Section A-Research paper
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Maxillofacial fracture detection using transfer learning for accident victims

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ABSTRACT— We present a novel method for identifying traumatic maxillofacial fractures using convolutional neural networks with transfer learning (MFDS). A model for the categorization of future computed tomography (CT) scans as "fracture" or "noFracture" was developed by re-training a convolutional neural network previously trained on non-medical pictures using CT scans. There were a total of of 148 CT scans used to train the model (120 patients were identified as having a fracture, and 28 were labeled as having no fracture). There were a total of 30 patients included in the validation dataset utilized for statistical analysis (5 with "noFracture" and 25 with "fracture"). An additional 30 CT scans were utilized as the test dataset, including 25 "fracture" pictures and 5 "noFracture" images. Both a focus on individual slices and on grouped slices for patients was used in the tests. If the likelihood of a fracture in two successive slices was more than 0.99, the patient was considered to have a fracture. Patient data demonstrates that the model achieves an 80% rate of success in diagnosing maxillofacial fractures. Even while the MFDS model can't take the position of a radiologist, it can be a huge help in many ways: lowering the likelihood of mistakes, keeping patients safe by shortening the time it takes to get a diagnosis, and lightening the load of being hospitalized

INTRODUCTION

The demand for radiology services in general, including computed tomography (CT) and magnetic resonance imaging (MRI), has skyrocketed in recent years [1].

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However, there is a shortage of radiologists because of difficulties in recruiting and numerous retirements. The examination of medical images is a complex and time-consuming process, but AI may aid radiologists with this. Radiologists' choices and uncertainties are still given priority, confirmed, or validated by these assistive technologies, but they are not replaced by AI-based tools.

Recent advances in deep learning, a subfield of AI, have allowed for more accurate representation and understanding of complicated data using picture analysis. There are a number of publications [2–6] that focus on the use of deep learning to orthopedic traumatology. When it comes to deep learning with CT images for fracture identification, however, the amount of research is very small is low. The quantity of data needed to construct and train a neural network from start is also substantial. Data in the billions are used to teach image categorization networks. the books, with the help of numerous servers operating for a month [7]. Most scientists engaged in medical research simply cannot use this method. So-called transfer learning is one approach to overcoming this challenge. This method involves leveraging the enhanced features of convolutional neural networks, which are neural networks that have been trained on millions of data points as a basis for a new model. Kim and MacKinnon [8] use deep convolutional neural networks (CNNs) pre-trained on pictures unrelated to medicine to validate the degree of fracture identification on wrist radiographs. On the evaluation dataset, they were able to get an AUC-ROC of 0.95 with the use of the inception V3 CNN [9]. This finding demonstrates the viability of using a CNN that has been pre-trained on pictures outside of the medical domain for radiography. Chung et al. [10] used a convolutional neural network to analyze plain anteroposterior shoulders radiographs for signs of proximal humerus fractures and to categorize them accordingly. When compared to general doctors and surgeons who don't specialize in shoulders, the deep neural network's performance was on par with that of shoulder specialists. This finding indicates that it may be possible to automatically identify fractures using plain radiographs. Tomita et al. [11] conducted another research in this area, this time looking at the ability of CT scans to identify vertebral fractures caused by osteoporosis. They used a convolutional neural network (CNN) to pull out useful information from CT scans, and then a recurrent neural network, or RNN, module to pull everything together and provide a diagnosis. The suggested technology performed at the same level as human radiology practitioners. This means that the method has the potential to be utilized for identifying and prioritizing instances of possible fracture.

Despite the fact that several authors have described certain AI applications in orthopedics, the possibility of using artificially neural networks, as well as specific a transfer learning approach, to detect maxillofacial breaks in 3D photographs (CT scans) of injured patients has not been investigated as of yet [12-15]. Because of the anatomical complexities of the region and the unique nature of this kind of fracture, radiographic diagnosis is notoriously difficult and often leads to unnecessary stays. Reduced treatment costs and patient pain would result from the widespread use of an AI-based fracture detection system capable of identifying maxillofacial fractures in clinical practice.

The purpose of this study is to create a transfer learning-based system that can identify and forecast maxillofacial fractures. After a trauma, a patient's CT scans serve as inputs to this system. The system's output reveals whether or not a crack is present. Figure 1 depicts the system's block diagram.

RELATED WORK

Title: "Deep Learning for Fracture Detection"

The phrase "artificial intelligence" (AI) refers to the practice of programming a computer to simulate intelligent behavior with little or no human input. Recent advances in AI, especially deep learning, have enabled computers to better encode and analyze complicated data, opening up new possibilities in perception tasks. Artificial neural network layers are used to represent the deep learning subfield of AI. In the past few years, the field of deep learning has seen explosive growth. Some research has been done to see whether deep learning may be used to detect fractures in x-rays, namely in the fields of orthopaedics and traumatology. There is even less research on using deep learning to identify and categorize fractures in CT images. We present a high-level summary of deep learning technologies in this narrative review: In this paper, we (1) discuss the state of fracture identification using deep learning in the context of radiographs and computed tomography scans. talk about the benefits of deep learning, (3) express your thoughts on where this technology is headed, and (4) share your thoughts on the future of this discipline.

"Deep neural network-based skin cancer classification at the dermatologist's level"

Visual inspection is the first step in diagnosing skin cancer, the most prevalent human malignancy1, 2, 3. This is followed by a clinical screening and, if necessary, a dermoscopy, a biopsy, and a histological evaluation. Due to their very varied appearances, automated skin lesion categorization from photographs is a difficult problem. In several fine-grained object categories, convolutional neural networks with deep layers (CNNs)4,5 have shown promise for broad and highly variable tasks.6,7,8,9,10,11. Here, we show that a single CNN can be trained from scratch on pictures alone, utilizing just pixel data and illness labels as inputs, to correctly classify skin lesions. We use a dataset if 129,450 clinical photos representing 2,032 disorders to train a convolutional neural network (CNN), which is two orders magnitude bigger than earlier datasets12. Using biopsy-proven clinical pictures, we compare its performance to that of 21 board-certified dermatologists in two crucial binary sorting use cases: identifying keratinocyte carcinomas from benign seborrheic keratoses and malignant melanomas from benign nevi. In the first scenario, the most prevalent tumors were discovered, whereas in the second scenario, the most lethal kind of skin cancer was found. To show that AI can identify skin cancer at a level that is equivalent to dermatologists, the CNN obtains performance on level with all evaluated professionals across both tests. With the use of mobile devices equipped with deep learning algorithms, dermatologists may soon be able to contact patients outside of traditional medical settings. By 2021, an estimated 6.3 billion people will have access to a smartphone, which might lead to ubiquitous, low-cost access to important diagnostic services.

"Development and Evaluation of a Deep Learning-Based Algorithm for Identification of Diabetes-related Retinopathy in Retinal Foundation Photographs."

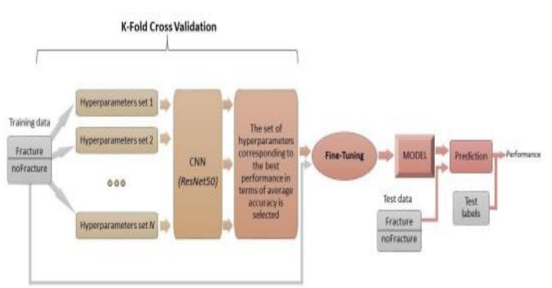
There is no longer a need to explicitly express rules when using deep learning, a family of mathematical methods that allows an algorithm to teach itself through instruction from a vast number of examples demonstrating the desired behavior. These approaches' potential for use in medical imaging still needs further testing and evaluation.

This is a preview of "Deep Learning in Medical Imaging:"

Inspired on the human neural synapse system, the artificial neural network, also known as an ANN, was developed as a machine learning technology in the 1950s. However, the ANN's past capability in solving real-world problems was limited by issues including gradient vanishing and over fitting with train of deep architecture, insufficient processing power, and, most importantly, a lack of appropriate data for conditioning the computer system. New techniques for training deep neural networks, together with improved computational power provided by modern graphics processing units, have sparked renewed interest in this idea in recent times. According to recent research, this technology has the ability to outperform humans in some optical and aural identification tasks, which might foreshadow its future use in the medical and healthcare industries, particularly in medical imaging. This survey article discusses the origins, evolution, and current uses of the technology for deep learning, with a focus on the field of medical imaging.

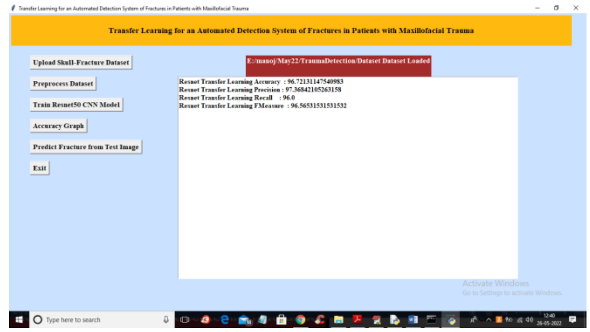
METHODOLOGY

After removing all identifying information, pictures from CT tests were used in this retrospective investigation. The research was sanctioned by the "Federico II" University Ethics Committee in Naples, Italy (permission number 81/20). The CAT scans came from the U.O.C. of Facial Surgery at the University Hospital "Federico II"'s internal database, which houses data from all exams performed at the hospital between the years 2000 and 2020. The face mass was examined using CT on a variety of machines (TC 16-64 slice) with thicknesses volumetric acquisition (0.2–2 mm) and varying in-plane resolution (0.5–1 mm). Only pictures made using the bone restoration method were used in the study. Each CT picture was independently inspected, interpreted, and categorized by a pair of radiologists (R.C., L.U.) based on the presence or absence of fracture patterns. Patients who had the non-traumatic facial masses condition served as controls for the CT scans. One CT scan is performed for each patient, therefore the total amount of CT scans is equal to the total number of people being scanned. There were a total of 208 patients in the dataset, with 170 patients having CT scans labelled with the word "fracture" (representing 11,260 individual slices) and 38 patients having CT scans labelled with the word "noFracture" (representing 49,762 individual slices). Separate training, validation, and testing sets were created from the whole dataset. More specifically, there were 148 CT scans used in the training dataset (120 patients identified as having "fracture" and 28 categorized as having "noFracture"). Thirty patients (5 with "noFracture" and 25 with "fracture") made up the validation dataset utilized for statistical analysis, and another thirty CT scans, including 25 "fracture" and 5 "noFracture" pictures, were used as the test dataset for the final evaluation. Notably, the majority of patients in the whole dataset had fractures, whereas the slices tagged "noFracture" had a lopsided advantage in the dataset as a whole. If we simply look at the patient-level data, we may conclude that the dataset is skewed toward "fracture" photos, but this is not the case.

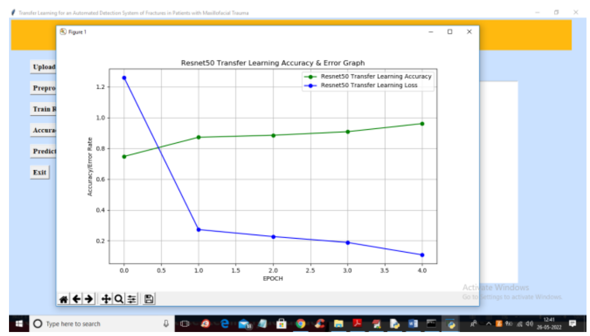


Block diagram of the system's implementation for detecting fractures in patients with maxillofacial trauma.

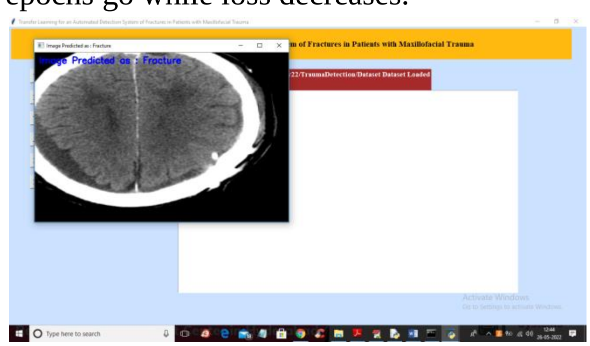
RESULT AND DISCUSSION



RESNET50 Knowledge Transfer On CNN, our predictions were spot on 96% of the time.



The following graph shows the relationship between training epoch (x-axis) and accuracy (y-axis) and loss (blue line) over time. As can be seen, accuracy improves as epochs go while loss decreases.



Prediction of Fracture

CONCLUSION

This work demonstrates the feasibility of using transferable knowledge from a CNN that has been pretrained on pictures that are not related to medicine to the diagnosis of maxillofacial fractures in CT scans. There is a gap in the research on maxillofacial fracture detection using transfer learning on CT images of wounded individuals. Our method was shown to have an 80% success rate in predicting maxillofacial fractures in patients. In the case of maxillofacial trauma, MFDC has the potential to become an invaluable tool for supporting radiologists in making a timely diagnosis, which in turn might minimize the likelihood of medical errors and protect patients from injury and anxiety. It would be beneficial for the individual, society, and healthcare system if an AI-based system could aid radiological examination in general clinical wards.

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