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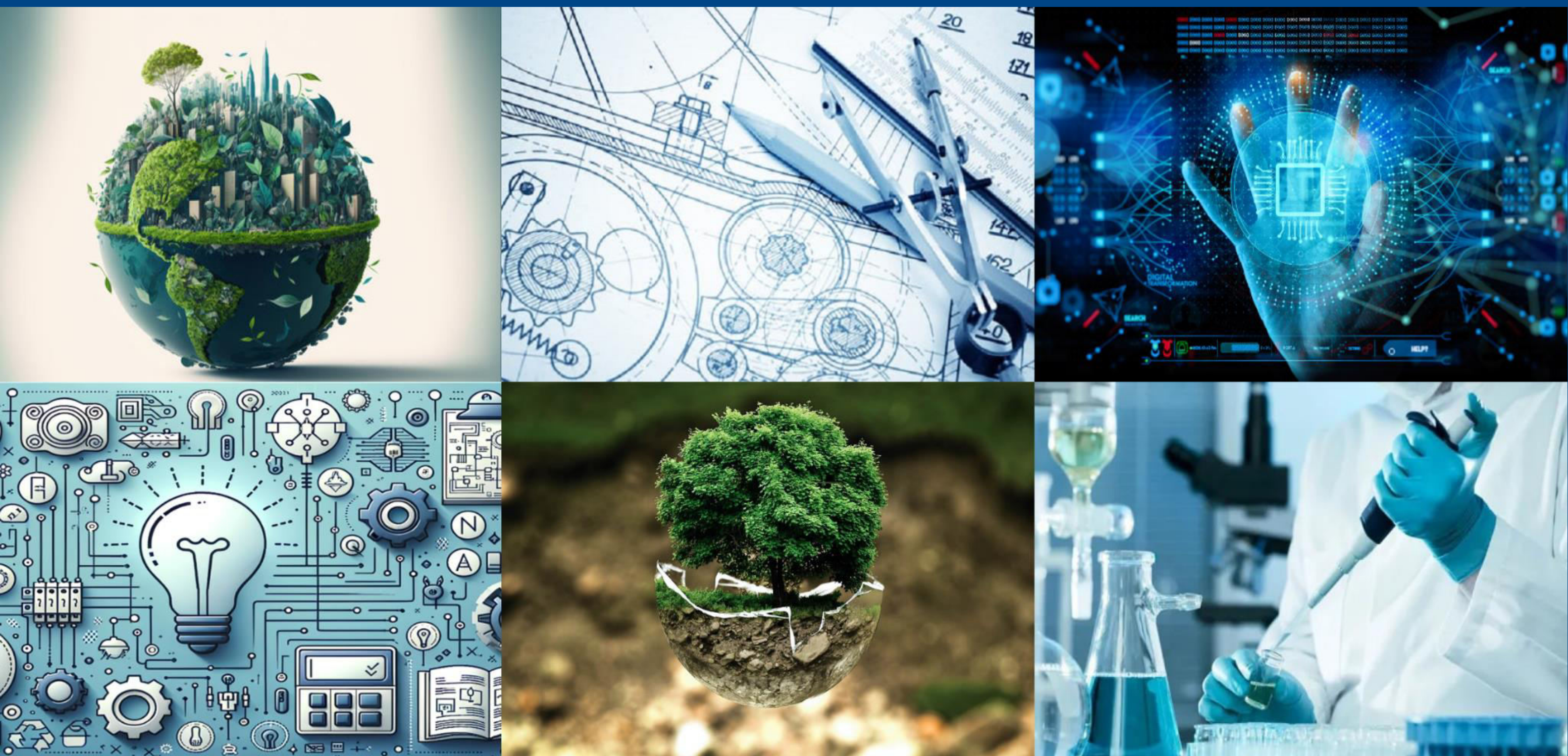

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Bone Tumor Detection using Image Processing AI Tools

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ABSTRACT: Cancer remains one of the most critical health challenges, posing a significant threat to human life due to the uncontrolled growth of abnormal cells. Among various types of cancer, bone tumors represent a particularly concerning category, as they can severely impact mobility and quality of life. Early detection of bone tumors is crucial for effective treatment and improved patient outcomes. However, identifying bone tumors at an early stage is often challenging due to their subtle appearance and similarity to other conditions in imaging studies. This study focuses on the detection of bone tumors using Magnetic Resonance Imaging (MRI), a widely preferred modality due to its ability to provide detailed images of soft tissues and bones without radiation exposure. The proposed methodology involves the use of preprocessing techniques to enhance MRI images, ensuring the elimination of noise and improving the clarity of relevant features. Post preprocessing, critical features are extracted from the images, capturing the essential characteristics of tumor and non-tumor regions. These extracted features are then fed into a Convolutional Neural Network, VGG16 and ResNet50, a state-of-the-art machine learning algorithm designed to analyze image data. This algorithm is chosen for its superior performance in image classification tasks, providing high accuracy and robust results with minimal loss. The proposed approach aims to streamline the diagnostic process, offering a reliable, automated solution for early bone tumor detection. This work holds the potential to significantly enhance diagnostic precision and support timely medical interventions.

KEYWORDS: CNN, VGG16, ResNet 50, Deep Learning, Real-Time Processing, Bone Tumor, MRI images.

I. INTRODUCTION

Cancer, which causes unlimited cell multiplication, will divide the cells and grow out of control, forming malignant tumors and targeting nearby body components. This tumor has the ability to develop and impede the digestive, neurological, and circulatory systems, as well as release hormones that can cause body function to change. Cells are classified as cancer cells when their DNA has been damaged. In a normal cell, when DNA is broken, the cell either fixes the damage or it may die. If the DNA which has been damaged is not repaired before a person dies, the body will make unnecessary new cells as a result of the broken DNA.

Cells in the body frequently travel to all the other parts of body, forming tumors that eventually turn back into normal tissue. Metastasis is the medical term for this. Cancer cells then reach the circulation or lymph arteries of the human body. Bone cancer is of two types that is benign which is non-cancerous and malignant which is most cancerous. They are frequently treated with surgical surgery. Bone tumours are dangerous because they can spread and endanger one's life. Bone cancer is a complicated disease that can result from a number of hereditary and physiological factors. It promotes uncontrolled cell proliferation, which leads to demonic bone tumours that spread throughout the body. At any joints there is a possibility of the bone that can turn to cancerous. Hemipelvectony, often known as a hindquarter removal, is a treatment that involves removing the complete leg. Magnetic resonance Imaging is better than other scanning images because this gives better accuracy. The term "segmentation" refers to the partition of an image into many parts and the subsequent extraction of usable data from these areas. A variety of segmentation approaches have been applied on the MR images.

Tumors are abnormal new tissue growths that can appear in any organ of the body. Various types of cancer include lung cancer, brain cancer, and bone cancer. When cells in the body go rogue, cancer occurs, and bone cancer develops in the bone. Other bodily tissues may be damaged as well. As a result, other parts of the body will be affected by these tissues. Bone cancer is today considered one of the most serious and lethal tumors in the world, with the lowest survival rate after diagnosis. It is impossible to stress the importance of early detection of the cancer-prone area in an MRI scan for successful diagnosis and treatment of bone cancer.

Despite the fact that the specific cause of bone cancer is unknown, scientists have determined that some factors are associated to a higher risk. When the bone is subjected to therapy for more times then, lot of radiations will be passed into the bones so this may lead to the bone cancer in future. When cells in the body go rogue, cancer occurs, and bone cancer develops in the bone. Other bodily tissues may be damaged as well. As a result, other parts of the body will be affected by these tissues. Based on MRI scans, this method attempts to classify tumors as non-cancerous or malignant. In this paper, to develop the model we will be using bone region Magnetic resonance imaging in order to identify the bone tumor. This collection of MRI images from the different sources is called dataset.

II. LITERATURE SURVEY

The application of image processing techniques in bone tumor detection has seen significant advancements in recent years, driven by the need for accurate, non-invasive, and efficient diagnostic tools. Traditional diagnostic methods, such as biopsies and radiological assessments, can be invasive, time-consuming, and prone to subjective interpretations. Image processing, coupled with machine learning and deep learning, offers a promising alternative for early detection, precise localization, and characterization of bone tumors.

Early research focused on utilizing conventional image processing techniques like segmentation, feature extraction, and classification. Segmentation algorithms, such as thresholding, region growing, and edge detection, were employed to delineate tumor regions from surrounding healthy bone tissue in MRI images. Feature extraction methods, including texture analysis, shape analysis, and statistical features, were used to quantify tumor characteristics. Traditional machine learning classifiers were applied to differentiate between benign and malignant tumors based on these extracted features. However, these methods often suffered from limitations related to variability in image quality, complex tumor morphology, and the need for manual feature engineering.

The advent of machine learning and, particularly, deep learning techniques has revolutionized bone tumor detection. Convolutional Neural Networks (CNNs) have emerged as powerful tools for automated feature learning and classification. Studies have demonstrated the effectiveness of CNNs in accurately classifying bone tumors from radiological images, often surpassing the performance of traditional methods. Pre-trained CNN architectures, such as VGG16, ResNet50, and Inception, have been fine-tuned for bone tumor detection tasks, leveraging their ability to learn complex hierarchical features.

Image processing, particularly when combined with deep learning, holds great promise for improving bone tumor detection. Continued research and development in this area will lead to more accurate, efficient, and patient-friendly diagnostic tools, ultimately improving patient outcomes.

III. PROPOSED METHODOLOGY

This study presents an efficient approach of the entire technique as shown (figure 1) for detecting bone cancer has three main components: MRI images are given as input and processed in three stages: image processing, image segmentation, and feature extraction and classification. The datasets are MRI pictures that are utilized for both training and testing. In the training set, we offer photographs of patients with bone cancer pneumonia and photos of persons who do not have bone cancer pneumonia. The Convolution Neural Network technique is used to train the model. Dicot is a technology that displays a two-dimensional depiction of bone density and detects all supplements in the bone. For detecting the degree of malignancy and bone fractures, MRI images provide excellent resolution.

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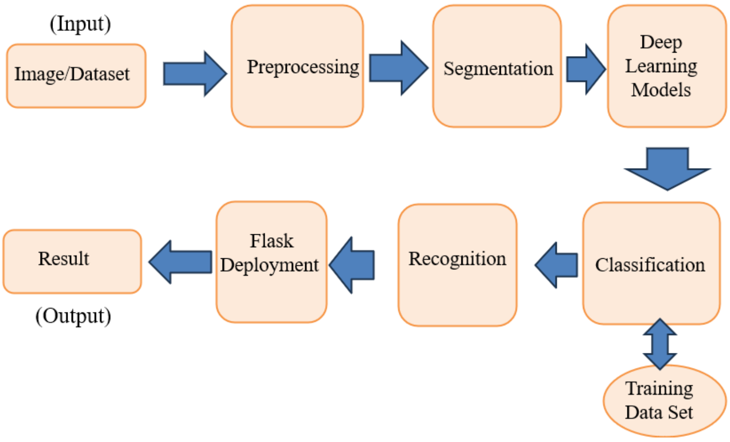

Figure 1: Proposed Methodology for Bone Tumor Detection

1. Dataset Preparation

The Bone Tumor Dataset available on Kaggle primarily consists of histopathological images, typically stained tissue samples, representing various stages and characteristics of osteosarcoma. These datasets aim to facilitate research and development of automated diagnostic tools using image processing and machine learning techniques. Researchers utilize these images to train algorithms capable of differentiating between healthy bone tissue and osteosarcoma, as well as potentially classifying tumor grade or predicting patient outcomes based on the visual features present in the tissue samples. The images often come with annotations or labels indicating the presence and location of tumor cells, aiding in the supervised learning process for developing accurate and reliable detection models.

2. Pre-Processing

This is the first stage in improving the image's quality. The filtering technique is used to begin the picture processing stage. Noises such as occlusions, fluctuations in illuminations, and so on are common in images. As a result, these sounds must be eradicated. The Gabor filter is used to smooth out the pictures and eliminate noise. When compared to other filters, the key advantage of this filter is that it delivers great noise reduction with minimal blurring. The grey conversion is the next stage in the pre-processing. This is the process of transforming RGB-level pixels to gray-level pixels. This is done because, in comparison to a colour image, the grey level image is easier to process. The purpose of this conversion is to keep the brightness while removing the hue and saturation information.

Edge Detection: A type of edge detector that is used to determine the boundary between two areas with different grey level attributes. In cancer dataset, edge detection was employed to extract important features for pattern identification. The Canny edge detector is used to identify an image's edge. It blurs the image first, then uses an algorithm to effectively thin the edges down to one pixel. This canny detector has the advantages of good detection, localisation, and reaction time.

Morphological operation: Morphological operations are used to determine the form, size, and connectedness of an object. The morphological technique's two main procedures are dilatation and erosion. To extend the zone, a dilation procedure is employed. Erosion is a technique for removing or destroying tiny items.

3. Segmentation

The technique of splitting a picture into several segments is known as segmentation. Super pixel segmentation and multilayer segmentation were employed in this approach. In comparison to previous segmentation approaches, this approach divides the picture into larger pixels.

Feature Extraction: The most significant approach in image processing is picture feature extraction. It is crucial in the early identification of cancer. To identify cancer, visual characteristics are taken from the picture after segmentation. Feature extraction is a crucial stage that reflects the final findings in predicting whether a picture is cancerous or not. The quantity of resources needed to explain a huge quantity of data is reduced via feature extraction. It is the technique of detecting and representing particular elements of interest inside a picture for subsequent processing.

4. Deep Learning Models

ResNet50:
It is a groundbreaking convolutional neural network (CNN) architecture that has revolutionized the field of deep learning, particularly in computer vision.

Residual Networks: ResNet-50 is a member of the ResNet family of models. The core idea behind ResNets is to address the "vanishing gradient" problem, which hinders the training of very deep neural networks.

Residual Blocks: The key innovation in ResNets is the use of "residual blocks." These blocks allow the network to learn residual functions, which represent the difference between the input and the desired output.

VGG 16:
It is a convolutional neural network (CNN) architecture that was proposed by the Visual Geometry Group (VGG) at the University of Oxford. It's known for its simplicity and effectiveness, achieving state-of-the-art results on image classification tasks when it was introduced.

Depth: VGG16 is a deep network, consisting of 16 layers, including 13 convolutional layers and 3 fully connected layers. This depth allows the network to learn complex features from images.

Small Convolution Filters: VGG16 primarily uses 3x3convolutional filters throughout its architecture. This choice was significant because:

Smaller receptive fields: 3x3 filters have a smaller receptive field compared to larger filters (e.g., 5x5 or 7x7).
Increased non-linearity: Stacking multiple layers of 3x3 filters with small strides achieves the same receptive field as a single larger filter while introducing more non-linearity, which improves the network's ability to learn complex features.

5. Classification (Trained Dataset)

This stage is the core of the automated detection system, where the preprocessed and segmented image is analyzed to determine the presence and type of bone tumor.

Model Selection and Training:
A suitable deep learning model, typically a Convolutional Neural Network (CNN), is chosen. Popular architectures include VGG16, ResNet50, Inception, or custom-designed CNNs. The model is trained on a labeled dataset of bone tumor images. This dataset contains images annotated with information about the presence of tumors, their types (e.g., osteosarcoma, Ewing sarcoma), and potentially their grades or stages.

The training process involves feeding the labeled images into the model, adjusting its internal parameters (weights and biases) to minimize the difference between the model's predictions and the actual labels. Techniques like data augmentation (e.g., rotating, flipping, or zooming images) are used to increase the dataset's size and improve the model's generalization ability.

Feature Extraction and Analysis:
The trained CNN automatically extracts relevant features from the segmented image. These features represent patterns and characteristics that are indicative of bone tumors. The CNN's convolutional layers learn to identify edges, textures,

and other visual cues that differentiate between healthy bone tissue and tumor regions. The fully connected layers of the CNN then combine these extracted features to make a final prediction.

6. Recognition

The detected tumors are then Recognized in the three categories based on the tumor maturity such as Viable, Non-Viable Tumor and Non-Tumor.

Viable:
A viable bone tumor refers to the portion of a tumor that contains living, actively proliferating cells. Distinguishing viable tumor tissue from necrotic or non-viable areas is crucial for assessing treatment response and guiding clinical decisions. In imaging, viable tumor tissue often exhibits increased metabolic activity and enhanced contrast uptake.

Deep learning models, when applied to medical images like MRI or PET scans, can effectively delineate these viable regions by analyzing texture, intensity, and metabolic patterns. This differentiation is vital for accurately monitoring tumor progression, evaluating the efficacy of therapies like chemotherapy or radiation, and planning surgical interventions, ensuring targeted treatment and improved patient outcomes.

Non-Viable:
A non-viable bone tumor refers to the portion of a tumor where cells are no longer living or actively dividing. This often results from treatment-induced necrosis or natural tumor degeneration. Imaging characteristics, such as reduced contrast enhancement and altered texture, can differentiate non-viable regions from viable tumor tissue. Deep learning algorithms, when trained on medical images, can effectively segment and identify these non-viable areas, aiding in treatment response assessment. Accurate delineation of non-viable tissue is crucial for monitoring treatment effectiveness, guiding further therapeutic decisions, and preventing unnecessary interventions. It allows clinicians to focus on viable tumor regions, optimizing patient care and improving prognosis

Non-Tumor:
In medical imaging, "non-tumor" signifies regions within the body that lack neoplastic tissue or abnormal cell growth. Distinguishing these areas from actual tumors is paramount for accurate diagnosis and treatment planning. Non-tumor regions exhibit normal tissue characteristics, displaying consistent texture, predictable intensity patterns, and regular anatomical structures. Deep learning models, trained to identify subtle variations, can effectively differentiate non-tumor tissue from potential malignancies. These models analyze image features like texture, shape, and intensity distributions, flagging deviations indicative of tumor presence. This differentiation ensures that healthy tissue is preserved during interventions and that treatment focuses solely on affected areas, minimizing patient morbidity and improving overall outcomes

7. **Flask Deployment**

Flask, a lightweight Python web framework, is used to create a web application that allows users to interact with the trained bone tumor detection model. This step makes the model accessible to clinicians and researchers through a user-friendly interface.

Web Application Development:
Flask routes are defined to handle different web requests (e.g., uploading images, displaying results). HTML templates are created to design the user interface, including file upload forms, result displays, and interactive elements. The trained deep learning model is integrated into the Flask application, enabling it to process uploaded images.

Image Upload and Processing:
Users can upload bone tumor images through the web interface. The Flask application receives the uploaded image and stores it temporarily. The image is then preprocessed and segmented using the same techniques used during model training. The segmented image is passed to the trained deep learning model for classification. The web application may also provide options for downloading the results or viewing additional information.

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Deployment and Accessibility:
The Flask application can be deployed on a local server or a cloud platform, making it accessible to users over the internet. This allows clinicians and researchers to use the bone tumor detection system from any device with a web browser. The web application can be designed to be user friendly, and to protect patient data.

IV. TESTING AND RESULTS

This Proposed model develops will overcomes limitations present in the existing model by developing the Computer Aided Detection systems. These systems utilize Machine Learning algorithms to analyze medical images, assisting radiologists in identifying potential tumors and improving diagnostic accuracy.

This model demonstrates the potential of Deep Learning models, specifically VGG16 and ResNet50, in the accurate prediction and classification of Bone Tumor from medical images. By leveraging advanced techniques such as transfer learning and rigorous image preprocessing, the models achieve reliable performance, assisting in early and precise diagnosis. In this model prediction of Bone Tumor observed in such as Viable (figure 2(a)), Non-Viable (figure 2(b)) and Non-Tumor (figure 2(c)) along with required precautions need to followed.

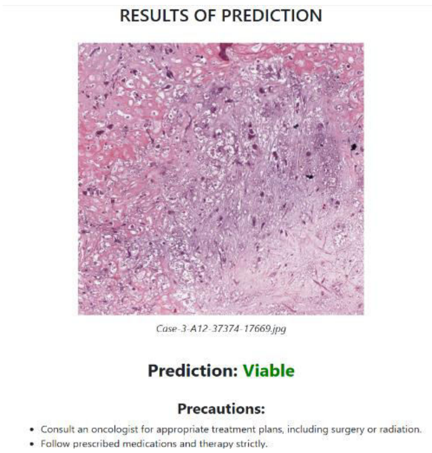

figure 2(a) Viable

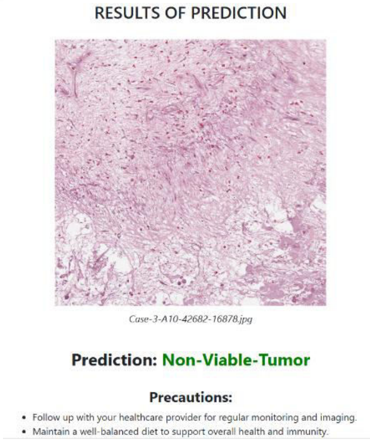

figure 2(b) Non-Viable

figure 2(c) Non-Tumor

The confusion matrix (Figure 3) provides an overview of the model's performance. The system correctly detected 90% of Tumor. The overall accuracy of the model is 90.`%, showing strong performance in real-world conditions as shown in figure 4.

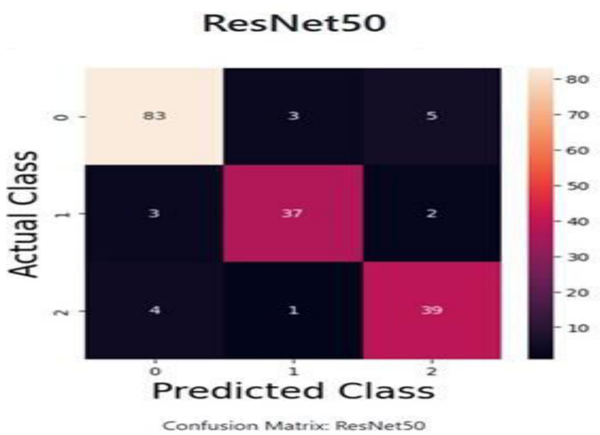

Figure 3: Normalized Confusion Matrix

	precision	recall	f1-score	support
Non-Tumor	0.92	0.91	0.92	91
Non-Viable-Tumor	0.90	0.88	0.89	42
Viable	0.85	0.89	0.87	44
accuracy			0.90	177
macro avg	0.89	0.89	0.89	177
weighted avg	0.90	0.90	0.90	177

Figure 4 : Overall Performance of a Proposed Model

Figure 5(a) represents the Visualization of Accuracy Results. As training progresses (especially within the first 50 epochs), both training and validation accuracies rapidly increase. After a certain number of epochs (around 75-100), the accuracy curves begin to plateau, indicating that the model's performance is stabilizing. Further training epochs yield diminishing returns in terms of accuracy improvement. The training accuracy is consistently higher than the validation accuracy throughout the training process. This is typical and expected. A perfect match between training and validation accuracy would be suspicious and might indicate issues like data leakage. The validation accuracy remains relatively stable and does not decrease even as the training accuracy continues to improve slightly. The final validation accuracy reaches a high level (around 0.90 or 99%), indicating that the model performs well on unseen data.

Figure 5(b) represents the Visualization of Loss Results, At the beginning of training (around epoch 0), both training and validation losses are high. Both lines show a steep decline in loss during the first few epochs. This indicates that the model is quickly learning to fit the training data and generalize to the validation data. After a certain number of epochs (around 50-75), the losses start to plateau and level off. There's a small gap between the training and validation loss throughout the training process. The training loss is consistently lower than the validation loss. This is normal and expected. The model is expected to perform better on the data it was trained on.

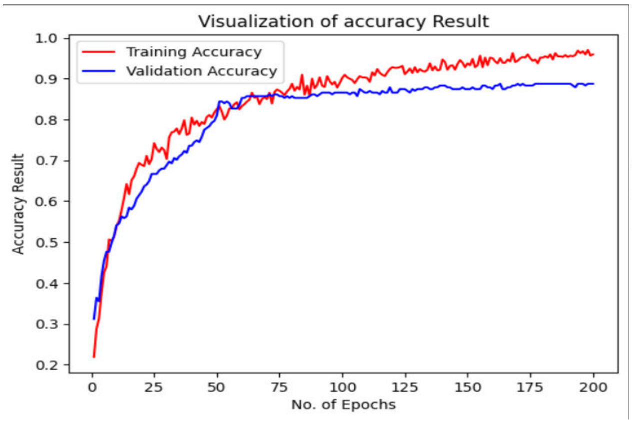

Figure 5(a) Visualization of Accuracy Results

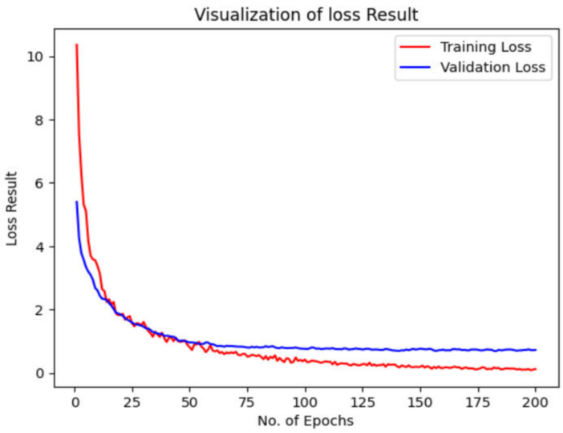

Figure 5(a) Visualization of Loss Results

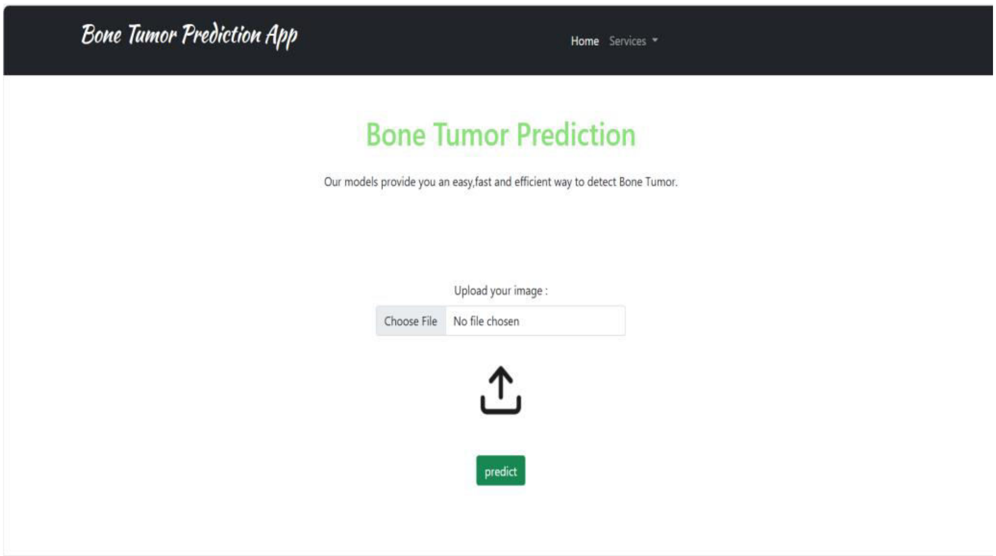

Figure 5(c): The developed model, Where we will input the image then displayed appropriate Result with required Precautions..

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V. CONCLUSION

The Bone Cancer is one of the most dangerous cancer, so this must be taken care in the early stages only. In this model Magnetic resonance images will be used as the input. Our proposed system detects whether the cancer is present or not also if the cancer is present then it detects at what stage the cancer is that is either it is first or second or third stage. If the image have no tumor segments then this model gives the result as normal. This model achieves expected desired result at the end of the model. The extracted features from the image contain some specific information to understand the details of the image. The main purpose of extracting the features is to reduce the process complication and also to isolate various desired shape of the image. The accuracy of the classification stage depends on extracted features.

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