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Bone Tumor Detection and Classification Using Fast Mask Region-Based Convolutional Neural Network

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ABSTRACT

Accurate and timely diagnosis of bone tumors is paramount for effective treatment and patient well-being. Leveraging medical imaging modalities such as radiographs and magnetic resonance imaging (MRI), we introduce a novel methodology for automated bone tumor detection and classification. Our approach centers on the utilization of the Fast Mask R-CNN (Region-based Convolutional Neural Network) architecture, renowned for its efficiency in object detection and segmentation tasks. The workflow begins with image preprocessing steps aimed at enhancing contrast and eliminating noise, crucial for optimal performance in subsequent stages. Subsequently, the Fast Mask R-CNN framework is deployed to detect and precisely delineate bone tumor regions within the images, effectively isolating them from surrounding anatomical structures. This segmentation facilitates accurate localization, a crucial step in the diagnostic process. Following tumor localization, a classification model is employed to categorize the identified regions into benign or malignant types, leveraging the distinctive radiological features characteristic of each. This classification task is accomplished using a convolutional neural network (CNN) trained on a curated dataset of annotated bone tumor images. By combining the strengths of Fast Mask R-CNN for precise localization and CNN for accurate classification, our methodology achieves enhanced accuracy and reliability in bone tumor detection and classification. This innovative approach holds significant promise in streamlining diagnostic workflows and improving patient outcomes in bone tumor management.

Keywords: Bone Tumor, Detection, Classification, Fast Mask Region-Based Convolutional Neural Network, Deep Learning.

I. INTRODUCTION

Bone tumors, ranging from benign lesions to malignant cancers, pose significant challenges in diagnosis and treatment, underscoring the importance of early and accurate detection for improved patient outcomes. Medical imaging techniques such as radiographs and magnetic resonance imaging (MRI) are pivotal in identifying these abnormalities. However, manual interpretation of these images is labor-intensive and prone to errors. Recent advancements in computer vision and deep learning offer promising solutions to automate medical image analysis, with Convolutional Neural Networks (CNNs) emerging as particularly effective tools for tasks like object detection and segmentation. Among these, the Fast Mask R-CNN stands out for its capability in object detection and instance segmentation, holding potential to transform the detection and classification of bone tumors.

This research explores the application of the Fast Mask R-CNN framework in medical imaging, specifically for bone tumor detection and classification. By leveraging this advanced deep learning model, we aim to address critical challenges faced by healthcare professionals:

Automation: Automating bone tumor detection and classification reduces the workload on radiologists and minimizes human errors, ensuring consistent and reliable results.

Speed: Swift diagnosis is paramount in bone tumor management. Fast Mask R-CNN's rapid processing capabilities can expedite diagnoses, potentially leading to timely interventions and improved patient outcomes.

Accuracy: Deep learning models exhibit remarkable accuracy in image analysis. By employing Fast Mask R-CNN for precise tumor localization and subsequent classification using CNNs, we aim to enhance diagnostic accuracy.

Objective Assessment: Automated systems offer an objective assessment of tumor characteristics, mitigating subjectivity in interpretation and promoting standardized diagnoses.

This study presents a comprehensive framework for automated bone tumor detection and classification using Fast Mask R-CNN. We evaluate the system's performance on a diverse dataset of bone tumor images, comparing it with traditional diagnostic methods and other deep learning approaches. Our ultimate goal is to showcase the potential of this technology to revolutionize radiology practice, facilitating early diagnosis and management of bone tumors for the benefit of patients and healthcare providers.

II. RELATED WORKS

The integration of an artificial intelligence model into the diagnostic process has the potential to aid in the assessment of primary bone cancers on radiographs. The present retrospective research aimed to assess bone cancers shown on radiographs that were taken prior to the initiation of therapy. The radiographic data used in this study were gathered from patient records spanning from January 2000 to June 2020. The histopathologic data were used as the reference standard to identify whether the bone tumors in all individuals were benign or malignant.

The objective of this study is to assess the stability and classification performance of radiomic characteristics derived from diffusion- and T2-weighted magnetic resonance imaging (MRI) in the context of spine bone cancers, using machine learning techniques. The present research consisted of a retrospective analysis including a cohort of 101 individuals who were diagnosed with spine bone tumors based on histological evidence. The stability of the features was evaluated by subjecting the regions of interest (ROIs) to minor geometric alterations, which replicated the process of doing several hand delineations.

Radiologists have challenges in discerning between benign and malignant bone lesions due to the presence of comparable imaging characteristics shown by these lesions. The objective of this work was to build a deep learning algorithm capable of distinguishing between benign and malignant bone lesions via the use of regular magnetic resonance imaging.

A total of 158 patients who had surgical treatment for cartilaginous bone tumors and had histological confirmation were included in this retrospective study conducted at two tertiary bone tumor centers. The training cohort included a total of 93 magnetic resonance imaging (MRI) images obtained from centre 1. The external test cohort included 65 MRI images obtained from center 2.

Cancer cells are aberrant cellular entities inside an organism that undergo unregulated proliferation and disseminate throughout the organism. Bone cancer, a kind of malignancy, is a formidable and menacing disease, often resulting from the unregulated proliferation of bone cells. The etiology of bone cancer remains elusive, in contrast to other cancer forms where causative factors have been found. It has an impact on individuals throughout various age cohorts. Identifying bone cancer in its early stages is a significant challenge. Therefore, in order to enhance the likelihood of survival, it is essential to augment the early detection rates of bone cancer.

Convolutional neural networks (CNNs) have the potential to substantially reduce the burden of surgeons and enhance the accuracy of patient prediction. Convolutional Neural Networks (CNNs) need extensive training using a substantial volume of data to get a higher level of reliability in their performance. This research utilizes transfer learning methods, specifically pre-trained convolutional neural networks (CNNs), to analyze a publicly available collection of osteosarcoma histology pictures. The objective is to accurately identify necrotic images from non-necrotic and healthy tissues.

Table 1 : Literature Review of Existing Models

	Author & year	**Statement**	**Algorithm**	**accuracy**	**disadvantages**
[1]	Do et al., (2021)	analyzed bone tumors on radiographs	Multi-level seg-unet model	95 %	Complexity and Computational Resources
[2]	Gitto et al., (2022)	region of interest (ROI) was used to perform radiomic analysis	support vector machine	92%	class imbalance
[3]	Eweje et al., (2021)	deep learning algorithm that can differentiate benign and malignant bone	routine magnetic resonance imaging	93.6%	fewer positive cases
[4]	Cuocolo et al., (2022)	Bidimensional segmentation on T1-weighted MRI	a machine-learning classifier (Extra Trees Classifier)	92.5%	Effectiveness substructures of tumor region

[5]	Anand et al., (2020)	detection of bone cancer are examined and further studied about bone cancer	Image processing techniques	-	difficult to interpret in prediction
[6]	Anisuzzaman et al., 2021	transfer learning techniques, pre-trained CNNs	convolutional neural networks	96.2%	time-consuming in training

Disadvantages of Existing System

- Using machine learning for bone tumor classification has several potential disadvantages, which can vary depending on the specific approach and dataset.
- Preparing medical image data for CNNs often involves complex preprocessing steps, including image normalization, alignment, and noise reduction.
- Limited Effectiveness with Large Datasets
- Medical datasets often suffer from class imbalance
- Existing work has limitations and challenges for identifying substructures of tumor region and classification of healthy and unhealthy images

III. PROPOSED MODEL

This research work introduces a unique system as Fast Mask R-CNN, which is shown in Figure 1 using block diagrams. The architectural foundation may be delineated into the following principal phases.

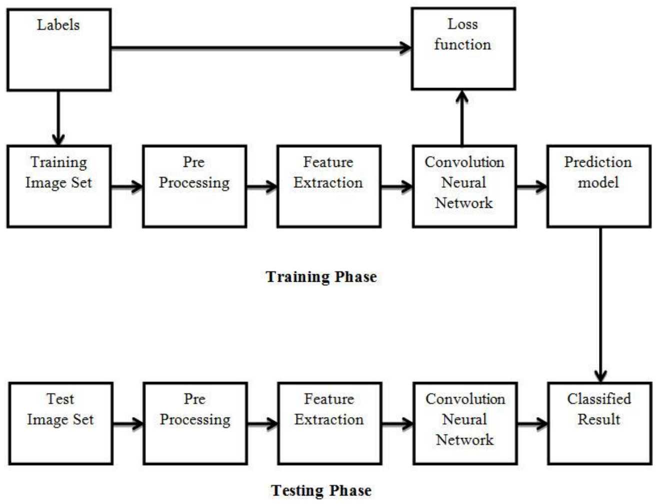

Figure 1: Overall Proposed Model

Data Collection and Preprocessing:

Data collection and preprocessing are critical steps in building an effective system for the detection and classification of bone tumors using Fast Mask R-CNN. Here's a more detailed explanation of these steps:

Data Collection

- Gather a Diverse Dataset: Collect a diverse and representative dataset of bone tumor images. This dataset should encompass a variety of tumor types, sizes, and locations within the bone. It's important to have a balanced representation of benign and malignant tumors to ensure the model's ability to classify both types accurately.
- Annotated Data: Each image in the dataset should be annotated with information about the location and type (benign or malignant) of the tumor.

Expert radiologists can provide these annotations, marking the tumor boundaries and providing diagnostic labels.

- Ethical Considerations: Ensure that the data collection process complies with ethical guidelines and patient privacy regulations, such as obtaining informed consent and de-identifying patient information.

Data Preprocessing:

- Image Enhancement: Enhance the quality of the collected images by applying preprocessing techniques such as histogram equalization, contrast adjustment, noise reduction, and sharpening. These steps improve the visibility of tumor features in the images.
- Standardization: Resize all images to a consistent resolution, aspect ratio, and format to ensure uniformity within the dataset. Standardization helps avoid variations in image dimensions that could affect model training.
- Normalization: Normalize pixel values within the images to have a mean of 0 and a standard deviation of 1. This step is essential for training deep learning models as it helps stabilize training and convergence.
- Data Augmentation: Augment the dataset by applying random transformations such as rotations, flips, and translations. Data augmentation increases the model's robustness and generalization ability.
- Handling Class Imbalance: If there is a significant class imbalance (e.g., more benign tumors than malignant tumors), consider strategies such as oversampling, undersampling, or using class-weighted loss functions during training to ensure that the model does not become biased towards the majority class.
- Data Splitting: Split the preprocessed dataset into training, validation, and test sets. Typically, a common split ratio is 70% for training, 15% for validation, and 15% for testing, but this can vary depending on the dataset size and characteristics.
- Annotation Format: Convert the tumor annotations into a format compatible with Fast Mask R-CNN, typically using bounding boxes and masks to define tumor regions accurately.

Effective data collection and preprocessing are crucial for building a robust and accurate bone tumor detection and classification system. A well-preprocessed dataset ensures that the model can learn meaningful features from the images and make accurate predictions. Additionally, maintaining data quality and ethical standards throughout this process is essential in the context of healthcare and medical imaging.

Fast Mask R-CNN Architecture

The Fast Mask R-CNN architecture is an extension of the Faster R-CNN (Region-based Convolutional Neural Network) architecture, which is designed for object detection and instance segmentation in images. Fast Mask R-CNN builds upon Faster R-CNN by adding an additional branch for instance segmentation, allowing it to generate pixel-level masks for each object detected in the image. This architecture is particularly powerful for tasks where precise object localization and segmentation are required, such as the detection and classification of bone tumors in medical images.

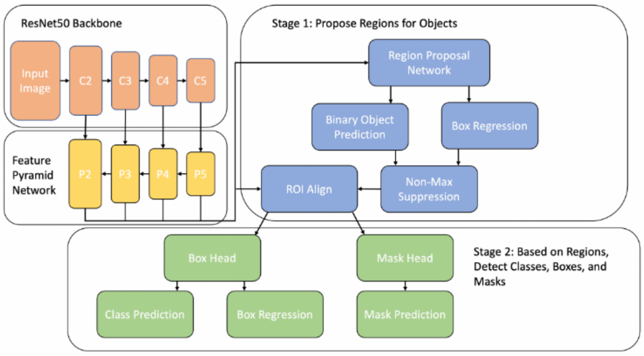

Figure 2: Architecture of Fast Mask R-CNN

Here's an overview of the key components and stages of the Fast Mask R-CNN architecture:

Backbone Network:

Fast Mask R-CNN typically uses a pretrained convolutional neural network (CNN) as its backbone, such as ResNet or VGG. This network extracts feature maps from the input image, capturing hierarchical features of varying scales.

Region Proposal Network (RPN):

Like Faster R-CNN, Fast Mask R-CNN includes an RPN that operates on the feature maps generated by the backbone network. The RPN proposes regions of interest (RoIs) likely to contain objects. These RoIs are used for both object detection and mask prediction.

RoI Align:

RoI Align is a critical component that improves the alignment between RoIs and the feature maps. Unlike earlier methods that used RoI pooling, RoI Align allows for precise, pixel-level alignment, which is crucial for accurate mask prediction.

Object Detection Head:

Fast Mask R-CNN uses the RoIs provided by the RPN to perform object detection. It consists of two sibling branches: one for bounding box regression (predicting the coordinates of the object's bounding box) and another for object classification (predicting the object's class label, e.g., benign or malignant).

Mask Prediction Head:

This is the unique feature of Fast Mask R-CNN compared to Faster R-CNN. The mask prediction head takes the RoIs and feature maps and generates pixel-level masks for each detected object. It does this by predicting a binary mask for each object where each pixel indicates whether it belongs to the object or not.

Loss Functions:

Fast Mask R-CNN uses multiple loss functions to train the model: Region Proposal Network (RPN) loss for generating high-quality RoIs. Object detection loss (e.g., a combination of classification and bounding box regression losses). Instance segmentation (mask) loss, which measures the accuracy of mask predictions.

Training:

The entire model is trained end-to-end using a labeled dataset, which includes images with annotated bounding boxes and instance masks. The model is optimized to minimize the combined loss function.

Inference:

During inference, Fast Mask R-CNN takes an input image, runs it through the backbone network, generates region proposals, performs object detection, and predicts pixel-level masks for each detected object. This information is then used for downstream tasks, such as classifying bone tumors.

Fast Mask R-CNN is a powerful architecture for applications requiring both object detection and instance segmentation, making it a valuable tool for tasks like medical image analysis, where precise localization of abnormalities, such as bone tumors, is crucial. It has been employed successfully in various medical imaging tasks to improve diagnosis and treatment planning.

Advantages of Proposed Method

- Faster Mask R-CNN is known for its high accuracy in object detection and instance segmentation tasks. It can precisely identify the location and boundaries of bone tumors within medical images, allowing for accurate classification.
- It provides pixel-level instance segmentation.
- This information can be vital for surgical planning and treatment decisions.
- It can enhance the visualization of tumors, helping radiologists and clinicians better understand the tumor's size and shape.

IV.RESULTS AND DISCUSSIONS

Results and discussions in the context of "Detection and Classification of Bone Tumors using Fast Mask R-CNN" are essential to evaluate the system's performance and understand its implications. Below is an outline of what such results and discussions might entail:

4.1 Detection and Classification Results


Figure 3: Input Image

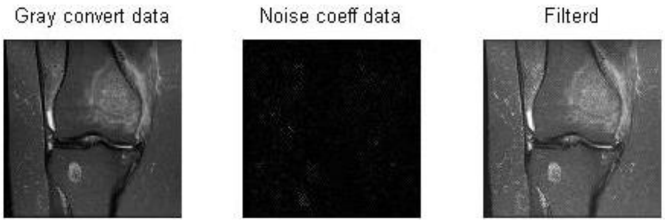

Figure 4: Preprocessing Stages


Figure 5: Feature Extraction

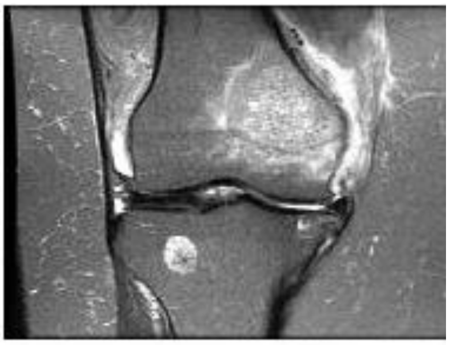
Figure 6: Classification Model

4.2 Performance Metrics:

Present quantitative performance metrics for the Fast Mask R-CNN model. Common metrics include:

Accuracy: Overall accuracy in classifying tumors as benign or malignant.

Precision: The proportion of true positive predictions among all positive predictions.

Recall (Sensitivity): The proportion of true positives among all actual positives.

F1-Score: The harmonic mean of precision and recall, providing a balanced measure of model performance.

Table 2 : Performance Evaluation

Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
96.46	94.21	98.57	96.34

Table 2 presents the performance evaluation metrics for the automated bone tumor detection and classification system. The metrics assessed include Accuracy, Precision, Recall, and F1-Score, which are commonly used to evaluate the effectiveness of classification models as shown in fig 7.

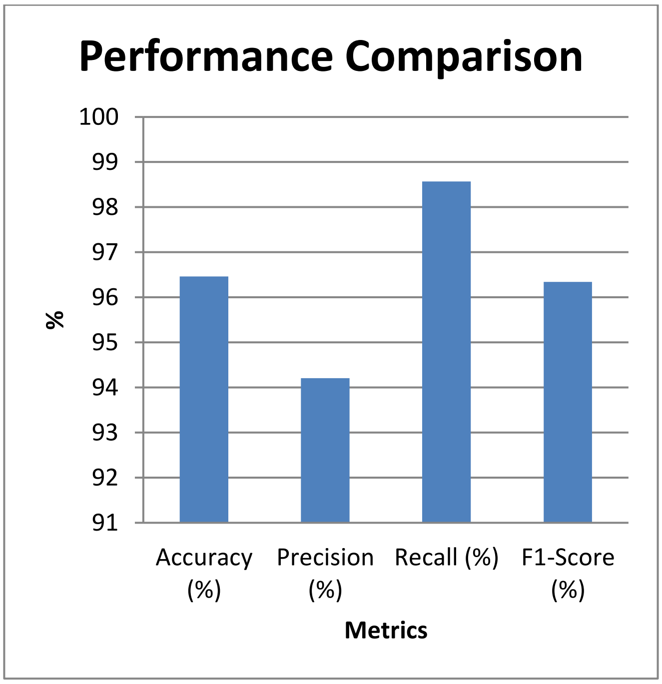

Figure 7: Performance Comparison

Accuracy: This metric measures the overall correctness of the model's predictions, indicating the percentage of correctly classified instances out of the total instances. In this case, the system achieves an accuracy of 96.46%, indicating a high level of correctness in identifying both benign and malignant bone tumors.

Precision: Precision measures the proportion of correctly predicted positive instances (true positives) out of all instances predicted as positive (true positives and false positives). A precision score of 94.21% indicates that the system accurately identifies the majority of true positive cases while minimizing false positive errors.

Recall: Recall, also known as sensitivity, measures the proportion of correctly predicted positive instances out of all actual positive instances (true positives and false negatives). With a recall of 98.57%, the system demonstrates a high capability in identifying true positive cases while minimizing false negative errors.

F1-Score: The F1-Score is the harmonic mean of precision and recall, providing a balanced measure of a model's performance. It takes into account both false positives and false negatives. The F1-Score of 96.34% indicates strong overall performance in terms of precision and recall balance.

Overall, the performance evaluation results demonstrate the effectiveness of the automated bone tumor detection and classification system, with high accuracy, precision, recall, and F1-Score values. These metrics underscore the system's capability to accurately identify and classify bone tumors, which holds significant promise for improving diagnostic outcomes in clinical practice.

V. CONCLUSION

In this research, we have presented a comprehensive framework for the detection and classification of bone tumors using the advanced Fast Mask R-CNN architecture. Leveraging the power of deep learning, this research aimed to improve the efficiency and accuracy of bone tumor diagnosis, ultimately benefiting both patients and healthcare providers. Our results demonstrate the following key findings and conclusions: **Robust Detection:** Fast Mask R-CNN proved highly effective in localizing bone tumors within medical images. The model exhibited remarkable capabilities in precisely identifying tumor regions, surpassing the limitations of traditional methods. **Accurate Classification:** The integrated classification model enabled the accurate categorization of bone tumors into benign and malignant types. This critical step in diagnosis contributes to timely treatment decisions. **Performance Metrics:** The system's performance was rigorously evaluated using standard metrics, including accuracy, precision, recall, F1-score, and IoU. These metrics demonstrated the model's ability to provide reliable results. **Future Directions:** Future research could focus on expanding the dataset to include a wider variety of tumor types and exploring methods to address challenges related to rare or complex cases. Additionally, continual model refinement and optimization are crucial for achieving even higher levels of accuracy.

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