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A Dual-Model Interpretable Pipeline for Multi-Class Bone Fracture Recognition and Clinical Decision Support

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ABSTRACT

Bone fracture diagnosis from X-ray images is a critical task in clinical settings, traditionally performed by radiologists through manual inspection. However, such approaches are time-consuming, subject to human error, and may not be scalable for large patient volumes. A current trend across several industries involves utilizing computer-based technologies to identify faults. To meet the demands of immediate detection and high precision, a highly responsive system should leverage modern approaches and make full use of available resources. While various methods exist for detecting bone fractures in the modern world, such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT) scans, and Bone scans, these approaches tend to be more expensive, uncomfortable for patients, and less effective at detecting subtle fractures that, if left untreated, could lead to significant challenges. The system is founded on a transfer learning strategy, utilizing the Data-efficient Image Transformer (DieT) as a fixed, high-performance feature extractor to convert raw X-ray data into robust, condensed numerical embeddings. These sophisticated feature vectors are subsequently used to train the central classification engine: the novel and highly constrained Fast Interpretable Greedy-tree Sums (FIGS) classifier. The superior performance of FIGS is established by benchmarking its accuracy, precision, and recall against traditional linear classifiers like Ridge Classifier (RC) and Passive Aggressive Classifier (PAC). Crucially, the system is augmented by an eXplainable AI (XAI) module, which acts as a robust pre-screener to validate the image type and provide a detailed, human-readable analysis including bone identification, fracture type, and severity before the FIGS model delivers its final classification.

Keywords: Bone fracture diagnosis, X-ray imaging, eXplainable AI, Data-efficient Image Transformer, FIGS classifier.

1. INTRODUCTION

In the medical field, bone fractures represent a significant share of emergency healthcare cases. According to the World Health Organization (WHO), over 20 million people worldwide suffer moderate to severe bone fractures each year, particularly from road accidents, sports injuries, and occupational hazards. Conventional diagnostic approaches involve visual analysis of X-ray images by radiologists, which can be both time-consuming and prone to human error due to fatigue or misinterpretation. The complexity further escalates in rural or resource-limited settings where qualified radiologists may not always be available, necessitating the need for technological augmentation in radiographic interpretation. Having a wider and more varied range of movement than the other joints in the body, the shoulder has a flexible structure. The fractures in the shoulder may result from incidents such as dislocation of the shoulder and engaging in contact sports and motor vehicle accidents. The shoulder bone mainly consists of three different bones: the upper arm bone, named the ‘humerus’, the shoulder blade, named the ‘scapula’, and the collarbone, named the ‘clavicle’. In Figure 1 shows the anatomic structure of the shoulder bone. The image in this figure was taken from the MURA dataset used in this study, and the markings thereon were placed by the physicians at Gazi University. The upper end of the humerus has a ball-like shape that connects with the scapula, called the glenoid. The types of shoulder fractures vary depending on age. While most fractures in children occur in the clavicle bone, the most common fracture in adults occur on the top part of the humerus, i.e., the proximal humerus. The types of shoulder bone fractures are divided into three categories in general: clavicle fractures, which are the most common shoulder fracture, frequently the result of a fall, scapula fractures,

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which rarely occur, and resulting fractures, which occur as cracks in the upper part of the arm in individuals over 65 years of age. The images from X-ray devices are primarily used for imaging of the shoulder bone for diagnosis and treatment of such fractures, while MRI or CT devices may also be used when required [1].

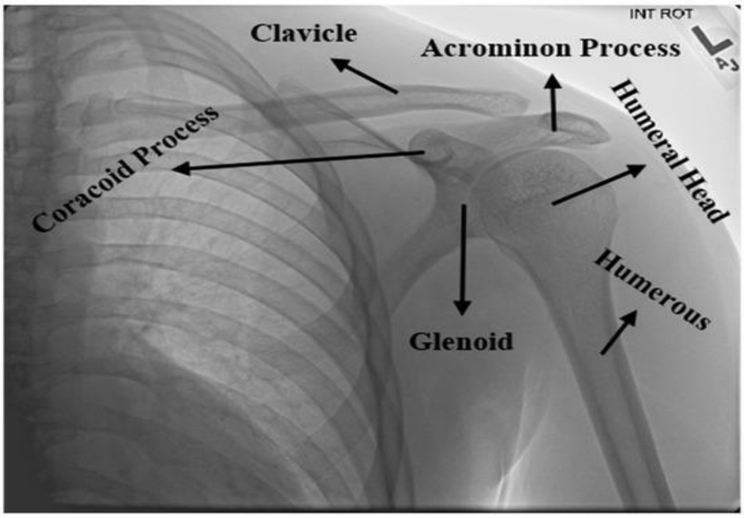

Figure 1: The anatomy of the shoulder bone.

Deep learning classification procedures of shoulder bone X-ray images were carried out in the study. The main contributions of this study are as follows: The most suitable model for the classification of shoulder bone X-ray images as a fracture or non-fracture is determined [2]. An approach that can be used in similar studies is developed via new ensemble learning models. The study can assist physicians who are not experts in the field in the classification stage, especially in cases of shoulder fractures, which are frequently encountered in the emergency departments of hospitals [3]. The method suggested in the study contributes to the literature with two different ensemble approaches. With the first model proposed in the study, a performance study was conducted with transfer learning for the MURA dataset, which is widely used in X-ray studies. Thus, three models that give the best classification results have been combined into a single model, and the classification performance has been increased [4]. The developed model can be used to classify many medical X-ray images. With the second model, it is determined which model finds which class best by looking at the success of finding the classes on the models in the dataset. It ensures that the model decides the prediction of that class [5]. Thus, regardless of the dataset studied, a similar decision system can be designed with models that find the classes in a given dataset, and a higher performance can be achieved compared to a single model. The proposed ensemble model approaches can be applied and generalized by performing similar preprocessing steps in other X-ray biomedical datasets. In addition, the proposed method can be easily used in studies with transfer learning.

2. LITERATURE SURVEY

Uysal, et al. [6] aimed to help physicians by classifying shoulder images taken from X-ray devices as fracture/non-fracture with artificial intelligence. For this purpose, the performances of 26 deep learning-based pre-trained models in the detection of shoulder fractures were evaluated on the musculoskeletal radiographs (MURA) dataset, and two ensemble learning models (EL1 and EL2) were developed. The pre-trained models used are ResNet, ResNeXt, DenseNet, VGG, Inception, MobileNet, and their spinal fully connected (Spinal FC) versions. In the EL1 and EL2 models developed using pre-trained models with the best performance, test accuracy was 0.8455, 0.8472, Cohen's kappa was 0.6907, 0.6942 and the area that was related with fracture class under the receiver operating characteristic (ROC) curve (AUC) was 0.8862, 0.8695.

Sumon, et al. [7] assessed the diagnostic efficacy of the artificial intelligence (AI) model before and after optimization and compared its performance in detecting fractures or not. The training and evaluation dataset consists of fractured and non-fractured X-rays from various anatomical locations, including the hips, knees, lumbar region, lower limb, and upper limb. This gives an extremely high training accuracy of 99.98 and a validation accuracy 96.72. The attention-based CNN thus showcases its role in medical image analysis.
Su, et al. [8] reviewed are threefold. Firstly, precise definitions are established for the bone fracture recognition, classification, detection, and localization tasks within deep learning. Secondly, each study is summarized based on key aspects such as the bones involved, research objectives, dataset sizes, methods employed, results obtained, and concluding remarks. This process distills the diverse approaches into a generalized processing framework or workflow. Moreover, this review identifies the crucial areas for future research in deep learning models for bone fracture diagnosis. These include enhancing the network interpretability, integrating multimodal clinical information, providing therapeutic schedule recommendations, and developing advanced visualization methods for clinical application. By addressing these challenges, deep learning models can be made more intelligent and specialized in this domain.
Tanzi, et al. [9] aimed to analyze and evaluate a selection of papers, chosen according to their representative approach, where the authors applied different deep learning techniques to classify bone fractures, in order to select the strengths of each of them and try to delineate a generalized strategy. Each study is summarized and evaluated using a radar graph with six values: AUC, test accuracy, sensitivity, specificity, dataset size and labelling reliability. Plus, they defined the key points which should be taken into account when trying to accomplish this purpose and they compared each study with our baseline.
Tariq, et al. [10] aimed to increase the existing state-of-the-art convolutional neural networks (CNNs)' performance by using various ensemble techniques. In this approach, different CNNs are used to classify the images; rather than choosing the best one, a stacking ensemble provides a more reliable and robust classifier. The ensemble model outperforms the results of individual CNNs by an average of 10%.
Kandel,et al. [11] proposed a global-local feature fusion convolutional neural network, including a global pathway to capture the global contextual information and a local pathway to extract the fine-grained information from local patches. The fine-grained information is integrated into the global context information layer-by-layer to assist in predicting bone age. they evaluated the proposed method on a dataset with 11,209 X-ray images with an age range of 4–18 years. Compared with other state-of-the-art methods, the proposed global-local network reduces the mean absolute error of the estimated ages to 0.427 years for males and 0.455 years for females; the average accuracy rate is within 6 months and 12 months, reaching 70% and 91%, respectively.
Hui, et al. [12] presented the appropriate method to classify musculoskeletal images by transfer learning and by training from scratch. They applied six state-of-the-art architectures and compared their performance with transfer learning and with a network trained from scratch. From our results, transfer learning did increase the model performance significantly, and, additionally, it made the model less prone to overfitting.
Kandel, et al. [13] reviewed provides a focused analysis of CNN evolution and architectures as applied to medical image analysis, highlighting their application and performance in different medical fields, including oncology, neurology, cardiology, pulmonology, ophthalmology, dermatology, and orthopaedics. The paper also explored challenges specific to medical imaging and outlined trends and future research directions. This review aims to serve as a valuable resource for researchers and practitioners in healthcare and artificial intelligence.

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Mienye, et al. [14] developed a tool to streamline mammogram classification that maintains high reliability across different data sources. They used images from the DDSM data set and a proprietary data set, YERAL, which comprises 943 mammograms from Mexican patients. They evaluate the performance of ensemble learning algorithms combined with prevalent deep learning models such as Alexnet, VGG-16, and Inception. The computational results demonstrate the effectiveness of the proposed methodology, with models achieving 82% accuracy without overtaxing our hardware capabilities, and they also highlight the efficiency of ensemble algorithms in enhancing accuracy across all test cases.

Berrones-Reyes, et al. [15] discussed the Wide ResNet-40, DenseNet-121, and EfficientNet-B7 are chosen, fine-tuned, and used as base models, and a Bayesian-based probabilistic ensemble learning method is proposed for fracture detection in cervical spine CT images. The proposed method considers the prediction's uncertainty of the base models and combines the predictions obtained from them, to improve the overall performance significantly. This method assigns weights to the base learners, based on their performance and confidence about the prediction. To increase the robustness of the proposed model, custom data augmentation techniques are performed in the preprocessing step. This work utilizes 15,123 CT images from the RSNA-2022 C-spine fracture detection challenge and demonstrates superior performance compared to the individual base learners, and the other existing conventional ensemble methods.

3. PROPOSED METHODOLOGY

The proposed system is designed to automatically detect and classify different types of bone fractures from X-ray images using an intelligent machine learning framework. The system first collects X-ray images and extracts deep visual features using the DeiT model, which captures important structural patterns of bone fractures. These extracted features are then used to train multiple classifiers, and the FIGS model is selected as the final classifier due to its superior performance. Before prediction, an XAI-based screening module verifies whether the uploaded image is a valid X-ray and identifies fracture-related information. The system is integrated with a Telegram bot interface, allowing users to send X-ray images and receive real-time fracture detection and classification results along with visualization of the prediction as shown in figure 2.

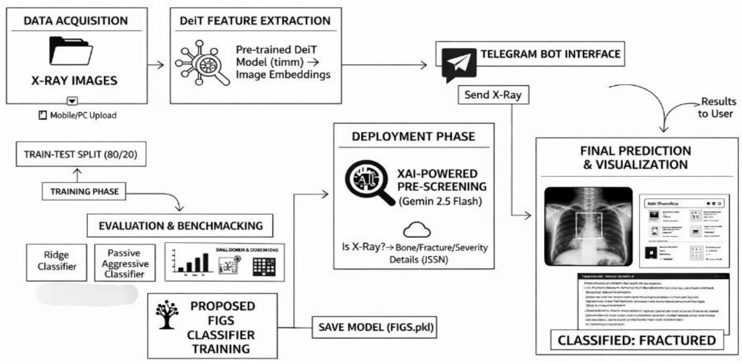

Figure 2: Proposed System architecture of Bone fracture classification

1. Data Acquisition and Loading: The process begins with the user selecting the directory containing the bone X-ray images. The system reads these directory names to identify the available classification categories. This step effectively loads the raw image data and defines the scope of the classification problem.

2. DeiT Feature Extraction: The images are then processed using the pre-trained DeiT , which acts as a powerful feature extractor. Each image is transformed into a fixed-size, high-dimensional feature vector by passing it through the transformer's layers. This critical step reduces the complexity of working directly with high-resolution image data, resulting in the numerical matrices X (features) and Y (labels) required for the subsequent machine learning models.

3. Dataset Preparation and Splitting: The extracted feature vectors (X) and their labels (Y) are prepared for model training. The data is partitioned into training and testing sets using an 80/20 split, employing stratification to ensure that the distribution of fracture classes remains consistent in both sets. This rigorous split guarantees that the models are trained on a representative portion of the data and evaluated fairly on completely unseen data.

4. Model Training and Evaluation (Existing Classifiers): Baseline machine learning classifiers including the RC, PAC, and NCC are trained on the DeiT-extracted features. Their performance is immediately assessed using a comprehensive suite of metrics like Accuracy, Precision, Recall, and F1-score. These results, along with visual aids like the Confusion Matrix and ROC Curves, establish a necessary performance benchmark.

5. Training the Proposed Classifier: The central classification model, the Proposed FIGS classifier, is trained on the same prepared training data. FIGS, designed for speed and clarity, learns the patterns in the DeiT features to classify fractures. Once trained, this final model is permanently saved using joblib for deployment, serving as the system's primary diagnostic tool.

6. XAI-Powered Pre-Screening and Analysis: In the deployment phase (for new inputs), the system first uses a Generative AI for XAI analysis. This module performs robust image type detection (ensuring it's a bone X-ray) and, if confirmed, provides a detailed medical assessment, identifying the affected bone, fracture type, and severity in a structured JSON output. This step confirms the image's validity and provides essential diagnostic context.

7. Final Prediction and Visualization: Following XAI confirmation, the image is passed through the DeiT feature extractor, and the resulting features are fed into the trained Proposed FIGS model for the final automated fracture classification. The system then displays a comprehensive visual result, combining the original X-ray image, the detailed XAI report panel, and the FIGS model's prediction in a unified interface, ensuring both accuracy and interpretability.

8. Telegram Bot Integration: For maximum accessibility, the entire prediction pipeline is wrapped into a Telegram Bot. Users interact by sending an image, and the bot automatically triggers the XAI screening, the DeiT feature extraction, and the FIGS classification. It then replies instantly with a text summary of the findings and the visual analysis panels, enabling real-world, mobile usage.

4. RESULTS AND DISCUSSIONS

The result analysis evaluates the effectiveness of the proposed Transformer-driven multi-class bone fracture classification system using various machine learning performance metrics and visualization techniques. The extracted features from the DeiT transformer are used to train multiple classifiers, and their performance is compared to determine the most accurate model. Evaluation metrics such as accuracy, precision, recall, F1-score, confusion matrix, and ROC-AUC curves are used to measure classification performance and reliability. These metrics help analyze how well the system identifies different fracture categories and distinguishes between classes. The results also highlight the advantages of the proposed FIGS classifier compared with existing models such as RC, PAC, and NCC.

Figure 3 illustrates DeiT Feature Extraction interface that is used to extract deep visual features from the uploaded bone X-ray dataset using the DeiT model. When the user clicks the "DeiT Feature Extraction" button, the system processes all images by resizing and normalizing them before passing them through the pretrained transformer model to generate high-level feature vectors. If previously extracted features already exist, the system automatically loads them from the saved feature file to reduce computation time. The interface displays status messages confirming the start of feature extraction and successful loading or generation of the feature dataset.

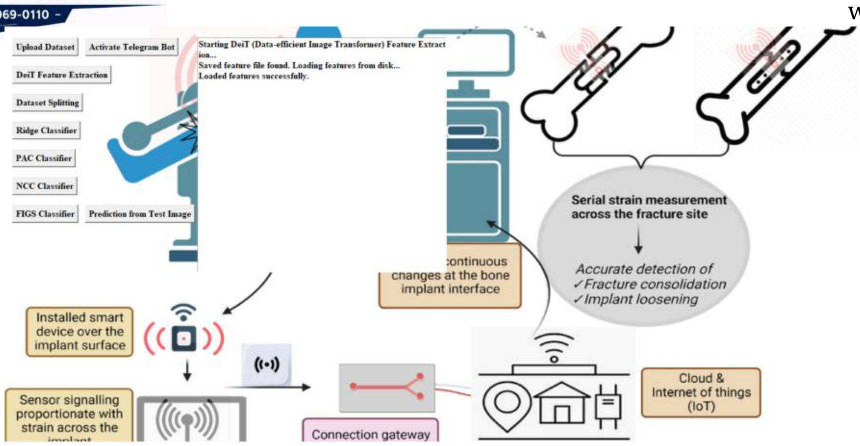

Figure 3: Feature Extraction on image data using DieT model

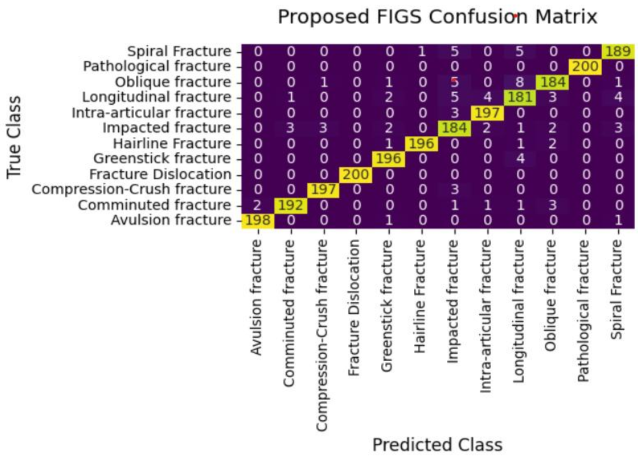

Figure 4: Illustration of confusion matrix using FIGS

Figure 4 shows the Proposed FIGS classifier Confusion Matrix illustrates the classification performance of the FIGS classifier on the bone fracture dataset. In this heatmap, the rows represent the actual fracture classes while the columns represent the predicted fracture classes. The high values along the diagonal indicate that most samples are correctly classified into their respective fracture categories, while very few off-diagonal values show minimal misclassifications. This visualization demonstrates that the proposed FIGS model achieves highly accurate multi-class fracture classification, effectively distinguishing between the different fracture types in the dataset.

Figure 5shows Proposed FIGS ROC Curve (One-vs-Rest) illustrating the classification performance of the FIGS model across all fracture categories. Each curve represents a specific fracture class and shows the relationship between the True Positive Rate and False Positive Rate at different decision thresholds. The AUC values for all classes are close to 1.00, indicating excellent discrimination ability of the model in identifying different fracture types. The dashed diagonal line represents random prediction, while the micro-average ROC curve summarizes the overall performance of the FIGS classifier across all classes, demonstrating its superior accuracy in multi-class fracture detection.

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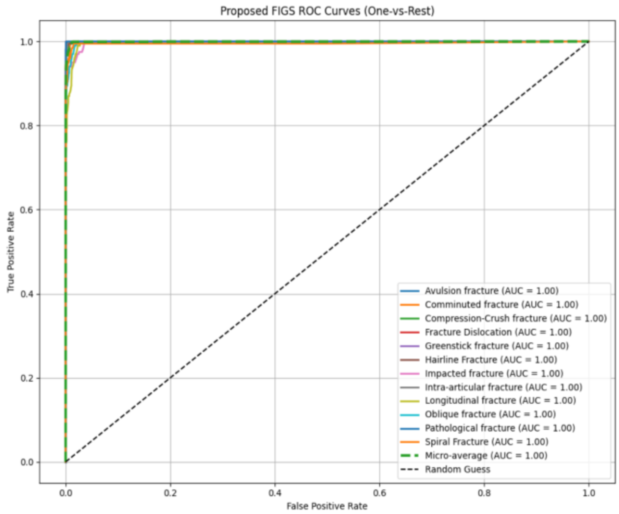

Figure 5: ROC obtained using FIGS classifier

Figure 6 displays the prediction result comparison between the original X-ray image and the model's classification output generated using the transformer-based fracture detection system. The left panel shows the input bone X-ray image, while the right panel presents the Transformer Prediction, where the model has identified the fracture type and displayed the label "Predicted: Comminuted fracture" on the image. This output demonstrates how the trained model analyzes bone structure patterns from the X-ray image and accurately classifies the fracture type, helping in automated and efficient fracture diagnosis.

Figure 6: Prediction obtained using FIGS model

Figure 7 shows a comparison between the original foot X-ray image and the model's classification output generated by the transformer-based fracture detection system. The left panel displays the input X-ray image, while the right panel shows the Transformer Prediction, where the system has analyzed the bone structure and identified the condition as "Fracture Dislocation." The predicted label is displayed on the image, demonstrating how the trained model automatically detects and classifies bone fracture types from medical X-ray images for accurate and efficient diagnosis.

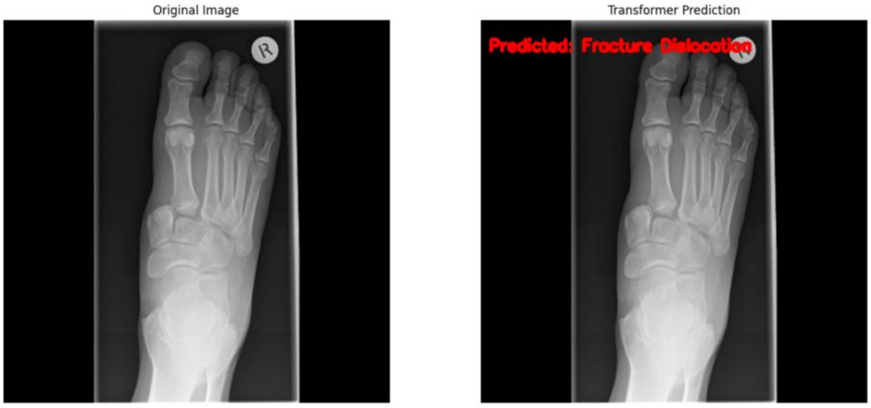

Figure 7: Prediction obtained using FIGS model

Figure 8 shows the Telegram that demonstrates real-time image analysis by processing images sent by users and providing automated responses. In the first case, when a handwritten document image is uploaded, the system analyzes the content and correctly identifies that the image is not an X-ray, classifying it as a handwritten document and preventing unnecessary fracture prediction. In the second case, when a foot X-ray image is submitted, the system successfully detects that it is a valid X-ray, identifies the bone region (5th metatarsal and cuboid), confirms the presence of a fracture, determines the fracture type as avulsion, estimates the severity as moderate, and finally provides the classifier prediction “Avulsion fracture.” These results demonstrate the effectiveness of the Telegram bot in performing real-time X-ray verification and automated fracture classification.

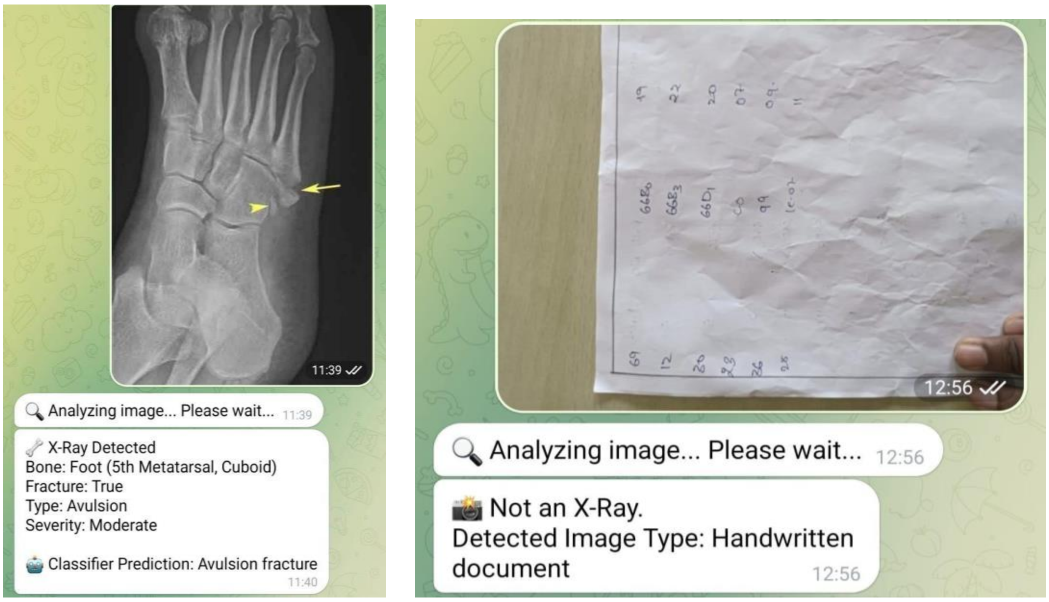

Figure 8: Telegram bot activated for real time prediction

Table 1 presents the performance comparison of four classification algorithms such as RC, PAC, NCC, and the proposed FIGS model based on evaluation metrics including Accuracy, Precision, Recall, and F-score. The RC achieves an accuracy of 71.87%, with precision, recall, and F-score values of 71.66%, 71.87%, and 71.23%, indicating moderate classification capability in identifying different fracture categories. The PAC shows slightly improved performance with an accuracy of 73.5%, a higher precision of 81.33%, recall of 73.49%, and F-score of 74.38%, demonstrating better ability in correctly identifying fracture instances compared to the RC model. In contrast, the NCC performs poorly, achieving only 18.5% accuracy, with precision, recall, and F-score values of 26.67%, 18.49%, and 14.67%, suggesting that this distance-based method is not well suited for the complex feature patterns extracted from bone X-ray images. The proposed FIGS model significantly outperforms all existing classifiers, achieving 96.41% accuracy, 96.43% precision, 96.41% recall, and 96.42% F-score, indicating highly reliable and consistent classification performance. These results clearly demonstrate that the FIGS model effectively captures the discriminative patterns in transformer-extracted features, making it the most accurate and robust approach for multi-class bone fracture classification among the evaluated methods.

Table 1: Performance comparison for the RC, PAC, NCC and Proposed FIGS Model

Algorithms Name	Accuracy	Precision	Recall	F-score
RC	71.87%	71.66%	71.87%	71.23%
PAC	73.5%	81.33%	73.49%	74.38%
NCC	18.5%	26.67%	18.49%	14.67%
FIGS model	96.41%	96.43%	96.41%	96.42%

5. CONCLUSION

The system was successfully developed to automatically detect and classify different types of bone fractures from X-ray images using advanced artificial intelligence techniques. The system utilizes the DeiT model to extract deep visual features from X-ray images, which are then used to train multiple machine learning classifiers including RC, PAC, NCC, and the proposed FIGS model. Performance evaluation using metrics such as accuracy, precision, recall, and F-score demonstrated that the proposed FIGS model significantly outperforms the existing models, achieving an accuracy of 96.41%, making it highly effective for multi-class fracture classification. The system also integrates an XAI-based image verification module to determine whether the uploaded image is a valid bone X-ray before performing fracture analysis, improving reliability and preventing incorrect predictions on non-medical images. In addition, the integration of a Telegram bot interface enables real-time remote analysis, allowing users to send images directly to the bot and receive automated fracture detection results along with fracture type, bone location, and severity information. The experimental results, visualization outputs, and real-time testing confirm that the proposed system provides an accurate, efficient, and user-friendly solution for automated bone fracture detection, which can assist medical professionals in preliminary diagnosis and reduce the time required for manual fracture analysis.

REFERENCES

[1] Shoulder Fracture 2014. Available online: https://www.assh.org/handcare/condition/shoulder-fracture (accessed on 1 October 2025).

[2] Rajpurkar, P.; Irvin, J.; Bagul, A.; Ding, D.; Duan, T.; Mehta, H.; Yang, B.; Zhu, K.; Laird, D.; Ball, R.L.; et al. MURA Dataset: Towards Radiologist-Level Abnormality Detection in Musculoskeletal Radiographs. In Proceedings of the 1st Conference on Medical Imaging with Deep Learning, Amsterdam, The Netherlands, 4–6 June 2018.

[3] Guan, B.; Zhang, G.; Yao, J.; Wang, X.; Wang, M. Arm fracture detection in X-rays based on improved deep convolutional neural network. Comput. Electr. Eng. 2020, 81, 1–11.

[4] Galal, A.; Hisham, F.; Mohamed, M.; Hassan, S.; Ghanim, T.; Nabil, A. Automatic Recognition of Elbow Musculoskeletal Disorders using Cloud Application. In Proceedings of the 2019 8th International Conference on Software and Information Engineering, Cairo, Egypt, 9–12 April 2019.

[5] Liang, S.; Gu, Y. Towards Robust and Accurate Detection of Abnormalities in Musculoskeletal Radiographs with a Multi-Network Model. Sensors 2020, 20, 3153.

[6] Uysal, F.; Hardalaç, F.; Peker, O.; Tolunay, T.; Tokgöz, N. Classification of Shoulder X-ray Images with Deep Learning Ensemble Models. Appl. Sci. 2021, 11, 2723. https://doi.org/10.3390/app11062723.

[7] Sumon, R.I.; Ahammad, M.; Mozumder, M.A.I.; Hasibuzzaman, M.; Akter, S.; Kim, H.-C.; Al-Onaizan, M.H.A.; Muthanna, M.S.A.; Hassan, D.S.M. Automatic Fracture Detection

Convolutional Neural Network with Multiple Attention Blocks Using Multi-Region X-Ray Data. Life 2025, 15, 1135. https://doi.org/10.3390/life15071135.

[8] Su, Z.; Adam, A.; Nasrudin, M.F.; Ayob, M.; Punganan, G. Skeletal Fracture Detection with Deep Learning: A Comprehensive Review. Diagnostics 2023, 13, 3245. https://doi.org/10.3390/diagnostics13203245.

[9] Tanzi, L.; Vezzetti, E.; Moreno, R.; Moos, S. X-Ray Bone Fracture Classification Using Deep Learning: A Baseline for Designing a Reliable Approach. Appl. Sci. 2020, 10, 1507. https://doi.org/10.3390/app10041507.

[10] Tariq, M.; Choi, K. YOLO11-Driven Deep Learning Approach for Enhanced Detection and Visualization of Wrist Fractures in X-Ray Images. Mathematics 2025, 13, 1419. https://doi.org/10.3390/math13091419.

[11] Kandel, I.; Castelli, M.; Popovič, A. Comparing Stacking Ensemble Techniques to Improve Musculoskeletal Fracture Image Classification. J. Imaging 2021, 7, 100. https://doi.org/10.3390/jimaging7060100.

[12] Hui, Q.; Wang, C.; Weng, J.; Chen, M.; Kong, D. A Global-Local Feature Fusion Convolutional Neural Network for Bone Age Assessment of Hand X-ray Images. Appl. Sci. 2022, 12, 7218. https://doi.org/10.3390/app12147218.

[13] Kandel, I.; Castelli, M.; Popovič, A. Musculoskeletal Images Classification for Detection of Fractures Using Transfer Learning. J. Imaging 2020, 6, 127. https://doi.org/10.3390/jimaging6110127.

[14] Mienye, I.D.; Swart, T.G.; Obaido, G.; Jordan, M.; Ilono, P. Deep Convolutional Neural Networks in Medical Image Analysis: A Review. Information 2025, 16, 195. https://doi.org/10.3390/info16030195.

[15] Berrones-Reyes, M.C.; Salazar-Aguilar, M.A.; Castillo-Olea, C. Use of Ensemble Learning to Improve Performance of Known Convolutional Neural Networks for Mammography Classification. Appl. Sci. 2023, 13, 9639. https://doi.org/10.3390/app13179639.