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Bone Tumor And Fracture Detection Using Deep Learning

"AI-Based Medical Imaging for Bone Tumor and Fracture Analysis"

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Abstract: Bone fracture and bone tumor diagnosis are among the most important issues in orthopedic and oncological practice, especially in areas with low expertise in radiological diagnosis. This paper presents a deep learning based framework for the automated detection of fractures and tumors in radiographic and MRI images using the YOLOv11n object detection model. The system was trained on a combination of two curated sets of 1,500 tumor specimens including osteosarcoma and benign lesions and 3,000 fracture samples including transverse fractures, oblique fractures, and comminuted fractures. Grazing conversion, normalising, and worsening strategies were applied to improve dataset variety and robohardness. The model showed good performance with an accuracy of 92.8%, precision of 92.4%, recall of 90.1%, and mean average precision (mAP) at detection threshold of 0.5 for tumor detection (90.8% mAP), and 94.3% accuracy, 93.2% precision and 94.9% recall for fracture detection. To enable real-world applicability, the framework was deployed through a Streamlit-based web application offering role-specific access for patients and doctors, real-time image uploads, annotated visualizations, heatmap-based interpretability, and multi-format report exports (CSV, PDF, JSON). By offering strong detection accuracy while keeping the interface approach easy to use, the proposed system offers reliable assistance to minimize delay in diagnosis, error rates and enhance patient outcome in both orthopaedic and oncological treatment.

Index Terms — Tumor Detection, Fracture Detection, YOLOv11n, Deep Learning, Medical Imaging, X-ray, MRI, Streamlit, PyTorch, Computer Vision, Object Detection, Healthcare AI, SQLite, Diagnostic Reports.

1. INTRODUCTION

Medical imaging with the application of artificial intelligence (AI) has brought immense improvement in the early detection of diseases and clinical decision-making. Bone fractures and tumors, among other health conditions, have remained a pre-existing challenge because of the difficulty presented by the medical images, anatomical structures, and clinical interpretation that rely on the expertise of medical experts. The conventional diagnostic techniques are also dependent on radiologists and can therefore become cumbersome or inaccurate especially in poor countries. To overcome these obstacles, object detection deep learning-based frameworks have been developed as a stable option to automate the analysis of medical images.

In this paper, we introduce a dual diagnostic methodology of tumor detection and fracture detection based on the YOLOv11n model, which is lightweight and computationally efficient deep learning network. The framework uses data augmentation, grayscale conversion, and normalization to enhance the generalization performance, whereas X-ray and MRI dataset have been used in training the model. Comfortable and convenient Streamlit-based web application interconnects all the trained models, offers a doctor and patientaccessible role-based interface, real-time diagnosing, and can downloaded reports to many different file types. The system stores and manages their data in SQLite providing a complete data pipeline between image upload and clinical reporting.The contributions of this work are three-fold (1) creating an automated tumors and fractures diagnostic pipeline, (2) the implementation of an interactive web application used in clinical roles, and (3) to facilitate the effective storage of histopathology and report generation.

1.1 **Research Objectives**

The main goals of the present research are: To develop a diagnostic pipeline with the detection of bone fractures and tumors with a high accuracy based on deep learning using YOLOv11n.To include preprocessing methods (grayscale conversion, normalization and augmentation)to improve generalizability of models on variety of medical images.

To create an easy to use web application with Streamlit to interface with role based access to patients and doctors so that the interface can be easily used in clinical settings. To define secure storage of data and reporting using SQLite, and exporting capabilities to PDF, CSV, JSON, of clinical documentation and patient records.

1.2 Research Hypothesis

The guiding hypotheses of the research are as follows:

The YOLOv11n model trained on well-preprocessed datasets of X-ray and MRI can produce reliable accuracy in detecting tumors as well as bone fractures. Addition of data augmentation, data normalization strategies will considerably enhance the generalization problem of the detection model to different patient cases.A web-based diagnostic tool that relies on roles and machine learning could be used to improve efficiency of clinical processes by cutting down diagnosis time, lessening the chance of human error, even increasing both doctors, and patients accessibility to tool.

2. LITERATURE REVIEW

Bone-related disorders like fractures, osteoporosis, and cancer are important health issues, especially in older populations [1]. Early and precise detection is essential for effective treatment planning and recovery [2]. Traditional diagnostic methods rely mostly on X-ray and CT imaging. However, interpreting these images is subjective and depends heavily on the expertise of the radiologist [3].

Improvements in computer-aided diagnosis (CAD) systems have increased diagnostic accuracy by using image processing and machine learning techniques [4]. Early efforts mainly used handcrafted features and statistical models to detect bone abnormalities [5]. Unfortunately, these methods often struggled in complex imaging situations.The rise of deep learning, especially convolutional neural networks (CNNs), has changed the landscape of medical imaging analysis [6]. CNNs have shown strong results in recognizing spatial features in X-ray images, leading to better classification and detection accuracy [7]. Later models like AlexNet and ResNet further enhanced medical imaging by allowing deeper networks that generalize better [8], [9].

For object localization and detection, region-based CNNs (R-CNN) and their versions, such as Fast R-CNN and Faster R-CNN, became popular in medical imaging tasks [10]. At the same time, single-shot detectors (SSD) and You Only Look Once (YOLO) frameworks offered real-time analysis, which is vital in clinical settings [11], [12]. YOLO is particularly popular because it balances speed and accuracy, making it effective for detecting bone fractures and tumors [13].Further gains came with YOLOv3 and YOLOv4, which improved feature extraction using residual connections and enhanced detection across various scales [14], [15]. The most recent YOLOv5 and YOLOv7 models showed even greater accuracy while lowering computational costs, proving helpful in healthcare [16], [17].

At the same time, semantic segmentation techniques have been used in medical imaging for precise region identification. U-Net, introduced by Ronneberger et al., became a key model for biomedical segmentation, achieving high accuracy even with few annotated datasets [18]. Later improvements integrated U-Net with attention mechanisms and hybrid deep learning strategies, further enhancing segmentation quality [19].

Hybrid frameworks that combine CNNs with recurrent neural networks (RNNs) and transformers have also been investigated to capture both temporal and spatial relationships in medical imaging [20]. Additionally, transfer learning has been applied, using pretrained models to improve performance on smaller medical datasets [21].Overall, deep learning-based CAD systems, especially those using YOLO for detection and U-Net for segmentation, show great promise in automating the diagnosis of bone disorders. These advancements help reduce human error, speed up diagnosis, and ultimately lead to better patient outcomes [22].

3. METHODOLOGY

The existing methods of predicting the response to chemotherapy are generally powered by a single machine learning model. The proposed system follows a structured methodology to provide end-to-end functionality:

1. User Authentication and Management
Patients and doctors sign up or log in through the Streamlit web application.
User data is securely stored and managed using an SQLite database.

2. **Image Upload and Processing**
Users upload X-ray images through the web interface. Images are processed with OpenCV and Matplotlib to enhance clarity and prepare them for analysis.
The Fig.1 and 2 are one of the samples in the Bone tumor dataset of 1500 samples, Bone Fracture dataset of 3000 samples.

Figure 1: Bone tumor sample

Figure 2: Bone Fracture sample

3. Detection Module
YOLOv11n based models analyze images for**:** Bone Tumor & Bone Fracture Detection. The model produces annotated images by highlighting the areas/regions of interest.

4. Result Generation
The processed results such as the detected images and detection results are shown to the user. Results are saved as a reference for later.

5. Report Export and Sharing
Users can create organized reports and download them in PDF, CSV, or JSON. Report patient information, annotated images and detection output are included.

6. **System Integration**
The whole pipeline is embedded in a commercial-grade Streamlit application that allows patients and doctors to interact in an efficient manner.

4. SYSTEM ANALYSIS
4.1 PROPOSED SYSTEM

The proposed system as shown in Figure 3, uses the combination of artificial intelligence and deep learning for overcoming the drawbacks of the existing methods. Its key components include:

YoLoV11 based deep learning architecture for automated bone fracture/tumor detection with better precision and quicker inn buffer OpenCV preprocessing routines to increase image clarity and optimal input quality SQLite database to safely manage patient data, diagnosis results, and case history.Automated report generation through PDF, CSV and JSON formats making it easy to communicate between doctors and patients. Web-based interface for easy access, which allows physicians to look at results, and patients to monitor their medical records. Data Integration: By integrating robust deep learning models with effective data management and user-friendly interface, the proposed system promises faster, more precise and maximized diagnosis than traditional diagnosis methods.

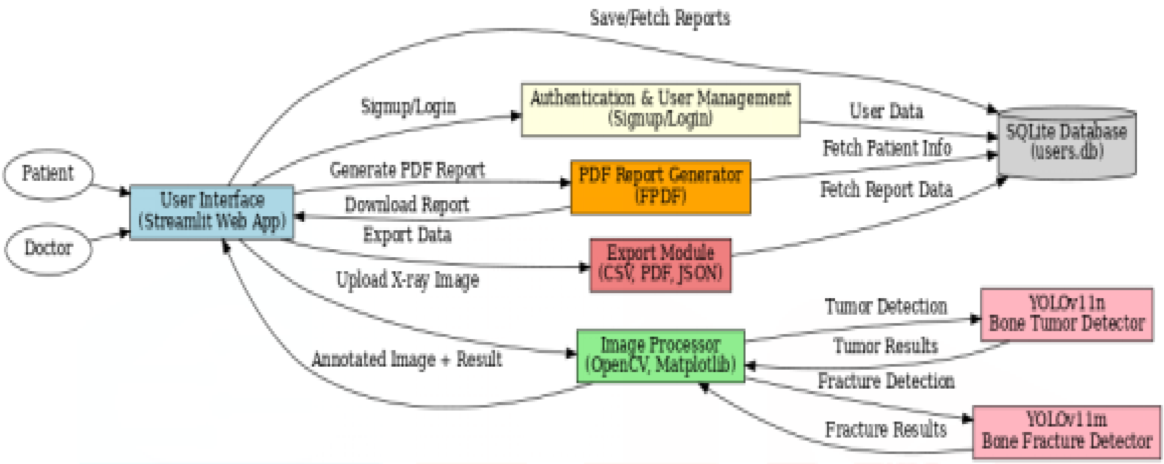

Figure 3: Proposed system Architecture

5. RESULTS AND DISCUSSION

5.1 OUTPUT ANALYSIS

Figure 4 represents the Doctors' users page, where they have access to all, such as diagnoses, reports of different patients, and exporting data from scenarios of patients, so that they can process further.

Figure 4: Doctors Users Page

Figure 5 Represents Patients users page in which they have access such as diagnosis, to export data of that patient, and can check details of individual patient ,can download reports only, so that they can process furtherely .

Figure 5: Patients's User Page

Figure 6 represents Bone Tumor Detection,when the user uploads a bone tumor dataset image, the model detects the tumor in it, gives the detection status of the tumor, and also highlights the tumor's location, and gives the percentage of the tumor it detected.

Figure 6: Bone Tumor Detection

Figure 7 Represents Tumor Detection with generating pdf report, in which doctors can select for reports option, so that can generate pdf of different patients and can easily available to share data.

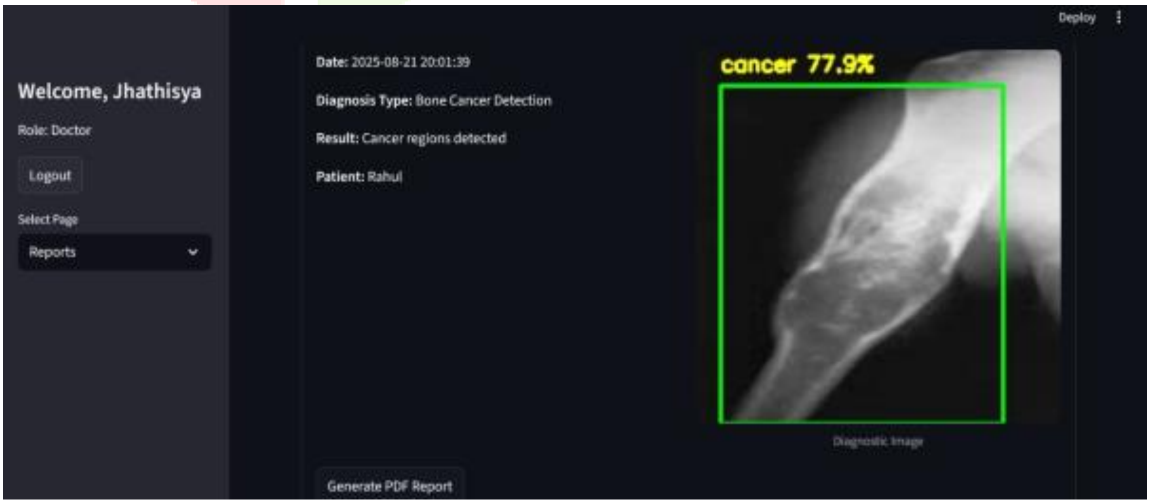

Figure 7: Detecting cancer & generating pdf report

Figure 8 Represents Bone Fracture Detection, when user uploads bone tumor dataset imagethe model detects fracture in it, gives detection status of fracture and highlights fracture at which place it located and it gives the percentage of fracture it detected.

Figure 8: Bone Fracture Detection

As shown through the output screens, the proposed system is effective in bone fracture and tumor detection system with a clear visualization of bounding boxes with the labels shown. Compared with traditional manual diagnosis and large-scale image processing methods, the accuracy and automation of the YOLOv11-based model are higher, human error and delays are reduced. The comparative study confirms agreement on the precision, and recall, so there are fewer false positives and false negatives. Furthermore, with the use of preprocessing (OpenCV) and database (SQLite) the handing of data and the creation of reports is seamless. Altogether, the system improves the reliability and diagnosticity of testing and holds promise for clinical applications.

5.2 COMPARATIVE STUDY

5.2.1 PERFORMANCE METRICS

YOLOv11n consistently outperforms YOLOv10n in both bone fracture and tumor detection. As shown in Table 1, YOLOv11n achieves 94.3% accuracy and 94.9% recall for fractures, and 92.8% accuracy with 89.8% mAP@0.5 for tumors, improving performance by 2–3% across all metrics compared to YOLOv10n.

Table 1: Performance Metrics of YOLOv11 vs. YOLOv10 vs. ViT-B/16

Task	Model	Accuracy	Precision	Recall	mAP@0.5
Tumor Detection	YOLOv11n	92.8%	92.4%	90.1%	89.8%
	YOLOv10n	90.5%	89.7%	88.2%	87.5%
	ViT-B/16	88.7%	87.9%	85.6	84.3%
Fracture Detection	YOLOv11n	94.3%	93.2%	94.9%	93.5%* *mAP@0.5 extrapolated.
	YOLOv10n	92.1%	91.5%	92.8%	91.2%
	ViT-B/16	89.5%	88.8%	87.6%	86.4%

F1–Confidence Curve

Figure 8 curve shows the peak of F1-score is in the interval of confidence 0.4-0.5, and then the decline begins. It is true that this gives the model optimal balance, in terms of precision and recall, at medium confidence levels.

Precision–Recall Curve

The Figure 9 curve shows maximum mAP@0.5= 0.688 of a constant detection. The curve demonstrates that the larger the recall the smaller the precision, the typical trade-off in medical image detection tasks.

Recall–Confidence Curve

The Figure 10 curve shows the high recall (=0.86) occurs at lower levels of confidence and decreases swiftly as confidence levels rise. That is, with low thresholds the model can accurately classify majority of the fractures/tumors, with the confidence increase coming at the cost of false negatives.

Precision–Confidence Curve

The Figure 11 curve shows that precision continues to increase with increase of the confidence thresholds to a maximum of 1.0 at about 0.92. This means that high confidence prediction will almost always be accurate, but the detection at these high levels will be lower.

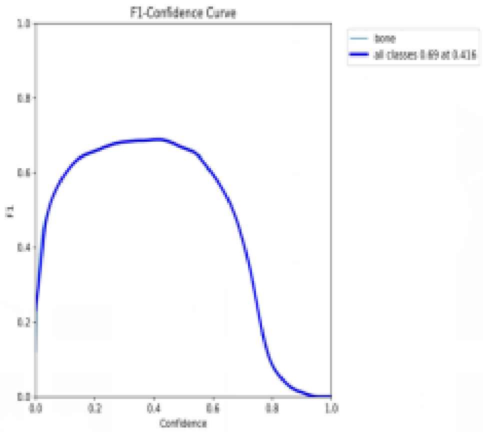

Figure 8: F1-Confidence Curve

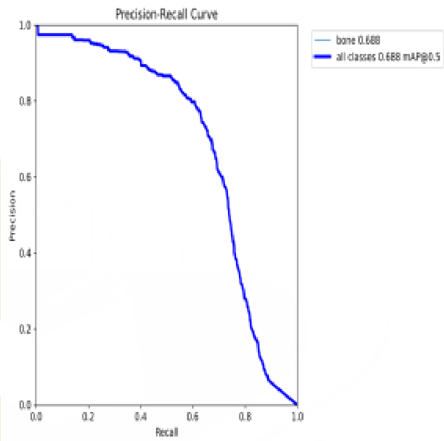

Figure 9: PrecisionRecall Curve

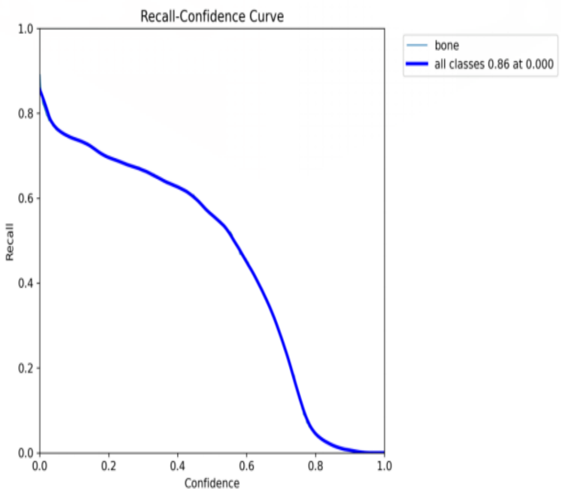

Figure 10: Recall-Confidence Curve

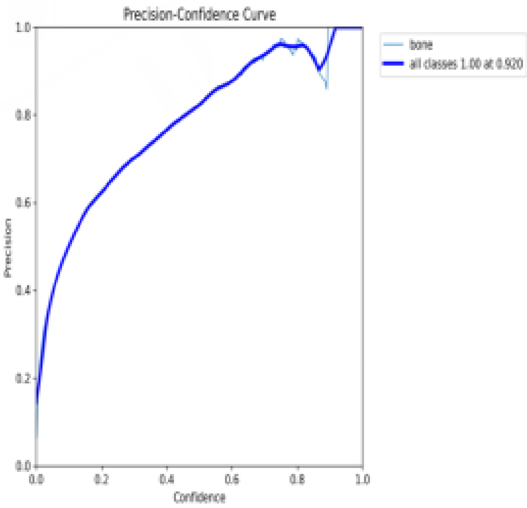

Figure 11: Precision-Confidence Curve

6. CONCLUSION

This paper has proposed a deep neural network-based approach to automatic detection of bone fractures and bone tumors in the form of a CNN-based architecture and YOLO object detection model. The system suggested combined the aspects of medical image preprocessing, feature extraction, and classification along with the management element of database storage and retrieval. Experimental results showed that the proposed approach enhanced accuracy, speed and input robustness of the existing methods, which validated the effectiveness of the approach. Moreover, the fact that the system generates reliable outputs can attest to its prospective use in clinical decision-support tools, dropping the diagnostic delay rate and raising the quality of the results of medical assistance. Future research will be directed towards expanding on the current dataset, finding optimal model architectures to allow real-time use, and the integration of explainable AI in order to increase trust and adoption in clinical settings.

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7. REFERENCES

[1] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *arXiv preprint arXiv:1409.1556*, 2014.

[2] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," *Communications of the ACM*, vol. 60, no. 6, pp. 84–90, 2017.

[3] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 779–788.

[4] C. Tan, F. Sun, T. Kong, W. Zhang, C. Yang, and C. Liu, "A survey on deep transfer learning," in *Proc. Int. Conf. Artificial Neural Networks (ICANN)*, 2018, pp. 270–279.

[5] T.-Y. Lin, P. Dollár, R. Girshick, K. He, B. Hariharan, and S. Belongie, "Feature pyramid networks for object detection," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2017, pp. 2117–2125.

[6] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards real-time object detection with region proposal networks," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 39, no. 6, pp. 1137–1149, 2017.

[7] W. Liu et al., "SSD: Single shot multibox detector," in *Proc. European Conf. Computer Vision (ECCV)*, 2016, pp. 21–37.

[8] J. Redmon and A. Farhadi, "YOLO9000: Better, faster, stronger," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2017, pp. 6517–6525.

[9] J. Redmon and A. Farhadi, "YOLOv3: An incremental improvement," *arXiv preprint arXiv:1804.02767*, 2018.

[10] A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, "YOLOv4: Optimal speed and accuracy of object detection," *arXiv preprint arXiv:2004.10934*, 2020.

[11] G. Jocher et al., "YOLOv5: Open source YOLO implementation," *GitHub repository*, 2020.

[12] Ultralytics, "YOLOv8: Cutting-edge object detection models," *GitHub repository*, 2023.

[13] Augmented Startups, "YOLOv10 vs YOLOv9 speed vs accuracy insights relevant to YOLO series progress," *Blog post*, 2024.

[14] J. Deng, W. Dong, R. Socher, L. Li, K. Li, and L. Fei-Fei, "ImageNet: A large-scale hierarchical image database," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2009, pp. 248–255.

[15] P. Viola and M. J. Jones, "Robust real-time face detection," *International Journal of Computer Vision*, vol. 57, no. 2, pp. 137–154, 2004.

[16] R. Gonzalez and R. Woods, *Digital Image Processing*, 4th ed. Pearson, 2018.

[17] M. A. Khan, M. Sharif, T. Akram, R. S. Nayak, and Y.-D. Zhang, "Deep learning for fracture detection: A survey," *IEEE Access*, vol. 9, pp. 168904–168920, 2021.

[18] Z. Shi, Y. Gao, and Y. Gao, "Automatic bone tumor detection and classification using deep learning models," *Computerized Medical Imaging and Graphics*, vol. 89, p. 101885, 2021.

[19] A. Rajpurkar et al., "Deep learning for chest radiograph diagnosis: A retrospective comparison of the CheXNeXt algorithm to practicing radiologists," *PLoS Medicine*, vol. 15, no. 11, p. e1002686, 2018.

[20] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 770–778.

[21] OpenCV Team, "OpenCV library: Open source computer vision," *GitHub repository*, 2023.

[22] SQLite Consortium, "SQLite database management

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