PROJECT REPORT ON

MINIMIZING OVER-ENHANCEMENT OF IMAGE THROUGH A CUSTOMIZED ICSO ALGORITHM FOR MULTI-MEDIA APPLICATIONS

Submitted in partial fulfilment of the Requirement for the award of the degree of

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CERTIFICATE

This is to certify that the dissertation entitled "MINIMIZING OVER-ENHANCEMENT OF IMAGE THROUGH A CUSTOMIZED ICSO ALGORITHM FOR MULTI-MEDIA APPLICATIONS" is being submitted by Y. Siva Manasa (20091A04H7), N. Mohan Reddy(20091A0494), C. Kalyani(20091A0463), B. Kundana (20091A0477) under the guidance of Mr. M.A. Vijay Kamalnath, Assistant Professor for Project of the award of B.Tech Degree in Electronics and Communication Engineering, Rajeev Gandhi Memorial College of Engineering and Technology, Nandyal (Autonomous) (Affiliated to JNTUA Anantapuramu) is a record of bonafide work carried out by them under our guidance and supervision.

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Date of Viva-Voce:

CANDIDATES’ DECLARATION

We hereby declare that the work done in this project titled **“Minimizing Over-Enhancement of Image through a customized ICSO Algorithm for Multi-Media Applications”** submitted for the completion of the main project in the IV Year II Semester of B. Tech (ECE) at **Rajeev Gandhi Memorial College of Engineering and Technology (Autonomous), Nandyal**, is an authentic record of our original work done under the guidance of **Mr. M.A. Vijay Kamalnath, Assistant Professor**, Dept. of ECE, RGMCET, Nandyal. We have not submitted the material embodied in this main Project for the award of any other degree in any other institution.

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ABSTRACT

Image enhancement is a fundamental technique of digital image processing. It is all about making visual appearance of an image better by revealing hidden details or highlighting specific features. However, the process of image enhancement, if not carefully controlled, can lead to over enhancement, resulting in unrealistic images.

To mitigate the risk of over-enhancement, Chicken Swarm Optimization (CSO) algorithm, which is well-suited for addressing low-density image details optimization problems. However, when dealing with high- density image details optimization, CSO may encounter challenges in avoiding local optimum. To address this limitation, we employ the Improved Chicken Swarm Optimization (ICSO) in our proposed approach.

In this project Improved CSO algorithm is being used to do enhancement on an localized details of the image at the same time to minimize over enhancement for high-density image details to preserve in original Gray intensity level. This proposed approach focuses on three main goals, maintaining the main details of image, generating an image with a uniform histogram, and reducing the spikes in the modifiedhistogram. In addition to the proposed algorithm, the removal of less noticeable information through the concept of Psycho-Visual Redundancy for some of the multi-media applications such as images, documents, and videos.

Keywords: *Image Over-Enhancement, Uniform-Histogram, ICSO Algorithm, Psycho-Visual Redundancy.*

CHAPTER –1

INTRODUCTION

1.1 DIGITAL IMAGE PROCESSING

Digital image processing is indeed a crucial subfield of signals and systems, leveraging the computational power of digital computers to analyze, enhance, and manipulate visual data. Its core lies in developing computer systems capable of executing diverse operations on digital images, ranging from simple tasks like resizing and cropping to more intricate procedures such as image restoration, feature extraction, and pattern recognition.

While image processing cannot increase the information present in the original image data, it can significantly improve visualization, comprehension, and analysis of the image information for specific applications. There's no magic trick in image processing to create something entirely new in the image, but it can seem almost magical when it highlights subtle details, making them obvious and distinctive.

Image analysis, on the other hand, involves extracting significant data from images, encompassing tasks like shape recognition, edge detection, object counting, and property measurement. Key algorithms in image analysis include edge detection, shape detection, color-based segmentation, and image thresholding. These techniques, when combined with region analysis functions, yield detailed statistics, augmenting human analysis with quantitative and qualitative insights.

Image analysis finds utility across diverse fields, aiding in medical diagnosis, satellite imagery interpretation, industrial quality control, and more. By harnessing these algorithms, researchers and professionals can uncover hidden patterns, quantify visual phenomena, and make informed decisions based on image-derived information.

In image processing, the alteration of an image aims either to improve its pictorial information for human interpretation or to render it more suitable for autonomous machine interpretation.

This image processing system may handle various problems and applications, predominantly involving the following processes known as basic classes in imaging processing:

- Image Acquisition
- Image Enhancement
- Image Restoration
- Color Image Processing
- Wavelets and Multi-Resolution Processing
- Image Compression
- Morphological Processing
- Image Segmentation

1.2 IMAGE ENHANCEMENT

Image enhancement involves improving the quality, clarity, and interpretability of digital images to facilitate more accurate and effective analysis, recognition, and understanding.Image enhancement techniques are crucial for enhancing image features, reducing noise, improving contrast, and preparing images for subsequent processing tasks such as object detection, segmentation, and recognition.

Image enhancement techniques aim to improve the quality, clarity, and interpretability of digital images. These techniques can be broadly categorized into several groups based on the aspects they target for improvement.

Here are some common image enhancement techniques:

1.2.1 Contrast Enhancement

Histogram Equalization: Redistribution of pixel intensities across the histogram to improve overall contrast.

Contrast Stretching: Expansion of the dynamic range of pixel intensities to enhance contrast.

Adaptive Histogram Equalization: Histogram equalization applied locally to different regions of the image for adaptive contrast enhancement.

1.2.2 Noise Reduction:

Median Filtering: Replacement of each pixel's intensity value with the median value of its neighborhood to reduce impulse noise.

Gaussian Smoothing: Convolution of the image with a Gaussian kernel to reduce high-frequency noise.

Bilateral Filtering: Simultaneous spatial and intensity filtering to preserve edges while reducing noise.

1.2.3 Sharpening:

Unsharp Masking: Unsharp masking enhances high-frequency components by subtracting a blurred version of the image from the original, revealing details and edges without duplicating content.

High-Pass Filtering: Extraction of high-frequency components using high-pass filters to enhance image details.

1.2.4 Color Enhancement:

White Balance Adjustment: Correction of color casts to achieve neutral colors.

Histogram Stretching: Expansion of color intensity ranges to improve color fidelity.

Color Space Transformations: Conversion between color spaces (e.g., RGB to LAB) for better color representation and manipulation.

1.2.5 Edge Enhancement:

Sobel Operator: Detection of edges using gradient-based operators to enhance image boundaries.

Canny Edge Detector: Multi-stage edge detection algorithm for accurate edge localization.

Prewitt Operator: Similar to Sobel operator, used for edge detection and enhancement.

1.2.6 Detail Enhancement:

Transform: Decomposition of the image into different frequency bands for detail enhancement.

Structure-Preserving Smoothing: Removal of noise while preserving important image structures and textures.

Adaptive Enhancement Techniques: Adjustment of enhancement parameters based on local image characteristics to preserve fine details.

1.2.7 Spatial Frequency Domain Techniques:

Fourier Transform: Transformation of the image into its frequency domain representation for frequency-based analysis and filtering.

Frequency Filters: Application of frequency domain filters (e.g., low-pass, high-pass) to enhance specific frequency components.

These techniques can be used individually or in combination to address specific image enhancement requirements, such as improving contrast, reducing noise, sharpening details, or enhancing color fidelity. The selection of appropriate techniques depends on the characteristics of the input image and the desired enhancement goals.

Techniques such as white balance correction, histogram stretching, and color space transformations (e.g., RGB to LAB) are employed to enhance color fidelity and visual appeal.

Detail enhancement techniques focus on preserving and enhancing fine details and textures in images without introducing artifacts or noise. These techniques are particularly important for applications requiring high-resolution image analysis, such as medical imaging, satellite imagery, and surveillance.

Methods like adaptive histogram equalization, wavelet transform-based enhancement, and structure-preserving smoothing are used to enhance details while preserving image structure and texture.

Adaptive and contextual enhancement techniques consider the local characteristics and content of images to perform targeted enhancement tailored to specific regions or features. These techniques adaptively adjust enhancement parameters based on local image properties, such as intensity gradients, texture complexity, or spatial context. Non-local means denoising, guided filter-based enhancement, and context-aware contrast enhancement are examples of such techniques used in computer vision.

Multiscale and pyramid-based enhancement techniques operate at multiple resolutions or scales to capture and enhance image features across different levels of detail. These techniques leverage image pyramids or multiscale representations to decompose images into coarse-to-fine levels and perform enhancement operations at each scale.

Multiscale retinex, Laplacian pyramid blending, and wavelet-based multiscale enhancement are examples of such techniques used for enhancing images in computer vision.

Contrast and brightness are indeed two essential factors in image enhancement, each serving a distinct purpose in improving the visual quality of an image.

- **Contrast** enhancement aims to increase the difference in brightness between the lightest and darkest parts of an image, thereby making the image appear sharper and more detailed.
- **Brightness** adjustment, on the other hand, focuses on globally shifting the overall luminance level of the image, making it appear brighter or darker without significantly affecting the contrast.

1.2.8 Contrast

Contrast plays a crucial role in enhancing the quality and visual appeal of images. It refers to the difference in brightness between different parts of an image and is a key aspect of image enhancement and analysis. Understanding and manipulating contrast is essential for improving image clarity, detail, and overall perception.

One of the primary methods used to adjust contrast in digital image processing is histogram equalization. Histogram equalization is a technique that redistributes the pixel intensities in an image to achieve a more uniform distribution, thereby enhancing the overall contrast.

Fig 1.1:Low and High Contrast Images

By stretching the histogram across the entire dynamic range of pixel values, areas of low contrast are expanded, while preserving the relative differences between pixel values.

Enhancement techniques primarily targeting contrast can be categorized into two main approaches: direct and indirect methods.

1.Direct Methods:

Direct methods in contrast enhancement involve defining a measure of contrast within the image and then finding a solution to improve it. These methods typically analyze the pixel values and their relationships to determine the overall contrast level of the image. Once the contrast measure is established, various algorithms and techniques are employed to enhance it effectively. Examples of direct methods include histogram equalization, contrast stretching, and adaptive contrast enhancement techniques.

2.Indirect Methods:

In contrast, indirect methods for contrast enhancement do not explicitly define a measure of contrast but rather focus on adjusting the dynamic range of pixel values or specific regions within the image to enhance overall contrast. These methods often involve techniques such as histogram modification, spatial filtering, and tone mapping. By increasing or decreasing the dynamic range, these methods aim to amplify the differences between pixel intensities, thereby enhancing the contrast without directly measuring it.

By combining contrast enhancement techniques with brightness adjustments, image enhancement algorithms can effectively improve the visual quality of images for various applications, including medical imaging, satellite imagery, digital photography, and more. These techniques are essential tools in digital image processing for enhancing image interpretability and analysis.

1.3 IMAGE OVER-ENHANCEMENT

While enhancement techniques undoubtedly improve the quality of images, there's a crucial aspect that's often overlooked: the risk of overenhancement. Overenhancement can occur when adjustment methods are applied excessively or inappropriately, leading to unnatural-looking images or the loss of important visual information.

Despite their effectiveness in increasing image quality, these techniques must be used judiciously to avoid undesirable outcomes.

Fig 1.2(a) Fig 1.2(b) Fig 1.2(c)

Fig.1.2: (a) Distorted Image
(b) Image After Enhancement
(c) Image with Over-Enhancement

One of the primary concerns with overenhancement is the introduction of artifacts or visual distortions in the image. For example, aggressive contrast stretching can result in exaggerated differences between adjacent pixel values, leading to unnatural-looking gradients or banding effects. Similarly, excessive histogram equalization may amplify noise or introduce unwanted texture, detracting from the overall visual appeal of the image. Boosting contrast too much can make the picture lose its small but crucial details.

Picture making the contrast super high, so the nice textures, smooth color changes, and soft shadows all look flat and blurry. This is a big issue, especially in fields like medicine or forensics, where every detail matters for accurate judgments. So, while making images look better with more contrast can be good, it's super important to not go overboard and lose important stuff.

Another issue associated with overenhancement is the alteration of the image's perceived brightness and color balance. For instance, aggressive contrast adjustments can cause certain areas of the image to appear unnaturally bright or dark, leading to an overall imbalance in luminance levels.Similarly, color distortion may occur when contrast enhancement affects the relative relationships between color channels, leading to shifts in hue, saturation, or color intensity.The timing of contrast enhancement is also crucial in avoiding overenhancement.

In some cases, overenhancement may not be immediately apparent during the processing stage but becomes more noticeable once the image is viewed in context or under different viewing conditions.

For example, an image that appears well-enhanced on a high-quality monitor may look oversaturated or overly sharpened when printed or viewed on a different display device.

To mitigate the risk of overenhancement, it's essential to adopt a cautious and iterative approach to image processing. Instead of applying contrast enhancement techniques uniformly across the entire image, consider using localized adjustments or targeted corrections to specific regions of interest. Additionally, leverage tools and algorithms that offer fine-grained control over the degree of enhancement, allowing for subtle adjustments that preserve the integrity of the original image.

Causes of Image Overenhancement:

1. **Aggressive Enhancement Parameters:** Excessive adjustment of enhancement parameters such as contrast, brightness, or sharpness can lead to overenhancement.
2. **Inappropriate Techniques**: Certain enhancement techniques, such as histogram equalization, may produce overenhancement if applied indiscriminately or without considering image characteristics.
3. **Insufficient Preprocessing**: Lack of preprocessing to remove noise or correct distortions before enhancement can amplify unwanted artifacts and lead to overenhancement.
4. **Subjective Preferences**: Subjective preferences of users or designers may lead to overenhancement when aesthetic appeal takes precedence over preserving image fidelity.

Disadvantages of Image Overenhancement:

1. **Loss of Original Information:** Overenhancement can obscure or distort important details in the original image, leading to loss of valuable information.

2. **Artifacts and Distortions:** Excessive enhancement may introduce artifacts, noise, or unnatural-looking features, detracting from the overall quality and realism of the image.
3. **Misinterpretation:** Overenhanced images may convey misleading or inaccurate information, leading to misinterpretation or misrepresentation of the underlying scene or content.
4. **Reduced Usability:** Overenhanced images may be less suitable for certain applications, such as medical diagnosis or scientific analysis, where accuracy and fidelity are paramount.

While image overenhancement may have certain applications in artistic, entertainment, and consumer contexts, it is essential to exercise caution and moderation to avoid detrimental effects on image quality, usability, and interpretation.Balancing enhancement techniques with the preservation of original content and fidelity is crucial for ensuring that enhanced images remain informative, accurate, and visually pleasing.

Histogram equalization is a method employed in image processing to enhance the contrast of an image. It operates by adjusting the distribution of pixel intensities to create a more uniform histogram, thereby improving the overall visual quality of the image. This technique involves mapping the cumulative distribution function of the original image's histogram to a linear function, effectively spreading out the intensity values across the entire range. As a consequence, regions with low contrast are amplified, making details more discernible and enhancing the overall clarity of the image. By equalizing the histogram, areas that were previously too dark or too bright become appropriately adjusted, resulting in a more balanced representation of the image. Histogram equalization is commonly utilized in various applications such as medical imaging, satellite imagery, and digital photography to improve image quality and facilitate subsequent analysis or processing tasks..

In a grayscale image, for example, if there are many pixels with low intensity values and few pixels with high intensity values, histogram equalization will spread out the intensity values so that they cover the entire range more evenly.

This results in enhanced contrast, making details in both dark and bright regions more visible.One of the key advantages of histogram equalization is its simplicity and effectiveness in improving image quality without requiring complex processing algorithms. However, it's worth noting that histogram equalization may sometimes amplify noise in an image, particularly in regions with low contrast.

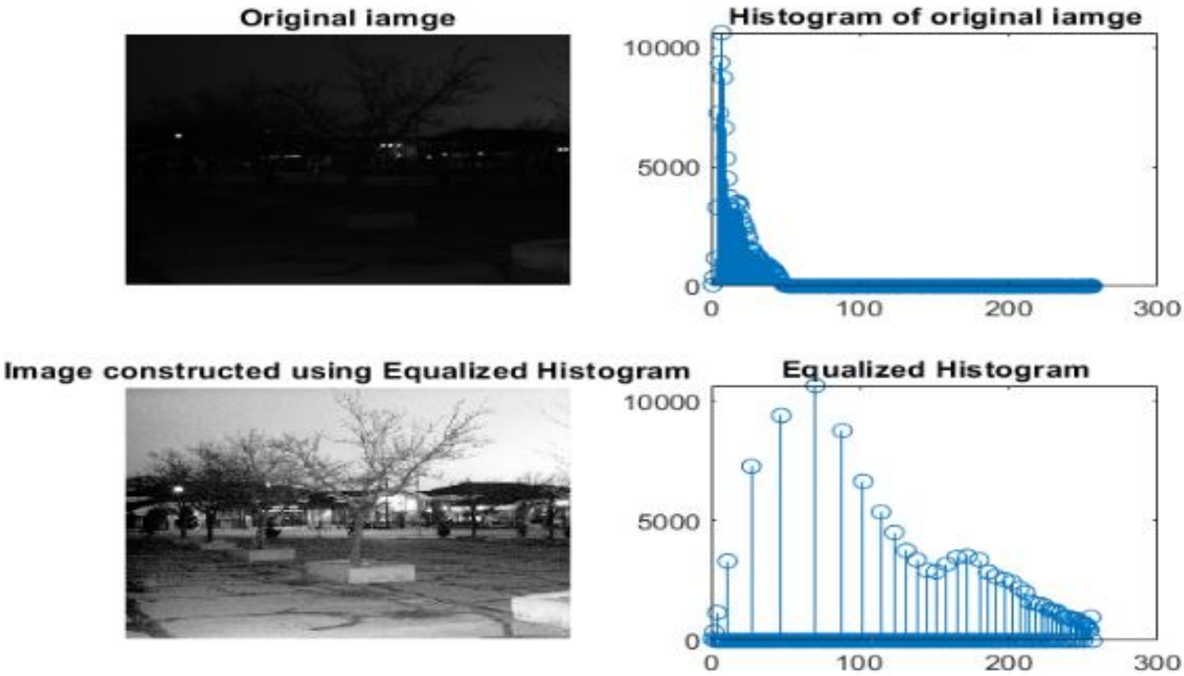

Fig 1.4: Histogram Equalization

In this proposed method, we concentrate on an enhanced version of the CSO optimization algorithm, referred to as ICSO. The purpose of ICSO is to address over-enhancement issues by introducing specialized objective functions designed to enhance both low-contrast and high-contrast images.

While CSO is effective for solving low-dimensional optimization problems, it may struggle with high-dimensional cases, leading to suboptimal results. To overcome this limitation, we propose the use of the improved ICSO algorithm.
The primary objectives of our study revolve around enhancing image quality while preserving essential details, achieving uniformity in the histogram, and reducing spikes in the modified histogram.

Here's an overview of each objective:

1. Preserving Main Details
2. Generating an Image with a Uniform Histogram
3. Reducing Spikes in the Modified Histogram

1.4 REDUNDANCY

In digital image processing, redundancy refers to the presence of unnecessary or repetitive information within an image data set. It represents an inefficiency in the representation of the image, as it contains information that does not contribute significantly to its content or quality. Redundancy can arise from various sources, including similarities between adjacent pixels, correlations between color channels, or imperceptible details in the image that do not affect its overall appearance.

Addressing redundancy is crucial in image compression, where the goal is to reduce the size of the image data without sacrificing its quality. By identifying and eliminating redundant information, compression algorithms can achieve significant reductions in file size, making images easier to store, transmit, and process.Efficient compression techniques exploit redundancies in the image data to create compact representations that preserve essential visual information while discarding redundant or less important details.

Redundancy in the context of digital image processing refers to the presence of unnecessary or repetitive information within an image. It can manifest in various forms, including:

Coding Redundancy: This type of redundancy occurs when the same information is encoded multiple times in the image data. For example, adjacent pixels in an image may have similar values, leading to redundant information in the encoded image.

Interpixel Redundancy: Interpixel redundancy arises from correlations between neighboring pixels in the image. In natural images, adjacent pixels often exhibit similar intensity values or color properties, resulting in redundant information that can be exploited for compression.

Psychovisual Redundancy: Psychovisual redundancy pertains to redundancies inherent in human visual perception.

It encompasses phenomena such as visual masking, where certain image details may be imperceptible to the human eye due to the presence of more salient features, allowing for the removal or compression of less noticeable information without significantly impacting image quality.

1.4.1 Psycho Visual Redundancy

Psycho-visual redundancy refers to the principle that human visual perception can tolerate certain levels of information loss or distortion without significantly impacting the perceived quality of an image or video. This concept is fundamental in various compression techniques, where reducing redundant information in a way that aligns with human perception allows for significant data savings without a noticeable loss in visual quality.

One aspect of psycho-visual redundancy is based on the human visual system's limited sensitivity to certain details or patterns. For example, the visual system is more sensitive to changes in luminance (brightness) than changes in color or fine details. Thus, compression algorithms can prioritize preserving luminance information while reducing color resolution or removing high-frequency details that are less perceptually significant.Another aspect is the phenomenon of spatial and temporal masking.

Spatial masking occurs when the presence of strong visual elements in an image reduces the visibility of nearby weaker elements. Similarly, temporal masking refers to the situation in videos where fast-moving objects may mask slower-moving or static details. Compression algorithms take advantage of these phenomena by allocating more bits to preserve important visual elements while reducing the fidelity of less noticeable ones.

Furthermore, psycho-visual redundancy encompasses concepts such as contrast sensitivity, spatial acuity, and color perception. Compression algorithms exploit these aspects by allocating fewer bits to imperceptible areas of an image or video while maintaining high fidelity in critical regions. For example, in a scene with uniform colors, fewer bits can be allocated compared to regions with intricate textures or sharp edges, where visual imperfections would be more noticeable.

CHAPTER -2

LITERATURE SURVEY

"A critical analysis on perceptual contrast and its use in visual information analysis and processing**"**.This method**[1]** involves a comprehensive examination of existing contrast measures and models, spanning disciplines such as vision, optics, and image processing.Future scope involves integrating recent findings from human vision research and machine learning into contrast models. Additionally, exploring novel techniques for quantifying and manipulating contrast could further enhance our understanding and utilization of this critical visual characteristic.

"Color image contrast enhacement method based on differential intensity/saturation gray-leveAls histograms**"**.This method**[2]** extends the concept of histogram equalization (HE) to color images by introducing a novel approach called differential gray-levels histogram equalization (DHE). Future scope lies in further refining the proposed DHE method and exploring its applications in various domains.

"3D color channel based adaptive contrast enhancement using compensated histogram system**"**.This method**[3]** presents a novel approach to contrast enhancement in low contrast images, aiming to preserve their natural appearance while effectively enhancing visual clarity. Future scope involves further refinement and optimization of the proposed method. This may include exploring alternative blending techniques for color channels, refining the adaptive brightness adjustment kernel, and investigating additional noise reduction methods to enhance the overall quality of the enhanced images.

"Improved chicken swarm optimization**"**.The paper**[4]** enhancements to the chicken swarm optimization algorithm offer a promising approach to tackling the issue of premature convergence in high-dimensional complex problems. By pursuing these directions, researchers can continue to advance the proposed method and extend its applicability to diverse optimization challenges across various domains.

"How good is too good? A subjective study on over enhancement of images**"**. The study**[5]** introduces the Subjective Enhanced Image Dataset (SEID) to address the underexplored issue of overenhancement in image enhancement techniques. SEID comprises 30 reference images presented to 15 observers at both low and high contrast levels. Observers were tasked with enhancing image quality until further improvement led to degradation. Moving forward, this research prompts the development of advanced image quality metrics aligned with human perception, algorithmic adjustments to prevent over-enhancement, and integration of SEID into evaluation processes for image enhancement methods.

"A histogram modification framework and its application for image contrast enhancement**"**.This paper**[6]** framework introduces a novel approach to image contrast enhancement through histogram equalization, reframing it as an optimization problem with a defined cost function.Future exploration includes fine-tuning penalty terms, integrating machine learning techniques, optimizing for real-time implementation, evaluating on diverse datasets, and extending to video processing applications.

"How do image quality metrics perform on contrast enhanced images?**"**.In the realm of image quality assessment**[7]**, the focus has long been on evaluating distorted images, with objective Image Quality Metrics (IQMs) playing a crucial role. Through these efforts, we aim to bridge the gap between objective IQM assessments and subjective human perception, ultimately advancing the field of image quality assessment in the context of contrast enhancement.

"Evaluation of spatial gamut mapping algorithms**"**.The study**[8]** proposes an independent evaluation of Spatial Gamut Mapping Algorithms (SGMAs) through a psychophysical experiment involving a comparison of five gamut mapping algorithms—two point-wise and three spatially adaptive—applied to fifteen images. For future exploration, avenues include refining IQMs for SGMAs, integrating human perception models into IQMs, exploring combined metrics, extending findings to real-world applications, and conducting longitudinal studies for a deeper understanding of SGMAs' performance across diverse contexts.

"FSIM: A feature similarity index for image quality assessment**"**.The paper**[9]** introduces a novel approach to Image Quality Assessment (IQA) with the Feature Similarity (FSIM) index, aimed at bridging computational models with subjective evaluations.Future research could focus on refining FSIM, extending its application to video and multimedia, integrating deep learning techniques, exploring real-world applications, and conducting user-centric evaluations to enhance its effectiveness in practical scenarios.

"Image quality assessment based on gradient similarity**"**.In this paper**[10],** we propose a novel Image Quality Assessment (IQA) scheme focusing on gradient similarity to capture structural and contrast changes in images. For future research, avenues include refining and optimizing the proposed scheme, extending it to assess multimedia content, integrating human perception models, exploring real-world applications, and conducting user-centric evaluations to enhance performance.

"A universal image quality index**"**.This paper**[11]** introduce a novel universal objective image quality index aimed at simplicity in calculation and applicability across diverse image processing applications. Moving forward, future research could explore several avenues to further enhance and extend our proposed image quality index. Additionally, exploring the integration of human visual system models or perceptual metrics could enhance the index's alignment with human perception.

"Image database TID2013: Peculiarities, results and perspectives**"**.This paper**[12]** introduces the TID2013 image database for evaluating full-reference visual quality assessment metrics. Compared to TID2008, TID2013 offers a larger dataset with 3000 test images derived from 25 reference images. It includes 24 types of distortions per reference image, with five levels for each type. MOS values collected from 985 subjective experiments provide a reliable benchmark for assessing visual quality metrics. The paper evaluates existing metrics using TID2013 and analyzes correlation with MOS, offering insights into metric performance and limitations. The database and MOS values are freely available for scientific use, facilitating further research in visual quality assessment.

"Most apparent distortion: Full-reference image quality assessment and the role of strategy**"**.This method**[13]** challenges the conventional approach to image quality assessment by proposing that the human visual system (HVS) employs multiple strategies, rather than a single one, to judge image quality. Moving forward, future research could explore the refinement and optimization of MAD, as well as its integration with other perceptual models, to further enhance its performance across a broader range of image types and distortion scenarios.

"Image enhancement based on equal area dualistic sub-image histogram equalization method**"**.The proposed method**[14]** presents a novel approach to histogram equalization called equal area dualistic sub-image histogram equalization, addressing limitations observed in traditional histogram equalization techniques. Moving forward, future research could focus on refining and optimizing the proposed method, exploring its applicability across various image types and conditions, and investigating its integration into real-world video systems to assess its performance in practical scenarios.

2.1 EXISTING METHOD

Image enhancement techniques have long been a focus of research in the field of image processing. Among these, Histogram Equalization (HE) has stood out for its simplicity and effectiveness in enhancing image contrast. However, traditional HE methods often suffer from under- or over-enhancement effects. To address these limitations, several extensions and alternative approaches have been proposed.One such method is Differential gray-level Histogram Equalization (**DHE**), which recursively separates the histogram into sub-histograms based on local minima and equalizes each sub-histogram within a specific range. This method effectively avoids checkerboard and washed-out effects while maintaining the original mean brightness.

The Differential Gray-level Histogram Equalization (DHE) method, initially presents a refined approach to enhancing image contrast. DHE operates by recursively partitioning the image histogram based on local minima and subsequently equalizing each sub-histogram within a designated range.

By doing so, DHE effectively mitigates undesirable effects such as checkerboard patterns and washed-out regions commonly observed in traditional histogram equalization methods. Importantly, DHE achieves these enhancements while preserving the original mean brightness of the image.

Recognizing the importance of extending such techniques to color images, researchers later developed the Differential Gray-level Histogram Equalization for Color Images (**DHECI**). This extension addresses the unique challenges posed by color images, where each pixel comprises multiple intensity channels (typically red, green, and blue).

DHECI adapts the principles of DHE to the domain of color images, allowing for the independent processing of each color channel's histogram. By applying DHE recursively to each color channel, DHECI enhances the overall contrast of color images while maintaining color balance and fidelity.

DHECI's reliance on histogram equalization based on local minima may not always adapt effectively to the diverse content complexities present in color imagesConsequently, the contrast enhancements provided by DHECI may vary in effectiveness across different types of color imagery. Moreover, the recursive nature of DHECI's histogram equalization process may inadvertently amplify noise and artifacts present in the image, leading to degraded image quality. Furthermore, the equalization process in DHECI may result in a loss of color detail, particularly in regions with subtle color variations, diminishing the overall visual fidelity of the enhanced image.

The extension of DHE to color images (DHECI) underscores the versatility and applicability of histogram equalization techniques across different image types and modalities. By preserving both contrast and color integrity, DHECI offers a comprehensive solution for enhancing the visual quality of color imagery in various applications, including medical imaging, satellite imagery analysis, and digital photography.Building upon DHE, the Brightness Preserving Dynamic Histogram Equalization (**BPDHE**) method applies Gaussian smoothing to the input histogram before equalizing sub-histograms, resulting in better image enhancement compared to DHE.

Further refinement led to the development of Brightness Preserving Dynamic Fuzzy Histogram Equalization (BPFDHE), which replaces Gaussian filtering with fuzzy histogram calculation, reducing computational time while preserving brightness.In terms of computational efficiency and brightness preservation, Brightness Preserving Dynamic Fuzzy Histogram Equalization (**BPDFHE**) emerges as a superior method to BPDHE. Additionally, joint HE-based methods have been introduced to leverage information from neighboring pixels, albeit with limitations in enhancing highly distorted images.The Adaptive Contrast Enhancement using Compensated Histogram (**ACECH**) system improves image contrast by separately applying compensated HE to red, green, and blue channels. While satisfactory for images with slightly low contrast, ACECH falls short in enhancing images with varying levels of contrast distortion.

Fuzzified Contrast Enhancement for Nearly Invisible Images (**FCENII**) aims to enhance perceptually invisible images while preserving color information but may lack in enhancing image details.

Naturalness Balance Contrast Enhancement (**NBCE**) utilizes adaptive gamma with cumulative histogram and median filtering to retain details successfully, albeit with limitations in removing hazy layers from extremely low contrast images.Among histogram-based methods, Exposure-based Sub-Image Histogram Equalization (**ESIHE**) stands out for enhancing images with low exposure by maximizing entropy while controlling the enhancement rate.

Its recursive extensions further improve enhancement by iteratively reducing exposure value differences between successive iterations.Dominant Orientation-based Texture Histogram Equalization (**DOTHE**) and AVeraging Histogram EQualization (**AVHEQ**) methods offer innovative approaches by combining linear channel stretching, histogram averaging, and adaptive division of histograms for improved contrast enhancement.

The Dominant Orientation-based Texture Histogram Equalization (DOTHE) method introduces a novel approach to overcome limitations in traditional Histogram Equalization (HE) techniques. By combining linear channel stretching with histogram averaging, DOTHE aims to enhance image contrast while preserving texture details and dominant orientations.

This approach allows for more effective contrast enhancement, particularly in textured regions of the image where traditional HE methods may fail to produce satisfactory results. One limitation is its reliance on dominant orientations, which may not always accurately capture the complexity of texture patterns in the image. In cases where textures are highly varied or irregular, DOTHE may struggle to adequately enhance contrast while preserving texture details.

Additionally, the effectiveness of DOTHE may be dependent on the accurate estimation of dominant orientations, which can be challenging in images with complex or ambiguous textures. DOTHE may not fully address issues related to color distortion or maintain color fidelity in color images, as it primarily focuses on texture enhancement in grayscale imagery.

In this proposed method, an Improved version of Chicken Swarm Optimization (**ICSO**) algorithm is introduced to prevent over-enhancement in image enhancement. By employing ICSO, the proposed technique aims to enhance images without under- or over-enhancement. Additionally, a new subjective dataset is presented, evaluating the proposed technique along with two other state-of-the-art methods on images with varying levels of contrast distortion. The study also investigates the performance of existing objective Image Quality Metrics (IQMs) on the enhanced images.

While conventional Histogram Equalization (HE) and its variations have been extensively employed to improve the quality of images affected by contrast issues, these methods often tend to produce over-enhanced results. In this study, we introduce a novel approach depicted in flow chart given below, which leverages an optimization algorithm known as Chicken Swarm Optimization (**CSO**) and its enhanced version. By defining new objective functions, our method aims to tackle both over- and under-enhancement in images, while simultaneously enhancing image brightness and contrast.

This innovative technique offers a promising solution to the challenges posed by traditional HE methods. By incorporating CSO and tailored objective functions, our approach can effectively mitigate the tendency towards over-enhancement commonly observed in conventional methods.

Furthermore, by addressing both over- and under-enhancement issues, our method ensures a more balanced enhancement process, resulting in improved image quality.The utilization of optimization algorithms such as CSO enables our method to efficiently search for optimal enhancement parameters, leading to enhanced image brightness and contrast without excessive amplification of image features.

Additionally, the incorporation of new objective functions allows for a more nuanced adjustment of enhancement levels, ensuring that the final output maintains a desirable balance between brightness, contrast, and overall image quality.The proposed method introduces the Improved Chicken Swarm Optimization (ICSO) algorithm, an enhanced version of the traditional CSO optimization algorithm, aimed at overcoming its limitations, particularly in optimizing high-dimensional cases.

CHAPTER - 3

METHODOLOGY

In the proposed approach, three main objectives are highlighted. Firstly, the proposed method aims to introduce a novel image enhancement technique utilizing the ICSO algorithm. This technique is designed to enhance images without introducing over-enhancement or under-enhancement artifacts, ensuring optimal enhancement results across various images and contrast levels The proposed method in this study aims to address the limitations of conventional histogram equalization (HE) and its variants, which often lead to over-enhancement of images. The approach introduces a new method based on an optimization algorithm called Chicken Swarm Optimization (CSO) and its improved version. By defining new objective functions, the method aims to handle over- and under-enhanced images while improving image brightness and contrast simultaneously.

While conventional Histogram Equalization (HE) and its variations have been extensively employed to improve the quality of images affected by contrast issues, these methods often tend to produce over-enhanced results. In this study, we introduce a novel approach depicted inflow chart given below, which leverages an optimization algorithm known as Chicken Swarm Optimization (CSO) and its enhanced version. By defining new objective functions, our method aims to tackle both over- and under-enhancement in images, while simultaneously enhancing image brightness and contrast.This innovative technique offers a promising solution to the challenges posed by traditional HE methods. By incorporating CSO and tailored objective functions, our approach can effectively mitigate the tendency towards over-enhancement commonly observed in conventional methods. Furthermore, by addressing both over- and under-enhancement issues, our method ensures amore balanced enhancement process, resulting in improved image qualityThe utilization of optimization algorithms such as CSO enables our method to efficiently search for optimal enhancement parameters, leading to enhanced image brightness and contrast without excessive amplification of image features.

Additionally, the incorporation of new objective functions allows for a more nuanced adjustment of enhancement levels, ensuring that the final output maintains a desirable balance between brightness, contrast, and overall image quality.The proposed approach utilizes an optimization framework using the Improved Chicken Swarm Optimization (ICSO) algorithm. This framework operates on each color channel in the RGB color space separately to enhance image contrast and brightness.

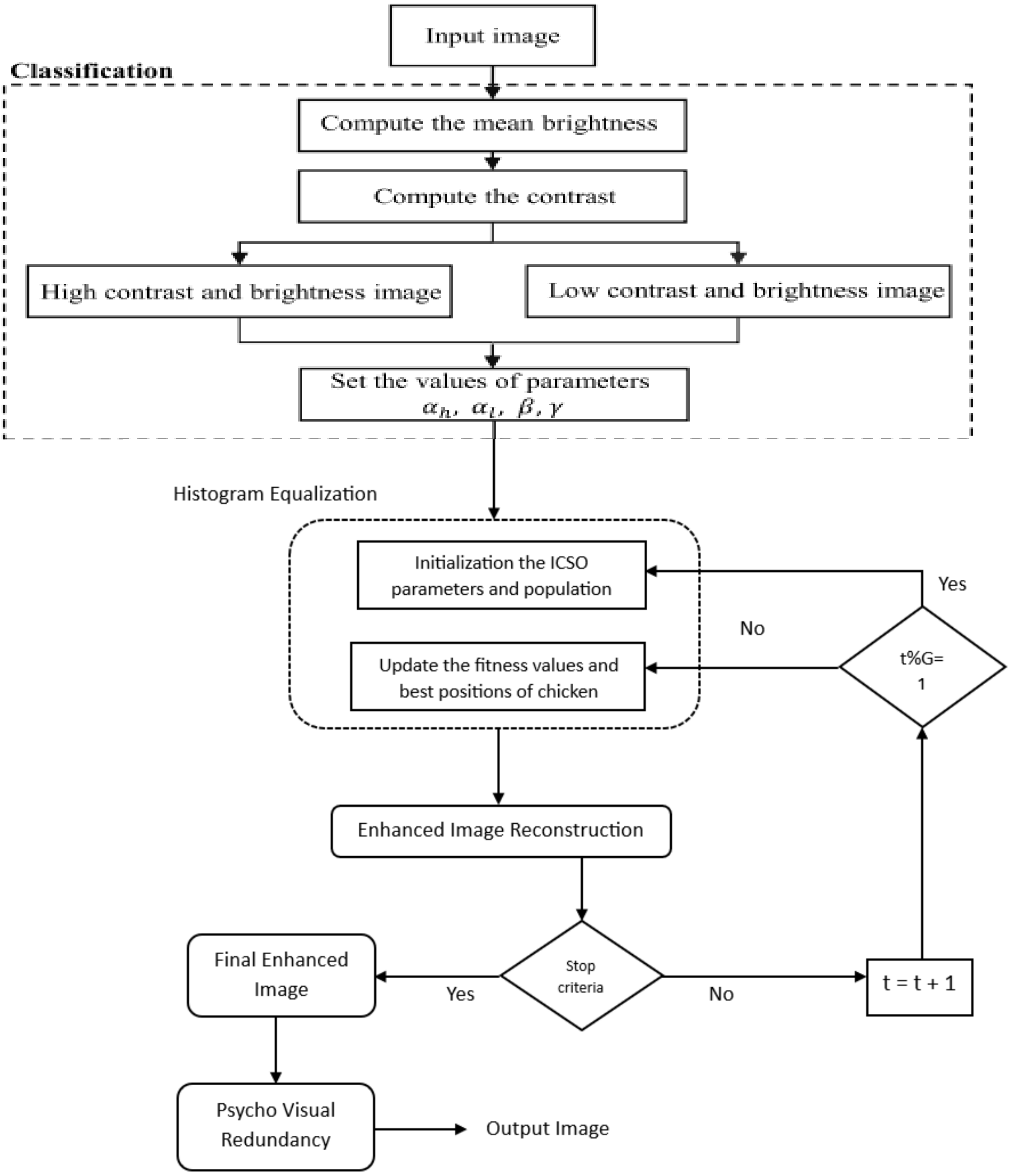

Fig 3.1 : Flow chart of proposed method

The optimization process involves several steps, starting with initialization. The total number of optimization parameters is determined, including the number of chickens representing different categories. These categories include roosters, hens, and chicks, with a subcategory of mother hens. Minimum and maximum numbers of optimization iterations are also specified. Population initialization is carried out using random histograms, which are modified in consecutive iterations to reach the optimal state.

The algorithm steps of the proposed method are mention below

A. Classification Of The Input Image
B. Histogram Optimization Framework Using Icso
    i. Initialization
    ii. Object Function
    iii. Ordering Fitness
    iv. Updating The Position Of The Chickens
    v. Selection Optimum Histogram
    vi. Reconstruction Of The Output Image
    vii. Stopping Condition Of Algorithm
C. Psycho Visual Redundancy

3.1 CLASSIFICATION OF THE INPUT IMAGE

In this study, a critical aspect is the initial classification of input images to determine their contrast characteristics, paving the way for tailored enhancement strategies. While existing image enhancement methods predominantly target low-contrast images or specific types of degradation, our approach seeks to encompass both low and high-contrast scenarios. To achieve this, images are initially classified into two distinct classes based on their average pixel values derived from the grayscale version of the input image.

The classification process hinges on computing the average pixel value, denoted as Lm, within the grayscale representation (Ig(x, y)) of the original color image (I(x, y)). Images with an average pixel value less than or equal to 100 are deemed underexposed, while those with values greater than or equal to 150 are identified as overexposed.

This classification scheme provides a fundamental basis for subsequent enhancement control parameter adjustments tailored to the specific contrast characteristics of each image.

Furthermore, the contrast level of each image is quantified through the calculation of a contrast index, denoted as Cin, formulated as (Lmax - Lm) / Lmax, where Lmax represents the maximum intensity within the grayscale representation Ig. Typically, underexposed images exhibit a low contrast when Cin is less than 0.5, while overexposed images manifest a high contrast when Cin exceeds 0.5. This quantification mechanism facilitates a nuanced understanding of each image's contrast profile, thereby guiding the subsequent enhancement process effectively.

$$C_{in} = \frac{L_{max} - L_m}{L_{max}}. \quad \text{.........3.1}$$

Cin < 0.5 - underexposed images show a low contrast

Cin < 0.5 - overexposed images show a high contrast

By systematically classifying input images and quantifying their contrast characteristics, our approach lays the groundwork for tailored enhancement strategies that cater to the specific needs of both low and high-contrast scenarios. This classification step ensures that enhancement control parameters are dynamically adjusted based on the unique contrast profile of each image, thereby optimizing the overall enhancement outcome. Through this detailed classification process, our method strives to provide a comprehensive solution for enhancing image quality across a wide spectrum of contrast levels, addressing the limitations of existing enhancement techniques focused on specific contrast scenarios.

3.2 HISTOGRAM OPTIMIZATION FRAMEWORK USING ICSO

The Histogram Optimization Framework, employing the Improved Chicken Swarm Optimization (ICSO) algorithm, constitutes a sophisticated methodology pivotal to our proposed image enhancement approach.

This framework operates meticulously on each color channel independently within the RGB color space, with a primary objective of significantly enhancing both the contrast and brightness attributes of images.

Let's delve into a more comprehensive breakdown of its key components and functionalities:

3.2.1 Initialization

At the onset of the optimization process, a meticulous configuration of several critical parameters lays the groundwork for the subsequent operations of the ICSO algorithm. Among these parameters, the total number of optimization states (N) holds paramount significance.

It's meticulously divided into distinct categories, comprising roosters, hens, chicks, and a subcategory known as mother hens, each serving specific roles in the optimization process. These categories are carefully allocated based on their respective roles and contribution potentials.

Additionally, other essential parameters such as

- G = minimum number of iterations for category element updates
- Min = minimum iterations for achieving stability,
- Max = maximum iterations allowed, and
- D = dimensionality of the problem

The selection of an appropriate initial value for the parameter G is particularly critical, as it profoundly influences the convergence behavior of the optimization algorithm. Striking a delicate balance between exploration and exploitation, G plays a pivotal role in ensuring the algorithm's efficiency and convergence towards optimal solutions.

Population Initialization

Following the meticulous parameter configuration, the optimization process transitions into the phase of population initialization. Here, the ICSO algorithm springs into action, iteratively manipulating a set of N random histograms to achieve the optimal state. The generation of these initial histograms involves a complex interplay of randomization and deterministic adjustments, aiming to strike an optimal balance between exploration of the solution space and exploitation of promising regions.Notably, the initial positions of a subset of chickens within the optimization space are strategically determined based on the characteristics of the input histograms.

Specifically, the first 75 chickens are positioned using information derived from the original input histogram, while the remaining chickens leverage insights from the equalized input histogram.

This strategic partitioning of the population initialization process aims to harness the inherent characteristics of both input histograms, facilitating a more efficient and effective exploration of the solution space.

Iterative Optimization Process

As the optimization process unfolds iteratively, the ICSO algorithm dynamically adjusts the positions of chickens within the optimization space, guided by the principles of swarm intelligence and optimization. Through a series of iterative updates, the algorithm progressively refines the histograms in each color channel, aiming to achieve an optimal balance between contrast enhancement and brightness preservation.

By meticulously configuring parameters, employing strategic population initialization techniques, and orchestrating a sophisticated iterative optimization process, the Histogram Optimization Framework utilizing the ICSO algorithm emerges as a powerful tool for enhancing image quality. Its meticulous attention to detail, coupled with its adaptive and iterative nature, enables the effective manipulation of histograms across various color channels within the RGB color space, ultimately leading to significant improvements in image contrast and brightness.

3.2.2 Objective Function

In the subsequent step of our method, we turn our focus to defining an objective function to guide the selection and ordering of histograms. This objective function is crucial for achieving our primary goal of enhancing images while mitigating the risk of over-enhancement. The comprehensive objective function, denoted as fi(t), incorporates multiple components to address various aspects of histogram modification and image enhancement.

The objective function fi(t) encompasses several key terms aimed at preserving the main details of the input image while ensuring effective histogram modification. Initially, it evaluates the discrepancy between the modified histogram (˜hi(t)) and the original input histogram (hi(t)), emphasizing the importance of maintaining fidelity to the original image details.

One crucial term in the objective function is αr, a control parameter that governs the extent of contrast enhancement for both low and high-contrast images. To adaptively adjust contrast enhancement, αr is tailored differently for low and high-contrast scenarios. For low-contrast images, αl is varied within a specific range, while for high-contrast images, αh undergoes a distinct range of variation. This adaptive adjustment of αr ensures that the degree of contrast enhancement is appropriately calibrated based on the characteristics of the input image.

The histograms should be selected ordered and based on an objective function. We define a comprehensive objective function

$$f_i(t) = \left\| \tilde{\mathbf{h}}_i(t) - \mathbf{h_i(t)}_2^2 \right\| + \alpha_r \left\| \mathbf{u} - \tilde{\mathbf{h}}_i(t) \right\|_2^2 + \|Q_i\|_2^2 + \beta \left\| \mathbf{D} \left[\tilde{\mathbf{h}}_i(t) \right\| = \right]_2^2, \qquad \text{......... 3.2}$$

- h˜ i(t) - modified histogram
- hi(t) - original input histogram
- u - vector in size histogram with uniform distribution
- Qi = u − hi(t)
- D[h˜i(t)] was used to measure gradients of h˜i(t) using differential operator D

- β is a control parameter of the output histogram smoothing that can vary in the range of [0, +∞)
- αr;r ∈ {l, h} is a control parameter of contrast enhancement for low and high-contrast input images. In the case of low contrast images, the best variation range for αl was in the range [11, 20]. In high contrast images, the optimal range for the variation of *αh* was found to be between 1 and 10.

An increase in the value of αr leads to an augmentation in the contrast of the image. For a low contrast input image, employing αl<10 results in an under-enhanced output image. Optimal enhancement is achieved at αl=13, striking a balance between enhancement and preservation of image details.

However, when $17 \leq \alpha l$, the output image tends to be over-enhanced, potentially leading to a loss of image fidelity.Conversely, in the case of a high contrast input image, using $\alpha h=3$ yields an under-enhanced modified histogram. A sufficiently enhanced output image with preserved details is obtained at $\alpha h=7$. Beyond $11 \leq \alpha h$, however, the output image becomes over-enhanced, resulting in a loss of details and potential distortion of the image.

Therefore, the choice of αr is crucial in achieving the desired level of contrast enhancement without compromising image quality or detail preservation.To ensure a balanced enhancement outcome, meticulous selection of αr within the specified ranges is crucial. Experimentally, the choice of αl and αh within their respective optimal ranges yields satisfactory enhancement results, preserving image details while effectively enhancing contrast.

3.2.3 Fitness

In the subsequent stages of our method, we proceed to compute the fitness values for all N considered histograms, which aids in categorizing them into distinct classes based on their fitness. The fitness values are crucial indicators, with lower values signifying better fitness. These histograms are classified into three categories: roosters (RN), hens (HN), and chickens (CN), as elaborated previously. Roosters, being the most fit histograms, lead their respective groups, followed by hens and chickens, which are distributed randomly among the rooster groups.

Following the organization of these subgroups, the positions of all chickens—whether rooster, hen, or chick—need to be updated to facilitate further optimization. This involves updating the positions of roosters, hens, and chicks using specific formulas tailored to each subgroup. For roosters, their positions are updated , where a Gaussian distribution with a mean of 0 and a standard deviation determined guides the updating process. Notably, the inclusion of ϵ prevents division by zero in cases where the fitness values are small.The positions of hens are then updated ,which involves a combination of factors related to the fitness values of the hen and its corresponding rooster, as well as a randomly selected chicken. These factors dictate the direction and magnitude of the position update, ensuring an effective exploration of the solution space while maintaining cohesion within the subgroup.

Finally, the positions of chicks updated , which incorporates elements of self-learning, maternal guidance, and learning from the rooster within the subgroup.The parameter w governs the self-learning coefficient of the chicks, with its value dynamically adjusted over iterations to strike a balance between exploration and exploitation. As the number of iterations increases, the self-learning coefficient decreases exponentially, reflecting a gradual shift towards greater reliance on maternal and group guidance.In essence, these position updating mechanisms ensure a coordinated and adaptive exploration of the solution space by the various subgroups within the optimization algorithm. By leveraging fitness values and incorporating adaptive learning mechanisms, the algorithm iteratively refines the positions of histograms, ultimately driving towards the optimization objective of enhancing image quality while avoiding over-enhancement.

In the optimization process, after each iteration, the fitness values are recalculated for all considered histograms .Subsequently, the histogram with the minimum fitness value, along with its corresponding configuration, is selected as the optimized histogram for that specific iteration. This selection process ensures that the histograms undergo iterative adjustments to enhance image quality while mitigating the risk of over-enhancement, thus striking a delicate balance between image enhancement and preservation of its original characteristics.

3.2.4 Updating the position of the chickens

The organization of chicken subgroups, comprising roosters, hens, and chicks, in the proposed method involves updating the positions (or generated histogram bin values) of each chicken subgroup. Specifically, for roosters, their positions are updated according to the equation:

$$\tilde{h}_{i,j}(t+1) = \tilde{h}_{i,j}(t) \cdot (1 + randn(0, \sigma^2)) \qquad \textbf{.........3.3}$$

where

$$\sigma^2 = \begin{cases} 1, & f_i(t) \leq f_k(t) \\ exp(\dfrac{f_k(t) - f_i(t)}{|f_i(t)| + \epsilon}), & f_k(t) < f_i(t) \end{cases}$$

- randn(0, σ2) is a Gaussian distribution with a mean of 0 and a standard deviation of σ2.
- ϵ is used to prevent a denominator of zero in case of small values for |fi(t).
- k ≠ i, k ∈ [1,N] is the index of other roosters that are randomly selected from the group of roosters.

Next, the positions of hens are updated using the equation:

$$\tilde{h}_{i,j}(t+1) = \tilde{h}_{i,j}(t) + S_1 \cdot rand \cdot (\tilde{h}_{r_1,j}(t) - \tilde{h}_{i,j}(t)) + S_2 \cdot rand \cdot (\tilde{h}_{r_2,j}(t) - \tilde{h}_{i,j}(t)) \qquad \text{.........3.4}$$

where S_1 and S_2

$$\begin{cases} S_1 = exp(\dfrac{f_i(t) - f_{r1}(t)}{|f_i(t)| + \epsilon}) \\ S_2 = exp(f_{r2}(t) - f_i(t)) \end{cases} .$$

Finally, the positions of chicks are updated as:

$$\tilde{h}_{i,j}(t+1) = w \cdot \tilde{h}_{i,j}(t) + FL \cdot (\tilde{h}_{m,j}(t) - \tilde{h}_{i,j}(t)) + C \cdot (\tilde{h}_{r,j}(t) - \tilde{h}_{i,j}(t)) \qquad \text{.........3.5}$$

where

$$w(t) = w_{min} \cdot (\frac{w_{max}}{w_{min}})^{1/(1+10 \cdot t/Max)}.$$

- m is the index of the mother hen for the i th chick
- h˜m,j(t) is its corresponding position.
- The parameter FL (FL ∈ [0, 2]) indicates that the chick will follow its mother for food.
- C indicates that the chicks learn from the rooster in the subgroup.
- w is the chicks' selflearning coefficient.
- t is the number of iterations

As mentioned in the introduction, in scenarios where the problem's dimensionality is high, the Chicken Swarm Optimization (CSO) algorithm may converge to a local optimum. This phenomenon occurs because in CSO, individual "chicks" only learn from their "mother hen," and their positions are not influenced by their associated "rooster." Consequently, if the mother hen becomes trapped in a local optimum, the chicks will likely follow suit.

To address this limitation, an improved version called Improved Chicken Swarm Optimization (ICSO) has been developed. In ICSO, the position update of each chick depends not only on its mother hen but also on its associated rooster. Additionally, two new parameters are introduced: the learning factor (C) and the self-learning coefficient. These parameters play crucial roles in determining the behavior of the algorithm and are incorporated into the update equation to enhance exploration and mitigate premature convergence.By integrating the influence of both the mother hen and the rooster, along with the introduction of new parameters for enhanced exploration, ICSO aims to overcome the tendency of CSO to converge prematurely to local optima, especially in high-dimensional problem spaces.

3.2.5 Selection Optimum Histogram

After each position update in the Improved Chicken Swarm Optimization (ICSO) algorithm, the fitness values are recalculated using equation (2). Subsequently, the histogram corresponding to the minimum fitness value is selected as the optimized histogram for the current iteration t. This process ensures that the histogram with the best fitness value, indicative of its effectiveness in solving the optimization problem, is retained and utilized for further iterations.By iteratively updating positions and selecting the histogram with the lowest fitness value, ICSO progressively refines the solution space, aiming to converge towards an optimal or near-optimal solution.

This approach allows the algorithm to effectively explore the solution space while exploiting promising regions, ultimately improving the chances of finding the global optimum, especially in complex, high-dimensional optimization problems.

3.2.6 Reconstruction Of The Output Image

Following the determination of optimized histograms, the focus shifts towards reconstructing the output image based on these histograms. Here, the histograms of each color channel in the input image, denoted as hk(n) for the red (r), green (g), and blue (b) channels, alongside their enhanced counterparts (˜hk(n)), serve as input and output, respectively, for each optimization iteration. This reconstruction process involves the application of conventional Histogram Equalization (HE) to the modified histograms.

The HE process unfolds in several steps. Initially, the Probability Density Function (PDF) is computed from the optimized histograms to derive the probability distribution of pixel intensities.

Subsequently, the Cumulative Distribution Function (CDF) is computed from the PDF to establish the cumulative distribution of pixel intensities. Leveraging the modified transform function, the optimized intensity values are then mapped to the reconstructed image, facilitating the preservation of image details while enhancing its overall quality.Furthermore, gamma correction is integrated into the final output image to enhance details in both darker and brighter areas. This corrective measure involves raising the reconstructed image to the power of gamma (γ), where gamma values within specified ranges are adaptively selected to ensure optimal enhancement across varying brightness levels. The careful adjustment of gamma parameters allows for nuanced enhancement, particularly beneficial in retaining details in regions of varying brightness.

To ensure the convergence and efficacy of the optimization algorithm, robust stopping conditions are essential. These conditions monitor changes in critical image characteristics, such as the gradient ratio (Rg(t)) and entropy ratio (Re(t)), over successive iterations. If these ratios exhibit minimal changes over a predefined number of iterations or if the maximum iteration limit is reached, the algorithm terminates. Such stopping conditions prevent unnecessary computational overhead and ensure timely convergence to optimal image enhancement results. In instances where the stopping conditions are not met, the algorithm iteratively updates histograms and reassesses fitness until convergence or the maximum iteration limit is reached.

This iterative refinement process underscores the algorithm's adaptive nature, allowing it to dynamically adjust and optimize image enhancement parameters based on evolving fitness landscapes. However, it's important to acknowledge the limitations of the proposed algorithm, particularly its reliance on image histograms. This reliance restricts its applicability to color spaces other than RGB, potentially resulting in unconventional color representation in the output image.

3.2.7 Stopping Condition Of Algorithm

The stopping condition of the algorithm is crucial to ensure that it converges to a steady state efficiently without unnecessary iterations. After a minimum number of iterations, typically set to 50, the algorithm transitions from a transient state to a steady state. At each iteration, the optimized histogram is used to reconstruct the new image (Io(x, y, t)).The algorithm employs three stop conditions to determine when to terminate the iterative process. The first stop condition, denoted as Rg(t), is based on the image gradient ratio. It is calculated using the second norm of the gradient for Io(x, y, t). If the change in Rg(t) is less than one percent over 50 successive iterations, the first stop condition is activated.

The second stop condition, denoted as Re(t), is based on the entropy of the image. It measures the change in entropy of the modified histogram at each iteration. Similar to Rg(t), if Re(t) changes by less than one percent over 50 successive iterations, the second stop condition is activated.Finally, a maximum number of iterations is defined as the third stop condition. If the algorithm does not meet the criteria of the first two stop conditions within this maximum limit, the iteration process is terminated.Additionally, if the iteration count (t + 1) is divisible by G (the minimum number of optimization iterations to update the categories), the algorithm updates the categories and resumes the iteration process. Otherwise, it continues with the previous process.

3.3 PSYCHO VISUAL REDUNDANCY

Understanding psycho-visual redundancy is crucial in compression algorithms like ICSO. This redundancy refers to less perceptually significant details in images or videos. Not all elements contribute equally to perceived quality; certain features, like edges and shapes, are more crucial to human perception than fine textures or subtle color variations. Selective compression techniques exploit these differences by allocating more bits to preserve critical information while reducing the bit rate for less important details.

When implementing the ICSO algorithm and incorporating psycho-visual redundancy, the process involves leveraging the human visual system's tendencies to prioritize certain visual information.

This technique optimizes image compression by reducing redundancies that are less perceptually significant, thus conserving bandwidth or storage space without compromising perceived quality. It's like streamlining data by focusing on what our eyes notice most, allowing for efficient compression while maintaining visual fidelity.

3.4 IQM

In the context of evaluating and comparing image enhancement methods, various Image Quality Metrics (IQMs) play a pivotal role in providing quantitative assessments. The metrics employed in this study encompass a range of factors, each offering unique insights into the quality of the output image.

Image Quality Metrics (IQMs) are objective measures used to assess the quality of digital images based on various perceptual criteria. These metrics provide quantitative evaluations of image fidelity, sharpness, color accuracy, and other visual attributes. IQMs play a crucial role in image processing, computer vision, and multimedia applications by enabling researchers and practitioners to objectively evaluate the performance of image enhancement, compression, and restoration algorithms.IQMs can be broadly categorized into structural, statistical, and perceptual metrics.

Structural metrics assess the similarity between reference and distorted images based on features such as edges, textures, and contours. Statistical metrics analyze statistical properties of pixel intensity distributions, histograms, and frequency spectra. Perceptual metrics incorporate models of human visual perception to evaluate image quality based on factors like contrast, sharpness, and visual acuity.

3.4.1 SSIM Color (Structural Similarity Index Measure Color):

SSIM is a widely used metric for assessing the similarity between two images. Specifically tailored for color images, SSIM color evaluates structural similarity by considering luminance, contrast, and structure. It provides a numerical score indicating the degree of similarity between the enhanced image and the original, with higher scores signifying greater similarity.

Calculation of SSIM

1.Convert images to grayscale:

- If the images are not grayscale, convert them to grayscale. Let's denote the grayscale versions of the images as I and K.
- Calculate the mean (μI and μK) and variance (σI2 and σK2) of the images I and K:

$$\mu_I = \frac{1}{N}\sum_{i=1}^{N} I(i) \quad \text{.........3.6}$$

$$\mu_K = \frac{1}{N}\sum_{i=1}^{N} K(i) \quad \text{.........3.7}$$

$$\sigma_I^2 = \frac{1}{N}\sum_{i=1}^{N} [I(i) - \mu_I]^2 \quad \text{.........3.8}$$

$$\sigma_K^2 = \frac{1}{N}\sum_{i=1}^{N} [K(i) - \mu_K]^2 \quad \text{.........3.9}$$

Where N is the total number of pixels.

2.Calculate the covariance (σIK) between images I and K:

$$\sigma_{IK} = \frac{1}{N}\sum_{i=1}^{N} [I(i) - \mu_I][K(i) - \mu_K] \quad \text{.........3.10}$$

3.Compute SSIM:

- SSIM is calculated using the following formula:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad \text{.........3.11}$$

Where $C1$C1 and $C2$C2 are constants to stabilize the division with weak denominator (they are usually small positive constants to avoid division by zero errors), and μI, μK, σI2, σK2, and σIK are computed as described above.

4.Return the SSIM value:

- The SSIM value ranges between -1 and 1. A value of 1 indicates perfect similarity between the images, while a value of -1 indicates perfect dissimilarity. A value of 0 means there is no correlation between the images.

3.4.2 FSIMc (Feature SIMilarity for color images):

FSIMc is another metric designed for color images, focusing on the similarity of structural features. It assesses the quality of the enhanced image by comparing its feature representation with that of the original image. FSIMc takes into account both global and local features, providing a comprehensive evaluation of image fidelity.

Calculation of FSIM

1. Gradient Magnitudes:

- Compute gradient magnitudes for both images:

$$\text{GradientMap1} = \sqrt{(\text{Gx1})^2 + (\text{Gy1})^2} \qquad \text{.........3.12}$$

$$\text{GradientMap2} = \sqrt{(\text{Gx2})^2 + (\text{Gy2})^2} \qquad \text{.........3.13}$$

where Gx1, Gy1,Gx2, and Gy2 are the gradient magnitudes of the two images.

2.Contrast Similarity:

- Calculate the correlation coefficient between the gradient maps:

$$\text{contrast\_sim=corr2(GradientMap1,GradientMap2)} \qquad \text{.........3.14}$$

3. Structural Similarity:

- Compute the structural similarity between the gradient maps

$$\text{struct\_sim} = \frac{\sum\sum(\text{GradientMap1} \times \text{GradientMap2})}{\sum\sum(\text{GradientMap1})^2} \qquad \text{......... 3.15}$$

4.FSIM (Feature Similarity Index):

- Calculate the FSIM as the product of contrast similarity and structural similarity:

$$\text{FSIM=contrast\_sim×struct\_sim} \qquad \text{......... 3.16}$$

$$\text{FSIM} = \frac{\sum\sum \text{GradientMap1} \times \text{GradientMap2}}{\sqrt{\sum\sum(\text{GradientMap1} - \bar{\text{GradientMap1}})^2} \times \sqrt{\sum\sum(\text{GradientMap2} - \bar{\text{GradientMap2}})^2}}$$

.........3.17

3.4.3 GSIM (Gradient SIMilarity):

GSIM measures the similarity between gradient representations of images. It evaluates the consistency of gradients between the enhanced and original images, offering insights into the preservation of edge details and overall sharpness. A higher GSIM score indicates better preservation of image gradients.

Calculation of GSIM

1.Calculate Gradients:

- Compute gradients for both images:

$$Gx1 = \frac{\partial \text{im1\_gray}}{\partial x}$$ **.........3.18**

$$Gy1 = \frac{\partial \text{im1\_gray}}{\partial y}$$ **.........3.19**

$$Gx2 = \frac{\partial \text{im2\_gray}}{\partial x}$$ **.........3.20**

$$Gy2 = \frac{\partial \text{im2\_gray}}{\partial y}$$ **.........3.21**

where $\partial/\partial x$ and $\partial/\partial y$ represent the partial derivatives in the x and y directions respectively.

2.Compute Gradient Similarity:

- Calculate the similarity map:

$$\text{sim\_map} = \frac{2 \cdot Gx1 \cdot Gx2 + \varepsilon}{Gx1^2 + Gx2^2 + \varepsilon} + \frac{2 \cdot Gy1 \cdot Gy2 + \varepsilon}{Gy1^2 + Gy2^2 + \varepsilon}$$ **.........3.22**

where ε is a small constant (to avoid division by zero).

3.Compute Score:

- Calculate the mean value of the similarity map:

score=mean(sim_map(:)) **......... 3.23**

3.4.4 Qcolor:

Qcolor is a quality metric specifically tailored for assessing color image enhancement. It quantifies the perceptual quality of the enhanced image by considering factors such as color fidelity, contrast, and sharpness.

Calculation of Qcolor

1.Convert images to Lab color space:

im1_lab=rgb2lab(im1)im1_lab=rgb2lab(im1)

im2_lab=rgb2lab(im2)im2_lab=rgb2lab(im2)

im1_lab and im2_lab represent the Lab color space representation of the input images im1 and im2, respectively. The Lab color space separates color information into three channels: L (lightness), a (green to red), and b (blue to yellow).

2.Calculate standard deviations of Lab channels:

std_dev1=std(reshape(im1_lab,[],3))

std_dev2=std(reshape(im2_lab,[],3))

std_dev1 and std_dev2 represent the standard deviations of the Lab channels of im1 and im2, respectively. The Lab channels are reshaped into a two-dimensional array where each row represents a pixel and each column represents a Lab channel.

3.Calculate mean of standard deviations:

mean_std_dev1=mean(std_dev1)

mean_std_dev2=mean(std_dev2)

mean_std_dev1 and mean_std_dev2 represent the mean of the standard deviations of Lab channels for im1 and im2, respectively. This step computes the average standard deviation across all pixels for each color channel.

4.Calculate QCOLOR:

QCOLOR=mean_std_dev2mean_std_dev1

QCOLOR score, which quantifies the similarity between the color distributions of the two images. It is calculated as the ratio of the mean standard deviation of color channels in im2 to the mean standard deviation of color channels in im1. If the score is closer to 1, it indicates that the color distributions of the two images are more similar.

CHAPTER-4

SOFTWARE DESCRIPTION

In the process of designing a new system, meticulous attention to both hardware and software specifications is imperative. Hardware selection is predicated upon critical factors such as CPU processing speed, memory access speed, peripheral channel speed, seek time, and communication speed. These parameters collectively determine the system's computational prowess, data handling efficiency, and interfacing capabilities with external peripherals.

Concurrently, the software configuration constitutes an integral aspect of system implementation. Specifying the requisite software components, versions, and dependencies ensures seamless operation, compatibility, and optimal performance. The requirement analysis meticulously delineates both the hardware and software configurations indispensable for the proposed system, thereby ensuring adherence to project objectives and fulfillment of user requisites.

4.1 HARDWARE SPECIFICATION

Processor	:	Core i7 CPU operating at 3.4GHz.
Hard Disk	:	64 GB
Disk Space	:	3–4 GB for a typical installation
RAM	:	8 GB
Keyboard	:	104 Keys
Mouse	:	HID Complaint Mouse

4.2 SOFTWARE SPECIFICATION

Operating system	:	Windows 11
Coding Language	:	MATLAB R2020aversion

4.3 LANGUAGE DESCRIPTION

MATLAB, short for "MATrix LABoratory," is a high-level programming language and interactive environment developed by MathWorks. It is widely used in engineering, science, and mathematics for data analysis, visualization, algorithm development, and numerical computation. MATLAB 2020a is one of the latest versions, offering numerous features and tools to facilitate a wide range of tasks for researchers, engineers, and educators.

4.3.1 The Language of Technical Computing

MATLAB, a high-level technical computing language, serves as an interactive environment for algorithm development, data visualization, data analysis, and numerical computation. Compared to traditional programming languages like C, C++, and FORTRAN, MATLAB offers expedited solutions to technical computing problems. Its applicability extends to diverse domains including signal and image processing, communications, control design, financial modeling, and computational biology.

4.3.2 Key Features and Enhancements:

Live Editor:

- MATLAB's Live Editor is an interactive environment that combines code, output, and formatted text in a single executable document.
- It allows users to create and share live scripts, which can contain MATLAB code, visualizations, and explanatory text.

App Building:

- MATLAB's App Designer provides a drag-and-drop interface for building custom graphical user interfaces (GUIs) without requiring prior programming experience.
- Users can create interactive apps for data analysis, visualization, simulation, and more, with full control over layout, behavior, and functionality.

Data Import and Export:

- MATLAB provides enhanced capabilities for importing and exporting data from various sources, including spreadsheets, databases, and web services.
- Users can easily read and write common file formats such as Excel, CSV, HDF5, and JSON, simplifying data integration and interoperability.

Data Analysis and Visualization:

- MATLAB offers a wide range of functions and tools for data analysis, statistical modeling, and visualization.
- Users can explore data, perform hypothesis tests, fit models to data, and generate interactive plots and charts to communicate results effectively.

Optimization:

- MATLAB's Optimization Toolbox offers a collection of algorithms for solving linear, nonlinear, and mixed-integer optimization problems.
- Users can optimize objective functions subject to constraints, with support for gradient-based and derivative-free optimization methods.

Symbolic Mathematics:

- MATLAB's Symbolic Math Toolbox provides tools for performing symbolic computations, including calculus, algebra, and equation solving.
- Users can manipulate symbolic expressions, solve equations, compute derivatives and integrals, and generate analytical solutions to mathematical problems.

Hardware Support:

- MATLAB supports interfacing with hardware devices and instruments through instrument control, data acquisition, and image acquisition toolboxes.
- Users can connect to sensors, actuators, cameras, and other peripherals for data acquisition, control systems, and image processing applications.

4.3.3 Development Tools

MATLAB incorporates a suite of development tools to enhance algorithm implementation efficiency:

MATLAB Editor:

Integrated development environment (IDE) for writing, editing, and debugging MATLAB code.Syntax highlighting, code folding, and code completion features.

Command Window:

Interactive interface for executing MATLAB commands and scripts.Immediate feedback and display of results.

Function Library:

Comprehensive library of built-in functions for mathematical computation, data analysis, and visualization.Functions categorized by domain for easy access.

Profiler:

Performance profiling tool for analyzing the execution time and memory usage of MATLAB code.Identifies bottlenecks and optimization opportunities.

Simulink:

Simulink is a companion product to MATLAB for modeling, simulating, and analyzing dynamic systems.Block diagram environment for designing and simulating multidomain systems.

Stateflow:

Stateflow extends Simulink with a graphical environment for modeling and simulating state machines and event-driven systems.Behavior modeling and control logic design.

4.3.4 Designing Graphical User Interfaces

Graphical User Interface Development Environment (GUIDE) enables intuitive layout, design, and editing of user interfaces.

It supports various elements such as list boxes, pull-down menus, buttons, sliders, plots, and ActiveX controls. Alternatively, GUIs can be programmatically created using MATLAB functions.

4.3.5 Analyzing and Accessing Data

MATLAB supports the entire data analysis process, encompassing data acquisition, preprocessing, visualization, and numerical analysis:

1.Data Analysis

Interactive tools and command-line functions facilitate various data analysis operations including

1. Interpolation
2. Decimation
3. Scaling
4. Averaging
5. Thresholding
6. Smoothing
7. Correlation
8. Fourier analysis
9. Filtering
10. Peak/valley/zero finding
11. Basic statistics
12. Curve fitting and
13. Matrix analysis.

2.Data Access

Efficient data access capabilities enable retrieval of data from files, external applications, databases, and external devices. MATLAB supports popular file formats such as Microsoft Excel, ASCII text or binary files, image, sound, and video files, as well as scientific files like HDF and HDF5. Low-level binary file I/O functions facilitate working with data files in any format, while additional functions enable data retrieval from web pages and XML.

3.Visualizing Data

MATLAB encompasses a comprehensive suite of graphics features essential for visualizing engineering and scientific data:

4.2-D Plotting

Various 2-D plotting functions cater to diverse visualization needs including line, area, bar, and pie charts, direction and velocity plots, histograms, polygons, surfaces, scatter/bubble plots, and animations. Customization options allow for the addition of multiple axes, altering line colors and markers, annotation, LaTeX equations, legends, and drawing shapes.

4.3.6 The MATLAB System

The MATLAB language supports fundamental vector and matrix operations integral to engineering and scientific problem-solving. It facilitates rapid development and execution by eliminating low-level administrative tasks such as variable declaration, data type specification, and memory allocation. In many cases, MATLAB obviates the need for loops, resulting in concise code. Despite its high-level nature, MATLAB retains traditional programming language features including arithmetic operators, flow control, data structures, data types, object-oriented programming, and debugging capabilities. Its interpretive nature enables command or group execution without compilation and linking, facilitating quick iteration towards optimal solutions.

4.3.7 Functions and Capabilities:

Matrix Manipulation:

MATLAB excels in matrix manipulation, offering functions for matrix creation, multiplication, inversion, and decomposition.Linear algebra operations for solving systems of equations and eigenvalue problems.

Plotting and Visualization:

Plotting functions like plot, scatter, and imshow create 2D and 3D visualizations of data.Customization options for adjusting colors, markers, and axis properties.

Data Analysis and Statistics:

Functions for descriptive statistics, hypothesis testing, and curve fitting facilitate data analysis tasks.Statistical distributions and probability functions for modeling random processes.

Signal Processing:

Signal Processing Toolbox provides functions for filtering, spectral analysis, and signal generation.Processing of audio, image, and biomedical signals.

Image Processing:

Image Processing Toolbox offers algorithms for image enhancement, segmentation, and feature extraction.Tools for morphological operations, geometric transformations, and object recognition.

Symbolic Mathematics:

Symbolic Math Toolbox enables symbolic computation of mathematical expressions, including differentiation, integration, and equation solving. Simplification and manipulation of symbolic expressions.

4.4 DATASET AND FEATURES

The dataset comprises 86,147 images portraying both diseased and healthy plants across 25 different plant species. These images are categorized into training, validation, and testing sets, each spanning the same 25 plant species. The training set encompasses 55,135 images, while the testing set contains 17,229 images, all segmented to remove background and resized to 64x64 pixels. This standardized preprocessing procedure ensures uniformity across the dataset, facilitating analysis and experimentation.

CHAPTER - 5

RESULTS AND ANALYSIS

Finally, the proposed method evaluates the performance of existing objective Image Quality Metrics (IQMs) on the enhanced images.The proposed method investigates how objective IQMs, such as PSNR or SSIM, perform in assessing image enhancement quality accurately. By comparing the results of subjective evaluations with those obtained from objective IQMs, the proposed method aims to gain insights into the effectiveness and reliability of these metrics in evaluating image enhancement quality. Overall, the proposed method presents a comprehensive approach to image enhancement using the ICSO algorithm, addressing both subjective and objective aspects of image quality evaluation and contributing to the advancement of image enhancement techniques and quality assessment methodologies.

In this study, we conducted a thorough comparison of the performance of our proposed approach with two other state-of-the-art methods for contrast enhancement. These methods include Differential Gray-level Histogram Equalization for Color Images (DHECI) and Dominant Orientation-based Texture Histogram Equalization (DOTHE).Each of these methods utilizes different techniques for contrast and brightness enhancement, such as histogram-based methods to mathematical morphology

To quantitatively assess and compare the proposed approach with the other methods, we employed several state-of-the-art Image Quality Metrics (IQMs). These metrics include SSIM color , Feature SIMilarity for color images (FSIMc), Gradient SIMilarity (GSIM) , Qcolor .

The results demonstrate a strong correlation between subjective evaluations and objective scores for our proposed approach, indicating its effectiveness in contrast enhancement compared to other state-of-the-art methods.For quantitative evaluation, we employed various IQMs, the results of which are presented in Tables given below.

5.1 SIMULATION RESULTS

5.1.1 Objective analysis

1.CSIQ DATASET:

An image from CSIQ Data set is taken as input for the proposed algorithm and output is shown in below fig 5.1

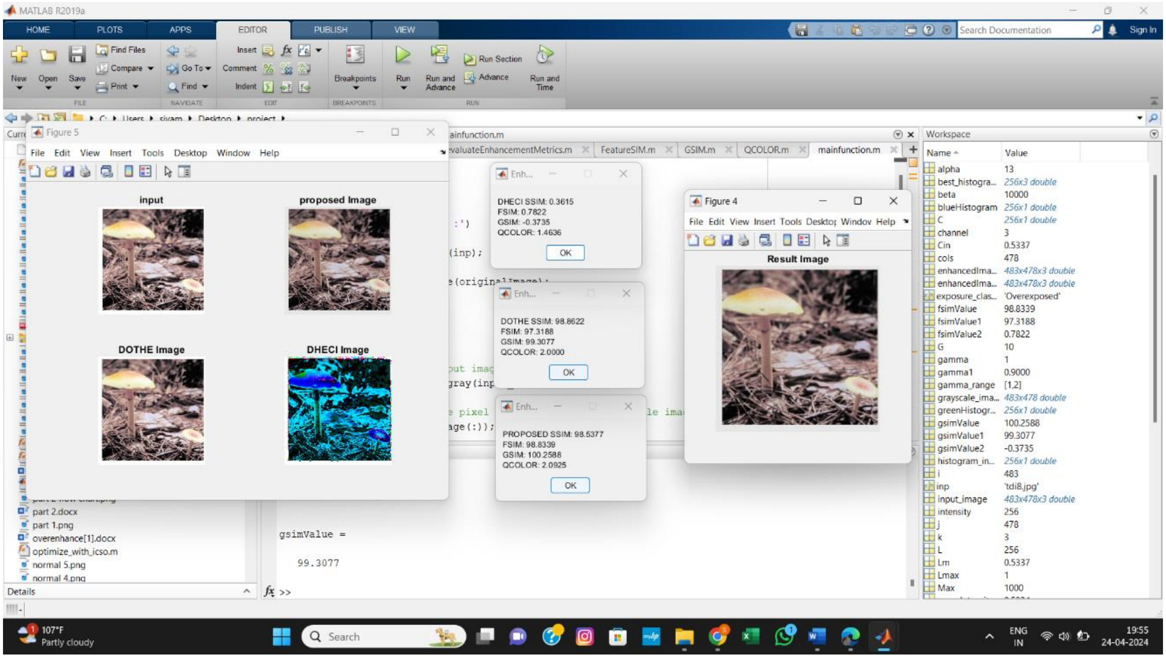

Fig 5.1: Simulation results of image 1 in CSIQ dataset

The figure 5.1 describes the output of proposed method compared with other two techniques subjectively and objectively**.**Visual comparison of different contrast enhancement techniques compared to the proposed approach and obejective analysis of proposed method with other two techniques by calculating the IQM's (SSIM,FSIM,GSIM.QCOLOR).Again we apply psycho visual redundancy to output of the proposed method.

Table 5.1 : Comparison of proposed method with other two algorithms using IQMs (CSIQ Dataset Image1)

	SSIM	**FSIM**	**GSIM**	**QCOLOR**
Proposed	0.994897	0.984090	0.994172	2.0925
DOTHE	0.986715	0.982075	0.987172	2.000
DHECI	0.996302	0.974889	0.990347	2.0764

An image from CSIQ Data set is taken as input for the proposed algorithm and output is shown in below fig 5.2

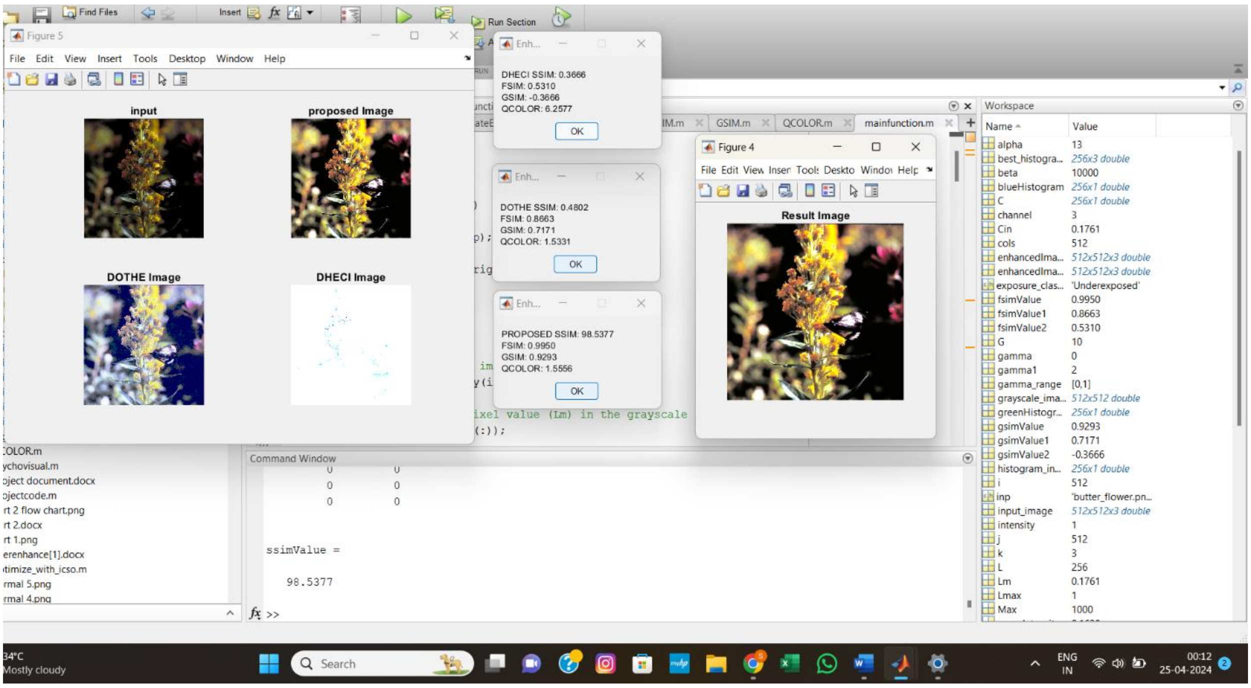

Fig 5.2: Simulation results of image 2 in CSIQ dataset

The figure 5.2 describes the output of proposed method compared with other two techniques subjectively and objectively**.**Visual comparison of different contrast enhancement techniques compared to the proposed approach and obejective analysis of proposed method with other two techniques by calculating the IQM's (SSIM,FSIM,GSIM.QCOLOR).Again we apply psycho visual redundancy to output of the proposed method.

Table 5.2: Comparison of proposed method with other two algorithms using IQMs (CSIQ Dataset Image2)

	SSIM	**FSIM**	**GSIM**	**QCOLOR**
Proposed	98.5377	0.9950	0.9293	1.5556
DOTHE	0.4802	0.8663	0.7171	1.5331
DHECI	0.3666	0.5310	-0.3666	6.277

2.SEID DATASET

An image from SEID Data set is taken as input for the proposed algorithm and output is shown in below fig 5.3

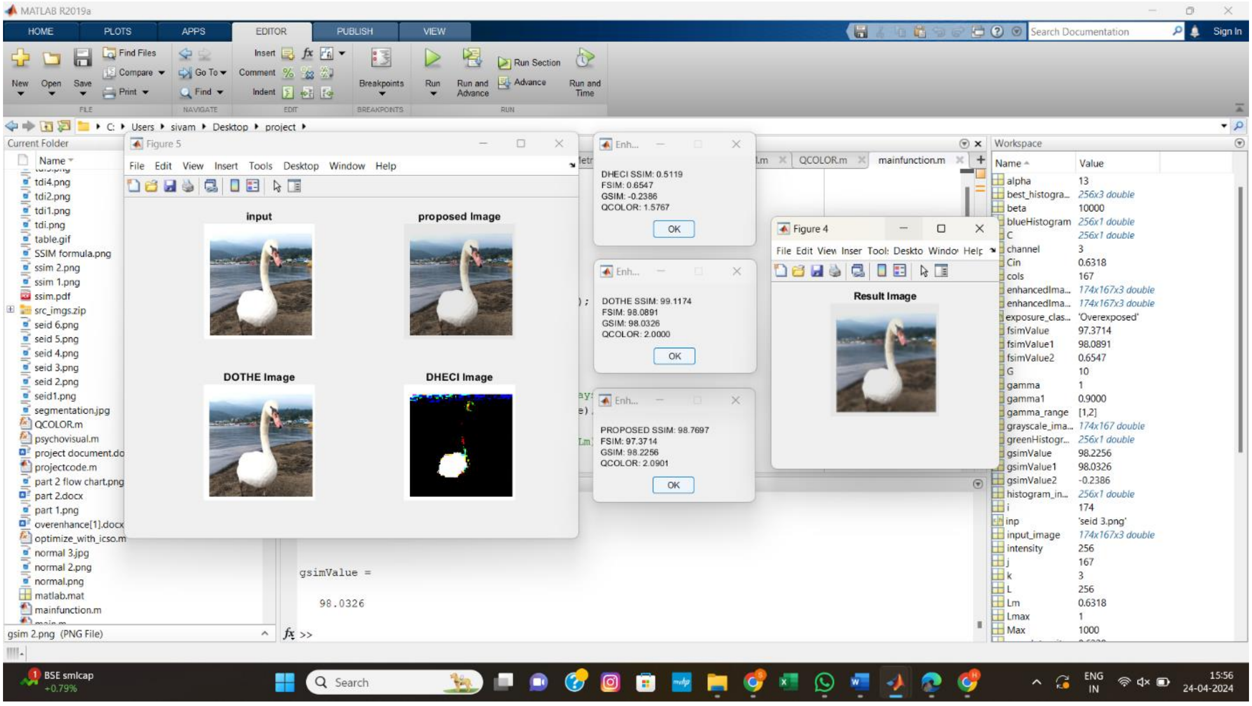

Fig 5.3: Simulation results of image 1 in SEID dataset

The figure 5.3 describes the output of proposed method compared with other two techniques subjectively and objectively**.**Visual comparison of different contrast enhancement techniques compared to the proposed approach and obejective analysis of proposed method with other two techniques by calculating the IQM's (SSIM,FSIM,GSIM.QCOLOR).Again we apply psycho visual redundancy to output of the proposed method.

Table 5.3: Comparison of proposed method with other two algorithms using IQMs (SEId Dataset Image1)

	SSIM	**FSIM**	**GSIM**	**QCOLOR**
Proposed	0.987697	0.973714	0.982256	2.0901
DOTHE	0.991174	0.980891	0.980326	2.0000
DHECI	0.5119	0.6547	-0.2386	1.5767

An image from SEID Data set is taken as input for the proposed algorithm and output is shown in below fig 5.4

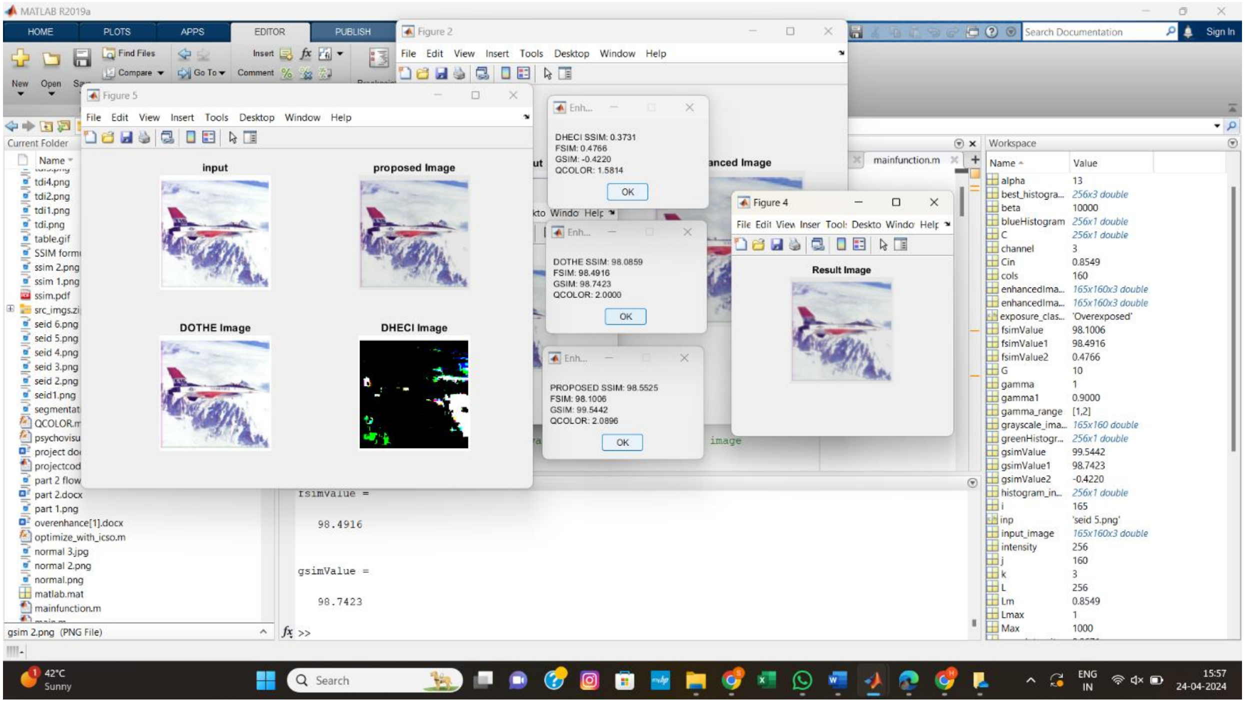

Fig 5.4: Simulation results of image 2 in SEID dataset

The figure 5.4 describes the output of proposed method compared with other two techniques subjectively and objectively.Visual comparison of different contrast enhancement techniques compared to the proposed approach and obejective analysis of proposed method with other two techniques by calculating the IQM's (SSIM,FSIM,GSIM.QCOLOR).Again we apply psycho visual redundancy to output of the proposed method.

Table 5.4: Comparison of proposed method with other two algorithms using IQMs (SEId Dataset Image2)

	SSIM	**FSIM**	**GSIM**	**QCOLOR**
Proposed	0.985525	0.981006	0.995442	2.0896
DOTHE	0.980859	0.984916	0.987423	2.0000
DHECI	0.3731	0.4766	-0.4766	1.5814

3.TID2013 DATASET:

An image from TID2013 Data set is taken as input for the proposed algorithm and output is shown in below fig 5.5

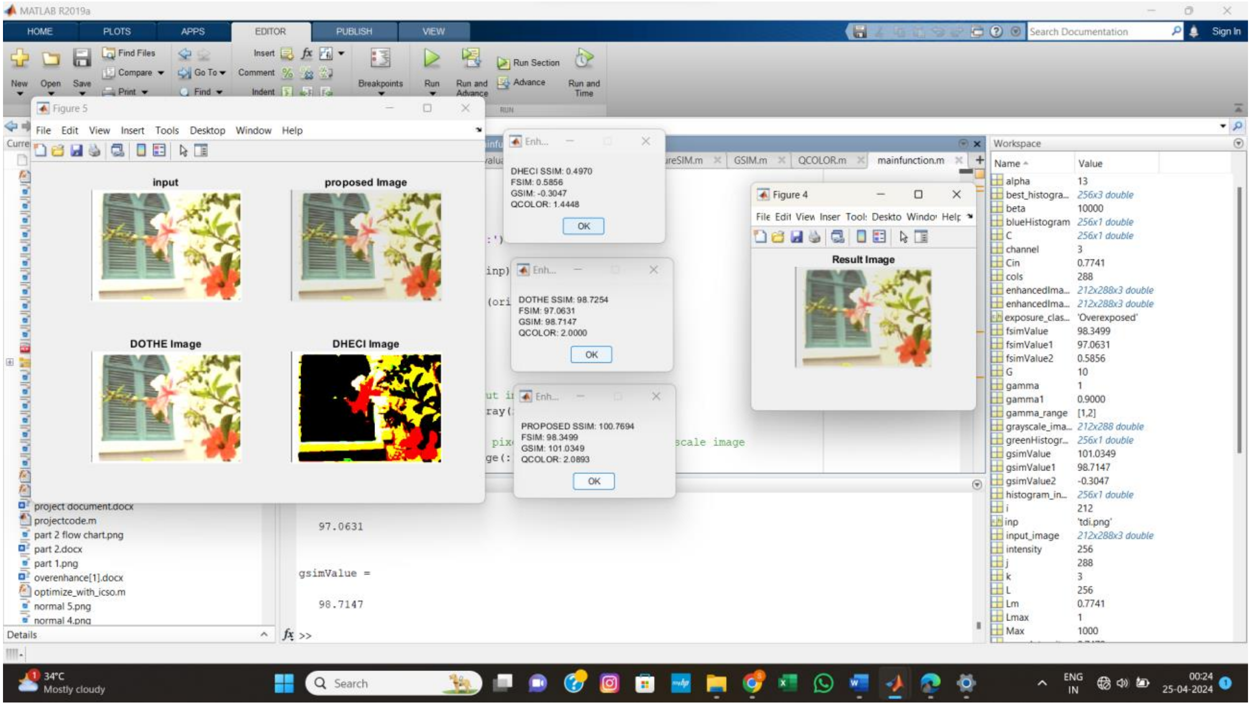

Fig 5.5 : Simulation results of image 1 in TID2013 dataset

The figure 5.5 describes the output of proposed method compared with other two techniques subjectively and objectively**.**Visual comparison of different contrast enhancement techniques compared to the proposed approach and obejective analysis of proposed method with other two techniques by calculating the IQM's (SSIM,FSIM,GSIM.QCOLOR).Again we apply psycho visual redundancy to output of the proposed method.

Table 5.5: Comparison of proposed method with other two algorithms using IQMs (TID2013 Dataset Image1)

	SSIM	**FSIM**	**GSIM**	**QCOLOR**
Proposed	0.107694	0.933499	0.1010349	2.0893
DOTHE	0.0987254	0.970631	0.0987147	2.0000
DHECI	0.4970	0.5856	-0.3047	1.4448

An image from TID2013 Data set is taken as input for the proposed algorithm and output is shown in below fig 5.6

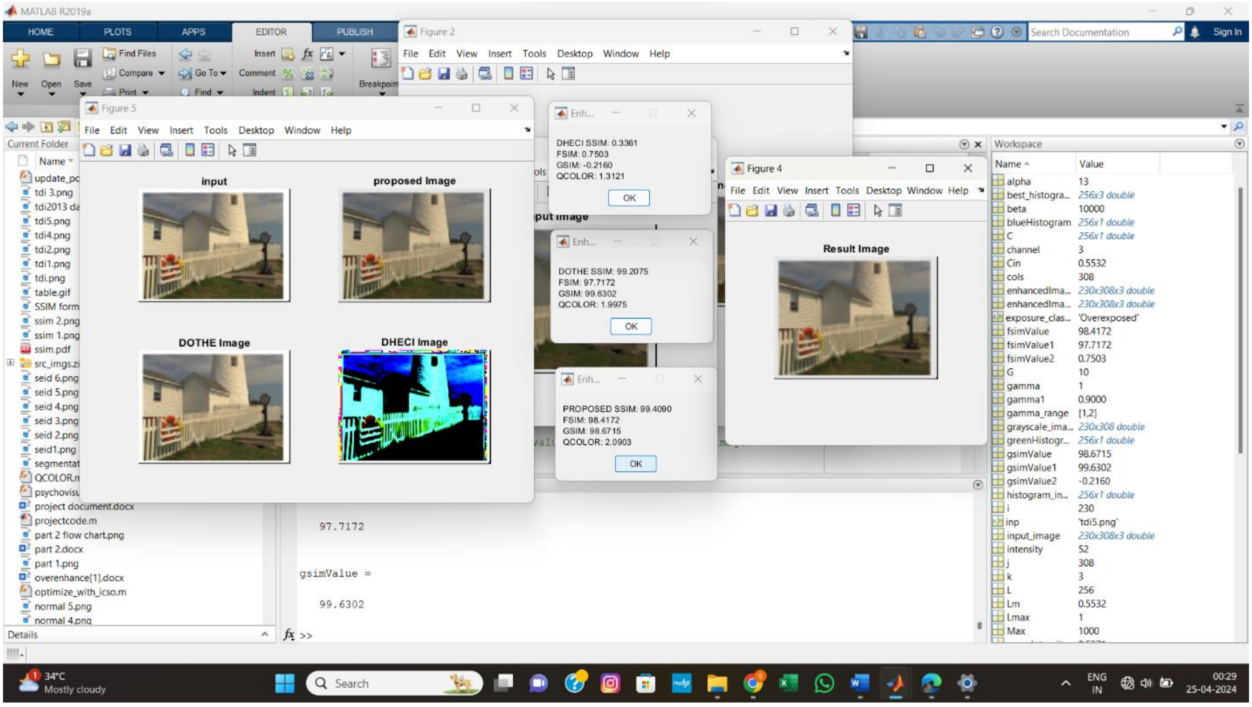

Fig 5.6 : Simulation results of image 2 in TID2013 dataset

The figure 5.6 describes the output of proposed method compared with other two techniques subjectively and objectively.Visual comparison of different contrast enhancement techniques compared to the proposed approach and obejective analysis of proposed method with other two techniques by calculating the IQM's (SSIM,FSIM,GSIM.QCOLOR).Again we apply psycho visual redundancy to output of the proposed method.

Table 5.6: Comparison of proposed method with other two algorithms using IQMs (TID2013 Dataset Image2)

	SSIM	**FSIM**	**GSIM**	**QCOLOR**
Proposed	0.994090	0.984172	0.986715	2.0903
DOTHE	0.992075	0.977172	0.996302	1.9975
DHECI	0.3361	0.7503	-0.2160	1.3121

4.Contarst Images:

A High Contrast image is taken as input for the proposed algorithm and output is shown in below fig 5.7

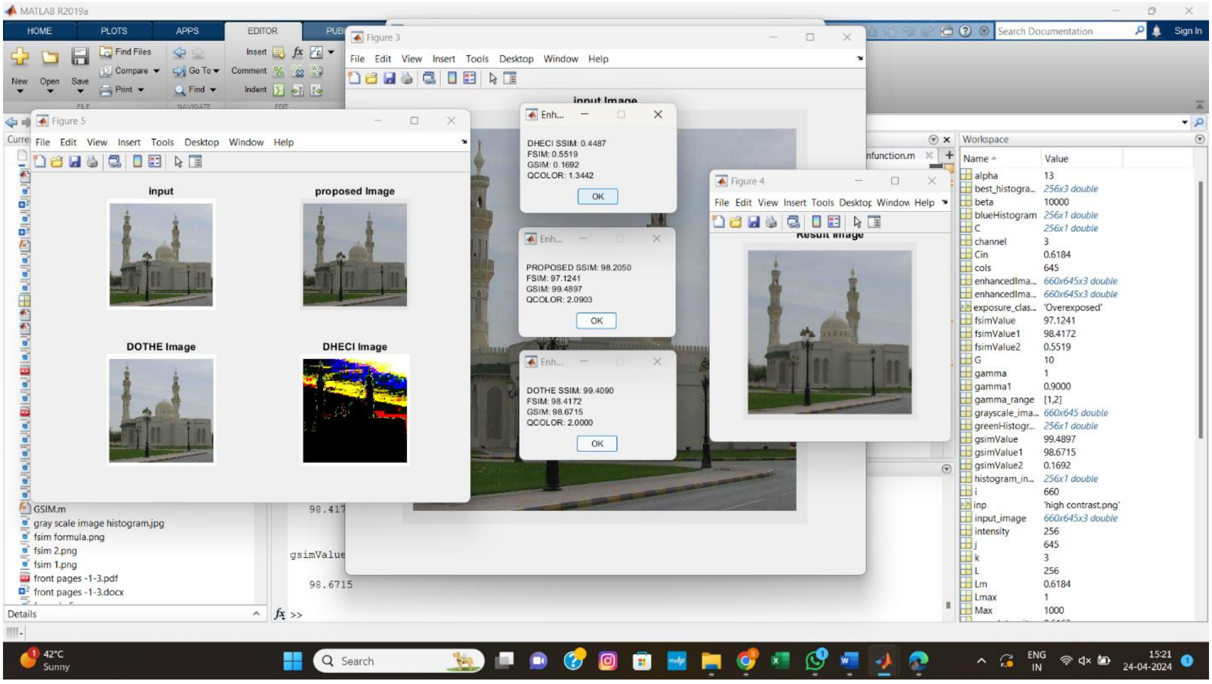

Fig 5.7: Simulation results of high contrast image

The figure 5.7 describes the output of proposed method compared with other two techniques subjectively and objectively**.** Visual comparison of different contrast enhancement techniques compared to the proposed approach and obejective analysis of proposed method with other two techniques by calculating the IQM's (SSIM,FSIM,GSIM.QCOLOR).Again we apply psycho visual redundancy to output of the proposed method.

Table 5.7 : Comparison of proposed method with other two algorithms using IQMs(High Contrast image)

	SSIM	**FSIM**	**GSIM**	**QCOLOR**
Proposed	0.982050	0.971241	0.994897	2.0903
DOTHE	0.994090	0.984172	0.1692	1.3442
DHECI	0.4487	0.5517	-0.2562	1.6254

A Low Contrast image is taken as input for the proposed algorithm and output is shown in below fig 5.8

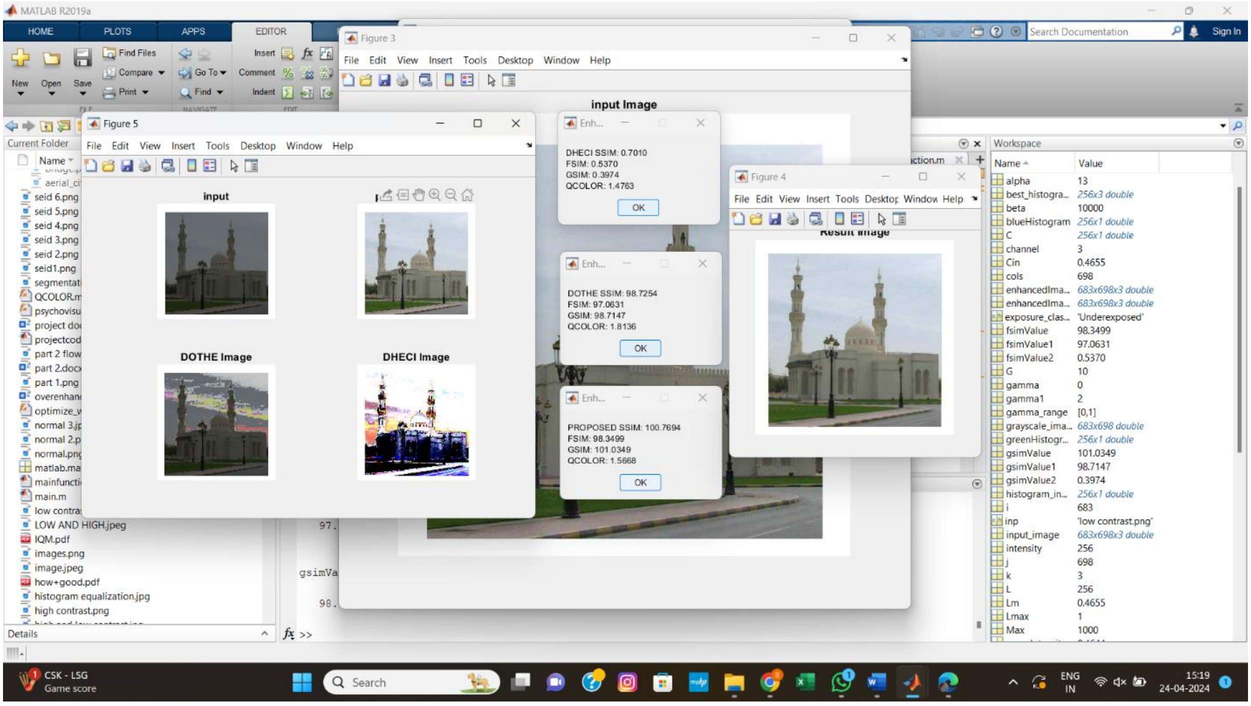

Fig 5.8: Simulation results of low contrast image

The figure 5.8 describes the output of proposed method compared with other two techniques subjectively and objectively**.**Visual comparison of different contrast enhancement techniques compared to the proposed approach and obejective analysis of proposed method with other two techniques by calculating the IQM's (SSIM,FSIM,GSIM.QCOLOR).Again we apply psycho visual redundancy to output of the proposed method.

Table 5.8 : Comparison of proposed method with other two algorithms using IQMs(Low Contrast Image)

	SSIM	**FSIM**	**GSIM**	**QCOLOR**
Proposed	0.100694	0.98349	0.101349	1.5668
DOTHE	0.987254	0.970631	0.987147	1.8136
DHECI	0.7010	0.03974	0.3974	1.4763

5.Normal images

An image is taken as input for the proposed algorithm and output is shown in below fig 5.9

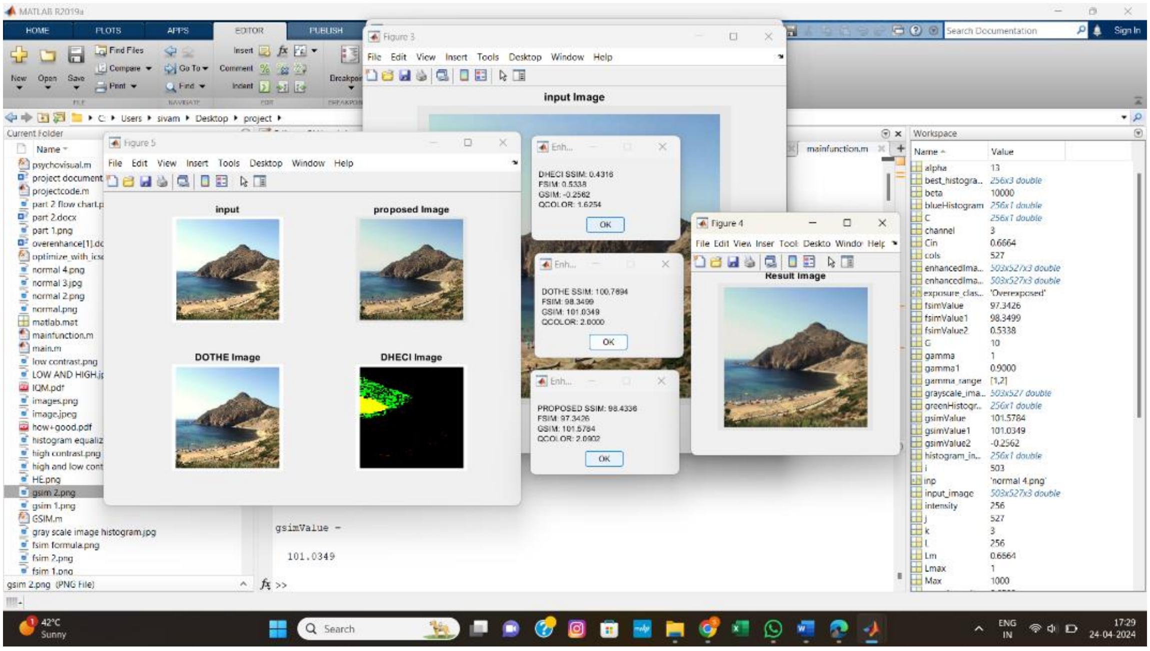

Fig 5.9: Simulation results of Normal image 1

The figure 5.9 describes the output of proposed method compared with other two techniques subjectively and objectively.Visual comparison of different contrast enhancement techniques compared to the proposed approach and obejective analysis of proposed method with other two techniques by calculating the IQM's (SSIM,FSIM,GSIM.QCOLOR).Again we apply psycho visual redundancy to output of the proposed method.

Table 5.9: Comparison of proposed method with other two algorithms using IQMs(Normal Image1)

	SSIM	**FSIM**	**GSIM**	**QCOLOR**
Proposed	0.984336	0.973426	0.1015784	2.0902
DOTHE	0.1007694	0.983499	0.1010349	2.0000
DHECI	0.4316	0.5338	-0.2562	1.6254

An image from CSIQ Data set is taken as input for the proposed algorithm and output is shown in below fig 5.1

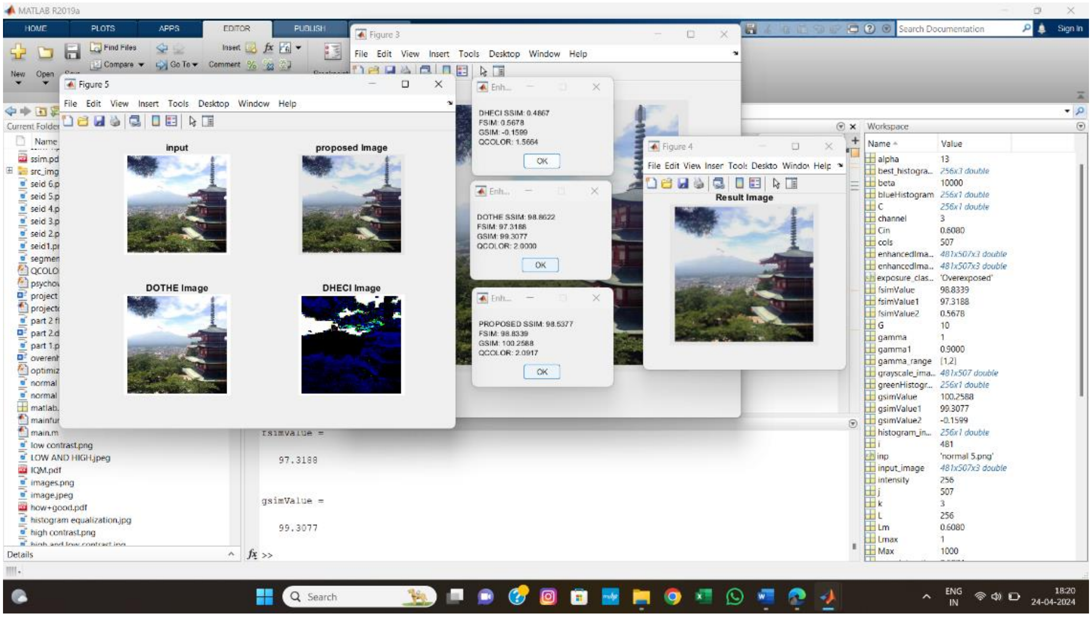

Fig 5.10: Simulation results of Normal image 2

The figure 5.10 describes the output of proposed method compared with other two techniques subjectively and objectively.Visual comparison of different contrast enhancement techniques compared to the proposed approach and obejective analysis of proposed method with other two techniques by calculating the IQM's (SSIM,FSIM,GSIM.QCOLOR).Again we apply psycho visual redundancy to output of the proposed method.

Table 5.10: Comparison of proposed method with other two algorithms using IQMs(Normal Image 2)

	SSIM	FSIM	GSIM	QCOLOR
Proposed	0.985377	0.988339	0.102588	2.0917
DOTHE	0.988622	0.973188	0.0993077	2.000
DHECI	0.4867	0.5678	-0.1599	1.5664

In objective analysis of the proposed algorithm with other two techniques, IQM's are used.After executing the proposed algorithm with CSIQ,SEID,TDI2013 data sets as input images ,there will be so many output images.Hence the average values of each data set are calculated in below tables(5.11.5.12,5.13).Metrics of proposed algorithm and other two algorithms are calculated and compared in below tables

Table 5.11: Average Metrics values of images in CSIQ Dataset

CSIQ Data Set

	SSIM	**FSIM**	**GSIM**	**QCOLOR**
Proposed	0.990137	0.99702	0.5017	1.82405
DOTHE	0.49984	0.99702	0.50067	1.8128
DHECI	0.49998	0.4933	0.4900	0.41767

Table 5.12: Average Metrics values of images in SEID Dataset

SEID Data Set

	SSIM	**FSIM**	**GSIM**	**QCOLOR**
Proposed	0.98661	0.97736	0.9888	2.08985
DOTHE	0.98601	0.98290	0.98387	2.0000
DHECI	0.4425	0.56565	-0.3576	1.57905

Table 5.13: Average Metrics values of images in TDI2013 Dataset

TDI2013 Data Set

	SSIM	**FSIM**	**GSIM**	**QCOLOR**
Proposed	1.00089	0.95883	0.9985	2.0898
DOTHE	0.98966	0.97390	0.99172	1.99875
DHECI	0.41655	0.66795	-0.26035	1.37845

5.1.2 Subjective Analysis:

Images from different datasets and low & high contrast images and normal images are given input to proposed algorithm.The below figures 5.11 shows the ouput of the proposed algorithm and comparison of proposed method with other two algorithms subjectively

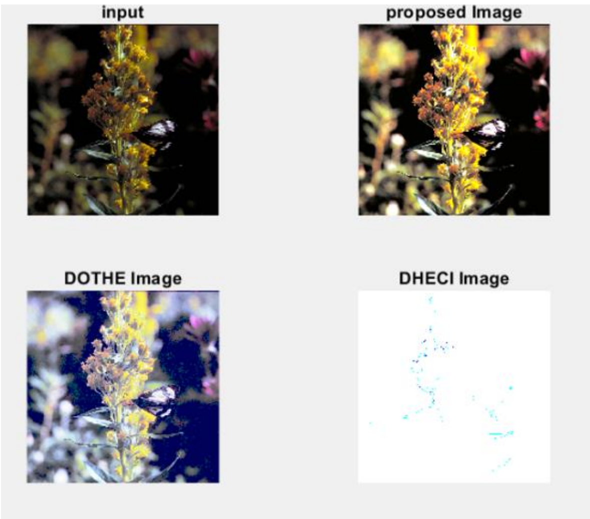

Fig 5.11(a)

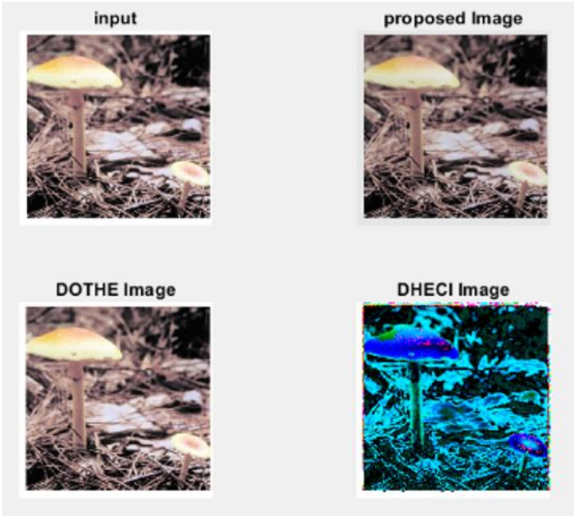

Fig 5.11(b)

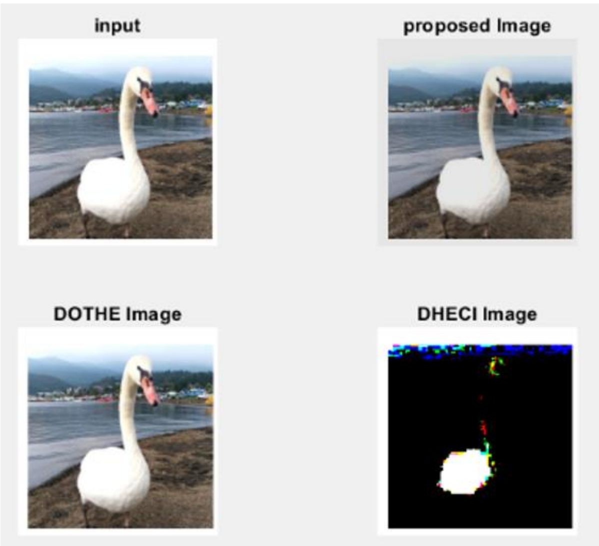

Fig 5.11(c)

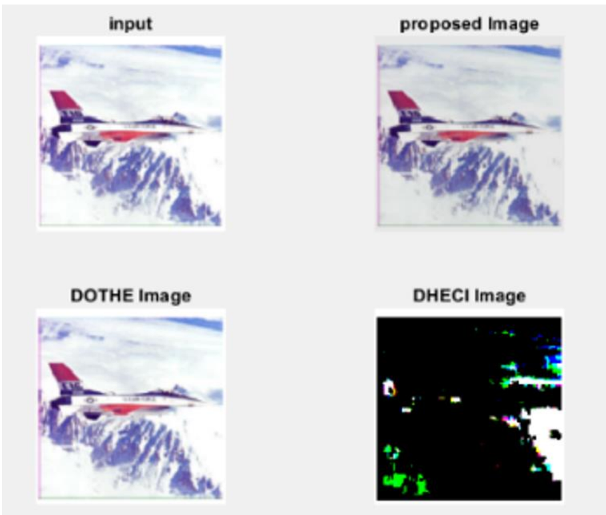

Fig 5.11(d)

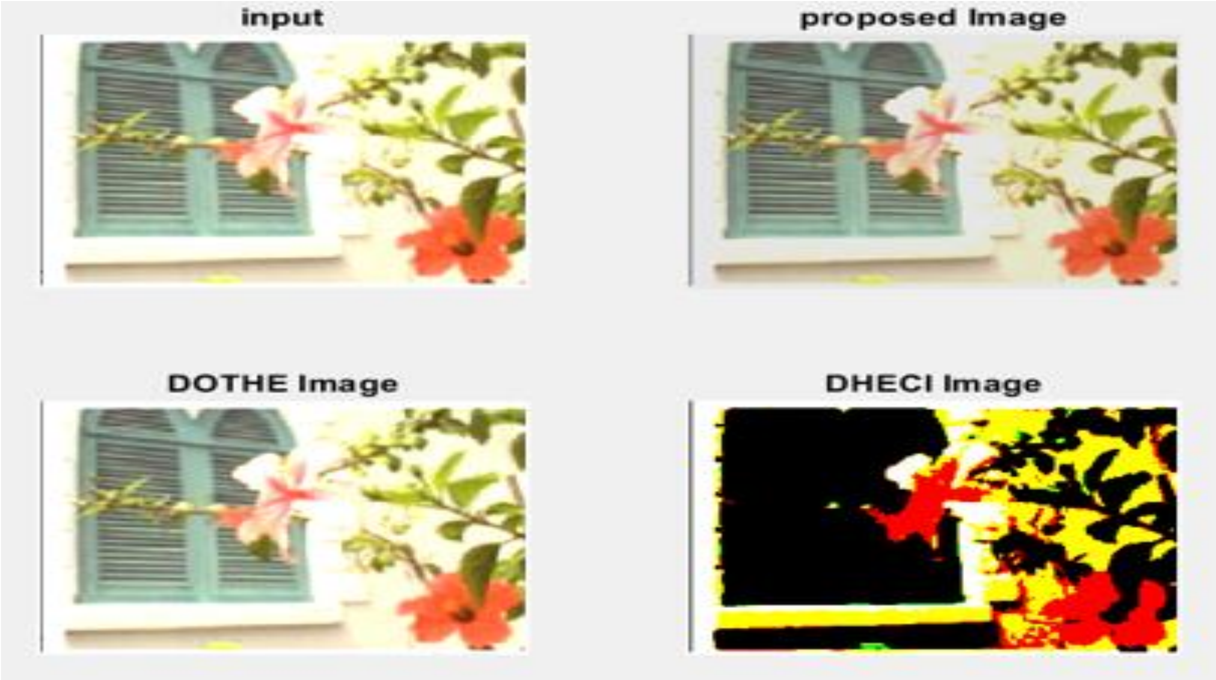

Fig 5.11(e)

Fig 5.11(a,b,c,d,e): Comparison of proposed method output with other two techniques with images from different datasets

CHAPTER - 6

CONCLUSION

In this investigation, we delved into the intricate realm of image enhancement, particularly focusing on the challenge of improving both low and high contrast images while mitigating the risk of over-enhancement. Our endeavor led us to adopt the refined algorithm of Improved Chicken Swarm Optimization (ICSO) as a robust tool for optimization.

A key highlight of our work lies in the meticulous crafting of terms within the criterion function. These terms serve a multifaceted purpose, facilitating the preservation of essential details present in the input image, ensuring a semblance between the modified and original histograms, fine-tuning the output histogram to conform more closely to a uniform distribution, and mitigating spikes in the modified histogram to avert over-enhancement. Furthermore, we laid down precise stopping conditions for the algorithm, enabling it to halt its operation upon achieving a stable state where the gradient and entropy of the output image exhibit stability.

Our method is distinguished by its utilization of three distinct parameters aimed at finely controlling the levels of brightness and contrast enhancement while safeguarding critical image details. Through an exhaustive subjective experiment coupled with a comprehensive evaluation using diverse Image Quality Metrics (IQMs), we garnered compelling evidence showcasing the superior performance of our proposed approach compared to existing techniques. This robust validation underscores the efficacy of our method in achieving a harmonious balance between image enhancement and the prevention of over-enhancement, thus offering a promising avenue for elevating image quality across a spectrum of contrast levels.

FUTURE SCOPE

The future scope of this research involves enhancing the efficiency of the Improved Chicken Swarm Optimization (ICSO) algorithm, which drives the Image Contrast Enhancement (ICE) method. By fine-tuning parameters and exploring alternative strategies, convergence speed and solution quality can be improved. Additionally, integrating ICE with deep learning techniques, such as CNNs or GANs, presents an exciting direction for superior contrast enhancement. Optimizing ICE for real-time implementation is crucial for its practical use in various applications, requiring efficient algorithm design and hardware acceleration. Furthermore, developing objective evaluation metrics tailored to specific scenarios would provide comprehensive assessments of contrast enhancement algorithms, guiding further improvements. Ensuring the generalization and robustness of ICE across diverse datasets and environmental conditions is vital for its real-world applicability, necessitating investigations into domain adaptation and robust optimization strategies. Overall, addressing these aspects will advance ICE's utility and contribute significantly to the field of image enhancement.We can extend the above proposed method to vedios along with other redundancy.

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