

## Web-Integrated AI System for Bone Cancer Prediction

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### ABSTRACT

Bone cancer detection from X-ray images is challenging due to subtle tumor characteristics, radiologist fatigue, and limited access to specialized expertise, particularly in resource-constrained settings. Early and accurate diagnosis is critical for improving patient outcomes. However, conventional methods rely heavily on manual interpretation, leading to delays and variability. This study proposes a web-integrated AI system for automated bone cancer prediction using deep learning. The system employs the EfficientNet-B0 architecture with transfer learning to classify bone X-ray images as normal or cancerous, supported by preprocessing, data augmentation, and class-weighting techniques to address data scarcity and class imbalance. The trained model is deployed as a user-friendly web application enabling X-ray upload, report generation, scan history management, and interaction through an integrated AI chatbot. The proposed system aims to provide an efficient, interpretable, and clinically supportive diagnostic tool for early bone cancer detection.

### I. Introduction:

Bone cancer is a serious condition caused by uncontrolled cell growth within bone tissue, often leading to severe complications if not detected at an early stage. Common symptoms include persistent bone pain, swelling, restricted mobility, and pathological fractures resulting from weakened bone structure. Early abnormalities are often subtle and difficult to identify on X-ray images, making manual diagnosis challenging even for experienced radiologists. Moreover, the growing volume of patients contributes to diagnostic fatigue, inconsistent interpretations, and delayed clinical decisions. Although bone cancer represents a relatively small percentage of overall cancer cases, timely and accurate detection significantly improves treatment outcomes and patient survival rates, emphasizing the need for automated diagnostic assistance.

Traditional bone cancer detection relies on imaging modalities such as X-rays, MRI, CT scans, and biopsies, along with classical machine-learning techniques including GLCM, SVM, KNN, and texture-based feature analysis. However, these methods present several limitations. Manual interpretation is time-consuming and prone to human error. Handcrafted features used in classical models often fail to generalize across diverse datasets and conventional image-processing techniques struggle with noise, low contrast, and indistinct tumor

boundaries. In addition, many existing systems lack transparency and interpretability, which reduces clinical trust and limits real-world adoption.

Recent advancements in artificial intelligence (AI), particularly in deep learning, have transformed medical imaging workflows. Convolutional Neural Networks (CNNs) have demonstrated exceptional ability to detect subtle and complex radiographic features that may be difficult to discern consistently through manual interpretation. Leveraging these capabilities, this research proposes a web-integrated AI system for early bone cancer prediction using X-ray imaging, offering a high-accuracy, user-friendly diagnostic aid.

The objectives of the proposed research work are as follows:

- To develop and train an EfficientNet-B0 deep learning model using transfer learning and image augmentation techniques for the accurate classification of bone X-ray images into normal and cancerous categories.
- To design and deploy a user-friendly web application using Flask, HTML, CSS, Bootstrap, and SQLite that allows users to upload X-ray images, receive predictions, generate PDF reports, and view historical scan results.

The subsequent sections of the paper are structured as follows. Section 2 summarizes various research activities carried on bone cancer detection. Section 3 contains the methodology. The architecture of bone cancer prediction system is outlined in section 4. Section 5 contains result findings and analysis. Conclusion of research work is highlighted in Section 6.

## **II. Related Work:**

Recent advances in artificial intelligence, particularly deep learning, have led to extensive research on automated bone cancer detection using medical imaging. Numerous studies have focused on improving diagnostic accuracy, reducing reliance on invasive procedures, and enhancing early detection capabilities for conditions such as osteosarcoma and other malignant bone tumors. Researchers have explored a variety of models including Convolutional Neural Networks (CNNs), transfer learning architectures, optimization algorithms, and multimodal frameworks to classify X-ray, MRI, CT, and histopathological images with increasing precision. These works collectively demonstrate the growing potential of AI-driven systems to support radiologists and clinicians by providing faster, scalable, and more reliable diagnostic tools.

Sushopti Gawade, Ashok Bhansali, Kshitij Patil and Danish Shaikh in their research paper “Application of the convolutional neural networks and supervised deep-learning methods for osteosarcoma bone cancer detection” presented a deep learning-based solution to automate the detection of osteosarcoma, a malignant bone cancer that primarily affected long bones in individuals aged 10–25 and above 60. They implemented and fine-tuned four pre-trained CNN models VGG16, VGG19, DenseNet201, and ResNet101 with domain-specific customization to enhance diagnostic performance. Among the models tested, ResNet101 achieved the best performance with an accuracy of 90.36%, demonstrating its effectiveness for osteosarcoma detection [1].

Sebastian Breden, Florain Hinterwimmer, Sarah Consalvo and Jan Neumann in their research paper “Deep learning-based detection of bone tumors around the knee in X-rays of children” proposed an AI-driven method to support early diagnosis of bone tumors in pediatric patients. The authors implemented extensive data augmentation and utilized a pretrained Vision Transformer (ViT) model to classify knee X-rays as healthy or pathological. The model integrated both discrete parameters such as incidence ratios and continuous parameters like median and variance to better represent clinical information. Performance evaluation using cross-validation demonstrated an accuracy of 89.1%, a sensitivity of 82.2%, and a specificity of 93.2%, with Grad-CAM visualizations confirming the plausibility of predictions [2].

Alabdulkreem, Saeed, Alotaibi, Allafi, Mohamed and M. A. Hamza in their research paper “Bone Cancer Detection and Classification Using Owl Search Algorithm with Deep Learning on X-Ray Images” proposed an automated method called OSADL-BCDC,

which combined transfer learning, hyperparameter optimization, and deep learning to detect and classify bone cancer from X-ray images. The model used Inception v3 for feature extraction and applied the Owl Search Algorithm (OSA) for hyperparameter tuning, followed by an LSTM network for classification into healthy or cancerous categories. The system reduced diagnostic time and achieved high precision, with a peak classification accuracy of 95%, outperforming existing approaches [3].

Aarthy, Muthupriya and Balaji in their research paper “Detection of bone cancer based on a four-phase framework generative deep belief neural network in deep learning” proposed a deep learning based four-phase framework for early and accurate bone cancer detection. The phases included noise removal using Mean Intensity and Bilateral Filters, edge detection with the Scaled Region Edge Detector, effective segmentation via Screen Cluster Area Segmentation and Relative Scalar Color Histogram, and feature extraction using a Gated CNN with Maximum Standard External Regions. The model achieved an accuracy of 80% with reduced loss, outperforming conventional CNN and U-Net models in terms of robustness and reliability [4].

Dama Anand, Osamah Ibrahim Khalaf, Fahima Hajje, Wing-Keung Wong, Shin-Hung Pan and Gogineni Rajesh Chandra in their research paper “Optimized Swarm Enabled Deep learning technique for bone tumor detection using Histopathological Image” presented a novel deep learning method for detecting bone tumors from histopathological images. Their pipeline used Tsallis Entropy for image processing, hybrid fusion for segmentation, EfficientNet-based CNN for feature extraction and augmented XGBoost with Whale optimization for classification. The proposed method achieved exceptional performance, reaching 99.48% accuracy, with 99.5% sensitivity and 99% specificity [5].

Vlad Georgeanu, Madalin L. Mamuleanu, Sorin Ghiea and Dan Selisteanu in their research paper “Malignant Bone Tumors Diagnosis Using Magnetic Resonance Imaging Based on Deep Learning Algorithms” proposed a deep learning-based method to predict bone tumor malignancy using MRI scans. Addressing the aggressive nature of malignant bone tumors, the study utilized MRI data from 23 patients (14 women and 9 men, aged 15–80). Two pre-trained ResNet50 models were used to classify T1 and T2 weighted MRI scans, and their outputs, combined with clinical data, were fed into a feed forward neural network (clinical model) to predict malignancy. The T1 and T2 classifiers achieved training accuracies of 93.67% and 86.67%, respectively, with both reaching 95.00% accuracy in validation. The clinical model achieved 80.84% training accuracy and 80.56% validation accuracy [6].

Srividya, Gangannagari Varunteja Reddy, Vishwaja Bakki and T. Adilakshmi in their research paper “AI-Based Bone Cancer Detection Using Image Processing and CNN” proposed an approach that integrated image preprocessing techniques with convolutional neural

networks (CNNs) for the early detection of bone cancer. Their study focused on enhancing diagnostic precision through a structured process involving image enhancement, data acquisition, CNN model development, training, validation, and performance evaluation. The model achieved a training accuracy of 94.64%, demonstrating strong potential for real-world medical application [7].

### **III. Methodology:**

The proposed Web-Integrated AI System for Bone Cancer Prediction follows a multi-stage pipeline that includes Data Acquisition and Preprocessing, Model Development and Training, Model Integration, Database Management, Result visualization and Report Generation. The complete workflow is described in the following subsections.

#### **3.1 Data Acquisition and Preprocessing**

The dataset consists of approximately 3,000 bone X-ray images collected from publicly available sources and curated for binary classification into cancerous and normal categories. The dataset was partitioned into training, validation, and testing sets using a 70:15:15 ratio to ensure robust model training and unbiased evaluation. All images are processed using a standardized preprocessing pipeline, which includes resizing to a fixed input resolution of 224×224 pixels, conversion to RGB format, and normalization of pixel intensities to the [0,1] range. To improve model generalization and reduce overfitting, data augmentation is applied to the training set in the form of random horizontal flipping, brightness adjustment, and contrast variation. These preprocessing steps ensure consistency across samples and enhance the robustness of the deep-learning-based classification model.

#### **3.2 Model Development and Training**

The EfficientNet-B0 architecture is initialized with ImageNet pretrained weights, and additional custom layers are added to perform binary classification. All input images are resized to 224×224 pixels. Model training is conducted in two phases: an initial stage in which the base network layers are frozen and only the classification head is trained for 8 epochs using the Adam optimizer with a learning rate of  $1 \times 10^{-4}$ , followed by a fine-tuning stage where approximately the top 40% of network layers (excluding batch normalization layers) are unfrozen and trained for 15 epochs with a reduced learning rate of  $1 \times 10^{-5}$ . Binary cross-entropy is used as the loss function with a batch size of 16. To address class imbalance, class-weighted loss is applied, and early stopping with patience values of 4 and 5 is employed to prevent overfitting. After training, the best-performing model is saved and later deployed within a Flask-based web application for inference.

#### **3.3 Model Integration and Inference Workflow**

The trained model is integrated into a Flask-based backend to support real-time predictions. When a user uploads an X-ray image, the system applies the same

preprocessing steps used during training. The model then outputs:

- Predicted class label
- Probability score for cancer presence
- Confidence metrics

All results including predictions and timestamps are stored in the SQLite database, allowing the system to maintain patient history and track diagnostic outcomes.

#### **3.4 Database Management and Dashboard Analytics**

All prediction results are archived in the SQLite database, enabling long-term storage, retrieval, and monitoring of diagnostic records. The dashboard retrieves aggregated information from the database and presents it using Chart.js, displaying analytics such as total scans performed, detected cancer cases, and normal cases.

#### **3.5 Report Generation and User Assistance**

The system generates downloadable PDF reports that include patient details, the original X-ray image, Grad-CAM heatmap, and model prediction summary. Additionally, a chatbot module is integrated to translate technical predictions into simple, understandable language and assist non-technical users, making the system suitable for real-time clinical support.

### **IV. System Architecture:**

The architecture of the proposed bone cancer prediction system is structured as a modular and scalable framework that incorporates deep-learning inference, and interactive web components. The architecture is fundamentally based on the EfficientNet-B0 deep learning model, which primarily classifies X-ray images as either cancerous or normal.

The system initiates with the user interface, where in authenticated users submit their bone X-ray scans for assessment. Upon upload, the image proceeds to the preprocessing layer, where it is resized, normalized, and transformed into the requisite format for model inference. The prediction module initializes the trained EfficientNet-B0 model and computes the cancer probability alongside the predicted label. Subsequent to prediction, Prediction data and heatmaps are stored in a compact SQLite database, facilitating long-term historical tracking and analysis. The dashboard layer obtains aggregated statistics, including total scans, cancer versus normal distribution, and daily trends, utilizing Chart.js visualizations. The report-generation module subsequently consolidates the scan details, prediction outcomes, into a downloadable PDF. Furthermore, a chatbot API offers concise elucidations and direction to users based on the predictive results. This architecture facilitates seamless data transfer from image upload to final report generation, providing precision, clarity, and functionality within a unified system.

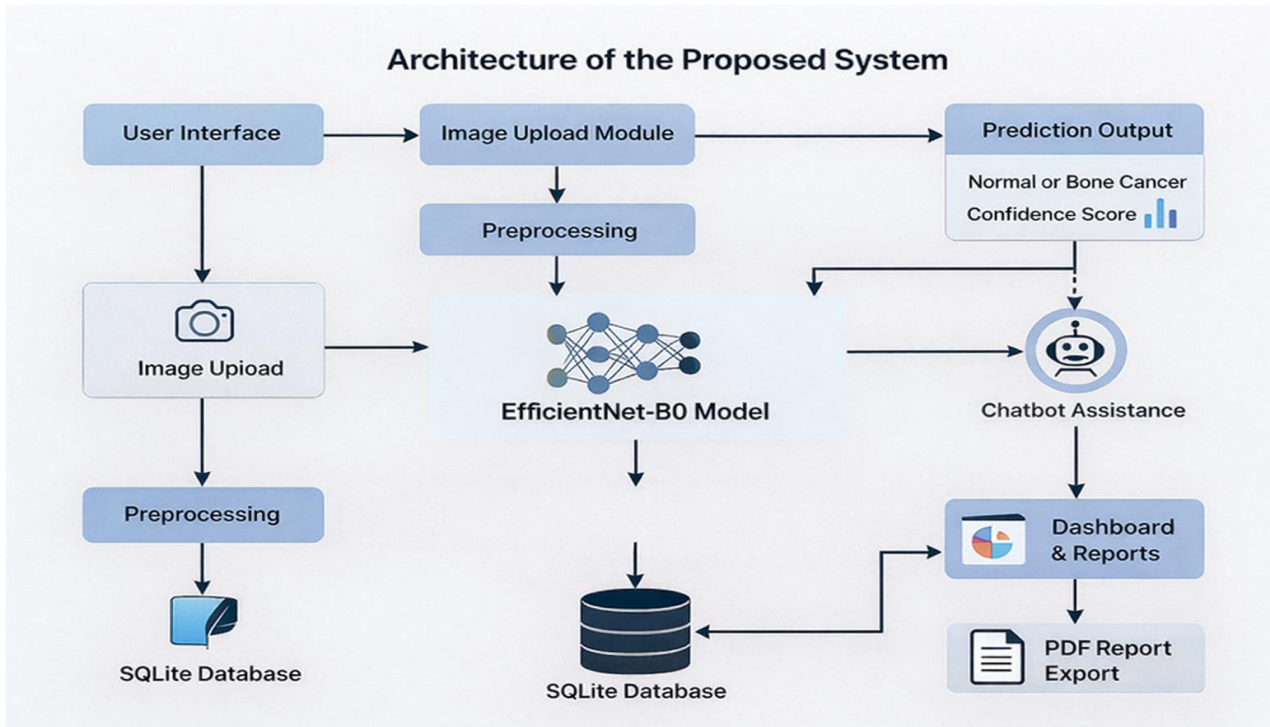


Fig 1\_Architecture of Bone Cancer Prediction System

**V. Results and Discussions:**

The user interface of the bone cancer prediction system is crafted to be straightforward, intuitive, and accessible to both medical professionals and non-technical users. The login page incorporates streamlined input fields and robust authentication to guarantee access exclusively for authorized users. Upon logging in, the dashboard presents a comprehensive overview of total scans, standard cases, cancer cases, and trend analytics, all illustrated through visually engaging charts. The X-ray upload page features a distinct drag-and-drop interface, accompanied by instructions and buttons for

image submission for prediction. The results page prominently features the predicted label, confidence percentage, and uploaded image, in a side-by-side arrangement for facile comparison. Distinct buttons enable users to download the PDF report or access other modules. A dedicated history page enumerates all prior scans extracted from the SQLite database, enabling users to examine or revisit earlier predictions. The chatbot interface employs a chat-style layout, enabling users to inquire about their results and obtain explanations in natural language.

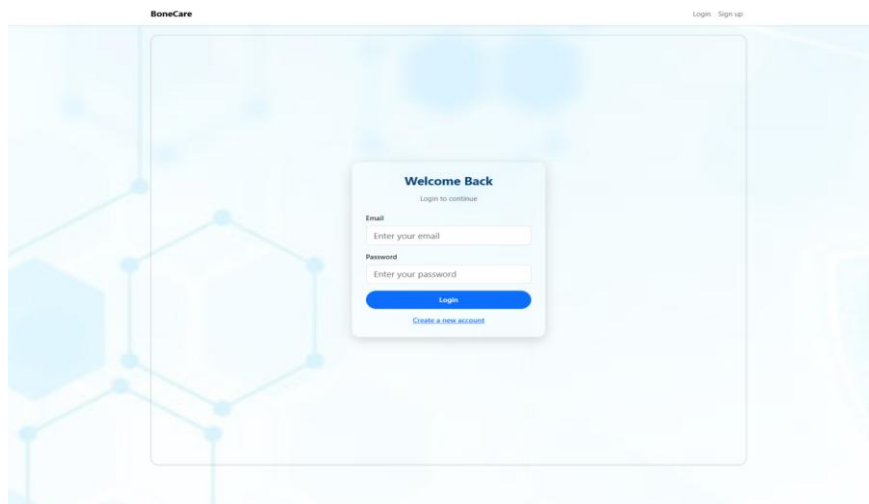


Fig 2\_Login Page

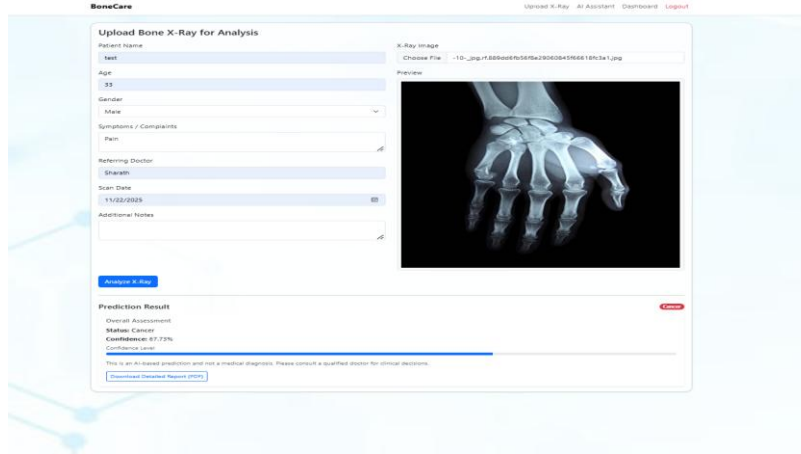


Fig 3\_Bone X-ray Result Analysis Page

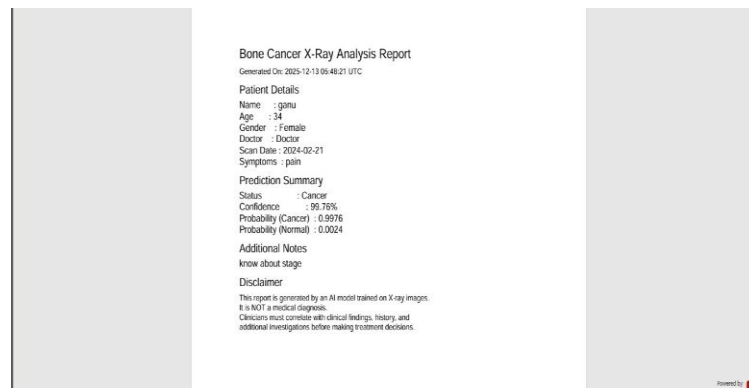


Fig 4\_Downloaded PDF

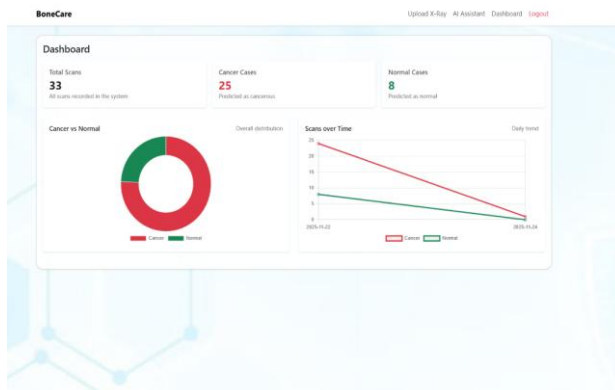


Fig 5\_Dashboard Page

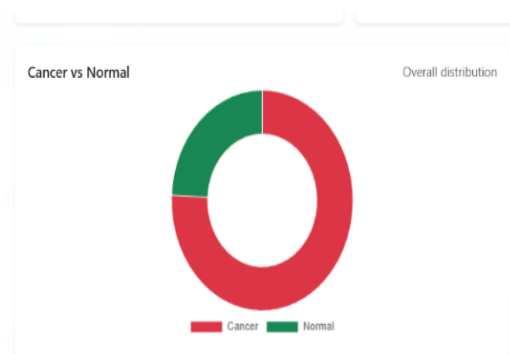


Fig 6\_Cancer vs Normal (Donut Chart)



Fig 7\_Scans over Time (Line Chart)

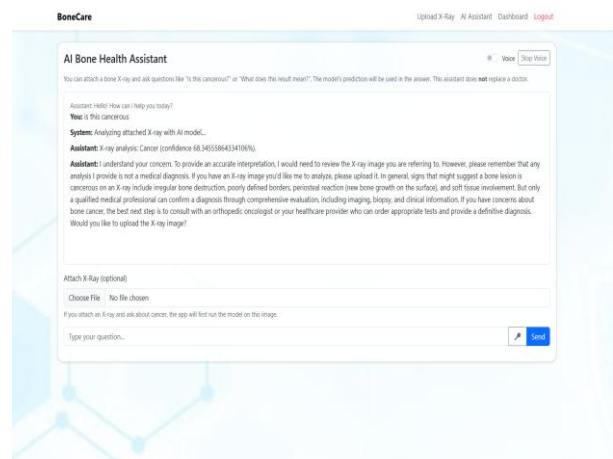


Fig 8\_Chatbot AI assistant Page

The performance of the EfficientNet-B0-based classification system is evaluated by calculating accuracy, precision, and recall. When an image belonging to the cancer class is correctly classified as cancerous, it is called true positive (TP). When an image belonging to the normal class is correctly classified as normal, it is called true negative (TN). If a normal image is incorrectly classified as cancerous, it is called false positive (FP). When a cancerous image is incorrectly classified as normal, it is called false negative (FN). Precision is defined as the ratio of true positives to the total predicted positive observations, while recall is defined as the ratio of true positives to the total actual positive observations.

**Table 1. Result Analysis**

Algorithm	Test Accuracy (%)	Precision (%)	Recall (%)
Baseline Convolutional Neural Networks (CNN)	89.60	86.40	88.10
EfficientNet-B0	96	92.3	94.1

**VI. Conclusion and Future Scope:**

The proposed Web-Integrated AI System for Bone Cancer Prediction effectively combines deep learning, explainable AI, and web technologies to deliver a practical diagnostic support tool. Leveraging the EfficientNet-B0 architecture, the system achieves high accuracy with low computational overhead, making it suitable for real-time deployment. A structured preprocessing pipeline ensures consistent image quality. The web interface allows users to upload X-rays, view predictions, access heatmaps, and download comprehensive reports, while the SQLite-based storage and analytics dashboard provide historical tracking and actionable insights. The integrated chatbot further improves accessibility by simplifying technical predictions, demonstrating how AI-driven systems can enhance early detection and support clinical decision-making in a reliable, user-friendly manner.

Future enhancements of the system could include expanding the dataset to incorporate diverse X-rays from multiple institutions, integrating multimodal imaging data such as CT and MRI, and enabling multi-class classification to distinguish tumor types or severity levels. Advanced segmentation models like U-Net++ or Mask R-CNN could improve tumor localization, while transformer-based architectures may further enhance predictive performance. Integration with hospital systems (PACS/EHR), mobile deployment, privacy-preserving methods such as federated learning, and more sophisticated explainability tools like GRAD-CAM, SHAP or LIME could improve clinical applicability, security, and interpretability. Enhancing the chatbot with multilingual support and role-based access, along with real-time alerting and continuous model monitoring,

would further ensure robust, scalable, and clinically deployable AI-driven bone cancer diagnostics.

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