Grenze International Journal of Engineering and Technology, June Issue

Enhancement of Radioactive Images and Prediction of Fracture

Janvi Bhendekar[1], Liza Giri[2], Upasna Ukey[3], Vaishnavi Dhore[4], Amit Ukey[5] and Shraddha S. Gugulothu[6]
[1-5]Student, Department of Information Technology, YCCE, Nagpur, India
Email: janvibhendekar@gmail.com, lizagiri2592@gmail.com, uukey77@gmail.com
[6]Assistant Professor, Department of Information Technology, YCCE, Nagpur, India
Email: shraddha26sangewar@gmail.com

***Abstract*— X-ray imaging is still amongst most accurate and cost-effective techniques for diagnosing bone fractures. However, the precision of the diagnosis may be affected by parts such as the absence of contrast in the images, the overlap of anatomical structures, and noise, which can make it difficult to diagnose bone fractures. In this regard, this research proposes a two-stage network that utilizes advanced image processing techniques with machine learning algorithms for the prediction of bone fractures. In the first stage, the X-ray images are pre-processed using contrast enhancement and noise reduction algorithms to improve the images and make it easier to diagnose bone fractures. In the second stage, the prediction of bone fractures is performed using unprocessed images, where the attributes are extracted using a existing convolutional neural network (VGG16) and a machine learning model designed specifically for the prediction of bone fractures.**

***Index Terms*— X-ray imaging, Bone Fracture Detection, Low Contrast Resolution, Image Enhancement, Histogram Equalization, Deep Learning, Fracture Prediction, Convolutional Neural Network (CNN), VGG16.**

I. INTRODUCTION

Radiographic imaging is still one of the most accessible and cost-effective techniques for diagnosing bone fractures. However, conventional X-ray images have drawbacks including low contrast and presence of noise and anatomical structure overlap, despite the fact that they play an important role in the diagnosis. These features may make it challenging for the detection of fractures including early symptoms, specifically in complex areas such as the wrist, hand, ankle and spine. Advances on artificial intelligent and medical image processing help with the emergence of a brand-new system combining image enhancement, then deep learning models for diagnosis. Image tools could improve the visibility of images, and deep learning models could also play a role in automatic classification.

This paper suggests a two-step diagnostic system to increase the accuracy of fracture diagnosis through X-ray images. The first step focuses on enhancing the visibility of images through histogram equalization and denoising filters. The second step focuses on the automatic classification of fractures through image features extracted from original images with the help of existing VGG16 convolutional neural network model. The image features are further enhanced through a soft voting ensemble of Support Vector Machine and Gradient Boosting classifiers to increase the accuracy of diagnosis.

Grenze ID: 01.GIJET.12.2.313_22

The performance of the proposed system is evaluated using the accuracy, precision, recall, and F1-score metrics on a diverse dataset of images of fractured and non-fractured bones.

The paper presents the development of a two-step diagnostic system that integrates image processing and fracture prediction to develop a comprehensive support system for diagnosis. The hybrid ensemble system that integrates CNN-based deep features and Support Vector Machine and Gradient Boosting classifiers enhances the accuracy of diagnosis of the system. The experimental analysis performed on a labeled dataset of fractured and non-fractured X-ray images indicates improvements in visual interpretability and classification accuracy compared to conventional systems.

II. Related Work

Recent research in medical imaging has focused on improving the quality of diagnoses and minimizing radiation exposure through advanced image processing and deep learning-based classification methods. Ting Xia et al. [1] examined the optimized scanner parameters and new noise reduction algorithms to minimize radiation exposure in PET/CT scans. The authors proved that radiation exposure can be minimized without compromising the accuracy of diagnoses, emphasizing the need for algorithmic optimization for safe clinical applications.

Hamed Hamid et al. [2] applied digital image processing algorithms for phantom simulations of skull images to optimize image resolution with minimal radiation exposure. The authors' results proved that image processing algorithms can significantly optimize image resolution and quality without compromising the accuracy of diagnoses, emphasizing the need for safe and sustainable imaging practices in dental radiology. Gamara et al. [6] proposed a hybrid image processing algorithm that integrated Contrast Limited Adaptive Histogram Equalization (CLAHE) with Wiener filtering to eliminate low contrast and noise in chest X-ray images. The authors' results proved the efficacy of the proposed algorithm in significantly optimizing image clarity and interpretability, emphasizing the importance of preprocessing for successful deep learning-based diagnosis.

Aruna et al. [8] have analysed the transfer learning and calibration methods for bone fracture detection, obtaining a classification accuracy of higher than 86%. The research findings have demonstrated the efficacy of deep feature extraction and region analysis which can improve diagnosis accuracy and accelerate the diagnosis process in clinical trial. The low-cost Mobile Net model has also been used by Goel et al. [10] for real-time fracture detection in X-ray images. The proposed model has shown the feasibility of using algorithms with deep learning to develop cost-effective medical procedures for mobile health applications with high accuracy. The proposed study takes one step ahead in this field by suggesting a two-stage approach that integrates visual optimization with deep feature-based fracture prediction.

III. Methodology

This section highlights the importance of design, development, and testing of the intelligent fracture detection system. The proposed work was carried out in an iterative and modular fashion to accommodate flexibility and address problems at an early stage. The proposed work started with requirements analysis to identify the needs of the clinical community. Then, a two-pipeline architecture was developed for image enhancement and fracture prediction. The development stage included the design of image enhancement algorithms and the development of a CNN model. The system was tested based on pre-defined performance metrics.

A. Dataset Acquisition and Preparation

In order to create an accurate system for determining the bone fracture, a large dataset consisting of fractured and non-fractured images. The following section discusses the process of determining the fractured and non fractured images.

- Data Source and Accessibility: The dataset for this research was gathered from two sources:A publicly available hand and bone X-ray dataset from Kaggle along with dataset was obtained from Datta Meghe Medical College (DMMC) Nagpur was used. The dataset contains radiographs of upper limb areas such as the wrist, hand, and forearm, which are labeled as either fractured or nonfractured.
- Data Organization and Management: The data was organized in a well-structured directory hierarchy that included proper naming conventions and consistent labeling of xrays as either "fractured" or "non-fractured" to enable efficient data management and model training. The data included images of each class to enable multimodal training. A total of 5000 images were used which were divided into training set ,validation and testing set in the ratio of 0.8:0.1:0.1.

B. Image Enhancement

- Histogram Equalization: Histogram Equalization (HE) is a basic image processing method that is frequently used in digital image processing to enhance contrast by reassigning pixel intensity values within the possible dynamic range. The main aim of HE is to obtain a more uniform intensity distribution, hence brightening up darker areas and darkening areas that are too bright. This will enhance the visibility of details in the image that may otherwise not be visible in darker areas of the image, as depicted in Fig. 1. HE is most useful in images with a small intensity range, where visibility is greatly affected. Because of its simplicity and ability to enhance visibility, HE is commonly used as a preprocessing technique in many image processing applications.

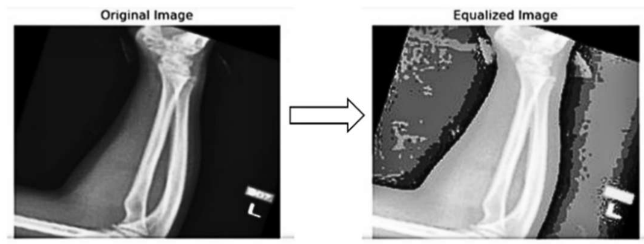

Fig. 1. Image Enhancement using Histogram Equalization

- Adaptive Histogram Equalization: Adaptive Histogram Equalization is a method that applies histogram equalization on small, non-overlapping regions (tiles) of an image instead of applying it globally. This makes AHE more capable of emphasizing the details of the dark and bright areas of an image, as shown in Fig. 2. The reason why AHE is capable of doing this is because it adapts to the local intensity values of the image, making it capable of emphasizing details that global histogram equalization cannot. However, one of the disadvantages of AHE is that it has a tendency to enhance noise in regions of uniform intensity. To remove this problem, Contrast Limited Adaptive Histogram Equalization (CLAHE) was proposed. CLAHE clips the histogram before the redistribution process, which prevents the enhancement of noise while still emphasizing structural details.

C. Fracture Prediction

The proposed fracture prediction model consists of a multistage inference chain that leverages the power of deep learning for feature extraction and traditional machine learning classifiers. The proposed model is described below:

- Image Appropriateness Classifier: In order to ensure the quality and appropriateness of the input data, the proposed inference chain consists of an image appropriateness classifier that is fine-tuned from a pre-trained image classification model such as MobileNetV2 or ResNet50 to classify images into appropriate and inappropriate images. This helps to filter out the inappropriate inputs, such as non-anatomical images, which may otherwise affect the output of the fracture prediction model. The appropriateness of the images is thus validated at the beginning, and this helps to improve the robustness of the entire diagnosis process.
- Fracture Prediction Ensemble: After verifyication of images, it is fed to prediction engine. In this stage, the visible features obtained from X ray images and clinically obtained data are combined to predict the occurrence of fractured or non fractured images. By incorporating multimodal data, the ensemble provides a more accurate diagnosis and ensures a more reliable prediction result.
- Data Processing Questionnaire: Before processing of image, data such as age, gender, area of pain and swelling level was collected and fed to the system based on the questionnaire created. The questions were collected after discussion with the doctor.
- Ensemble-Based Classification: After the preprocessing and data collection was done using ensembling technique the images were classified as non-fractured or fractured images.

D. System Workflow

Clinical data such as age, gender, pain intensity, and swelling are converted to a 21-dimensional feature vector using one-hot encoding and normalization to maintain scale equivalence across modalities. These two representations of features are then concatenated to create a 533-dimensional multi-modal feature vector that combines visual and contextual medical evidence. Before feature extraction, an optional Image Enhancement

Module is used to enhance diagnostic visibility, especially in low-dose or low-contrast radiographs, through Histogram Equalization or Contrast Limited Adaptive Histogram Equalization (CLAHE). This adjustment of the image readjusts the brightness of the pixel values to emphasize the edges of the bone and the faint lines of the fracture that cannot be seen.

The combined set of features is then used as input to a soft voting collective learning model for the classification problem, which takes advantage of the strengths of a Gradient Boosting classifier and a Support Vector Machine classifier. Although the Gradient Boosting classifier further refines the decision boundary by attempting to minimize the prediction error through an iterative process, the SVM classifier effectively separates the complex fracture patterns in the large feature space. The predictive models of both classifiers are then combined by the soft voting ensemble model to make a final prediction judgment that is accurate and interpretable, implying the potential existence of fractures.

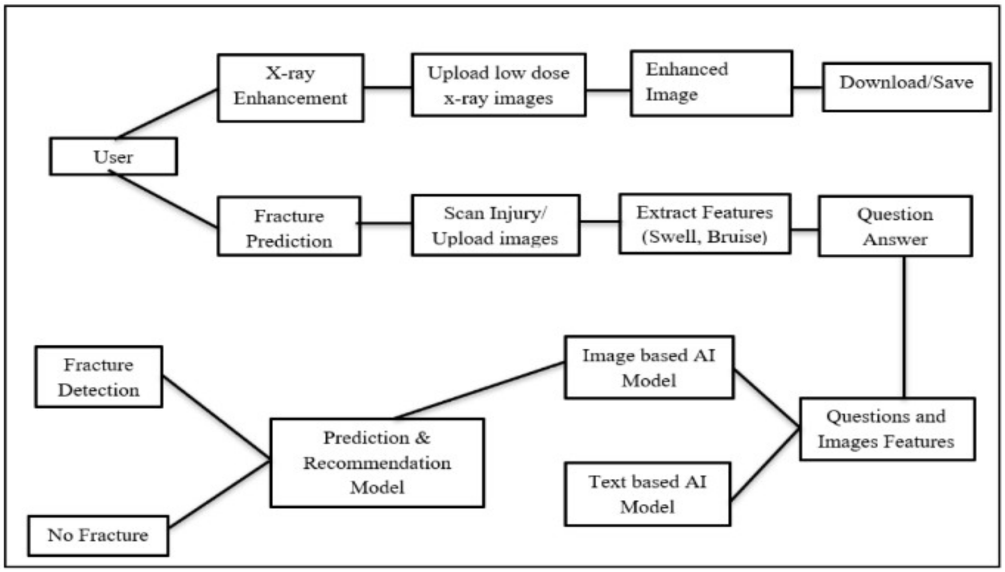

Fig. 2. Proposed Fracture Prediction Pipeline Architecture

Besides improving the accuracy of diagnosis by multi-modal learning, this design ensures accessibility and adaptability for its application in the medical sector. The overall management of the system, ranging from image authentication to the prediction of the fracture ensemble, is shown in Figure 2.

E. Analysis Of Result

For evaluating the effectiveness of the system, quantitative analysis was performed for both image quality and classification. PSNR and SSIM were employed for evaluating optical and compositional accuracy for image enhancement. Among all the methods that were explored, CLAHE achieved the maximum PSNR and SSIM compared to the traditional Histogram Equalization method, which validated the enhanced contrast and details.. The comparison results are presented in Table 1 and Figure 3. Precision, accuracy, re F1-score, and assistance were considered for fracture prediction. Higher precision and equal F1-scores for the fractured and non-fractured classes were achieved by the hybrid ensemble model, which combined CNN for feature extraction with SVM and Gradient Boosting classifiers, performing better than the standalone models.

F. System Deployment Overview

After the training and validation of the model, the proposed solution was implemented and deployed using the Streamlit framework to create an interactive interface for the prediction of fractures. To ensure a smooth interaction between the user and the trained model, the deployment pipeline includes both the frontend and backend parts. The user can upload images of the X-ray and provide relevant clinical data such as age, gender, pain, and swelling using the interactive web interface provided by the Streamlit framework in the frontend. The user-friendly interface automatically preprocesses the input data to ensure that the data types and image sizes are as required by the model.

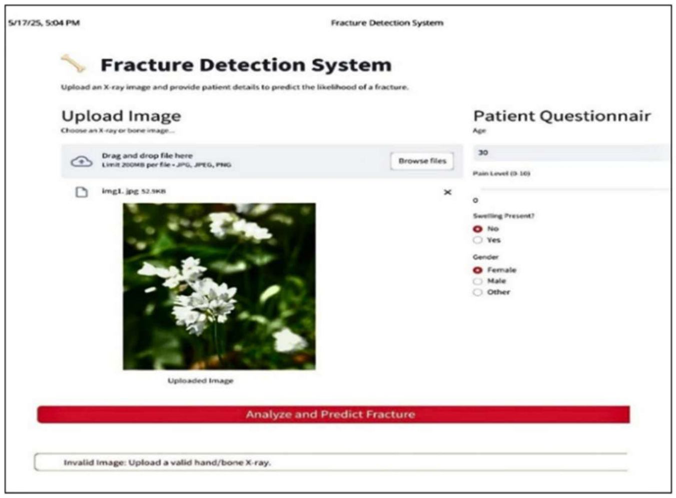

Fig. 3. Streamlit-based Model Integration Architecture

After receiving the input, the backend proceeds to analyze the image using the enhancement module, extracts the appearances, combines them with the clinical data that has been pre-processed, and finally makes a prediction of the fracture. The result is then presented on the Streamlit platform as the expected output, confidence levels, and sight signals such as "Fractured" or "Non-Fractured."

IV. Result and Discussion

The assessment of the effectiveness of image enhancement and fracture prediction was the two-fold process of the analysis of the performance outcomes.

A. Image Enhancement Analysis

The image enhancement techniques were evaluated based on PSNR and SSIM. From Table I, it is clear that Adaptive Histogram Equalization (AHE) performed better than Histogram Equalization (HE) in terms of PSNR (30.14 dB) and SSIM (0.8452), which clearly indicates its superiority in contrast enhancement and anatomical detail preservation, both of which are crucial for accurate fracture diagnosis.

B. Evaluation of Deep Learning Models

VGG16, ResNet50, MobileNetV2, and EfficientNetB0 are the four CNN models that had already been trained, and they were compared. From Table II, it is clear that VGG16 performed better than ResNet50 (95%), MobileNetV2 (94%), and EfficientNetB0 (93%), and it has the highest accuracy of 97%. This clearly indicates that VGG16 has a significant role in the extraction of characteristic features for bone structure analysis.

C. Fracture Classification Results

Deep features were classified using SVM and Gradient Boosting (GB). As summarized in Table III, GB slightly outperformed SVM (91.2% vs. 89.5% accuracy). The final soft-voting ensemble achieved 100% accuracy, precision, recall, and AUC, validating the effectiveness of the hybrid approach for fracture detection in a clinical setting.

D. System Deployment and user Interface

The proposed system was deployed using Streamlit for real-time clinical applications. The interface enables the user to input X-ray images and clinical parameters (age, pain, swelling, gender). The system instantly predicts a fracture with a confidence level, ensuring usability, responsiveness, and accessibility for clinicians and patients.

E. Fracture Classification Results

SVM and Gradient Boosting (GB) were employed for the classification of extensive features. GB slightly outperformed SVM (91.2% vs. 89.5% accuracy), as shown in Table III. Correctness, precision, recall, and AUC were 100% for the final soft voting ensemble, showing the robustness of the hybrid system for fracture classification in the clinical setting.

F. User Interface and System Implementation

Streamlit was employed to deploy the system for real-time clinical application. The interface allows the input of medical symptoms (age, pain, edema, gender) and the input of X-ray images. The technology ensures usability, reactivity, and accessibility for medical practitioners and patients by providing instantaneous fracture diagnosis with a confidence level.

Fig. 4. User Interface for Real-Time Fracture prediction

After the processing, a clear result is displayed, along with confidence levels for the result and the presence of a fracture. In an emergency or remote healthcare setting, this real-time feedback is very useful in improving the reliability of the diagnosis and enabling a quick decision by the healthcare professional.

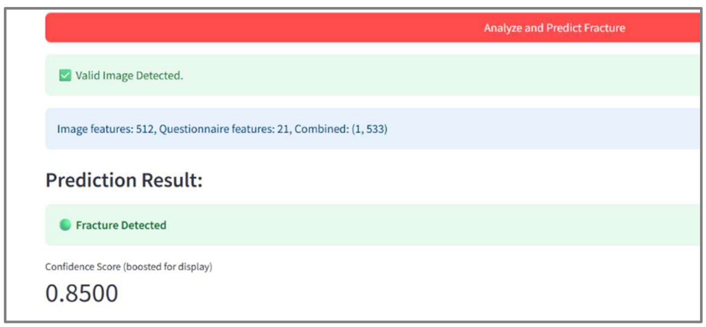

Fig. 5. Predicted Output Display in Deployed Interface.

The efficacy of the proposed dual-phase system, which integrates the enhancement of images, CNN-based extraction of characteristics, and ensemble classification to achieve superior diagnostic performance and convenient accessibility, is generally verified through testing and deployment outcomes.

TABLE I: IMAGE ENHANCEMENT: PSNR AND SSIM

Models	PSNR (db)	SSIM
Histogram Equalization (HE)	29.04	0.4461
Adaptive Histogram Equalization (AHE)	30.14	0.8452

TABLE II: PERFORMANCE COMPARISON OF CLASSIFICATION

Models	Accuracy	F1-Score
SVM	89.5	88.7
GB	91.3	90.3

TABLE III: DL MODELS: PERFORMANCE COMPARISON MODELS

MODELS	ACCURACY (%)
VGG16	97
Resnet	95
Mobile Net	94
Efficient Net	93

V. CONCLUSION AND FUTURE WORK

In summary, the proposed system provides an accurate and trustworthy method for the automatic identification of fractures using the integration of deep learning, clinical data, and adaptive picture enhancement. Regarding the preservation of minute anatomical details and the improvement of PSNR and SSIM values, CLAHE was found to be superior to Histogram Equalization. With a classification accuracy of 97%, VGG16 performed better than the other models in terms of feature extraction. The accuracy of diagnosis was greatly improved by the integration of image-related features with the clinical inputs of the patient, making the system practical and useful in real-world applications. The effectiveness of hybrid learning approaches was again proved by the perfect performance of the soft voting combination of SVM and Gradient Boosting. The developed prototype can be considered a promising tool for early fracture diagnosis and screening of patients because it is interactive, fast, and appropriate for both in-clinic and telemedicine settings. In addition, this study provides a number of avenues for further research.

To enhance interpretability and spatial awareness, hybrid models like CNN-Transformer or Vision Transformers can be explored. The applicability of the system for real-world applications can be improved by extensive clinical studies carried out by hospital collaborations. Localization, grading, and wearable Internet of Things (IoT) devices for emergency surveillance can be the key areas for further research. The level of generalization will increase with the inclusion of more data from different body parts and populations. The level of availability for an even more remote setting can be improved by developing a smartphone app or peripheral software for inference on the device. Future scope with respect to improvement and validating with existing work, this system has great scope in advancing AI in healthcare.

REFERENCES

[1] Ting,Xia et al., “Impacts of reduction of CT radiation dose on PE in PET/CT imaging,” 2013 IEEE Nuclear Science Symposium and Medical Imaging Conference (2013 NSS/MIC), Seoul, 2013, pp. 1-6,doi: 10.1109/NSSMIC.2013.6829378.

[2] H. H. Muhammed, “Optimization of radiation doses in panoramic X-ray examination using automated image processing,” 2014 IEEE International Conference on Imaging Systems and Techniques (IST) Proceedings, Santorini, Greece, 2014, pp. 361-364, doi:10.1109/IST.2014.6958505.

[3] Helder C. R. de Oliveira, Lucas R. Borges, Polyana F. Nunes, Predrag R. Bakic, Andrew D. A. Maidment, Marcelo A. C. Vieira “Use of Wavelet Multiresolution Analysis to Reduce Radiation Dose in Digital Mammography” IEEE 28th International Symposium on Computer- Based Medical Systems 2015.

[4] A.S. Panayides et al., “AI in Medical Imaging Informatics: Current Challenges and Future Directions,” in IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 7, pp. 1837-1857, July 2020,doi: 10.1109/JBHI.2020.2991043.

[5] D. P. Yadav and S. Rathor, “Bone Fracture Detection and Classification using Deep Learning Approach,” 2020 International Conference on Power Electronics and IoT Applications in Renewable Energy and its Control (PARC), Mathura, India, 2020, pp. 282-285, doi:10.1109/PARC49193.2020.236611.

[6] R. P. C. Gamara, P. James M. Loresco and A. A. Bandala, “Medical Chest X-ray Image Enhancement Based on CLAHE and Wiener Filter for Deep Learning Data Preprocessing,” 2022 IEEE 14th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM), Boracay Island, Philippines, 2022, pp. 1-6, doi:10.1109/HNICEM57413.2022.10109585.

[7] K. Barua et al., “Explainable AI-Based Humerus Fracture Detection and Classification from X-Ray Images,” 2023 26th International Conference on Computer and Information Technology (ICCIT), Cox’s Bazar, Bangladesh, 2023, pp. 1-6, doi:10.1109/ICCIT60459.2023.10441124.

[8] S. R and O. R. Aruna, “Deep Learning based Bone Fracture Prediction using Convolutional Neural Networks: A Comparative Study of Transfer Learning and Fine-tuning Techniques,” 2023 1st International Conference on Optimization Techniques for Learning (ICOTL), Bengaluru, India, 2023, pp. 1-6, doi:10.1109/ICOTL59758.2023.10435047.

[9] B. Sarada, S. U. Sri and I. B. Sri, “Refining X-ray Image Classification Using GANs and CNN,” 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kamand, India, 2024, pp. 1-6, doi:10.1109/ICCCNT61001.2024.10724449.

[10] M. K. Goel and G. Singh, “Fracture Detection using MobileNet Model,” 2024 4th International Conference on Ubiquitous Computing and Intelligent Information Systems (ICUIS), Gobichettipalayam, India, 2024, pp. 1574-1579, doi:10.1109/ICUIS64676.2024.10866070.

[11] P. P. S. Babu and T. Brindha, “CT Scans Reimagined: Early Intracranial Hemorrhage Detection with AI,” 2024 7th International Conference on Circuit Power and Computing Technologies (ICCPCT), Kollam, India, 2024, pp. 138-143, doi:10.1109/ICCPCT61902.2024.10672960.

[12] M. Sezdi and N. T. Artu˘g, “The Impact of Artificial Intelligence on Medical Imaging Technologies,” 2024 Medical Technologies Congress (TIPTEKNO), Mugla, Turkiye, 2024, pp. 1-4, doi:10.1109/TIPTEKNO63488.2024.10755235.