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IMPROVEMENT OF ELECTRON MICROSCOPE VIRUS IMAGES THROUGH SEGMENTATION AND CONTRAST ENHANCEMENT

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ABSTRACT

High-resolution imaging techniques are essential for accurately studying viruses and their effects. Due to their small size, viruses often require sophisticated imaging tools for successful detection and analysis. Microscopy techniques, such as electron microscopy or fluorescence microscopy, are commonly used to capture images of viruses. However, these images can sometimes lack contrast and detail, making it challenging to identify important structural features. This paper introduces a new method to enhance the gray-scale images of 36 electron microscope virus images by increasing contrast and brightness using dark channel prior and adapted histogram equalization used Otsu's segmentation. To determine the efficiency of the proposed method in improving microscopic images, it was compared with several other methods. The quality measurements demonstrated significant success, with entropy (EN) at 7.800, average gradient (AG) at 16.996, mean standard deviation (MSTD) at 44.321, and contrast enhancement measurement (CEM) at 0.8752. The results indicate the algorithm's effectiveness in preserving image clarity and enhancing its features in a superior manner.

KEYWORDS

Microscope Virus images, Image enhancement, Dark Channel Prior, Adopted Histogram Equalization.

1. INTRODUCTION

Viruses are tiny infectious agents that are too small to be visible with a light microscope, yet can create significant disruption (Gergerich and Dolja, 2006). Like other organisms, viruses contain genetic information in their nucleic acids, which usually directs the production of three or more proteins (Matuszewski and Sintorn, 2019). As obligate parasites, viruses rely on the host cell's machinery to reproduce. Imaging has become essential in many fields of medical and laboratory research and clinical practice (McAuliffe et al., 2001). Image Processing is the analysis and manipulation of images using mathematical operations and algorithms to enhance, extract, or interpret information (Thahab, 2015). It involves techniques such as filtering, segmentation, and feature extraction to improve image quality or prepare it for further analysis. Image processing is widely used in fields like computer vision, medical imaging, and pattern recognition (Sultan, 2016;Alaa, Hussein and Al-libawy, 2024). Virus imaging is a critical aspect of virology that involves capturing and analyzing detailed visual representations of viruses (Sikder et al., 2024; Daway, Al-Alawy and Hassan, 2019). These images are essential for understanding virus morphology, interactions with host cells, and the mechanisms of infection (Dos Santos et al., 2015). Given the tiny size of viruses, specialized imaging techniques are required to visualize them effectively (Szerlip et al., 2007) . Enhancing virus images is crucial for improving the clarity and detail of microscopic observations, which is vital for research, diagnostics, and treatment development (DAWAY, ABDULAMEER and DAWAY, 2022). Viruses, being extremely small and often transparent, can be challenging to visualize in microscope images. Enhanced imaging allows for better visualization of viral structures, which can aid in identifying specific virus types, understanding their morphology, and studying their interactions with host cells (Valentine, 1962)(Kohno et al., 1998).

2. RELATED WORKS

Many of studies were introduced to enhancement the microscopy virus images using different methods. Fuzzy contextual information-based contrast enhancement techniques (FCCE) were presented in 2017 by the teams of A. S. Parihar, O. P. Verma, and C. Khanna for images of beans and houses, the fuzzy contrast factor for each pixel is used by the fuzzy dissimilarity histogram (Kadhim and Daway, 2023). The contrast-enhanced image is produced by utilising normalised data to construct a cumulative distribution function. The technique maintains the natural properties of the visual contrast while enhancing them (Parihar, Verma and Khanna, 2017). In 2020 H. G. Daway, E. G. Daway, and H. H. Kareem developed of Fuzzy Logic based on Sigmoid Membership Function (FLBSMF). Enhanced the contrast and luminosity of colored visuals. The color compounds were unaltered when the FLBSMF method was applied solely to the YIQ color space for the brightness component. The proposed technique was put up against existing algorithms, like multiscale retinex with color restoration by applying multiple criteria, fuzzy logic based on the histogram, fuzzy logic enhancement utilizing membership function modification based on square operation, and fuzzy logic based on histogram (For et al., 2020). In2021 S. Saravanan and R. Karthigaivel, enhanced contrast of medical images, a Fuzzy and spline-based Histogram Equalisation (FSDHE) is proposed in this study. The suggested FSDHE approach uses a fuzzy membership function to identify the kind of component after it has divided the image into connected components. For every component, a separate application of the dynamic hierarchy equalization is made. The global histogram, which is inconsistent because dynamic histogram equalization handled the intensity range for each connected component differently, is driven by the equalized sub-histograms. Therefore, in this study work, a spline-based histogram smoothing is proposed (Saravanan and Karthigaivel, 2021) . In 2024 A. H. Sheer and H. G. Enhancement MRI Image using Nonlinear Mapping and Adaptive Histogram Equalization-based (NMAHE) Segmentation by Otsu’s Method. The methodology involved segmenting the region of interest (ROI) using Otsu’s thresholding technique, followed by enhancing the ROI through nonlinear mapping and adaptive histogram equalization. Experimental results demonstrated significant improvements, achieving a contrast enhancement metric of 0.841 , an average gradient of 5.645 , and an entropy value of 6.151 (Sheer and Daway, 2024).

3. SUGGESTED METHOD

The proposed approach includes enhanced brightness and contrast of the 36-electron microscope virus images (gray images) from the Kaggle database.
[https://www.kaggle.com/datasets/saurabhshahane/virus-images] using Dark Channel Prior (DCP) and adopted histogram equalization (AHE), based of segmentation of these images using Otsu's methods to segmentation each image and enhancing the contrast and lightness of each (DCP) to find the final image enhancement. Enhancement of the Electron Microscope images using Dark Channel Prior. The electron microscope virus images suffer from a kind of blurring. Therefore, use Dark Channel Prior techniques (DCP), These methods have been effective in improving contrast, as :(He, Sun and Tang, 2010)(Wang, Li and Yang, 2021) :

$$C(i) = J(i)\, tr(i) + Rr\,(1 - Tr(i)) \quad (1)$$

wher R(i) is Observed image at pixel I .

J(i) is True scene radiance (haze-free image) at pixel I.

Tr(i) is Transmission map (describes light attenuation through the medium).

And ar is Atmospheric light . The Dark Channel Prior (DCP) is described for any given image Jn as:

$$J_{Dark}(i) = Min_{n \in \{r,g,b\}} (min_{y \in \Omega(i)} (Jn(y)) \tag{2}$$

The intensity of the DC , Jn is low and tends towards zero when it represents a haze-free image. In this context, , and Ω(i) represents a local patch centered at pixel i. Hence, we obtain:

$$J_{dark}(i) \cong 0 \tag{3}$$

The Tr is calculated as:

$$Tr(i) = 1 - w_{Minn \in \Omega(x)} \left(Min_{n \in \{r,g,b\}} \frac{I_n(y)}{ar} \right) \tag{4}$$

Soft mapping can be applied to improve the transmission. Direct removal of haze might result in a strange appearance of the image. w is set between 0 and 1, with w=0.95. The ideal ambient light value is A=0.1 with a patch size of 15×15. Finally, the scene illumination is restored as (He, Sun and Tang, 2010) (Wang, Li and Yang, 2021):

$$C(i) = \frac{I(i) - A}{Max(tr(n), 0.1)} + A \tag{5}$$

3.1. Adaptive Histogram Equalization

The Adaptive Histogram Equalization (AHE) method records multiple histograms, compares each to a specific section of the topic, and then adjusts the subject's intensity estimates accordingly. Typically, this technique enhances the visibility of edges within different areas of the subject. Here's a rephrased version of the sentence. The enhancement of noisy pixels in AHE (Adaptive Histogram Equalization) happens by distinguishing between background pixels and their corresponding data, with the refined pixels represented as the baseline data (Mishra, 2021).

3.2. OTSU'S METHOD

It plays a crucial role in automatic threshold selection. However, it is sensitive to noise and object size, and it only performs well on images with a single peak in variance. When tested on a variety of images, it often requires refinement. Otsu's method is a global thresholding technique used in image processing to automatically convert a grayscale image into a binary image. It finds the optimal threshold value to separate the image into two classes: foreground and background In this sectioning method, the threshold value depends on the distribution of the histogram and varies from image to image, if there is a significant difference in the variances between two classes, the method may misclassify additional pixels from the class with larger variance into the other class, leading to suboptimal segmentation results (Zhao et al., 2019) . In this study the introduced algorithm represented the scheme. Fig. 1. The steps of the proposed algorithm to enhance this microscopy virus image can be listed in the following:

1.Input gray electron macroscopy virus images

2.Removed blur using dark channel prior

3.Applied adopted histogram equalization to enhance the contrast and lightness

4.Used Otsu's segmentation for each image of step 3

5.Using the Dark channel prior to step 4.

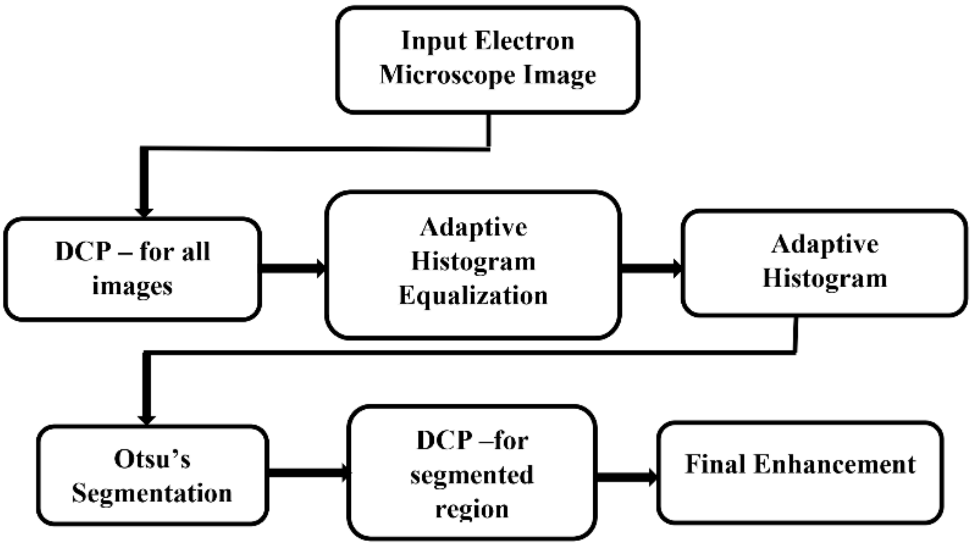

Fig 1. The scheme of the suggested method.

4. IMAGE QUALITY ASSESSMENT (IQA)

Image Quality Assessment (IQA), is the process of assessing how well a distorted image compares to its original (Abd-Alameer, Daway , Rashid, 2020 ; Habeeb, 2020). Techniques for evaluating image quality fall into two categories: subjective approaches and objective methodologies. When it comes to the demands of real-time assessment, subjective approaches are challenging and time-consuming. This process is very costly and requires human intervention. Conversely, objective approaches use computer models to quantify image quality. Require automated or impartial techniques for real-time evaluations (Varga, 2023;Ameer, Daway and Kareem, 2019).

4.1. Entropy scale

The entropy scale is defined by the maximum amount of information contained within the displayed image. A higher combination entropy indicates a greater amount of information present in the image (C, 2009):

$$\mathrm{EN} = -\sum_k p_k \log(p_k) \tag{6}$$

Where p_k is the histogram of the lightness.

3.1 Average Gradient (AG)

Represents the contrast between the pattern's characteristics fluctuation on the image, consequently, the image's outstanding contrast, textural diversity, and clarity are all displayed in the average gradient (AG). As can be seen below, when the value of AG is higher, the image is crisper and has a higher intensity value (Rafid Hashim, Daway and Kareem, 2022;Wang and Chang, 2011).

$$\nabla \bar{g} = \frac{1}{KL} \sum_{i=1}^{K} \sum_{j=1}^{L} \left[\left(\frac{\partial F(i,j)}{\partial X} \right)^2 + \left(\frac{\partial F(i,j)}{\partial Y} \right)^2 \right]^{\frac{1}{2}} \tag{7}$$

Where K and L are the image's row and column counts, respectively, and ($\frac{\partial F(i,j)}{\partial X}$ and ($\frac{\partial F(i,j)}{\partial Y}$) are the one-order differentials of pixels (i, j) in the x- and y-direction.

4.2. Mean of Local Standard Deviation (Mstd)

As a higher standard deviation (σ) results in a higher contrast in the image, σ is used to measure the average of contrast, and the mean of the local standard deviation is used to assess the lightness and contrast as follows(Rafid Hashim, Daway and Kareem, 2022) :

$$\sigma = \sqrt{\sum_{i=1}^{u} \sum_{i=1}^{v} \left(\frac{X(i,j)}{u\,v} - (\mu)^2 \right)} \tag{8}$$

Where $x(i,j)$ is the pixel value, u and v are the image dimension, the mean of the standard deviation is $\overline{\sigma} = \frac{\sigma}{n}$, where n is the number of locals.

4.3. Contrast enhancement measurement

This makes sense since the difference could be large or small, high or low (Qidwai and Chen, 2009). The contrast was computed using Michelson's equation as a periodic pattern. When defining contrast, the image's spatial frequency content must be considered. Therefore, spatial frequency determines how sensitive a person is to human contrast. With a value between 0 and 1, This non-referential scale assesses the contrast and detail in images; a high Cem indicates a satisfactory outcome and is supplied by (Setiawan et al., 2013) .

$$Cem_{local} = \frac{Vmax - Vmin}{Vmax + Vmin} \tag{9}$$

5. RESULT AND DISCUSSION

This study introduced a novel approach for processing grayscale electron microscopy virus images. All computations were conducted in MATLAB (R2021a) on an i7 processor with 12 GB of RAM. The analysis utilized 36 images from the Kaggle dataset, as shown in Fig. 2. [https://www.kaggle.com/datasets/saurabhshahane/virus-images], type TIF. In Fig. 3, they chose the 3rd,18th, and 35th from Kaggle data images as an example to enhance contrast by using the suggested methods and removing the noise from these images. The suggested method was applied of the image's label (3rd, 18th, and 35th). In Fig. 4, and 7 the result of the suggested method and compared with four methods (the Fuzzy contextual information-based contrast enhancement techniques (FCCE), (FLBSMF), and (NMAHE). In Fig. 5, and 9, the enlarged part of these result for 3rd and 35th images and compared with other method. The values of quality parameters calculated, including Entropy (EN, Average Gradient (AG), Mean Standard deviation (MSTD), and Contrast enhancement measurement (CEM) to test the result of the suggested methods compared these values with the four methods; the result listed in Table 1, To assess the performance of image enhancement techniques applied to electron microscope images, five methods were compared based on four quantitative image quality metrics: Entropy (EN), Average Gradient (AG), Mean Standard Deviation (Mstd), and Contrast Enhancement Measure (CEM). The proposed method ("suggest") outperformed all competing techniques, achieving the highest scores across all evaluation criteria. Specifically, it recorded an entropy of 7.8007, indicating a high level of information content and image detail. It also achieved the highest AG (16.9968), reflecting superior edge sharpness and texture clarity, and the highest Mstd (44.3216), signifying improved contrast distribution and intensity variation. Moreover, the method excelled in CEM with a score of 0.8753, suggesting a more visually pleasing and enhanced contrast appearance. We can see in contrast, traditional methods such as FLSMF and FSBDHE showed substantially lower performance, especially in AG and CEM, with AG values as low as 0.0038 and CEM at 0.5063, indicating weak detail enhancement and contrast quality. Even more advanced methods like FCCE and NMAHE fell short in comparison, particularly in Mstd and AG. These findings validate the effectiveness of the proposed method in enhancing critical features in electron microscopy, making it a valuable tool for biomedical and material science imaging applications where precision and clarity are crucial. Figs 6 and 8 show the distribution of the histogram. We notice from them that the widest distribution was for the proposed method, which indicates its success in improving the contrast.

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Table 1. Comparison Of The Result Average Quality Scale Of Images From Kaggle Data With Four Methods.

Methods	EN	AG	Mstd	CEM
suggest	7.800748	16.99682	44.3216	0.87529
FCCE	7.761677	7.512366	20.4528	0.61505
FLSMF	7.155342	0.003814	19.2775	0.56387
FSBDHE	7.205352	6.674552	18.6748	0.50633
NMAHE	7.660058	10.50692	28.2472	0.57353

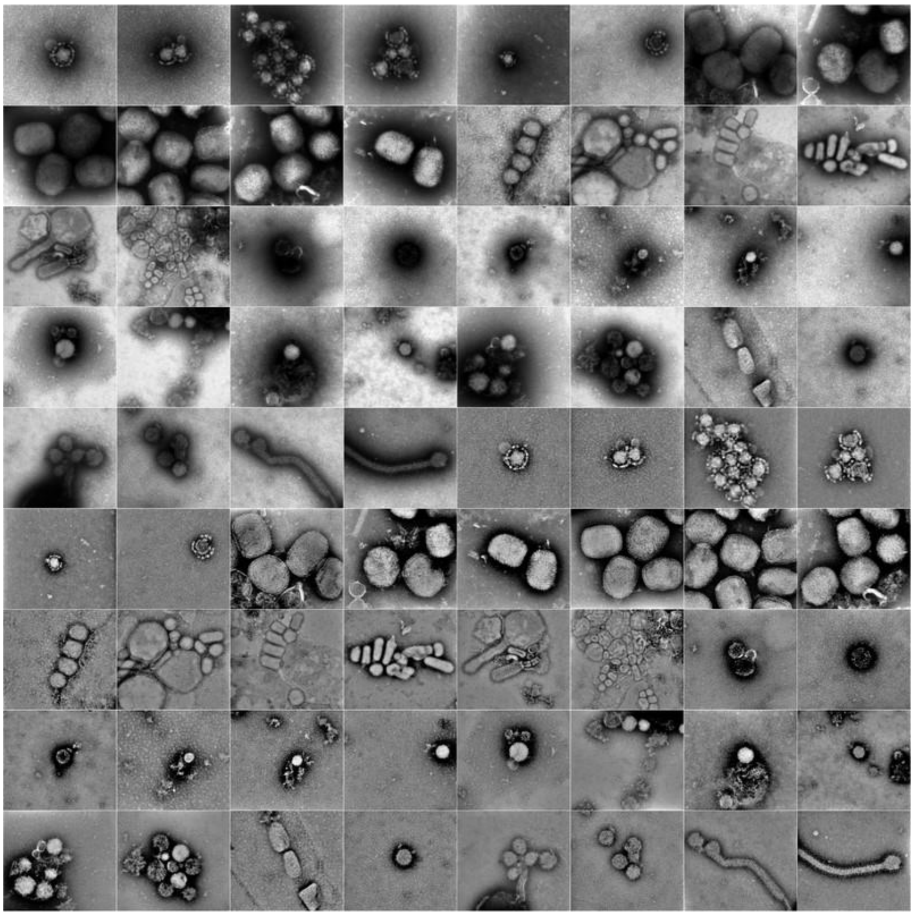

Fig. 2. Using 36 images from Kaggle data.

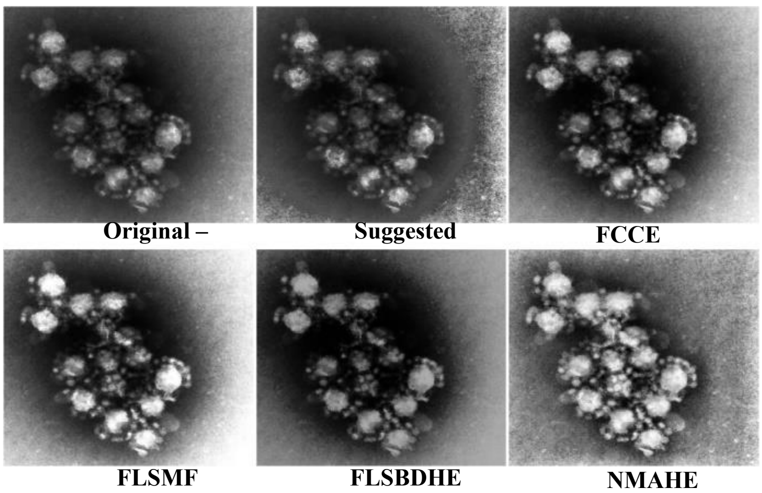

Fig. 3. The original images Kaggle data and selected images (a) 3rd, (b) 18th, and (c) 35th

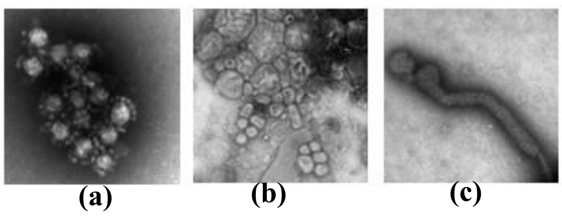

Fig. 4. The result enhanced the electron microscopy virus image label- 3rd by the Suggested method and compared with the other methods.

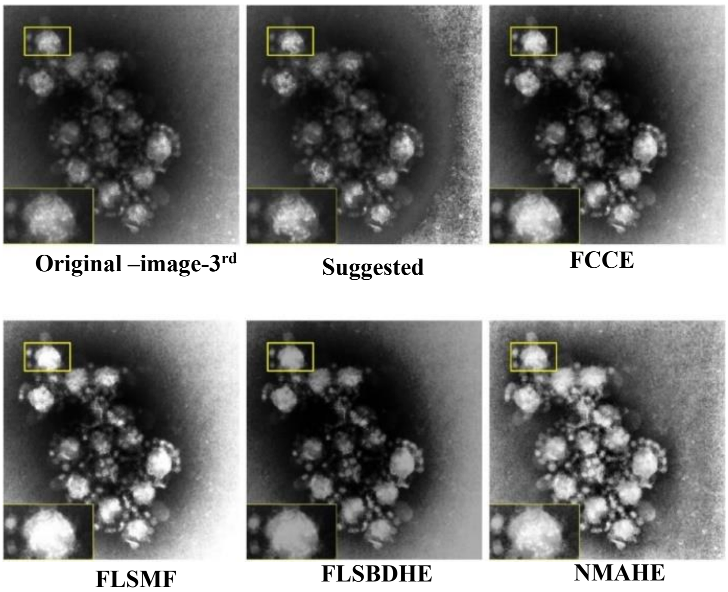

Fig. 5. The zoomed-in section of the original image labeled as the 3rd, compared with other methods

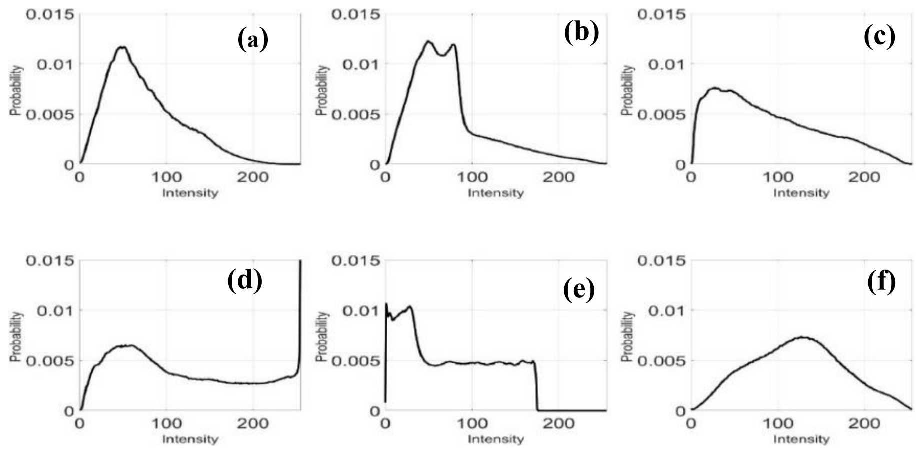

Fig. 6. The histogram of the original image labeled as the 3rd, compared with the results fro m other methods: (a) Original –image-3rd (b) Suggested,(c) FCCE, (d)FLSMF, (e) FSBDHE, and (f) NMAHE.

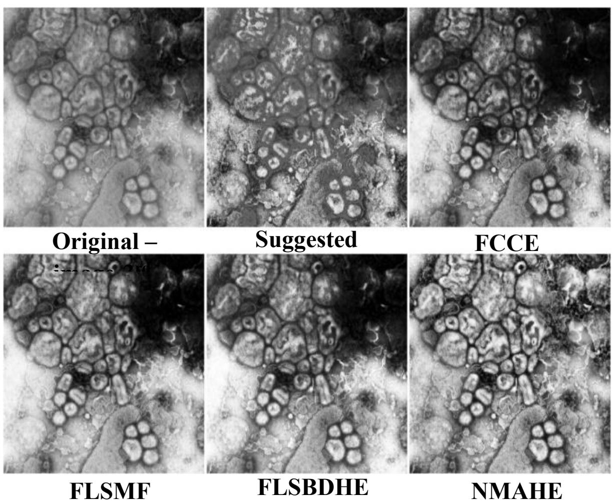

Fig. 7. The result enhanced the electron microscopy virus image label- 3rd by the Suggested method and compared wit the other methods.

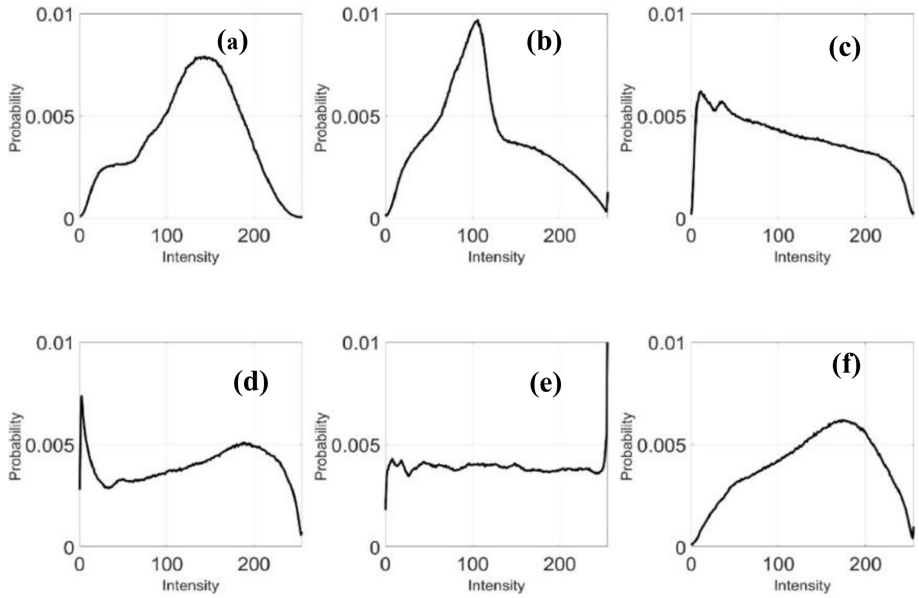

Fig. 8. The histogram of the original image labeled as the 3rd, compared with the results from other methods: (a) Original Image 18 (b) Suggested, (c) FCCE, (d)FLSMF,(e) FSBDHE, and (f) NMAHE.

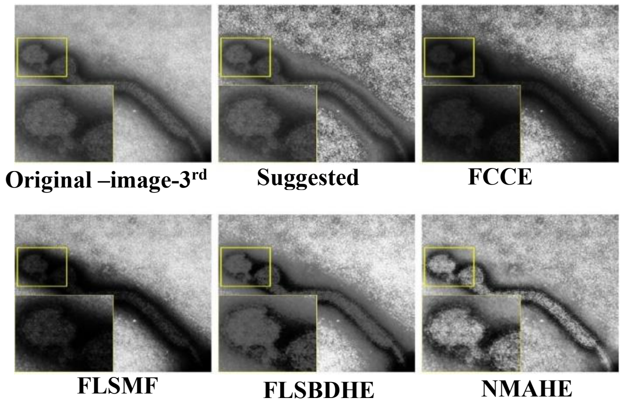

Fig. 9. The zoomed-in section of the original image label 35th and compared with other methods.

6. CONCLUSION

This study introduced a novel algorithm designed to enhance electron microscopic images of viruses that suffer from low contrast and inconsistent lighting. The proposed method's effectiveness was assessed using quality metrics including En, AG, Mstd, and CEM, and compared against existing algorithms (FCCE, FLSMF, FSBDHE, and NMAHE). The data analysis demonstrated that the proposed algorithm significantly improved the quality of electron microscopy images of viruses, outperforming all other compared methods. When evaluated across 36 images using various quality metrics, the method consistently delivered superior results. As summarized in Table 1, the algorithm achieved the highest average values for entropy (7.8000), AG (16.9968), Mstd (44.3216), and CEM (0.8752), confirming its accuracy and effectiveness.

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