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Ameliorated Automated Facial Fracture Detection System using CNN

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Abstract: *The fracture of the bone is common issue in human body occurs when the pressure is applied on bone or minor accident and also due to osteoporosis and bone cancer. Therefore the accurate diagnosis of bone fracture is an important aspects in medical field. In this work X-ray/CT images are used for the bone fracture analysis. The main aim of the this project is to develop an image processing based efficient system for a quick and accurate classification of bone fractures based on the information gained from the x-ray / CT images of the skull. X- ray/CT scan images of the fractured bone are collected from the hospital and processing techniques like pre-processing method, segmentation method, edge detection and feature extraction methods are adopted. The images are tested out by considering the image slice of single slice and also grouping the slices of the patients. The patients CT scan/X-ray image was classified if bone is fractured then if two following slices were categorized with a probability fracture higher than 0.99. The results of the patient x-ray images show that the model accuracy of the maxillofacial fractures is contains 80%. Even the radiologist's work is not replaced by the MFDS model system, it is useful only for the providing valuable assistive support, it reduces the human error in the medical field, preventing the harm for the patients by minimizing the diagnostic delays, and reducing the incongruous burden of hospitalization.*

Keywords: Convolution Neural Network; Maxillofacial Fractures; Computed Tomography Images; Radiography

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