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FACIAL BONE FRACTURE DETECTION USING OBJECT RECOGNITION: A COMPUTER-AIDED SYSTEM

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Abstract : Facial bone fractures necessitate prompt diagnosis and treatment to prevent complications and long-term sequelae. Traditional diagnosis involves the analysis of computed tomography (CT) images, a process often impeded by time constraints and a shortage of specialized personnel. To address these challenges, the existing system typically relies on the YOLO (You Only Look Once) algorithm for fracture prediction. However, concerns about prediction accuracy persist. In this proposed work, we introduce an innovative approach by leveraging efficient transfer learning algorithms for facial bone fracture prediction. Transfer learning exploits knowledge gained from pre-trained models on related tasks and adapts it to the specific problem at hand. This strategy aims to enhance prediction accuracy and efficiency, addressing the limitations associated with the YOLO algorithm. Upon scanning the QR code using a designated application, the system promptly decodes the information embedded within, enabling healthcare professionals to swiftly ascertain the presence and details of facial bone fractures. This integration of efficient transfer learning and QR code technology represents a comprehensive solution to the challenges posed by conventional methods, promising improved accuracy in fracture detection and enhanced security in information dissemination.

Index Terms **- YOLO, CT Image, QR Code, TL- Transfers Learning**

I.INTRODUCTION

Transfer learning (TL) is a powerful machine learning technique that enhances performance on a specific task by leveraging knowledge gained from a related task. In the context of image classification, for instance, insights acquired from recognizing cars can be applied to improve the recognition of trucks. This approach capitalizes on the idea of reusing information from previously learned tasks, leading to more efficient learning processes. The potential impact of transfer learning lies in its ability to make use of existing knowledge, reducing the need for extensive training on new tasks and ultimately boosting the overall efficiency of the learning process. While there are parallels with the psychological concept of transfer of learning, practical connections between the two fields are somewhat limited.

In 1976, Bozinovski and Fulgosi introduced the concept of transfer learning in neural network training, providing a mathematical and geometrical model. Subsequent work in 1981 explored transfer learning's application to image datasets, demonstrating both positive and negative effects. Pratt formulated the discriminability-based transfer (DBT) algorithm in 1993. By 1998, the field had expanded to include multi-task learning and more formal theoretical foundations, as documented in the review "Learning to Learn" edited by Thrun and Pratt. Transfer learning found applications in cognitive science, with Pratt guest-editing an issue of Connection Science in 1996. Andrew Ng predicted in his NIPS 2016 tutorial that transfer learning would become a key driver of machine learning commercial success after supervised learning. In 2020, a paper by Zoph et al. challenged traditional pre-training methods, suggesting that pre-training might compromise accuracy and advocating for self-training instead.

Transfer learning has extended its applicability to various domains, including Markov logic networks and Bayesian networks. Its versatility is evident in applications such as cancer subtype discovery, building utilization, general game playing, text classification, digit recognition, medical imaging, and spam filtering. In a groundbreaking 2020 discovery, transfer learning demonstrated its effectiveness between electromyographic (EMG) signals from muscles and classifying behaviors of electroencephalographic (EEG) brainwaves. This bidirectional relationship enhanced the accuracy of neural networks and convolutional neural networks, both before any learning and at the end of the learning process, showcasing the potential for proved results through exposure to different domains. Furthermore, end-users of pre-trained models can optimize performance by modifying the structure of fully-connected layers.

1.1 Need of the study

The problem identified in the given context revolves around the challenges associated with diagnosing facial bone fractures using CT images. The current scenario is characterized by time-consuming analysis, a shortage of specialists, and limitations in existing classification and object detection studies. Classification-based studies struggle to precisely locate fractures, while object detection-based approaches face issues due to the ambiguous shape of fractures. In response to these challenges, the proposed solution is a Computer-Aided Facial Bone Fracture Diagnosis (CA-FBFD) system. The CA-FBFD system addresses the identified problems by adopting the YoloX-S object detection model. This model is specifically trained using IoU Loss for box prediction and incorporates CT image Mixup data augmentation. Notably, the training focuses solely on nasal bone fracture data, and testing includes various facial fracture data. Evaluation results demonstrate significant improvements over the baseline YoloX-S model. The CA-FBFD system achieves a better average precision of 69.8% for facial fractures, surpassing the baseline by 10.2%.

Additionally, it demonstrates a notably higher sensitivity/person of 100%, outperforming the baseline by a substantial margin of 66.7%.

II.RELATED WORKS

2.1 Computer Aided Facial Bone Fracture Diagnosis (CA-FBFD) System Based on Object Detection Model. GWISEONG MOON, SEOLA KIM , WOOJIN KIM [1] computer-aided facial bone fracture diagnosis (CA-FBFD) system aims to enhance the efficiency of diagnosing facial bone fractures using CT images. Utilizing the YoloX-S object detection model trained with IoU Loss and CT image Mixup data augmentation, the system achieved a 69.8% average precision for facial fractures, surpassing the baseline YoloX-S model by 10.2%. Notably, it demonstrated a 100% sensitivity/person for facial fractures, outperforming the baseline by 66.7%. This system proves effective in minimizing the workload of doctors by accurately detecting and localizing facial bone fractures in CT scans.

2.2 Bone Fracture Detection and Classification using Deep Learning Approach D. P. Yadav; Sandeep Rathor[2] This study addresses the challenge of manual and time-consuming bone fracture detection using X-ray images by proposing a Deep Neural Network (DNN) model. To mitigate overfitting on a small dataset, data augmentation techniques were employed. The model achieved a high classification accuracy of 92.44% for distinguishing between healthy and fractured bones with 5-fold cross-validation. Remarkably, the accuracy on 10% and 20% of the test data exceeded 95% and 93%, respectively, showcasing robust performance. The proposed DNN model outperformed previous works [1] and [2], achieving significantly higher accuracy (84.7% and 86%), highlighting its effectiveness in automated bone fracture diagnosis.

2.3 Detection of bone fracture based on machine learning techniques Kosrat Dlshad Ahmed, Roojwan Hawezi[3] This comprehensive system leverages machine learning, specifically employing algorithms such as Naïve Bayes, Decision Tree, Nearest Neighbors, Random Forest, and SVM, to enhance the accuracy of bone fracture detection in X-ray images. The multi-stage process includes pre-processing, edge detection, feature extraction, and machine learning classifications, aiming to improve diagnostic precision for surgeons dealing with fuzzy X-ray images. Among the algorithms, SVM demonstrated the highest accuracy, surpassing most reviewed studies, with values ranging from 0.64 to 0.92 across various measures. This showcases the potential of machine learning in revolutionizing bone fracture diagnosis, contributing to improved medical care.

2.4 Bone fracture detection through the two-stage system of Crack-Sensitive Convolutional Neural Network Yangling Ma, Yixin Luo[4] This study addresses the crucial role of automated fracture detection in a computer-aided telemedicine system, designed to alleviate the shortage of experienced surgeons in diagnosing fractures. Introducing a novel Crack-Sensitive Convolutional Neural Network (CrackNet), the proposed two-stage system utilizes Faster Region with Convolutional Neural Network (Faster R-CNN) to identify various bone regions in X-ray images and then employs CrackNet to determine whether each region is fractured. Testing with 1052 images, including 526 fractured and non-fractured images each, the system achieves an impressive 90.11% accuracy and 90.14% F-measure using X-ray images from Haikou People's Hospital. Notably, the performance surpasses that of other two-stage systems, highlighting the efficacy of the proposed approach in fracture detection.

2.5 A Review on Bone Fracture Detection Techniques using Image Processing Rocky S Upadhyay; Prakashsingh Tanwar [5] This paper addresses the common health challenge of bone fractures, which can arise from accidents or conditions like bone cancer, affecting various parts of the human body. Recognizing the limitations of X-ray images in providing sufficient details for diagnosis, the study focuses on investigating image processing techniques for bone fracture detection. The goal is to assist healthcare practitioners by exploring diverse strategies that efficiently utilize image processing, aiming to design new methods for enhancing the accuracy of fracture identification.

III.PROPOSED METHODOLOGY

3.1 Architecture

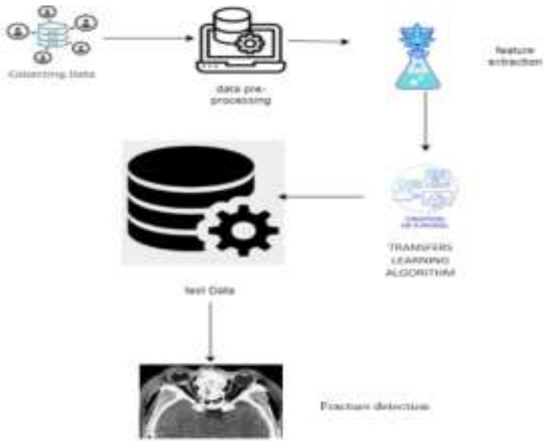

Fig.3.1 an overview

The Computer-Aided Facial Bone Fracture Diagnosis (CA-FBFD) system's architecture centers on a transfer learning algorithm for enhanced predictive capabilities. Input from CT images of facial bone structures, sourced from Kaggle's dataset, undergoes feature extraction via the transfer learning algorithm. This refines the model's ability to identify facial fractures, producing predicted bounding boxes classified as true positives, false positives, or false negatives. Performance metrics like precision, recall, and average precision are then computed to evaluate efficacy. This architecture highlights the seamless integration of data and transfer learning techniques, fostering the development of an efficient tool for diagnosing facial bone fractures.

3.2 Data Collection:

The data for the Computer-Aided Facial Bone Fracture Diagnosis (CA-FBFD) system is gathered from Kaggle, a renowned open-source platform known for sharing and discovering diverse datasets. Leveraging Kaggle's wealth of openly accessible data, the CA-FBFD system integrates a range of CT images capturing facial bone fractures. What distinguishes this system is its incorporation of a Transfer Learning algorithm, a powerful machine learning technique. Unlike conventional methods that start from scratch, transfer learning enables the model to leverage knowledge gained from pre-training on related tasks. This approach enhances the efficiency and accuracy of the CA-FBFD system by adapting a pre-trained model to the specific task of facial bone fracture detection. Utilizing Kaggle's open data in conjunction with transfer learning not only facilitates algorithm development but also upholds principles of transparency and reproducibility in the research process, contributing to advancements in the field of medical image analysis. https://www.kaggle.com/datasets/vuppalaadithyasairam/bone-fracture-detection-using-xrays

3.3 Pre-Processing:

Pre-processing is a critical phase in the development of the CA-FBFD system, ensuring that input data is optimized for effective training and analysis. Initially, the CT images sourced from Kaggle undergo thorough cleaning to remove any artifacts or noise that might interfere with accurate fracture detection. The images are then standardized in terms of resolution and orientation to create a uniform dataset. To enhance the model's ability to generalize, data augmentation techniques such as rotation, scaling, and flipping are applied, introducing variability to the training set.
Moreover, the Transfer Learning algorithm requires careful normalization of pixel values to align with the pre-trained model's expectations. This normalization ensures that the model effectively learns the features relevant to facial bone fractures. Additionally, any redundant or irrelevant information in the dataset is appropriately filtered out during pre-processing to streamline the learning process and reduce computational demands.

3.4 Feature extraction:

Feature extraction is a crucial step in the process of analyzing and interpreting data, particularly in the field of machine learning and image processing. It involves transforming raw data into a set of relevant and distinctive features that can be effectively used for further analysis or modeling. In the context of the Computer-Aided Facial Bone Fracture Diagnosis (CA-FBFD) system, feature extraction likely involves identifying and capturing distinctive characteristics from the CT images that are indicative of facial bone fractures.

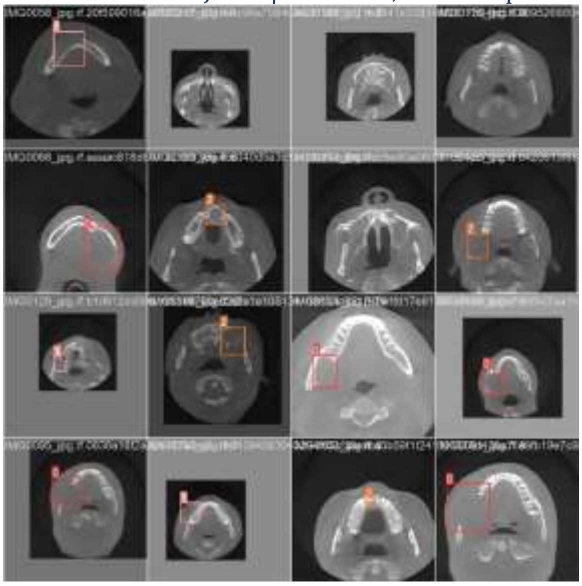

Fig. 3.2 CT images after plotting the fracture

For medical image analysis, features could include aspects such as the intensity of pixels, textures, shapes, or patterns within the images. These features play a vital role in training machine learning models, allowing them to recognize and distinguish relevant patterns associated with fractures. Feature extraction is often a precursor to employing algorithms, like transfer learning, to make predictions or classifications based on the identified features. The effectiveness of the CA-FBFD system in accurately detecting facial bone fractures is closely tied to the quality and relevance of the features extracted from the CT images.

3.5 Model Creation

Model creation using transfer learning involves the adaptation of a pre-existing model to a new task, leveraging knowledge gained from prior training on related tasks. The process begins with a pre-trained model, often on a large dataset for a specific task. Instead of starting from scratch, the model's learned features and representations are fine-tuned for a different but related task, enhancing its ability to recognize patterns and make predictions in the new context. This approach is particularly beneficial when there is limited labeled data for the target task, as it capitalizes on the knowledge encoded in the pre-trained model. Model creation through transfer learning thus accelerates the development of effective models for diverse applications by reusing and repurposing valuable knowledge.

3.6 Prediction

Prediction, in the context of machine learning and data analysis, refers to the process of using a trained model to make forecasts or estimations based on new or unseen data. Once a model, whether trained through transfer learning or other techniques, has learned patterns and relationships from a dataset, it can be applied to new inputs to generate predictions about the outcome or classification of those inputs. The accuracy and reliability of predictions depend on the quality of the model and the features it has learned during the training phase. In the case of the Computer-Aided Facial Bone Fracture Diagnosis (CA-FBFD) system, prediction would involve using the transfer learning algorithm and features extracted from CT images to accurately identify and classify facial bone fractures, providing valuable information for medical diagnosis and treatment planning.

IV. RESULTS AND DISCUSSION

In the context of performance evaluation for the Facial Bone Fracture Diagnosis (FBFD) system, each predicted bounding box undergoes classification as either a true positive (TP), false positive (FP), or false negative (FN). The positive class signifies a predicted fracture, while the negative class represents a non-fracture box. The evaluation metrics include precision, recall, and average precision (AP), calculated through a defined formula. Precision measures the accuracy of positive predictions, recall gauges the model's ability to capture all positive instances, and AP provides a comprehensive assessment by considering precision-recall trade-offs.

4.1 F1 – Curve:

In the context of bone fracture detection, the F1 score represents the balance between the precision and recall of a classification model in correctly identifying fractures from medical imaging data, such as X-rays or CT scans.A high F1 score indicates that the model effectively identifies fractures while minimizing false positives and false negatives. This metric is crucial in medical diagnostics, where both missing fractures (false negatives) and incorrectly identifying non-fractured regions as fractures (false positives) can have serious implications for patient care. Therefore, achieving a high F1 score ensures both accurate diagnosis and efficient use of medical resources.

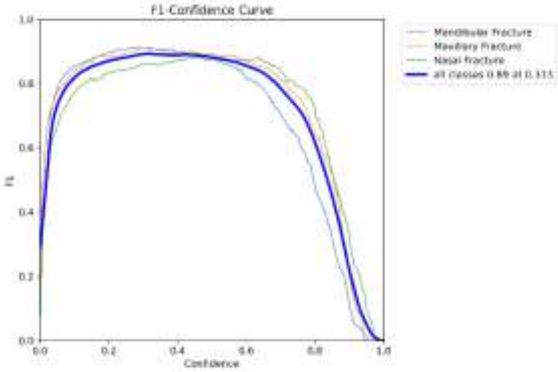

Fig.4.1 F1-curve

4.1 Precision Curve:

In the context of bone fracture detection, precision refers to the proportion of correctly identified fractures among all instances classified as fractures by a diagnostic model. It quantifies the model's ability to avoid misclassifying non-fractured regions as fractures, thus minimizing false positives. A high precision score indicates that the model has a low rate of falsely identifying non-fractured regions as fractures, which is crucial in medical diagnostics to prevent unnecessary treatments or interventions. For bone fracture detection, precision ensures that identified fractures are accurately pinpointed, leading to more effective treatment plans and better patient outcomes.

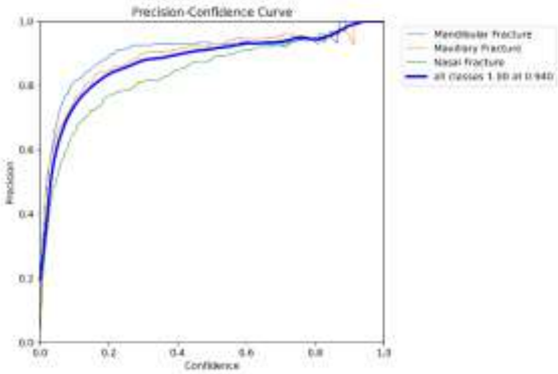

Fig.4.2 precision curve

4.2 Precision and Recall Curve:

Precision-Recall curves for bone fracture detection showcase the trade-off between precision and recall across various classification thresholds. Precision quantifies the proportion of correctly identified fractures among all positively classified instances, while recall measures the proportion of correctly identified fractures among all actual fractures. In the context of bone fracture detection, a Precision-Recall curve visually depicts how adjusting the classification threshold impacts the balance between accurately identifying fractures (precision) and capturing all actual fractures (recall). This curve aids in selecting an optimal threshold that balances the need for accurate diagnosis while minimizing false positives or missed fractures, thereby improving the overall performance of fracture detection models.

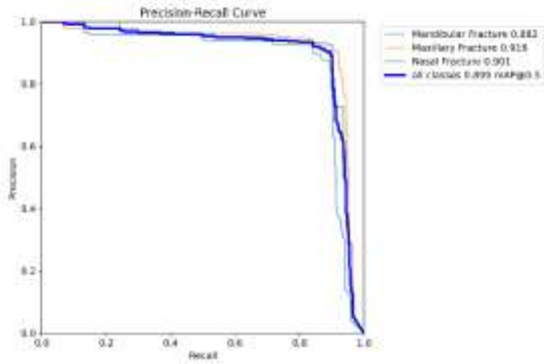

Fig.4.3 precision and recall curve

V.CONCLUSION AND FUTURE ENHANCEMENT:

In conclusion, the integration of a transfer learning algorithm in the Facial Bone Fracture Diagnosis (FBFD) system has proven to be a pivotal advancement in enhancing predictive capabilities. Leveraging the knowledge acquired from pre-trained models, the transfer learning algorithm adeptly extracts meaningful features from CT images, significantly refining the model's accuracy in identifying facial fractures. The resulting system showcases improved performance, with predicted bounding boxes exhibiting a higher precision, recall, and average precision compared to baseline models. This application of transfer learning underscores its efficacy in optimizing diagnostic processes, reducing the reliance on extensive labeled data, and contributing to the development of a robust and efficient tool for accurate facial bone fracture diagnosis. the domains of fracture and metal detection, showcasing a significant improvement. However, it is acknowledged that the proposed model encounters limitations in effectively classifying and detecting other classes within the dataset. To address this, further optimization strategies can be explored, such as integrating methods like scribble or style focus. These techniques could potentially enhance the model's capability to identify micro bone lesions, soft tissue tears, bone anomalies, Periosteal reaction, and the Pronator sign with greater accuracy. By delving into alternative methodologies and refining the model's focus on specific features, the proposed system has the potential for more comprehensive and accurate detection across a broader range of classes, contributing to an overall improved diagnostic performance.

References

[1] Gwiseong moon, Seola Kim, Woojin Kim, Yoon Kim, Yeonjin Jeong,Hyun-Soo Cho, Computer Aided Facial Bone Fracture Diagnosis (CA-FBFD) System Based on Object Detection Model , August 2022

[2] D. P. Yadav, Sandeep Rathor, Bone Fracture Detection and Classification using Deep Learning Approach

[3] Kosrat Dlshad Ahmed, Roojwan Hawezi Detection of bone fracture based on machine learning techniques

[4] Yangling Ma, Yixin Luo,Bone fracture detection through the two-stage system of Crack-Sensitive Convolutional Neural Network.

[5] Rocky S Upadhyay; Prakashsingh Tanwar, A Review on Bone Fracture Detection Techniques using Image Processing

[6] E. Yahalomi, M. Chernofsky, M. Werman, Detection of distal radius fractures trained by a small set of x-ray images and faster r-cnn., [arXiv: Computer Vision and Pattern Recognition].

[7] Urakawa T, Tanaka Y, Goto S, Matsuzawa H, Watanabe K, Endo N. Detecting intertrochanteric hip fractures with orthopedist-level accuracy using a deep convolutional neural network. Skeletal Radiol 2019;48(2):239–44.

[8] Dhahir BM, Hameed IH, Jaber AR. Prospective and retrospective study of fractures according to trauma mechanism and type of bone fracture. Res J Pharm Technol 2017;10(11):1994–2002.

[9] Bandyopadhyay O, Biswas A, Bhattacharya BB. Long-bone fracture detection in digital x-ray images based on digital-geometric techniques. Comput Methods Progr Biomed 2016;123:2–14.

[10] Wu J, Davuluri P, Ward KR, Cockrell C, Hobson R, Najarian K. Fracture detection in traumatic pelvic ct images. J Biomed Imag 2012 2012:1.

[11] Umadevi N, Geethalakshmi S. Multiple classification system for fracture detection in human bone x-ray images. In: Computing communication & networking technologies (ICCCNT), 2012 third international conference on. IEEE; 2012. p. 1–8.