



A Survey on Cervical Spine Fracture for Detecting the Ankylosing Spondylitis

Kanajam Rishi Madhur^a, Korada Ganesh^a, Kalla Surya Prakash^a, Kolluru Bhargav^a, Jayavarapu Lokesh^a

^a Department of Computer Science and Engineering, GMR Institute of Technology, Rajam, Andhra Pradesh, India

ABSTRACT

Ankylosing spondylitis (AS) is a chronic inflammatory disease that primarily affects the spine and sacroiliac joints. One of the complications of AS is a vertebral fracture, which can lead to pain, disability, and even spinal cord injury. Early detection of fractures is important for timely intervention and prevention of further damage. In recent years, various imaging techniques, such as X-ray, computed tomography (CT), and magnetic resonance imaging (MRI), have been used to detect fractures in patients with AS. Additionally, computer-aided detection and diagnosis (CAD) systems based on machine learning algorithms have been developed to improve the accuracy and efficiency of fracture detection. Cervical spondylitis is a degenerative condition that affects the cervical spine and can cause neck pain, stiffness, and other symptoms. The use of computed tomography (CT) scans has become the preferred method for imaging adult spine fractures, as it provides more detailed information compared to x-rays. The use of a hybrid deep learning model that combines segmentation, efficient net models, transfer learning with CNN, and unsupervised methods such as fuzzy c-means have shown promise in accurately diagnosing fractures in the cervical spine. Early detection of cervical spondylitis is important for preventing further disease development and avoiding neurologic deterioration and paralysis

Keywords: Cervical Spine Fracture, Cervical Spondylitis, Image Segmentation, Fuzzy C-means, Efficient Net.

1. Introduction

Little to severe cervical spine fractures can cause a variety of symptoms and results, such as pain, stiffness, paralysis, and even death. The course of treatment for a cervical spine fracture frequently varies on the kind and extent of the fracture, the patient's age, and general condition. Non-surgical options like bracing, physical therapy, and pain management may be sufficient in some circumstances. Surgery may be required in more serious situations to stabilize the fracture and stop further damage or problems. Age, osteoporosis, and prior injuries are just a few of the risk factors for cervical spine fractures that people should be aware of. Putting measures in place to keep up a balanced diet and exercise schedule, Furthermore to donning the necessary safety equipment while engaging in high-risk activities, will assist lower the chance of suffering a cervical spine fracture. For deep learning models to be used in clinical practice, they must first undergo clinical validation. This entails proving the models' dependability, efficacy, and safety as well as addressing moral and legal concerns regarding their application to medical imaging. That is a fantastic review of deep learning's promise in the area of medical imaging and its uses in identifying fractures in the cervical spine. It emphasizes the significance of investigating the application of deep learning algorithms and approaches, as well as the requirement to weigh the benefits and drawbacks of this strategy. The use of deep learning in medical imaging has the potential to significantly increase diagnostic efficiency and accuracy, resulting in better patient outcomes. Deep learning models can understand intricate characteristics and patterns in pictures by using a lot of data, which can dramatically increase the accuracy of diagnosis compared to more conventional techniques. It's also crucial to keep in mind that deep learning is a discipline that is always developing, so there is still plenty of space for new research and practical uses. Deep learning has the potential to improve patient outcomes and diagnostic performance when combined with other technologies like wearables and artificial intelligence. All things considered, this publication is an invaluable resource for scholars, medical specialists, and anybody interested in the subject of medical imaging the use of deep learning to diagnose fractures in the cervical spine.

2. Methods:

The study [1] gathered cervical vertebrae CT data from two locations: Severance and Gangnam Severance Hospitals for illness data (N=17) and Seoul National University Bundang Hospital for data on healthy controls (N=24). For picture segmentation, the [1] U-Net, a CNN version, was employed. It is composed of two layers: encoding layers that utilize max pooling for downsampling and decoding levels that use transposed convolutional layers for upsampling. It has been demonstrated that U-Net performs well when segmenting biomedical images.

Networks of synthetic neurons known as artificial neural networks (ANNs) [2] help machine learning techniques. The collection includes 681 single sacroiliac joint grayscale JPEG pictures that were taken from tagged CT scan DICOM frames from 53 patients [2]. Grey-level texture characteristics were less able to differentiate between erosion and normal-old than they were between erosion and normal-young, giving the E vs. Y classifier the greatest

average recall of 92.9%. A deterministic classification technique, the k-nearest neighbors (k-NN) algorithm produces the class related to the space of the provided sample. A decision tree is used as a prediction model for deterministic classification by decision tree classifiers.

Answers to the [3] BDI-II test from 484 hospital patients are included in the data set. Fuzzy rules, which can be derived from data or expert views, are generated using the data. Fuzzy rules may be extracted using clustering techniques, such as the Mutual Information Feature Selection with Adaptive Parameters algorithm. The accuracy of the suggested approach varies from 63% to 100% for each level of depression, and defuzzification is done using the centroid technique. The section explains how data from 484 hospital patients using the BDI-II test were collected, creating a database of 484 rows and 21 columns. [3] This information may be gleaned via professional judgments or retrieved utilizing clustering strategies such Selection of Mutual Information Features Using Adaptive Parameters. A 95% accuracy rate for the normal stage, 73% for the mid-stage, 63% for the moderate stage, and 100% for the severe stage are achieved by the suggested approach for determining depression severity. Defuzzification was performed using the centroid approach. In lateral X-ray images, the cervical vertebral body's [4] horizontal and angular displacement is measured as the primary approach for assessing cervical instability. Retrospective clinical data collection and digital radiographs of 121 cervical spondylosis patients were performed, and the diagnosis was made based on clinical symptoms present for at least one month. The intensity of neck discomfort was assessed using the visual analog scale, and patients were split into two groups depending on their symptoms.

A total of 183 research participants were separated into three groups after healthy volunteer subjects were gathered. The means of the groups were compared using one-way [4] ANOVA testing on quantitative data, which were represented as mean SD. The study's main objective is to assess cervical instability in cervical spondylosis patients. In lateral X-ray images, the cervical vertebral body's horizontal and angular displacement is measured as the primary way of assessment. The study gathered clinical information and digital radiographs of 121 individuals with cervical spondylosis, who were identified based on the presence of symptoms for at least a month before diagnosis. Using the visual analog scale (VAS) [4], which may be used to classify neck discomfort as mild, moderate, or severe, patients were separated into two groups depending on their symptoms. 62 healthy volunteer participants were also included in the study, making a total of 183 participants who were split into three groups. One-way ANOVA tests were performed to compare the means of the groups. Quantitative data are given as mean SD.

The study [5] classified pixels using image segmentation utilizing K-means clustering on de-identified flexion-extension radiographs from cervical spine fusion patients. The created approach enables the quantitative study of variations in vertebral motion and curvature as well as alterations to implanted hardware. The average processing and segmentation time for a picture was 3.53 seconds, and it took three to four passes to find the best parameter settings. The graft settling during fusion and larger stresses being transferred through the stiff construct are two theories that might account for the discrepancies that have been observed.

The study [6] assessed the severity of cervical spondylosis (CS) based on FA and ADC values. It used DTI technology to measure the microstructural alterations of the compressed spinal cord and nerve roots. According to the findings, DTI values are connected to clinical assessments of CS patients and may be useful in determining how serious the problem is. The most often utilized diagnostic techniques for CS are MRI, CT, and X-ray. to diagnose cervical spinal fractures using CT images, researchers developed an AI-based decision support system called AI-doc [7] and used failure mode analysis to pinpoint the system's weak points.

According to the study [7], the system's diagnostic findings were not very reliable, and further investigation and assessment are required to identify the problems and make the system better before it is made available to the general public. Information from attending neuroradiologist pictures was manually extracted during data processing and analysis, including the existence and kind of fracture, the number of broken vertebrae, an estimate of the age of the fracture, and the study indication.

The segmentation algorithm [8] is broken down into three sections and employs a convergence segmentation process, PointNet++, and an adaptive threshold filter to increase accuracy. The methodology beat other approaches in testing, with an accuracy rate of 96.15%—the highest recorded on the dataset [8]. With cervical spine instability, which can compress spinal cords and nerve roots and result in symptoms like numbness and paralysis, the algorithm is used to recognize and diagnose the issue. To automatically identify cervical spine fractures in CT axial images, researchers suggested

A deep convolutional neural network (DCNN) [9] with a bidirectional long-short-term memory (BLSTM) layer. The model's classification accuracy for positive and negative instances was 70.92% after being trained on a dataset of 3,666 CT images. The study found that while categorizing an imbalanced dataset, accuracy was 80.01%, and when classifying a balanced dataset, accuracy was 77.61% [9]. Ankylosing spondylitis (AS), a chronic rheumatic illness that affects young individuals and produces inflammatory back pain, was the subject of a research investigation [10]. The study included 13 patients with non-traumatic chronic lower back pain as a control group and 15 individuals with AS. On plain radiographs, the AS patients exhibited active illness and displayed indications of sacroiliitis with grades ranging from 2 to 4.

According to the study [10], the AS group's demographics and illness features, including the BASDAI, Bath Ankylosing Spondylitis Functional Index, and inflammatory markers including CRP and ESR, are described

The high prevalence of vertebral artery injuries (VAIs) (11), which can be prevented by early detection and timely anticoagulation, and the related stroke rate in patients with blunt cerebrovascular injury (BCVI). To maximize yield while minimizing the use of invasive procedures, routine screening should include complex cervical spine fractures involving subluxation, extension into the foramen transversarium, or upper C1 to C3 fractures. Four-vessel cerebrovascular angiography is the standard screening test for patients at risk for BCVI. Due to the close closeness of the vertebral arteries and cervical spine, the literature [11] also challenges whether all patients with cervical spine fractures require arteriography to rule out VAI.

The application of several image segmentation methods, such as patch-based classification, SegNet, [12] SVM, and U-Net, for pixel-by-pixel segmentation of pictures, notably for discriminating between various spinal segments and recognizing vertebral discs, is described. These methods employ supervised learning algorithms, convolution layers, and deep neural networks to precisely segment pictures.

46 individuals with cervical spondylosis IJV compression syndrome were included in this research [13] and received regular medical care. The first cervical vertebra (C1), which predominated in most individuals with osseous impingement or compression, was the main culprit. A significant risk factor for the degradation of cervical vertebrae, which results in osseous impingement-induced IJVS, is long-term work requiring repeated neck movements or inappropriate alignment. Data analysis was performed using SPSS 19.0, and one-way ANOVA [13] or the t-test was employed to examine continuous variables with Gaussian distributions. We have observed that the first cervical vertebra (atlas, C1) is the primary contributor in a significant portion of IJVS patients who exhibit osseous impingement or compression. Jugular vein narrowing below the base of the skull is a frequent occurrence. It's cervical spondylosis. Long-term employment that necessitates repetitive neck movements or incorrect alignment may be the most significant risk factor for the deterioration of cervical vertebrae in young individuals, which culminates in osseous impingement-induced IJVS. Due to longer life expectancies, upper cervical spine fractures in older individuals are becoming more common worldwide.

The non-union rates [14] for these fractures range from 8.9% to 62.5%, with no appreciable variation across various treatment techniques. The halo-vest had the highest non-union rate at 62.5%, whereas surgical therapy had the lowest non-union rate at 8.9%. In assessing fractures of the upper cervical spine, the odontoid fracture is of special importance and a frequent occurrence. It's cervical spondylosis. Long-term employment that necessitates repetitive neck movements or incorrect alignment may be the most significant risk factor for the deterioration of cervical vertebrae in young individuals, which culminates in osseous impingement-induced IJVS. Due to longer life expectancies, upper cervical spine fractures in older individuals are becoming more common worldwide.

The goal of the study [15] was to better understand cervical spondylitis myelopathy (CSM) by measuring the amount of cord compression in 13 CSM patients and 15 control subjects using cervical spine MRI. A neural network model was created to segment the spinal cord's various sections and gather volumetric and cross-sectional measurements to interpret the data. The study's findings revealed that the neural network model had a median accuracy of 90%, demonstrating its ability to correctly identify the spinal cord areas impacted by CSM. The study also found that an average inaccuracy of 0.5 m JOA points or less was seen around 48.5% of the time, indicating that the model was able to effectively predict the level of cord compression in a sizable percentage of cases. Overall, by precisely detecting and measuring the degree of cord compression, the study shows the possibility of employing neural network models to enhance CSM diagnosis and therapy.

The degenerative condition known as cervical spondylosis, which affects the cervical spine, has the potential to crush the spinal cord and nerve roots. Cervical spondylosis symptoms might include headaches, numbness, paralysis, tingling, discomfort, and stiffness in the neck. In research [16], 3900 individuals' sociodemographic and physical measuring index data were gathered through in-person interviews. A total of 3859 individuals were included in the final analysis after some participants were excluded owing to missing data. The purpose of the study was probably to investigate the prevalence and risk factors for cervical spondylosis. The researchers may have been able to pinpoint possible risk factors and connections between particular traits and the onset of cervical spondylosis by gathering sociodemographic and physical measurement index data.

A cross-sectional investigation [17] was carried out on patients aged 30 to 60 who were suffering from neck discomfort. This included patients with cervical spondylosis (CS) and age-matched healthy control subjects. The prevalence of cervical degeneration syndrome (CS), which is defined as "neck discomfort subjects with radiological evidence indicating cervical degeneration," is 3.3 patients per 1000 persons in the general population. Although higher levels may potentially be implicated, the C5-C6 and C6-C7 levels are where CS typically manifests itself. Age, gender, and baseline body mass index (BMI) did not significantly differ between the CS and healthy control groups, according to [17] statistical analysis.

A chronic inflammatory condition called ankylosing spondylitis (AS) causes new bone growth as well as bone loss in the axial skeleton, peripheral joints, and sacroiliac joints. Research [18] has discovered that AS patients had a greater frequency of osteoporosis than controls. According to recent research [18], individuals with AS had higher BMD at the entire hip and lumbar spine and lower BMD at the femoral neck and total radius after five years (for both AP and lateral projections). BMD dropped when CRP or ESR, two indicators of inflammation, were elevated. The hip region and the AP projection of the lumbar spine have been the main areas of interest in previous longitudinal BMD investigations in AS patients.

The findings revealed [19] that portable ultrasonography was capable of quickly and painlessly assessing possible damage by successfully seeing the cervical spine in unconscious individuals. Moreover, the anterior triangle method and the use of the linear array probe produced comprehensive pictures that helped lessen the possibility of erroneous interpretation. It's crucial to remember that conventional imaging methods like x-rays and CT scans shouldn't be replaced by the use of portable ultrasonography in the cervical spine. To make a conclusive diagnosis, the study's [19] findings should be taken into account alongside other clinical data, including the patient's physical examination and neurological condition. Finally, the use of portable ultrasonography on the cervical spine of individuals with significant In emergencies with limited resources, and head damage is a viable alternative. The results of this study indicate that portable ultrasonography may be useful in the early evaluation and treatment of these patients, assisting in the prompt identification of probable cervical spine injuries and directing suitable treatment choices.

Serious consequences from cervical injuries can result in spinal cord damage, paralysis, and even death. Hence, early and precise diagnosis is crucial to ensuring that the right therapy is started as soon as possible. Although the NEXUS and Canadian C-Spine criteria offer excellent specificity for identifying cervical injuries, they also have shortcomings that may result in needless imaging and medical expenses. To choose whether or not to do a cervical spine MRI, it is crucial to thoroughly assess the patient's clinical presentation [20] and risk factors. Elderly people are more prone to cervical trauma than trauma patients because falls among them might cause significant injury. Healthcare professionals should be mindful of this danger and diligent in their

assessment. Older individuals who have fallen should be examined for possible cervical injuries. Overall, a complete approach [20] can assist to guarantee that cervical trauma is appropriately identified and treated, resulting in improved results for patients. This strategy includes a thorough history and physical examination with the right imaging. In CT imaging, motion artifacts can be a frequent problem, especially in individuals who find it difficult to remain motionless.

Images exhibiting these artifacts may be misdiagnosed, leading to needless further testing or treatment. In the situation you described, motion artifacts on the CT scan seemed to be a cervical dens fracture, raising questions about the patient's health. Since helical CT has great diagnostic performance, it should be noted that it is not impervious to artifacts. Radiologists are taught to identify and interpret CT scans while keeping an eye out for any possible artifacts, like in this instance [21]. An in-depth examination of the axial CT scan revealed motion artifacts that may have contributed to the results that suggested a dens fracture. Other imaging methods, such as plain radiography and MRI, can be useful in verifying or ruling out suspected abnormalities on CT to minimize misunderstanding owing to motion artifacts. Motion artifacts can also be reduced by making sure patients are positioned correctly and told to keep motionless throughout the CT scan. All things considered, medical professionals must be aware of the possibility of motion abnormalities in CT imaging, especially in patients who could have trouble staying still throughout the scan. Working together with other members of the medical team, including radiologists, can assist guarantee that appropriate diagnoses are made and appropriate treatment is initiated. Then the proper course of treatment is started. The

radiographic clearing of cervical spine injuries is a crucial component of treating individuals with significant trauma. There are several options for clearing, therefore it's crucial to give quick and precise clearance to prevent overlooking possible injuries. A considerable portion of c-spine fractures may be found using sideways radiographs, which are often employed in clinical practice. Even with three images of the spine, a large proportion of fractures could still be hidden. Here, the sensitivity of plain radiographs can be increased by paying attention to minor signs including misalignment, expansion or narrowing of disc gaps, and soft tissue edema. Although they have been employed in the acute environment, flexion-extension radiographs—which involve imaging the cervical spine in both flexion and extension—had an unacceptably high rate of false-positive and false-negative results. The highly sensitive imaging method known as CT can identify 97% to 100% of fractures [22]. The effectiveness of CT in identifying solely ligamentous lesions hasn't been widely studied, though. Injuries that may not be seen on standard radiographs, such as ligamentous instability and spinal cord damage, can also be found using CT. Another imaging method that can be utilized to find c-spine injuries, especially ligamentous injuries, is magnetic resonance imaging (MRI), however due to the time needed for acquisition and interpretation, it is not as frequently used in acute situations. In conclusion [22], various options are available for treating c-spine damage, and each has advantages and disadvantages. To avoid overlooking potential injuries, radiographic clearing should be carried out quickly and precisely. Paying attention to minute details can also increase the sensitivity of plain radiographs. While MRI is useful in detecting ligamentous injuries but is less frequently utilized in the acute environment, CT is very sensitive and can detect a variety of lesions.

It's intriguing to learn that cervical spine imaging may one day support computer-aided injury detection. It's crucial to lower the possibility of a false positive and boost radiograph sensitivity. With great sensitivity and specificity in locating and recognizing vertebral centers, the suggested framework [23] for fully automatic vertebrae segmentation in X-ray images is noteworthy. The accuracy of injury detection and diagnosis may be increased using this paradigm [23] for additional cervical spine images. According to the study [24], it is crucial for medical personnel to be aware of the high rates of mortality and morbidity linked to these fractures and to carefully assess the appropriate course of action for each patient. Also, preventative actions like fall prevention and cancer screening. The prevalence of these fractures in the aged population may be decreased by osteoporosis.

3. Conclusion

Because people with Ankylosing Spondylitis are more likely to experience spinal fractures, particularly in the cervical spine, a survey on cervical spine fracture can be useful in identifying the disease. To identify patients who may have Ankylosing spondylitis and need additional testing and treatment, healthcare providers might use surveys that ask patients about their history of cervical spine fractures or neck pain. Ankylosing spondylitis can also be confirmed by imaging tests like X-rays or MRI scans, which can also be used to check for any related spine fractures. This claim—that pre-trained Convolutional Neural Networks (CNNs) can be a useful tool for identifying cervical spine fractures—is true. These models can learn by being trained on massive image datasets. as well as distinguish between the traits of fractures and non-fractures. Yet, utilizing the native image formats, like DCM and. Due to their size, can cause processing to take longer. The identification and classification process can be speeded up and processing time decreased by converting the photos to PNG or JPEG format. The conversion process may cause some information loss, so it's crucial to keep that in mind while weighing the benefits of processing speed versus image quality.

Under The Esteemed Guidance Of Dr. K. Lakshmana Rao

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