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BONE CANCER DETECTION USING MACHINE LEARNING

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Abstract - *Cancer is a fatal condition that affects people of all ages. With over one out of every three people will experience cancer and at a certain point in their lives. By evaluating diagnostic medical techniques such as X-ray scans, CT scans, and PET scans, the overall purpose is to accurately determine the afflicted area in the bone tract, i.e. abnormal growth and disease phase. Because the scanned visuals may not have a high resolution due to the sheer number of slices per pixel and noise, it is necessary to pre-process the images with a median filter to eliminate the noise. Specific characteristics in the pre-processed image will be evaluated using a genetic approach and retrieved employing CNN. The retrieved pictures are categorized and recorded using a CNN classifier in order to determine the stage of illness, which helps the clinician make treatment recommendations. The outcomes of the suggested method demonstrate a higher incidence of early diagnosis of bone cancer.*

***Key Words*: Bone Cancer Detection, Cancer stage classification, CNN Algorithm**

1.INTRODUCTION

Bio Medical pictures are one of the most useful diagnostic tools since they show the function and structure of human bodily organs. Medical pictures are a unique tool for monitoring the therapeutic effect. There are a variety of diagnostic imaging technologies utilized within our bodies to detect disease or contaminated tissue. Cancer is a leading cause of death in both men and women. Early cancer detection has the potential to totally cure the disease. Because bone cancer is caused by the uncontrolled development of bone structures, the demand for methods to detect the existence of a cancer nodule in its early stages is identified. The growth expands beyond the bone and potentially spreads to other parts of the body in a stage known as metastatic illness. Many malignancies that arise from epithelial cells, known as carcinomas, develop in the bone.

Excessive expansion has been effectively detected at an early phase, but it prefers to pursue numerous therapeutic methods, lowering the danger of needless operation and boosting survival rates. Surgical intervention, chemotherapeutic, and radiation are all options for treatment. Life expectancies vary depending on the kind of cancer, overall health, and other factors, but on average, around 14% of individuals treated with bone cancer live five years following their diagnosis. There are often a few medical images that are difficult to understand and accurately describe the phase of illness. X-Ray is a diagnostic imaging method or technique that uses a single gateway system that includes both a positron emission tomography scanning and a computer tomography scanner, allowing pictures from both devices to be captured in much the same appointment and then combined into a single overlaid picture.

The degree of the condition can be described by X-Ray, both anatomically and functionally. Bone cancer develops in the body when cells become feral, and malignancy develops. Tumors can form in practically any part of the body and spread to other parts of the body. Due to a variety of hereditary and physiological variables, bone cancer is considered a multi-disease. It causes unregulated cell growth, resulting in demonic bone tumors that spread throughout the body. The current system technique is utilized to determine the size of the bone tumor and the cancer levels discovered. A randomized area growth algorithm was employed to segment bone MR images. The algorithm's efficiency is determined by a sufficient seed point collection, from which the regions begin to extend to surrounding points based upon particulars.

After segmenting the tumor, a formula is used to determine the tumor region, from which the stage of bone cancer is derived. The proposed technique recognizes bone characteristics that allow them to improve input efficiency. Bone density indicates the specific amount of density as well as the position of all compounds in the bone in this example. It has a multiple peaks for assessing the extent of a malignancy and a dislocation in the picture of a bone. It's a way of distinguishing bone characteristics that uses a combination of methods. The application of a good imaging method is considered as a crucial stage in improving the overall visual representation of medical pictures and, as a consequence, improving diagnostic and stage classification outcomes. Numerous image analysis techniques and tools, including as edge detection, contrast enhancement, and image fusion, are used in this study to provide a simple, quick, and accurate approach for detecting cancer tissue in bone. The suggested technique may create images with the afflicted section of the illness evident at the edge, categories the stage of cancer, and give ideas for preclinical studies in the lack of spatial and spectral disruptions, according to experimental findings.

2. RELATED WORKS

According to HelaBoulehmi's approach [1,] the approach begins with the creation of sub-images of certain sizes, bone MRI processing, and GGD analysis of sub-images. Sub-images with maximum amounts of shape parameters, alpha chosen from the initial MRI, are referred to as region of interest (ROI). The ROI was adjusted using the Euclidean distance criteria, and the bone tumor was detected using the template matching analysis technique. Using digitized MRI, GGD analysis has also been proven to be helpful in identifying bone tumors. A proper estimate of the bone cancer segmentation frequency is hampered by a lack of real data and inadequate precision.

Dr. M. Yuvaraju1 proposed the system [2], which is utilized for image analysis to determine the bony injury and also assesses the person's bone tumor. Because each person's bones have varying sizes, image processing is used to determine the length of the bone. The bone tumor is a cancer that forms a muscle over the physical substance rather than a cancer that lowers the bony intensity. It primarily relates to bone mass and also examines all potential reasons of bone fragility. It also provides a three-dimensional representation of the individual body's widespread consumption. It also provides the profile dimensions, as well as human body size. The technique helps with kinematic lower-limb analysis calculations. It takes into account GRF between the human body and the ground. It has the ability to predict bone illnesses such as bone cancer as well as other bone diseases. The following image processing raises the output's absorption coefficient. The bone mass measurement was not implemented. Because the emphasis is on identifying any type of bone illness rather than focusing on a specific condition, intelligent prediction is not accessible.

According to Terapap Apiparakoon [3], the majority of object recognition and instance segmentation algorithms are designed for supervised learning, which requires a large number of training dataset. Model over fitting is a concern since our medical image dataset comprises only a small amount of labeled images. Given the limited availability of labeled examples, we focused on maximizing the use of unlabeled data and developing the most effective approaches possible. As an outcome, we developed MaligNet, a semi supervised learning-based ladder network augmentation of Mask R-CNN for skeletal imaging lesions instance segmentation. Despite the similarity of the photos, the input data are bone scintigraphy photos with similar patterns, characteristics, and permutations. As a consequence, the LFPN may profit from the statement's originality, allowing the student to learn how to read unlabeled bone scan images effectively. Furthermore, employing global features assists in the categorization of lesion types based on the entire quality of the image, which is more similar to a doctor's clinical diagnosis.

The primary goal of this study, according to Prabhakar Avunuri [4], is to examine the situation in ability to track tumor in bone cancer pictures. In this work, K-means and fuzzy C-Means clustering methods are used to identify pre-size accuracy tumor percent in the bone. In this study, the segmentation mechanism is examined first, and then the k-means and fuzzy C-means algorithms are employed to locate the precise position of the tumor in the bone. For importing and segregating pictures, this work makes considerable use of MATLAB as a computer program. Using the fuzzy c-means method, the tumor area may well be identified with 86 percent accuracy. Therefore two methods are used for grouping and classification. Because the accuracy of the two techniques used for clustering and identification of tumor areas is low, the test result predictions may be affected.

Sami Bourouis [5] claimed that the study paper's segmentation technique comprises the registration stage, multiple picture modalities, the Fuzzy Possibility Classification (FPCM) phase, and lastly the segmentation phase relying on nonlinear model. The registrations and FPCM approaches were used to properly identify and initialize flexible models so that they could develop properly and define the expected tumor boundaries. This study presented a 2D bone cancer segmentation approach that has a 91 percent accuracy. Except for the first tumor region extraction, which involves selecting one pixel after classification, the overall process is automated, making the whole thing relatively subjective for the user, leading to increased time taken.

3. SYSTEM DESIGN AND IMPLEMENTATION

In this research paper novel system which is proposed has block diagrams as shown in Fig 3.1. The architectural foundation can be broken down into the following major stages.

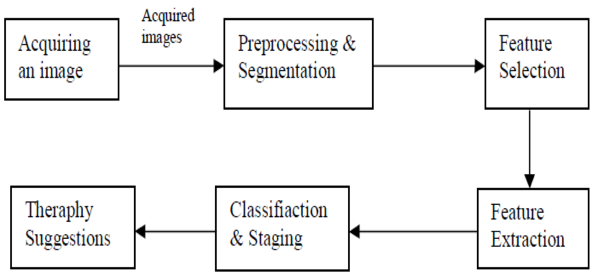

Fig - 1: Architecture Diagram

3.1 Image Acquisition

Images are captured by the use of a lens or by discreetly removing them from the contraction. That whatever source, it's critical that the information's portrayal is both obvious and careful. This will necessitate a stunning image.

3.2 Image Pre-processing

In this step, the shot is normalized by removing the disturbance, which hides hair and bones that could confound the analysis. Consequently, the image provided as metadata may not be of the standard design specified by the figure, making it critical to collect the image size desired.

3.3 Data storage to retain information images for testing and training

Disciplined development is to take place, as it is here, data sets must be established. The photographs gathered during the image acquisition procedure make up the practice questions.

3.3 Classifier to perform classification of Bone disease

The predictor is the system's final layer, and it determines the genuine likelihood of each activity. The process is divided into two sections: image processing and categorization. The image is enhanced by the material processing system, which removes cacophony and loud pieces. After the picture characteristics are cleared to check whether or not the Bone is compromised, the Bone and the image will be separated into various regions to segregate the Bone from operating the machine.

Noise reducing unit eliminates undesired colors from the image. Image improvement component and optimization isolates the affected area from the usual scanned image by enhancing the area and splitting it into multiple aspects. Edge-Detection Component spotlight extraction is a crucial advancement in almost any gathering-centered concern. For both organizational and inspection purposes, appearance is the most important factor.

This aspect includes important visual data that will be needed to diagnose the condition. Unit of Cancer Disease Diagnosis determines whether the malignancy is harmless or dangerous. Input attributes such as notable qualities, such as asymmetries, edge, camouflage, distance, momentum, and so on, that have already been removed from the image are now offered as a committed to section II, the classification part. Classifier engine categorizes the photos by assigning them to one of the established diseases.

4. ALGORITHM

4.1 Convolution Layer

A Convolution Neural Network (ConvNet/CNN) is a deep neural networks method that can accept an image as input, give priority to numerous perspectives in the image (learnable weights and biases), and differentiate between them. The amount of pre-processing required by a ConvNet is far less than that required by other classification methods. Despite the fact that filters are hand-engineered in rudimentary processes, ConvNets can learn these filters/characteristics with sufficient training. The Visual Cortex organization affected the layout of a ConvNet, which is akin to that of Neurons as in Human Cognitive connectivity pattern.

Neural networks only send signals in a restricted area of the peripheral vision known as the Receptive Field. A group of such sectors spans to embrace the full visual zone. This layer entails scanning the entire image for similarities and converting the results into a 3x3 matrix. Kernel is the name given to the image's binarized feature vector. The weight vector is the name given to each element in the kernel.

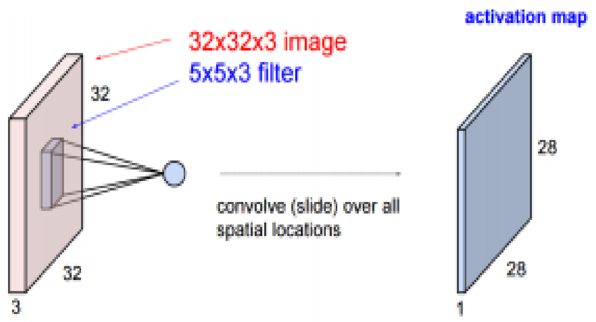

Fig - 2: Convolution Layer

4.2 Pooling Layer

The Pooling division is in charge of shrinking the Convolved Format's spatial size. This is done to lower the amount of processing power process data using dimension reduction. It can also be used to remove rotational and temporal affine dominant traits while keeping the model's training loop intact. There are two kinds of pooling: maximum and average. Max-Pooling returns the whole amount of the area of the image held by the Kernel. On the other hand, Average-Pooling delivers an aggregate of all the data from the picture portion sheltered by the Kernel. Max Pooling also functions as a noise reducer. It completely eliminates noisy events and even de-noises along with dimensionality improvements.

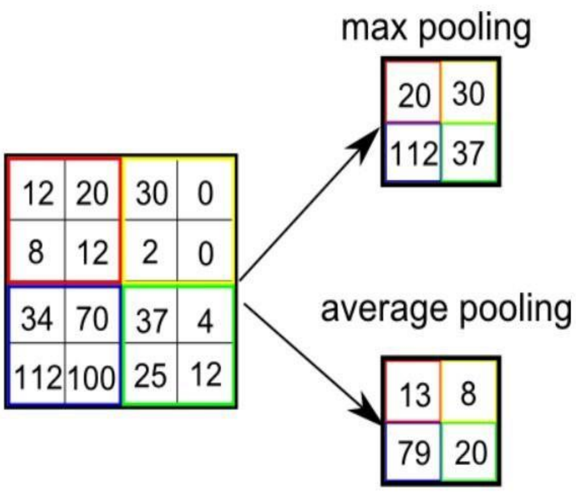

Fig - 3: Pooling Layer

Average-Pooling, from the other hand, reduces heterogeneity as a noise reduction strategy. As a result, we could argue that Peak Pooling outperforms Normal-Pooling. The pooling layer's key benefit is that it improves performance of a computer system while lowering the risk of over-fitting.

4.3 Activation Layer

It's the part of the CNN at which data are normalized, or adjusted, inside a given range. The convolutional layers function employed is ReLU, that only really accepts positive inputs and subsequently rejects negative values. It's a low-cost computing routine.

4.4 Fully Connected Layer

The Fully-Connected layer is a (typically) low-cost method of learning the high-level properties of non-linear topologies as expressed by the convolution kernel output. The Fully-Connected layer is acquiring a potentially non-linear variable in that space. Now that we've changed our image representation into a shape suitable for our Multi-Level Perceptron, we need to flatten it into a linear combination. The smoothed output appended to each training cycle is fed into a feed-forward neural net with back propagation.

Over a series of epochs, the model will distinguish between dominant and low-level features in images and categorize them by using soft-max classification method. The features are compared to test image's attributes, and relevant traits are correlated with the provided label. Labels are typically coded as figures for computational

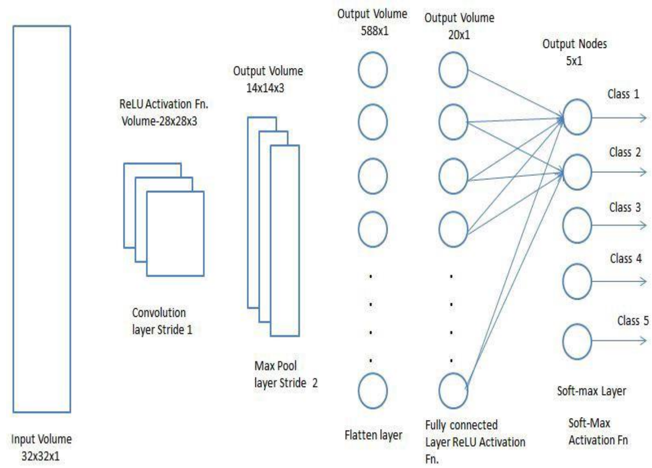

Fig - 4: Fully Connected Layer

Convenience; however, they will be translated to their appropriate strings afterwards.

5. RESULTS AND DISCUSSIONS

The results obtained with the analysis of dataset images using CNN Algorithm for classifcation and staging are discussed below :

Dataset is a collection of X-ray ,CT scan images. Figure 5 shows the dataset containing images. Dataset contains various images of different parts of the bone, it consists of both cancerous and non-cancerous images.

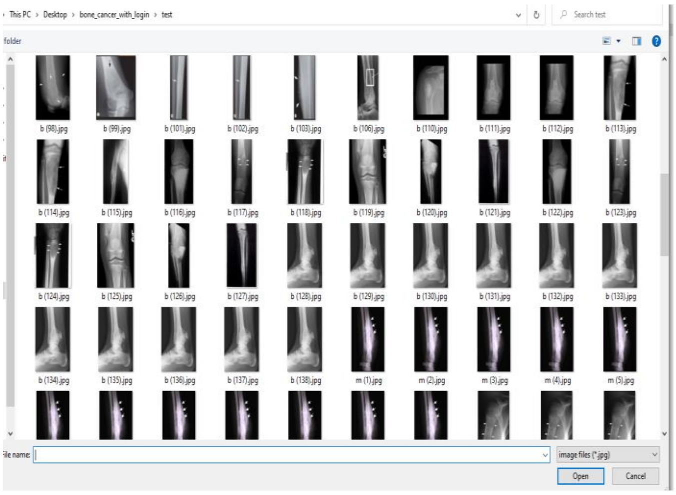

Fig - 5: Data Stored in Dataset of the project

The model is trained and the dataset is split in a certain ratio as training and testing data . We use the test images to classifiy and categorize the images and predict the stage for the images that are classified as cancerous images.

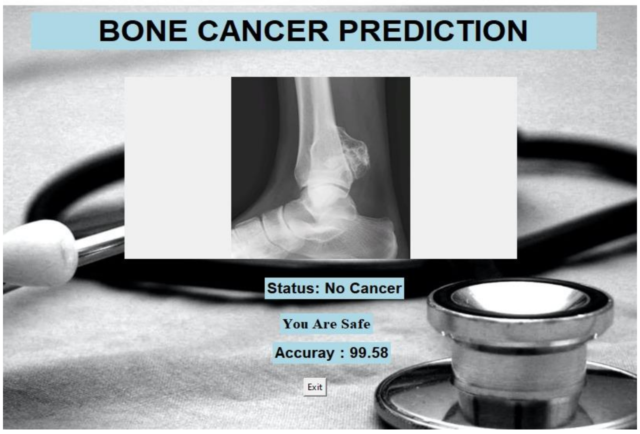

Fig - 6: No Cancer Prediction and Accuracy Calc.

The above figure 6 shows no cancer classification of the image input. In this the classifier has classified the test image as non-cancerous image, based upon the calculations made using CNN Algorithm employed for the prediction functionality. An message is displayed to the viewer as 'You are safe' based on the result as no cancer specifying that the image is not found to be malignant. Accuracy is calculated as a function of loss determined by the CNN classifier and displayed and an exit button is provided to exit the GUI Window.

The figure 7 shows that the image is classified as Stage-1 cancer ,it displays a message as the image is a cancerous image and then the stage is displayed below which is calculated based on the pixel area calculated for the different contour regions.

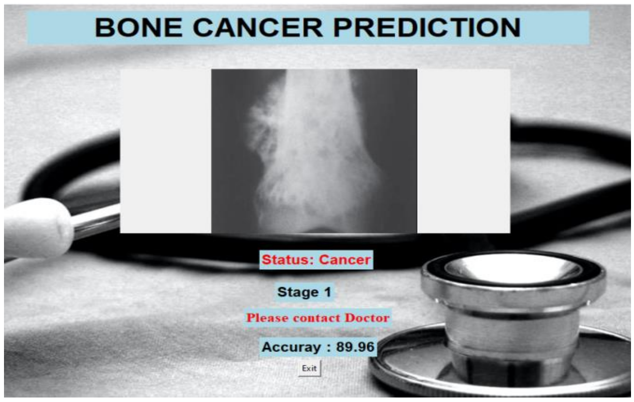

Fig - 7: Stage 1 Cancer Prediction and Accuracy Calc.

A message is alerted implying to concer a doctor as the bone image is classified as cancerous and is in beginning stage. Accuracy is calculated and displayed based on the loss calculations and exit button for closing the classification window.

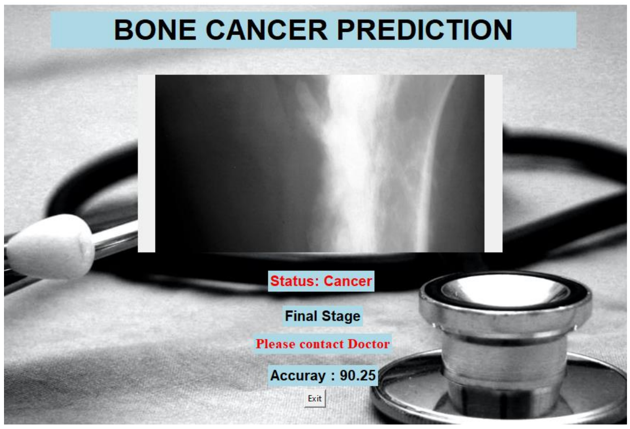

Fig - 8: Final Stage Cancer Prediction and Accuracy Calc.

Figure 8 presents a final stage classification of a bone image where based on the results obtained after analysis, classification and staging the stage is determined to be in its end stage as well a message is displayed and the predicted accuracy is displayed on screen .

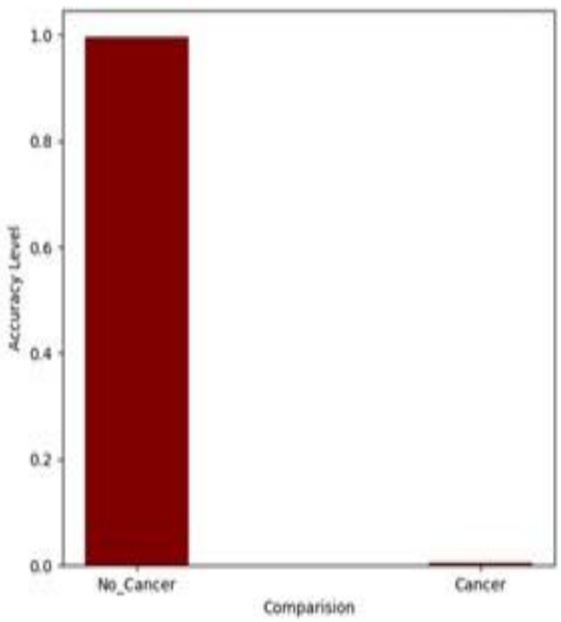

Fig - 9: Graphical representation of accuracy level

The above figure 9 shows the graphical view of accuracy level obtained and for the images classifed as cancerous and non-cancerous. It plots the accuacry calculated by the CNN classifier.

6. CONCLUSION AND FUTURE WORK

In this paper CNN and Open CV Python are used for bone tumor identification with pixel segmentation is built. The suggested technology is specifically designed to identify bone cancer. The system uses training data to discriminate among malignant and non-cancerous pictures, predicts cancer stage, and displays the results on a graphical user interface. Bone cancer detection is conducted out using the pictures provided.

This paper may be used for a variety of diagnostic and therapeutic purposes, as well as computer-assisted surgeries and categorization tasks. This will assist healthcare practitioners in classifying and comprehending the stage of cancer in various bones, which may be a highly useful, time-saving, and life-saving element in medical treatments. This method is more cost-effective, classification-wise, and needs less human interactions. The same approach may be used to distinguish between various tumors and categories.

The proposed method can be improved to recognize and forecast cancer stage in various images such as CT, X-Ray, and MRI. It could be enhanced to be more accurate in predicting phases. Because of the encouraging results achieved, our approach may be used in telemedicine, and the suggested technique could be implemented in smart phones or cloud computing, with the advantages of decreased computational burden, cheap cost, and very few parameters to setup.

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