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A DEEP LEARNING APPROACH ON CERVICAL SPINE FRACTURE DETECTION

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***Abstract*— Cervical spine fractures need time-consuming study by skilled radiologists, which might present problems for institutions with limited resources. They are a major concern in the area of radiology. Computer-aided diagnosis (CAD), which employs the cutting-edge imaging method of multi-detector CT, has grown in favor for identifying cervical spine fractures as a solution to this problem. To avoid neurologic degeneration and paralysis brought on by trauma, early detection of vertebral fractures is essential. In this study, we design and train a deep learning model to identify fractures in the cervical spine, both at the patient's overall level and at the level of specific vertebrae, using CT scan pictures. Our goal is to improve the model's performance in correctly diagnosing cervical spine fractures. The suggested deep learning model analyzes CT images and offers automated aid in fracture detection by utilizing cutting-edge methods and developments in computer vision. We demonstrate the efficiency of our model in localizing cervical spine fractures through thorough training and assessment on a variety of datasets, which can help radiologists with their diagnosis and expedite treatment planning. Reduced interpretation times, higher accuracy, and expanded accessibility to high-quality treatment are all possible advantages of this strategy, particularly in healthcare institutions with limited resources.**

***Keywords*— CAD, C1, C2, C3, C4, C5, C6, C7, C8, Efficienetv2s, LSTM, CNN**

I. INTRODUCTION

Despite the rarity of cervical spine injuries, they can have catastrophic and long-lasting repercussions due to the flexibility and shape of the spine. Trauma, which can occur from falls, sports injuries, auto accidents, or diving occurrences, is the main cause of cervical injuries. Cervical injuries can also result from non-traumatic causes such osteoporosis-related compression fractures, arthritis, inflammation of the spinal cord, or cancer. There are several different kinds of cervical injuries that can happen, including spinal cord flexion, rotation, compression, contusion, and extension, with injuries to the C2, C5, C6, and C7 regions being the most frequent. A comprehensive history and physical examination are essential in identifying probable cervical injuries because pathophysiological mechanisms underlie spinal cord damage. Neck stiffness or soreness may be an indication of cervical fractures or dislocations, and doctors will use CT scans to precisely pinpoint any cervical spine fractures. To handle these diagnostic pictures, many hospitals do not have enough competent radiologists. Computer-aided diagnosis (CAD) has grown in prominence recently as a solution to this problem. Doctors may effectively identify cervical spine fractures with the use of CAD, which has been widely utilized to analyze medical pictures. It is essential to locate vertebral fractures as soon as possible to stop neurologic decline and paralysis after trauma.

The use of computer-aided diagnosis (CAD) for medical image analysis has increased as a result of the lack of skilled radiologists in many institutions. This method has received increasing attention recently and is frequently used by doctors to detect cervical spine fractures. In order to avoid the neurological deterioration and paralysis that might happen as a result of trauma, it is essential to find any vertebral fractures as soon as possible. Given the close link between the cervical spine and the brain, any injury to or failure to recognize problems in this area might raise death rates. Our lives are not complete without information technology since it makes managing the unexpected parts of daily life much easier. It offers a wide variety of strategies to encourage the growth and exchange of knowledge. Medical technology, which includes both low- and high-risk medical equipment, has been created to diagnose, treat, and improve the health and wellbeing of humans. Doctors can gain from increased diagnosis accuracy by analyzing CT (Computed Tomography) pictures of patients using computational techniques. By giving clinicians a useful tool to overcome the difficulties they have while analyzing medical pictures, this method aims to help patients. 13 Given the dearth of qualified radiologists in many institutions, the use of CAD in medical imaging is crucial. Medical gadgets and other forms of technology have been crucial in advancing research and enhancing healthcare results. The study of medical pictures using computational methods has improved diagnostic precision, eventually raising the standard of care given to patients.

II. LITERATURE SURVEY

A deep learning system that is capable of recognizing traumatic fractures on TL spine sagittal radiographs was suggested in this work [1]. The authors acquired data from 362 individuals who had serious fractures to their vertebrae. Of these patients, 171 had sagittal radiographs that were annotated by a team of competent spine surgeons. Using the dataset, deep learning classifiers based on the ResNet18 and VGG16 architectures were trained, verified, and evaluated. We evaluated the accuracy, sensitivity, specificity, and precision of the models' capacities to find the fracture zone inside the vertebral body. According to the data, ResNet18 and VGG16 both achieved accuracy values of 88% and 84%, respectively, with each model having a sensitivity of 89%. When compared to VGG16, ResNet18 demonstrated superior specificity with an 88% accuracy rate. On 81% of the heatmaps, the fracture zone was located with pinpoint accuracy. The researchers arrived at their conclusion that their artificial intelligence model successfully spotted anomalies in sagittal radiographs that were indicative of vertebral fractures because it properly located the fracture zone inside the vertebral body. It is possible that the adoption of this kind of instrument in clinical settings might reduce the number of vertebral fractures that are missed by emergency departments.

This study [2] presented a deep convolutional neural network (DCNN) as a screening tool, identification tool, and location tool for vertebral fractures (VFs) by using basic abdominal frontal radiographs (PARs). Because they are associated with an increased risk of later fractures, vertebral fractures (VFs) are an essential indicator in the prevention of secondary fractures. However, in the initial PARs reports, only 46.6% of VFs were identified, highlighting the requirement for improved VF detection methods that are both more accurate and more efficient. To find a solution to this problem, the scientists made use of a deep convolutional neural network (DCNN) that had been pretrained with ImageNet and then retrained with 1304 photographs from the PARs database that had been taken between August 2015 and December 2018. For the purpose of model interpretation, the gradient-weighted class activation mapping (Grad-CAM) method was used. Additionally, the accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC) of the model were investigated. The outcomes of the study indicated that the DCNN had an AUC of 0.72 for the identification of VF, along with an accuracy of 73.59%, a sensitivity of 73.81%, and a specificity of 73.02%. The authors reach the conclusion that computer-driven approaches paired with DCNNs have the potential to detect VFs with great accuracy when used opportunistically on PARs acquired for a range of therapeutic aims. This was the result reached by the writers. The current treatment pathway for treating fragile fractures may be made more successful and cost-efficient with the help of this proposed model, which can also assist clinicians in becoming more effective.

This work [3] sought to compare the diagnostic performance of AI and physicians in fracture detection by first looking at peer-reviewed papers and gray literature published between January 2018 and July 2020 (updated to June 2021), and then utilizing peer-reviewed publications as a baseline. In other words, the peer-reviewed articles would serve as a baseline. Among the 6 studies were the 42 studies, 115 contingency tables, and a combined total of more than 55,000 photographs that were obtained from the investigations that included the 32 studies. According to the findings, there were no statistically significant differences between the two groups in terms of diagnostic performance for fracture diagnosis between AI and doctors. This was the case even though the research focused on AI rather than doctors. The pooled sensitivity and specificity for AI and clinicians both revealed modest variations, and these variations were dependent on the type of validation set that was applied. The study did, however, highlight some of the causes of data heterogeneity, such as the possibility of bias and the different types of fractures. Radiography, computed tomography (CT) scans, and magnetic resonance imaging (MRI), among other imaging modalities, have all been examined as potential applications of artificial intelligence for the purpose of fracture detection. Several research that has used AI to reach outstanding levels of accuracy in fracture detection have proven that there is potential for better diagnostic efficiency and accuracy in clinical practice. This has been demonstrated by the findings of these investigations. Despite this, there are still challenges associated with the need for sufficient governance and standards, as well as ensuring the validity and generalizability of AI models.

According to the findings of this study [4], the C-spine convolution neural network developed by Aidoc and authorized by the FDA is able to identify fractures of the cervical spine on CT images with a high level of diagnostic accuracy. Following the examination of 665 CT scans, the research project utilized retrospective CT visualization to identify the underlying reality. The diagnostic precision of both the convolution neural network and the radiologists' judgments, as well as their level of agreement with the actual world, were evaluated in this study. According to the findings, the convolution neural network had a detection accuracy of 92% for cervical spine fractures, with a sensitivity of 76% and a specificity of 97%, respectively. Radiologists had an accuracy rate of 95%, with a sensitivity rate of 93% and a specificity rate of 96%. Both the convolution neural network and the radiologists failed to notice some fractures, such as those in the lower cervical spine that were hidden by the attenuation caused by the CT beam, as well as fractures in the anterior osteophytes, transverse processes, and spinous processes. The research indicates that convolution neural networks can help radiologists prioritize their to-do lists when recognizing cervical spine fractures on CT scans; however, more work has to be done to boost their sensitivity. It is essential to have a full understanding of the benefits and drawbacks associated with the convolution neural network before putting it to use in the medical field.

This study [5] suggests assessing the performance of a deep convolutional neural network (CNN) in recognizing and classifying proximal humerus fractures by using basic anteroposterior (AP) shoulder radiographs. During the course of the experiment, a dataset consisting of 1,891 photographs was utilized. These pictures depicted healthy shoulders as well as four distinct types of proximal humerus fractures, which were distinguished by three specialists. The CNN showed performance that was superior to that of general practitioners and orthopaedic surgeons, and performance that was equivalent to that of

Orthopaedists performed even better than humans when it came to the classification of complex fractures with three and four parts. These data suggest that AI is capable of properly recognizing and classifying proximal humerus fractures on plain shoulder AP radiographs, which may increase the efficacy and precision of existing orthopaedic tests. Additional study is necessary in order to determine whether or not AI algorithms can be successfully implemented in the diagnostic and treatment planning of fractures.

This research [6] presented an automated strategy for recognizing unintentional osteoporotic vertebral fractures (OVFs) in a CT scan of the chest, abdomen, and pelvis. These fractures are caused by osteoporosis. A deep convolutional neural network, also known as a CNN, was utilized by the system in order to extract radiological data. Following that, a feature aggregation module was used to analyze these characteristics so that a final diagnostic could be obtained for the full CT scan. We looked into a variety of different methods for aggregating features, one of which being the usage of an LSTM network. After being trained and evaluated on a total of 1432 CT images, the system achieved a score of 90.8% on the F1 scale and achieved an accuracy of 89.2%. The findings indicate that the suggested technique may be useful in assisting with and improving OVF diagnosis by pre-screening typical CT images and flagging troublesome instances for radiologists to examine. These results are comparable to that of experienced radiologists in their field.

Research was carried out in the manner that is described in this study [7] in order to answer the question of whether or not using scout CT lateral radiographs to diagnose vertebral fractures (VFs) is accurate. Three musculoskeletal radiologists independently examined 300 CT images of the thoracic and/or lumbar spine by using a semi-quantitative approach for VF assessment on CT. This technique was used to either the thoracic or the lumbar spine. When a VF was found, morphometric analysis was performed, and the gold standard was generated from the results of multiplanar sagittal CT reconstructions performed by the nine radiologists with the most expertise. According to the findings of the study, CT exhibited high levels of interobserver and intraobserver agreement in addition to superior diagnostic accuracy, sensitivity, and specificity when it came to the detection of VFs. The effectiveness of this technique was unaffected by arthrosis, the level of the vertebrae, as well as the kind and degree of VFs. The researchers reached to the conclusion that CT is an easy yet highly accurate approach for VF diagnosis, and that it should be utilized as a spine evaluation tool for VF detection in CT scans that are carried out for other diagnostic purposes. This was one of the main findings of the study.

This work [8] evaluated the inter-reader and intra-reader agreement for diagnosing vertebral fractures using spinal images taken from CT scans of 100 individuals. The images were taken from the backs of the participants. A method that is only semi-quantitative was utilized in order to determine the severity of the fractures. According to the data, there was good to exceptional inter-reader agreement for fractures that were more severe, whereas the agreement ranged only from acceptable to good for fractures that were less severe. There was fair to high intra-reader agreement, with the level of agreement increasing with the severity of the fracture. The degree of agreement was at its lowest for fractures in the upper thoracic levels, and the lumbar region was much easier to analyze than the thoracic region. According to the findings of the research conducted, CT scout pictures are particularly useful in clinical research settings for diagnosing vertebral fractures. Nevertheless, it is essential to take into account the variety of possible interpretations, in particular in the case of mild fractures and fractures in the upper thoracic region. For the purpose of bolstering consensus, it is vital to standardize interpretive procedures and conduct further research.

In order to explore the incidence of cervical spine fractures in relation to demographic data and the cause of injury, the author of this paper [9] undertook a retrospective analysis. This allowed them to evaluate the processes of such fractures and investigate the link between cervical spine fractures and the cause of damage. The study included 934 patients who had CT scans performed on them at one of 16 hospitals and one level I trauma center over the course of two years as part of their treatment for cervical spine injuries. Patients were only included into the study if there was at least one positive result obtained from a CT scan, regardless of their demographics. According to the results of the study, males were affected more frequently than females at a ratio of 2.1, and the age groups of 21–30 and 31–40 had the highest frequency of cervical spine injury. This was the case in both countries. Accidents involving motor vehicles were the leading cause of injury, accounting for 66.1% of all cases, followed by falls from heights of less than 8 feet, which caused 12.2% of all injuries. Hispanics made up 23.3% of the population, making them the second largest ethnic group, behind only Caucasians (46.9%). The vertebrae C1 and C2 were the ones that fractured the most frequently, with C2 being the one that was most commonly affected. There was no statistically significant difference in the incidence of odontoid fractures compared to body and lateral mass fractures. These findings may provide crucial knowledge to medical practitioners, allowing them to better manage patients who have injuries to their cervical spine.

This research [10] proposed a computer-assisted method that takes use of deep learning techniques in order to automatically detect and categorize fracture regions in calcaneus CT images. The goal of this strategy was to automate the identification and classification of fracture locations. Comparing the accuracy with which two different convolutional neural network (CNN) architectures, ResNet and VGG, categorized CT scans into fracture-related or non-fracture-related categories utilizing coronal, sagittal, and transverse 11 views was the objective of this study. The findings showed that ResNet, which has a neural network architecture that is more complicated than VGG's, performed better while still obtaining the same level of accuracy (98%) as VGG. The SURF method for matching the fracture region, Canny edge detection, and contour tracing are the three components that make up this technology for identifying bone fractures. The researchers used actual patient fracture data sets in order to demonstrate the viability of applying deep CNN and SURF for computer-assisted classification and identification of calcaneus fracture sites in CT images. This was done so that the researchers could demonstrate the viability of employing deep CNN and SURF.

III. PROPOSED SOLUTION

The cervical vertebrae (C1–C7), which are located in the region of the neck, are the smallest of the vertebrae that make up the spinal column. They have a unique anatomical structure that allows for more mobility in their necks. The purpose of this endeavour is to make a prognosis regarding the chance of fracture for each of the seven cervical vertebrae, which are denoted by the letters C1, C2, C3, C4, C5, C6, and C7, as well as the probability that the cervical spine as a whole would suffer any fractures. Vertebrae in the neck can break for a number of different causes, including being in an automobile accident, slipping and falling, or being injured while playing sports. Because they can cause damage to the spinal cord and other neurological disorders, these injuries are considered to be severe and may even be deadly. The early and accurate detection of fractures is vital to providing appropriate treatment and care for patients. The training data for the deep learning model consists of a data frame holding patient details and fracture labels, a bounding box data frame for precisely locating the location of the fracture, and a folder containing CT scan photographs in.dcm format. These three data frames are contained within a single folder. It is necessary to correctly identify and label the cervical vertebrae in CT images in order to perform fracture investigation and diagnosis in a timely manner.

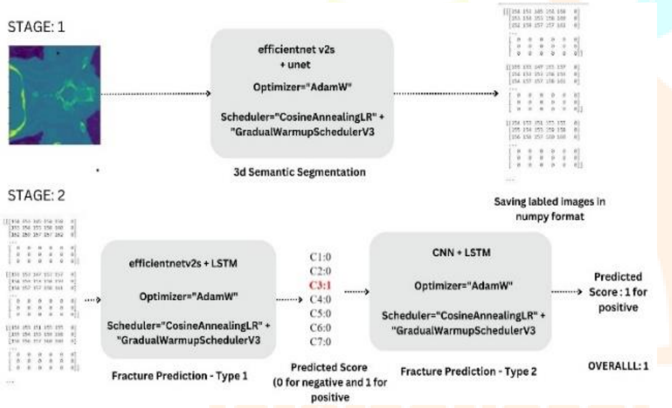

Fig.1. Workflow

Based on the findings of this research, a first stage strategy for 3D semantic segmentation utilizing a deep learning model constructed using the U-Net architecture is proposed. The U-Net network serves as the decoder for this method, while an EfficientNetV2-S backbone is utilized for feature extraction. In order to ensure the robustness and generalizability of the segmentation model, a technique known as 5-fold cross-validation is utilized throughout the training process. The incorporation of data augmentation procedures results in an improvement to the performance of the model, and assessment measures demonstrate how accurate the recommended strategy is. In order to facilitate the process of segmentation, a new Data Frame is built and then populated with the filenames of the mask files as well as the necessary study instance IDs. This Data Frame is joined with the initial training Data Frame based on the study instance IDs that were provided. It is crucial to have data augmentation techniques available in order to improve the performance of models and reduce instances of overfitting. Valid PyTorch data augmentation transforms are utilized in the training and transformations that are being performed. The segmentation model design relies heavily on the U-Net framework as its primary building block. It requires an input picture that is 128 by 128 by 128 pixels and has three channels as a batch size requirement. In order to extract feature representations from the input image, the encoder makes use of the EfficientNetV2-S backbone. Skip connections are utilized in order to merge the feature maps generated by the encoder and decoder blocks. The semantic segmentation process is finished when the decoder block provides an output image with 7 channels that is 128x128x128 and shows the likelihood that each vertebra is present. This picture has a dimension of 128x128x128. The model is trained by employing a methodology known as 5-fold cross-validation. During the training process, both the dice loss and the binary cross-entropy (BCE) loss are calculated in order to improve the performance of the model. An assessment of the training set and the validation set is performed throughout each epoch so that convergence may be monitored. In order to draw additional conclusions from the best-performing models, each fold that is preserved. An evaluation of the trained models is performed on a training picture, and test pictures are utilized to determine how accurate the segmentation model is. Evaluation methods are utilized in order to ascertain whether or not segmenting each individual vertebra was successful. The cervical vertebrae can be located and labeled with a high degree of precision using the segmentation model that has been suggested. The evaluation metrics for the segmentation model are presented in Table 1, together with the accuracy ratings for each individual vertebra. The recommended method is effective, as demonstrated by the average accuracy of 95% across all of the vertebrae, which was found to be the case. Following the phase of labeling the data, it was then saved in numpy format so that the next step could be completed.

The outcomes of the first stage are used as input for the second phase, which is called fracture identification, and the goal of this step is to locate fractures in each of the seven vertebrae for each individual patient ID. The seven cervical vertebrae (C1-C7) from each CT scan with an input size of 224x224 and utilizes 15 slices per channel are employed to forecast the possibility of fracture by employing efficientnetv2s backbone, which is a pretrained encoder. The Type 2 model utilizes Conv, a pretrained encoder and LSTM layers, as well as two fully connected layers with an input size of 224x224, and it uses 15 slices per channel with 7 vertebrae [C1-C7], in order to determine the overall likelihood of fracture in each CT scan. Additionally, the Type 2 model has an input size of 224x224. The output of the previous model, which contains the projected probabilities of fracture for each of the cervical vertebrae (C1-C7), is used by the Type 2 model to estimate the overall fracture probability. This is accomplished by using the earlier model. Following its journey through a series of Convolutional and LSTM layers, the input to the Type 2 model is particularly a concatenation of the projected probabilities of each cervical vertebra. These probabilities are then fed into two fully connected layers, which are responsible for the final prediction of the total fracture risk.

IV. RESULTS AND DISCUSSION

The performance of the model was evaluated based on the classification metrics included in the findings. Table **I** displays the criteria that were utilized to evaluate the effectiveness of the stage 1 segmentation model in precisely localizing and labelling the cervical vertebrae while making use of the EffnetV2 architecture. The model was able to correctly identify each individual vertebra, with accuracy scores ranging from 0.94 to 0.96 for the first through seventh cervical vertebrae. It was discovered that the procedure that was recommended yielded an accuracy of 0.95 when it came to the segmentation of the cervical spine across all of the vertebrae.

While Table I provides informative information on the performance of the model in terms of segmentation, it is equally as important to assess how effectively it can locate fractures in the cervical spine. Table I can be found here. In order to do this, it is necessary to take into consideration classification metrics. These metrics assess how well the model performs in reliably categorizing occurrences as fractured or non-fractured.

As a consequence of this, in addition to the assessment of segmentation, a separate evaluation was carried out to grade the model's skill to recognize fractures, and the results of this evaluation are presented in Table **II**. The categorization metrics, which included sensitivity, specificity, accuracy, and F1-score, were given to the patient as a whole (Prediction 2) as well as each individual vertebra (Prediction 1) in order to make a prediction.

Table **I**: Evaluation Metrics of the Segmentation Model

MODEL	VERTABRA	ACCURACY
EffnetV2	C1	0.96
EffnetV2	C2	0.94
EffnetV2	C3	0.95
EffnetV2	C4	0.96
EffnetV2	C5	0.95
EffnetV2	C6	0.95
EffnetV2	C7	0.94
EffnetV2	Average	0.95

The stage 2 model produces two outputs: Prediction 1, which predicts the presence of fractures in each of the cervical vertebrae (C1–C7), and Prediction 2, which predicts the presence of fractures throughout the patient as a whole. Both of these predictions are referred to as "predictions." The basis for the examination was a collection of CT scans with binary markers for each cervical vertebra and the patient's overall existence of fractures. These CT scans were used to determine whether or not the patient had any fractures. Before averaging the results, we calculated the evaluation metrics on an individual basis for both Predictions 1 and 2 and then obtained the overall assessment metrics.

The following is a list of the evaluation's findings:

Table **II**: Comparison of Evaluation Metrics

Metric	Prediction 1	Prediction 2	Overall Performance
Sensitivity	0.025	0.797	0.411
Specificity	1.0	0.81	0.90
Accuracy	0.50	0.80	0.65
F1-score	0.049	0.805	0.427

Table **II** demonstrates how successful our method is in determining whether or not there are fractures in the cervical spine. As a result of the model's overall accuracy of 0.65 and F1-score of 0.427, it has the potential to be of assistance to radiologists in the process of diagnosing fractures to the cervical spine. Based on these measures, it appears as though our method has the potential to reduce the amount of time and effort required for manual CT image evaluation. Nevertheless, more research on more extensive It is essential to validate the generalizability of the model as well as its potential therapeutic usefulness by making use of other datasets with a wide variety of characteristics.

CONCLUSION

The suggested technique for diagnosing cervical spine fractures makes use of a pipeline that combines 2D+LSTM classification models with 3D segmentation. After being cropped, the portions of the CT images corresponding to the vertebral bodies are retrieved using a 3D segmentation model, and then they are submitted to 2D classification models for fracture detection. In the first stage, the 87 segmentation photographs are used to label the training images, and in the second stage, a separate model is used to integrate the slice-level predictions and provide a final fracture prediction. The 87 segmentation pictures may be found here. The technique that has been suggested involves recording the fracture probability on the validation set of the dataset. In conclusion, the multi-stage technique that has been described demonstrates encouraging results for the task of identifying fractures in the cervical spine, and it may be able to assist radiologists in making accurate and efficient diagnoses.

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