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IDENTIFYING TUMOR USING X-RAY IMAGES

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ABSTRACT:

Bone cancer originates from bone and rapidly spreads to the rest of the body affecting the patient. A quick and preliminary diagnosis of bone cancer begins with the analysis of bone *X*-ray or MRI image. Compared to MRI, an *X*-ray image provides a low-cost diagnostic tool for diagnosis and visualization of bone cancer. In this paper, a novel technique for the assessment of cancer stage and grade in long bones based on *X*-ray image analysis has been proposed. Cancer-affected bone images usually appear with a variation in bone texture in the affected region. A fusion of different methodologies is used for the purpose of our analysis. In the proposed approach, we extract certain features from bone *X*-ray images and use support vector machine (SVM) to discriminate healthy and cancerous bones. A technique based on digital geometry is deployed for localizing cancer-affected regions. Characterization of the present stage and grade of the disease and identification of the underlying bone-destruction pattern are performed using a decision tree classifier. Furthermore, the method leads to the development of a computer-aided diagnostic tool that can readily be used by paramedics and doctors. Experimental results on a number of test cases reveal satisfactory diagnostic inferences when compared with ground truth known from clinical findings.

1. INTRODUCTION:

X-ray image analysis provides one of the cheapest primary screening tools for the diagnosis of brain cancer. As reported in the medical literature [16], a primary brain tumor usually appears with unsuspecting symptoms such as fracture of a brain, swelling around a brain, a new brain growth, or swelling in the soft tissues surrounding a brain. Oftentimes, an X-ray image of cancer-affected brain appears different from its surrounding healthy brains and flesh region. The X-ray absorption rate of brain cells in the cancer-affected region differs from that in healthy brain cells [16]. As a result, the image of cancer-affected brains appears in the form of a “ragged” surface (permeative brain destruction), tumor (geographic brain destruction), or holes (moth-eaten pattern of brain destruction) [7]. Grading of brain cancer and identification of the underlying brain-destruction pattern are two essential components needed for treatment of the disease. The stage and grade of brain cancer represent a measure of the severity of the disease. Progressive identification of destruction pattern in a cancer-affected brain also helps doctors to estimate the rapidity of growth of the disease, or prognosis of the treatment. Hence, automated classification of brain-cancer stage, grade, and destruction pattern will be useful to medical practitioners in order to plan for the course of treatment. In the past few years, researchers have proposed different approaches for brain-tumor detection. Conventional imageanalysis techniques such as thresholding, region growing, classifiers, and Markov random field model have been used for the detection of tumor region in X-ray and MRI1 images [11]. Frangi et al. [12] have used multi-scale analysis of MRI perfusion images for brain-tumor segmentation. They proposed a two-stage cascaded classifier for hierarchical classification of healthy and tumor tissues, and subsequently, to discriminate viable and non-viable tumors. Ping et al. [23] have proposed an approach based on intensity analysis and graph description for the detection and classification of brain tumor from clinical X-ray images. The method analyzes a graph representation to locate the suspected tumor area. It can also classify the benign and malignant tumor depending on the number of pixels extracted from the analysis of brightness values. Brain CT images have also been widely used for fracture detection and disease diagnosis. A fusion between CT2 and SPECT3 images is proposed for the identification of cancerous regions in brain image [22]. Yao et al. [28] have designed an automated lytic brain metastasis detection system. The procedure uses adaptive thresholding, morphology, and region growth for the segmentation of spine region. An approach based on watershed model is used for the detection of lytic brain lesions, and a support vector machine (SVM) classifier is used for feature classification and to diagnose the affected lesions. Automated diagnosis of secondary brain cancer from a CT image of brain vertebrae was proposed by Huang et al. [18]. Their technique involves texture-based classifiers and an artificial neural network (ANN), which are used for the detection of abnormality. Fuzzy-possibilistic classification and variational model are also utilized for multimodal brain cancer detection from CT and MRI images [6]. Most of the researchers have focused on the identification of brain tumor or cancer-affected region from CT or MRI. To the best of our knowledge, no automated method for determining the destruction pattern caused by brain cancer along with classification of its stage and grade is yet known. In this paper, we have proposed a computer-aided diagnostic method that can perform an automated analysis of brain X-ray images and identify the cancer-affected region. Our method can be used to localize the destruction pattern and to assess the severity of the disease based on its stage and grade. The rest of the paper is organized as follows. "Methods" discusses various phases of the proposed method and the features used for brain cancer detection. An algorithm for localizing the cancer-affected zone is presented in "Localization of Cancer-Affected Region." Procedures for classifying stage and grade of the disease are described in "Cancer Severity Analysis." Results on test cases and performance of the proposed method are reported in "Identification of Brain-Destruction Pattern." Discussions of test results and concluding remarks appear in "Results" and "Discussion," respectively.

1.1 Objective of the project:

Brain cancer originates from brain and rapidly spreads to the rest of the body affecting the patient. A quick and preliminary diagnosis of brain cancer begins with the analysis of brain *X*-ray or MRI image. Compared to MRI, an *X*-ray image provides a low-cost diagnostic tool for diagnosis and visualization of brain cancer. In this paper, a novel technique for the assessment of cancer stage and grade in long brains based on *X*-ray image analysis has been proposed. Cancer-affected brain images usually appear with a variation in brain texture in the affected region. A fusion of different methodologies is used for the purpose of our analysis. In the proposed approach, we extract certain features from brain *X*-ray images and use support vector machine (SVM) to discriminate healthy and cancerous brains. A technique based on digital geometry is deployed for localizing cancer-affected regions. Characterization of the present stage and grade of the disease and identification of the underlying brain-destruction pattern are performed using a decision tree classifier. Furthermore, the method leads to the development of a computer-aided diagnostic tool that can readily be used by paramedics and doctors. Experimental results on a number of test cases reveal satisfactory diagnostic inferences when compared with ground truth known from clinical findings.

2. LITERATURE SURVEY:

"Long-brain fracture detection in digital X-ray images based on digital-geometric techniques."

Automated fracture detection is an essential part of a computer-aided tele-medicine system. In this paper, we have proposed a unified technique for the detection and evaluation of orthopaedic fractures in long-brain digital X-ray image. We have also developed a software tool that can be conveniently used by paramedics or specialist doctors. The proposed tool first segments the brain region of an input digital X-ray image from its surrounding flesh region and then generates the brain-contour using an adaptive thresholding approach. Next, it performs unsupervised correction of brain-contour discontinuities that might have been generated because of segmentation errors, and finally detects the presence of fracture in the brain. Moreover, the method can also localize the line-of-break for easy visualization of the fracture, identify its orientation, and assess the extent of damage in the brain. Several concepts from digital geometry such as relaxed straightness and concavity index are utilized to correct contour imperfections, and to detect fracture locations and type. Experiments on a database of several long-brain digital X-ray images show satisfactory results.

"Automatic segmentation of brains in X-ray images based on entropy measure."

In this paper, we introduce an efficient method for segmenting the brain region of an X-ray image from its surrounding muscles and tissues. Automated segmentation of the brain part in a digital X-ray image is a challenging problem because of its low contrast with the surrounding flesh. The presence of noise and spurious edges further complicates the segmentation. Most of the existing methods either suffer from noisy contour detection or need training samples for manual tuning of certain thresholding parameters. We propose a fully automated segmentation technique, which utilizes a variant of entropy measure of the image. This scheme has been shown to be useful for fast and efficient analysis of a wide class of human X-ray images including skull, chest, pelvic region and ortho-dental zones. In order to quantify the quality of segmentation, we propose a new metric called *average contour distortion index* (ACDI) based on certain neighborhood properties of the contour pixels. Experiments on several X-ray images reveal encouraging results compared to other approaches as evident from the ACDI metric. We also re-validate the quality of several segmented brain images using *segmentation entropy quantitative assessment* (SEQA), and boundary-based precision–recall profile. All three metrics establish the superiority of the proposed technique to prior art.

"On the measurement of curvature in a quantized environment."

Some aspects of the application of the mathematical concept of curvature as a practical descriptor of shape for pattern recognition and image processing applications are investigated.

3. SYSTEM ANALYSIS

3.1 EXISTING SYSTEM*: X*-ray image analysis provides one of the cheapest primary screening tools for the diagnosis of brain cancer. As reported in the medical literature a primary brain tumor usually appears with unsuspecting symptoms such as fracture of a brain, swelling around a brain, a new brain growth, or swelling in the soft tissues surrounding a brain. Oftentimes, an *X*-ray image of cancer-affected brain appears different from its surrounding healthy brains and flesh region. The *X*-ray absorption rate of brain cells in the cancer-affected region differs from that in healthy brain cells . As a result, the image of cancer-affected brains appears in the form of a "ragged" surface (permeative brain destruction), tumor (geographic brain destruction), or holes (moth-eaten pattern of brain destruction)

Disadvantages:

- Low accuracy
- a small increase in the possibility that a person exposed to X-rays will develop cancer later in life. ...
- tissue effects such as cataracts, skin reddening, and hair loss, which occur at relatively high levels of radiation exposure and are rare for many types of imaging exams.

3.2 PROPOSED SYSTEM:

The retrospective study analyzed brain tumors on radiographs acquired prior to treatment from January 2000 to June 2020. Radiographs from 934 patients were evaluated including 667 benign brain tumors and 267 malignant brain tumors. Researchers used more than 600 cases to train the deep learning model and then 140 cases to validate and test it.The model achieved 80% accuracy and 88% specificity in the classification of brain tumors as malignant or benign. The models' accuracy in classifying tumors as malignant or benign was higher than that of two fourth year radiology residents and was comparable with that of two highly experienced musculoskeletal fellowship-trained radiologists.

ADVANTAGES:

- High accuracy
- noninvasively and painlessly help to diagnose disease and monitor therapy;
- support medical and surgical treatment planning; and.
- guide medical personnel as they insert catheters, stents, or other devices inside the body, treat tumors, or remove blood clots or other blockages.

4. Modules Information:

In this project we are implementing deep learning Convolution Neural Network (CNN) to predict brain tumor and to train this algorithm we have used brain images with and without tumor.

To implement this project we have designed following modules

1) Dataset upload: using this module we will upload dataset to application
2) Dataset Preprocessing: using this module we will read all images and then convert them into GREY format and then resize all images to equal size and then normalize pixel values.

3) Features Extraction: features or pixel values will be extracted from processed images and then input this features to CNN to trained tumor prediction model
4) Segmentation & Classification: using this module we will read test image and then apply segmentation to extract tumor part and then predict weather image is normal or contains any tumor. Edge detection technique will be applied to surround bounding box across tumor part

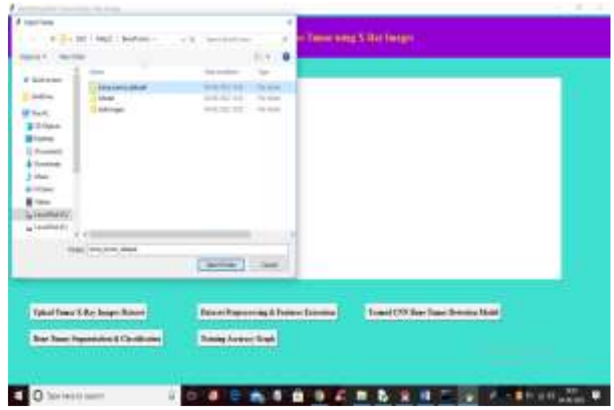
4. SCREENSHOTS:

Identifying Brain Tumor using X-Ray Images

In this project we are implementing deep learning Convolution Neural Network (CNN) to predict brain tumor and to train this algorithm we have used brain images with and without tumor.

To run project double click on run.bat file to get below screen

In above screen click on ‘Upload Tumor X-Ray Images Dataset’ button to upload X-Ray images dataset and get below output



In above screen selecting and uploading brain tumor dataset and then click on ‘Select Folder’ button to load dataset and then get below output

In above screen dataset loaded and now click on ‘Dataset Preprocessing & Features Extraction’ button to read all images and then process and extract features to train with CNN

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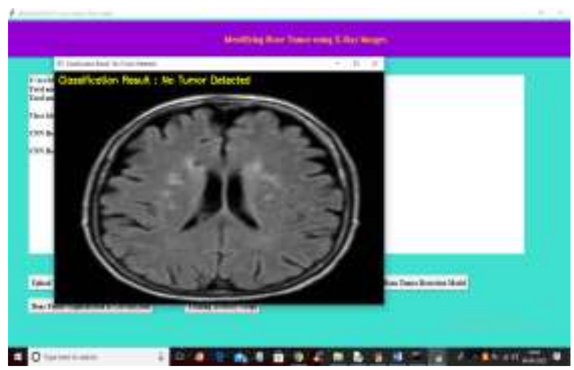
In above screen all images are processed and to check images are loaded properly so I am displaying one sample processed image and now close that image to get below output

In above screen we can see dataset contains 253 images with and without tumor class label and now click on 'Trained CNN Brain Tumor Detection Model' button to train CNN with above extracted features and get below output

In above screen CNN training completed and we got it accuracy as 96% and now click on 'Brain Tumor Segmentation & Classification' button to upload test image and get below output

In above screen selecting and uploading 5.jpg file and then click on 'Open' button to get below output



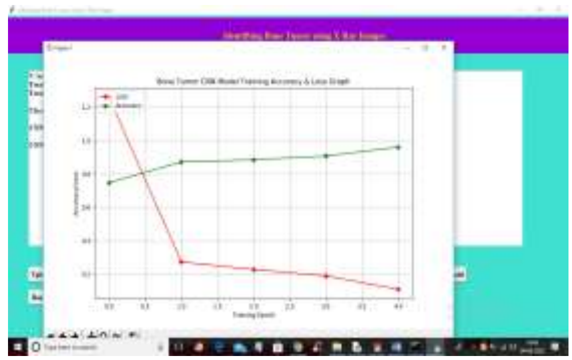
In above image 'No Tumor Detected' and now try another image

In above screen selecting and uploading '10.jpg' and then click on 'Open' button to get below output

In above screen first image is the original image which classified as tumor detected and second image is tumor segmented image and 3rd image is the tumor edge detected image and see another image is below screen

In above screen uploading 9.jpg image and click open button to get below output

In above screen we can see tumor detected with segmented out tumor image and with tumor edge detected. Similarly you can upload other images and test and now click on 'Training Accuracy Graph' button to get below graph



In above graph x-axis represents training EPOCH and y-axis represents training accuracy and loss values and green line representing accuracy and red line represents LOSS and in above graph we can see with each increasing epoch accuracy got increase and loss got decrease

5. CONCLUSION:

In this work, we have proposed a technique for automated long-brain cancer diagnosis for the first time that is solely based on the analysis of an input *X*-ray image. The proposed method integrates several interdisciplinary concepts such as statistical runs-test, local entropy- and standard deviation-based tools, digital-geometric analysis, SVM classification, and decision tree. The notion of ortho-convex cover of a cluster of marked pixels is used for convenient visualization and diagnosis of the disease and for grading the severity of cancer-affected regions. The use of digital-geometric tools leads to a fast estimation of the area of ROI as the required computation needs only integer-domain operations. Experimental results on a medical database of healthy and cancer-affected *X*-ray images reveal that the proposed method is fairly accurate as

AUC for brain cancer detection is more than 0.85. Further, in 85% of cases, the brain-destruction pattern, stage, and grade of cancer predicted by the automated tool correctly match with the actual findings as judged by the doctors and medical professionals

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