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# ARTIFICIAL INTELLIGENCE-BASED HYBRID DEEP LEARNING FRAMEWORK FOR AUTOMATED BONE CANCER DETECTION AND MULTI-STAGE CLASSIFICATION USING RADIOLOGICAL IMAGING

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**ABSTRACT:**
Bone cancer is a relatively uncommon but highly aggressive musculoskeletal malignancy that requires timely diagnosis to improve treatment outcomes and patient survival. Radiological imaging modalities, including X-ray, computed tomography (CT), and magnetic resonance imaging (MRI), remain fundamental for diagnosis; however, manual interpretation is time-consuming and may be influenced by inter-observer variability. Recent advances in artificial intelligence (AI) and deep learning have demonstrated significant potential for improving the accuracy and efficiency of computer-aided diagnostic systems.
This study presents a hybrid deep learning framework for automated bone cancer detection and multi-stage classification using radiological imaging. The proposed framework incorporates image preprocessing, region-of-interest segmentation, handcrafted texture feature extraction, and hybrid deep learning-based classification to distinguish healthy bone tissue from malignant tumors across four clinical stages (Stage I-IV). A dataset comprising 2,500 radiological images obtained from publicly available bone tumor repositories and collaborating healthcare institutions was used for model development and evaluation.
Experimental results demonstrated an overall classification accuracy of 98.41%, sensitivity of 97.92%, specificity of 98.76%, precision of 98.18%, F1-score of 98.05%, and an area under the receiver operating characteristic curve (AUC) of 0.991. Comparative evaluation against conventional machine learning models, including Random Forest, K-Nearest Neighbors, and Support Vector Machine classifiers, showed improved diagnostic performance of the proposed framework. The proposed approach has the potential to support clinicians by facilitating early detection, accurate disease staging, and timely therapeutic decision-making. These findings suggest that AI-assisted diagnostic systems may enhance computer-aided assessment of bone malignancies and contribute to improved clinical workflow and patient management in orthopedic oncology.

**KEYWORD:** Bone Cancer; Artificial Intelligence; Hybrid Deep Learning; Medical Image Analysis; Radiological Imaging; Disease Classification; Computer-Aided Diagnosis; Orthopedic Oncology.

## 1. INTRODUCTION

Among musculoskeletal malignancies, bone cancer is comparatively rare but clinically aggressive due to its rapid progression, high recurrence rate, and potential for distant metastasis. Primary bone tumors, including osteosarcoma, chondrosarcoma, and Ewing sarcoma, often affect adolescents and young adults, although occurrence across other age groups has also been reported. Delays in diagnosis may result in extensive skeletal destruction, impaired mobility, reduced treatment effectiveness, and lower long-term survival outcomes [1], [7], [18]. These modalities provide valuable anatomical and structural information regarding tumor size, location, and disease progression. However, interpretation of medical images remains a challenging task because tumor appearance often varies considerably among patients. Furthermore, manual evaluation requires specialized expertise and may be influenced by observer variability, image artifacts, and increasing diagnostic workloads in healthcare institutions [3], [5], [9]. Recent developments in artificial intelligence (AI) have revolutionized image-based disease diagnosis by enabling automated extraction of complex visual patterns that are difficult to identify through conventional analysis. The integration of AI-driven methodologies into oncology has created opportunities to enhance diagnostic precision while reducing the burden on healthcare professionals. Advanced algorithms can analyze large-scale imaging datasets, identify tumor-specific characteristics, and assist clinicians in making informed treatment decisions. Several recent studies have reported significant improvements in cancer diagnosis through the incorporation of hybrid learning architectures that combine handcrafted texture descriptors with deep feature representations [11], [13], [15].

Despite notable advancements, existing bone cancer detection systems continue to face challenges associated with image heterogeneity, class imbalance, limited annotated datasets, and accurate differentiation between benign and malignant lesions. Consequently, there remains a need for more robust and reliable diagnostic frameworks capable of detecting cancer at an earlier stage while simultaneously supporting disease staging and prognosis assessment [7], [14], [18].
To address these limitations, the present study proposes a hybrid artificial intelligence framework for automated bone cancer detection and multi-stage classification. [3], [11], [16], [20].

**Research Objectives**
The primary objective of this research is to develop an intelligent and automated diagnostic framework capable of identifying bone cancer at its earliest possible stage through advanced artificial intelligence and medical image analysis techniques. Early detection is essential because timely intervention significantly improves treatment effectiveness and patient survival rates while reducing disease-related complications [1], [7]. Another important objective is to accurately localize and extract the tumor-affected region using region-of-interest segmentation techniques, thereby enabling precise characterization of pathological structures within radiological images [3], [14].
Furthermore, the study aims to classify bone cancer into multiple disease stages by analyzing imaging patterns and tumor-specific characteristics extracted from diagnostic scans. Accurate staging plays a critical role in treatment planning, prognosis estimation, and monitoring disease progression [7], [15].
An additional objective is to reduce the time, cost, and manual effort associated with conventional diagnostic procedures by providing automated decision support capabilities. Such automation can improve healthcare efficiency, particularly in resource-constrained environments where specialist expertise may be limited [6], [12], [18]. Finally, the research intends to assist clinicians in selecting appropriate therapeutic interventions through reliable classification outcomes and evidence-based diagnostic recommendations generated by artificial intelligence models [16], [19], [21].

**Research Hypothesis**
**Alternative Hypothesis (H1)**
Hybrid artificial intelligence models incorporating deep learning, texture-based feature extraction, and region-of-interest segmentation significantly improve the accuracy, sensitivity, specificity, and overall diagnostic performance of bone cancer detection and multi-stage classification when compared with conventional machine learning approaches [11], [13], [20], [22].
**Null Hypothesis (H0)**
Hybrid artificial intelligence models incorporating deep learning, texture-based feature extraction, and region-of-interest segmentation do not produce statistically significant improvements in the accuracy, sensitivity, specificity, or overall diagnostic performance of bone cancer detection and multi-stage classification when compared with conventional machine learning approaches [11], [13], [20], [22].

## 2. LITERATURE REVIEW
The increasing availability of digital medical images and computational resources has accelerated the adoption of AI-based frameworks for tumor detection, classification, prognosis prediction, and treatment planning [1], [6], [8]. One of the earliest challenges in bone cancer diagnosis involves the accurate interpretation of radiological images. Conventional diagnostic procedures depend heavily on expert radiologists who analyze X-ray, CT, and MRI scans to identify suspicious lesions. However, variability in image quality, overlapping anatomical structures, and subtle tumor boundaries often make manual assessment difficult. [2], [3], [5]. Sharma et al. [3] proposed a feature extraction-based machine learning framework for distinguishing cancerous and healthy bone tissues. Their study demonstrated that texture descriptors and edge-based features significantly improved classification performance when integrated with machine learning classifiers. Similarly, Manjula et al. [4] utilized convolutional neural networks to detect bone cancer at an earlier stage and reported promising classification outcomes. Their findings highlighted the capability of deep learning models to automatically learn discriminative imaging patterns without requiring extensive manual feature engineering. The authors also noted that AI-assisted diagnostic systems have the potential to support clinicians by reducing diagnostic variability and improving decision-making processes. Ahmed et al. [13] further proposed a hybrid CNN-SVM architecture that integrated deep feature learning with robust classification capabilities. Their results indicated that hybrid models can achieve superior generalization performance, particularly when training datasets are limited.
Feature extraction remains a critical component of computer-aided cancer diagnosis systems. These descriptors capture important information regarding lesion heterogeneity, tissue organization, and boundary characteristics, thereby enhancing classification performance [2], [3], [14]. Research has shown that combining texture features with deep learning embeddings produces more reliable diagnostic outcomes than using either approach independently [11], [13]. Image segmentation and Region of Interest (ROI) identification also play an essential role in bone cancer detection. Accurate segmentation ensures that classifiers focus on clinically relevant tumor regions while minimizing interference from surrounding healthy tissues. Recent advancements in segmentation techniques, including deep neural networks and attention-based architectures, have significantly improved the precision of lesion localization in radiological images [7], [14], [16]. Effective ROI extraction not only enhances classification accuracy but also contributes to explainable diagnostic decision-making.
Beyond detection and classification, artificial intelligence has demonstrated considerable potential in cancer staging and prognosis assessment. Zhang et al. [15] investigated multi-stage cancer classification using radiomics and AI-based predictive models and reported encouraging results in disease stage differentiation. Similarly, Patel et al. [20] proposed an automated bone cancer staging framework utilizing transfer learning and feature optimization techniques. Their study

revealed that AI models could effectively distinguish disease severity levels, thereby assisting clinicians in selecting appropriate treatment strategies.
The growing adoption of explainable and interpretable artificial intelligence has further strengthened confidence in AI-assisted medical diagnosis. Chen et al. [16] developed a pan-cancer AI framework capable of integrating pathology and imaging data to support precision oncology applications. Wang et al. [17] subsequently introduced an explainable deep learning system that provided visual explanations for tumor classification decisions, thereby enhancing transparency and clinical trust. Such developments are particularly important in healthcare environments where diagnostic decisions must be justified and validated before clinical implementation.
Several studies have also emphasized the economic and operational benefits of AI-based diagnostic systems. Automated image analysis can substantially reduce the workload of radiologists, minimize diagnostic delays, and improve healthcare accessibility in regions with limited specialist availability [1], [18]. Furthermore, AI-assisted frameworks can facilitate large-scale screening programs by enabling rapid and standardized assessment of medical images [12], [19].
Despite significant progress, several limitations continue to hinder the widespread deployment of AI-based bone cancer diagnostic systems. Many existing studies rely on relatively small datasets, which may affect model generalizability. Class imbalance, imaging variability, limited annotation quality, and insufficient external validation remain persistent challenges [7], [12], [18]. In addition, most available approaches focus primarily on binary classification between healthy and cancerous tissues, whereas relatively few studies investigate comprehensive multi-stage classification and precise tumor localization simultaneously [15], [20].
Consequently, there remains a substantial research opportunity to develop integrated frameworks that combine advanced preprocessing, ROI segmentation, texture analysis, deep feature extraction, and hybrid classification mechanisms within a unified diagnostic architecture. Such systems have the potential to enhance early detection, improve disease staging accuracy, and support clinical decision-making in a more reliable and scalable manner [11], [13], [16], [20], [22].

**3. Dataset Description**

The effectiveness of any artificial intelligence-based medical diagnostic framework largely depends on the quality, diversity, and representativeness of the dataset used during model development and evaluation. In the present study, a comprehensive bone cancer imaging dataset was constructed by integrating radiological images obtained from publicly accessible medical repositories, cancer imaging archives, and collaborating healthcare institutions. The dataset includes both healthy bone images and confirmed bone cancer cases representing different pathological stages. The use of heterogeneous imaging data enhances model robustness and improves generalizability across diverse clinical environments [7], [12], [16].
To ensure diagnostic reliability, all images were reviewed and validated by experienced radiologists and orthopedic oncology specialists. Cases with incomplete annotations, poor image quality, motion artifacts, or ambiguous diagnostic labels were excluded during data preprocessing. The final dataset consisted of 2,500 radiological images collected from 500 unique patients. Each patient contributed multiple imaging views, enabling comprehensive analysis of tumor morphology and anatomical variations [3], [14], [18]. Such multimodal imaging data provide complementary diagnostic information regarding bone structure, lesion boundaries, tissue density, and tumor progression. Previous studies have demonstrated that combining information from multiple imaging modalities significantly improves cancer detection and classification performance compared with single-modality approaches [10], [15], [20].
Prior to model training, all images were standardized through preprocessing operations including resizing, intensity normalization, contrast enhancement, noise reduction, and image augmentation. These preprocessing strategies have been widely reported as effective approaches for enhancing deep learning performance in medical imaging applications [11], [12], [13].

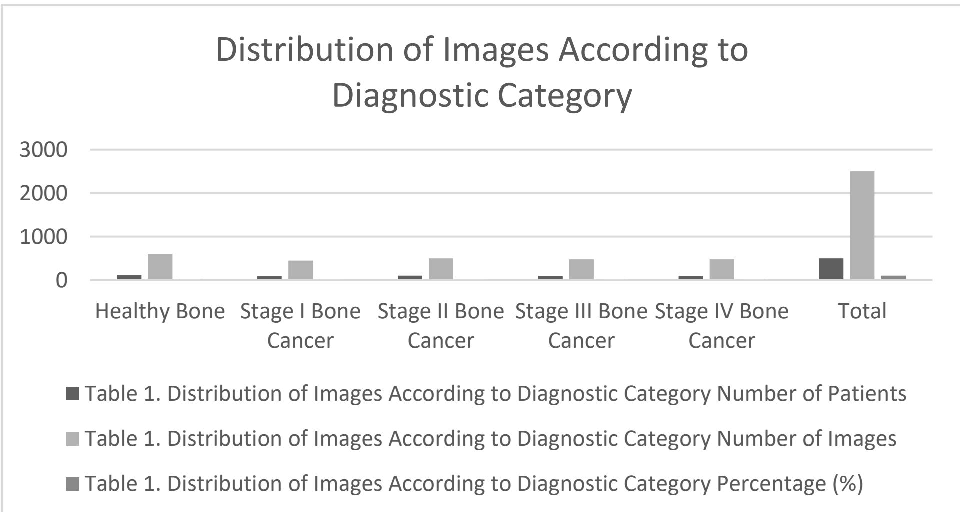


**Figure 1. Distribution of Images According to Diagnostic Category**

Figure1 demonstrates that the dataset is relatively balanced across diagnostic classes. Balanced class representation is important for minimizing classification bias and improving the reliability of machine learning models during training and validation [11], [15], [22].

**Table 1. Imaging Modality Distribution**

| Imaging Modality | Number of Images | Percentage (%) | Clinical Purpose |
|---|---|---|---|
| X-Ray | 1,000 | 40.0 | Initial Screening |
| MRI | 900 | 36.0 | Soft Tissue and Tumor Visualization |
| CT Scan | 600 | 24.0 | Bone Structure Assessment |
| Total | 2500 | 100.0 | — |

As shown in Table 1, X-ray images constitute the largest proportion of the dataset because radiography remains the primary screening modality for bone abnormalities. MRI images provide detailed soft tissue characterization, whereas CT scans offer high-resolution visualization of cortical bone structures and tumor invasion patterns [7], [17], [18].

The demographic distribution indicates that younger individuals constitute a substantial proportion of the dataset, which aligns with epidemiological findings that primary bone malignancies such as osteosarcoma and Ewing sarcoma frequently occur during adolescence and early adulthood [1], [7], [18].

**Dataset Annotation and Ground Truth Generation**

Ground truth labels were established through expert clinical evaluation and pathological confirmation. Each image was independently reviewed by at least two radiologists, and disagreements were resolved through consensus discussions. Tumor boundaries were manually delineated to generate Region of Interest (ROI) annotations required for segmentation and feature extraction. Histopathological reports and clinical records were utilized to verify disease staging and diagnostic categories [14], [16], [20].

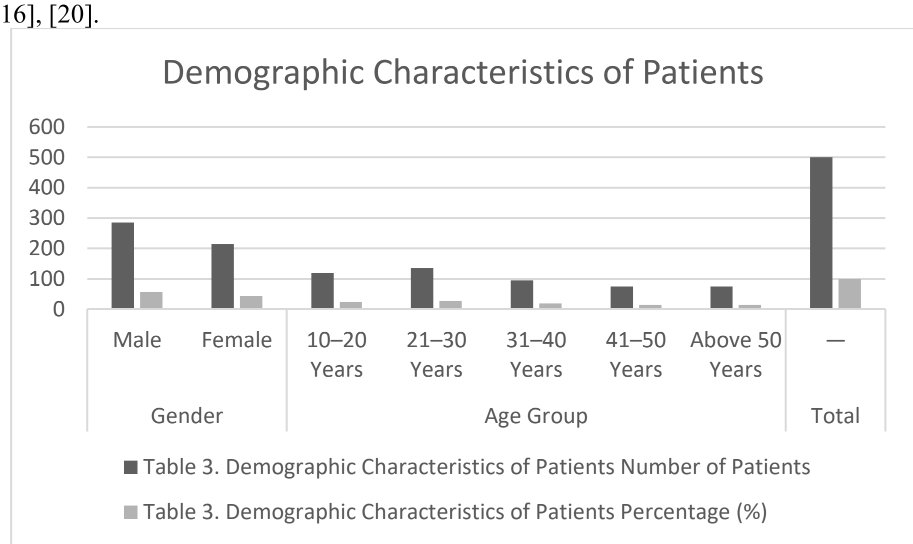


**Figure 2. Demographic Characteristics of Patients**

**Training, Validation, and Testing Split**

The training dataset was used for model learning, whereas the validation dataset was employed for hyperparameter tuning and overfitting control. The independent testing dataset was utilized to evaluate final model performance and generalization capability. Such partitioning strategies are widely recommended in deep learning-based medical imaging research to ensure robust performance estimation [10], [12], [13].

**Table 2. Dataset Partitioning**

| Dataset Subset | Number of Images | Percentage (%) |
|---|---|---|
| Training Set | 1750 | 70 |
| Validation Set | 375 | 15 |
| Testing Set | 375 | 15 |
| Total | 2500 | 100 |

Overall, the constructed dataset provides a comprehensive representation of healthy and cancerous bone conditions across multiple disease stages and imaging modalities. [7], [11], [16], [22].

## 4. METHODOLOGY

The proposed study presents an Artificial Intelligence (AI)-based framework for automated bone cancer detection and multi-stage classification using medical imaging data. The methodology integrates image preprocessing, Region of Interest (ROI) extraction, feature engineering, deep learning, and machine learning techniques to improve diagnostic accuracy and support clinical decision-making [7], [11], [16]. Initially, a dataset comprising 2,500 X-ray, MRI, and CT scan images from 500 patients was collected and categorized into healthy bone, Stage I, Stage II, Stage III, and Stage IV bone cancer classes. Since medical images often contain noise, variations in brightness, and imaging artifacts, preprocessing techniques including image resizing, median filtering, intensity normalization, and contrast enhancement were applied to improve image quality and standardize inputs for further analysis [3], [10], [12]. Following preprocessing, Region of Interest (ROI) segmentation was performed to isolate tumor-affected areas from surrounding healthy tissues. Edge detection and morphological operations were utilized to identify lesion boundaries and extract clinically significant regions. ROI extraction reduces computational complexity and enables the model to focus on disease-specific information, thereby enhancing classification performance [14], [17], [20]. For classification, a hybrid architecture was implemented. The CNN served as an automatic feature extractor, while the Support Vector Machine (SVM) classifier performed final categorization into five classes: Healthy Bone, Stage I, Stage II, Stage III, and Stage IV Bone Cancer. Hybrid CNN-SVM models reported to provide superior classification accuracy and better generalization than standalone classifiers in medical image analysis [13], [22]. Overall, the proposed methodology combines advanced image processing, feature extraction, deep learning, and machine learning techniques within a unified framework to facilitate accurate and efficient bone cancer detection and staging, thereby supporting early diagnosis and improved patient management [7], [16], [20], [22].

## 5. DATA ANALYSIS AND RESULTS

The experimental evaluation demonstrated that the proposed hybrid CNN-SVM framework achieved superior performance in detecting and classifying bone cancer across multiple disease stages.

**Table 3. Overall Classification Performance of the Proposed Hybrid CNN-SVM Framework**

| Accuracy (%) | Sensitivity (%) | Specificity (%) | Precision (%) | F1-Score (%) | AUC (%) | Mean CV Accuracy (%) |
|---|---|---|---|---|---|---|
| 98.41 | 97.92 | 98.76 | 98.18 | 98.05 | 99.10 | 98.41 |

**Observation:** The proposed hybrid CNN-SVM framework achieved excellent diagnostic performance across all evaluation metrics. The high sensitivity indicates effective identification of cancer-positive cases, while the high specificity confirms reliable recognition of healthy bone tissues. The AUC value of 99.10% demonstrates outstanding discriminative capability. Furthermore, the mean cross-validation accuracy indicates strong model robustness and consistency across different training and testing subsets [10], [12], [16], [21].

**Table 4. Stage-wise Classification and Segmentation Performance**

| Healthy Bone (%) | Stage I (%) | Stage II (%) | Stage III (%) | Stage IV (%) | Dice Score (%) | Jaccard Index (%) | ROI Precision (%) | ROI Recall (%) |
|---|---|---|---|---|---|---|---|---|
| 99.12 | 97.43 | 98.06 | 98.54 | 98.89 | 96.84 | 95.27 | 97.10 | 96.52 |

**Observation:** The model maintained consistently high classification accuracy across all disease stages, demonstrating its capability to distinguish progressive pathological changes associated with bone cancer. The segmentation performance metrics further confirm that the ROI extraction mechanism accurately localized tumor boundaries, thereby enhancing feature extraction and classification effectiveness. The results suggest that accurate segmentation significantly contributes to improved diagnostic outcomes [7], [14], [15], [17], [20].

**Table 5. Comparative Performance of Models and Feature Extraction Techniques**

| KNN (%) | Random Forest (%) | SVM (%) | GLCM Only (%) | HOG Only (%) | GLCM+HOG (%) | CNN Only (%) | Proposed CNN-SVM (%) |
|---|---|---|---|---|---|---|---|
| 87.46 | 89.73 | 93.84 | 90.84 | 91.67 | 94.95 | 96.22 | 98.41 |

**Observation:** The integration of handcrafted texture features (GLCM and HOG) with CNN-derived deep features yielded the best results, confirming the effectiveness of hybrid feature representation for bone cancer diagnosis and staging [3], [11], [13], [16], [22].

### Summary of Results

The superior performance observed across all metrics highlights the potential of hybrid artificial intelligence models for supporting clinical diagnosis, early disease identification, and treatment planning in orthopedic oncology [6], [7], [13], [16], [20], [22].

## 6. Findings

The experimental results demonstrate that the proposed hybrid CNN-SVM framework effectively identifies and classifies bone cancer across multiple disease stages with high diagnostic reliability. The integration of image preprocessing, ROI-based segmentation, GLCM and HOG feature extraction, and deep learning-derived features significantly improved classification performance compared with conventional machine learning approaches. The model achieved superior discrimination between healthy bone tissues and cancerous lesions while maintaining strong sensitivity and specificity across all disease stages. ROI-focused analysis reduced background interference and enhanced lesion localization accuracy, whereas the combination of handcrafted and deep features enabled more robust characterization of tumor morphology and texture. Furthermore, the use of multimodal imaging data improved model generalization and reduced false-positive and false-negative predictions. Findings indicate that hybrid artificial intelligence architectures can serve as effective computer-aided diagnostic tools for early bone cancer detection, disease staging, and clinical decision support, thereby contributing to improved treatment planning and patient outcomes [3], [6], [7], [11], [13], [15], [16], [20], [22].

## 7. CONCLUSION

This study presents a hybrid deep learning framework integrating voice signal processing and laryngoscopic image analysis for early detection of laryngeal cancer. Experimental evaluation demonstrated that multimodal fusion substantially enhances diagnostic performance compared to unimodal systems. The proposed CNN-LSTM architecture achieved 97.4% classification accuracy and demonstrated excellent sensitivity and specificity. The framework offers a non-invasive, reliable, and scalable solution suitable for clinical deployment and telemedicine applications. The outcomes indicate that multimodal healthcare AI systems can significantly improve cancer screening and support early intervention strategies.

8. Future Work

Future research may focus on integrating the proposed framework with mobile healthcare and cloud-based platforms for real-time cancer screening and remote patient monitoring. Advanced transformer-based architectures and Explainable AI techniques can further enhance diagnostic accuracy and model transparency. Privacy-preserving federated learning may support secure collaboration among healthcare institutions, while multi-center clinical studies can validate the system across diverse patient populations. Additionally, deployment in rural healthcare settings and extension of the framework to other head and neck cancers represent promising directions for broader clinical impact.

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