TransFigX: An Explainable Transformer-Based System for Multi-Fracture Identification in Radiographic Images

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ABSTRACT

Fracture identification from X-ray images is challenging when multiple cracks, small hairline fractures, or low-contrast regions are present. Manual diagnosis often becomes slow in emergency rooms and rural healthcare centres where radiologists may not be immediately available. To address this real-time issue, our project proposes a Data Efficient Image Transformer (DEiT) model capable of detecting multiple fractures accurately from X-ray images. To strengthen feature extraction and decision-making, the system integrates Ridge regression for reducing overfitting, Passive Aggressive Classifier (PAC) learning principles for improving model generalization, and Nearest Centroid Classifier (NCC) to enhance similarity matching between fracture patterns. Additionally, Fast Interpretable Greedy Sums are used to generate lightweight, transparent scoring for model decisions, allowing doctors to understand why a fracture was detected. In real-time medical environments such as emergency rooms, trauma centres, and rural hospitals, patients with injuries often require immediate X-ray analysis to confirm bone fractures. Small or multiple fractures are especially difficult to detect quickly, increasing the risk of misdiagnosis and improper treatment.

Key words: bone fracture detection, X-ray image analysis, explainable AI, Machine Learning, Transformers, emergency radiology

1. OVERVIEW

Accidents, falls, sports injuries, and occupational hazards result in a significant number of bone fractures worldwide. Among developing countries, India records one of the highest fracture rates, primarily due to the increasing number of road accidents and rapid urbanization. According to several medical surveys, road accidents contribute to more than 50% of orthopedic injuries in India, and the number continues to rise every year. Early diagnosis of fractures plays a crucial role in ensuring appropriate treatment, preventing long-term disability, and improving patient recovery. X-ray imaging is the first and most widely used technique for fracture diagnosis, due to its low cost, fast scanning time, and ability to visualize bone structure clearly. Reports indicate nearly 26% increase in orthopedic fractures in the last ten years. Young adults aged 18–35 experience the highest rate of fractures, followed by elderly individuals above 60 years who suffer fractures due to osteoporosis and falls. Graphical trends show that fractures involving lower limbs (tibia, femur, ankle) and upper limbs (wrist, radius, shoulder) are most common and frequently misdiagnosed when multiple fractures occur simultaneously. Therefore, a multi-fracture detection system trained on diverse datasets becomes essential for real-time healthcare support. Multiple bone fractures occur when more than one bone is broken at the same time, either in the same limb or in different parts of the body. These injuries usually happen due to high-impact trauma, and they require rapid diagnosis and immediate medical attention. Figure 1 show types of classification methods, which are discussed as follows:

- **Transverse Fracture:** The break is straight across the bone, forming a horizontal line. Common in direct impacts, road accidents, and sports injuries. Often easy to identify on X-ray due to clear separation.
- **Oblique Fracture:** The break is diagonal across the shaft of the bone. Usually caused by a force applied at an angle.

- **Comminuted Fracture:** The bone shatters into three or more fragments. Seen in high-energy trauma such as vehicle crashes or falls from height. Requires complex treatment and sometimes multiple surgeries.

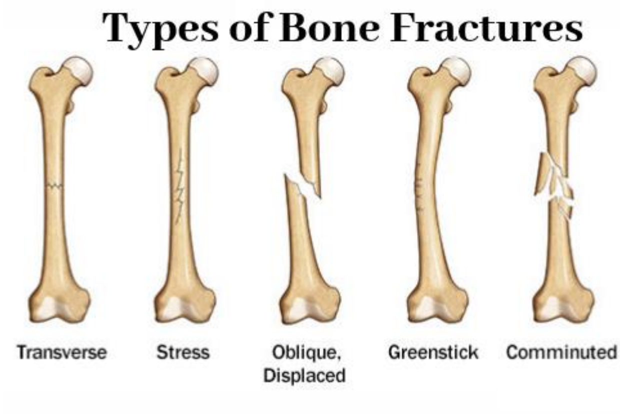

Figure 1: Types of Bone Fractures

- **Hairline / Stress Fracture:** A very thin, partial crack in the bone. Caused by repetitive stress common among athletes and military recruits. Often missed early X-ray interpretation due to low visibility.
- **Greenstick Fracture:** Bone bends and cracks on one side only. Seen mostly in children, because their bones are softer and more flexible.

2. LITERATURE SURVEY

Yadav, et.al [1] proposed the innovation behind this research is that it works with an improved canny edge algorithm to obtain edges in the images that localize the fracture region. After that, grey images and their corresponding canny edge images are fed to the proposed hybrid SFNet for training and evaluation. Furthermore, the performance is also compared with the state-of-the-art deep CNN models on a bone image dataset. Showed that SFNet with canny (SFNet + canny) achieved the highest accuracy, F1-score and recall of 99.12%, 99% and 100%, respectively, for bone fracture diagnosis. It showed that using a canny edge algorithm improves the performance of CNN. Panchal, et.al [2] proposed the bone is a major component of the human body. Bone provides the ability to move the body. The bone fractures are common in the human body. The doctors use the X-ray image to diagnose the fractured bone. The manual fracture detection technique is time consuming and also probability of error is high. Therefore, an automated system needs to develop to diagnose the fractured bone. The Machine Learning is widely used for the modelling of the power electronic devices. In the present study, a deep neural network model has been developed to classify the fracture and healthy bone. Deep learning has rapidly become the cutting-edge method of enhancing performance in medial image analysis with the use of Convolutional Neural Networks (CNN), which are well suited for analyzing images, and has led to a decrease in the classification error rate. It also comprises a neural network with multiple hidden layers that enhance image recognition accuracy Meena, et.al [3] developed bone diseases are common and can result in various Musculoskeletal Conditions (MC). An estimated 1.71 billion patients suffer from musculoskeletal problems worldwide. Apart from musculoskeletal fractures, femoral neck injuries, knee osteoarthritis, and fractures are very common bone diseases, and the rate is expected to double in the next 30 years. Therefore, proper and timely diagnosis and treatment of a fractured patient are crucial. Contrastingly, missed fractures are a common prognosis failure in accidents and emergencies. This causes complications and delays in patients' treatment and care. abnormalities, particularly fractures. They have also discussed the challenges and problems faced in the DL-based method, and the future of DL in bone imaging. Kuo, et.al [4] utilized patients with fractures are a common emergency presentation and may be misdiagnosed at radiologic imaging. There were no statistically significant differences between clinician and ML performance. There were 22 of 42 (52%) studies that were judged to have high risk of bias. Meta-regression identified multiple sources of heterogeneity in the data, including risk of bias and fracture type Joshi, et.al [5] developed radiologists interpret X-ray samples by visually inspecting them to diagnose the presence of fractures in various bones. Interpretation of radiographs is a time-consuming and intense process involving manual examination of fractures. In addition, clinician's shortage in medically under-resourced areas, unavailability of expert radiologists in busy clinical settings or fatigue caused due to demanding workloads could lead to false detection rate and poor recovery of the fractures.

Cha, et.al [6] proposed the emergency room, clinicians spend a lot of time and are exposed to mental stress. In addition, fracture classification is important for determining the surgical method and restoring the patient's mobility. Recently, with the help of computers using Machine Learning (ML), diagnosis and classification of hip fractures can be performed easily and quickly. The purpose of this systematic review is to search for studies that diagnose and classify for hip fracture using ML, organize the results of each study, analyse the usefulness of this technology and its future use value. Ashkani-Esfahani, et.al [7] proposed early and accurate detection of ankle fractures are crucial for optimizing treatment and thus reducing future complications. Radiographs are the most abundant imaging techniques for assessing fractures. Deep Learning (DL) methods, through adequately trained Deep Convolutional Neural Networks (DCNNs), have been previously shown to faster and accurately analyze radiographic images without human intervention. Herein, we aimed to assess the performance of two different DCNNs in detecting ankle fractures using radiographs compared to the ground truth.

Golding, et.al [8] utilized infrastructure, such as buildings, bridges, pavement, etc., needs to be examined periodically to maintain its reliability and structural health. To address this limitation, this study proposes a Deep Learning (DL)-based autonomous crack detection method using the Convolutional Neural Network (CNN) technique. To improve the CNN classification performance for enhanced pixel segmentation, 40,000 RGB images were processed before training a pretrained VGG16 architecture to create different CNN models. The chosen methods (grayscale, thresholding, and edge detection) have been used in Image Processing (IP) for crack detection, but not in DL. Safaei, et.al [9] proposed there is a massive necessity to develop fully automated and efficient distress assessment systems to evaluate pavement conditions with the minimum cost. Due to having complex training processes, most of the current supervised learning-based practices in this area are not suitable for smaller, local-level projects with limited resources. This paper aims to develop an automatic crack assessment method to detect and classify cracks from 2-D and 3-D pavement images. A tile-based image processing method was proposed to apply a localized thresholding technique on each tile and detect the cracked ones (tiles containing cracks) based on crack pixels' spatial distribution. Guermazi, et.al [10] Utilized missed fractures are a common cause of diagnostic discrepancy between initial radiographic interpretation and the final read by board-certified radiologists. This retrospective diagnostic study used the multi-reader, multi-case methodology based on an external multicenter data set of 480 examinations with at least 60 examinations per body region (foot and ankle, knee and leg, hip and pelvis, hand and wrist, elbow and arm, shoulder and clavicle, rib cage, and thoracolumbar spine) between July 2020 and January 2021. Fracture prevalence was set at 50%. The ground truth was determined by two musculoskeletal radiologists. Guerrasio, et.al [11] Developed the most important problems in orthopedics is undiagnosed or misdiagnosed bone fractures. This can lead to patients receiving an incorrect diagnosis or treatment, which can result in a longer treatment period. In this study, fracture detection and classification are performed using various machine learning techniques using of a dataset containing various bones (normal and fractured). Then, in addition to the Canny and Sobel edge detection methods used in the image processing stage, feature extraction of X-ray images is performed with the help of Houhg line detection and Harris corner detector. Mehta, et.al [12] proposed medical field is a complex term where the diagnosis is of the most importance. If there is a correct diagnosis made on time in the appropriate time duration then the treatment can be started in a timely manner and this treatment will be beneficial in curing the patient. There are many different techniques that are available to find the abnormalities in an image given but we will review some of them which are most recently developed and will compare the results of each of them. The dataset which we would consider is the MURA dataset. Discussion about further research in this area is also done to help researchers in exploring new dimensions in this field. Wu, et.al [13] conducted this systematic review and meta-analysis to explore the predictive efficiency of ML for the risk of fracture in patients with osteoporosis .ML has a favourable predictive performance for fracture risk in patients with osteoporosis. However, most current studies lack external validation. Thus, external validation is required to verify the reliability of ML model.

3. PROPOSED SYSTEM

The proposed system presents an intelligent X-ray fracture detection framework that uses DEiT-based deep feature extraction combined with multiple machine learning classifiers and a user-friendly interface. The system begins with a well-organized X-ray dataset and applies image preprocessing to enhance quality and standardize inputs. DEiT is then used to extract meaningful and discriminative features from X-ray images. These features are evaluated using existing classifiers such as Passive Aggressive, Ridge, and Nearest Centroid to establish baseline performance. The proposed FIGS classifier is introduced to improve classification accuracy and stability. The system compares all models using standard performance metrics and finally generates fracture predictions. To make the system practical and accessible, the complete pipeline is integrated into a Tkinter-based graphical interface, allowing users to upload X-ray images and obtain predictions easily in real time as illustrated in Figure 2.

Step 1: DEiT Dataset: In this step, a structured dataset of bone X-ray images is collected from reliable sources. The images are grouped into meaningful classes such as normal, single fracture, and multiple fractures. Care is taken to ensure correct labeling and removal of low-quality or duplicate images. The dataset is then divided into training, validation, and testing sets to support proper model learning and evaluation.

Step 2: Image Preprocessing: The collected X-ray images are preprocessed to make them suitable for DEiT input. Each image is resized to a fixed resolution and pixel values are normalized to maintain consistency. Noise reduction and basic enhancement techniques are applied to improve bone visibility. Data augmentation is also performed to increase dataset diversity and help the model generalize better.

Step 3: DEiT Feature Extraction: After preprocessing, images are passed into the DEiT model for feature extraction. Each image is split into patches and transformed into embeddings, which are processed through transformer encoder layers. The model learns high-level and fine-grained fracture-related patterns. The extracted feature vectors serve as compact and informative representations of X-ray images.

Step 4: Existing Passive Aggressive Classifier: The extracted DEiT features are first given to the Passive Aggressive Classifier. This classifier learns quickly and adapts well to large datasets. It provides a baseline understanding of how well linear online learning models can classify fracture patterns from deep features.

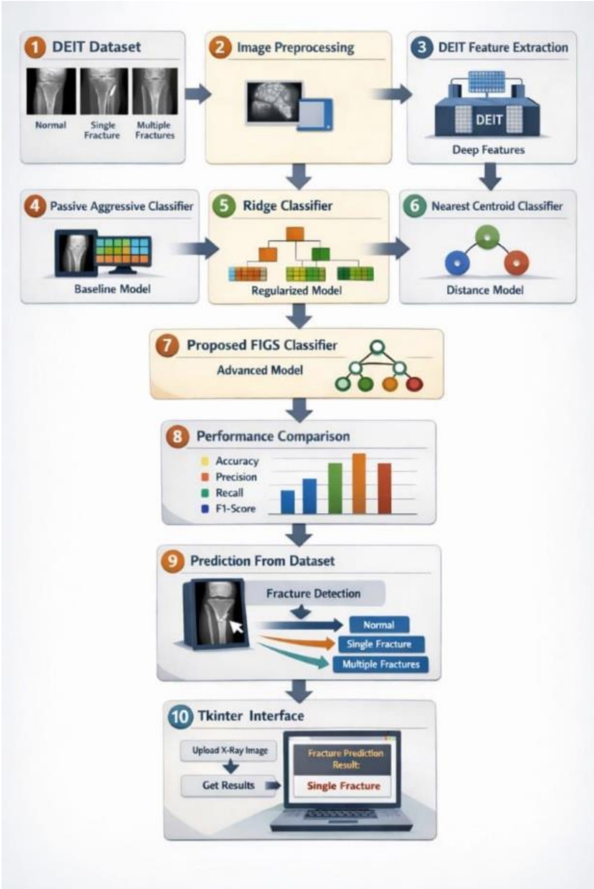

Figure 2: System Architecture

Step 5: Existing Ridge Classifier: In this step, the same feature set is evaluated using the Ridge Classifier. Ridge regularization helps reduce overfitting and improves model stability. This step highlights how regularized linear models perform on transformer-based features.

Step 6: Existing Nearest Centroid Classifier: The Nearest Centroid Classifier is then applied to the extracted features. This method classifies images based on their closeness to class centroids. It offers a simple yet effective baseline and helps compare distance-based classification with other approaches.

Step 7: Proposed FIGS Classifier: The proposed FIGS classifier is introduced to enhance classification performance. It learns structured decision rules from the DEiT features and handles complex feature interactions more effectively. This step aims to achieve better accuracy and interpretability compared to existing classifiers.

Step 8: Performance Comparison: All classifiers are evaluated and compared using metrics such as accuracy, precision, recall, and F1-score. The results clearly show the strengths and weaknesses of each method. This comparison helps demonstrate the effectiveness of the proposed FIGS classifier over existing approaches.

Step 9: Prediction From Dataset: Once the best-performing model is identified, it is used to generate predictions on unseen X-ray images. The model classifies each image into its respective fracture category. This step validates the system's ability to generalize to real-world data.

Step 10: Integration With Tkinter: Finally, the trained model is integrated into a Tkinter-based graphical user interface. Users can upload X-ray images through the interface and receive instant fracture predictions. This integration makes the system practical, interactive, and suitable for clinical or educational use.

4. RESULTS AND DISCUSSIONS

Figure 3 illustrates the Graphical User Interface (GUI) of the proposed research work, showcasing an integrated environment for transformer-driven multi-class bone fracture classification with Telegram bot support. The GUI enables users to upload fracture image datasets, perform DEiT-based feature extraction, and execute dataset splitting for training and testing. It provides selectable options for multiple classifiers, including NCC, Ridge, PAC, and the proposed FIGS model, allowing systematic performance evaluation and prediction from test images. In addition, the figure conceptually links smart implant sensing, serial strain measurement at the fracture site, and IOT-based cloud connectivity, highlighting the system's capability for continuous monitoring and accurate detection of fracture consolidation or implant loosening. Overall, the GUI serves as a unified and user-friendly interface that bridges medical imaging, machine learning analysis, and real-time clinical decision support.

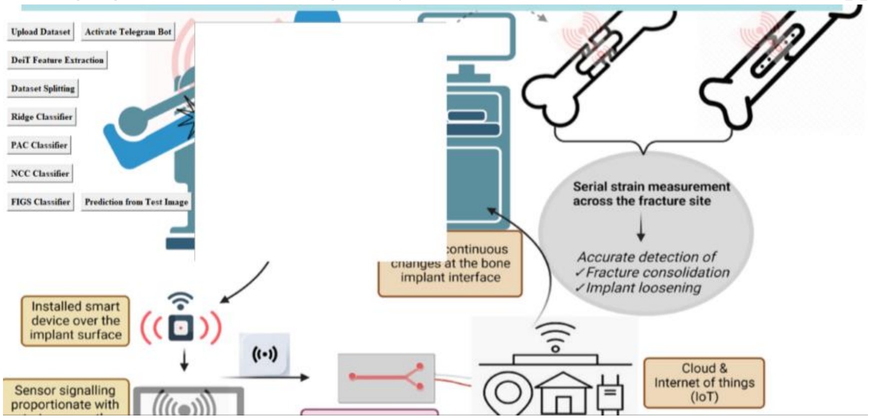

Figure 3: GUI of Research Work

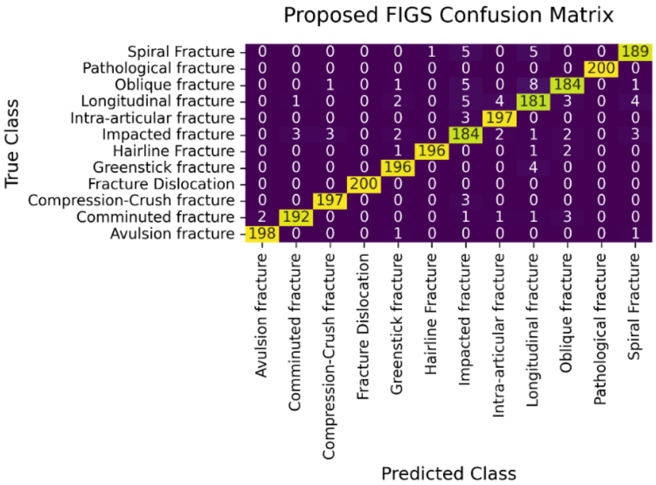

Figure 4: Confusion Matrix of Proposed FIGS

Figure 4 Proposed FIGS ROC Curves (One-vs-Rest) in Figure 9.9 demonstrate the model's exceptional classification performance, with every individual fracture category achieving a perfect AUC (Area Under the Curve) score of 1.00. The plot shows all 12 fracture classes, including Avulsion, Comminuted, and Spiral fractures, following a nearly vertical trajectory toward the top-left corner, indicating a True Positive Rate of 100% with effectively zero false positives. This near-ideal performance is further reinforced by the Micro-average AUC of 1.00, which confirms consistent high-level accuracy across the entire dataset. The significant distance between the model's curves and the dashed diagonal Random Guess line highlights the robustness of the FIGS approach in reliably distinguishing between complex bone fracture patterns.

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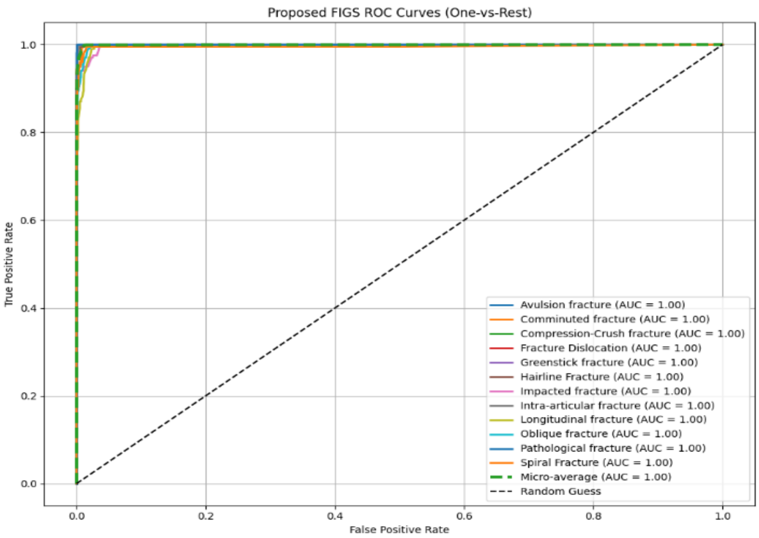

Figure 5: Proposed FIGS ROC Curves (One-vs-Rest)

Figure 6 illustrates the end-to-end prediction outcome of the proposed fracture classification system for a fracture dislocation case. The left panel shows the original elbow X-ray image of the humerus, which serves as the input to the model. The middle section presents the explainable AI (XAI)–based analysis results, indicating that the image is a bone X-ray of the humerus with a confirmed fracture presence, identified as a supracondylar fracture with moderate severity. The right panel displays the final model output, where the system confidently classifies the image as "Fracture Dislocation", highlighted in red for clarity. Overall, the figure demonstrates the model's ability to accurately analyze X-ray images, provide interpretable diagnostic details, and generate reliable fracture dislocation predictions to support clinical decision-making**.**

Figure 6: Prediction Results of Fraction Dislocation

Figure 7 depicts the prediction results of the proposed system for a comminuted fracture case. The left panel shows the original hand X-ray image used as input to the model, clearly displaying multiple bone fragments characteristic of a comminuted fracture. The central panel presents the explainable AI (XAI)–based X-ray analysis, confirming that the image is a bone X-ray of the hand with a fracture present, identified as a comminuted type and classified with severe severity. The right panel illustrates the final model output, where the fracture is correctly labeled as "Comminuted fracture" in red text. This figure demonstrates the system's effectiveness in accurately detecting complex fracture patterns and providing interpretable diagnostic information to support clinical assessment.

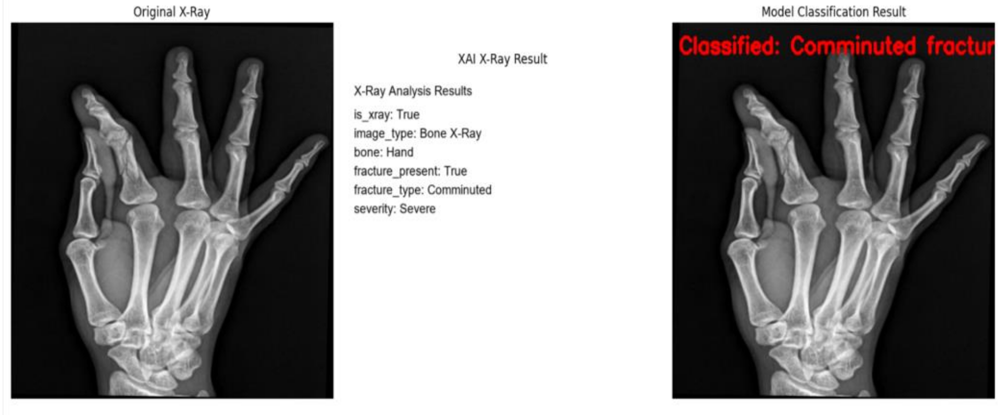

Figure 7: Prediction Results of Comminuted Fracture

Figure 8 illustrates the prediction outcome of the transformer-based fracture classification model for a hairline fracture case. The left panel shows the original ankle/foot X-ray image used as input, where the fracture line is subtle and difficult to observe visually, reflecting the challenging nature of hairline fractures. The right panel presents the model's prediction, clearly labeling the image as "Predicted: Hairline Fracture" in red text. This figure highlights the model's capability to detect fine and minimally displaced fracture patterns that are often missed during manual inspection, demonstrating the effectiveness of transformer-based feature learning in identifying subtle structural abnormalities in bone X-ray images.

Figure 8: Prediction Results of Hairline Fracture

Figure 9 presents the prediction results of the transformer-based model for an intra-articular fracture case. The left side shows the original medical images (labeled A and B), highlighting the fracture region within the joint surface using circled annotations, where the fracture extends into the articular space. The right side displays the corresponding transformer-based prediction, which correctly classifies the condition as "Predicted: Intra-articular", shown prominently in red. The consistent highlighting of the affected joint region in both the original and predicted images demonstrates the model's ability to accurately recognize fractures involving joint surfaces, emphasizing its effectiveness in identifying clinically significant intra-articular fractures that require careful diagnosis and management.

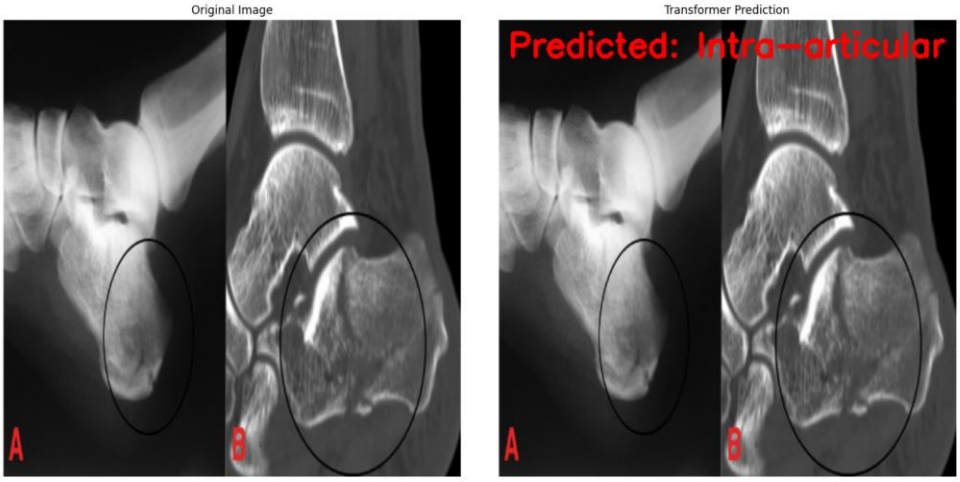

Figure 9: Prediction Results of Intra- Articular Fracture

5. CONCLUSION

The experimental results confirm the strong performance of the transformer-driven FIGS model for multi-class bone fracture classification using X-ray images. The model achieves an overall accuracy of 96.42%, along with precision (96.44%), recall (96.42%), and F1-score (96.42%), outperforming NCC (18.50%), Ridge (71.88%), and PAC (73.50%). This improvement highlights the effectiveness of transformer-based feature extraction in capturing both global and fine-grained fracture patterns. Class-wise evaluation shows highly reliable predictions, with avulsion fractures reaching 0.99 precision and recall, while fracture dislocation and pathological fractures achieve perfect scores (1.00). The AUC results further demonstrate strong discriminative ability, with a perfect score of 1.00 across all classes and a micro-average of 0.999. These findings indicate high robustness and consistency of the model across different fracture types.

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