

Impact of Image Enhancement Techniques on CNN Performance for Bone Fracture Detection Using X-ray Images

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Article's Information	Abstract
Received: 12.05.2025 Revision: 19.07.2026 Accepted: 02.08.2026 Published 07.10.2026 Keywords: Bone fracture Classification CNN Image enhancement X-ray image.	The study offers a thorough analysis of the influence of image-enhancing methods on the classification of bone fractures in X-ray images. The FracAtlas labeled dataset is utilized to train and assess a convolutional neural network (CNN) classifier. Precision, accuracy, F1-Score, and recall are used as performance evaluation metrics for the CNN classifier. The outcomes revealed that methods such as contrast-limited adaptive histogram equalizer, wavelet transformation, and Gaussian filters significantly enhance classification accuracy, increasing it from 80.20% to 92.52%. The study proves that the use of optimization methods along with the CNN classifier improves fracture classification and considers an additional diagnostic tool for radiologists. The research's findings advance the image interpretation of medicine realm, showing that the use of a deep learning model combined with image enhancement approaches is clinically diagnostic important.

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1. INTRODUCTION

X-ray imagery is a commonly used means for bone fracture detection based on its inexpensiveness, speed, and capacity to emphasize fracture anatomy [1]. In the sphere of medical diagnostics, accurate detection of musculoskeletal injuries, especially fractures, presents great challenges due to the growing amount of injuries around the globe [2]. Traditional diagnostic procedures can often be inconsistent because of visual evaluations performed by professionals, making it necessary to introduce some automated diagnosis solutions to improve bone fracture identification [3]. The primary issue this study seeks to resolve is the limitations of traditional diagnosis methods and the quality characteristics of X-ray image such as noise, low contrast, or inability to show details. Despite advances in imaging devices, the interpretation of these images requires specialized expertise, which may lead to mistakes caused by the human factor. This issue is further complicated by the large number of cases that the medical practitioners need to diagnose, which leads to delayed diagnoses and reduced efficiency in healthcare institutions. The amalgamation of deep learning algorithms with image enhancement procedures provides an option for radiologists in

improving their diagnosis capabilities through introducing an automated instrument that can swiftly and precisely detect fractures in X-ray bone images. A current study investigates the impact of image-enhancing methods on the CNN deep learning performance of models in feature extraction and bone fracture diagnosis using the dataset FracAtlas, which comprises a comprehensive collection of classified X-ray images. A study focuses on integrating deep learning algorithms with sophisticated image enhancement techniques, CLAHE, Gaussian filter, and wavelet transform, to increase the accuracy of fracture identification in bone X-rays markedly. A study has four phases: data collection and preprocessing, implementation of image enhancement techniques, construction of the classifier model with training and testing, and finally, performance evaluation of the classifier and assessment of the image enhancement method's influence.

2. LITERATURE SURVEY

A wide variety of studies were performed to detect fractures in X-ray bone images utilizing various architectures of deep neural networks, such as:

A. K. Bharodiya & A. M. Gonsai (2019). Introduced a new algorithm for detecting fractures in X-ray hand-finger images, utilizing image processing to enhance contrast, reduce noise, preserve edges and gradients, and smooth other parts. The algorithm result assists a doctor or orthopedist in identifying fractures in the finger bones. The performance of the proposed algorithm exceeds 80% accuracy [4].

G. Kitamura et al. (2019). Proved the possibility of training a CNN de novo utilizing a small set of data of 596 instances to detect fractures in X-ray wrist images. The Xception, Inception, and ResNet models of CNN were built. Following training, ensembles of CNNs were generated, yielding the highest accuracy of 76% [5].

J. Luo et al. (2021). Suggested a novel deep learning strategy, guided by medical knowledge, for diagnosing fractures in X-ray images of the elbow by applying an algorithm that updates the selection likelihoods at every epoch. The outcomes reveal that the suggested strategy attains a classification accuracy of 81% for a fracture/normal binary categorizing task [6].

Y. Ma & Y. Luo (2021). Designed a novel two-phase fracture diagnosis system. After identifying different bone areas from X-ray images with Faster Region CNN, CrackNet was applied to distinguish whether the bone region was broken. The proposed system's evaluation found performance with 88.39% accuracy[7].

P. K. Mall & P. K. Singh (2022). Fused the image enhancement technique with ChampNet to create a Boost model. The main objective is to advance a categorization model that is more precise and effective to Musculoskeletal Radiograph Bone Classification. An assessment of classification was performed using ChampNet with CLAHE and demonstrated a high-value accuracy of 95.88% [8].

R.-Y. Ju & W. Cai (2023). Developed the "Fracture Detection Using YOLOv8 App," a software that analyzes pediatric X-ray wrist injury images to identify fractures. The app aims to assist pediatric surgeons in image interpretation. The evaluation's findings indicate that the application has achieved an accuracy of 63.8%, significantly better than the enhanced YOLOv7 and classic YOLOv8 models [9].

G. Marullo et al. (2024). Utilized A modern structure of YOLOv8 optimized to improve the Arbeitsgemeinschaft für Osteosynthesefragen/Orthopedic Trauma Association (AO/OTA) system's classification of X-ray images of femur fractures effectively, aiding clinicians in prompt and precise diagnoses. The refined YOLOv8 architecture attained 90% accuracy [10].

W. Wei et al. (2025). Proposed a YOLOv11-based multitasking learning method for fracture detection of X-ray images. Learning model multitasking eases fracture category and identification, enhancing real-time fracture analysis, maximizing diagnostic precision, and reducing radiologists' workflow. The model exhibited exceptional performance, attaining an average accuracy of 96.8% [11].

Table 1 represents a brief description of the literature review.

Table 1. A Summary of Literature Survey.

No.	Reference	Dataset	Method	Accuracy%
[4]	I. A. K. Bharodiya & A. M. Gonsai, (2019)	50 of X-ray hand images.	Novel algorithm and image processing.	80
[5]	G. Kitamura et al., (2019)	596 of ankle Radiology images.	CNN and an ensemble model.	76
[6]	J. Luo et al., (2021)	1,865 elbow radiographic images.	Deep learning algorithm.	81
[7]	Y. Ma & Y. Luo, (2021)	Radiopaedia dataset of 1052 images.	Faster R-CNN and CrackNet.	88.39
[8]	P. K. Mall & P. K. Singh, (2022)	MURA-BC dataset with 40561 images.	Champ-Net merges with image processing.	95.88
[9]	R.-Y. Ju & W. Cai, (2023)	20,327 X-ray of GRAZPEDWRI-DX dataset.	Deep learning model YOLOv8.	63.8
[10]	G. Marullo et al., (2024)	4233 of femur fractures X-ray images.	YOLOv8 DL model.	90
[11]	W. Wei et al., (2025).	15,666 musculoskeletal images.	Multi-task learning based on YOLOv11	96.8

3. PROPOSED APPROACH AND MATERIALS

For the medical categorization of bone X-ray images, a convolutional neural network was created, and image-enhancing techniques were applied to boost the quality of the images. The enhancement method produces superior image quality, aiding the capability of CNN to distinguish the images. The enhanced images serve as input in the training and testing procedures of the deep learning model. An outline of the entire approach is provided in Figure 1, which highlights the four primary phases: preprocessing, image enhancement, classification, and evaluation.

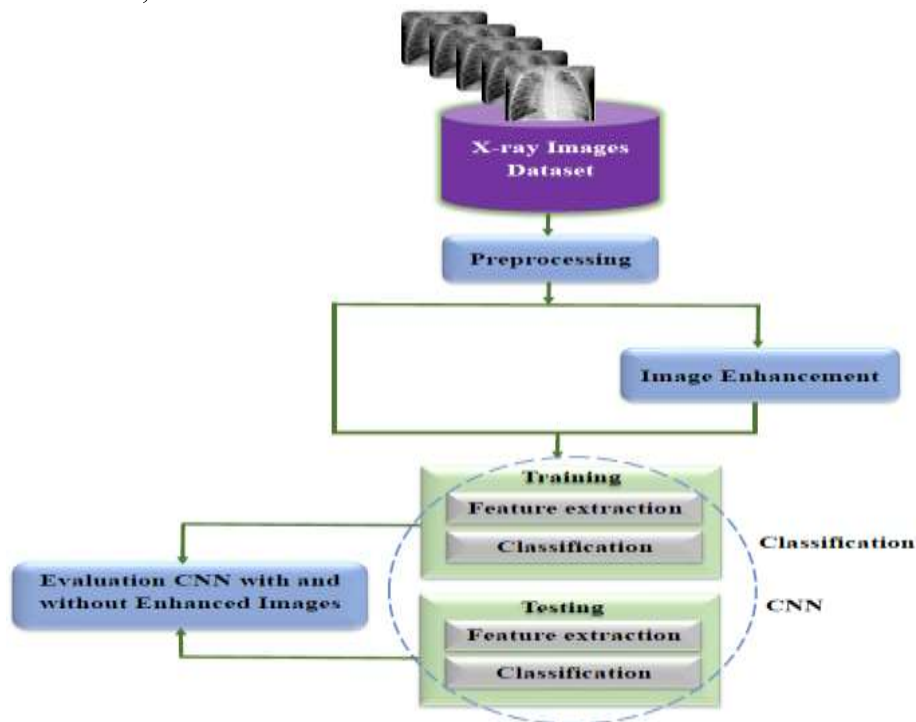


Fig.1. The Proposed Approach Structure.

3.1. DATASET ACQUISITION

The Fracture Classification Dataset, or FracAtlas, was obtained from Kaggle at <https://www.kaggle.com/datasets/akshayramakrishnan28/fracture-classification-dataset>. The musculoskeletal fracture bone dataset comprises 4,083 X-ray bone images of various fractures, including the hip, shoulder, leg, and hand, as illustrated in Figure 2. The images are separated into two classes, fracture/nonfracture, and have indications for deep learning jobs, such as localization, classification, and segmentation.



**Fig. 2. Sample Images from the FracAtlas Dataset of Different Parts of the Body:
a. Image Fracture, b. Image Nonfracture.**

3.2. PREPROCESSING STAGE

Preprocessing is necessary in medical imaging modelling because of real-world data's inherent inconsistency, messiness, and incompleteness [12]. Each image was resized to a similar size of 180×180 pixels to prepare it for the deep learning model. Data augmentation is used on the dataset to enhance the training model and guarantee a balanced distribution of fracture and nonfracture cases. The final dataset, after augmentation, had 6,732 images. To appropriately evaluate the model, the dataset is separated into a training collection of 70% (4,712 images) and a testing collection of 30% (2,020 images). Figure 3 explains the flowchart of the preprocessing stage.

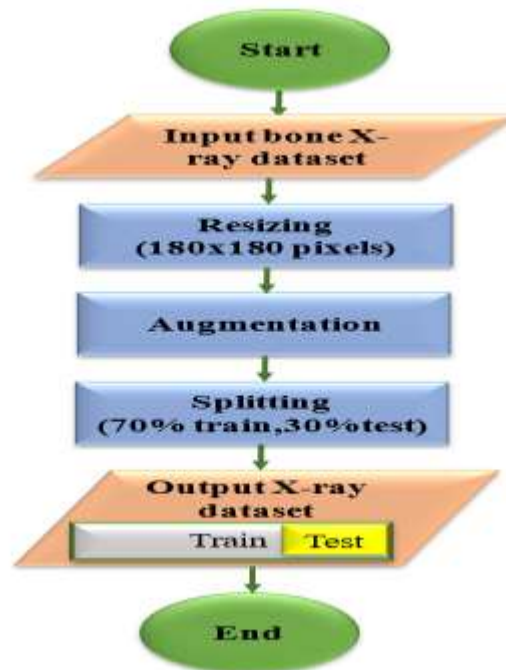


Fig. 3. Flowchart of Preprocessing Stage.

3.3. IMAGE ENHANCEMENT STAGE

Due to several issues, such as poor scanning, transmission protocols, and the type of imaging equipment, clinical images often have low contrast, noise, and poor visibility [13]. Image optimization is essential for artifact removal through enhancement approaches; the methods applied in this study include wavelet transform, Gaussian filter, and CLAHE. Figure 4 represents the flowchart of the image-enhancing stage.

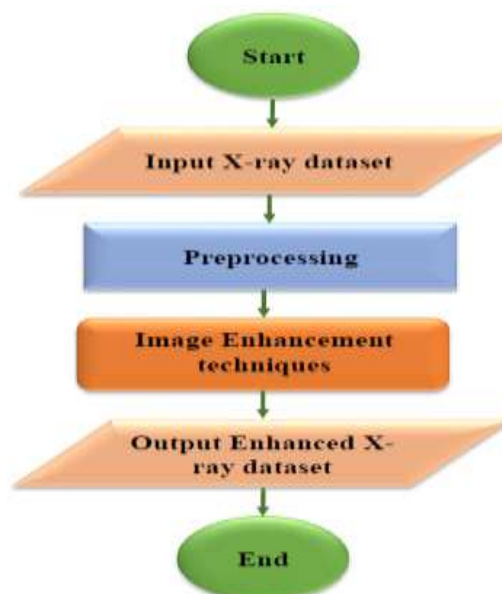


Fig. 4. Flowchart of Image Enhancement Stage.

- **Contrast Limited Adaptive Histogram equalization (CLAHE)**

Contrast Limited Adaptive Histogram Equalization is an improvement technique that enhances the preceding method, Adaptive Histogram Equalization. Given AHE's propensity for excessive contrast, CLAHE is designed to enforce a contrast limitation to achieve the intended results [14]. The problem of the AHE approach's extreme contrast improvement can be mitigated by utilizing CLAHE, which restricts the histogram. The CLAHE approach aims to improve visual contrast while maintaining image integrity [15]. This approach functions on a confined image segment referred to as a tile. A contrast of each tile is adjusted to ensure the resultant histogram aligns with the designated histogram shape. Adjacent tiles are linked using bilinear interpolation. This approach guarantees that the results of the tile merging are smooth [16].

- **Gaussian filter (blur filter)**

The Gaussian blur feature is obtained by applying a Gaussian function to blur an image. This approach enhances the quality of images and aids in finding insufficient information for the analysis of images. This approach employs spatial filtering, slicing, stretching, edge sharpening, and several other ways. The technique diminishes noise and enhances visual smoothness. The procedure is accomplished by convolving an image using a Gaussian kernel [17]. The equation utilized for the procedure is explained in Equation (1):

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (1)$$

A distribution by standard deviation is represented by σ , whereas x and y act as location indices. The mean value of the Gaussian distribution is contingent upon the value of σ , which affects the degree of blurring surrounding the pixel. A Gaussian filter processes the (x, y) pixel to get a singular value by computing the weighted average according to the normal distribution [18].

- **Wavelet Transform**

The wavelet transform is a transform with extended and shifted copies of its basis functions; therefore, it involves spatial information in addition to frequency information. The discrete wavelet transform is required for digital images, which divide an image into four subsampled or decimated images [19]. The result includes one image that has been low-pass filtered in both directions, one image that has been high-pass filtered in both directions, one that has been high-pass filtered in the horizontal and low-passed in the vertical, and one that has been high-pass filtered in the vertical and low-passed in the horizontal [20].

3.4. CLASSIFICATION

Classification in Machine learning represents the process that classifies data into predefined groups or classes depending on their attributes. A convolutional neural network has been proposed for a binary category (fracture/nonfracture) and is structured to include convolutional, pooling, flattening, and dense layers. CNN autonomously collects features from the input image and employs a fully connected layer for image classification [21]. This study first classifies original X-ray scans and then enhanced X-ray scans using a CNN architecture, as shown in Figure 5 and Table 2, coupled with the parameters listed in Table 3. The best parameter values were found by experimenting with different values for each parameter.

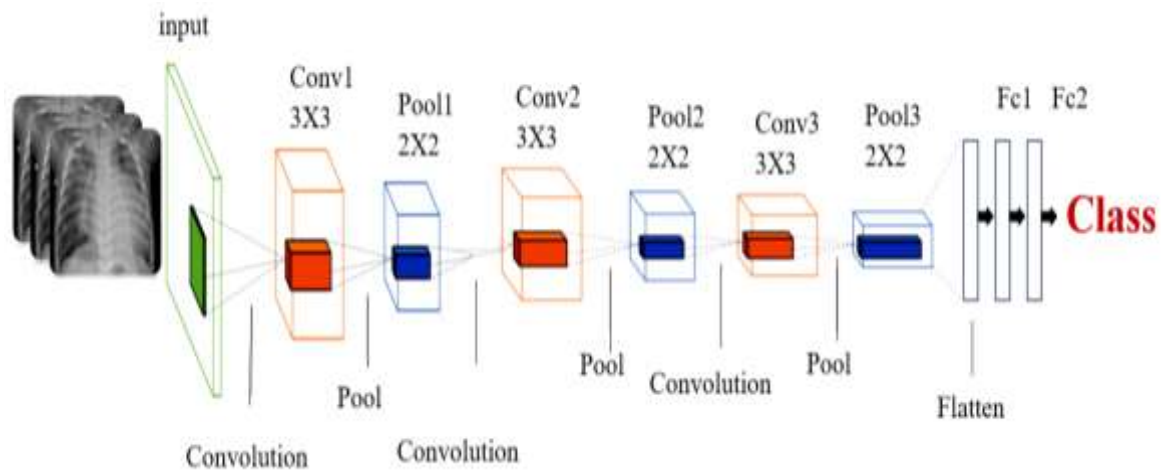


Fig.5.CNN Model Architecture.

Table 2. CNN Model Details.

Layer (Type)	Output Shape	Parameters
conv2d_48 (Conv2D)	(None, 179, 179, 32)	896
batch_normalization_48	(None, 179, 179, 32)	128
max_pooling2d_48 (MaxPooling2D)	(None, 89, 89, 32)	0
dropout_64 (Dropout)	(None, 89, 89, 32)	0
conv2d_49 (Conv2D)	(None, 87, 87, 64)	18,496
max_pooling2d_49 (MaxPooling2D)	(None, 43, 43, 64)	0
dropout_65 (Dropout)	(None, 43, 43, 64)	0
conv2d_50 (Conv2D)	(None, 41, 41, 128)	73,856
max_pooling2d_50 (MaxPooling2D)	(None, 20, 20, 128)	0
dropout_66 (Dropout)	(None, 20, 20, 128)	0
flatten_16 (Flatten)	(None, 51200)	0
dense_32 (Dense)	(None, 64)	3,276,864
dropout_67 (Dropout)	(None, 64)	0
dense_33 (Dense)	(None, 1)	65

Table 3. Parameters of Proposed CNN Model.

Parameter	Value
Batch-Size	64
Optimizer Adam	0.001
Image size	180
Epoch	20
Loss Function	Binary Cross-Entropy
Training set	70%
Testing set	30%

3.5. EVALUATION

3.5.1 EVALUATE CLASSIFICATION MODEL

The suggested classification model's efficiency assessment using standard evaluation metrics: precision, accuracy, recall, and F1-score.

- **Accuracy:** The proportion of cases within a designated group of test images that are accurately identified.
- **Precision:** The proportion of true positives relative to the total positive detections.
- **Sensitivity**, sometimes referred to as Recall, is the proportion of correctly identified positive instances to the total number of actual positives.
- **F1-Score:** The F1 Score is computed using the harmonic mean of Recall and precision.

The calculation of these metrics is detailed below; the terminology employed includes False Negative (FN), True Negative (TN), True Positive (TP), and False Positive (FP) [22].

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (2)$$

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

$$Sensitivity(Recall) = \frac{TP}{TP + FN} \quad (4)$$

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (5)$$

3.5.2 EVALUATE THE IMPACT OF ENHANCED IMAGE ON CLASSIFICATION MODEL

This study employs CNN as a measure to assess the impact of the image-optimizing method on the precision of fracture diagnosis. It compares the CNN classification results of the enhanced images with the CNN classification results of the original images before enhancement to determine the effect of the enhancement method on the accuracy of medical classification.

4. EXPERIMENTAL RESULTS AND DISCUSSION

This section analyzes the outcomes acquired from tests performed in three distinct scenarios. The experiment used Python programming with Keras and TensorFlow libraries on the Google Colab platform. The environment had a graphics processing unit (L4GPU) with 22.5 GB of GPU memory and 53 GB of RAM.

4.1 EXPERIMENTAL RESULTS WITHOUT IMAGE ENHANCEMENT (SCENARIO 1)

The following findings belong to scenario 1; after preprocessing and hyperparameter adjustment, original input images are sent to a CNN model, which will categorize them as either fracture or nonfracture.

During the training, CNN first deals with the input training group to train a model. The efficiency of the classifier is then assessed using an input test bone group. The convolutional neural network's confusion matrix using the original images is displayed in Figure 6.

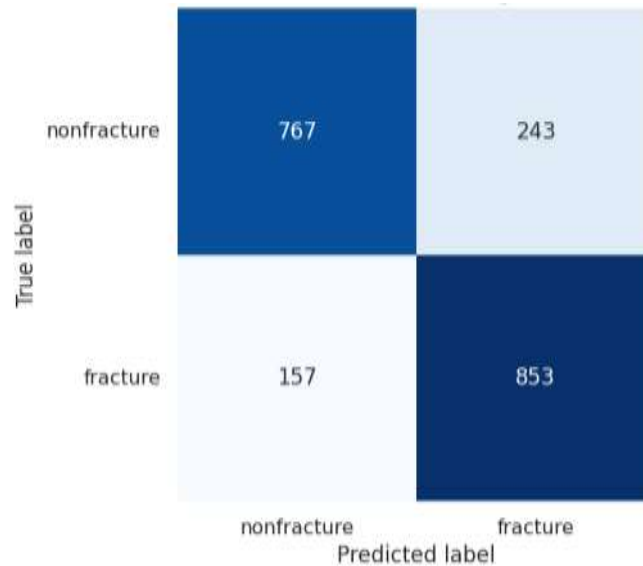


Fig. 6. Confusion Matrix on Scenario 1.

A confusion matrix, depicted in Figure 6, reveals the effectiveness of the classification model intended to classify images as "fracture" or "nonfracture." From a total of 1010 samples in each category, the model achieved good diagnostic accuracy, correctly diagnosing 853 fracture cases and 767 nonfracture cases while incorrectly classifying 243 nonfracture cases as fractures and 157 fracture cases as nonfractures. This performance illustrates the model's capacity to accurately identify the majority of fracture instances, which is crucial for medical models.

Figure 7 explains the CNN model's training and testing accuracy and loss function per 20 epochs with scenario 1. The proposed model with original images gives 82.19% train and 80.20% test accuracy.

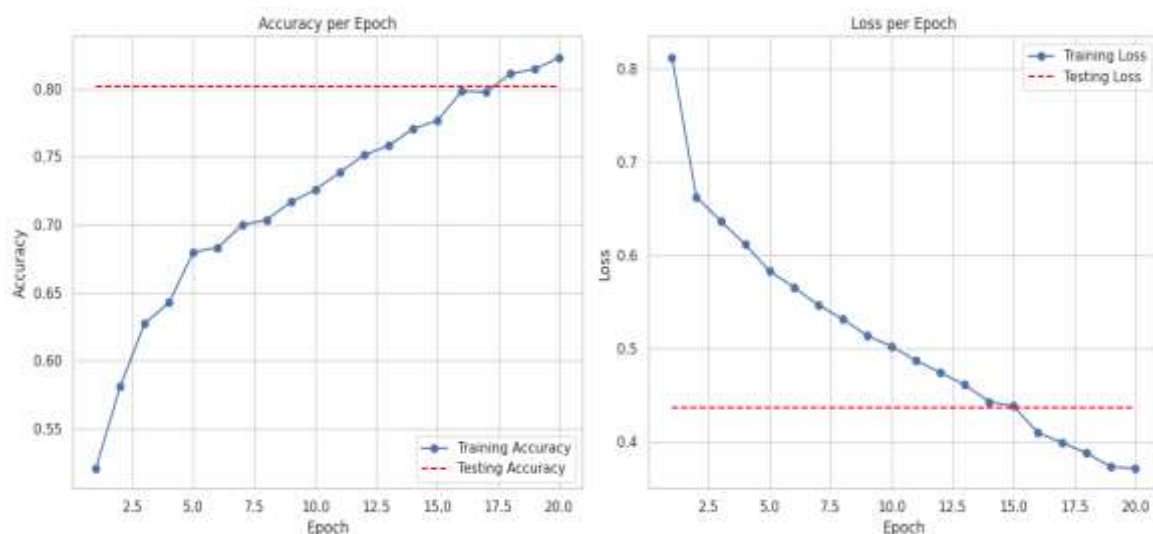


Fig. 7. CNN Training and Testing Accuracy and Loss Function per Epoch on Scenario 1.

Table 4 displays the performance metrics acquired in scenario 1, including the F1-score, recall, and precision values.

Table 4. Classifier's Results by Evaluation Metrics for Scenario 1.

Classes/Metric	Precision	Recall	F1-Score	Samples
Fracture	0.84	0.83	0.84	1010
Nonfracture	0.83	0.83	0.84	1010

4.2 EXPERIMENTAL RESULTS WITH IMAGE ENHANCEMENT (SCENARIO 2)

The subsequent results pertain to scenario 2, i.e., in the image enhancement stage, the X-ray images are enhanced to handle the issues of low contrast, noise, and lack of detail clarity. This helps obtain a higher-quality image that supports classification in the subsequent stage and improves accuracy. A merge enhancement method was applied to the entire dataset, starting with optimizing bone X-ray image contrast by applying the CLAHE technique (tile=8 and clip=2). After that, a Gaussian filter is applied (window size =3 and sigma =1) to the images resulting from CLAHE to acquire a high-quality dataset with better details, smoothed, less noise, and high contrast from this scenario.

In scenario 2, the CNN model receives the enhanced bone dataset (CLAHE + Gaussian) and classifies it as either fracture or nonfracture. The confusion matrix for scenario 2 is shown in Figure 8, which highlights the increasing data classification rate of the suggested model. Out of 1010 instances in each group, it correctly detects 960 fracture instances and 909 nonfracture instances but incorrectly classifies 101 nonfracture cases as fractures and 50 fracture cases as nonfracture.

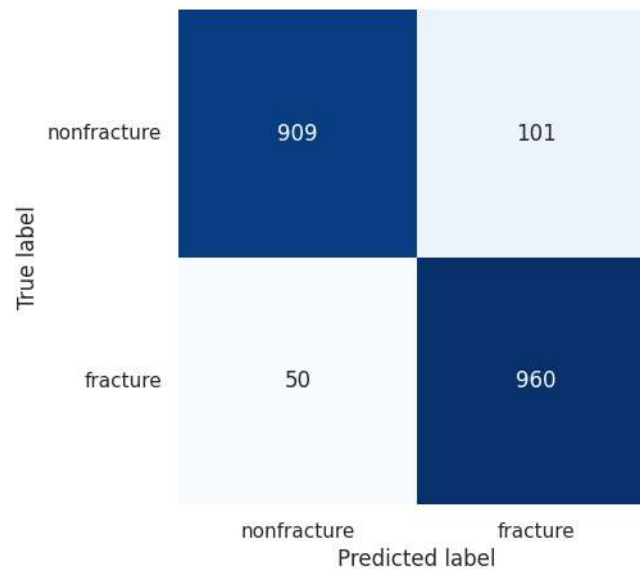


Fig. 8. Confusion Matrix on Scenario 2.

Figure 9 explains the CNN model's training and testing accuracy and loss function per 20 epochs. The proposed model with scenario 2 achieves 94.51% train and 92.52% test accuracy.

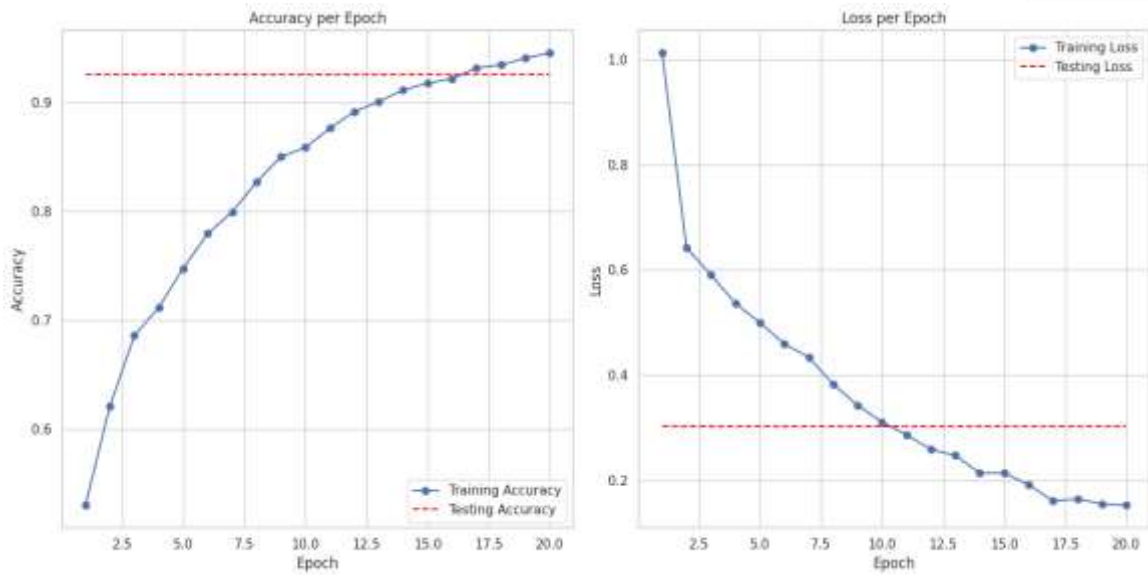


Fig. 9. CNN Training and Testing Accuracy and Loss Function per Epoch on Scenario 2.

Table 5 displays the model's F1-score, recall, and precision value in scenario 2. A CNN model with enhanced images improved performance using high contrast, low noise, and smoothing images, increasing classification test accuracy from 80.19% to 92.52%.

Table 5. Classifier's Results by Evaluation Metrics for Scenario 2.

Classes/Metric	Precision	Recall	F1-Score	Samples
Fracture	0.95	0.90	0.92	1010
Nonfracture	0.90	0.95	0.93	1010

4.3 EXPERIMENTAL RESULTS WITH IMAGE ENHANCEMENT (SCENARIO 3)

The subsequent results pertain to scenario 3, i.e., the X-ray images are enhanced to address the issue of low contrast, edge highlighting, improved curvature, and appearance of fine details, which assists in obtaining a better-quality image that boosts the classification and accuracy. A merge enhancement method was applied to the dataset, beginning with enhancing X-ray image contrast by implementing the CLAHE technique (tile=8 and clip=2). After that, a wavelet transform (type Biorthogonal Wavelet and level = 2) is applied to the images resulting from CLAHE to acquire a high-quality dataset with optimized edges, less noise, better details, and high contrast from this scenario.

The CNN model is fed the improved bone dataset (CLAHE + Wavelet) to determine whether the bone is fractured or nonfractured. The confusion matrix for scenario 3 is shown in Figure 10, which highlights the increasing data classification rate of the suggested model. It correctly classifies 982 fracture cases and 851 nonfracture cases out of 1010 instances for each group, but incorrectly classifies 159 nonfracture instances as fractures and 28 fracture instances as nonfracture.

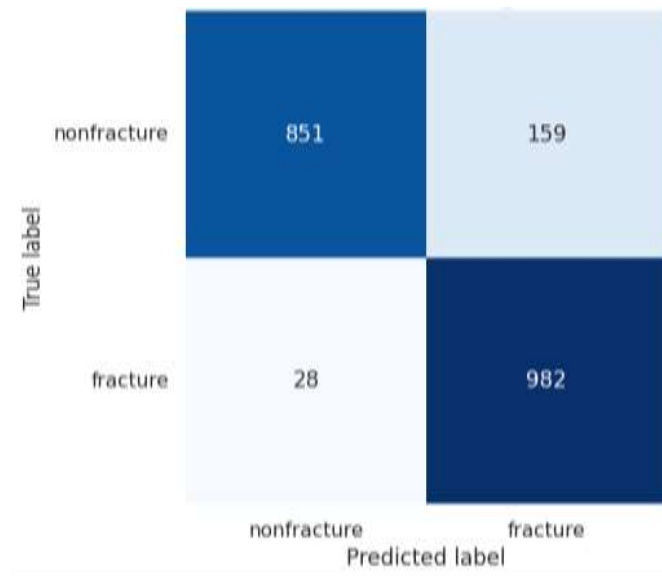


Fig. 10. Confusion Matrix on Scenario 3.

Figure 11 explains the CNN model's training and testing accuracy and loss function per 20 epochs. The proposed model with scenario 3 obtains 94.87% train and 90.74% test accuracy.

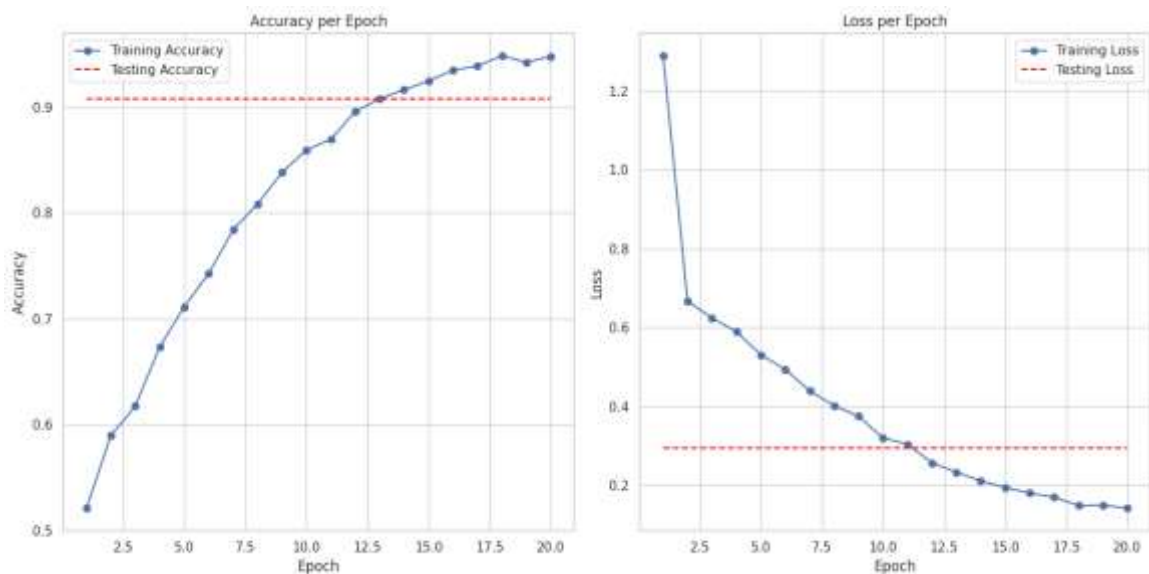


Fig. 11. CNN Training and Testing Accuracy and Loss Function per Epoch on Scenario 3.

Table 6 displays the classifier's results by Precision, recall, and the model's F1-score in scenario 3. The CNN classifier with scenario 3 improved performance using high contrast, less noise, and better fine-detail images, increasing classification accuracy from 80.19% to 90.74%.

Table 6. Classifier's Results by Evaluation Metrics for Scenario 3.

Classes/Metric	Precision	Recall	F1-Score	Samples
Fracture	0.97	0.84	0.90	1010
Nonfracture	0.86	0.97	0.91	1010

5. COMPARISON OF RESULTS

This section juxtaposes the current study findings in two different directions. The first direction involves juxtaposing the results of the three scenarios, while the second direction juxtaposes the current study findings on improved images with the most prominent results of recent studies that use the same dataset, FracAtlas.

5.1 COMPARATIVE OF THE THREE SCENARIOS: The primary findings from the three earlier scenarios are shown in this direction. Preprocessing, applying image enhancement, classification, and evaluation are the four stages of the suggested method for identifying bone fractures from X-ray images. Three scenarios serve as the basis for the approach's outcomes: original image results, improved image results using CLAHE+ Gaussian, and improved image results using CLAHE+ wavelet. Table 7 illustrates that when comparing the accuracy of CNN models with and without image enhancement techniques, the CNN performs better with improved bone imagery than with the original bone images.

Table 7. Impact of Enhancement Images on Classifier Accuracy.

Classification/ Accuracy	Scenario 1 (original images)	Scenario 2 (CLAHE+ gaussian)	Scenario 3 (CLAHE+ wavelet)
Train accuracy	82.19	94.84	94.87
Test accuracy	80.20	92.52	90.74

Table 8 displays the evaluation metrics of three scenarios; it shows that the scenario with enhanced images outperforms the scenario without enhanced images in all metrics. In contrast, when comparing the enhanced image scenario observed, the scenario with CLAHE+ Gaussian gives the maximum precision, accuracy, and F1-score, making it better than the other scenario, while the CLAHE+ wavelet scenario surpasses in recall.

Table 8. Performance of Proposed Approach.

Classification/ Metric	Accuracy	Precision	Recall	F1-Score	Samples
Scenario 1	80.19	83.33	84.16	83.74	2020
Scenario 2	92.52	90.48	95.05	92.71	2020
Scenario 3	90.74	80.06	97.23	91.31	2020

Tables 7 and 8 demonstrate that the classification performance has improved significantly, reflecting the enhanced impact of the images on the CNN model in feature extraction, pattern learning, and diagnostic decision-making. Based on this, the second scenario was tested using the proposed CNN model in a real clinical environment, and the system successfully classified cases with 100% accuracy.

5.2 COMPARATIVE OF THE PROPOSED APPROACH (ENHANCED IMAGES) WITH STATE-OF-THE-ART APPROACHES: The proposed approach with enhanced images is compared to comparable studies using the FracAtlas dataset for detecting bone fracture in Table 9.

Table 9. Comparison of Enhancement Images with Comparable Research Utilized FracAtlas Dataset.

Ref.no	Reference authors and year	Method	Accuracy
[23]	R. Riska,2024.	ML (decision tree) + Canny Segmentation	74.05%
[24]	P. Chen et al.,2024	CNN+WCAV algorithm	76.2%
[3]	A. Alshahrani and A. Alsairafi,2024	YOLO8 + VGG16	81%
[25]	F. Akhlaq et al.,2024	YOLOv8	83.1%
[26]	J. Zou and M. R. Arshad,2024	YOLOv7	86.2%
[27]	S. Sanzida Ferdous Ruhi et al.,2024	InceptionV3+DenseNet121 with BAM model	90.48%
[28]	R. Hrubý et al.,2024	CNN	91%
	The proposed system	CNN with CLAHE+ Gaussian	92.52%
	The proposed system	CNN with CLAHE+ Wavelet	90.74%

Table 9 shows the proposed approach with enhanced images, achieving remarkable outcomes. It has a testing accuracy of 92.52% and 90.74% with CLAHE+ Gaussian and CLAHE+ Wavelet, respectively, surpassing traditional techniques and comparable research utilizing the same dataset. These results indicate the better generalizability and performance of the proposed system.

6. CONCLUSION

The analysis and exploration of implement CNN classifier in data set FracAtlas yielded important revelations concerning its efficiency in detecting bone fractures in X-ray images. The classifier proved to have high precision, accuracy, F1-score, and recall, implying its feasibility as a supplementary diagnostic tool. The performance analysis through a confusion matrix illustrated the high efficiency of the CNN in distinguishing between fractured and non-fractured bones. From the point of view of medical diagnostics, the findings confirm the model's high performance in achieving an ideal balance between sensitivity and specificity, crucial for clinical settings. The study confirmed the efficiency of implementing a combined approach, whereby deep learning models, such as convolutional neural networks, are applied alongside image processing approaches. Thus, the integration allowed enhancing the efficiency of bone fracture classification up to 92.52% and improved diagnostic accuracy. The study contributes to medical informatics in terms of enhancing the capacity of these models, possibly even streamlining procedures in radiology practices. Future research in the field should expand upon this foundation to build a model by using more complex deep learning models, a bigger and more diverse database, and applying advanced image improvement techniques. Such actions would improve the ability to make accurate diagnoses, thus allowing for the merging of such models into healthcare settings.

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