixel and Pk is specified as the function that focuses the group of the k-cluster. The K-means clustering algorithm has some of the following procedures and are given step by step [26],

Step 1: The centre and the cluster K must be determined.

Step 2: The Euclidean distance E_d is specified for every pixel and is expressed in the Eqn. (8).

$$E_d = \left||h(i,j) - Pk|\right| \quad (8)$$

Step 3: All the pixels are allocated to the centre point under the basis of E_d.

Step 4: By ensuing the task assigned to all the pixels, the new centre positions are re-computed by Eqn. (9)

$$Pk = \frac{1}{k}\sum_{j\in Pk}\sum_{i\in Pk} h(i,j) \quad (9)$$

Step 5: Repeat the procedure till the condition met.

This algorithm possesses some difficulties because it has several more characteristic processes. The voluntary option for the initial centroid is more important for the clustering process. When the necessary centroid is psyche-assuredly selected, some different outcomes are produced for the centres that are necessary for the clustering. To achieve the wanted separation, important centres should be chosen exactly. When using K-means clustering, the computational complex eminence must be taken into attention whether it has infinite quantity of data parts, numerous groups and quantity of sequences. The usage of K-means clustering algorithm for the separation of image frequently comes under the basis of topographies. The outcome of the process of removing highlight is secluded into K-numbers that is used by the soul. The major difficulty of this method is if the dimension of K grows, the method will slog against us. As a consequence, if the sections grow bigger, it is more difficult to discover the affected parts. If the valuation of K reduces, it will speed the mixture of some regions that have undesirable influence on the exactness of image parting.

D. Feature Extraction using GLCM

The procedure of converting initial facts obsessed by arithmetical characteristics may be treated although maintaining the evidence in the unique form is recognized as feature extraction. Features are elements of information that are pertinent for dealing with particular applications and for illustrating important aspects of pictures [27] . When compared to machine learning, it produces superior results. Feature extraction helps in reducing the redundant data from the dataset. This paper uses a Gray-Level Co-Occurrence Matrix (GLCM) for the feature extraction process.

Under feature extraction, the foundation data is transformed into arithmetical topographies deprived of constructing any changes in the odd datasets and its characteristics is based on its pixel. For eliminating the statistical texture feature from the image, it uses some functions like correlation, energy, homogeneity, contrast, entropy, etc. are estimated as second-order image individualities.

1) Correlation: Correlation value designates the resemblance of texture of the image in two orthogonal directions specifically the horizontal and vertical directions. It is given in Eqn. (10),

$$\mathrm{C_{orrelation}} = \sum_{\mathrm{x,y=0}}^{\mathrm{K-1}} \mathrm{M_{xy}} \frac{(\mathrm{x}-\mu)(\mathrm{y}-\mu)}{\sigma^2} \quad (10)$$

2) Energy: Energy is well-defined as the summation of squares with grayscale standards that are frequently higher and require unreliable concentrated values in images. It is given in Eqn. (11),

$$\mathrm{Energy} = \sum_{\mathrm{x,y=0}}^{\mathrm{K-1}} \left(\mathrm{M_{xy}}\right)^2 \quad (11)$$

3) Homogeneity: It defines the likeness of pixels. The value of GLCM medium of consistent copy is given as 1. The GLCM medium should be very stumpy to get least altered image texture. The homogeneity is given in Eqn. (12),

$$\mathrm{Homogeneity} = \sum_{\mathrm{x,y=0}}^{\mathrm{K-1}} \frac{\mathrm{M_{xy}}}{1+(\mathrm{x}-\mathrm{y})^2} \quad (12)$$

4) Contrast: Features are hand-me-down to extent the resident dissimilarity of an image, and it is forecasted to be small in the even concentrated values. The creative image's entire grayscale content is then estimated in Eqn. (13),

$$\mathrm{Contrast} = \sum_{\mathrm{x,y=0}}^{\mathrm{K-1}} \mathrm{M_{xy}}\,(\mathrm{x}-\mathrm{y})^2 \quad (13)$$

5) Entropy: The randomness of the image will be calculated by entropy and it will produce lower entropy values. It is given in Eqn. (14)

$$\mathrm{Entropy} = \sum_{\mathrm{x,y=0}}^{\mathrm{K-1}} -\ln\left(\mathrm{M_{xy}}\right) \mathrm{M_{xy}} \quad (14)$$

E. Feature Selection using Grey Wolf Optimization

While emerging an analytical model the input variables are reduced by feature selection process. The number of input variables is lowered by this process while creating an analytical model. In certain cases, while dropping the computational cost and contribution variable of the model, the execution process will be improved. The recognition of highlights in the image has been executed by a method known as Enhanced Grey Wolf Optimization (EGWO). Its standard is to make a replica of the behaviour of grey wolves to quest in a supportive method. The EGWO will improve efficiency and accuracy. EGWO is dissimilar as of others in conditions of traditional arrangement [28]. The most informative features are chosen using the EGWO. The EGWO is meant for resolving universal enhancement and engineering design complications. Thus, the method undergoes two major changes to the EGWO. Firstly, the intelligent initialization phase, which creates the population by using the data since the filter-based method. Secondly, the implementation of the Extreme Learning Machine is used as the vile sorter to deal with the greater difficulty [29].

GWO is scalable, adaptable and simple to use. In the framework of search process, the algorithm gains a balance between utilization and investigation that generates an outstanding resolution [30]. Engineers and scientists who work in a variety of disciplines have consequently grown fascinated towards the GWO. When compared to other optimization techniques GWO is the strongest and fastest algorithm.

The GWO algorithm follows the grey wolf's group dynamics and hunting tactics. The four wolf varieties that make up the leadership sequence are α (the acceptable), β (the second-fittest), δ (the third-fittest), and Ω (the left particulars of the aspirant resolutions). The procedure additionally includes three primary killing techniques of pursuing, encircling, and hitting targets.

Grey wolves enclose their prey and trudge during hunting; this is identified in the following Eqn. (15),

$$\overrightarrow{A} = \left|\vec{F}.\overrightarrow{Y_k}(u) - Y(u)\right|$$

$$Y^{\to}(u+1) = (Y\_k)^{\to}(u) - C^{\to}.A^{\to} \quad (15)$$

The subsequent connections are used to alter the geographical positions of different wolfs that search using data from alpha, beta, and delta under Eqns. (16), (17) and (18),

$$\left.\begin{aligned} \overrightarrow{A_\alpha} &= \left|\overrightarrow{F1}.\overrightarrow{Y_\alpha} - \vec{Y}\right| \\ \overrightarrow{A_\beta} &= \left|\overrightarrow{F2}.\overrightarrow{Y_\beta} - \vec{Y}\right| \\ \overrightarrow{A_\delta} &= \left|\overrightarrow{F3}.\overrightarrow{Y_\delta} - \vec{Y}\right| \end{aligned}\right\} \quad (16)$$

$$\left.\begin{aligned} \overrightarrow{Y_1} &= \overrightarrow{Y_\alpha} - \overrightarrow{C_1}.\overrightarrow{A_\alpha} \\ \overrightarrow{Y_2} &= \overrightarrow{Y_\beta} - \overrightarrow{C_2}.\overrightarrow{A_\beta} \\ \overrightarrow{Y_3} &= \overrightarrow{Y_\delta} - \overrightarrow{C_3}.\overrightarrow{A_\delta} \end{aligned}\right\} \quad (17)$$

$$\vec{Y}(u+1) = \frac{\overrightarrow{Y_1}+\overrightarrow{Y_2}+\overrightarrow{Y_3}}{3} \quad (18)$$

Where,

u signifies the present repetition.

$\vec{A}$ displays the moment path.

$\overrightarrow{Y_k}$ designates prey's spot path.

$\vec{C}$ and $\vec{F}$ are represented as the co-efficient vectors.

$\vec{Y}$ denotes the grey wolf's spot path.

The subscripts α, β, δ denote the alpha, beta and delta wolfs. Therefore, to finish the quest with ending attack. The last violence is demonstrated by lowering the $\vec{a}$ standards since 2 to zero. $\vec{A}$ is an arbitrary value in the series of $\overrightarrow{-2a}$ and $\overrightarrow{2a}$. Decreasing $\vec{a}$ would also reduce $\vec{A}$. The wolves get closer to the prey if $|\vec{A}| < 1$. The grey wolves will keep an eye on the leader wolf and they will separate individually to find and attack their prey.

Number of Wolves (NW) and the Generation Number (NG) are the two most important factors assigned by the GWO technique. Where NW actually characterizes the purpose assessments in all group, and every group characterizes the conclusion movement of a wolf. The sum of Objective Function Evaluations (OFEs) will be equal to NG increased by NW. The determination of OFEs is indicated in Eqn. (19),

$$OFEs = N_W \times N_G \quad (19)$$

F. Detection of Highlights using GAN

Generative Adversarial Networks (GANs) ensured realized outcomes in image handling, and they are more prevalent in commercial and also in intellectual worlds [31]. GAN is a useful tool to instruct a particular reproductive prototype, thus the confrontational exercise among the originator and differentiator has the capability of generating realistic images. One essential presentation of GANs is model-to-model transformation. It may be implemented to a vast number of responsibilities, especially design transmission and image resolution. Further highlight removal method is included to demonstrate the legitimacy of the method. Deep illustrations can be learned without training material using generative adversarial networks (GANs). The co-existence of a generator and a discriminator that work against every adversarial process is the basic tenet of GAN. The generator intends for the distribution of the instances it produces to match that of the training set. By examining such examples and determining whether they are genuine or artificial, the discriminator learns using conventional supervised learning techniques. The originator needs to absorb how the models are taken from similar dissemination data in order to produce synthetic data that can't be distinguished from actual data [32].

An unsystematic illustration is taken from hidden place x that acts as the generator's input. The differentiator reorganizes the originator's output G(x) using a model of actual distribution. Even though the differentiator gives the importance of supplemental commitments, it will verify that the given principles are fake or genuine. In order to reduce the utility of log (1 - D(G(x)), the generator is trained. This instructs the generator to create pictures as the discriminator can't verify the fake in it (i.e., D(G(x)) ≈ 1). To increase the likelihood that it will correctly distinguish between the real models (D(y)) and the made-up models (D(G(x)), the differentiator is additionally taught how to create the function $\log\left(D_{(y)}\right) + \log(1 - D(G_{(x)}))$. The above image explains about the architecture of Generative Adversarial Network. Various datasets are given as the input image here. After some predictions the highlights in the images will be removed. Fig. 2 shows the Architectural diagram of the Generative Adversarial Network.

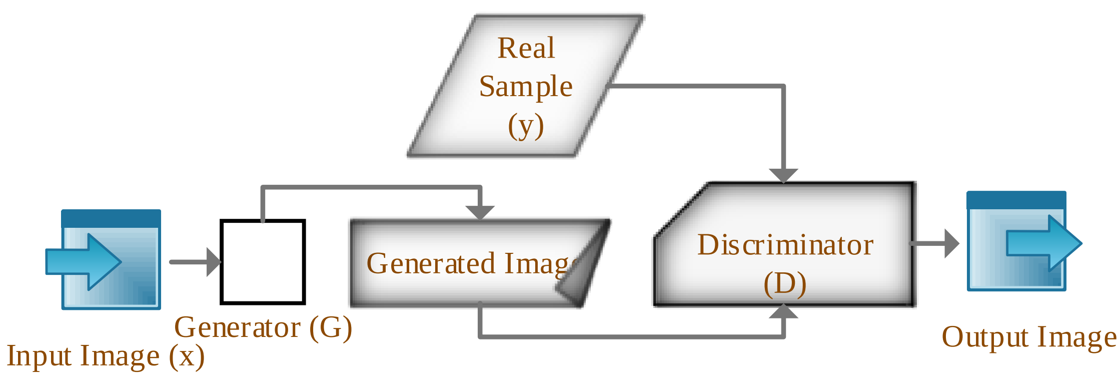

Fig. 2. Architectural diagram of generative adversarial network.

1) Creation of artificial data using GAN: The generator and discriminator are designed as multiple perceptions with layers in the initial GAN structure. The procedure continues by picking a fixed-length vector at random from the Gaussian distribution. The generator then receives vector as input, and it acts as an arbitrary seed for the generative process. A data distribution has been projected into the vector space, also known as the tucked space. The GAN will enable the originator to investigate how a quantified inactive galaxy allocates consequence to fundamentals, how to allow it to accept new concepts from the inactive space for the contribution, and how it creates new output from the input that is already available. The Contribution blast is also auxiliary to the originator because it enables the GAN to produce an extensive range of samples commencing various locations within the target distributions and the algorithm permits the GAN to produce a broad range of data. The discriminator functions as a classifier and forecasts as a binary class label for an unidentified model from either the originator or actual preparation data. The training module is determined as follows in Eqn. (20),

$$\min_G \max_D * K(D,G) = E_y \sim Q_{data}(y)\left[\log\left(D(y)\right)\right] + E_x \sim Q_x(x)[\log(1 - D(G(x)))] \quad (20)$$

Here,

x is denoted as the input of the image.

D is the represented as the Discriminator.

G is the generator.

E is the Expectation operator.

y is denoted as the real samples.

G. Elimination of Highlight using Structure Texture Layering Algorithm

After the detection of highlights, it can be removed using a highlight removing technique. This paper uses Structure texture layering algorithm to eradicate the high spot from a sole image [33]. An integrated mechanism is conveyed simultaneously to tackle the removal of reflection and artifact destruction. Here, the unique input image is divided into two strata, namely, the structure and the texture layer. Any image can be considered as contrasted and nested collection of dark and light objects it only appears in a particular range of resolution is defined as the structure. Whereas, the brightness intensity of the pixels spatial fluctuation is used to determine the texture. The modification amongst the input image and the x and its structured layer x_S is calculated using the Eqn. (21). The formulation used for the total variant image restoration is based on the relative total dissimilarity measurements and a soul object generates the illusion of eradicating the texture stratum from the image is given in Eqn. (22)

$$x_T = x - x_S \quad (21)$$

$$\min_S \sum_k \left|\left|S_k - x_k\right|\right|^2 + \lambda\left(\frac{\sigma i(k)}{\delta i(k) + \varepsilon} + \frac{\sigma j(k)}{\delta j(k) + \varepsilon}\right) \quad (22)$$

Where,

x is the input image.

x_T is the texture layer.

x_S is the structure layer.

S is the structure image.

K is the 2D pixel.

$(S_k - x_k)^2$ is used to define the structure that is comparable to those of the input image.

$\sigma_{i(k)}$ and $\sigma_{j(k)}$ is strong-minded as the windowed total variation in i and j direction from the pixel k

$\delta_{i(k)}$ and $\delta_{j(k)}$ is determined as the windowed inherent variations

λ is denoted as the weight

The algorithm of EGWO-GAN is given below and followed by that the flow diagram of the proposed EGWO-GAN is shown in Fig. 3.

Algorithm for EGWO-GAN

Input: *Image containing highlight*
Output: *Highlight detection in hyperspectral images*
Load data for provided images
X = $\{X_1, X_2, X_3, \ldots.\}$
//Data Acquisition
Image Pre-processing
//Wavelet Decomposition Anisotropic Filter
W_{WDAF} *is given in Eqn. (7)*
Image Segmentation
//K-means clustering
Identify the number of K clusters for assigning
Specify Euclidean distance E_d *for each pixel using Eqn. (8)*
Allocate all the pixel to the centre point under E_d
After assigning the tasks, new centroid points are re-computed using Eqn. (9)
Do the process till it reaches the correct criteria
Feature Extraction
// Grey-Level Co-Occurrence Matrix
Feature Selection
//Grey Wolf Optimization
Feature Selection is given in Eqn. (19)
Encircling prey
Knowledge of alpha, beta, delta wolfs
Getting closer to the prey
Seeking and attacking the prey
Setting parameters for representing NW and NG //
Objective Function Evaluation (OFE)
Detecting image highlights
//Generative Adversarial Network
The highlights in the images are detected using Eqn. (20)
Removing image highlights
//Structure texture algorithm
The highlights in the images are removed using Eqn. (22)

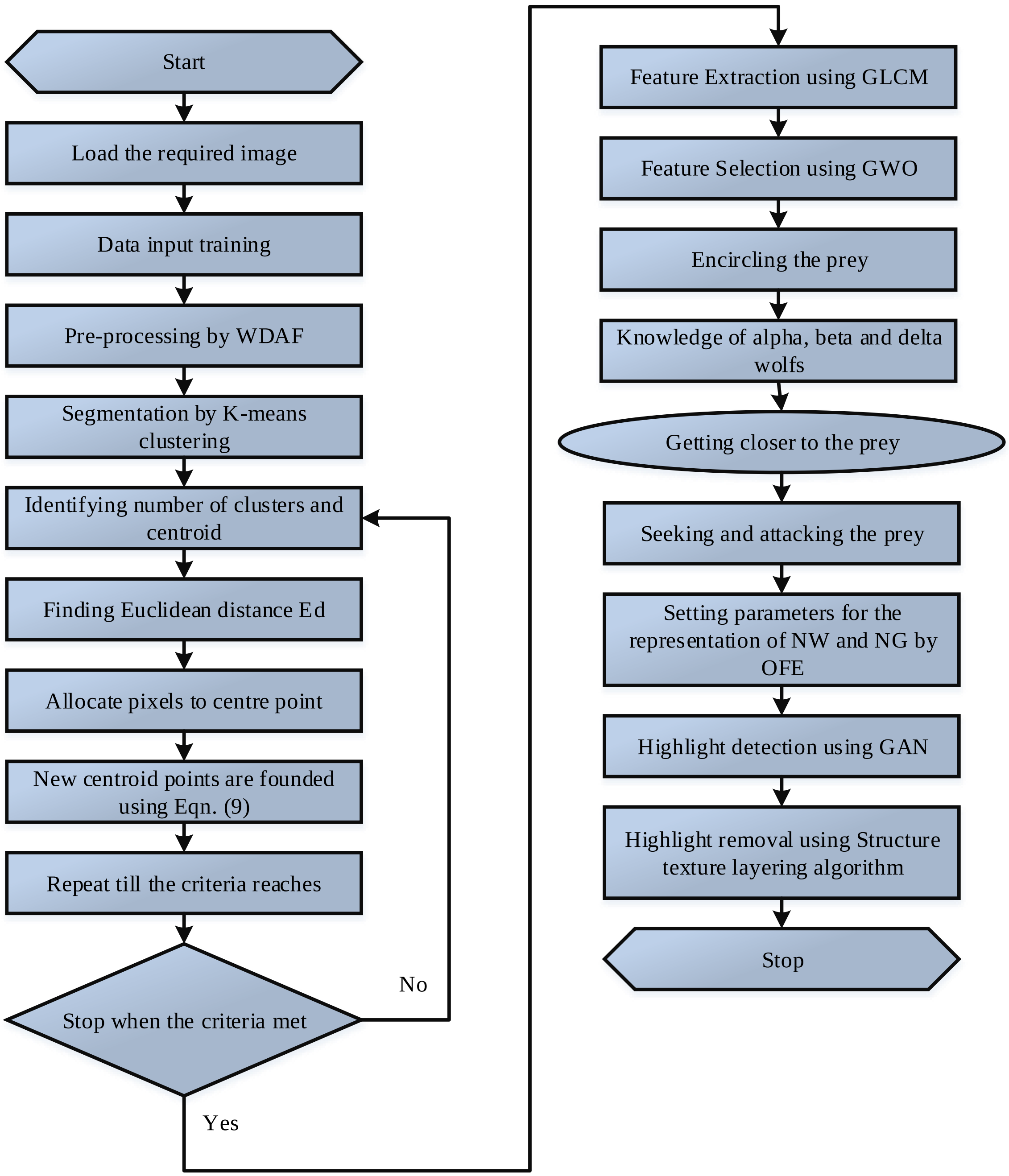

Fig. 3. Workflow of EGWO-GAN model.

V. Result and Discussion

The proposed method has been examined by some datasets. The Enhanced Grey Wolf Optimization based Generative Adversarial Network is utilized to eliminate the highlights in the image. The input image is taken and pre-processed using WDAF. Then, the segmentation process is done by k-means clustering process. Then the feature is extracted using GLCM. After that the feature selection is done by GWO. After that the highlighted part is detected using GAN. Finally, the highlight spectral is removed using structure texture layering algorithm.

Fig. 4. Initial input image.

Fig. 5. Processed output image.

Fig. 4 shows the initial input image with specular highlights and Fig. 5 shows the processed highlight detected image.

The planned method can be compared using some parameters like Accuracy, Precision, Recall, F1-score.

A. Performance Metrics Evaluation

1) Accuracy: The accuracy may be defined as the proportion of properly classified illustrations. Accuracy is expressed in Eqn. (23),

$$\text{Accuracy} = \frac{T_{\text{Positive}}+T_{\text{Negative}}}{T_{\text{Positive}}+T_{\text{Negative}}+F_{\text{Positive}}+F_{\text{Negative}}} \quad (23)$$

2) Precision: The ratio of suitable examples between the obtained incidences is known as precision or positive prediction value. Precision is computed from Eqn. (24),

$$\text{Precision} = \frac{T_{\text{Positive}}}{T_{\text{Positive}}+F_{\text{Positive}}} \quad (24)$$

3) Recall: The proportion of the applicable occurrences that is returned is termed as recall or sensitivity. Recall is uttered in Eqn. (25),

$$\text{Recall} = \frac{T_{\text{Positive}}}{T_{\text{Positive}}+F_{\text{Negative}}} \quad (25)$$

4) F1-score: The weighted average of the image augmentation measurements, compared between 0 and 1 is used to estimate the score function. It is signified in Eqn. (26),

$$\text{F1} - \text{score} = \frac{2\times\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \quad (26)$$

Table I and Fig. 6 show the comparison and performance evaluation of Accuracy, Precision, Recall and FI-score. When comparing those parameters with the following three existing methods, i) Exemplar-based inpainting algorithm ii) Intrinsic image layer separation method iii) Computer aided diagnosis algorithm, the proposed EGWO-GAN algorithm produces greater accuracy (99.91%), greater precision (97.92%), greater recall (97%) and greater score function (96.5%).

TABLE I. COMPARISON TABLE OF ACCURACY, PRECISION, RECALL, FI-SCORE

Method	Accuracy (%)	Precision (%)	Recall (%)	FI-score (%)
Exemplar-based inpainting algorithm [34]	98.49	75.75	88.69	81.71
Intrinsic image layer separation method [35]	99	59	71	64
Computer aided diagnosis algorithm [36]	90.6	92.8	86.7	89.7
Proposed EGWO-GAN algorithm	99.91	97.92	97	96.5

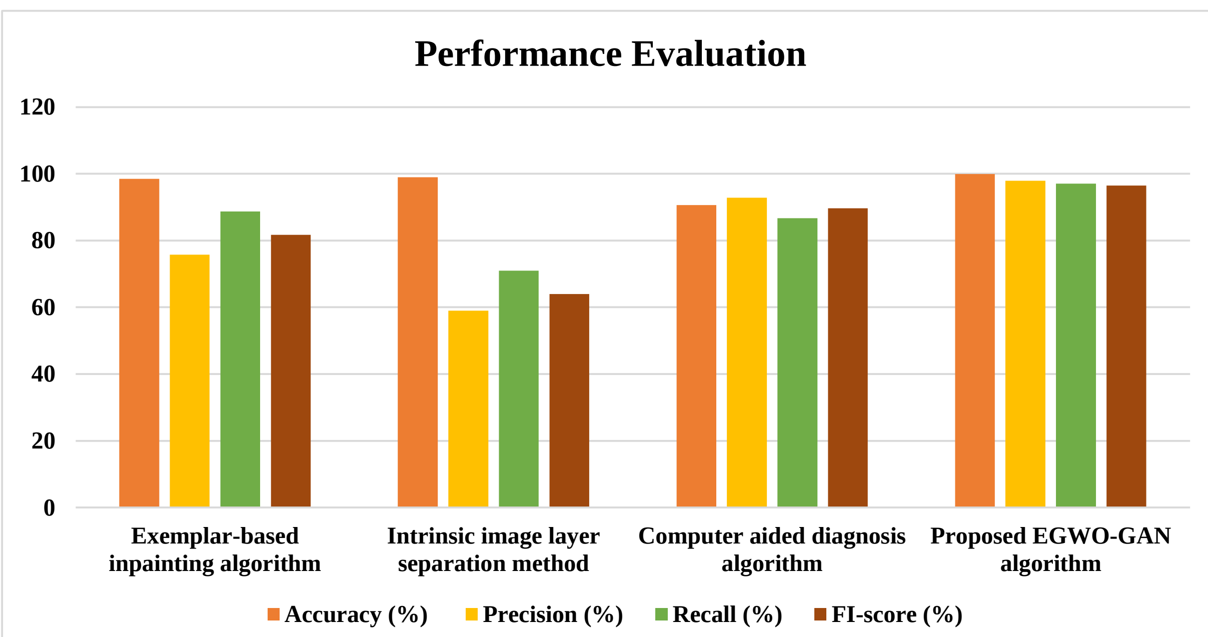

Fig. 6. Performance comparison chart for Accuracy, Precision, Recall and FI-score.

B. Discussion

Comparing the suggested EGWO-GAN approach the previously used highlight removal techniques like Exemplar-based inpainting algorithm, Intrinsic image layer separation, Computer aided diagnosis algorithm in Table I results in greater efficiency. The accuracy of the Enhanced GWO based Generative Adversarial Network is higher than that of the performance measured using EGWO and GAN separately. By using this EGWO-GAN model the accuracy level reached is 99.91%. This indicates that the EGWO based GAN will reduce the highlights from the hyper spectral image.

Table I inclines the evaluation outcomes of different algorithms that are based under the Kaggle dataset. When comparing with various approaches the value of Accuracy, Precision, Recall and FI-score in the planned techniques illustrate healthier results. When comparing the accuracy of the proposed method with [35]'s accuracy, the planned method is (0.91%) higher than [35] and lower than [36]. Then, the planned method is better in precision of about (5.12%) when compared to [36]'s precision and the precision is less than [35]. Furthermore, the recall of the proposed method is very much higher (8.31%) than [34]'s recall and lower than [35]. The score function of the proposed method also provides (7.5%) higher score function than that of [36] and provides lesser score function than that of [35].

In this work, K-means clustering is cast-off for the separation process. It will convert the nameless dataset information into various cluster elements. When comparing to the previous techniques, the highlights cannot be removed easily because the hyperspectral images contain heavy noisy particles and the exact particulars are also unclear. The parameters of accuracy, precision, recall and score function of the suggested method gives healthier outcomes than the existing approaches. This will also provide greater efficiency.

VI. Conclusion and Future Work

Image processing is one of the latest resources in the domain of hyperspectral photography. But in some circumstances the images will be unspecified due to noise. Therefore, to classify, identify and to divide the planned technique highlight removal process is emphasized. Various datasets are used to detect highlight in the image. To remove the unwanted noise from the hyperspectral images a Wavelet Decomposition Anisotropic Filter (WDAF) is used in the pre-processing stage. Then the Gray-Level Co-Occurrence Matrix (GLCM) in the feature extraction process will determines exactly how frequently a combination of pixels with a particular value appears in the image while defining an image's characteristics. Moreover, the proposed method, Enhanced Grey Wolf Optimization based on the Generative Adversarial Network (EGWO-GAN) is employed to separate the highlighted spots from the hyperspectral images. Improved recognition and estimated accuracy also investigated using this EGWO-GAN process. Then the highlighted region is removed using Structure texture layering algorithm. Finally, the estimated accurateness of the technique was found to be 99.5% and the efficacy of this method is enhanced by the Generative Adversarial Network (GAN) that is based under the machine learning (ML) process.

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