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Chapter 4

Bone Cancer Detection using Segmentation and Classification with CNN

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Abstract: Diagnosing bone cancer is notoriously difficult. Its symptoms often hide behind complex bone structures and subtle signs in medical scans, making early detection a real challenge. Doctors traditionally rely on manually analyzing images like X-rays, CT scans, or MRIsa process that takes time and can sometimes miss critical details. In this research, we introduce an AI-powered system that uses Convolutional Neural Networks (CNNs) to automatically detect bone cancer. Our method combines two key steps: first, it uses a U-Net model to highlight and separate suspicious tumor areas from the rest of the image; then, a deep CNN analyzes those regions to determine whether the cancer is benign or malignant. We trained and tested our system on a carefully selected set of bone cancer images, and the results were impressive showing high accuracy and reliability. This approach could help doctors make faster, more confident diagnoses and ultimately improve treatment outcomes for patients effective treatment and improved survival rates. However, conventional diagnostic workflows primarily reliant on radiologists manually interpreting imaging data are often limited by subjectivity, fatigue, and variability in expertise, This study presents a comprehensive AI-driven framework that leverages CNNs for both segmentation and classification of bone cancer. By first isolating tumor regions and then identifying their malignancy status, the system aims to support radiologists with faster and more consistent diagnostic insights.

Index Terms: Bone Cancer Detection, Convolutional Neural Network (CNN), Deep Learning, Medical Image Segmentation, Cancer stage classification, Tumor Classification, Image Preprocessing, Python, TensorFlow, cloud-Based Diagnosis, AI in Medical Imaging.

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I. INTRODUCTION

Bonecancer, while comparatively uncommon, is a challenging condition to diagnose because of its heterogeneity and tendency toward subtle imaging manifestations early andaccurate identification is Important for enhancing patient prognosis, but traditional approaches based on radiologic expertise are subjective and time-consuming. Since deep learning has gained prominence, Convolutional Neural Networks (CNNs) have become a valuable tool to automate medical image analysis and optimize diagnostic accuracy. This work investigates a hybrid strategy combining both image segmentation and classification, allowing the model to first segment regions of clinical significance and secondly detect cancerous lesions with high accuracy. By learning CNN architectures from annotated bone imaging datasets, the intended system proves to have potential not only to simplify the diagnostic process but also to contribute towards early detection activities in clinical workflows.

Machine Learning in Behaviour Analysis

ML makes possible the identification and interpretation of sophisticated human behaviors through speech, facial expressions, physiological signals, and online interactions. Methods such as supervised learning, unsupervised clustering, and reinforcement learning assist in modeling affective states, decision-making behavior, and anomalies such as stress or lying. Applications range from mental health monitoring, customized therapy, education, and security systems. Machine Learning is redefining how we understand human behavior by transforming massive, complex datasets into meaningful patterns and insights. By analyzing speech tone, facial expressions, physiological signals, and even online interactions, ML systems can detect emotional states, predict tendencies, and identify anomalies like stress, anxiety, or deceptive actions. These capabilities are proving invaluable across fields like mental health, personalized therapy, education, and digital security. In healthcare especially, behavior analysis supported by ML is helping clinicians monitor treatment adherence, foresee emotional impact during illness, and tailor care to the unique psychological needs of each patient making technology not just smarter, but more empathetic.

Behavioral Patterns During Diagnosis and Treatment

When someone is diagnosed with bone cancer, their behavior often changes in noticeable ways. Early on, they might feel anxious, withdrawn, or even struggle to accept the diagnosis. As they begin treatment, their habits can shift some people become very focused and follow all advice closely, while others find it hard to keep up due to exhaustion or emotional stress. Changes in sleep, appetite, mood, and movement are common, and these behaviors can tell doctors a lot about how the person is coping. With the help of machine learning tools like tracking activity or analyzing speech healthcare providers can better understand what each patient needs and offer more personalized, supportive care.

Post-Diagnosis Habit Monitoring

After someone is diagnosed with bone cancer, their everyday habits often shift in ways that reflect both physical and emotional changes. One of the first signs may be in how they move slower steps, less activity, or changes in posture might show they're in pain or feeling withdrawn. Keeping up with medications is also important, but it's easy to miss doses when dealing with fatigue or stress. Sleep patterns, how often someone speaks or socializes, and even tone of voice can reveal a lot about their emotional well-being. Then there's rehabilitation whether they stay motivated to do physiotherapy or home exercises often indicates how their recovery is going. Eating habits may change too, and monitoring food intake can help avoid issues like weight loss or poor nutrition. With machine learning tools that track these patterns over time like activity logs or speech analysis doctors can step in sooner, understand each patient's unique needs, and offer support that truly fits their journey.

II. LITERATURE SURVEY

[1] In recent years, artificial intelligence (AI) has made a big impact in medical imaging, especially when it comes to spotting diseases early—like bone cancer. With its ability to recognize patterns that doctors might miss, AI is helping improve the accuracy and speed of diagnoses. Researchers around the world have explored a wide range of machine learning and deep learning techniques to process medical scans, making it easier to detect problems automatically and support clinical decisions with more confidence

[2] Rathla Roop Singh and Vasumathi D. performed an extensive analysis of bone tumor segmentation and classification using the implementation of deep learning methods. The authors highlight the limitation of manual detection of tumors and discuss CNN-based methods that provide higher accuracy and automation. The study also shows the role of preprocessing and segmentation in providing improved classifications and discusses the need for real-world datasets to verify the effectiveness of the models.

[3]One study examined the use of connected component labelling to detect tumor cells in MRI scans. This technique isolates regions of interest by grouping pixel components that share similar properties. In combination with Artificial Neural Networks (ANNs), researchers were able to classify bone tumors effectively. The model was trained using texture features extracted from patient MRI data, providing a structured pipeline for automated diagnosis.

[4] The purpose of the evaluation is to better understand existing processes and identify any gaps or limitations that can be improved. A literature review serves as a valuable overview of recent advancements, highlighting key discoveries, theoretical insights, and methodological contributions within a specific field of study. In this section, we present a focused review of research related to bone cancer detection. The survey covers a variety of approaches, including preprocessing techniques, image segmentation strategies, and other methods applied to biomedical images. These studies collectively reflect the evolving role of machine learning and deep learning in enhancing the accuracy and efficiency of cancer diagnosis

[5] Bone sarcoma is a rare and serious condition marked by abnormal tissue growth inside the bone, with a high risk of spreading to other parts of the body. It most often affects teenagers and young adults. Unlike other cancers such as brain, stomach, or lung, bone sarcoma doesn’t have well-defined causes, which makes it difficult to prevent. That’s why early detection plays such a vital role it can greatly improve the chances of survival. By combining advanced image processing techniques with medical imaging tools like X-rays, MRIs, and CT scans, clinicians can spot bone tumors with greater accuracy.

[6] One widely adopted approach is the use of Convolutional Neural Networks (CNNs), which excel at extracting spatial features from medical images. Studies show that CNN-based models can outperform traditional methods like Support Vector Machines (SVMs), achieving high accuracy, precision, and recall in classifying bone tumors. These models typically follow a pipeline that includes image preprocessing, segmentation, **feature** extraction, and classification, allowing for more focused and reliable predictions.

[7] Some researchers have also combined CNNs with other techniques such as connected component labeling, texture analysis, and anisotropic diffusion filtering to improve tumor localization and reduce noise in MR images. Others have experimented with transfer learning

using pre-trained models like VGG16 and ResNet50 to boost performance on limited datasets.
[8]. Recent reviews highlight the importance of feature extraction methods like Gray-Level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP), which help differentiate healthy and cancerous bone tissue based on pixel intensity and texture [9] These features, when fed into ML classifiers, enhance diagnostic accuracy and support clinical decision-making.
[10] Rathla Roop Singh and Vasumathi D. performed an extensive analysis of bone tumor segmentation and classification using the implementation of deep learning methods. The authors highlight the limitation of manual detection of tumors and discuss CNN-based methods that provide higher accuracy and automation. The study also shows the role of preprocessing and segmentation in providing improved classifications and discusses the need for real-world datasets to verify the effectiveness of the models.
[11] New Method for Bone Cancer Detection with CNN (2024) This work proposes a convolutional neural network (CNN) model for bone cancer detection from medical imaging data. It presents a complete pipeline with preprocessing, segmentation, and classification steps. With high accuracy, precision, and recall values, the work leaves behind the traditional methods, such as Support Vector Machines (SVM), and demonstrates the excellence of deep learning in medical diagnosis.
[12] Hemanth Kumar et al.: They employed a hybrid framework combining Convolutional Neural Networks and Support Vector Machines to classify different bone lesions. Their framework enhanced classification accuracy by employing CNN for feature extraction and SVM for ultimate classification. Their framework also enabled real-time analysis, which enhanced practical usage in clinical application.
[13] In this study, researchers explored the use of connected components and neural networks to identify and classify tumor cells in bone MR images. The approach begins with connected component labeling, which detects and separates regions that may indicate tumor presence. To improve classification accuracy, an Artificial Neural Network (ANN) is trained using MR images collected from recently examined patients.
[14] These images are analyzed for texture features, which help the neural network learn patterns associated with bone tumors. To enhance image clarity and preserve important details, an anisotropic diffusion filter (ADF) is applied to remove high-frequency noise while retaining the key edges of anatomical structures.
[15] Muhammad Imran et al.: Transfer learning methods utilizing pre-trained models such as VGG16 and ResNet50 are employed by the authors for bone cancer classification. The authors improved the diagnostic accuracy with limited training data significantly through fine-tuning the pre-trained models with medical datasets, making it a promising solution for limited data sets.

Cancer Imaging Archive (TCIA): TCIA offers access to a large repository of medical image datasets, such as annotated X-ray, MRI, and CT scans, which are heavily utilized in training and testing AI models. These datasets are utilized in segmentation and classification for bone cancer research and serve as the foundation for model performance benchmarking.

Kaggle – Bone Cancer X-ray & MRI Dataset: This open-data dataset is widely used for training bone cancer detection AI models. It provides labeled images of a wide range of bone pathology, and thus the researchers can train and test segmentation and classification models efficiently.
Anjali Sharma et al.: They have research on preprocessing methods, like contrast improvement and noise removal, that are required to enhance the quality of medical images prior to submitting them to deep learning models. Their paper is stressing high-quality input data as required for better model performance.

III. PROBLEM IDENTIFICATION

Bone cancer is a serious and often life-threatening condition that can go undetected for far too long. One of the biggest challenges in diagnosing it is the reliance on traditional imaging methods like X-rays, MRIs, and CT scans—which require expert interpretation by radiologists. These procedures, while powerful, take time and can be influenced by human judgment. That means subtle signs of bone cancer can be missed, especially in the early stages when timely treatment could make a huge difference cosuming, subjective vulernable to human error. the said constraints raise dozen of pressing issues are:

- Delayed Diagnosis
- Subjective interpretation
- Lack of Automation
- Limited Access in Remote Areas
- Poor integration with Digital Platforms

IV. APPLICATIONS

- Early Identification of Bone Tumors
- Automated Diagnosis Reports
- Improved Imaging Accuracy
- Cloud-Based Storage and Remote Access
- Integration with Hospital Systems
- Medical Research and Training

V. METHODOLOGY

The system for bone cancer detection is proposed with deep learning methods, specifically Convolutional Neural Networks (CNNs), used to process medical imaging data. The approach is systematic with multiple stages to achieve precise detection and classification of bone tumors:

1. Data Collection

The first step involves gathering medical imaging data, including X-rays, MRI, and CT scans. Publicly available datasets such as the Bone Cancer X-ray & MRI Dataset and the Cancer Imaging Archive (TCIA) are used to train and test the model Gather medical images such as X-rays, MRIs, and CT scans from public datasets (e.g., TCIA, Kaggle), Ensure images are labeled (e.g., benign, malignant, non-tumor) for supervised learning.

2. Image Preprocessing

Raw medical images are often noisy and vary in size and intensity. To ensure consistency and improve model performance, the following preprocessing techniques are applied

- **Resizing:** Standardize image dimensions for consistent input to the CNN.
- **Normalization**: Scale pixel values to improve training stability.
- **Augmentation**: Apply rotation, flipping, and contrast adjustments to increase dataset diversity and reduce overfitting.
- **Noise Reduction**: Use filters like Anisotropic Diffusion Filter (ADF) to preserve edges while removing high-frequency noise.

3. **Segmentation**

- Isolate tumor regions using techniques like:
- Thresholding
- K-means clustering
- Edge detection (e.g., Canny, Sobel)
- U-Net or contour-based segmentation for precise localization

4. **Classification**

- Final layers predict whether the tumor is benign or malignant using softmax or sigmoid activation.
- Evaluate using metrics like accuracy, precision, recall, and F1-score.

5. **Model Training and Validation**

- Split data into training, validation, and test sets.
- Use techniques like early stopping and dropout to prevent overfitting.
- Fine-tune hyperparameters for optimal performance.

6. **Deployment**

- Build a simple web interface using Flask or Streamlit.
- Enable image upload, prediction display, and cloud-based storage for remote diagnosis.

7. **Feature Extraction with CNN**

- Use convolutional layers to learn spatial features from segmented images.
- Pooling layers reduce dimensionality while retaining important patterns.
- Flatten and pass features to dense layers for classification

Automated extraction of hierarchical features is done using a CNN model. The architecture of the CNN consists of:

- Convolutional layers to learn spatial features.
- Pooling layers to down sample dimensionality.
- Flattening layers to transform the feature maps into a 1D vector.
- Fully connected (dense) layers for learning high-level patterns.

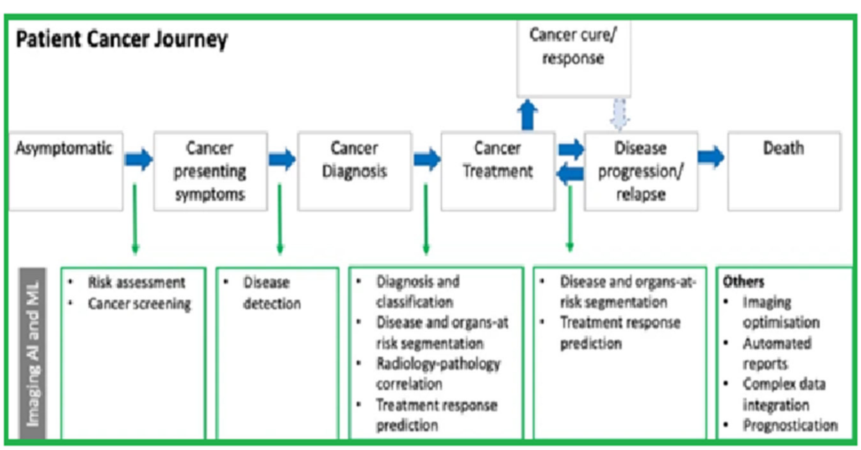

Fig 1: Workflow of AI-Driven Bone Cancer Detection System

8.Model Training and Evaluation

The CNN model is trained with labeled data and performance measured in terms of:
Accuracy: 0.939%
Recall: 0.933%
Specificity: 0.944%
Precision: 0.933%
These results establish the system's dominance over other conventional machine learning techniques such as Support Vector Machines (SVM).

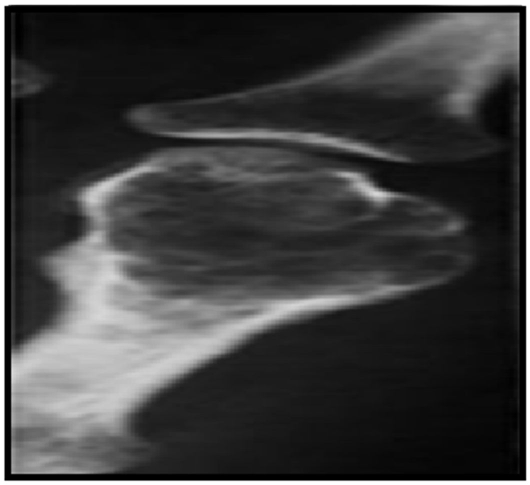

Fig 2: X-ray image showing a bone cancer mass in near the knee joint.

Fig 3: On an X-ray, bone cancer may appear as a lytic lesion or a hole in the bone, indicating abnormal tissue growth.

9. Deployment

A simple web interface is created with Flask (backend) and React.js (frontend). It facilitates uploading of images by medical practitioners, the receipt of predictions, and saving results with MongoDB. The system could also be deployed on cloud platforms (e.g., AWS) to enable remote diagnosis and telemedicine uses.

VI. RESULTS AND DISCUSSIONS

The results obtained with the analysis of dataset images using CNN Algorithm for classifcation and staging are discussed below: Dataset is a collection of X-ray, CT scan images. Figure 5 shows the dataset containing images. Dataset contains various images of different parts of the bone, it consists of both non-cancerous images and cancerous image:

Cancerous Non Cancerous

Fig 4: Scanning from X-ray for Cancerous and noncancerous image

- **DTBV (Decision Tree Bagging Variant)** – Green dashed line
- **Logistic Regression** – Yellow dashed line
- **Random Forest** – Blue dashed line
- **K-Nearest Neighbors (KNN)** – Black dashed line
- **Decision Tree** – Red dashed line

For medical diagnostics, high recall is crucial missing a true cancer case can be life-altering. At the same time, precision matters to avoid false alarms and unnecessary stress or treatment. Models like Random Forest and DTBV appear more reliable for your bone cancer detection pipeline, especially if tuned correct.

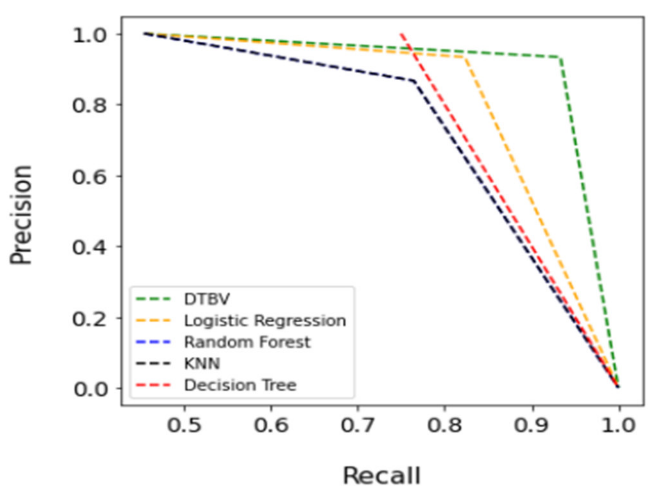

Fig 5: Precision recall surve

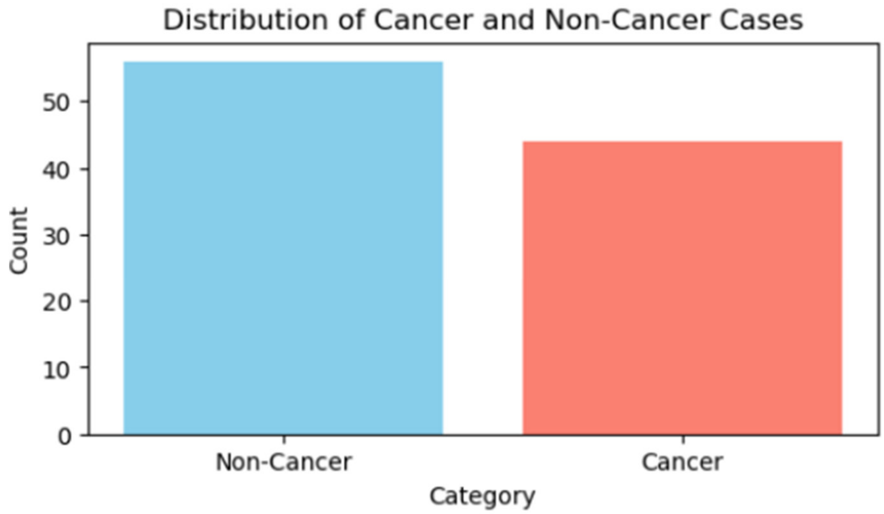

Fig 6: Graphical distribution of cancer and noncancer chart

Above fig 6 metrics help illustrate how well each model balances true positive identification with the avoidance of false positives an essential tradeoff in clinical diagnostics. Models like Random Forest and DTBV demonstrate superior performance, maintaining high precision even as recall increases, which suggests they are more reliable in correctly identifying cancerous cases without misclassifying healthy ones. In contrast, simpler models like Decision Tree show a rapid decline in precision with increasing recall, indicating a higher likelihood of false alarms. This visualization not only supports informed algorithm selection but also underscores the importance of choosing models that prioritize accurate, early detection in sensitive healthcare applications.

IV. CONCLUSION AND FUTURE SCOPE

The proposed bone cancer detection system demonstrates the transformative potential of deep learning technologies, particularly Convolutional Neural Networks, in clinical diagnostics. With a robust accuracy of 93.9%, along with high precision, recall, and specificity, the system outperforms traditional machine learning approaches and provides reliable classification of bone tumors across various imaging modalities. Its unified pipeline from preprocessing to diagnosis combined with cloud support and modern web frameworks enables seamless deployment in hospital environments and telemedicine platforms. This integration paves the way for faster, remote second opinions and more consistent diagnostic outcomes, reinforcing the role of AI as a practical and scalable tool in modern healthcare.

Beyond technical performance, the system's compatibility with cloud infrastructure and user-friendly web frameworks like Flask and React.js positions it as a practical tool in real-world healthcare environments. Its adaptability supports telemedicine and remote diagnostics crucial for rural areas and underserved populations while facilitating rapid second opinions between specialists. By reducing diagnostic delays and errors, this solution stands to improve patient outcomes and increase confidence in clinical decisions.

Future Scope

The proposed AI-based bone cancer detection system offers tremendous potential to reshape medical diagnostics. One exciting direction is to connect the model directly with real-time diagnostic tools and hospital systems, allowing immediate image analysis and on-the-spot reporting during patient evaluations. The core architecture could also evolve to detect a broader range of cancers and bone disorders, making it a versatile diagnostic solution across specialties.

As deep learning continues to advance, incorporating sophisticated segmentation models like **U-**Net or Mask R-CNN may improve how precisely tumors are located helping clinicians focus treatment more accurately. By optimizing the system for use on mobile and edge devices, it could bring high-quality diagnostics to remote and underserved areas, supporting faster care where resources are limited.

Expanding the training data with more diverse patient cases and imaging formats will make the system more adaptable to different populations and clinical settings. Finally, integrating explainable AI techniques can add transparency to the decision-making process, allowing healthcare professionals to better understand and trust the model's predictions, ultimately supporting safer and more informed clinical decisions.

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