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Maxillofacial Fracture Detection Using Transfer Learning Models : A Review

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ABSTRACT

Early detection and treatment of face bone fractures reduce long-term problems. Fracture identification needs CT scan interpretation, but there aren't enough experts. To address these issues, researchers are classifying and identifying objects. Categorization-based studies can't pinpoint fractures. Proposed Study Convolutional neural networks with transfer learning may detect maxillofacial fractures. CT scans were utilized to retrain and fine-tune a convolutional neural network trained on non-medical images to categorize incoming CTs as "Positive" or "Negative." Model training employed maxillofacial fractogram data. If two successive slices had a 95% fracture risk, the patient had a fracture. In terms of sensitivity/person for facial fractures, the recommended strategy beat the machine learning model. The recommended approach may minimize physicians' effort identifying facial bone fractures in face CT. Even though technology can't fully replace a radiologist, the recommended technique may be helpful. It reduces human error, diagnostic delays, and hospitalization costs.

Keywords: Maxillofacial Fracture, Transfer Learning, AlexNet, VggNet, ResNet.

I. INTRODUCTION

In recent years, the number of requests for computed tomography (CT), magnetic resonance imaging (MRI), and, in general, radiology services have grown dramatically [1]. Nevertheless, there is a lack of radiologists due to recruitment challenges and many retirements. In this scenario, artificial intelligence (AI) can help radiologists in the time-consuming and challenging medical image analysis task. In any case, the AI-based tools do not replace medical staff, but assistive technologies prioritize, confirm, or validate radiologists' decisions and doubts.

The maxillofacial fractures are often complex, so the imaging findings should be familiar to the clinicians. To diagnose maxillofacial fractures, several radiographic approaches have been utilized.

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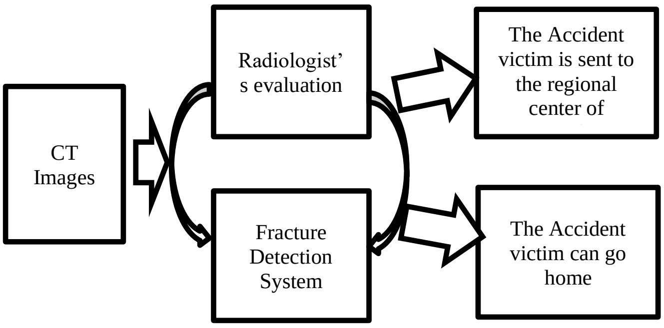

Figure 1. Traditional Methodology

This research aims to develop a fracture detection system, based on the transfer learning approach, able to predict the presence of maxillofacial fractures. The inputs for this system are the CT images of a patient after a trauma. The output of the system indicates the existence or not of a fracture.

II. LITERATURE STUDY

No.	Paper Title	Publication-Year	Methods	Limitation/ Future Work
1	Computer Aided Facial Bone Fracture Diagnosis (CA-FBFD) System Based on Object Detection Model	IEEE-2022	YoloX-S	It is classifying whether a person has a fracture or not, but the performance is only 69.8%.
2	Facial fractures: classification and highlights for a useful report	Springer-2020	Descriptors such as naso-orbito-ethmoidal complex, zygomaticomaxillary complex, and orbital "blowout"	Surgeons require information about the anatomic landmarks and features of the fracture such as the degree of displacement and comminution so they can plan treatment and predict possible complications.
3	Facial Fracture in the Setting of Whole-Body CT for Trauma: Incidence and Clinical Predictors	AJR-2015	Clinical method Glasgow coma scale	Prospective study in which all severely injured patients undergo maxillofacial CT as part of a standard head-to-pelvis trauma scanning protocol to screen for facial fractures may add further insights.
4	The Diagnosis and Management of Facial Bone Fractures	Elsevier-2019	Clinical Methods	The timely and appropriate utilization of these consultants can

				help to minimize a patient's risk of long-term morbidity and mortality.
5	Deep Sequential Learning for Cervical Spine Fracture Detection On Computed Tomography Imaging	IEEE-2021	DCNN with a bidirectional long-short term memory (BLSTM)	The validation results show a classification accuracy of 70.92% and 79.18% less.
6	Do Radiologists and Surgeons Speak the Same Language? A Retrospective Review of Facial Trauma	AJR-2016	Descriptors such as naso-orbito-ethmoidal complex, zygomaticomaxillary complex	Surgeons require information about the anatomic landmarks and features of the fracture such as the degree of displacement and comminution so they can plan treatment and predict possible complications.
7	Multidetector computed tomography of maxillofacial fractures	ScienceDirect-2013	Multi detector computed tomography (MDCT) with multiplanar reformation (MPR)	Maxillo-facial fractures require accurate radiologic diagnosis using MDCT and surgical management to prevent severe functional debilities and cosmetic deformity.
8	Transfer Learning for an Automated Detection System of Fractures in Patients with Maxillofacial Trauma	MDPI-2021	CNN, ResNet-50	This system proved to be capable of predicting maxillofacial fractures in patients with an accuracy of 80% which is very less.
9	Artificial intelligence in oral and maxillofacial radiology: what is currently possible?	Dentomaxillofacial Radiology (2021)	CNN	The limitations of in terms of data accessibility and the computing power required to solve complex problems are

				high.
10	The use and performance of artificial intelligence applications in dental and maxillofacial radiology: A systematic review	Dentomaxillofacial Radiology (2020)	artificial intelligence (AI)	Using adequate, representative images from multiple institutions prior to transferring and implementing deep learning models.
11	Ameliorated Automated Facial Fracture Detection System using CNN	IJARSCT-2022	CNN	By adding transfer learning concept, we can increase prediction accuracy and avoid model over-fitting problem which may rises due to less amount of dataset images.
12	A survey of fracture detection techniques in bone X-ray images	Springer-2020	Machine Learning, Deep Learning	The interpretation and classification of radiographic images by expert radiologists is a time-consuming and intense process, which could be solved using automated fracture classification models.

III. METHODS AND MATERIAL

A. Resnet [2,10]

ResNet-50 is a convolutional neural network that is 50 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database [1]. It is a construction piece that was destroyed but which still contains a bridged connector (formerly known as a legacy connection) that permits data to flow through it without being altered in any way despite the destruction. The data signal x is converted into an output signal F by the activation curve layer. It is composed of two types: layer 1 and layer 2, which are interconnected (x). The transfer seems to be comparable to those of a connection that has been skipped in this instance. The residual unit in this specific design demonstrates how it control signal x varies from those of the thanks to advances F, which is a result of the construction process itself (x). In accordance with the findings of this study, if the infrastructure has also fruitfully recreated the linear mapping that is assembled on a given spot, the improvements may be effective to minimize muscular endurance in the unavailable slabs on varying scales to essentially zero, but also guarantee that the output passes across the disconnect with next to no damage.

The ResNet architecture follows two basic design rules. First, the number of filters in each layer is the same depending on the size of the output feature map. Second, if the feature map's size is halved, it has double the number of filters to maintain the time complexity of each layer. ResNet-50 has an architecture based on the model depicted above, but with one important difference. The 50-layer ResNet uses a bottleneck design for the building block. A bottleneck residual block uses 1×1 convolutions, known as a "bottleneck", which reduces the number of parameters and matrix multiplications. This enables much faster training of each layer. It uses a stack of three layers rather than two layers.

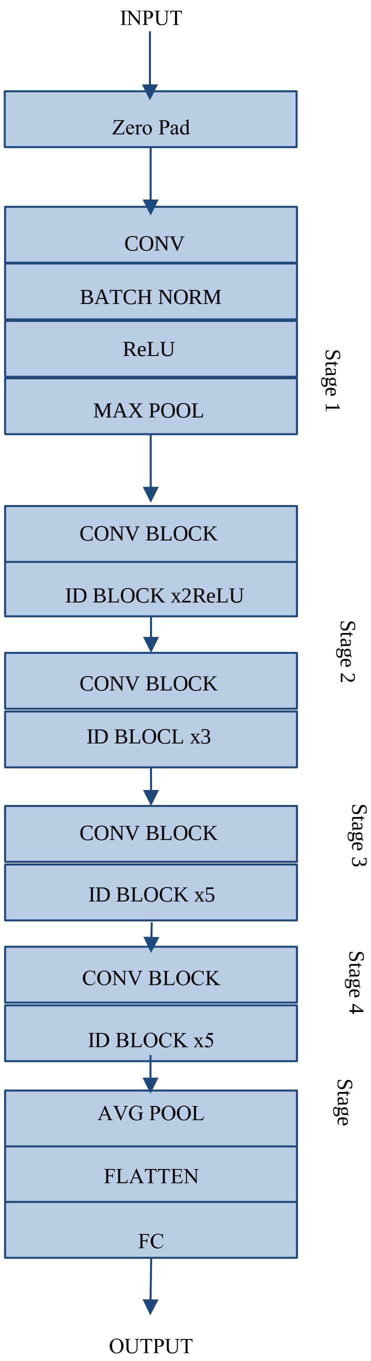

Figure 2. ResNet Model Layers

B. **VGGNet [1,10]**

The input to cov1 layer is of fixed size 224 x 224 RGB image. The image is passed through a stack of convolutional (conv.) layers, where the filters were used with a very small receptive field: 3×3 (which is the smallest size to capture the notion of left/right, up/down, centre). In one of the configurations, it also utilizes 1×1 convolution filters, which can be seen as a linear transformation of the input channels (followed by non-linearity). The convolution stride is fixed to 1 pixel; the spatial padding of conv. layer input is such that the spatial resolution is preserved after convolution, i.e., the padding is 1-pixel for 3×3 conv. layers. Spatial pooling is carried out by five max-pooling layers, which follow some of the conv. layers (not all the conv. layers are followed by max-pooling). Max-pooling is performed over a 2×2-pixel window, with stride 2. Three Fully Connected (FC) layers follow a stack of convolutional layers (which has a different depth in different architectures): the first two have 4096 channels each, the third performs 1000-way ILSVRC classification and thus contains 1000 channels (one for each class). The final layer is the soft-max layer. The configuration of the fully connected layers is the same in all networks.

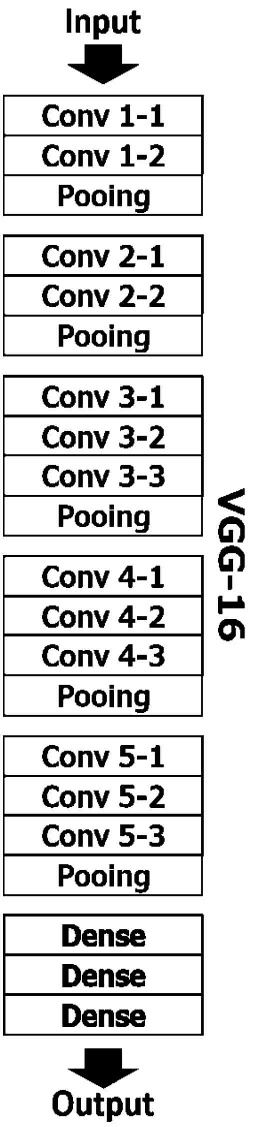

Figure 4. Vgg-16 Model Layers

All hidden layers are equipped with the rectification (ReLU) non-linearity. It is also noted that none of the networks (except for one) contain Local Response Normalisation (LRN), such normalization does not improve the performance on the ILSVRC dataset but leads to increased memory consumption and computation time.

C. AlexNet [1,5]

A large perceptron (RNN) may be able to achieve high excellent on a highly difficult dataset by using solely supervised learning methodologies, according to the findings of the AlexNet study. In the year after the debut of AlexNet, a competition was launched that has continued to this day.

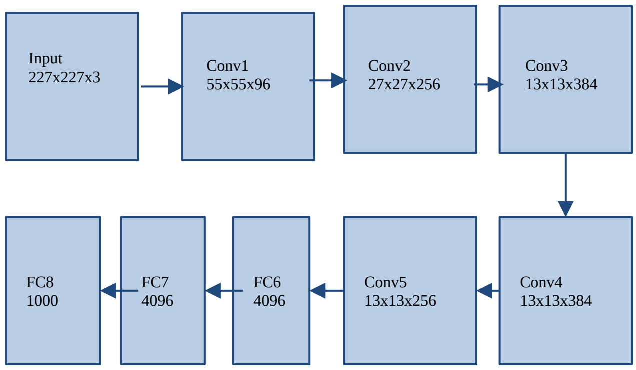

Figure 4. AlexNet Model Layers

The Convolutional Neural Network is used to categories all contributions to the ImageNet database. CNN is a pioneer in biomedical research, ushering in a new age with AlexNet, which was created in collaboration with the National Institutes of Health and launched in 2004. Because a variety of deep learning are readily available, the mounting of AlexNet is rather basic.

IV. Comparative Analysis

TABLE I

COMPARATIVE ANALYSIS

Method	Pros.	Cons.
ResNet [2]	It is possible to skip connections. It makes use of batch normalization to boost efficiency while maintaining accuracy.	Implementation is time-consuming.
AlexNet [5]	Unlike a convolutional layer, which depends on local spatial coherence and a narrow receiving field, a fully connected layer learns	Complicated layers with many connections are very computationally costly to create.

	features from all the combinations of the features of the preceding layer.	
VggNet [1,5,10]	It only contains 80 percent of the whole number of parameters.	Accuracy decreases in a very progressive manner.

V. CONCLUSION

Maxillofacial Fracture Detection early stages is very difficult and time-consuming process. Computer aided system uses past information based on that information it may identify the Fracture. Less accuracy of diagnosis Maxillofacial Fracture. To overcome problem of false diagnosis by unexperienced doctors may lead to increase survival rate of Maxillofacial Fracture patients.

In Future when it comes to classifying Maxillofacial Fracture classes depending on sub types of CT images transfer learning model perform better than other CNN models. In different models fine-tuning perform better than traditional CNN layers, by utilising the RESNET as transfer learning technique.

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