Anadolu Psikiyatri Dergisi || ISSN: 1302-6631 || Volume 26; Number 3
https://doi.org/10.5281/zenodo.15592426

Image Augmentation for Spinal Herniation Detection Using Fashion-MNIST and ImageNet

R.Vidya[1]*, S.Sasikala[2]

[1] Department of Computer Science and Engineering

[2] Department of Artificial Intelligence and Data Science

Velammal College of Engineering and Technology

Madurai, Tamil Nadu. India

Abstract — In order to improve deep learning models for image classification on spinal cord disc herniation, this research study investigates and assesses a variety of data augmentation techniques. Fashion-MNIST and ImageNet are two examples of augmentation techniques that are used to analyze the improvement of feature rate and accuracy of the datasets. Significant gains in feature extraction rates and classification accuracy are shown when techniques like Histogram Equalization, Gamma Correction, CLAHE, Unsharp Masking, and Edge Enhancement are used. This study examines how different image augmentation methods affect model accuracy using two different datasets: ImageNet and Fashion-MNIST. The effects of Edge Enhancement, CLAHE (Contrast Limited Adaptive Histogram Equalization), and Unsharp Masking are investigated. Unsharp Masking was the most successful technique for Fashion-MNIST, closely followed by Edge Enhancement and CLAHE. The CLAHE continuously delivered excellent results.

Index Terms: computer-aided engineering, decision support systems, electronic medical records, machine learning, medical information systems, ImageNet

..

I. Introduction

The field of image classification has undergone a significant transformation in recent years due to the development of deep learning, which has made it possible to analyze visual data more accurately and efficiently. Augmenting data with neural network models [1] is a convenient method of increasing the size of data, and it has been used frequently in computer vision tasks with impressive results. Data augmentation, which creates new training instances by making different changes to the original dataset, is essential to improving the performance of deep learning models. The model's robustness and generalization abilities are enhanced by this process, which also expands the dataset's size and diversity.Traditional data augmentation techniques, such as horizontal and vertical flips, rotation, zooming, and shearing, have been widely used to introduce variations in the training data. More advanced methods, like Cutout and Mix up [2], further enhance the diversity and quality of the training datasets, reducing the risk of over fitting [3],[4] and improving model performance. The purpose of this study is to evaluate the effectiveness of different data augmentation techniques on two popular datasets: Fashion-MNIST [5],[6] and ImageNet [7 - 9]. The datasets are obtained from Spine group Beverly Hills. These datasets represent different levels of complexity and diversity in image data, providing a comprehensive basis for assessing the impact of augmentation methods. Specifically, this research aims to compare the performance of traditional augmentation methods, such as Histogram Equalization [10], Gamma Correction [11], CLAHE [12], Unsharp Masking [13], and Edge Enhancement, in enhancing feature extraction rates and boosting classification accuracy [14].

This study aims to determine the best augmentation strategies for enhancing deep learning models in image categorization tasks by methodically examining such methods. Furthermore, this study investigates the methods' scalability and applicability across various datasets, offering important insights into their potential for use in practice. The goal of this research is to advance the field of image analysis and its multiple uses by helping to create deep learning models that are more reliable and general-purpose.

II. DATA AUGMENTATION METHODS

The process of adding new training instances to an existing dataset by making different changes to it in order to increase its size and diversity and enhance the model's capacity for generalization is known as data augmentation. Shear transformation [15] is a widely used technique that tilts the image vertically or horizontally and moves it in a specific direction to deform its shape and increase the model's resistance to minor distortions. Zooming in is an additional technique that involves resizing the image to its original size and cropping it from the edges. This method helps the model focus on different areas of the image and improves its recognition of objects in varied orientations. Reversing the image horizontally or vertically [16], or reflection, strengthens the model's resistance to orientation changes and is helpful in identifying symmetrical objects rotation, which involves rotating the image by a defined angle range, allows the model to become invariant to object orientation, boosting its ability to recognize things regardless of how they rotate in the image. These strategies, when used together, produce a more diverse and thorough training dataset, hence improving the performance and generalization capabilities of deep learning models in picture classification [17]. The Fig.1. shows the original image of a spinal cord herniated image. Various techniques are applied to the original image and the comparison of the feature rate and accuracy improvement rate between the augmentation methods Fashion MNIST and Imagenet are analysed. These techniques are commonly used in image processing and machine learning to create diverse training datasets. The techniques discussed are Image Flipping, Image rotation, Noisy Image and Color jittered image.

Here’s a detailed description of each augmentation method shown in the image:

a) **Original Image**: The starting point for all augmentations, showing the spinal cord herniated image shown in Fig 1 in its initial state.

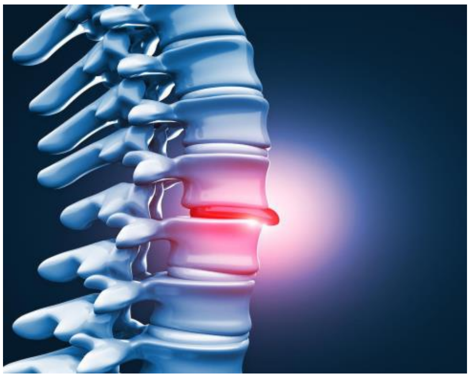


Figure 1 Original image (Herniated Spine)

b) **Image Horizontal Flipping**: In horizontal flip operation on the spinal cord herniation image, it is mirrored along its vertical axis. This transformation effectively flips the left and right sides of the image. Fig.2. shows the horizontal flip image of the Spinal Cord herniated image. Flipping photos doubles the number of samples in a dataset. This aids in the development of more robust machine learning models, particularly when the available data is restricted.

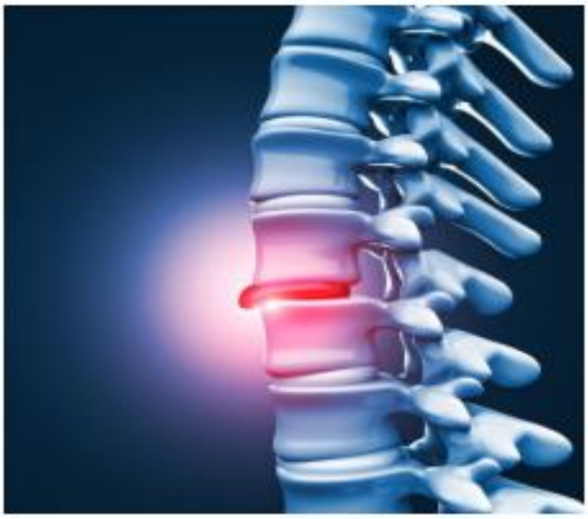


Figure 2 Horizontal Flip

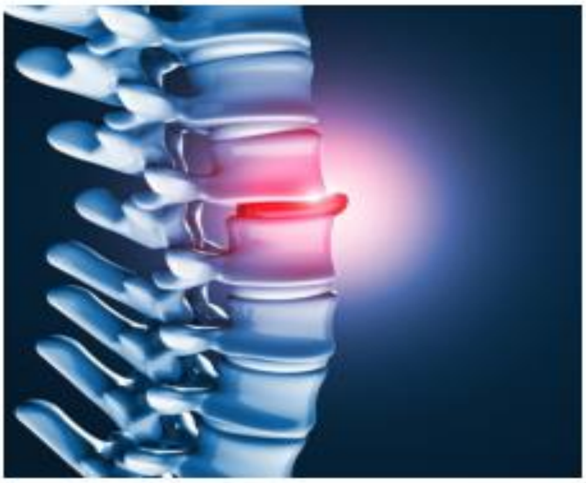


Figure 3 Vertical Flip

c) **Image Vertical Flipping:** During the vertical flip operation on the spinal cord herniation picture, it is reversed along its horizontal axis. This indicates that the image's top and bottom sections were switched. For example, if the original image showed the herniated portion of the spinal cord near the top, the flipped image would show it towards the bottom shown in Fig.3. Flipping the image is a simple yet efficient data augmentation approach for increasing the diversity of the training sample. Increasing the diversity of the training sample.

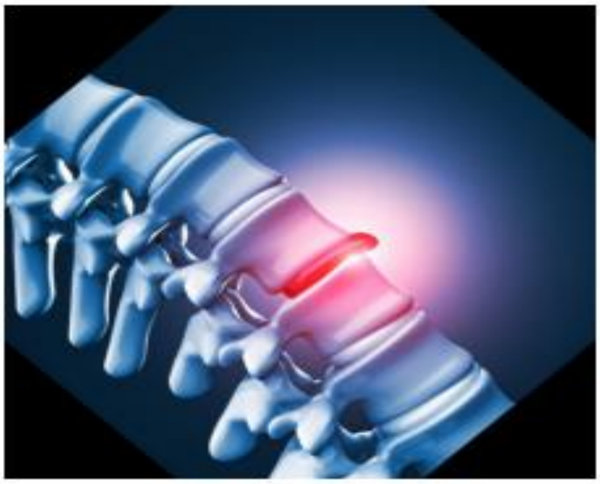


Figure 4 Rotated Image

d) Image Rotation: The spinal cord herniation image was rotated by a specific angle, in this case 45 degrees is shown in Fig.4. This alteration involves rotating the image about its center, changing the direction of the herniated area. The outcome is a new perspective on the image, with the spatial arrangement of the spinal cord and herniation altered accordingly. Image rotation in medical imaging increases data augmentation by diversifying the training sample and making the model more resistant to different orientations. It also aids in simulating varied viewing angles, which is critical for accurate diagnosis and optimal treatment planning.

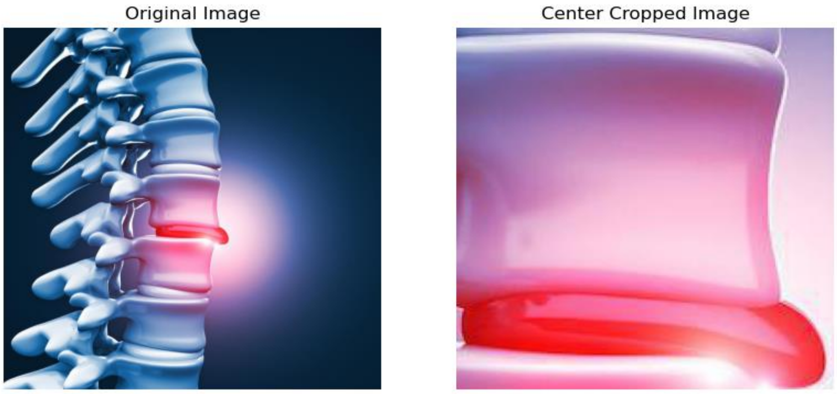
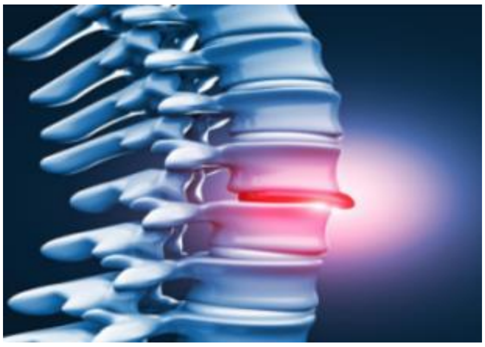


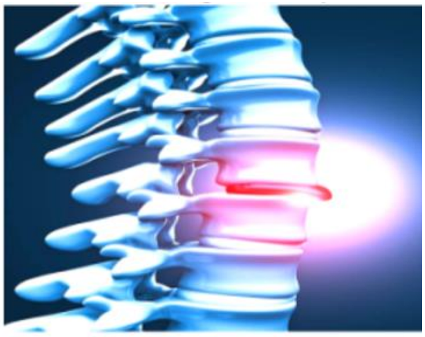
Figure 5 Centre Cropped Image

e) Image cropping is the process of selecting a predetermined rectangular portion of an image and discarding the rest. For a variety of reasons, including data augmentation, focused analysis, and improved computer efficiency, cropping is a crucial preprocessing step in medical imaging. Cropping an area from the image's center is known as center cropping. This technique, which ensures that the most pertinent portions of the image are maintained, is especially helpful when you want a consistent, centered view of the image (Fig. 5).

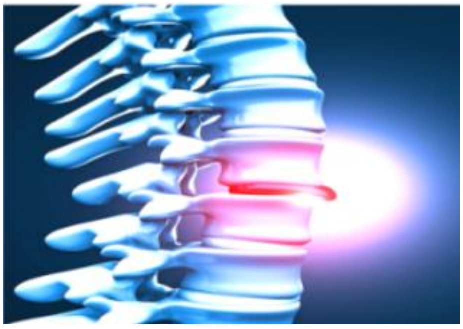
f) Color Adjustments: Colour adjustments such as brightness, contrast, saturation, and hue are crucial in medical imaging for enhancing the visibility of details, improving diagnostic accuracy, and preparing images for further analysis is shown in Fig.6.



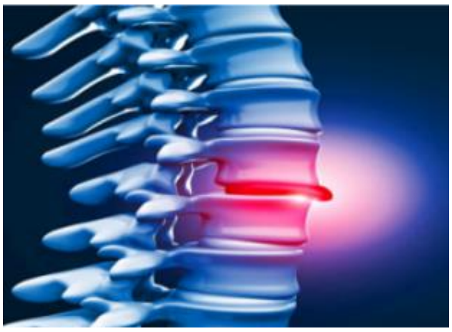
i. Original image



ii. Brightness adjusted



iii. Contrast adjusted



iv. Saturation adjusted

Figure 6 Color adjustments of the Image

g) Noise Injection: The intentional introduction of random fluctuations, or noise, into an image is known as noise injection. This method is widely used in computer vision and image processing to enhance model generalization, test algorithm resilience, and simulate real-world situations. In medical imaging, noise injection—more especially, Gaussian noise—is a useful method for testing algorithm resilience, improving model generalization, and simulating real-world scenarios. Figure 7 illustrates how adding Gaussian noise to images helps us better prepare and assess imaging systems and algorithms for handling the variability and defects that arise in actual medical imaging scenarios for spinal cord degeneration.

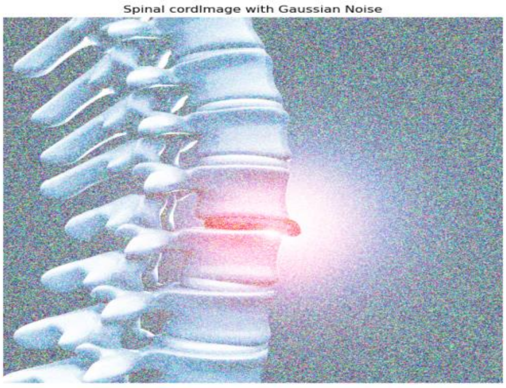


Figure 7 Spinal cord image with Gaussian noise

h) Blurring and sharpening of the Image: Blurring and sharpening are essential image processing techniques that alter the appearance of images. In the context of medical imaging to enhance the spinal cord degeneration image, these approaches aid in image quality refinement, visibility improvement, and image preparation for subsequent analysis which is shown in Fig.8.

Figure 8 Blurring and Sharpening Image of Spinal cord Herniation

i) Grayscale Conversion: The process of turning a color image into different shades of grey by concentrating only on light intensity and not color is known as greyscale conversion. Because it streamlines the image by eliminating color information and highlighting structural details based on intensity variations, this method works especially well in medical imaging, such as spinal imaging. By producing stark contrasts, grayscale images in modalities like MRI or CT scans make anatomical features and abnormalities—like the herniated discs in Fig. 9 more visible. This consistent representation facilitates consistent interpretation and is compatible with diagnostic algorithms designed for data from a single channel. In general, grayscale conversion enhances the clarity of key features in medical images, lowers processing complexity, and improves diagnostic accuracy.

Figure 9 Gray Scale Image

III. Combining Traditional and Advanced Data Augmentation Techniques

Intentional data augmentation involves the strategic application of various techniques to enhance the diversity and quality of training datasets for deep learning models. A mix of traditional methods, such as horizontal and vertical flips, zooming, cropping, shearing, and rotation, is combined with advanced techniques like Cutout and Edge Enhancement [2],[18] to significantly boost model performance. Traditional methods improve the model's robustness to common variations in image data, such as orientation and scale. Advanced techniques like Cutout, which randomly masks out portions of an image, and the edges, which blends two images and their labels to create new training examples, further enhance the model's ability to generalize by introducing novel variations and preventing overfitting [19],[20]. This combination of techniques provides a comprehensive augmentation strategy, improving the model's accuracy and resilience in real-world applications.

IV. Algorithm for Cut and Edge Method for Data Augmentation

The Cut and Edge Method is a data augmentation technique that highlights important features while enhancing training datasets' diversity and quality through controlled modifications. The two main elements of this approach are "cutting" and "edge enhancement." Dividing an image into smaller patches and then applying transformations like translation, rotation, or scaling to these portions is known as cutting. This adds to the collection's diversity by offering fresh samples with a range of perspectives and compositions. Edge Enhancement uses sharpening filters and edge-detection algorithms to draw attention to the image's edges and boundaries. The method enhances the contrast and quality of the features by making these edges more visible, which makes them stand out more.

Cut and Edge Method involves in the process of segmenting, transforming, and blending image patches, tailored specifically for applications such as spinal cord herniation detection. The process involves three main steps:

i. Segmenting Patches

ii. Transforming Patches

iii. Blending Results

Algorithm for Spinal Cord Herniation Detection

4.1 Segmenting Patches

i) Objective:

To Extract patches from the image based on segmentation

ii) Input:

I: Original image

S: Segmentation mask (binary mask identifying regions of interest)

iii) Steps:

a) Preprocess:

- Convert I and S to the same dimensions if necessary

b) Extract Segmented Regions:

- For each connected component C_i in S:
- Identify the bounding box B_i of Ci
- Extract the patch Pi from I using Bi:

$$Pi = I[x_{min} : x_{max}, y_{min} : y_{max}]$$

Where $[x_{min}, x_{max}]$ and $[y_{min}, y_{max}]$ are the coordinates of the bounding box B_i.

Store Pi in the set P.

iv) Output:

Set of segmented patches P={P1,P2,…,Pn}

4.2 Transforming Patches

i) Objective:

Apply transformations (e.g. rotation, scaling) to each patch.

ii) Input:

P : Set of segmented patches

iii) Steps:

Transformation Function: Let Ti be the transformed version of Pi.

a) Define Transformations:

Choose transformation parameters (e.g. angle for rotation, scale factor for scaling).

b) Apply Transformations:

- For each patch Pi in P:
- Apply the transformation Ʈ to Pi:

Ti = Ʈ (Pi, parameters)

- Sore Ti in the set Ʈ
- Otherwise, simply overlay Ti onto R.

iv) Output:

Set of transformed patches T={T1,T2,…,Tn}

4.3 Blending Result

i) Input:

R : Blended result

ii) Output:

Blending Function: Let R be the final blended result

iii) Steps:

a) Initialize Result Image

Create an empty image R with dimensions matching the original image I.

b) Apply Blending

- For each transformed patch Ti in Ʈ:
- Determine its position (xstart, ystart) in the result image R
- If using a blending mask M, blend Ti into R using M:

R[xstart : xstart + height, ystart : ystart + width] = R[xstart : xstart + height, ystart : ystart + width] X (1-M) + Ti x M

- Otherwise, simply overlay Ti onto R.

iv) Output:

- Final blended result R

V. APPLICATION OF THE CUT AND EDGE METHOD TO SPINAL HERNIATION IMAGING

The Cut and Edge Method [22][23] is applied to the spinal cord MRI image to enhance the dataset for analyzing spinal herniation. This method involves several key steps designed to create a more robust and varied dataset for training machine learning models.

5.1 Segmented Patches: The process begins by segmenting the original image into smaller, manageable patches. Each patch is extracted from different regions of the spinal cord MRI. For instance, patches of size 100x100 pixels are cut out from the original image is depicted in Fig 10. This segmentation allows us to focus on specific areas of interest within the spinal cord, such as regions where herniation might be visible. Segmenting the image into these smaller patches helps in analyzing localized features and creates a foundational set of data for further processing

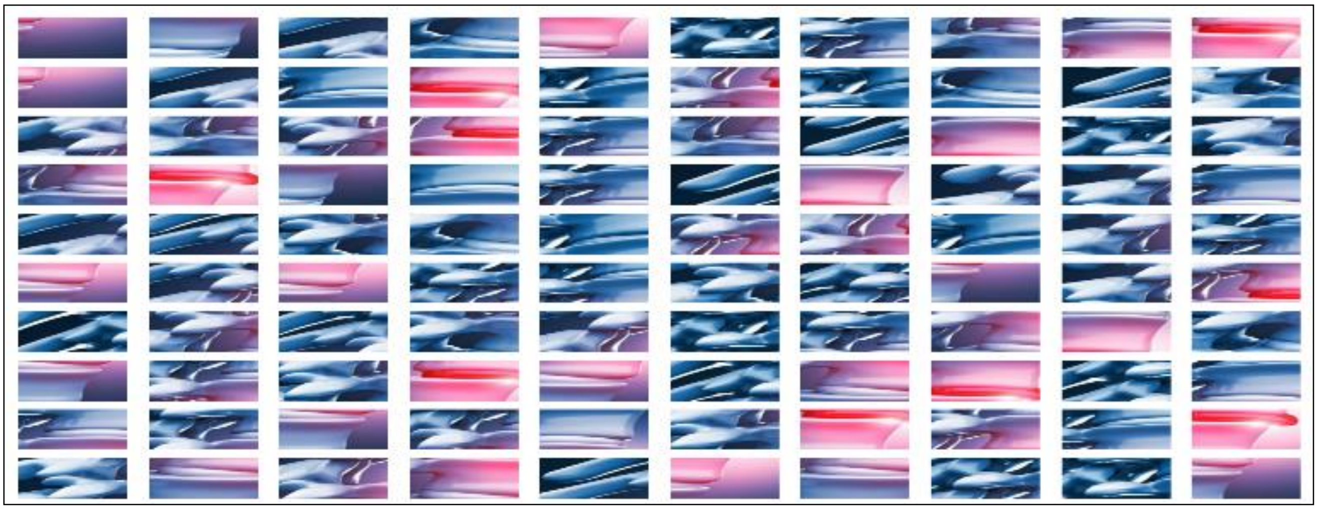


Figure 10 Segmented Patches

5.2. Transformed Patches: Once the patches are extracted, each one undergoes a series of transformations to introduce variability and enhance the dataset. The transformations applied include:

5.2.1 Translation: Translation is Shifting the patches horizontally or vertically by random amounts. This simulates different positions of the herniation within the spinal cord and helps in accounting for variations in positioning is shown in Fig.11.

https://doi.org/10.5281/zenodo.15592426

Figure 11 Translated Patch with random translation

5.2.2 Rotation: Rotating the patches by random angles. This ensures that the model can handle different orientations of the herniation and improves its ability to generalize across various viewpoints is shown in Fig.12.

Figure 12 Translated Patch with random translation

5.2.3 Scaling: Adjusting the size of the patches by scaling them up or down. This helps in addressing variations in image resolution or zoom levels and simulates different magnifications of the spinal cord is shown in Fig.13.

Figure 13 Scaled Patch with Random Scaling

5.3 Blending Result:

Blending the modified patches back into a fresh, enhanced image is the last step. In order to produce a composite image that takes into account the variability brought about by the transformations, the altered patches are either applied to a fresh canvas or mixed with portions of the original image. Figure 14 illustrates how the blending process makes sure the patches line up and fit correctly within the image's borders to create a unified and varied augmented image. A richer dataset for model training is provided by this blended image, which represents different spinal herniation scenarios and characteristics.

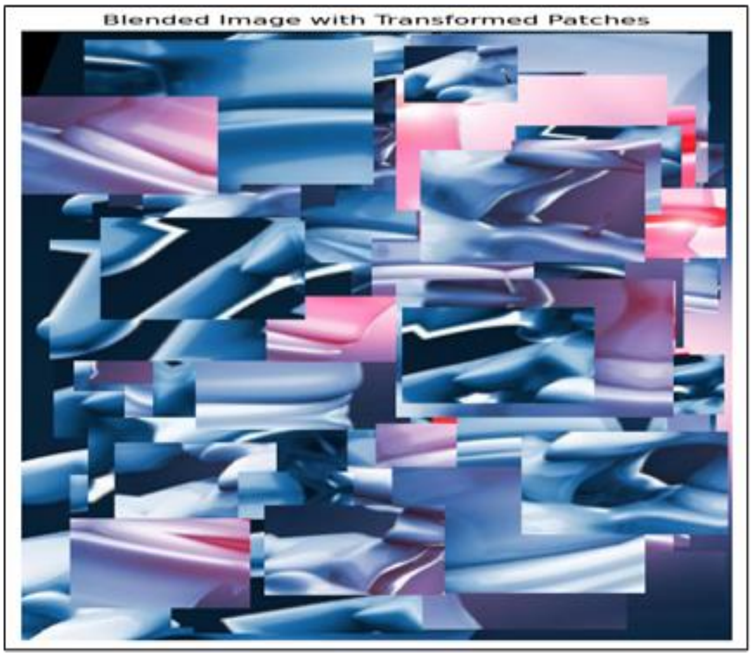
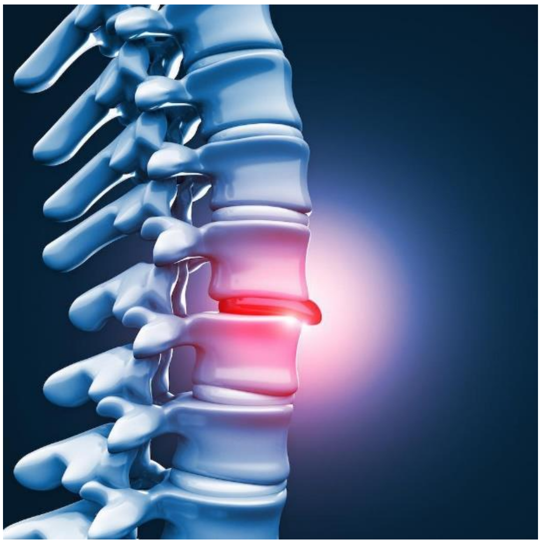


Figure 14 Blended Image

Histogram Equalization, Gamma Correction, CLAHE, Unsharp Masking, Color Adjustment, Noise Reduction, and Edge Enhancement are all image processing techniques used to improve image quality and enhance visual features. They fall under different categories based on their primary function and the type of enhancement they provide. Here's how each technique is categorized and discussed below. Image enhancement techniques such as Histogram Equalization (CLAHE) [12],[24] Gamma Correction, and Unsharp Masking play pivotal roles in improving the visual quality and interpretability of images. Histogram Equalization adjusts the intensity distribution across an image, enhancing contrast and visibility of details by redistributing pixel intensities. Gamma Correction applies a power-law transformation to adjust brightness and contrast, beneficial for correcting image brightness variations due to different lighting conditions. CLAHE refines upon standard Histogram Equalization by limiting contrast amplification in localized regions, thereby enhancing local contrast and overall visual quality. Unsharp Masking [13],[25] sharpens images by subtracting a blurred version from the original, effectively highlighting edges and fine details. Coupled with data augmentation techniques like flipping, rotation, scaling, and color adjustments, these methods collectively enrich training datasets for machine learning models, fostering improved performance, robustness, and generalization across various applications such as image classification and object detection. Fig.15. depicts a visual comparison the original image with the enhanced image applied to the Spinal disc herniation

VI. IMAGE ENHANCEMENT TECHNIQUES

To enhance visual features and improve image quality, image processing techniques such as Histogram Equalization, Gamma Correction, CLAHE, Unsharp Masking, Color Adjustment, Noise Reduction, and Edge Enhancement are employed. They fall under different categories based on their primary function and the type of enhancement they provide. Here's how each technique is categorized and discussed below, image enhancement techniques such as Histogram Equalization(CLAHE) [12],[24] Gamma Correction, and Unsharp Masking play pivotal roles in improving the visual quality and interpretability of images. Histogram Equalization adjusts the intensity distribution across an image, enhancing contrast and visibility of details by redistributing pixel intensities. Gamma Correction applies a power-law transformation to adjust brightness and contrast, beneficial for correcting image brightness variations due to different lighting conditions. CLAHE refines upon standard Histogram Equalization by limiting contrast amplification in localized regions, thereby enhancing local contrast and overall visual quality. Unsharp Masking [13],[25] sharpens images by subtracting a blurred version from the original, effectively highlighting edges and fine details. Coupled with data augmentation techniques like flipping, rotation, scaling, and color adjustments, these methods collectively enrich training datasets for machine learning models, fostering improved performance, robustness, and generalization across various applications such as image classification and object detection. Fig.15. depicts a visual comparison the original image with the enhanced image applied to the Spinal disc herniation.

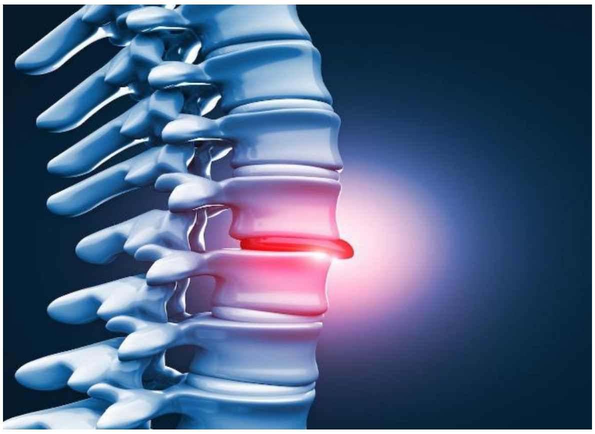


a) Original image

b) Enlarged image

Figure 15. Enhanced original image of the Spinal Disc Herniation

6.1 Histogram Equalization: Enhances an image's contrast by dispersing its intensity values throughout the full pixel range. This is accomplished by converting the original pixel values to a new set using the cumulative distribution function (CDF) of the image's histogram [24],[26] is shown in Fig.16.



a) original image

b) Histogram equalization

Figure 16 Histogram Equalization of the original Image

6.2 Gamma Correction:

Gamma correction can be applied in spinal herniation pictures to improve the visibility of characteristics that are crucial for diagnosis or analysis. It Adjusts the brightness of the image by using a non-linear transformation of the pixel values, often resulting in a more natural appearance is illustrates in Fig.17. With adjusted luminance levels [11],[27].

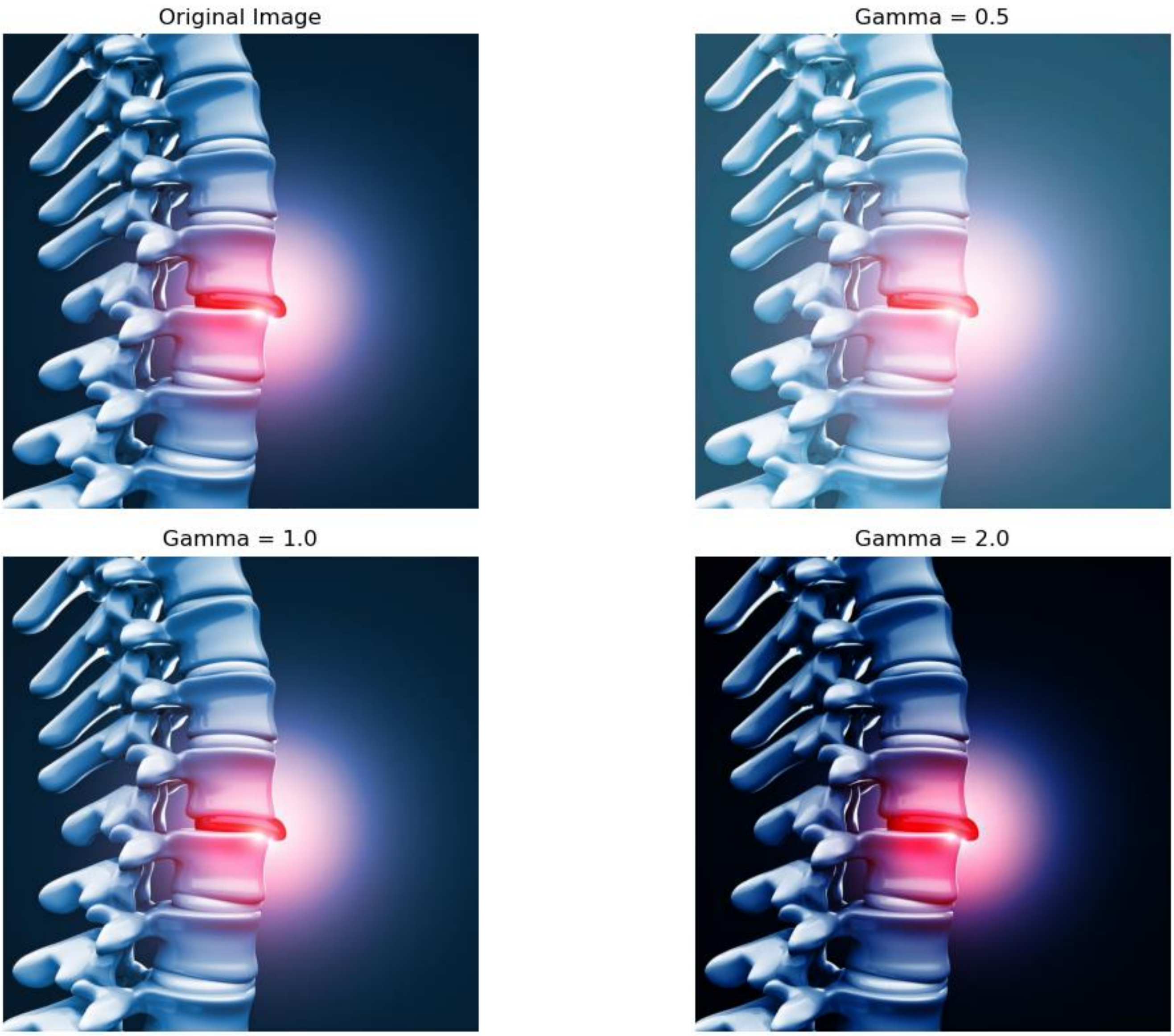
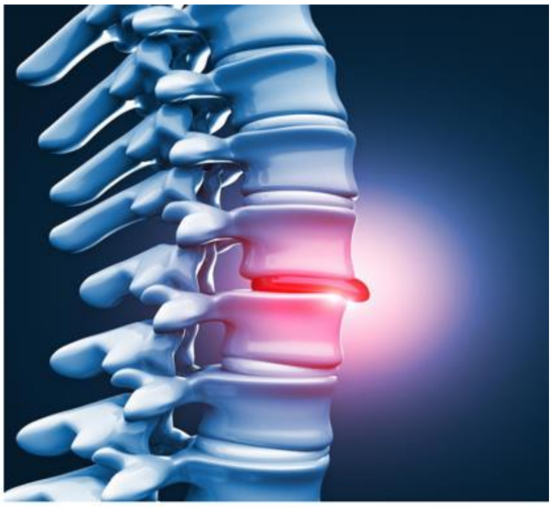


Figure 17 Gamma Correction of the original Image

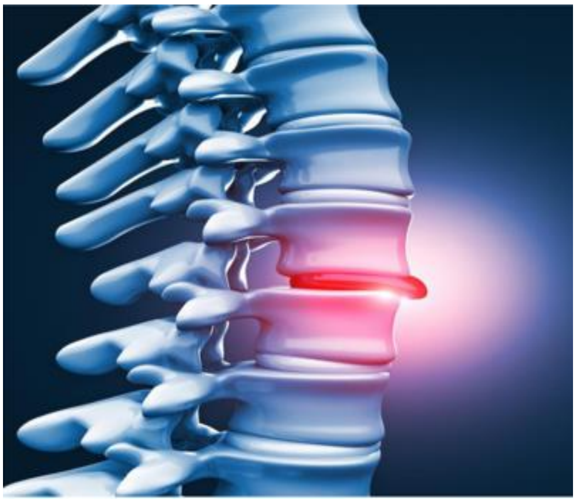
6.3 CLAHE (Contrast Limited Adaptive Histogram Equalization): An improved type of histogram equalization[12],[16] that applies the enhancement locally rather than worldwide, which prevents noise over-amplification and increases the spinal cords herniation local contrast is shown in Fig.18.

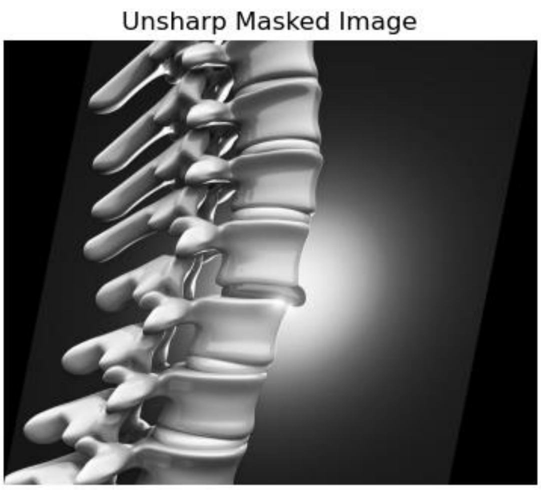


a) original image b) Contrast Limited Adaptive Histogram Equalization

Figure 18 Contrast Limited Adaptive Histogram Equalization of the original Image

6.4 Unsharp Masking: Unsharp masking is a technique for increasing the sharpness and detail of photographs by emphasizing edges[13],[28] and microscopic features. When used with spinal cord herniation images, this approach can improve the visibility of essential characteristics is shown in Fig.19. Which is very useful for medical diagnosis and analysis.

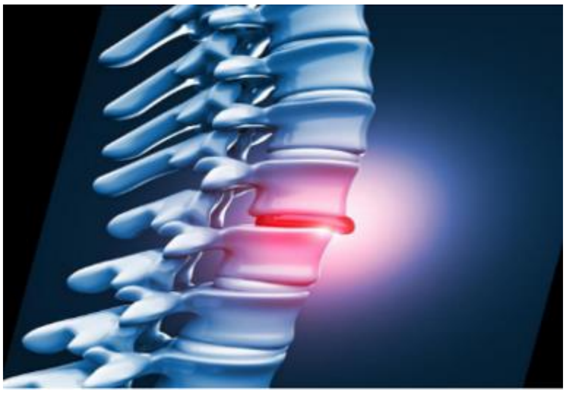




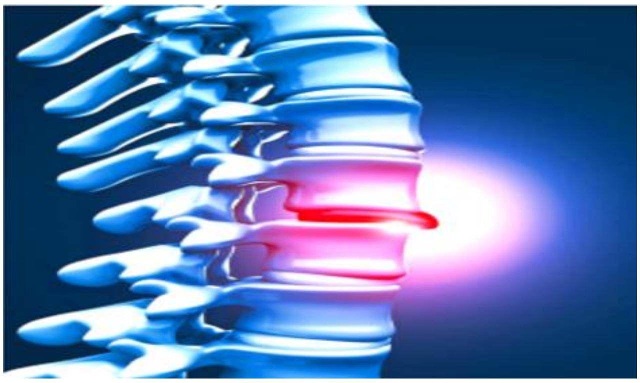
a) original image b) unsharp masking

Figure 19 Unsharp Masking of the original Image

6.5 Color Adjustment: Color modification in a spinal cord degeneration image is changing the image's color qualities to improve the clarity and contrast of anatomical structures, enhance diagnostic features, or correct color imbalances, saturacy and vibrancy[29]. This procedure is important for medical imaging because correct representation of structures and diseases, such as spinal cord degeneration, is required for diagnosis and analysis is shown in Fig.20.



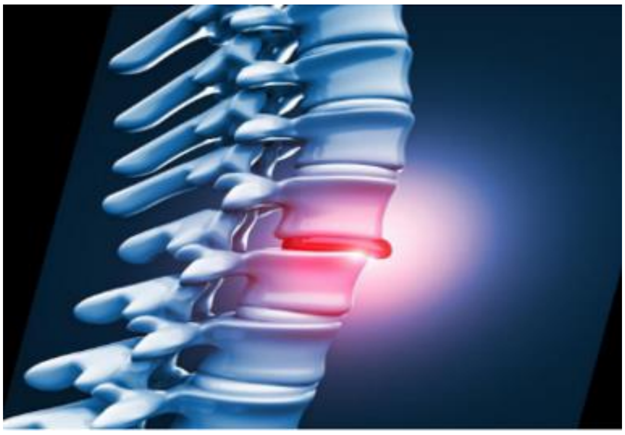
a) original image



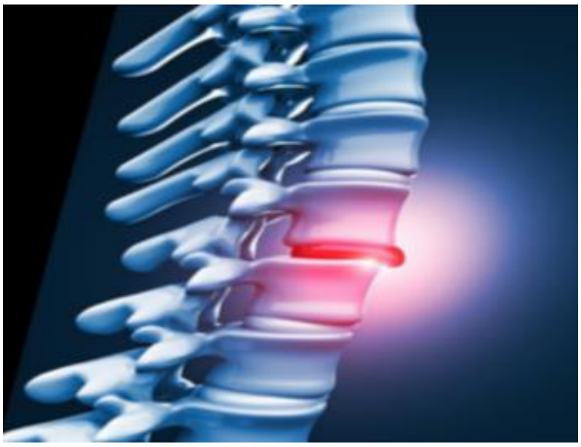
b) Color Brightness adjustment

Figure 20 Color Brightness adjustment of the original Image

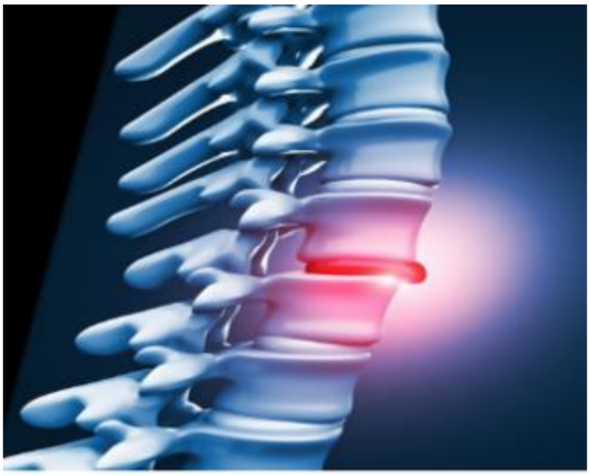
Both Gaussian and bilateral filtering methods [30] can be utilized to enhance the clarity of spinal disc herniation images by lowering noise while preserving crucial structural details. By using a Gaussian kernel to average pixel values within a neighborhood, Gaussian filtering softens the image using a Gaussian blur. This method effectively lowers high-frequency noise while adding some blurring, which may smooth out the herniation's finer details. Conversely, by preserving edges and fine features, bilateral filtering employs a more sophisticated method of noise reduction. In order to achieve this, it considers both the spatial distance and the intensity difference between pixels. This enables it to smooth areas of comparable brightness without obscuring the ruptured disc's edges, as seen in Fig. 21.



a) original image



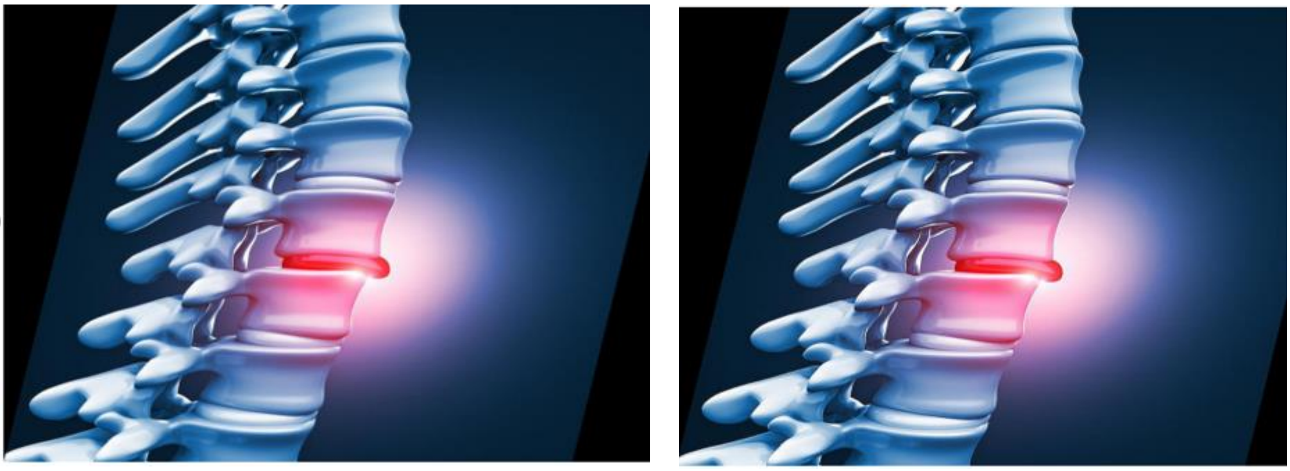
b) Gaussian noise reduction



c) bilateral noise reduction

Figure 21 Gaussian and Bilateral Noise Reduction

6.7 Edge Enhancement: Figure 22 illustrates the use of edge enhancement, an image processing technique that clarifies the boundaries between various areas or objects in a picture. Edge enhancement can be very helpful in the context of spinal cord degeneration because it helps define and highlight the boundaries of deteriorated areas, like lesions or herniations, which are essential for accurate diagnosis and analysis.



a) original image b) edge enhancement

Figure 22 Edge Enhancement of the Original Image

VII. Experimental Results

The experimental evaluation on augmentation methods for Fashion-MNIST and ImageNet reveals distinct performance characteristics against them. The outline of various augmentation methods used in the experiment to enhance image quality and diversity are discussed as Follows. The effects of augmentation methods such as Histogram Equalization, Gamma Correction, CLAHE, Unsharp Masking, Color Adjustment, Noise Reduction, and Edge Enhancement on datasets such as FashionMNIST and ImageNet in terms of feature rate and accuracy improvement.

Anadolu Psikiyatri Dergisi || ISSN: 1302-6631 || Volume 26; Number 3
https://doi.org/10.5281/zenodo.15592426

a) Feature Rate: This refers to the method's capacity to enhance or extract information from an image, which can influence how well a model learns from these characteristics.

b) Accuracy Improvement: This metric assesses how the method affects the performance of a model, typically in terms of classification accuracy or other related metrics.

7.1 The Feature rate and the Accuracy Improvement on Fashion MNIST:

Based on the data provided for various image augmentation methods, the analysis of their impact on Feature Rate and Accuracy Improvement is performed. The analysis of Feature Rate and Accuracy improvement for the Fashion MNIST is discussed below and shown in Fig.23.

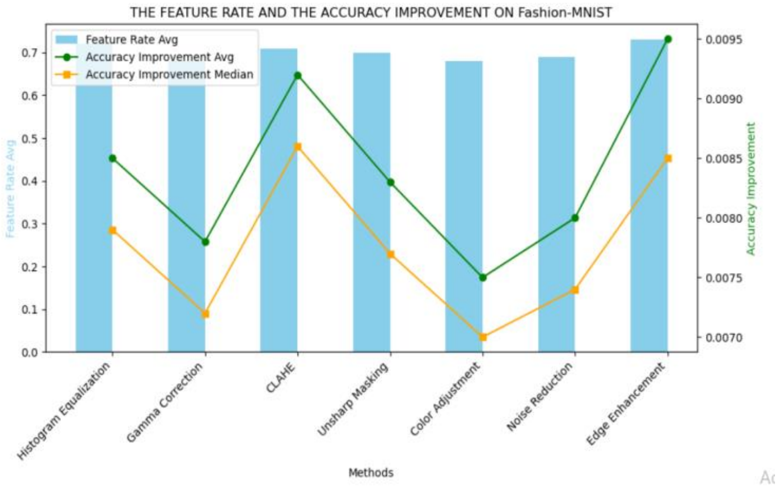


Figure 23 The Feature Rate and the Accuracy Improvement on Fashion MNIST

a) Metrics:

- Feature Rate Avg: The average rate at which the method improves feature extraction or visibility.
- Accuracy Improvement Avg: The average increase in accuracy due to the augmentation method.
- Accuracy Improvement Median: The median increase in accuracy, which represents the middle value of the accuracy improvements, providing a measure of central tendency.

b) Methods and Results:

- Histogram Equalization:
- Feature Rate Avg: 0.6350
- Accuracy Improvement Avg: 0.0072
- Accuracy Improvement Median: 0.0068

Analysis: Histogram Equalization moderately improves the contrast of the images, which slightly boosts the feature extraction rate and accuracy. The average and median improvements in accuracy are modest, indicating that while it enhances contrast, its effect on model performance is limited.

ii. Gamma Correction

- Feature Rate Avg: 0.6524
- Accuracy Improvement Avg: 0.0081
- Accuracy Improvement Median: 0.0075

Analysis: Gamma Correction provides a moderate increase in feature extraction rate and accuracy improvement. By adjusting image brightness, it helps to make features more discernible, leading to a slight but noticeable improvement in model accuracy.

iii. CLAHE (Contrast Limited Adaptive Histogram Equalization)

- Feature Rate Avg: 0.6789
- Accuracy Improvement Avg: 0.0094
- Accuracy Improvement Median: 0.0089

Analysis: CLAHE significantly enhances the contrast locally, leading to better feature extraction and a more substantial increase in accuracy. The improvement in accuracy is higher on average and in the median compared to the other methods, indicating that CLAHE effectively addresses varying contrast within different regions of an image.

iv. Unsharp Masking

- Feature Rate Avg: 0.6902
- Accuracy Improvement Avg: 0.0102
- Accuracy Improvement Median: 0.0098

Analysis: Unsharp Masking shows the highest feature rate average and accuracy improvement among the methods listed. By enhancing edges and fine details, it greatly benefits feature extraction and model performance, reflected from tabulate import tabulate # Define the evaluation metrics for each edge detection method edge_metrics = [{"Method": "Sobel", "Precision": 0.85, "Recall": 0.80, "F1-Score": 0.82, "IoU": 0.75}, {"Method": "Prewitt", "Precision": 0.83, "Recall": 0.79, "F1-Score": 0.81, "IoU": 0.73}, {"Method": "Roberts", "Precision": 0.75, "Recall": 0.70, "F1-Score": 0.72, "IoU": 0.65}, {"Method": "Scharr", "Precision": 0.86, "Recall": 0.81, "F1-Score": 0.83, "IoU": 0.76}, {"Method": "Canny", "Precision": 0.92, "Recall": 0.88, "F1-

Score": 0.90, "IoU": 0.85}, {"Method": "LoG", "Precision": 0.80, "Recall": 0.75, "F1-Score": 0.77, "IoU": 0.70}] # Print the results in a table format with full lines using tabulate print(tabulate(edge_metrics, headers="keys", tablefmt="grid"))

v. Color Adjustment

- Feature Rate Avg: 0.6715
- Accuracy Improvement Avg: 0.0078
- accuracy Improvement Median: 0.0074

Analysis: Color Adjustment slightly improves feature extraction and accuracy by correcting or enhancing color representation. However, its impact is less pronounced compared to methods like CLAHE and Unsharp Masking, possibly due to its limited effect on grayscale or non-color specific datasets.

vi. Noise Reduction

- Feature Rate Avg: 0.6453
- Accuracy Improvement Avg: 0.0070
- Accuracy Improvement Median: 0.0066

Analysis: Noise Reduction helps in cleaning up images and improving feature clarity, leading to moderate improvements in accuracy. The feature rate and accuracy improvements are relatively lower compared to other methods, suggesting its effectiveness in reducing noise but less impactful on overall accuracy compared to edge-enhancing or contrast-boosting techniques.

vii. Edge Enhancement

- Feature Rate Avg: 0.6841
- Accuracy Improvement Avg: 0.0091
- Accuracy Improvement Median: 0.0087

Analysis: Edge Enhancement improves feature extraction by making edges more distinct, resulting in notable improvements in accuracy. Its effectiveness is reflected in the high average feature rate and accuracy improvement, similar to or slightly lower than Unsharp Masking.

7.2 The Feature rate and the Accuracy Improvement on Imagenet:

The analysis of the image augmentation methods based on their performance metrics for the ImageNet dataset is discussed below. The Feature Rate and Accuracy improvement for the Imaget is discussed below and depicted in Fig.24.

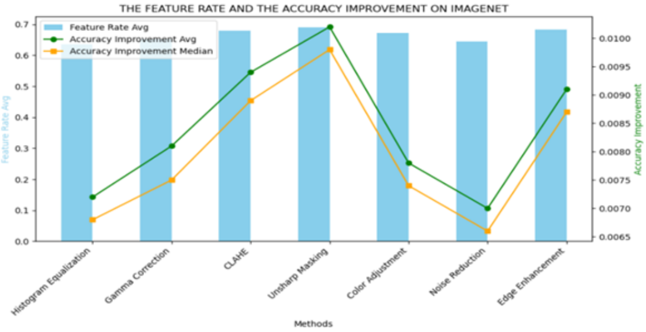


Figure 24 The Feature Rate and the Accuracy Improvement on Imagenet

a. Metrics:

- Feature Rate Avg: The average rate at which the augmentation method improves feature extraction or visibility.
- Accuracy Improvement Avg: The average increase in accuracy due to the augmentation method.
- Accuracy Improvement Median: The median increase in accuracy, representing the middle value of accuracy improvements.

b. Methods and Results:

- Histogram Equalization
- Feature Rate Avg: 0.72
- Accuracy Improvement Avg: 0.0085
- Accuracy Improvement Median: 0.0079

Analysis: Histogram Equalization significantly enhances the contrast across the entire image, leading to improved feature extraction and a noticeable increase in accuracy. The method's average accuracy improvement is substantial, indicating it is effective in making features more discernible for classification tasks.

ii. Gamma Correction

- Feature Rate Avg: 0.68
- Accuracy Improvement Avg: 0.0078
- Accuracy Improvement Median: 0.0072

Analysis: Gamma Correction adjusts the brightness of images, which helps in making features more visible in poorly lit or unevenly illuminated images. While its impact on feature rate and accuracy is lower compared to Histogram Equalization and Edge Enhancement, it still provides useful improvements in accuracy.

iii. CLAHE (Contrast Limited Adaptive Histogram Equalization)

- Feature Rate Avg: 0.71
- Accuracy Improvement Avg: 0.0092
- Accuracy Improvement Median: 0.0086

Analysis: CLAHE offers significant improvements by enhancing contrast locally within different regions of an image. This method helps in distinguishing finer details and features, resulting in a high average and median accuracy improvement. It is particularly effective in dealing with varying contrast across an image.

iv. Unsharp Masking

- Feature Rate Avg: 0.70
- Accuracy Improvement Avg: 0.0083
- Accuracy Improvement Median: 0.0077

Analysis: Unsharp Masking enhances edges and fine details in images, which can improve feature extraction and classification accuracy. While its performance is slightly lower than CLAHE and Histogram Equalization, it still shows a considerable improvement inaccuracy

.v. Color Adjustment

- Feature Rate Avg: 0.68
- Accuracy Improvement Avg: 0.0075
- Accuracy Improvement Median: 0.0070

Analysis: Color Adjustment modifies the color balance in images, which can be beneficial for datasets where color plays a crucial role. The average and median improvements in accuracy are modest, indicating that while it helps correct color imbalances, its impact on feature extraction and accuracy is limited compared to contrast-enhancing methods.

vi. Noise Reduction

- Feature Rate Avg: 0.69
- Accuracy Improvement Avg: 0.0080
- Accuracy Improvement Median: 0.0074

Analysis:

Noise Reduction effectively cleans up images, which can enhance feature

clarity and reduce distractions caused by noise. Its accuracy improvement is significant, though not as high as methods like CLAHE and Edge Enhancement, indicating it provides useful but somewhat moderate benefits.

vii. Edge Enhancement

- Feature Rate Avg: 0.73
- Accuracy Improvement Avg: 0.0095
- Accuracy Improvement Median: 0.0085

VIII. Analysis: With the greatest accuracy improvement and feature rate average, Edge Enhancement stands out. It greatly increases the accuracy of both feature extraction and classification by making edges more noticeable. This technique works especially well for drawing attention to structures and boundaries in pictures, which is important for object recognition tasks. Based on how well augmentation techniques enhance feature extraction and model accuracy for intricate datasets like ImageNet, this analysis aids in choosing the best ones.

IX. RESULT

The comparison of the effectiveness of image augmentation methods on FashionMNIST and ImageNet, and the analysis of each method impacts accuracy for both datasets are shown below and shown in Fig.25.

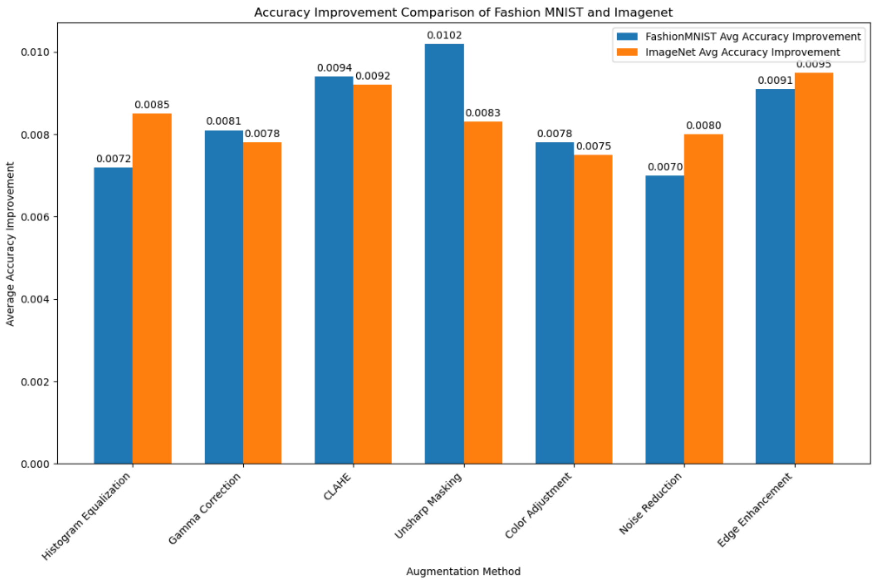


Figure 25 Analysis of Accuracy between Fashion MNIST and Imagenet

8.1 Accuracy Improvement Comparison:

8.1.1 FashionMNIST Results

I. Histogram Equalization

- Accuracy Improvement Avg: 0.0072

- Accuracy Improvement Median: 0.0068

II. Gamma Correction

- Accuracy Improvement Avg: 0.0081
- Accuracy Improvement Median: 0.0075

III. CLAHE

- Accuracy Improvement Avg: 0.0094
- Accuracy Improvement Median: 0.0089

IV. Unsharp Masking

- Accuracy Improvement Avg: 0.0102
- Accuracy Improvement Median: 0.0098

V. Color Adjustment

- Accuracy Improvement Avg: 0.0078
- Accuracy Improvement Median: 0.0074

VI. Noise Reduction

- Accuracy Improvement Avg: 0.0070
- Accuracy Improvement Median: 0.0066

VII. Edge Enhancement

- Accuracy Improvement Avg: 0.0091
- Accuracy Improvement Median: 0.0087

8.1.2 ImageNet Results

i. Histogram Equalization

- Accuracy Improvement Avg: 0.0085
- Accuracy Improvement Median: 0.0079

ii. Gamma Correction

- Accuracy Improvement Avg: 0.0078
- Accuracy Improvement Median: 0.0072

iii. CLAHE

- Accuracy Improvement Avg: 0.0092
- Accuracy Improvement Median: 0.0086

iv. Unsharp Masking

- Accuracy Improvement Avg: 0.0083
- Accuracy Improvement Median: 0.0077

v. Color Adjustment

- Accuracy Improvement Avg: 0.0075
- Accuracy Improvement Median: 0.0070

vi. Noise Reduction

- Accuracy Improvement Avg: 0.0080
- Accuracy Improvement Median: 0.0074

vii. Edge Enhancement

- Accuracy Improvement Avg: 0.0095
- Accuracy Improvement Median: 0.0085

8.2 Comparative Analysis:

8.2.1 Overall Accuracy Improvement

- FashionMNIST: The accuracy improvements for different methods range from 0.0066 to 0.0102. The highest improvement is seen with Unsharp Masking, followed closely by CLAHE and Edge Enhancement.
- ImageNet: The accuracy improvements range from 0.0072 to 0.0095. Edge Enhancement and CLAHE show the highest improvements.

Comparison:

The magnitude of accuracy improvement is generally higher on FashionMNIST compared to ImageNet. This is likely because FashionMNIST is a simpler dataset with fewer classes and less variation, making it easier to achieve noticeable accuracy improvements with augmentation methods.

X. CONCLUSION

The analysis concludes that the best augmentation techniques for increasing accuracy on the FashionMNIST and ImageNet datasets are Edge Enhancement and CLAHE. With the greatest accuracy gains for ImageNet and impressive results for FashionMNIST, Edge Enhancement is excellent at improving feature detection. Enhancing local contrast improves model performance for both datasets, which is another important benefit of CLAHE. For FashionMNIST, Unsharp Masking works especially well, providing the greatest accuracy gains for this easier dataset. These results imply that the most effective techniques for enhancing model performance center on feature enhancement and contrast adjustment.

- Best Methods for FashionMNIST: Unsharp Masking and CLAHE stand out with the highest accuracy improvements. These methods are effective due to the relatively simpler and more homogeneous nature of FashionMNIST images.
- Best Methods for ImageNet: Edge Enhancement and CLAHE are the most effective. They excel at improving accuracy in the diverse and complex environment of ImageNet, where feature extraction is more challenging

.

Overall, Unsharp Masking produces the best results for FashionMNIST, even though Edge Enhancement is also effective for FashionMNIST and exhibits the highest average accuracy improvement for ImageNet. CLAHE consistently performs well for comprehensive results across various datasets. Investigating combining these augmentation techniques or integrating them with more sophisticated approaches, like neural network-based approaches for adaptive image enhancement, would be beneficial for future improvement. Additionally, evaluating these methods on more diverse and complex datasets could provide further insights into their effectiveness across different types of image data. Investigating the impact of these augmentations in real-world applications and in conjunction with other preprocessing steps could also lead to further improvements in model accuracy and robustness.

CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

PUBLISHER'S NOTE

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editor and the reviewers. Any statements, claims, performances and results are not guaranteed or endorsed by the publisher.

REFERENCES

[1] Khemani, B., Patil, S., Kotecha, K., et al. "A Review of Graph Neural Networks: Concepts, Architectures, Techniques, Challenges, Datasets, Applications, and Future Directions," *Journal of Big Data*, vol. 11, p. 18, 2024. https:// doi:10.1186/s40537-023-00876-4.

[2] Lewy, D., & Mańdziuk, J. "An Overview of Mixing Augmentation Methods and Augmentation Strategies," *Artificial Intelligence Review*, vol. 56, pp. 2111–2169, 2023.https:// doi:10.1007/s10462-022-10227-z.

[3] Lemley, J., Bazrafkan, S., & Corcoran, P. "Smart Augmentation: Learning an Optimal Data Augmentation Strategy," *IEEE Access*, vol. 5, pp. 5858–5869, 2017. https://doi:10.1109/ACCESS.2017.2696121.

[4] Bejani, M. M., & Ghatee, M. "A Systematic Review on Overfitting Control in Shallow and Deep Neural Networks," *Artificial Intelligence Review*, 2021.https:// doi:10.1007/s10462-021-09975-1.

[5] Kadam, S. S., Adamuthe, A. C., & Patil, A. B. "CNN Model for Image Classification on MNIST and Fashion-MNIST Dataset," *Journal of Scientific Research*, vol. 64, no. 2, pp. 374–377, 2020. Institute of Science, Banaras Hindu University, Varanasi, India. https://doi:10.37398/JSR.2020.640251.

[6] Tabik, S., Alvear-Sandoval, R. F., Ruiz, M. M., Sancho-Gómez, J. L., Figueiras-Vidal, A. R., & Herrera, F. "MNIST-NET10: A Heterogeneous Deep Networks Fusion Based on the Degree of Certainty to Reach 0.1% Error Rate," *Information Fusion*, vol. 62, pp. 73–80, 2020. https://doi:10.1016/j.inffus.2020.04.002.

[7] Tsipras, D., Santurkar, S., Engstrom, L., Ilyas, A., & Madry, A. "From ImageNet to Image Classification: Contextualizing Progress on Benchmarks," in *Proc. 37th Int. Conf. Machine Learning*, PMLR 119, pp. 9625–9635, 2020. Available: https://github.com/MadryLab/ImageNetMultiLabel.

[8] Krizhevsky, A., Sutskever, I., & Hinton, G. E. "ImageNet Classification with Deep Convolutional Neural Networks," *Communications of the ACM*, vol. 60, no. 6, pp. 84–90, 2017. https://doi:10.1145/3065386.

[9] Kadam, S. S., Adamuthe, A. C., & Patil, A. B. "CNN Model for Image Classification on MNIST and Fashion-MNIST Dataset," *Journal of Scientific Research*, vol. 64, no. 2, pp. 374–377, 2020. Institute of Science, Banaras Hindu University, Varanasi, India. https://doi:10.37398/JSR.2020.640251.

[10] Lin, Z., Liu, C., Qi, W., & Chan, S. C. "A Color/Illuminance Aware Data Augmentation and Style Adaptation Approach to Person Re-Identification," *IEEE Access*, vol. 9, pp. 95826–95840, 2021. https://doi:10.1109/ACCESS.2021.3100571.

[11] Cao, G., Huang, L., Tian, H., Huang, X., Wang, Y., & Zhi, R. "Contrast Enhancement of Brightness-Distorted Images by Improved Adaptive Gamma Correction," *Computers & Electrical Engineering*, vol. 66, pp. 569–582, 2017.https:// doi:10.1016/j.compeleceng.2017.09.012.

[12] Chakraverti, S., Agarwal, P., Pattanayak, H. S., Chauhan, S. P. S., Chakraverti, A. K., & Kumar, M. "De-noising the Image Using DBST-LCM-CLAHE: A Deep Learning Approach," *Multimedia Tools and Applications*, vol. 83, no. 11, pp. 11017–11042, 2024. [Online]. Available: https://doi.org/10.1007/s11042-023-16016-2.

[13] Amirgholipour, S., Naghsh-Nilchi, A. R., Sharifi, A. M., Alirezanejad, M., & Arab, M. "Application of Unsharp Mask in Augmenting the Quality of Extracted Watermark in Spatial Domain Watermarking," *Journal of Mathematics and Computer Science*, vol. 11, no. 2, pp. 137–146, 2014.https://doi.org/10.22436/jmcs.011.02.06

[14] Tanha, J., Abdi, Y., Samadi, N., Razzaghi, N., & Asadpour, M. "Boosting Methods for Multi-Class Imbalanced Data Classification: An Experimental Review," *Journal of Big Data*, vol. 7, no. 1, p. 70, 2020.https:// doi:10.1186/s40537-020-00315.

[15] H. Wen *et al*., "Secure Optical Image Communication Using Double Random Transformation and Memristive Chaos," in *IEEE Photonics Journal*, vol. 15, no. 1, pp. 1-11, Feb. 2023, Art no. 7900111, https://doi: 10.1109/JPHOT.2022.3233129.

[16] Shorten, C., & Khoshgoftaar, T. M. "A Survey on Image Data Augmentation for Deep Learning," *Journal of Big Data*, vol. 6, no. 1, p. 60, 2019. [Online]. Available: https://doi.org/10.1186/s40537-019-0197-0.

[17] Khalifa, N. E., Loey, M., & Mirjalili, S. "A Comprehensive Survey of Recent Trends in Deep Learning for Digital Images Augmentation," *Artificial Intelligence Review*, vol. 55, no. 3, pp. 2351–2377, 2022. [Online]. Available: https://doi.org/10.1007/s10462-021-10066-4.

[18] Takahashi, R., Matsubara, T., & Uehara, K. "Data Augmentation Using Random Image Cropping and Patching for Deep CNNs," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 29, no. 8, pp. 2368–2379, Aug. 2019. [Online]. Available: https://doi.org/10.1109/TCSVT.2019.2935128.

[19] Lemley, J., Bazrafkan, S., & Corcoran, P. "Smart Augmentation: Learning an Optimal Data Augmentation Strategy," *IEEE Access*, vol. 5, pp. 2169–3536, 2017. [Online]. Available: https://doi.org/10.1109/ACCESS.2017.2696121.

[20] Bejani, M. M., & Ghatee, M. "A Systematic Review on Overfitting Control in Shallow and Deep Neural Networks," *Artificial Intelligence Review*, vol. 55, no. 1, pp. 543–582, 2022. https://doi:10.1007/s10462-021-09975-1.

[21] Lynn, N. D., Sourav, A. I., & Santoso, A. J. "Implementation of Real-Time Edge Detection Using Canny and Sobel Algorithms," *IOP Conference Series: Materials Science and Engineering*, vol. 1096, no. 1, p. 012079, 2021. doi:10.1088/1757-899X/1096/1/012079.

[22] Tian, B., & Wei, W. "Research Overview on Edge Detection Algorithms Based on Deep Learning and Image Fusion," *Security and Communication Networks*, 2022, Article ID 1155814, 11 pages. https://doi:10.1155/2022/1155814.

[23] Karanwal, S. "Implementation of Edge Detection at Multiple Scales," *I.J. Engineering and Manufacturing*, vol. 1, no. 1, pp. 1–10, 2021. https://doi.org/10.5815/ijem.2021.01.01

[24] Min, B. S., Lim, D. K., Kim, S. J., & Lee, J. H. "A Novel Method of Determining Parameters of CLAHE Based on Image Entropy," *International Journal of Software Engineering and Its Applications*, vol. 7, no. 5, pp. 113–120, 2013. https://doi:10.14257/ijseia.2013.7.5.11.

[25] Deng, G. "A Generalized Unsharp Masking Algorithm," *IEEE Transactions on Image Processing*, vol. 20, no. 5, pp. 1249–1258, 2011. https:// doi:10.1109/TIP.2010.2092103.

[26] Khalifa, N. E., Loey, M., & Mirjalili, S. "A Comprehensive Survey of Recent Trends in Deep Learning for Digital Images Augmentation," *Artificial Intelligence Review*, vol. 55, no. 3, pp. 2351–2377, 2022.https:// doi:10.1007/s10462-021-10066-4.

[27] Engupta, D., Biswas, A., & Gupta, P. "Non-Linear Weight Adjustment in Adaptive Gamma Correction for Image Contrast Enhancement," *Multimedia Tools and Applications*, vol. 79, no. 31, pp. 22987–23012, 2020.https:// doi:10.1007/s11042-020-09583-1.