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Aircraft Accident and Crash Images Processing with Machine Learning

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Abstract

The aviation industry is in constant need of innovations in terms of safety and operational efficiency. In this context, low-light image enhancement technologies play an important role in a numerous areas of disciplines, from night flights to accident and collision investigations. Machine learning, deep learning methods and traditional methods not only provide the aviation industry with an effective image processing and improvement capacity in low light conditions, but also reveal important information by analysing the data of low-light images of crashed and destroyed aircraft.

Within the scope of the study, traditional methods, deep learning method and machine learning are combined in order to enhance and process low-light ambient images of crashed and destroyed aircraft. By using Swish and Tanh activation functions together in the deep learning model, the performance of the neural networks used in the process of improving low-light environment images was improved and the image quality was increased. The enhanced images were evaluated and compared using PSNR and MSE as objective quality assessment measures. According to the PSNR and MSE criteria, the numerical results obtained from the image enhancement studies of the deep learning model were calculated as 29.85 and 100.44, respectively. The results introduce that the deep learning model provides better image enhancement than traditional methods. In conclusion, improvement of low-light image and processing is an important technological advancement in the aviation industry, enabling safer and more efficient operations. The successful of machine learning include deep learning and traditional methods shows that the aviation industry will achieve a safer and innovative structure in the future.

1. Introduction

The aviation industry continues its development on safer, effective and innovative flight systems with technological advances. In this context, the analysis of accident and crash images using machine learning can enable new developments in the aviation industry. Thanks to the enhancement of low-light ambient images obtained after aircraft accidents, it is an important source for analysing and investigating the causes of the event. Thanks to this, it can be used to improve the safety standards of the aviation industry, prevent similar incidents and improve flight systems.

Machine learning, an integral part of artificial intelligence, enables algorithms to acquire knowledge by analyzing large and complex datasets. By using machine learning, software applications can make result prediction more precise without the need for explicit programming. The basis of machine learning is to accept input data through algorithms and predict the output with the help of statistical analysis (Dhankar & Gupta, 2021).

Machine learning algorithms serve a crucial role in various domains. They are expert systems at classifying events, identifying relevant samples, making predictions, and even arriving at informed decisions. These algorithms can be employed individually or in combination to enhance accuracy when handling intricate and unpredictable data. (Karaburun, Arik Hatipoğlu & Konar, 2024).

Thanks to its ability to recognize objects, vehicles and people in the images, machine learning can determine the factors that caused the accident and their effects in detail. After the processing and enhancement of low-light ambient images obtained after the accident and breakdown, it provides a fast and precise analysis, allowing the evaluation of the condition of the aircraft involved in the accident and breakdown. This enables rescue teams to intervene more quickly and effectively at the scene.

Within the scope of the study, conventional methods and deep learning methods were used to enhance and analyze low-light ambient images of crashed aircraft. In this way, important features in the images are made clear and understandable. With traditional methods, basic corrections and filtering techniques were applied to the images to improve them. In the deep learning method developed on the basis of the knowledge and experience obtained, Convolutional Neural Networks (CNN) were used to reveal the important features in the images and to maximize the visual quality. Finally, the enhanced and restored versions of low-light environment images were processed using machine learning methods. In this way, it is aimed to enable the analysis of the damaged systems and the electronic, mechanical and structural parts of the aircraft in a short time after the accident and breakage of the aircraft.

1.1. Literature Review

In the study conducted by Perla et al., image enhancement can be performed quickly and effectively in images obtained under low-light conditions. In this study, the contrast-based fusion method was used, which overcomes the disadvantages of traditional methods and at the same time achieves more effective results (Perla & Dwaram, 2023).

Chen et al., use deep learning to enhance low-light images with text and numbers. In order for the enhancement of images to be effective, weighing feature maps are utilized together with a channel attention layer to increase the detail of images containing text and numbers (Chen et al., 2023).

Singh et al., utilized deep neural networks to improve image quality due to distortions in images acquired in low-light weather. The images acquired during the flight of the unmanned aerial vehicle include multi-resolution branches for a better understanding of different local and global context levels through various streams (Singh et al., 2022).

Zhang et al., proposed a deep learning method for self-supervised low-light image enhancement. In order to realize self-supervised learning, a constraint was added that the maximum channel of the reflection should be compatible with the maximum channel of the low-light image and the entropy should be maximized in the proposed model (Zhang et al., 2020).

Öztürk et al., explained the method obtained by using the transformation function, histogram expansion and histogram matching methods together, which are image enhancement techniques. Thanks to the Artificial Bee Colony Algorithm introduced in this study, images were improved by adjusting natural contrast and brightness (Öztürk & Öztürk, 2016).

Zhu et al., made improvements to the images using a multiple exposure fusion module used to solve high contrast and color problems to improve low-light images, and an edge enhancement module to improve the initial images using edge information (Zhu et al., 2020).

Tico et al., improved the images by using an image enhancement algorithm based on combining the visual information in two images taken with different exposure times under the same environmental conditions, taking advantage of the differences between the image distortions that affect both images (Tico & Pulli, 2009).

Park et al., proposed a learning-based low-light image enhancement algorithm, a histogram-based transform function estimation network that estimates transform functions using the histogram of an input image. This method was applied to low-light image enhancement using channel-wise intensity transform to obtain enhanced images (Park et al., 2022).

Liu et al., proposed an enhancement method for low-light Unmanned Aerial Vehicle images. This method aimed to increase global brightness and enhance local contrast. A brightness and chromaticity optimization process based on linear stretching was used to optimize the developed images (Liu et al., 2022).

Yu et al., introduced a new color constancy-based method to improve the visibility of low-light environment images, which involves applying a proper color constancy technique to the set of active pixels throughout the image (Yu & Liao, 2010).

2. Materials and Methods

Traditional methods, deep learning models and machine learning techniques play an important role in the analysis, enhancement and processing of low-light images of crashed and destroyed aircraft. These techniques are used to improve the quality of the images, to reveal important details and features, to improve contrast, to adjust brightness and to process the images.

Low light refers to environmental conditions that do not comply with general lighting standards (Perla & Dwaram, 2023). This situation can often lead to a decrease in image quality and distortion due to insufficient illumination or low illumination. The aim of low-light image enhancement is generally to increase the contrast of the image, improve the visual appearance and transform the image into a structure more suitable for human understanding or computer analysis, while at the same time reducing the noise in the images and obtaining the closest possible form to the original image (Öçer et al., 2022).

Image processing aims to obtain a more advanced image by performing the necessary operations on an image or to extract useful information from this image (Shen et al., 2017). Image enhancement refers to the operations performed to make an image that is useless or contains insufficient information for various reasons more visually or functionally usable. (Chen et al., 2023). A general mathematical expression of image enhancement can be written as in Equation 1, where *f(x, y)* represents the original image, *g(x, y)* represents the enhanced image, and the function a represents a particular enhancement process:

$$g(x, y) = a(f(x, y)). \tag{1}$$

With the integration of machine learning, traditional methods and deep learning models, by improving and processing low-light environment images, important details can be revealed and image quality can be improved and a clear and understandable image can be obtained. In this way, it provides an important visual contribution to better understand the causes of accidents and events. The analysis of low-light environment images allows for a more detailed examination of the events at the time of the accident. This helps rescue teams to intervene in a more effective and informed manner. In addition, the enhancement of the images can be used to evaluate post-accident events and improve safety standards in the aviation industry. The block diagram of the study is shown in Figure 1.

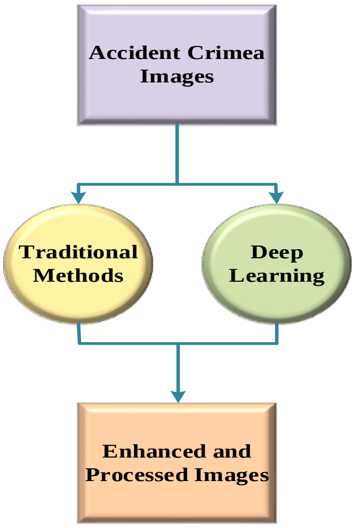

Figure 1. Block diagram of the study

2.1. Traditional Methods

Traditional methods are the most basic methods used for image enhancement. These methods are generally used to improve image quality or to emphasize certain features. In Google Colab application, Python programming language was used to enhance the images of crashed and destroyed aircraft.

2.1.1. Brightness Adjustment

It is used to increase or decrease the overall brightness levels of the image. Luminance refers to the amount of light a pixel reflects and is usually expressed as grayscale. This value is expressed in a range between 0 and 255, with 0 representing black (darkest tone) and 255 representing white (lightest tone) (Chen et al., 2023). In Figure 2, brightness adjustment was applied in order to better reveal the details of the image obtained in low light conditions of the crashed and destroyed aircraft.

Figure 2. Image with brightness adjustment applied

2.1.2. Contrast Adjustment

It gives more liveliness to the image by expanding or compressing the color ranges in the image. This method facilitates visual analysis by increasing the perceptibility of colors and can emphasize certain color tones (Chaney, 2013). Figure 3 shows the image of the crashed aircraft and the image with contrast adjustment applied.

Figure 3. Image with contrast adjustment applied

2.1.3. Thresholding Process

It is used to divide the image into black and white regions. By determining a certain threshold value, pixels larger or smaller than this value can be assigned to different colors. This method is used in various applications such as highlighting certain objects or features on the image, reducing noise, or adjusting the brightness contrast according to a certain threshold value (Gonzales & Woods, 2002). Figure 4 shows the original image of the crashed aircraft and the image with thresholding applied.

Figure 4. Image with thresholding applied

2.2. Deep Learning Method

Deep learning is a machine learning method designed to perform difficult-to-understand tasks. This method performs these tasks using artificial neural networks. It is a machine learning method used effectively in low-light image enhancement and object recognition systems. This methodology aims to improve image quality and gain the capacity to recognize objects by processing low-quality or low-light images through multi-layer artificial neural networks (Kayaalp & Süzen, 2018).

Artificial Neural Networks are known as machines equipped with a neural network consisting of thousands of artificial neurons or processing units that mimic the functioning of the human brain to perform certain tasks. These artificial neurons are brought together for the purpose of processing information and communicating, and they can work in interaction with each other to perform complex tasks. Artificial Neural Networks have the ability to learn patterns from data sets and are used especially in areas such as image recognition and image processing. In this way, significant successes are achieved in image enhancement and they play an effective role in applications such as sharpening low-resolution, noisy or damaged images (Haykin, 2009).

Convolutional Neural Networks (CNN), which stand out with their ability to recognize complex visual patterns by detecting different features, are an artificial neural network generally preferred in image analysis and enhancement applications. The filtered data sets obtained by CNN using large data sets in the training phase are prepared to process the input data in the inference phase. In the training phase, it is achieved by creating a feature matrix of the features extracted from the input data through convolution and pooling layers. It is possible that this feature matrix can be made more effective in recognizing complex visual patterns by increasing the learning capabilities of the network. In the inference phase, it is accurately determined which class the input image belongs to, with the information obtained during the training process. These operations, performed using full connection layers and activation functions, perform the correct classification using the operations learned by the network and ultimately complete the inference phase (Ahmadian et al., 2021).

The match between inputs and hidden layers in artificial neural networks is determined by activation functions. These functions take the data in the input layer, calculate the weighted sums of the neurons in the hidden layer, and then convert it into output. Activation functions play an important role in the learning process and information transmission of the neural network. Thanks to this process, the network has the capacity to learn complex relationships and patterns.

Within the scope of the study, Swish and Hyperbolic Tangent activation functions were used. Swish is an activation function discovered by Google in 2017. The Swish function is obtained by multiplying the input value by the sigmoid function and is generally preferred to the ReLU function because it is thought to have smoother gradients (Sharma, Sharma & Athaiya, 2017). The Swish function is expressed mathematically according to the formula in Equation 2.

$$swish(x) = x.sigmoid(x). \tag{2}$$

In the given equation, the x value grows and as it gets closer to x regarding negative values, it provides a smoother and more continuous output approaching 0.

The hyperbolic tangent (tanh) activation function is an activation function used in many artificial neural network models. The Tanh function provides a symmetrical structure around the origin by compressing the input values in the range [-1, 1]. Symmetry around the origin makes the tanh function a preferred activation function in many applications (Sharma, Sharma & Athaiya, 2017). The hyperbolic tangent function is given mathematically in Equation 3.

$$tanh\,(x) = \frac{e^{2x}-1}{e^{2x}+1}. \tag{3}$$

According to the mathematical expression given in Equation 3, the output values of the function vary between -1 and 1. The function value is zero at the origin (0,0) and approaches -1 or 1 as the input values increase or decrease. This feature allows us to obtain a symmetric distribution around the origin when using the tanh function. The Tanh activation function is often used in output layers, especially in classification problems.

Deep learning is also used in an important field such as improving and analyzing low-light images of crashed aircraft. This method performs an improvement process using learned representations to make low-quality or distorted images clearer, sharper and more meaningful. At the same time, processing crash images with machine learning makes a significant contribution to the process of understanding the causes and effects of accidents. Figure 5 shows a deep learning model applied to a low-light image of an aircraft that has suffered an accident and destruction.

Figure 5. Image with deep learning model applied

Machine learning is used to extract details from crash images, recognize objects, extract features and understand accident events. These techniques can help rescue teams respond quickly and effectively. Additionally, machine learning algorithms can provide important information about accident causes and effects by analyzing patterns in images. Deep learning and machine learning are helping to improve safety and better understand accident consequences in the aviation industry.

Enhancements to low-light images were conducted utilizing the Python programming language's Tensorflow library within the Google Colab environment. TensorFlow, an open-source software library created by Google, is designed for the execution of machine learning algorithms and deep learning applications. Its adaptable architecture empowers developers to execute computations across various platforms. TensorFlow boasts attributes such as remarkable computational efficiency, flexibility, robust portability, support for multiple languages, and optimized performance. (Kirac & Özbek, 2024).

The dataset has been specifically used for the purpose of enhancing low-light images. It comprises 80 images designated for training purposes and an additional 20 images allocated for testing. Within this dataset, each pair of images comprises a low-light input image alongside its corresponding well-exposed reference image. This setup facilitates the training and evaluation of algorithms aimed at enhancing images captured under low-light conditions, thereby offering a reliable benchmark for assessing the effectiveness of various image enhancement techniques.

In the deep learning method performed in the Google Colab environment using the Python programming language, this structure is a flat CNN consisting of a symmetric combination of seven layers. Each layer is in the 3x3 range and consists of 32 convolutional kernels with one step. After this stage, Swish is used as the activation function. In the last evolution layer, the generation of 24 parameters for 8 iterations using the Tanh activation system consists of a structure containing three curved parameter maps for three channels. Finally, the learning rate parameter for the deep learning model was set as 0.0001 and the process was carried out. The deep learning model is shown in Figure 6, and the hyperparameters and values used for this model are given in Table 1.

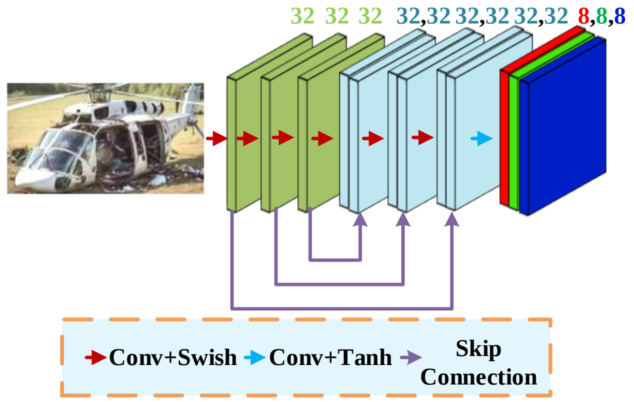

Figure 6. Deep learning architecture

Table 1. Hyperparameters and values used in the deep learning model

Hyperparameters	Value
Learning Rate	0.0001
Activation Function	Swish, Tanh
Epoch	100
Neural Network	CNN
Convolutional Layers	7
Size	3 × 3

2.3. Loss Functions

Loss functions play an important role in image enhancement. These functions are used to provide the closest approximation to the original of an image with corrupted or missing pixels. 5 loss functions were used in the deep learning model: Color Constancy, Exposure, Lighting Uniformity, Spatial Consistency and Total losses.

2.3.1. Color Constancy Loss

Color constancy loss is used to correct possible chromatic aberrations in enhanced images. With this loss function, it aims to obtain more accurate and realistic colors by increasing the color consistency in images.

2.3.2. Exposure Loss

Exposure loss is used to limit under- or over-exposed areas in images. This method aims to obtain a more balanced and visually better image by balancing the contrast.

2.3.3. Illumination Smoothness Loss

To preserve monotonicity relationships between neighboring pixels, illumination smoothness loss is added to each curve parameter map. This loss function ensures smooth and natural illumination of the image, making the transitions between pixels smooth and natural, thus preserving the details in the image.

2.3.4. Spatial Consistency Loss

Spatial consistency loss aims to increase the spatial coherence of the image by preserving the contrast of neighboring regions between the input image and the enhanced image. In this way, the details in the improved image are revealed more consistently.

2.3.4. Total Loss

It refers to the total loss occurring during Color Constancy, Exposure, Lighting Uniformity and Spatial Consistency losses. This total loss covers the differences between the original image and the processed image as a result of the processing, and is generally tried to be optimized to preserve or improve image quality.

2.4. Evaluation Criteria

These are metrics used in the fields of image enhancement and image processing to quantitatively evaluate the quality of an image. These metrics generally aim to measure the differences between a reference image and a damaged or enhanced image. Mean Square Error (MSE) and Peak Signal-to-Noise Ratio (PSNR) are the metrics used in image evaluation. MSE measures the similarity of the damaged image to the reference image by calculating the average of the error squares on a pixel basis. PSNR expresses the similarity of the damaged image to the reference image in the logarithmic scale of MSE.

2.4.1. Peak Signal-to-Noise Ratio (PSNR)

Peak Signal-to-Noise Ratio (PSNR) is a full-reference quality assessment metric used to measure and evaluate differences between a damaged image and a reference image. This metric expresses the similarity level between two images in logarithmic decibels. In this formula, the maximum pixel value is usually 255. MSE represents the Mean Square Error between the damaged and reference image. The mathematical calculation of the *PSNR* value is given in Equation 4.

$$PSNR = 10.log_{10}\left(\frac{Maximum\ Pixel\ Value^2}{Mean\ Square\ Error}\right). \quad (4)$$

PSNR quantitatively evaluates image quality by taking into account the ratio between signal and noise while determining the degree of similarity between two images. A higher PSNR value means lower MSE and better similarity. As the PSNR value increases, it indicates an image that is less damaged and has better image quality.

2.4.2. Mean Square Error (MSE)

It is a metric used to measure the differences between the reference and enhanced image. In particular, it is used to evaluate how similar one image is to another. MSE is expressed as the average square of the differences in pixel values between images. The mathematical expression of *MSE* is given in Equation 5. In this equation, N represents the total number of pixels, I_i represents the value of the i-th pixel in the original image, and K_i represents the value of the i-th pixel in the damaged image. The lower the value of MSE, the higher the similarity between two images.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(I_i - K_i)^2. \quad (5)$$

3. Result and Discussion

A methodology has been developed to measure the image processing techniques used in the field of aviation on the low-light ratios of aircraft exposed to accidents and crashes and to evaluate the obtained results objectively. This algorithm includes the processing of details and machine learning techniques, analysis and lens evaluation of the results obtained. Initially, different image enhancement techniques and machine learning methods are applied to aircraft with crash and refraction, low light ratios. These techniques are rated as performance ratio, such as increasing the brightness of images, contrast light, reducing noise, improving their performance and clarity. By operating low light environment rates with machine settings, it is possible to detect electronic, mechanical and durable damages of the aircraft more clearly and understandably by revealing important details and features in the images.

As a result of the operations performed on the low-light environment image of the aircraft that was subject to accident and breakage, it was observed that the deep learning model was more vivid, clear and perceptible than other computer monitoring. This highlights the superior properties of the deep learning model in relation to the view. Complex patterns of the deep learning model are learned more effectively, allowing important details in the images to be revealed more accurately. As a result, it appears that the deep learning model can be preserved more effectively in terms of visual quality and perceptibility.

The improvement and processing of images was carried out using the Python programming language in the Google Colab application. In this process, objective image quality evaluation such as mean square error (MSE) and Peak Signal-to-Noise Ratio (PSNR) were used to compare image processing methods.

Figure 7 shows the graph showing the test and verification values of color constancy loss. According to the color constancy loss graph, the training and validation values approached approximately 0.09 and 0.04, respectively. These values tend to be parallel to each other. In this way, the color constancy loss function minimizes color changes and brings it closer to the original image.

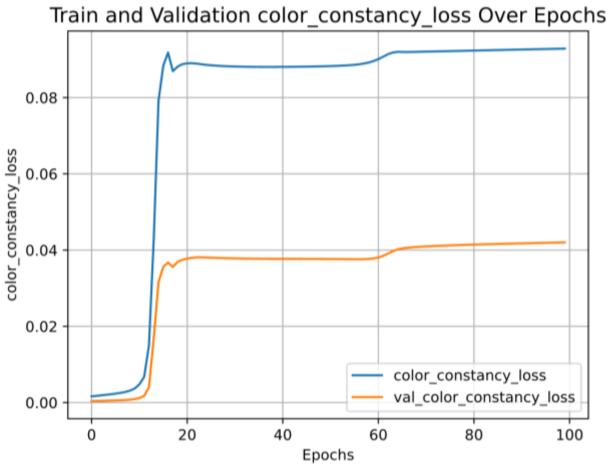

Figure 7. Training and validation plot of color constancy loss

Figure 8 shows the graph showing the test and verification values of exposure loss. According to the graph, training and validation values converge to 1 and 0.5, respectively. Training and verification values vary balancedly with each other. In this way, it provides a more balanced and accurate illumination of the images to be improved, thus revealing the details in the images better.

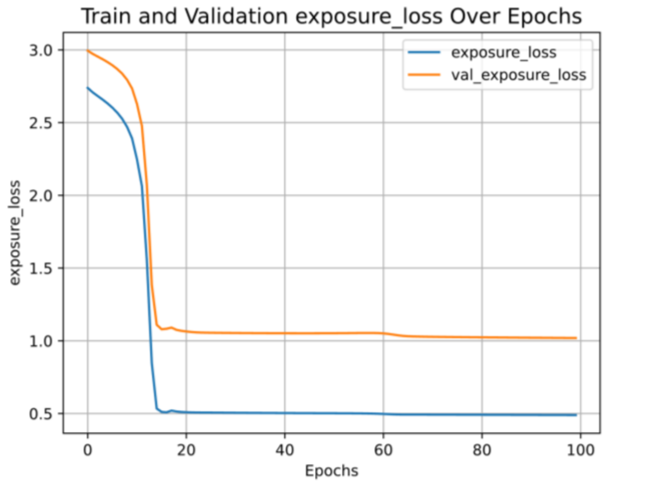

Figure 8. Training and validation plot of exposure loss

Figure 9 shows the graph showing the test and verification values of illumination uniformity loss. According to the illumination uniformity loss graph, training and validation values converge to 0.1. As a result of the convergence of training and validation values towards the same value, it makes the lighting more balanced in all regions of the images.

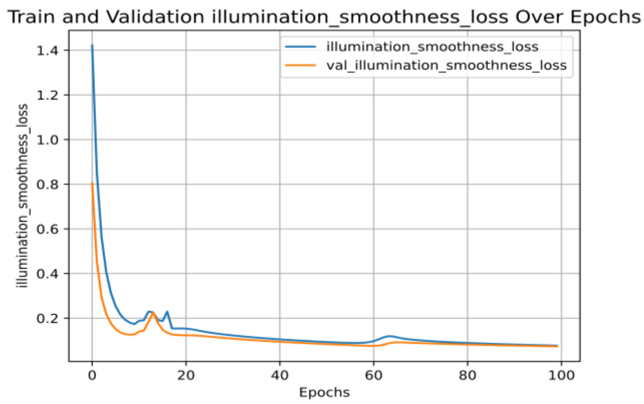

Figure 9. Training and validation plot of illumination smoothness loss

Figure 10 shows the spatial consistency loss graph showing the test and validation values. According to the graph, training and validation values converge to approximately 0.35 and 0.26, respectively. Data regarding training and validation values change in parallel with each other. In this way, the improved images are more balanced and more natural.

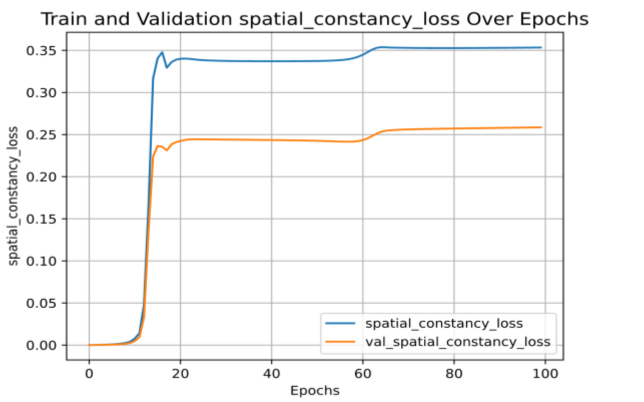

Figure 10. Training and validation plot of spatial consistency loss

Figure 11 shows the graph showing the test and verification values of the total loss. In the total loss graph, training and validation values converge to approximately 1 and 1.4, respectively. Training and validation values vary evenly. In this way, the total loss function minimizes the quality lost during image improvement and ensures that the image obtained as a result of the process is of the highest possible quality.

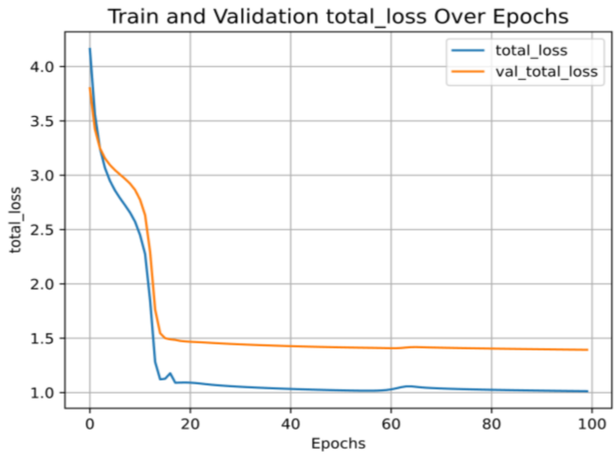

Figure 11. Training and validation graph of total loss

Numerical results of the evaluation made with image evaluation criteria are recorded in Table 2. These results were used to compare the effectiveness of different image enhancement techniques and machine learning algorithms and to determine the most suitable methods for enhancing images of crashed aircraft in the aviation industry.

Table 2. Image quality evaluation criteria

Methods	PSNR	MSE
Thresholding Adjustment	25.74	111.31
Brightness Adjustment	27.84	106.86
Contrast Adjustment	27.95	104.01
Deep Learning	29.85	100.44

As a result of the evaluation using image evaluation criteria, it was seen that the deep learning model was more successful than traditional methods. The PSNR values of the brightness adjustment and the deep learning model were calculated as 27.84 and 29.85, respectively. The high PSNR value obtained shows that the deep learning model improves image quality more effectively. In addition, the MSE values of the contrast adjustment and the deep learning model were obtained as 104.01 and 100.44, respectively. According to these results, it appears that the deep learning model is more successful. The decrease in the MSE value indicates that the model's predictions are closer to the real values and therefore the model improves more effectively.

This study aims to objectively evaluate the effectiveness of image enhancement techniques in the field of aviation on crashed aircraft and to reveal the potential of these techniques in security and analysis applications. In this way, it is aimed to detect electronic, mechanical and structural damages of aircraft more effectively and to increase the safety of the aviation industry.

5. Conclusion

This study aims to reveal the potential of the methods used in security and analysis applications by evaluating their effectiveness on low-light ambient images of crashed and crashed aircraft from an objective perspective. In this process, where machine learning algorithms are applied, image enhancement methodologies are used to determine the electronic, mechanical and structural damages of aircraft in more detail and precision. Finally, the findings demonstrate the effectiveness of the techniques used on crashed aircraft and can be used in aviation safety and analysis. This study may shed light on future research, aiding advances in image processing, image enhancement, and machine learning in the aviation industry.

Ethical approval

Not applicable.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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