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Detection and Classification of Bone Tumor from X-Ray Images Using CNN Algorithm

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Abstract

The most prevalent form of bone cancer is osteosarcoma. The potential for early identification to enhance treatment approaches and enhance patient outcomes is enormous, highlighting the importance of technology developments in medical diagnostics. We suggest a Convolution Neural Networks (CNNs) based computer-aided diagnosis system for identifying osteosarcoma on radiographs of the bones. The image's potentially tumor-containing regions are indicated by the CNN Algorithm. We suggest splitting the image into windows and using a CNN algorithm to categorize each window separately in order to identify these locations on the image. Using the CNN Algorithm, the features are taken out of the picture windows.

Keywords: Osteosarcoma, CNN algorithm, tumor detection, pre-processing, interdisciplinary collaboration.

Introduction

Convolutional neural networks (CNNs) are very effective tools in the realm of deep learning, especially when it comes to analyzing visual information. Convolution is a special method that CNNs use, in contrast to typical neural networks that mostly rely on matrix multiplication. As a substantial medical problem, bone tumours account for 2% to 3% of all cancers and are becoming more common. These tumours start in the skeletal system and have the ability to spread, harming large areas of tissue.

They are roughly divided into primary and secondary tumours, with the distinction between benign and malignant primary tumours made. Malignant tumours are usually aggressive, but benign tumours usually stay localized. Recent developments in deep learning algorithms have demonstrated impressive improvement in outperforming human performance in visual tasks, providing encouraging opportunities for enhancing the diagnosis of bone cancer. To overcome these issues, a proposed system consists of four primary stages:

1. **Pre-processing:** To improve quality and get ready for more analysis, raw imaging data, like X-rays, go through preliminary processing.
2. **Segmentation:** This step entails separating interest areas inside the bone structures. Segmentation methods based on CNN, like RELU, can distinguish tumour boundaries precisely from surrounding tissues.
3. **Identification:** Structures are further examined to extract pertinent traits and characteristics after regions of interest have been divided. CNNs are very good at extracting hierarchical representations from images, which helps them to efficiently capture complex patterns.
4. **Classification:** Based on the traits that were extracted, the last step involves grouping the discovered bone

tumours into several categories. Classification techniques such as random forests and support vector machines are frequently employed for features collected from pictures and metabolomic data.

A proposed CNN-based computer-aided diagnosis system seeks to identify possible tumour locations and classify Osteosarcoma on radiographs, or plain X-ray pictures. The photos are split into windows and each window is classed separately using CNN in order to identify these regions.

Section 1 provides an introduction to the project, section 2 includes a literature survey, section 3 outlines the proposed work, section 4 details the project's operation, section 5 presents the project's results and output, section 6 concludes the project, and section 7 lists the project's references.

Literature Survey

Using mean pixel intensity from MR images, Avula and colleagues (2014) [1] suggested a method for differentiating between benign and malignant bone growths. In a similar vein, Ranjitha et al. (2019) [2] used MRI pictures to distinguish between benign and malignant tumours. To divide the tumour area, they used the k-means clustering technique and extracted texture features. To ascertain malignancy, the mean pixel intensity was computed after the total count of pixels from the segmented tumour region was determined. If the mean intensity of a pixel exceeds a predefined threshold, it is classified as malignant.

Avula et al. (2014) [3] suggested a method for utilizing mean pixel intensity from MR images to distinguish between benign and malignant bone tumours. MRI pictures were also used by Ranjitha et al. (2019) [4] to differentiate between benign and malignant tumours. They extracted texture features and segmented tumour regions using the k-means clustering algorithm. After segmentation, they find the total number of pixels in the tumor region and found the average intensity of the pixels to evaluate malignancy. A tumour is categorized as malignant if the mean pixel intensity is higher than a predetermined threshold.

Kaushik and Sharma (2016) [5] presented a methodology for estimating the number of tumours that are sick. Their method for region of interest (ROI) segmentation to compute tumour volume can be used in malignant locations. Sinthia and Sujatha (2016) [6] presented a novel method for identifying bone cancer that makes use of the edge detection methodology and the k-means clustering algorithm. To detect tumour boundaries, our approach uses Sobel edge detection and only looks at boundary pixels. To define the tumour region, the k-means clustering algorithm is used.

Asuntha and Srinivasan (2018) [6] highlighted the seriousness of bone cancer, which takes many lives. They emphasized how crucial it is to have a system in place for early cancer identification and categorization because doing so greatly increases patients' chances of survival. Clinical diagnosis is a challenging task when it comes to classifying cancer. The system for tumour identification and cancer classification that uses image processing techniques is discussed in the study. The time required for cancer categorization and detection has been significantly decreased by this method.

Torki (2019) [7] established a framework for identifying bone diseases and emphasized tumours as a serious medical concern. The goal of this paradigm is early cancer prediction. Through performance analysis and an experimental setup based on MATLAB, the predictive model was assessed.

Reddy et al. (2016) staged and identified bone cancer using MRI scans. To reduce noise, they used denoising algorithms, which group pixels based on certain attributes. The cancer stage was predicted using the pixel intensity mean and a value of 245. To assess the size of the tumour, regions of interest (ROIs) were taken from the pictures and compared to a preset threshold.

Reddy et al. (2015) presented a novel method that uses developed area computation to determine the size of tumor and stage of bone cancer. The area-growth system was used in this strategy to segment the region of interest. The pixels count from the extracted tumour region was there to find the size of the tumour. The overall pixel value was used to determine the cancer stage. However, choosing the right seed point depends on the image and can be difficult to determine with precision.

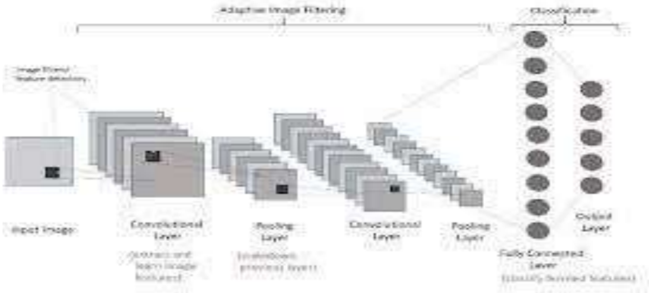
Proposed Work

In order to discover and separate unique properties inside an image for study, feature extraction is the process of applying convolutional methods. A typical feature extraction network consists of fully connected layers that use the output of the convolutional process to categorize the picture based on the extracted features, as well as convolutional and pooling layers. By creating new features that combine old ones into a single new feature, this CNN feature extraction approach aims to lower the dimensionality of the dataset.

3.1 Convolutional Neural Network:

The architecture is made up of different layers piled on top of one other. The activation function and the dropout layer, two further essential parts that are also vital to CNNs, are described below (Figure 1).

Figure 1. Architecture of CNN



1. **Input Layer:** The width x height (e.g., 224x224) dimensions of the raw input data, which is commonly a picture of a bone, are represented by this first layer. Six classes of distinct bone tumours are taken into consideration for classification by CNN.
2. **Convolutional Layer: S**everal features are extracted from the input photos by this layer. Convolution is achieved mathematically by combining the input image with a filter of a given size (MxM). A "Feature Map" that offers information about the image, such as its edges and contours, is created as the filter advances across the input image by calculating the dot product in between the filters and relevant areas of the image.
3. **Activation Layer** Following the convolution operation, an activation function (typically ReLU - Rectified Linear Unit) is applied element-wise to the feature maps. ReLU presents non-linearity, enabling the network to learn multifaceted patterns and make the model more expressive.
4. **The Pooling Layer** The process of extracting different features from the input photos starts with this layer. In this layer, convolution is carried out by merging the input image with a particular size (MxM) filter. The dot product is calculated between the filters and corresponding regions of the input image as the filter moves across the image, resulting in a "Feature Map" that encodes information in the RGB channels. An important component of this method is feature extraction, especially from aligned faces.
5. **Fully Connected Layer** A fully connected graph is created when every neuron in this layer is linked to the above layer. Based on all of the features that the preceding

layers have taught them, these layers conduct regression or classification. For classification tasks, the output of the fully connected layer usually passes through a softmax activation function to get class probabilities.

6. **The Output Layer:** Based on the learned features from earlier levels, the last layer of the neural network gives us the result, taking into account factors like accuracy, precision, recall, F1 score, and support.
7. CNNs is capable of analyzing images on its own and recognize elements like edges or textures without explicit guidance. By arranging these characteristics into meaningful frameworks, they make it possible to accurately identify objects or patterns in pictures.

Working

Bone Tumour identification using x-ray pictures CNN.

Images from X-rays of the bones: We have studied bone tumours in six different classes. It is a vital tool for medical diagnosis since it gives an image of the irregularities and bone formations. By employing the X-ray beams depicted in Fig. 1 to capture the interior makeup of bones, these images aid in the identification of fractures, tumours, and other disorders.

Extracting Characteristics from Datasets: We take significant characteristics out of datasets of X-ray images of bones in order to train our model efficiently. In order to improve image quality and retrieve pertinent information like edges, textures, and shapes, preprocessing techniques are used.

Datasets into Train and Test Subsets: To ensure that the model can generalize successfully to fresh X-ray images, we separate our dataset into subsets for training and testing. This allows us to teach the model patterns and assess its performance on unknown data.

CNN training: Because it is very good at classifying images so it is utilized for training. The CNN gains the ability to identify different forms of bone tumours by learning to extract information from X-ray pictures through convolutional and fully connected layers.

Flask Web Application: To make our model available, we create a Flask web application. Users have the option to input X-ray images, which the model processes and analyses to provide predictions about the type of bone tumour that is there.

Feature extraction: To extract pertinent features from bone X-ray pictures and create a compact representation that our model can predict with accuracy, we use techniques like edge detection and texture analysis.

The Trained Model's Input: Our trained model uses the extracted features as input, which encodes the information needed to forecast the kind of bone tumour seen in the photos.

Predicts the Type of Bone Tumour: Our model helps medical practitioners diagnose bone problems quickly and accurately by predicting the type of bone tumour that is present based on the input features.

Figure 1. Bone tumor Datasets

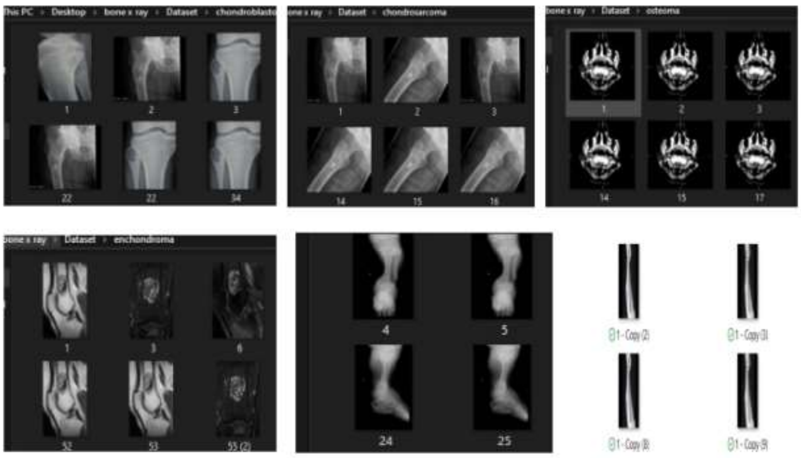
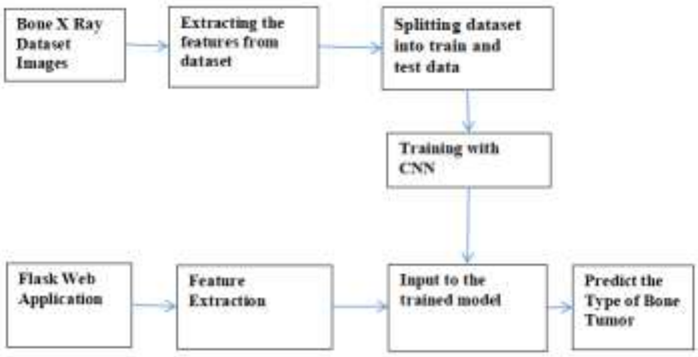


Figure 2. Block Diagram



Results and Discussions

The project's objective is to construct a CNN model that predicts which type of bone tumor it is. when the image is provided. We have developed the Flask web application Firstly we have to register on that website upload the bone x-ray images and click on predict image there we can see which type of bone tumor we have taken 6 different classes of bone tumor . These are some of the results of the flask web in Figure 3-7.

Figure 3. Chondrosarcoma

Figure 4. enchondroma

Figure 5. Maffucci Syndrome

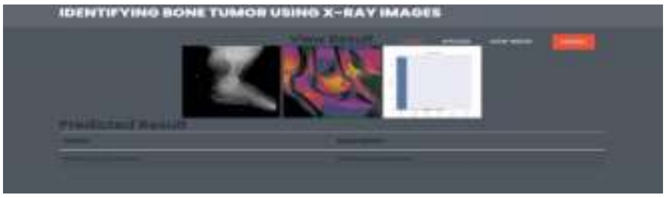


Figure 6. Osteoma

Figure 7. Chondroblastoma

We have also taken different parameters to compare SVM (Existing System) and CNN Fig 8.

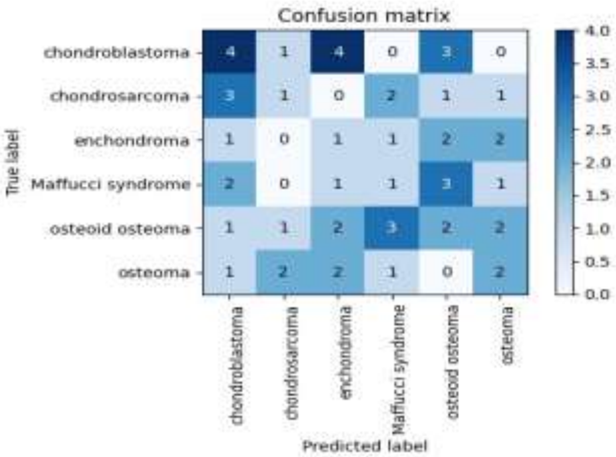
Table I: Comparison Table

Parameters	SVM	CNN
Accuracy	87%	93%
Precision	0.88	0.97
Recall	0.85	0.92
F1 score	0.80	0.93

Figure 8. Comparision Table

Fig 9 tells us how exactly cnn model predicts the bone tumor

Figure 9. Confusion Matrix



Conclusion

In conclusion, the use of CNNs in this paper's presentation to identify and categorize bone tumours from X-ray pictures represents a substantial development in the field of medical imaging analysis. CNNs' superior feature learning capabilities and innate spatial awareness make them perform better than more conventional techniques like Support Vector Machines (SVMs). CNNs improve diagnostic accuracy by automatically identifying complicated patterns and textures and capturing spatial hierarchies, particularly in complex spatial configurations like tumours next to vital structures like joints. The process is further streamlined by its end-to-end learning capabilities, which do away with the requirement for manual feature engineering and opens up intriguing options for increasing diagnostic accuracy and enabling more successful medical interventions.

As we move forward, the broad use of CNNs in bone tumour identification is an important step in utilizing state-of-the-art technology to enhance healthcare outcomes. CNNs have the potential to completely change diagnosis and treatment procedures as medical imaging research and development continue to advance, ultimately improving patient care and prognosis.

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