

# Optimized Deep Learning Framework Based On EfficientNetB0- for Bone Cancer Detection

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## ABSTRACT

Bone cancer detection from X-ray images is a challenging task due to the subtle differences between normal and cancerous tissues and the variability in image quality. In this study, an efficient deep learning framework is proposed for the automatic classification of bone cancer using radiographic images. The proposed model is based on the EfficientNetB0 architecture, which is employed as a feature extraction backbone. To improve the model performance, a modified Whale Optimization Algorithm (WAOA) is utilized to optimize key hyperparameters. The training process is conducted in two stages: Stage A focuses on feature extraction with frozen backbone layers, while Stage B performs fine-tuning by unfreezing a subset of layers to enhance model generalization. The proposed approach is evaluated using standard performance metrics such as accuracy and area under the ROC curve (AUC). Experimental results demonstrate that the optimized EfficientNetB0 model achieves strong classification performance and provides a reliable solution for early bone cancer detection with high accuracy reached to 95.5%. The integration of metaheuristic optimization with deep learning significantly enhances model stability and predictive capability.

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## Introduction

Bone cancer is considered one of the most serious diseases affecting the skeletal system due to its aggressive behavior and relatively low survival rates. Although malignant bone tumors are rare compared to other cancers, they pose a significant clinical challenge, particularly when diagnosis is delayed. [1] Osteosarcoma is the most common primary malignant bone tumor, especially among children and adolescents, and is associated with rapid progression and a high risk of metastasis. [2]

The diagnosis of bone tumors typically involves a combination of clinical evaluation, medical imaging, and histopathological analysis. However, early symptoms are often non-specific, making accurate diagnosis difficult in

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the initial stages of the disease. Imaging techniques such as X-ray and MRI play a crucial role in tumor detection, yet manual interpretation is time-consuming and depends heavily on the expertise of clinicians .[3][4]

With the rapid advancement of artificial intelligence, deep learning techniques have become widely adopted in medical image analysis. Convolutional neural networks (CNNs) have demonstrated strong performance in tasks such as tumor detection, classification, and segmentation, contributing to improved diagnostic accuracy and efficiency [5][6]. In particular, deep learning-based computer-aided diagnosis systems have shown promising results in detecting osteosarcoma and reducing the workload of medical professionals .[7][8]

Despite these advancements, several challenges remain, including the complexity of medical images, variability in tumor appearance, and the need for effective feature extraction and model optimization techniques. Recent studies have explored advanced deep learning models and ensemble approaches to improve classification performance and reliability in osteosarcoma detection .[9]

In this study, an EfficientNetB0-based deep learning model is proposed for bone cancer classification from X-ray images. The proposed framework incorporates a hybrid pooling strategy and a customized classification head to enhance feature representation. Furthermore, a Whale Optimization Algorithm (WOA) is employed to optimize key hyperparameters, aiming to improve the overall performance and robustness of the model .

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## 1. Related Works

In this section present an a review and analysis of related work of researcher for method as shown in table 1 :

von Schacky et al. [10] suggest Deep learning based CNN model to bone cancer detection they used multitask deep learning capable of simultaneous bounding box placement, segmentation, and classification of primary bone tumors on radiographs. This approach aimed to enhance diagnostic efficiency and accuracy compared with radiologists, the study limited because only histologically proven bone tumors were included, thus inferring selection bias. no patients with normal Their model achieved 80.2%accuracy .

Chen et al. [11] ] have proposed A machine-learning model to predict patient prognosis with Ewing's Sarcoma .They performed a System/Method Retrospective Review using SEER database., four machine learning models were compared Random Forest, Boosted Decision Tree, Support Vector Machine and Neural Network. The model lack of external validation, missing variables in SEER (e.g., surgical margin), data imputation required , Their model archive 86% accuracy.

Yan et al. [12] suggest Machine learning combined with deep learning model to bone cancer detection they used compared multiple survival prediction models, including DeepSurv, Neural Multi-Task Logistic Regression (N-MTLR), and Random Survival Forest (RSF), against the traditional CoxPH model , Their used SEER data set model achieved 90.7 % accuracy , the paper is limited by the retrospective design, reliance on SEER data without external validation, and lack of treatment-specific and molecular/genomic variables .

Gitto et al. [13] present an MRI radiomics-based machine learning method to differentiate atypical cartilaginous tumours from grade II chondrosarcomas of long bones , After feature-selection (LASSO + RFE) and class balancing (SMOTE on the training set) they trained an Extra Trees Classifier (an ensemble tree-based method similar to a random forest but with extra randomization) as the final machine learning model in this study specifically using an Extra Trees classifier technique their used Extra Trees Classifier ,Radiomic feature extraction To ensure the model's robustness, features were selected using stability testing, variance and correlation analysis, and iterative deletion to retain the most informative predictions. The selected features were then used to train and validate a machine learning classifier (e.g., a random forest method or a cluster method , The study was retrospective and used data from two centers and the dataset was imbalanced it achieved 92% accuracy .

von Schacky et al. [14] applied Machine learning model based on Artificial neural network (ANN) to distinguish between benign and malignant bone . they used ANN combining radiomic and demographic features (age, sex,

tumor location) Their model achieved Phase1 acc 94.4%, Phase2 acc 90.3%. dataset was small , imbalanced and limiting generalizability .

Meem & Hasan,[15]proposed Deep learning based CNN model to bone cancer detection they The authors propose using four different pre-trained transfer learning (TL) models EfficientNetB7, InceptionResNetV2 , NasNetLarge, and ResNet50 Transfer learning is a suitable approach because it doesn't require training models from scratch and can work effectively with small datasets. These models were pre-trained on the ImageNet database and fine-tuned for the specific task of osteosarcoma detection using a dataset of H&E-stained histopathology images , the study limited availability of large datasets Their model achieved 93.29% accuracy .

Ho et al.[16]have proposed a Deep learning (DL) to Necrosis ratio assessment in osteosarcoma. They have used A deep learning pipeline using Deep Multi-Magnification Network (DMMN) for pixel-wise segmentation of Hematoxylin & Eosin (H&E) whole-slide images (WSIs) H&E WSIs, to objectively calculate necrosis ratio and predict patient outcomes. Multi-institutional datasets and cell-level annotations are needed for further ,They have found the model achieved 90% accuracy.

Vezakis et al.[17] suggest Deep learning model hybrid with vision transform to Medical Image Analysis and Histopathology Classification to Bone cancer diagnosis The authors conducted a comparative study of multiple deep learning architectures (MobileNetV2, EfficientNet, Residual Networks (ResNet) , Visual Geometry Group Network (VGG) , Vision Transformer, etc.) for classifying histopathological images of osteosarcoma into three categories : Non-Tumor (NT) , Viable Tumor (VT) And Necrosis (NC) the model was limited by They authors recommend further work using regularization, dropout, dimensionality reduction, and pretraining on related datasets to improve generalization They authors recommend further work using regularization, dropout, dimensionality reduction, and pretraining on related datasets to improve generalization , There model achieved 91% accuracy .

Song et al. [18] have proposed a Primary Bone Tumor Classification Transformer Network (PBTC-TransNet) To Accurately classifying primary bone tumors.They have used a PBTC-TransNet, designed to integrate incomplete multimodal images (X-ray, CT, MRI) with patients' clinical characteristics. The model leverages a flexible fusion strategy that allows robust classification even when some imaging modalities are missing , the model need for further optimization and larger, multi-center validation to enhance its generalizability They have found that PBTC-TransNet achieved 84.3% accuracy .

Yamana et al.[19] have proposed Convolution neural networks (CNN)-based Object Detection and Vision Transform to Detecting and classifying bone tumours in full-field limb radiographs. The study proposed a transformer-based object detection model (DINO ) Detection with transformers with Improved deNoising anchOr boxes) to automatically detect and classify benign versus malignant bone tumours, and compared it with YOLO(You Only Look Once) and human expertsThey, the study was limited by small sample size, focus on limb radiographs only, and exclusion of non-tumour conditions, which restricts generalizability and necessitates further validation before routine clinical adoption. Their model achieved 77% accuracy

Zhao et al. [20] have proposed Machine Learning model to prediction to assess osteosarcoma outcomes They have used The researchers developed a Machine Learning Derived Prognostic Signature (MLDPS) by integrating 66 combinations of 10 ML algorithms. The optimal model was constructed using combinations, LASSO (Least Absolute Shrinkage and Selection Operator) Random Survival Forest (RSF), Its clinical application is limited by reliance on retrospective datasets, small cohort sizes, and lack of real-world clinical validation. The model achieved 86.6% .

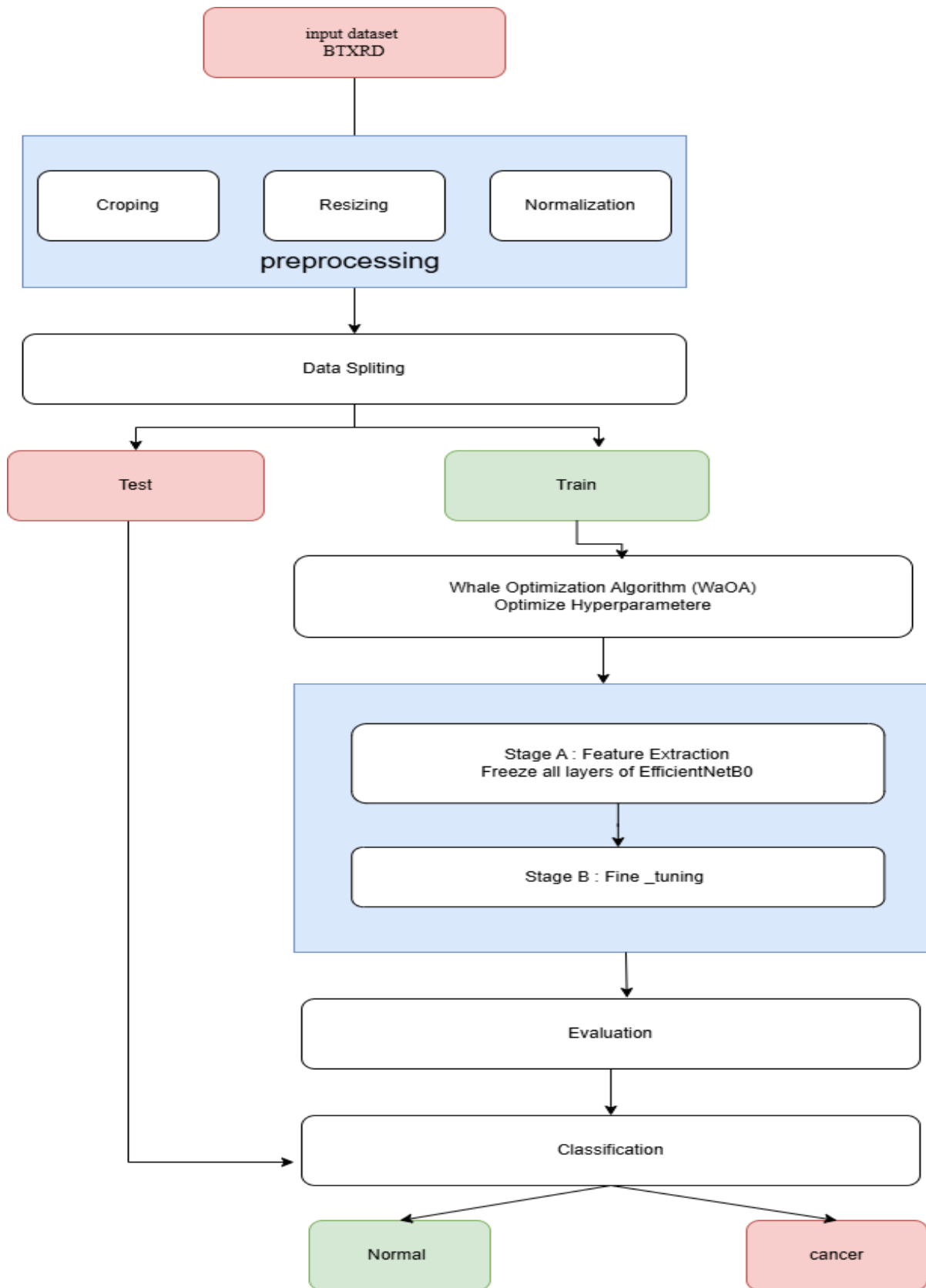
Wang et al. in [21] have proposed deep learning combined with vision transform to bone cancer detection they are used ensemble deep learning framework that integrates multicenter radiographs with extensive clinical features, comparing its performance against imaging-only models based on EfficientNet-B3, EfficientNet-B4, Vision Transformer, and Swin Transformer. The study was limited by reliance on multicenter retrospective data, challenges in model interpretability, and the need for further validation in broader clinical settings to ensure generalizability, There model achieved 94.8% accuracy.

### 3. Methodology

In this paper, we present a deep learning-based approach for bone cancer classification using X-ray images. There are four stages in the workflow: image preprocessing, dataset preparation, model development and performance tuning. Firstly, the input X-ray images are preprocessed using a specifically designed pipeline, which involves image cropping, resizing, and normalization to maximise image quality and feature extraction. The preprocessed images are then input to a convolutional neural network with the EfficientNetB0 backbone for feature extraction.

To enhance feature discrimination and classification performance, a modified classification head is used with a hybrid pooling approach that includes both global average pooling and global max pooling. The features are then fine-tuned by fully connected layers with batch normalization, Swish activation, and dropout regularization to avoid overfitting. Additionally, a Whale Optimization Algorithm (WaOA) is introduced to automatically fine-tune crucial hyperparameters such as learning rate, neuron counts, and dropout rate during training as shown in figure 1 .

The training stage is divided into two stages. In Stage A, the backbone network is frozen, and only the classification layers are trained to learn high-level features. In Stage B, the network is partially fine-tuned by unfreezing the last few layers of the network and keeping batch normalization layers frozen for training stability. The model's classification performance is then evaluated using commonly used metrics.



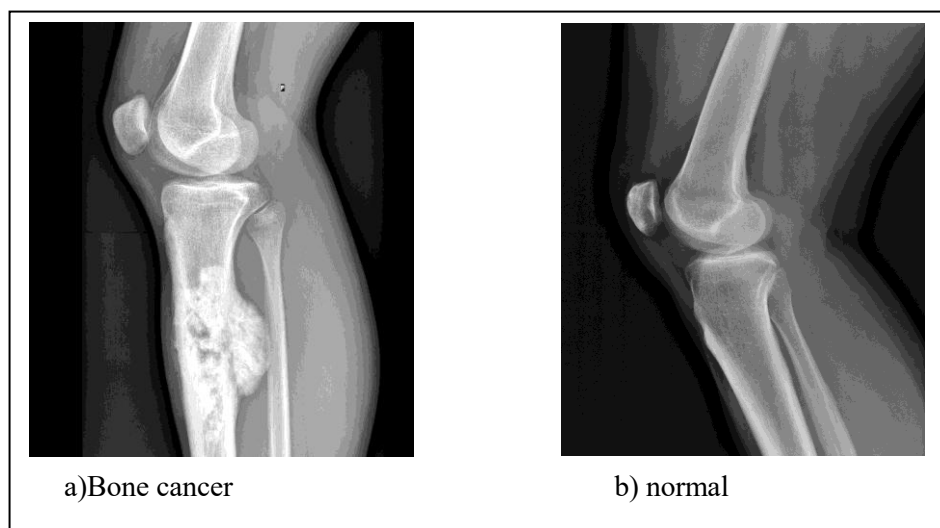
**Fig .1- Block diagram of the proposed model .**

### 3.1 Dataset Description

The Bone Tumor X-ray Radiograph Dataset (BTXRD) was used in this study to classify bone cancer. The dataset includes 3,746 X-ray images, 1,879 of which are normal bone images, 1,525 are benign tumor images, and 342 are malignant tumor images. The images were sourced from a variety of sources, including Chinese medical institutions, Radiopaedia.org and the open-access database of medical images MedPix.[23]

The dataset has X-ray images of different anatomical locations, including upper limbs, lower limbs and the pelvis, and from different projection views, including anterior-posterior, lateral and oblique. The dataset also includes labels of anatomical site, tumor type and imaging view. The images were all checked by medical experts to guarantee the quality of the dataset.

In this study, the dataset was transformed into a binary classification task, with both benign and malignant tumor images belonging to the "cancer" class, and normal bone images belonging to the "normal" class. The dataset was then split into training, validation and testing sets. The training subset was used to train the model, the validation subset was used to select the model and tuning the hyperparameters, and the testing subset was used to test the performance of the model as shown in figure 2. Prior to training, the images were cropped to a uniform size of  $768 \times 768$  pixels to fit the EfficientNetB0 model.



**Fig.2 - BTXRD sample**

### 3.2 Image Preprocessing

In order to maintain high-quality input data and increase the model performance, all X-ray images were preprocessed using a preprocessing pipeline before training.

#### 1- Cropping Stage:

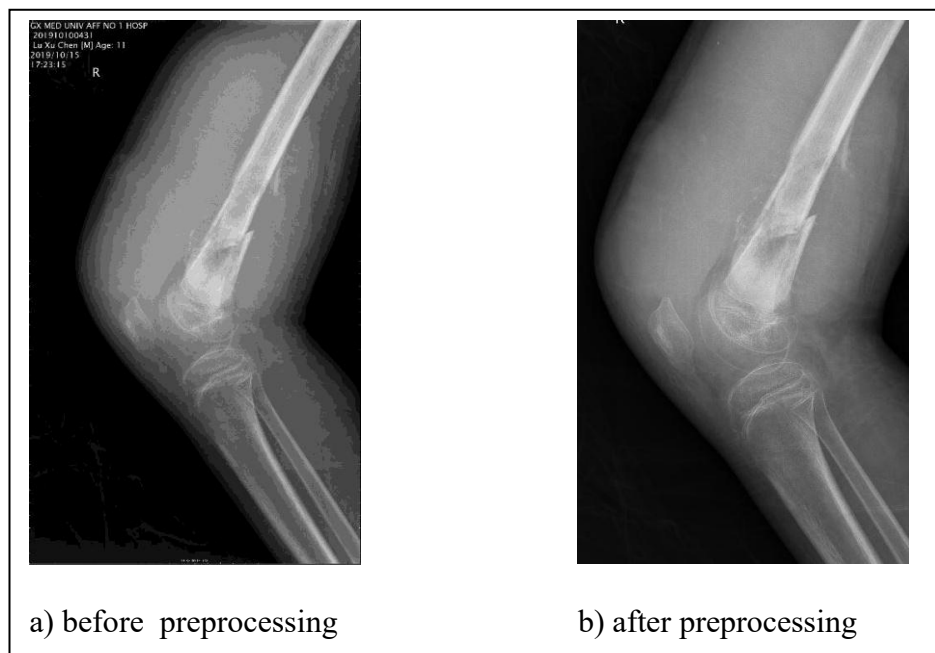
The first step involved a cropping operation to remove non-relevant areas that were at the edges of the images. Around 10 percent of the picture was cut off on each side (top, bottom, left and right). This process aids in the elimination of undesired contents like dark borders, picture frames, and textual notes which can adversely affect the learning process as shown in figure 3 .

#### 2- Image Resizing:

Following the cropping stage, each image was resized to a constant size of 768 x 768 pixels. This will provide consistency throughout the dataset and enable the images to fit the input needs of the EfficientNetB0 model. Image size standardization also helps to stabilize and improve consistency in training.

#### 3- Conversion and Normalization of Data Type:

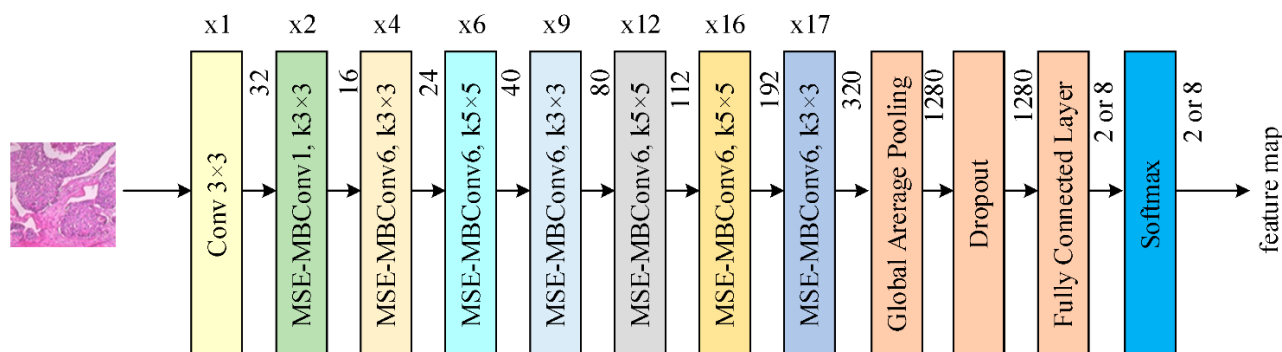
Lastly, all images were turned into floating-point format and normalized with the EfficientNet preprocess\_input function. This normalization step brings the pixel values within a range that is compatible to the pretrained model, and thus it can contribute to better convergence rate and overall training stability.



**Fig.3- show the data set before and after preprocessing**

### 3.3.1 EfficientNetB0

EfficientNetB0 architecture was used as the basic network in this study to perform feature extraction because it is implemented on an efficient scaling strategy and good representation.[22] EfficientNet leverages a compound scaling strategy to balance network depth, width, and resolution, allowing it to scale to high performance at relatively low computational cost. This allows it to be suitable in medical image analysis tasks, particularly in cases of small datasets. The model was started without the top classification layer, which enabled the model to be a feature extractor. A bespoke classification head was subsequently developed to change the network to the binary classification of bone cancer. In order to boost the feature representation a hybrid pooling approach was embraced by using a combination of Global Max Pooling (GMP) and Global Average Pooling (GAP) so that the model could obtain complementary spatial data on the feature maps. The concatenated features were run through fully connected layers and the learning was stabilized by batch normalization and non-linearity was added by Swish activation function. As shown in figure 4 . The dropout regularization was used as well to decrease overfitting and enhance generalization. The last step involved application of a sigmoid activation in the output layer to effect binary classification of cancer and normal.



**Figure 4: Architecture of a EfficientNetB0 [22]**

### 3. 3. 2 Whale Optimization Algorithm (WaOA) :

To improve the functionality of the proposed model, a Whale Optimization Algorithm (WaOA) was used to optimize the important hyperparameters automatically. WaOA is a metaheuristic algorithm that uses social hunting behavior of humpback whales, especially bubble-net feeding strategy, as a population-based algorithm. It is popular because it is easy to use and converges rapidly, and is able to solve complex optimization problems.

WaOA was implemented in this study to find the best set of hyperparameters, such as the learning rate, the number of neurons in the fully connected layers, as well as the dropout rate. The algorithm starts with initializing a pool of candidate solutions (search agents) within prescribed limits and successively changes the locations of the search agents under exploration and exploitation models. During optimization, a fitness function based on performance of the model on the validation set is used to evaluate every candidate solution. In particular, the Area Under the ROC Curve (AUC) was adopted as the main measure of fitness because it is strong in the binary classification problems. The algorithm considers exploration, migration, and local refinement as three important behaviors which are simulated to refine the candidate solutions by balancing between global search and local refinement.

Optimization process is repeated until convergence or a specified number of iterations. The most optimal hyperparameters through WaOA are then employed in training the final model. It can be used to enhance stability of the model, minimize the tuning efforts, and generalization results.

### 3.4 Training Configuration

The training parameters were selected based on preliminary experiments and evaluation of the model's performance on the validation set. The batch size was fixed at 8 due to the high image resolution ( $768 \times 768$ ) and limited memory during training. The number of training cycles was set to 35 for Phase A and 25 for Phase B to ensure sufficient learning while minimizing overshoot. The Swish activation function was adopted for its effectiveness in deep learning models, while the Adam optimizer was used for its ability to converge quickly. Additionally, different learning rates, neuronal counts, and dropout values were investigated during the WaOA optimization process, and the optimal combination was selected based on the validation AUC performance.

### 3.5 Dataset Availability

(BTXRD), which is publicly available for research purposes. The dataset can be accessed via the Figshare repository via the following DOI: <https://doi.org/10.6084/m9.figshare.27865398>. Detailed information regarding the dataset is also available in the corresponding publication by Yao et al. [23].

## 4 Experimental Results

The proposed EfficientNetB0-based model was tested with the help of the test dataset at the end of the two training sessions. The performance of the classification between normal and cancer classes was evaluated with the help of standard measures, such as accuracy and confusion matrix, to evaluate the classification performance.

In Stage A (feature extraction), both the training and validation accuracy curve improved steadily across the epochs, which is indicative of the learning behavior being steady. Both curves as shown in Figure 4 were learning the features successfully as they rose steadily without any drastic changes. Likewise, the loss curves (which are not presented) exhibited a downward trend in both training and validation sets indicating that the model converges appropriately.

Figure 5 shows the results of the confusion matrix of Stage A. The model was able to classify 458 cancer cases and 494 normal cases correctly and misclassify 70 cancer cases and 41 normal cases that it classified as such. These findings suggest a sensible classification performance during the first stage of training.

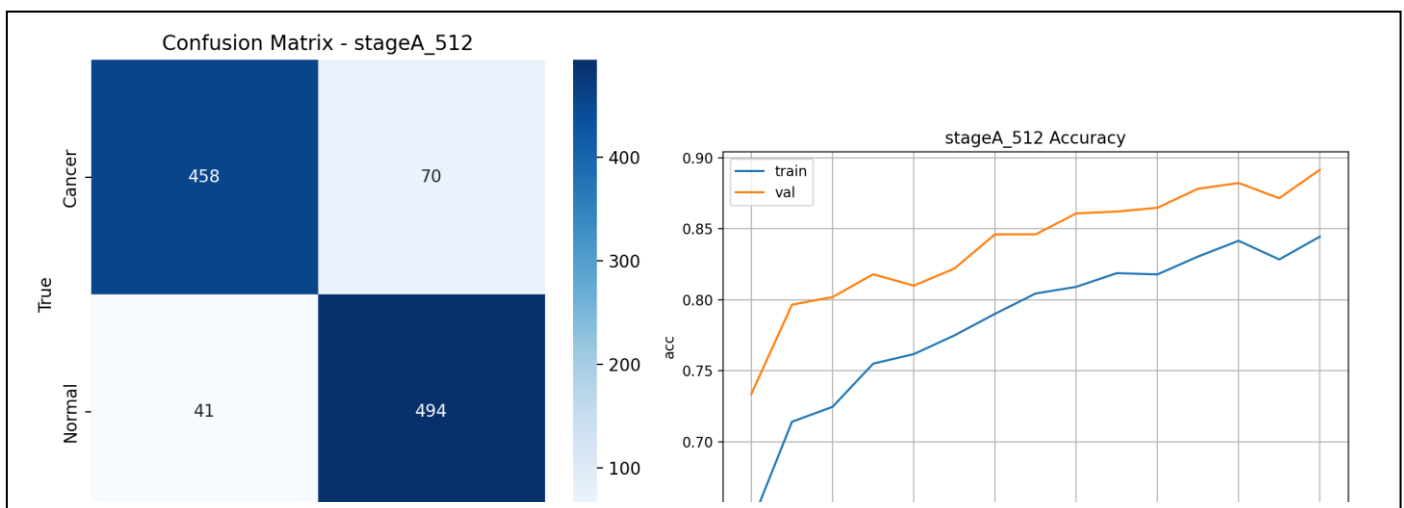
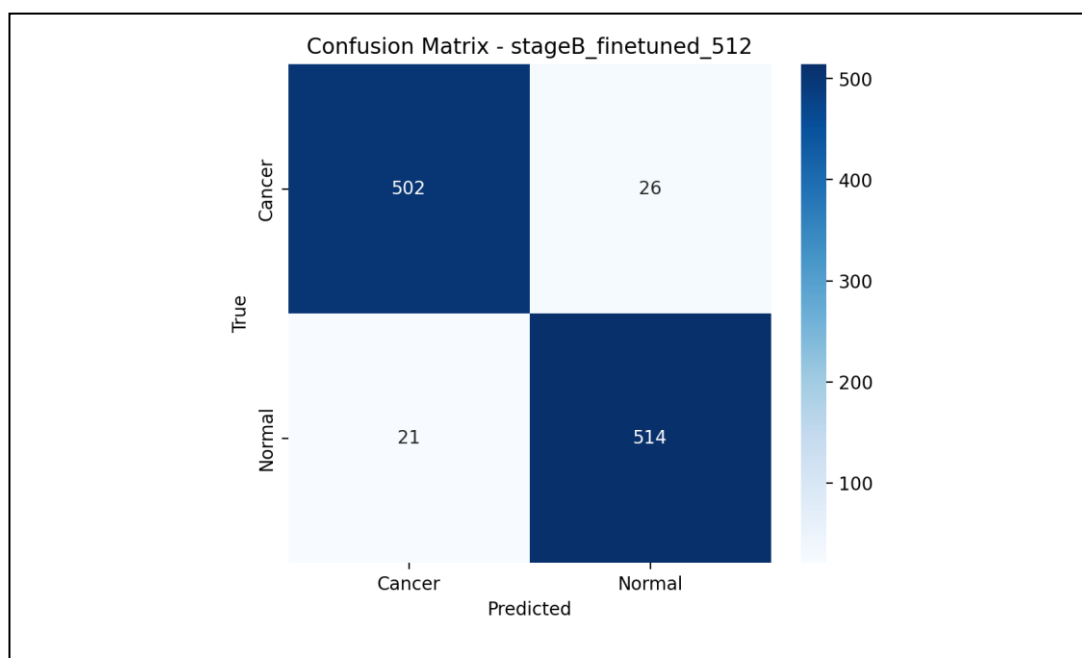


Fig.5- confusion matrix for stage A and accuracy curve

The model performance in Stage B (fine-tuning) became very good with the last layers of the network unfreezing. The accuracy curves were further improved with an increase in the validation accuracy as compared to Stage A, which is an indicator of improved generalization. The loss curves kept on decreasing, which validated the claim that fine-tuning helped to produce more refined feature representations.

The stage B confusion matrix is presented in Figure 6. The model accurately referred to 502 cancer cases and 514 normal cases and misclassifications were minimized to 26 cancer cases and 21 normal cases. This shows an evident increase in the accuracy of classification over Stage A.



**Fig.6 confusion matrix for stage B**

In general, the experimental findings indicate that the two-phase training plan, with the assistance of hyperparameter optimization using WaOA, is effective in improving the model performance. The fact that both accuracy trends and the results of the confusion matrices have improved illustrates the strength of the proposed method when it comes to detecting bone cancer.

Initial experiments were conducted using the AdamW optimizer to evaluate the model's performance during the initial training phase. Subsequently, the WaOA algorithm was introduced to optimize hyperparameters, resulting in improved classification performance, and was therefore adopted in the final proposed framework. As shown in Table 2 :

**Table X. Comparison of optimization strategies used during preliminary experiments**

| Experiment | Optimizer / Strategy  | Description                                                                  | Accuracy |
|------------|-----------------------|------------------------------------------------------------------------------|----------|
| Exp-1      | AdamW+ EfficientNetB0 | Initial training experiment using AdamW optimizer                            | 93.2 %   |
| Exp-2      | WaOA + EfficientNetB0 | Hyperparameter optimization using learning rate, neurons, and dropout tuning | 95.6 %   |

The proposed method has the highest accuracy of 95.6% compared to all the studies in Table 3. Existing approaches using transfer learning model (InceptionResNetV2) and traditional CNN model achieved accuracy between 89% and 93%.

**Table 2: Comparison of the proposed method with existing studies in bone cancer detection:**

| Study                        | Dataset                                        | Model                               | Accuracy |
|------------------------------|------------------------------------------------|-------------------------------------|----------|
| Meem et al. (2024)           | Histopathology images (4 classes, 80/20 split) | InceptionResNetV2                   | 93.29%   |
| Vandana et al. (2021)        | 1000 histopathology images                     | CNN                                 | 92%      |
| Wang et al. (2025)           | Radiographs + clinical data (1992 patients)    | Ensemble DL model                   | 89.5%    |
| Proposed Method (This Study) | BTXRD X-ray dataset                            | EfficientNetB0 + WaOA + Fine-tuning | 95.6%    |

## 5. Conclusion

The paper depicted an EfficientNetB0-based deep learning model together with a Whale Optimization Algorithm (WaOA) to classify bone cancer using X-ray-based images. The suggested method involved a two-phase training plan, feature extraction and fine-tuning to improve the capacity of the model to learn discriminative features. The experimental findings proved that the model gained a good performance, and its final classification accuracy was 95.6% following the fine-tuning process. The enhanced performance demonstrates the effectiveness of the combination of hyperparameter optimization and staged training in enhancing model generalization and stability. In general, the results prove that EfficientNetB0, WaOA optimization, and fine-tuning are reliable and efficient to detect bone cancer. Further research can be done in the future to use bigger and more diverse datasets and to investigate the possibilities of better and more robust deep learning architectures.

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