CLASSIFICATION OF BONE TUMOR USING EFFICIENT-NET B0

Sri P. Anil Kumar[1], Thanuri Bhanu Harshitha[2], Yarlagadda Rajeswari[3], Sanaka Venkata Karthikeya[4], Ramireddy Usha Kumari[5]

[1] *Assistant professor, Department of Electronics and Communication Engineering, Seshadri Rao Gudlavalleru Engineering college, Andhra Pradesh, India*

[2,3,4,5] *U.G Student, Department of Electronics and Communication Engineering, Seshadri Rao Gudlavalleru Engineering college, Andhra Pradesh, India*

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Abstract - *Accurately diagnosing bone tumors is crucial for patient management and creating effective treatment plans. In this study, we propose a unique approach that uses deep learning algorithms to diagnose bone tumors using medical imaging data. Our method combines picture segmentation and the EfficientNetB0 architecture to enable high-performance tumor classification. First, pre-processing and segmentation of the input medical images are done to identify regions of interest that might be malignancies. The convolutional neural network EfficientNetB0 is then fed the segmented areas to carry out feature extraction and classification. EfficientNetB0 is known for its exceptional performance and computational efficiency, which enables strong learning from the separated tumor zones. We train and validate our model on a large dataset of annotated bone tumor images to guarantee generalizability and reliability. Our method's exceptional levels of sensitivity, specificity, and accuracy in diagnosing bone tumors are demonstrated by the results of our experiments. This method offers a scalable and efficient way to automatically identify tumors from medical images, which presents a potential way to improve clinical judgment in the diagnosis and treatment of bone malignancies.*

***Key Words*: Deep Learning, Bone Tumors, Image Segmentation, EfficientNetB0, Classification, Radiology.**

1.INTRODUCTION

Bone tumors are common growths or masses of tissue that develop inside the bones. These tumors can be benign or malignant; malignant tumors pose a major risk to health, including the possibility of spread and death, if treatment is not received. For patients with bone malignancies, timely planning of their treatment and an accurate diagnosis are crucial. Bone malignancies are usually diagnosed by a clinical examination, imaging techniques such as CT, MRI, and X-rays, and histological analysis of tissue samples obtained through biopsy.

In recent years, deep learning methods have become more and more popular for use in medical image analysis, particularly when dealing with issues like tumor segmentation and classification. The artificial intelligence field of deep learning has demonstrated remarkable outcomes in computer vision, natural language processing, and healthcare, among other domains. Deep learning models, and in particular convolutional neural networks (CNNs), have shown promising results in automated medical image interpretation applications. Compared to traditional methods, these models may offer benefits including improved accuracy, consistency, and efficiency.[2]

Image segmentation is crucial for medical image analysis because it makes it easier to identify and separate areas of interest—like cancers—from the surrounding anatomical structures. By accurately segmenting bone tumor locations, clinicians can obtain valuable information on tumor features, such as size, shape, and texture, which are useful for diagnosis and therapeutic planning. Moreover, segmentation facilitates the extraction of quantitative elements from image data that serve as algorithmic input for classification, enabling automatic tumor categorization.[3]

2. LITERATURE SURVEY

[1] Several scientists have seen trends in the information and data that they have obtained from large databases and pertinent websites. Learning vector quantization, fuzzy theory, probabilistic neural networks, association rule mining, and supporting vector machines are the most widely used methods for diagnosing and classifying bone cancer. In order to segment bone pictures, the k means clustering algorithm was used in this work. To process the segmented image further for the aim of identifying bone cancer, the mean intensity of the detected area is evaluated. It is recommended to classify medical images based on the presence or absence of bone cancer using threshold values.

[2] The basis of this work is the fusion of computer science with the biomedical field. Numerous image segmentation methods, including Sobel, Prewitt, Canny, K-means, and Region Growing, are described in this paper. These methods can be helpful in understanding MRI and X-ray images as well as in predicting the type of bone cancer. In order to use MATLAB to detect osteosarcoma cancer present on bone, the study also displays the outcomes of edge-based and region-based image segmentation techniques applied to X-ray pictures.

[3Traditional methods that used very small images were time-consuming and noisy. The research offers automated image processing techniques like Wavelet denoising, which improve image quality and remove noise while preserving diagnostic information, as a solution to this problem. By utilizing pre-processing methods and algorithms like K-means and edge segmentation, the study successfully detects bone cancer and establishes its stage. Furthermore, genetic algorithms are used to distinguish benign from malignant tumors.

[4] A novel approach for determining the grade and stage of cancer in long bones is presented in this paper, which is based on X-ray image processing. According to the recommended approach, support vector machines (SVM) are trained to identify healthy and cancerous bones based on certain features extracted from X-ray images of the bones. The sites where cancer is present are identified using a digital geometry-based technique. The present stage and grade of the disease, as well as the underlying pattern of bone degeneration, are all described by means of a decision tree classifier. More importantly, the method produces a computer-aided diagnostic tool that doctors and paramedics can use with ease.

[5] This study uses the adaptive neuro-fuzzy inference system (ANFIS) in conjunction with feature selection to provide a unique method of early breast cancer diagnosis. This method employs ANFIS as an intelligent classifier and the association rules (AR) technique as a feature selection algorithm. The value of radius has a big influence on how accurate the ANFIS system is. As a result, in order to obtain the optimal radius value, the cuckoo optimization algorithm (COA) was utilized in the recommended technique. The results show that the suggested technique has great detection accuracy when applied to the Wisconsin Breast Cancer Database (WBCD).

[6] The bone is a vital component of the human body. Bones provide the body its ability to move. Bone fractures are common in the human anatomy. The doctors diagnose the fractured bone based on the X-ray image. The manual fracture diagnosis approach is laborious and prone to large errors. Therefore, it is necessary to develop an automated method for recognizing fractured bones. Deep Neural Networks (DNNs) are a popular model for power electrical systems. This study has developed a deep neural network model to discriminate between bone that is fractured and healthy. The small dataset causes the deep learning model to overfit. As such, strategies for data augmentation have been used to increase the amount of the data collection. Three tests with the softmax and Adam optimizers were conducted to evaluate the model's performance.

3. PROPOSED WORK

Picture segmentation and the EfficientNetB0 architecture are proposed to be used in a deep learning-based bone cancer classification system. We preprocess the bone tumor images first in order to enhance their quality and remove noise. Next, we apply a state-of-the-art image segmentation technique such as U-Net to accurately distinguish the tumor regions. Afterwards, we utilize the segmented tumor regions as input for our EfficientNetB0 architecture, which serves as our classification backbone. EfficientNetB0 is a suitable choice for this task since it achieves a balance between model size and accuracy. We refine the pre-trained EfficientNetB0 model to make it appropriate for bone tumor classification using our segmented tumor dataset. To improve our models' performance and generalization, we use techniques like data augmentation and transfer learning. We use industry-standard criteria including accuracy, precision, recall, and F1-score to assess our suggested approach. EfficientNetB0's remarkable accuracy in identifying patterns and characteristics makes it the perfect choice for seat belt detection and drowsiness detection. One of EfficientNetB0's features that is particularly useful for applications needing real-time detection is rapid data analysis. EfficiencyNetB0 produces state-of-the-art outcomes. In generalization, EfficientNetB0 performs admirably.

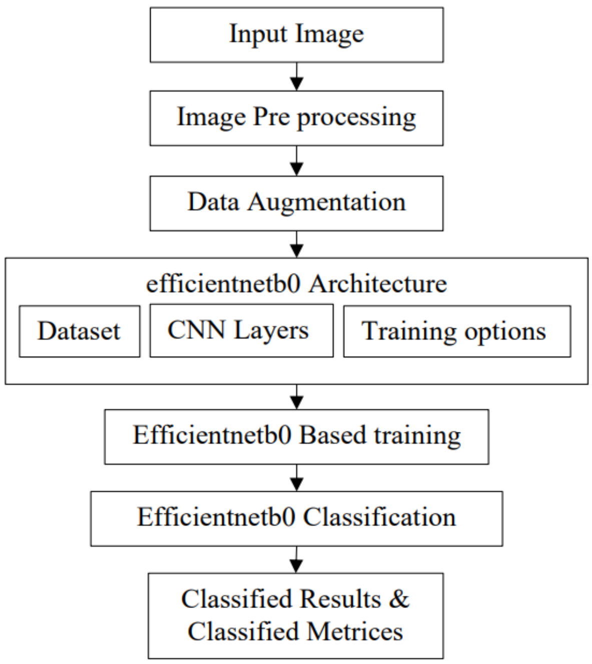

Fig -1: Block Diagram for Proposed method

3.1 Image Pre-processing

Images must be pre-processed in order to extract noise from the data and find pertinent properties. By leveling input scaling and enhancing generalization through dataset updates, it guarantees consistent model performance.

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Robustness to variations improves model reliability while continuous scaling maintains uniformity for effective model processing. In the end, preprocessing improves interpretability for people and models by assisting in the identification of certain regions of interest and adapting to hardware constraints.

3.2 Data Augmentation

The data augmentation technique is widely used for training convolutional neural network (CNN) models, particularly in computer vision applications. It involves artificially expanding the training dataset by applying various modifications to the preexisting pictures while preserving their semantic value. In order to improve the CNN model's resilience and generalization, data augmentation exposes it to a wider range of input data perturbations. Increasing the CNN model's resistance to modifications in the input data is the primary objective of data augmentation. Real-world images can vary due to a variety of elements such as illumination, scaling, translations, rotations, distortions, and more. The model is less prone to overfit to certain training examples and is better able to generalize to new data when these changes are added to the training set.

3.3 Dataset

A well-constructed dataset is necessary for training a model to recognize patterns and produce accurate predictions within preset categories. The dataset is typically divided into training and testing sets in order to assess the model's performance on untested data. It offers the structure for creating and refining classification models that may be applied to a range of tasks, such as image recognition and natural language processing.

4. MODULE DESCRIPTION

EfficientNet B0

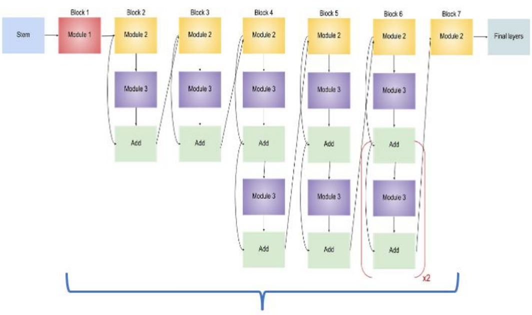

Fig-2: Architecture of EfficientNet B0

4.1 Stem Layer and Final Layer

The neural network starts at the stem layer, where it performs its first convolutions and gets the data ready for layers that come after. The stem layer of EfficientNet-B0 prepares the ground for feature extraction that follows. The retrieved features are refined in the last layer, readying them for precise predictions in tasks like picture categorization.

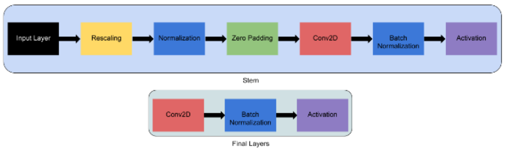

Fig-3: Overview of Stem Layer and Final Layer

4.1.1 Input Layer

The input layer of EfficientNet B0 accepts input images of size 299x299 pixels, typically in RGB format.

4.1.2 Rescalling

Changes to an image's proportions or size are referred to as image processing. It is a typical preprocessing method that is utilized for a number of reasons, including improved performance and consistency, uniformity for machine learning algorithms, and speedier processing.

4.1.3 Normalization

In order to modify the range of pixel intensity values within an image, normalization is an essential approach. Normalization assists with efficient categorization by bringing pixel values into a more known or standard range and enhancing the contrast and visibility of features in an image.

4.1.4 Zero Padding

In image processing, zero padding is the process of enlarging an image's edges with additional rows and columns of zeros. It stabilizes computations, avoids artifacts at image boundaries, and guarantees consistent dimensions during operations such as convolution.

4.1.5 Conv2D Layer

In Convolutional Neural Networks (CNNs), the Conv2D layer applies 2D convolution to pictures. It extracts features by swiping filters over the input. Kernel size, strides, padding, and activation function are important characteristics. Conv2D is essential for object detection and image categorization.

4.1.6 Batch Normalization

Batch Norm is not done on raw data, but rather in between layers of a neural network. During training, it uses mini-batches rather than standardizing the entire dataset.

4.1.7 Activation

In a neural network, activation functions are the decision-makers. Every neuron has an activation function that controls whether or not the neuron needs to be stimulated. Whether or not the input a neuron receives is pertinent to the network's prediction determines whether or not it gets activated.

4.2 Mobile Inverted Bottleneck (MBConv) Layers

EfficientNet's fundamental components. Mix residual blocks that are inverted and depth-wise separable convolutions. For feature recalibration, include squeeze-and-excitation (SE) optimization. A stack of different-depth and breadth MBConv layers is part of the design.

Each layer of MBConv is made up of:

4.2.1 Depth-wise separable convolution

Reduces computation.

4.2.2 Inverted residual block

Captures rich features.

4.2.3 Squeeze-and-excitation mechanism

Enhances feature importance.

5.RESULTS AND ANALYSIS

Based on the developed model, the bone tumors are classified. After testing a number of models, we selected the most practical one. These are the layer network algorithms for Resenet50, VGG16, EfficientNet B0, and 10*1. By comparing those to other algorithms, EfficientNet B0 was able to accurately identify the bone tumors. With 92.5% precision and 95.2% accuracy, the EfficientNet B0 method produces the best results out of all the others.

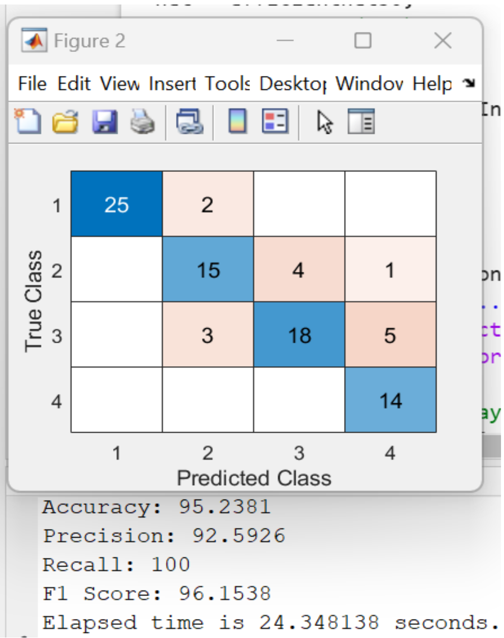

Fig-4: Results of EfficientNet B0

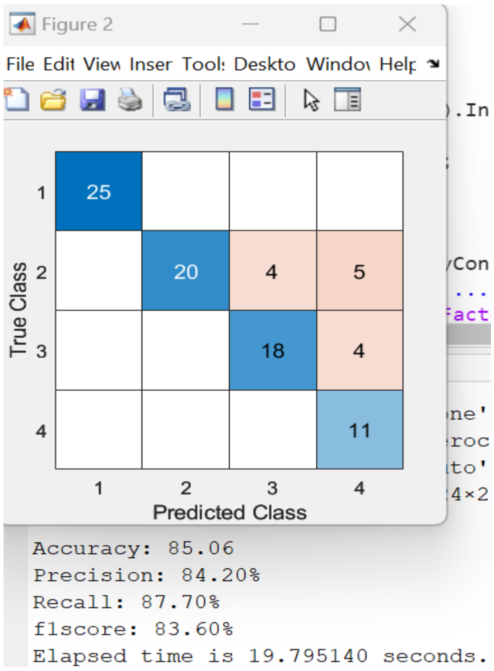

Fig-5: Results of ResNet 50

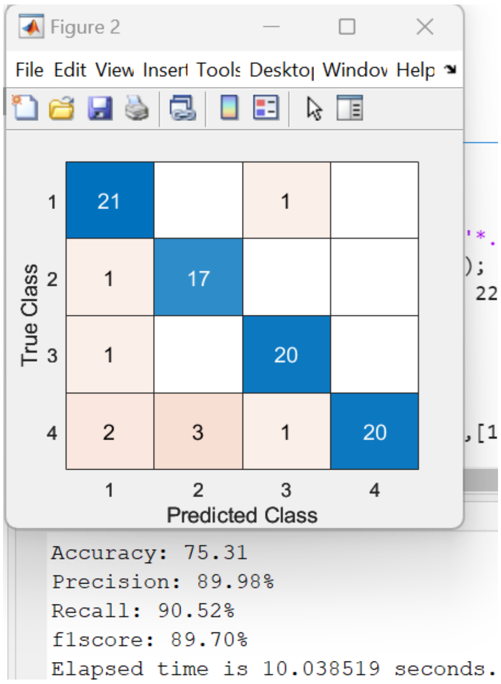

Fig-6: Results of 10*1 layer network

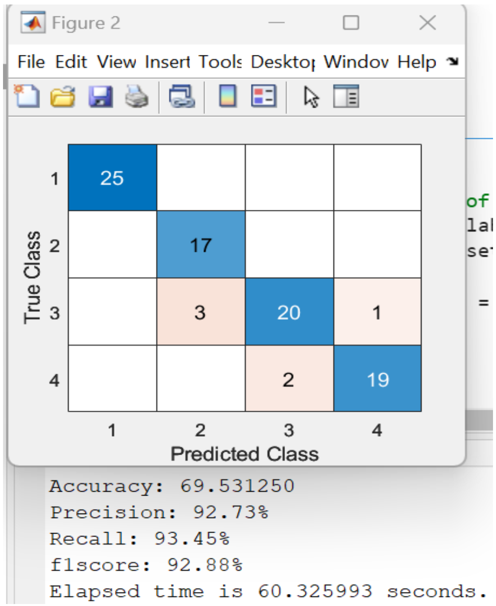

Fig-7: Results of VGG

Table -1: Algorithms performance Table

Name of the algorithm	Accuracy	Precision	Recall	F1 Score
10*1 Layer Network	75.31	89.98	90.52	89.7
vgg16	69.53	92.3	93.45	92.88
ResNet-50	85.06	84.2	87.7	83.6
efficientnetb0	95.2	92.5	100	96.15

6. CONCLUSION

One significant development in the accurate classification of bone tumors is the use of state-of-the-art picture segmentation techniques, particularly those that make use of the EfficientNetB0 architecture. Through this study, we have demonstrated the efficacy and reliability of this approach in enhancing diagnostic precision and efficiency in healthcare settings. Thanks to the application of deep learning and sophisticated algorithms, tumor categorization has advanced significantly, enabling medical professionals to act swiftly and decisively. The implementation of EfficientNetB0 shows how well it can handle complex medical imaging data, outperforming conventional methods and, in certain cases, even outperforming human-level accuracy. This advancement may speed up the diagnosis procedure and improve patient care, which in turn may lead to better treatment results and reduced medical expenses.

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