Maxillofacial Fracture Detection System in Accident Victims using Convolution Neural Network (CNN) Transfer Learning

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Abstract

It is proposed that a novel maxillofacial fracture detection system (MFDS) be developed to identify traumatic fractures in patients, using the use of deep learning and transfer techniques. To classify future computed tomography (CT) scans as "fracture" or "no Fracture," we re-trained a convolutional neural network on CT scans after it had been initially trained on non-medical images. A total of 148 CT scans were used for training the model (120 patients were annotated as having a fracture, and 28 were annotated as having no fracture). Five patients were classified as having "no Fracture," and the remaining 25 were classified as having a fracture; these 30 patients made up the statistical analysis validation data set. The whole dataset used for validation included 30 CT images, 25 of which had "fracture" labels and 5 had no such labels, and both sets were used. Both a focus on individual slices and on grouped slices for patients was used in the tests. Patients were considered to have fractures if two successive slices had a fracture probability of more than 0.99. In terms of classifying maxillofacial fractures, the model has an 80% accuracy rate, as evidenced by the patients' outcomes. The MFDS model may not be able to fully take over the radiologist's duties, but it can certainly help by lowering the likelihood of mistakes, protecting patients from harm by shortening the time it takes to make a diagnosis, and alleviating the disproportionate load of staying in the hospital.

Keywords:Deep Learning, Fracture, Statistical, Dataset, Convolutionand Radiologist.

1. Introduction

In recent years, there has been a noticeable rise in demand for radiology services, including but not limited to computed tomography (CT) and magnetic resonance imaging (MRI). Unfortunately, there is now a scarcity of radiologists due to challenges in recruiting and a large number of retirements. Radiologists have a tedious and time-consuming duty in evaluating medical pictures, but AI may help. Radiologists may use the AI-based tools as a complement to their own clinical judgment and expertise to better establish priorities, verify hypotheses, and reduce uncertainty.

The field of artificial intelligence has seen significant progress in recent years, particularly in the area of deep learning. Through the use of advanced algorithms and image analysis, deep learning has greatly improved the understanding and representation of complex data.In orthodontic traumatology, transfer learning is addressed in a number of published works [2, 3, 4, 5, 6]. However, there is a dearth of literature on the use of machine learning to CT scanners for the purpose of fracture diagnosis. In addition, a huge quantity of data is required to construct and train the neural network system right from the start. Image classification methods grounded in the literature are often built over numerous servers and several weeks' worth of data [7]. In practice, this approach is infeasible for the vast majority of medical researchers. The use of transfer learning is one approach to overcoming this barrier. Our initial approach involves utilizing a convolutional neural network that has undergone extensive training on millions of data points. Kim and MacKinnon [8, 9] utilized transfer learning techniques to increase the accuracy of identifying wrist fractures on radiographs. Specifically, they employed convolutional neural networks with deep learning (CNNs) that had been previously trained on non-medical images. The validation data showed that a Convolutional Neural Network (CNN) [9] achieved an AUC-ROC of 0.95. This study found that a convolutional neural network (CNN) trained on non-medical images can be effectively utilized for analyzing chest radiographs in healthcare environments. Using a Classifier to analyze plain posterior shoulder radiographs for trochanteric fractures, Kang et al. [10] conducted a separate study. The deep neural network performed as good as or better than both general doctors and those who had no expertise in shoulder surgery when their results were compared to those of shoulder-specialist orthopedic surgeons. This study suggests that it would be feasible to use plain radiographs to provide an automated diagnosis of fractures. Tomita et al. [11] did a different research on the topic, this time examining the accuracy of CT scans for detecting osteoporotic vertebral fractures. Both a network of convolutional neural networks (also known as CNN for obtaining radioactive information from recurrent neural network (RNN) and a Computed Tomography Scan(CTs) component to cumulate the derived items into a final diagnostic were crucial to their approach. The suggested technology was just as effective as a team of human radiologists. This technique might be used to determine which instances of probable fracture are the most urgent and then rank them accordingly.

By employing transfer learning techniques, specifically within artificial neural networks, the study aimed to improve the accuracy of the system, to detect reconstructing plastic fractures in three-dimensional models (CT scans) of patients with injuries has not yet been investigated [12,13,14,15], despite the fact that multiple researchers have described specific AI applications in orthopedics. Due to the anatomical complexity of the region and the rarity of this kind of fracture, radiographic identification is sometimes challenging and is associated with an ongoing risk of discordant admissions. Having an artificial intelligence (AI) based fractures detection device that could recognize maxillofacial injuries in clinical practice would be immensely beneficial in lowering treatment costs and improving patient comfort.

2. Related Work

Deep learning is used to the issue of fracture detection.

The term "artificial intelligence" (AI) is used to describe the practice of emulating human intellect using technology with little to no input from actual humans. Robots' capacity to represent and understand complex data has vastly improved because to recent advancements in AI, notably deep learning. Deep learning is a specialization of artificial intelligence that makes use of many "layers" of artificial neurons. In the past few years, deep learning's popularity has skyrocketed. There has been investigation on whether deep learning techniques may be utilized in the disciplines of orthopedic surgery and traumatology to detect fractures in x-rays. Even little work has been done in the field of deep learning(DL) is used to detect and label fractures in Computed Tomography (CT) scans. In the following narrative summary, we present a broad overview of deep learning, including topics such as: In this work, we (1) provide an overview of how deep learning has been used so far to enhance fracture recognition in Computed Tomography(CT) scans and radiographs. Explain how deep learning has helped the area thus far and what you think the future holds for it.

"Deep neural networks for dermatologist-level skin cancer classification"

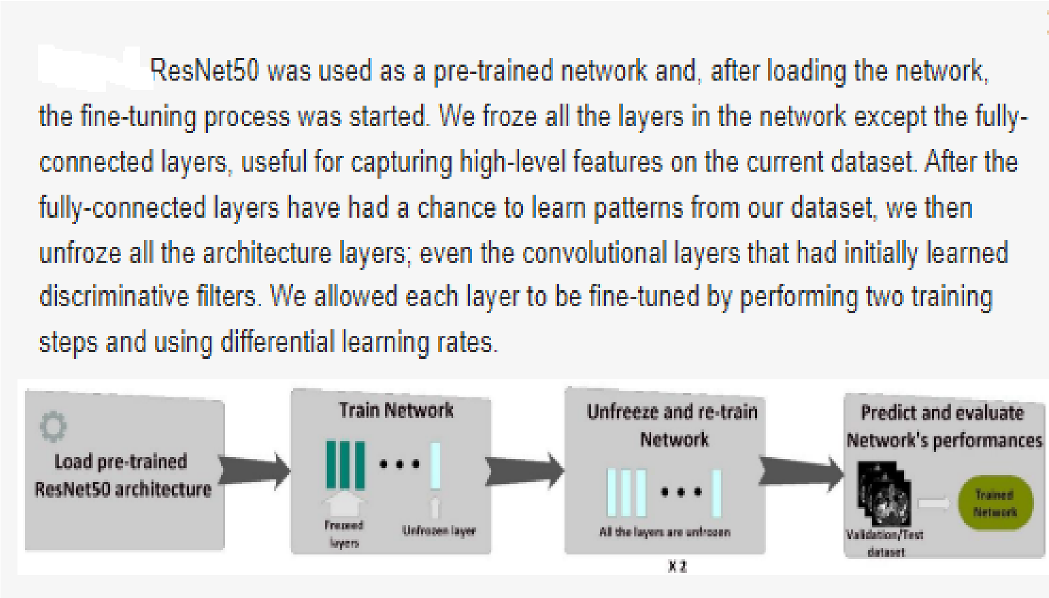
The most common kind of cancer in humans may usually be detected with a simple clinical screening1, 2, 3. Dermatoscopy, a biopsy, and a histological study are all possible next steps if additional investigation is warranted. Automatic image classification is challenging because skin lesions vary so finely in appearance. Across a diverse range of fine-grained object categories, deep convolutional neural networks (CNNs) have demonstrated significant potential and versatility, as evidenced by several studies6-11. In this study, we demonstrate how to diagnose lesions on the skin using one convolutional neural network (also known as CNN that was trained pixel-by-pixel on images with just disease labels. We employ a dataset that is two orders magnitude larger than previous datasets12 to train a neural network based on convolution (CNN), which includes 2,032 diseases and 129,450 clinical photos. Using proven-biopsy clinical images and use cases of two critical binary classification, we evaluate its performance in comparison to that of 21 dermatological specialists. These use cases include distinguishing keratinocyte tumors from normal seborrheic keratoses and melanoma from benign nevi. Both the most common types of tumors and the worst kind of tumors on the skin were found in the first scenario. Results from both tests demonstrate that the CNN works at exactly the same degree as all examined professionals, demonstrating that AI is capable of identifying skin cancer without the same degree of accuracy as dermatologists. With the advent of deep neural networks on smartphones and tablets, dermatologists could be able to see patients outside of regular business hours. There will likely be 6.3 billion smartphone owners by 2021, which might provide widespread access to low-cost diagnostic services.

Title: "Development and Validation of a Deep Learning System for Identification of Diabetic Retinopathy in Retinal Fundus Images"

An ensemble of computational algorithms, deep machine learning eliminates the need for explicit rule definition, instead relying on a large corpus of examples to enable the algorithm to learn the desired behavior autonomously. More research and testing is required before these methods may be employed in diagnostic imaging.

3. Methodology

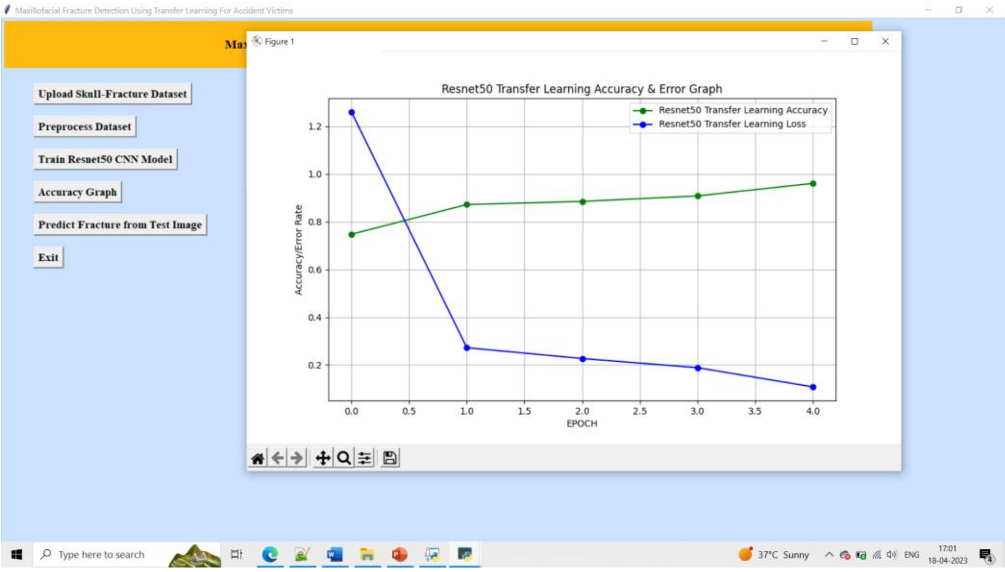
By implementing fine-tuning techniques, pre-existing neural networks can be adapted to recognize new classes that were not originally within the scope of the system's design.
The convolutional layers have previously been trained to function as discriminative filters. Selecting the hyperparameters as detailed allowed us to swap out the pre-trained CNN's final set of completely linked layers. For this, we used random weights to create an additional set of fully-connected layers. In this way, the completely linked layers might do any arbitrary action. Yet, the pre-trained network's robust features are at risk if such unknowns and the entirety of the network are used to backpropagate gradients.
Last but not least, we trained the last layer by initially freezing every other layer inside the network's body aside from it, and then applying the model's weights (acquired from ImageNet training) to it. In this method, we trained the final layer.
When the final stack had started to recognize patterns in our data, the researchers thawed every single parameter and trained the entire model at a slow pace of learning. It was important to keep the convolutional filters relatively untouched.


ResNet50 was used as a pre-trained network and, after loading the network, the fine-tuning process was started. We froze all the layers in the network except the fully-connected layers, useful for capturing high-level features on the current dataset. After the fully-connected layers have had a chance to learn patterns from our dataset, we then unfroze all the architecture layers; even the convolutional layers that had initially learned discriminative filters. We allowed each layer to be fine-tuned by performing two training steps and using differential learning rates.

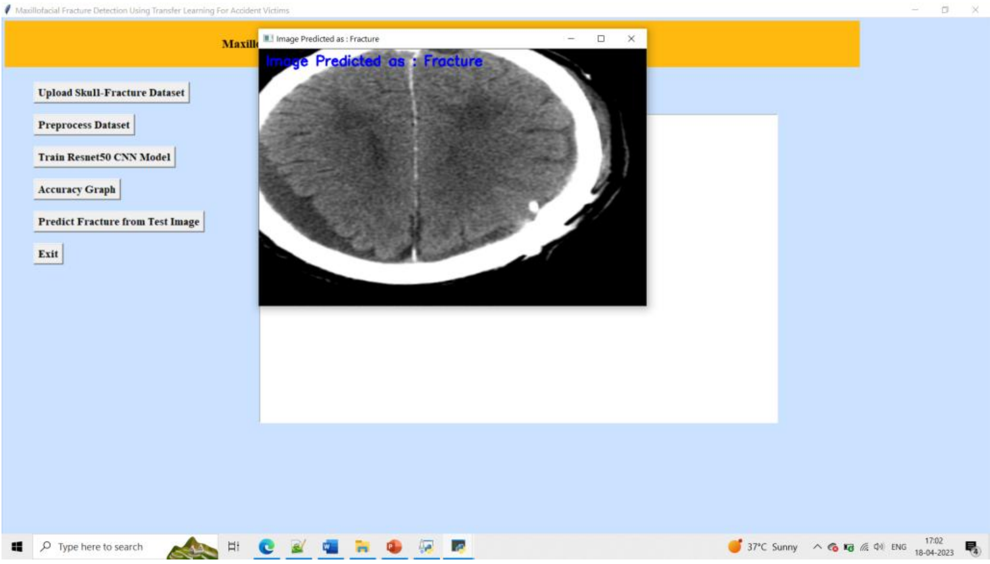
We utilized the whole dataset to fine-tune the network. In specifically, the training dataset included 34,962 "noFracture" slices and 8023 "fracture" slices, corresponding to a total of 148 individuals. A portion of this training dataset was utilized for both the validation and training stages of the k-fold cross validation. We utilized CrossEntropyLoss as a loss function, but we gave the "fracture" and "noFracture" classes (wf & wnf, respectively) different weights due to the imbalance between them:

4. Result and Discussion

Thereafter, the dataset is placed in either the fracture or non-fracture folder, and the resulting skull fracture dataset is uploaded. The accuracy of CNN models trained with preprocessed datasets, namely the Resnet50 model, is much higher.



The following graph shows the relationship between training epochs The x-axis shows time, while the y-axis shows precision and loss (represented by the y-axis), with a rise in accuracy and a reduction in loss as epochs progress.



The above picture shows a fracture that is expected to occur.

5. Conclusion

This work demonstrates the viability of using transfer learning from a CNN that has been pretrained on pictures that are not related to medicine to the diagnosis of maxillofacial fractures in CT scans. No research on using transfer learning on CT images of wounded individuals to identify maxillofacial fractures has been found in the existing literature. Maxillofacial fractures may be predicted with 80% accuracy using our approach. With the potential to aid radiologists in establishing a prompt diagnosis of maxillofacial injuries, MFDC might help reduce the risk of medical mistakes and save patients from harm. The implementation of an AI-based system for radiological inspections in general clinical wards would benefit not only individual patients, but also society and the healthcare system as a whole.

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