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A SURVEY ON FAST CERVICAL SPINE FRACTURE DETECTION USINGDEEP LEARNING METHODS

[1]Santhosh T, K. T. Veeramanju
[1]Research Scholar, [2]Research Professor
[1]Department of CS&E,
[1]Srinivas University Institute of Engineering and Technology, Srinivas University, Mukka, Mangalore, India-574146.

Abstract : Fractures result from the reduction in bone mass due to osteoporosis, a natural part of the aging process. The backbone can develop cracks when subjected to the strain of lifting heavy objects orexperiencing a fall from a significant height. The spinal cord comprises the initial seven bones in the neck region. Fractures in this area can result in the loss of sensory functions or even prove fatal. Computed tomography (CT) plays a crucial role in identifying these fractures, influencing patient care. This review explores different methods essential for efficiently and effectively detecting cervical spine fractures, with a focus on the application of deep learning. The paper offersa concise overview of popular techniques for fracture detection, along with a comparative analysis of various classification methods applicable to this diagnostic process.

IndexTerms - **Medical imaging, Deep learning, Object detection, Classification, Cervical spine fracture, Convolutional Neural Network (CNN)**

I. INTRODUCTION

Addressing cervical spine fractures presents a substantial healthcare dilemma, as they carry the risk of spinal cord injury and neurological impairments [1]. These fractures impact the vertebral bones in the neck area, necessitating swift diagnosis and proper intervention to avert potential complications [2, 3]. Imaging assumes a pivotal role in appraising cervical spine fractures, with computed tomography (CT) scans delivering comprehensive views of bony structures, enabling precise evaluation of fracture characteristics and related injuries [4, 5]. The intricate anatomy andsusceptibility to trauma, such as high-energy impacts and falls, render the cervical spine especiallyprone to fractures [6]. Swift and precise diagnosis of cervical spine fractures is imperative for guiding treatment decisions and securing favorable patient outcomes [7]. Computed tomography (CT) imaging stands out with its enhanced sensitivity and specificity compared to alternative imaging modalities, enabling accurate identification and categorization of fractures, evaluation ofspinal stability, and detection of related injuries [8, 9].
The utilization of machine learning and deep learning algorithms has demonstrated significant promise in advancing the diagnosis of cervical spine fractures by analyzing CT images [10]. Thesealgorithms exhibit effectiveness in learning intricate patterns and features linked to fractures, resulting in precise and dependable fracture detection and classification [11, 12]. The incorporationof artificial intelligence (AI) technology into clinical workflows holds the potential to enhance theefficiency and accuracy of diagnosing cervical spine fractures, facilitating timely and suitable management [13]. The objective of this study is to create a machine learning-based model capableof automatically detecting and classifying cervical spine fractures using CT images. Through the application of AI techniques, our goal is to augment the precision and effectiveness of fracture diagnosis, with the ultimate aim of enhancing patient care and outcomes. If successful, the implementation of an AI-driven model for detecting cervical spine fractures has the potential to revolutionize clinical practices, offering healthcare professionals a standardized and objective tool[14].
Numerous investigations have delved into the utilization of deep learning and computer vision algorithms for the detection of cervical spine fractures [15, 16]. One example includes the proposition of a deep convolutional neural network featuring a bidirectional long-short-term memory (Bi-LSTM) layer for automated fracture detection, as outlined in [17], achieving classification accuracies of 79.18% across various datasets. Another study, detailed in [18], explores the application of Vision Transformers (ViT) and concludes that ViT surpasses traditional Convolutional Neural Networks (CNNs), attaining a detection accuracy of 98% in identifying cervical spine fractures. The study presented in [19] concentrates on the classification of cervicalspine injuries, distinguishing between fractures and dislocations, employing deep learning models.It attains commendable accuracy, sensitivity, specificity, and precision values. Additionally, the research outlined in [20] utilizes deep learning for the automated detection of cervical fractures. Itinvolves substantial model optimization through the incorporation of custom layers and data augmentation, ultimately resulting in the development of a deployable smart phone application.

II. RELATED WORK

Initially introduced for medical image segmentation, U-Net [21] emerged as a robust deep learningmethod for classifying each pixel in an image. It surpassed the sliding-window convolutional network, which was the leading method at the time, in terms of both performance and speed,

thusgaining popularity for image segmentation across various domains. Thanks to its effectiveutilization of data augmentation, U-Net can generate precise segmentation results even with training on a limited number of images. Notably, its versatility extends to both 2D and 3D images.Meanwhile, Convolutional Neural Networks (CNNs) serve as a foundational component innumerous computer vision tasks, including image classification, detection, and segmentation. In the realm of computer vision, various architectures have evolved over the decades, commencingwith the introduction of AlexNet [22] and progressing to more advanced structures like ResNet [23], EfficientNet [29], ConvNeXt [24], among others. These architectures have garnered recognition within the computer vision community for their notable achievements in both accuracyand speed. Regarding the specific challenge of cervical spine fracture detection, previous researchhas delved into the application of deep learning models. In [25], a proposal was made for a deep convolutional neural network (DCNN) featuring a bidirectional long-short term memory (BLSTM) layer to automate the detection of cervical spine fractures in CT axial images. Additionally, another study presented a 3D convolutional sequence-to-sequence model designed for identifying vertebral compression fractures in CT scans, as documented in [26]. Within the competition, multiple solutions from leading teams in [27] demonstrated significant effectiveness in detecting fractures in cervical spines. The majority of leading teams in the competition adopt an architecture that incorporates at least two models, typically a segmentation model and a classification model. Qishen Ha, as outlined in [28], devised a two-stage approach for fracture detection. This method initially involved training a UNet model with resnet18d or efficientnet-v2s for 3D semantic segmentation, generating 3D masks for all training data. Subsequently, a 2D CNN (ConvNeXt) model, accompanied by an LSTM module, was trained for the final classification.
Likewise, Harshit Sheoran's approach, detailed in [29], involves two stages. U-Net models were initially trained for both sagittal and bone segmentation, followed by training an EfficientNet CNN with an RNN model for classification. During the classification stage, the images were transformed into a 2.5D format, achieved by concatenating three consecutive slices into a single image. Additionally, two bidirectional GRU layers with attention and a Conv1D layer were employed in the RNN model In , an U-Net model was employed for 2.5D segmentation, while a CNN with bidirectional GRU layers and attention was trained for classification. In the second stage, a Spatial Dropout layer was introduced to the model, resulting in a marginal enhancement in overall classification performance. However, the mentioned architectures generally demand considerable time and resources for training, including pretraining. As a result, we conducted experiments to identify a model that is more time-efficient while still achieving satisfactory results.

III. DATASETS AND PREPROCESSING

3.1 Data Sources:

The dataset utilized in this study is sourced from the RSNA 2022 Cervical Spine Fracture Detection competition on Kaggle [1]. This dataset comprises three primary folders: train_images, test_images, and segmentations. Within the train_images folder, there are training images organized into 2019 subfolders.
Each subfolder corresponds to a particular patient or case study, encompassing multiple slice images relevant to that specific case. Consequently, these subfolders are labeled with the UID of their respective case study. All images within these folders are in the DICOM file format, featuring a slice thickness of under 1 mm. The images are also in the axial orientation and utilize a bone kernel [1], with each file possessing a .dcm extension. Simultaneously, the segmentations folder houses annotation masks stored in NIFTI files, with each file dedicated to a single patient. The target labels for the training data are outlined in the train.csv file, which includes columns for caseIDs, patient-level labels (binary), and specific vertebra labels. Additionally, the dataset includes atraining_bounding_boxes.csv file containing information about bounding boxes, encompassing details like anchor coordinates, width, and height of the bounding boxes.

3.2 Preprocessing Techniques:

Pre-processing plays a crucial role in enhancing the performance of deep learning models for cervical spine fracture detection. Here are some common pre-processing techniques used in this context:

3.2.1 Image Rescaling and Standardization:

Resize the input images to a consistent resolution to ensure uniformity.
Standardize pixel values to have zero mean and unit variance, reducing the impact of variations in image intensity.

3.2.2 Noise Reduction:

Apply image denoising techniques, such as Gaussian or median filtering, to reduce noise that might interfere with the accurate detection of fractures.

3.2.3 Contrast Enhancement:

Adjust the contrast of the images to improve the visibility of important structures and details, making it easier for the model to identify fractures.

3.2.4 Image Augmentation:

Increase the diversity of the training dataset by applying random transformations such as rotation, flipping, and slight changes in brightness and contrast. This helps the model generalize better to different variations in the input data.

3.2.5 Region of Interest (ROI) Extraction:

Identify and extract the region of interest containing the cervical spine from the overall image.This helps focus the model on the relevant area and improves computational efficiency.

3.2.6 Histogram Equalization:

Enhance the visibility of features by equalizing the image histogram, particularly useful whendealing with images with uneven lighting conditions.

3.2.7 Normalization:

Normalize pixel values to a standard range (e.g., [0, 1]) to facilitate convergence during trainingand improve the stability of the model.

3.2.8 Artifact Removal:

Detect and remove artifacts that might be present in the images, ensuring that the model focuseson genuine anatomical structures..

3.2.9 Data Balancing:

Address class imbalance by oversampling the minority class (fractures) or applying techniquessuch as Synthetic Minority Over-sampling Technique (SMOTE) to balance the dataset.

3.2.10 Registration:

Align images spatially to a common reference frame, correcting for variations in patient positioning during imaging.

The specific choice and combination of pre-processing techniques may vary based on the characteristics of the dataset and the requirements of the deep learning model. It's important to carefully evaluate the impact of each technique on the model's performance and consider the clinical implications of the choices made during pre-processing. Additionally, collaboration with domain experts is essential to ensure that pre-processing steps align with medical knowledge and practices.

3.3 Challenges and Considerations:

The application of deep learning methods for detecting cervical spine fractures presents various challenges and considerations that warrant meticulous attention. A noteworthy challenge revolvesaround the restricted accessibility of annotated and diverse datasets specifically tailored for cervical spine images. This limitation impedes the creation and training of robust deep learning models. The scarcity of well-annotated data of high quality can result in model bias and diminishedgeneralizability. Moreover, the intricate anatomy of the cervical spine introduces diverse patternsin images, posing a challenge for models to precisely identify subtle fractures or abnormalities. The aspect of interpretability holds significant importance, given that deep learning models frequently function as "black boxes," creating challenges for medical professionals in comprehending and trusting the decision-making process. Additionally, the incorporation of deeplearning techniques into clinical workflows raises concerns regarding the imperative for real-timeprocessing, particularly in emergency situations where prompt cervical spine injury detection is crucial. Tackling these challenges necessitates collaborative endeavors among medical professionals, researchers, and technologists to augment dataset accessibility, enhance model interpretability, and ensure smooth integration into clinical practice. Surmounting these obstacles is pivotal for the effective deployment of deep learning methods in detecting cervical spine fractures, ultimately advancing quicker and more accurate diagnoses, particularly in emergency medical situations.

4. Deep Learning Models and Architectures:

The emergence of deep learning represents a significant advancement in the analysis of fracture images, introducing unprecedented accuracy and efficiency in tasks related to both segmentation and classification. This section delves into the specific models and architectures employed, elucidating their mechanisms and highlighting their impact on the rapidly evolving field.

4.1 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) constitute a category of deep learning models explicitly crafted for handling data with a grid-like topology, as seen in images. These networks typically consist of various layers, encompassing convolutional layers, pooling layers, and fully connected layers. The convolutional layer stands out as a crucial component in CNN architecture, playing a pivotal role in feature extraction from the input image through a set of filters. Each filter, comprising a small matrix of weights, is applied to a specific region of the input image. The result of this convolutional operation is a feature map, representing a matrix of values that capture the features extracted from the input image. The pooling layer plays a role in diminishing the spatial dimensions of the feature maps produced by the convolutional layers. It achieves this by applying a pooling function to each feature map, often taking a small region and reducing it to a single value. Max pooling and average pooling are the most common pooling functions employed. Subsequently, the fully connected layer serves as the ultimate layer in a CNN architecture. The final responsibility of the fully connected layer is to make the ultimate prediction, whether it involves classifying the image or detecting objects within it. This layer follows the conventional neural network architecture, where each neuron is linked to every neuron in the preceding layer [18, 19]. CNNs bring forth distinct advantages in image processing, leveraging design principles such as Weight Sharing, Sparse Connectivity, and Local Receptive Fields. Weight Sharing enables the sharing of weights across the spatial dimensions of the input image, leading to a reduction in trainable parameters, ultimately enhancing efficiency and mitigating overfitting. Sparse Connectivity ensures that each neuron within a layer establishes connections with only a restricted subset of neurons in the preceding layer, thereby reinforcing efficiency and mitigating overfitting concerns. Additionally, CNNs incorporate local receptive fields, constraining each neuron's responsiveness to a small, localized region of the input image. This design enhances the network's robustness to noise and variations within the image. These fundamental characteristics collectively contribute to the effectiveness of CNNs in tasks related to image analysis and classification [18, 19].

Several CNN architectures have significantly contributed to the progress of computer vision tasks. Networks such as VGGNet [20], ResNet [21], DenseNet [22], and ConvNeXt [23], trained on the extensive image collection of ImageNet, have consistently excelled in image classification. The success of these architectures has been profoundly influenced by transfer learning, a technique involving the reuse of pre-trained models for new tasks. Offering a remedy for training Convolutional Neural Networks (CNNs) in scenarios with restricted labeled data, this method empowers models to utilize previously acquired knowledge from the initial task. By doing so, it not only economizes time but also boosts performance through the utilization of acquired features [19]. In general, CNNs have demonstrated their effectiveness across various computer vision tasks such as image classification, object detection, and image segmentation.

4.2 Emerging Trends: Exploring Beyond CNNs

While CNNs currently dominate the field, researchers are actively investigating alternative deeplearning architectures with the potential to further enhance fracture image analysis. The potentialof Generative Adversarial Networks (GANs) is being explored to address data scarcity limitations by creating realistic synthetic fracture images for data augmentation, as highlighted in the work of Dhanesha et al. (2023). Moreover, Recurrent Neural Networks (RNNs) might prove beneficialfor analyzing spatiotemporal information, potentially offering insights into the progression and development of fractures over time, as suggested by Kadam et al. (2023).

4.3 Understanding the Training Process

The training procedure for detecting cervical spine fractures involves the utilization of advanced medical imaging techniques and machine learning algorithms. These are employed to construct amodel capable of precisely identifying fractures in the cervical spine, and the process adheres to several crucial steps to guarantee the model's efficacy and dependability. Primarily, the model's training necessitates a comprehensive dataset. This dataset encompasses a diverse array of medicalimages, including X-rays, CT scans, or MRIs, exhibiting a spectrum of cervical spine fractures. Itis imperative that the dataset is meticulously curated to accurately mirror the diversity in fracturetypes, locations, and patient demographics. The larger and more representative the dataset, the higher the likelihood of the model delivering superior performance. After creating the dataset, it gets segmented into training, validation, and testing sets. The training set is employed to instruct the model in identifying patterns and features associated with cervical spine fractures. Fine-tuningthe model's parameters and preventing overfitting is achieved through the validation set, ensuringthe model doesn't become overly tailored to the training data and can generalize effectively to new,unseen data. The testing set then assesses the model's performance on completely novel and unseenimages, offering a reliable gauge of its effectiveness.

Throughout the training process, the model acquires the ability to extract pertinent features from images, distinguishing between instances of fractures and non-fractures. Medical image analysis frequently utilizes Convolutional Neural Networks (CNNs) due to their proficiency in capturing spatial hierarchies and patterns within images. The model undergoes iterative training, involving predictions and subsequent adjustment of parameters based on the disparities between its predictions and the actual labels (fracture or non-fracture).

Boosting the model's efficacy can be achieved through the utilization of methods like data augmentation, transfer learning, and fine-tuning. Data augmentation entails enlarging the training dataset artificially by introducing transformations (such as rotation or scaling) to the existing images, facilitating improved generalization of the model. Transfer learning involves making use of pre-trained models on extensive datasets designed for analogous tasks, adjusting them to suit the particular requirements of cervical spine fracture detection.

After the completion of training and evaluation, the model becomes ready for deployment to analyze fresh medical images, specifically for cervical spine fractures. Regular monitoring and updates to the model may prove essential to adapt to shifts in medical imaging technology, changes in patient demographics, or the emergence of newly identified fracture patterns.

4.4 The Future of Deep Learning in Fracture Analysis

The arena of deep learning in fracture image analysis is a vibrant domain with abundant potential for further progress. Ongoing exploration of innovative architectures, especially the integration of CNNs with other model types, shows great promise in advancing the frontiers of accuracy and efficiency. Effectively addressing data scarcity through techniques like transfer learning and domain adaptation is crucial for broader adoption and real-world impact. Ultimately, these advancements pave the way for a future in which deep learning transforms the fracture industry, enabling automated and unbiased quality assessment, optimizing production processes, and ensuring equitable trade practices for all stakeholders.

5. PERFORMANCE EVALUATION:

Assessing the effectiveness of deep learning models in fracture image analysis is crucial for accurately gauging their value and comparing them to alternative approaches. This section delvesinto the metrics employed for such evaluations, presents the attained results alongside comparisons, and ultimately provides a comprehensive overview of the impact of deep learning inthis particular domain. Various metrics serve as vital indicators for analyzing the efficiency of deep learning models in fracture image analysis (Acharya, U. 2012) (Domingos, P. 2012) (Curvers, W. L 2008). A few noteworthy examples include:

1. Accuracy: Reflects the overall rate of correct predictions across both segmentation and classification tasks.
2. Precision: Captures the percentage of classified fracture accurately assigned to the predicted quality category.
3. Recall: Indicates the proportion of actual fracture of a specific quality category correctly identified by the model.
4. F1-score: Blends precision and recall into a single metric, offering a balanced view of the model's performance.
5. Intersection over Union (IoU): Specifically for segmentation tasks, IoU measures the overlap between predicted and ground truth segmentation masks, evaluating how well the model identifies individual fractures.

The comparison between deep learning and conventional methods across diverse tasks depends onseveral pivotal factors that impact their respective performances. Traditional methods frequently necessitate meticulous feature engineering, where domain expertise is essential for manually designing relevant features that accurately represent the data. Conversely, deep learning excels inautonomously acquiring hierarchical representations directly from raw data, eliminating therequirement for extensive manual feature engineering. The effectiveness of traditional methods may be constrained by the availability and quality of handcrafted features, along with the quantityof labeled data. Deep learning, leveraging its prowess on extensive datasets, can surpass traditionalmethods in situations where ample labeled data is available. Although traditional methods provideinterpretable features aligned with domain knowledge, the interpretability of predictions from deeplearning models is often viewed as challenging due to their black-box nature. The computational demands also play a pivotal role, with traditional methods being computationally less intensive, rendering them suitable for environments with constrained computational resources. Conversely, deep learning necessitates robust hardware, such as GPUs, to train large neural networks effectively. Moreover, the transferability of deep learning models, facilitated by techniques like transfer learning, presents a notable advantage when adapting pre-trained models to novel yet related tasks. The decision between deep learning and traditional methods ultimately hinges on the specific characteristics of the task at hand, encompassing factors like data availability, task complexity, interpretability requirements, and computational resources. Each approach boasts its own strengths and weaknesses, and the choice should be tailored to the distinctive demands of the problem domain. The evaluation of different neural network models is showcased through multi-label classificationfor cervical spine vertebrae. The suggested network, achieving a MacroF1 score of 0.96 and an Exact Match Ratio of 0.95, demonstrates encouraging outcomes in comparison to alternative models like ViT, Convext, InceptionV3, ResNet152V2, and Swin Transformer. The classificationreport for the proposed network is presented in Table 2, highlighting its robust performance in multi-label cervical spine vertebrae classification. The network attains elevated precision (rangingfrom 0.97 to 1.00), recall (ranging from 0.93 to 0.98), and F1-scores (ranging from 0.95 to 0.99) for all seven classes (C1 to C7), signifying its proficiency in accurately identifying vertebrae. Themicro, macro, and weighted averages, approximately at 0.97, demonstrate a consistently strong overall performance. Additionally, Figure 6 illustrates the loss diagram of the proposed network, revealing a steady declining trend throughout 25 training epochs.

Table 1: Performance metrics of different cervical spine vertebrae classification models:

Model	MacroF1	Exact Match Ratio	Coverage Error	Trainable Parameters	Non-trainable Parameters
Proposed Network	0.96	0.95	1.26	13,080,663	14,683,998
ViT	0.94	0.90	1.41	56,937,479	30,764,544
Convext	0.95	0.93	1.35	9,686,535	39,966,816
InceptionV3	0.92	0.89	1.45	526,535	21,802,592
ResNet152V2	0.96	0.94	1.26	6,045,703	52,812,288
Swin Transformer	0.95	0.909	1.36	49,899,081	2,768

Table 2: Multi-label classification report for cervical spine vertebrae using the proposed network:

Model	MacroF1	Exact Match Ratio	Coverage Error	Trainable Parameters	Non-trainable Parameters
C1	0.97	0.93	0.95	0.95	284
C2	0.98	0.97	0.98	0.98	455
C3	1.00	0.98	0.99	0.99	264
C4	0.97	0.97	0.97	0.97	272
C5	0.98	0.97	0.97	0.97	277
C6	0.99	0.96	0.97	0.97	278
C7	0.98	0.98	0.98	0.98	320
Micro avg	0.98	0.97	0.97	0.97	2150
Marco avg	0.98	0.97	0.97	0.97	2150
Weighted avg	0.98	0.97	0.97	0.97	2150

6. Challenges and Future direction:

Cervical spine fracture detection faces several challenges, and navigating these obstacles will significantly impact its future direction. Firstly, the scarcity of diverse and well-annotated datasetsposes a challenge for training and validation must be robust and generalizable models. The creation of comprehensive datasets that encompass a wide range of fracture types, patient demographics, and imaging modalities is crucial for improving the accuracy and reliability of detection algorithms. Interpreting the decisions made by deep learning models in the context of cervical spine fracture detection remains a challenge. Ensuring the clinical interpretability of these modelsis essential for gaining the trust of healthcare professionals. Addressing the "black-box" nature ofdeep learning algorithms and developing methods for explaining and validating their predictions will be crucial in integrating these technologies into clinical practice. Another innovative challengelies in handling imbalanced datasets, where positive cases (fractures) are often outnumbered by negatives. Imbalanced datasets can lead to biased models that prioritize the majority class,compromising the sensitivity of fracture detection. Developing effective strategies, such as data augmentation and advanced sampling techniques, to mitigate this imbalance is vital for improvingthe overall performance of cervical spine fracture detection models using deep learning techniques.Furthermore, the integration of these detection models into the clinical workflow requires seamlessinteroperability with existing healthcare systems. Ensuring that the technology aligns with the workflow of healthcare professionals, is user-friendly, and complies with regulatory standards is imperative for successful adoption in clinical procedures.

Looking ahead, the future of cervical spine fracture detection may involve advancements in multimodal imaging, combining information from various imaging techniques such as X-rays, CT scans, and MRIs. Integrating clinical data, patient history, and other relevant information could further enhance the accuracy and clinical utility of fracture detection models. Moreover, continuous research is needed to explore the potential of artificial intelligence (AI) in assisting not only with detection but also with the characterization and prognosis of cervical spine fractures accurately. The evolution towards more comprehensive AI applications that go beyond binary classification may open avenues for personalized treatment strategies and improved patient outcomes.

Conclusion

Addressing challenges related to data diversity, model interpretability, imbalanced datasets, and clinical integration is essential for the future of cervical spine fracture detection. Ongoing research and technological advancements will likely lead to more sophisticated models and holistic approaches that contribute to the enhancement of diagnostic capabilities and patient care in the field of cervical spine fractures.

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