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CERVICAL SPINE FRACTURE DETECTION USING DEEP NEURAL NETWORKS

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Abstract: Detecting cervical spine fractures, especially in elderly individuals with underlying degenerative conditions, poses challenges. To address this, a study introduces a pioneering method employing deep neural networks (DNNs), specifically the U-Net architecture, to automate fracture detection in computed tomography (CT) scans. The approach focuses on accurately identifying and localizing cervical vertebrae, vital for precise fracture assessment. Utilizing U-Net's adeptness in semantic segmentation, the model accurately delineates cervical vertebrae boundaries, capturing intricate details and spatial relationships within the images. Moreover, by integrating multi-class classification layers, the framework extends U-Net's capabilities for fracture detection, distinguishing between fractured and intact regions within segmented cervical vertebrae, thus enhancing diagnostic accuracy. Trained on a diverse dataset of cervical spine injuries, the proposed methodology offers significant clinical advantages, including real-time fracture assessment, enabling prompt diagnosis and timely intervention to improve patient outcomes. Leveraging the potency of deep learning, this approach holds promise for enhancing the efficiency and accuracy of cervical spine fracture detection, ultimately contributing to enhanced patient care and treatment outcomes.

Key-words: U-Net architecture, computed tomography (CT) images, cervical vertebrae, semantic segmentation.

I. INTRODUCTION

Spinal fractures represent a significant global health concern, with an alarming annual incidence exceeding 1.5 million cases. Among these fractures, those afflicting the cervical spine present particularly daunting challenges due to their critical location and potential complications. Elderly individuals, in particular, face an elevated risk of spinal fractures, often compounded by underlying degenerative conditions and osteoporosis. The timely and accurate detection of cervical spine fractures is paramount for initiating appropriate medical interventions and ultimately improving patient outcomes. In recent years, the landscape of medical image analysis has undergone a transformative shift propelled by advancements in deep learning technology, notably the application of deep neural networks (DNNs). This project endeavors to harness the capabilities of DNNs to devise an automated methodology for detecting cervical spine fractures using computed tomography (CT) imaging. By leveraging the prowess of deep convolutional neural network (DCNN) architecture, the proposed approach aims to significantly enhance the accuracy and efficiency of fracture detection. Conventional methodologies for identifying cervical spine fractures often rely heavily on manual interpretation of radiographic images by skilled healthcare professionals. However, this manual process is inherently time-consuming and susceptible to human error, particularly when fractures are subtle or obscured by degenerative changes. Moreover, in elderly populations, the presence of superimposed degenerative diseases and osteoporosis further complicates fracture detection on imaging studies. To address these formidable challenges, this project introduces an innovative approach that capitalizes on deep neural networks, with a specific emphasis on the U-Net architecture. Renowned for its effectiveness in semantic segmentation tasks, U-Net is exceptionally well-suited for accurately delineating cervical vertebrae boundaries in medical images. By harnessing the capabilities of U-Net, the proposed framework aims to achieve outstanding performance in segmenting the intricate structures of the cervical spine. Furthermore, the methodology extends the capabilities of U-Net for fracture detection by integrating pre trained models as transfer learning libraries. This enhancement enables the model to discriminate between fractured and intact regions within the segmented cervical vertebrae, thereby augmenting diagnostic accuracy. Through extensive training on a diverse dataset comprising radiographic images of cervical spine injuries, the framework learns to identify and localize fractures with remarkable precision. Comprehensive evaluations of the proposed U-Net model demonstrate superior performance in terms of segmentation accuracy and fracture detection sensitivity compared to traditional methods and alternative deep learning architectures. The methodology offers the significant advantage of real-time fracture assessment, thereby facilitating prompt diagnosis and timely intervention to enhance patient care.

II. LITERATURE REVIEW

This literature review will explore recent studies that investigate the application of deep learning techniques such as CNNs, recurrent neural networks (RNNs), and advanced segmentation architectures like U-Net and Faster R-CNN for spinal fracture detection and classification. By synthesizing the findings of these studies, this review aims to identify trends, challenges, and future research directions in the field of automated spinal injury diagnosis. Germann et al. (2023) demonstrated the potential of deep convolutional neural networks (DCNNs) in accurately measuring vertebral bodies and detecting insufficiency fractures in lumbar spine MRI. Their study underscores the utility of DCNNs in achieving precise diagnoses, offering promising prospects for improved patient care [1]. Bhavya et al. (2022) leveraged DCNNs to differentiate between traumatic and non-traumatic causes of cervical spine fractures from CT scans.

Their work aimed to achieve precise classification, highlighting the role of deep learning in enhancing diagnostic accuracy and guiding appropriate treatment strategies [2]. Small et al. (2021) proposed a deep learning model that integrates convolutional neural networks (CNNs) with bidirectional long-short term memory (BLSTM) for automated detection of cervical spine fractures in CT axial images. Their approach promises efficient diagnosis, potentially streamlining clinical workflows and expediting patient care [3]. Vong and Dinh (2021) demonstrated high accuracy in medical image analysis by employing UNet++ with EfficientNet for pneumothorax segmentation in chest X-ray images. Their study showcases the effectiveness of advanced deep learning architectures in achieving precise segmentation, essential for accurate diagnosis [4]. Ahmad et al. (2021) introduced MH UNet, a novel architecture that achieved state-of-the-art performance in medical image segmentation. Their work signifies significant advancements in deep learning architectures, paving the way for more accurate and efficient diagnosis of various medical conditions [5].

Salehinejad et al. (2021) proposed a deep sequential learning model for cervical spine fracture detection on CT imaging. Their approach enhances diagnostic capabilities in spinal injury assessment, offering potential improvements in patient outcomes and treatment planning [6]. Zhao et al. (2021) enhanced medical image segmentation accuracy through the incorporation of attention mechanisms in CBAM-Unet++. Their work showcases the importance of attention mechanisms in improving segmentation accuracy, crucial for precise diagnosis and treatment planning [7]. Saini and Sood (2021) introduced a modified UNet++ model for lung segmentation in chest X-ray images, achieving high accuracy in image analysis tasks. Their approach demonstrates the effectiveness of customized architectures in addressing specific diagnostic challenges [8]. Sha et al. (2020) demonstrated promising results in lesion detection using an improved version of the YOLOv2 algorithm for detecting spinal fracture lesions. Their study highlights the potential of advanced object detection techniques in improving diagnostic capabilities [9]. Sha et al. (2020) emphasized the importance of precise localization in spinal fracture detection by employing an improved Faster R-CNN model. Their work underscores the significance of accurate localization for guiding appropriate treatment strategies and improving patient outcomes [10]. Liu et al. (2020) proposed a multi-receptive-field CNN for semantic segmentation of medical images, contributing to improved segmentation accuracy and efficiency. Their approach offers potential advancements in automated image analysis, facilitating more precise diagnoses [11].Ahammad et al. (2019) developed a fast and accurate segmentation framework for spinal cord injury severity classification. Their work advances diagnostic capabilities in injury assessment, potentially aiding clinicians in making informed treatment decisions [12]. Tomita et al. (2018) showcased the effectiveness of DCNNs in early detection of osteoporotic vertebral fractures in CT examinations. Their study underscores the utility of deep learning in fracture detection, offering promising prospects for improving patient care and treatment outcomes [13].

Overall, these studies collectively highlight the transformative potential of deep learning in revolutionizing the diagnosis and management of spinal injuries and fractures. By leveraging advanced deep learning techniques and architectures, clinicians can enhance diagnostic accuracy, streamline clinical workflows, and ultimately improve patient outcomes.

III. Implementation & Methodology

The implementation and methodology for detecting cervical spine fractures using deep learning encompass a series of interconnected modules and processes aimed at achieving accurate and efficient fracture assessment. The system architecture diagram (Fig-1) illustrates the key components and their functionalities in the workflow.

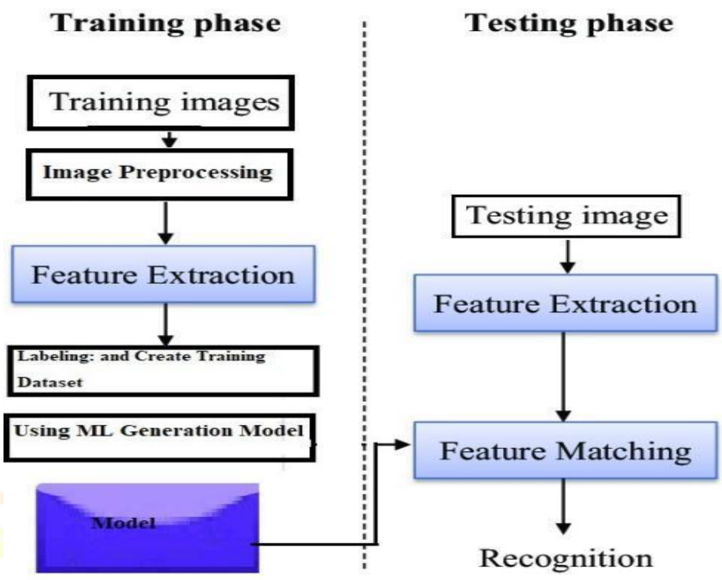

Fig-1: System Architecture

1. Load Dataset Module: Responsible for loading the dataset containing cervical spine images. Reads dataset files and organizes them for further processing.
2. Data Cleaning and Preprocessing: Cleans and preprocesses the loaded data to remove noise or inconsistencies. Tasks may include artifact removal, standardizing image formats, and pixel value normalization.
3. Image Resizing: Resizes the images to a uniform size suitable for input into the neural network model. Ensures consistency in image dimensions to facilitate model training and inference.
4. Features Extraction: Extracts relevant features from the preprocessed images to feed into the neural network. Identifies key characteristics in the images, such as edges or textures, aiding in distinguishing between fractured and intact vertebrae.
5. Labeling: Assigns labels to the preprocessed images indicating the presence or absence of fractures and the vertebral class (C1-C7). Annotates the dataset with ground truth labels for training the neural network model.
6. Create Training and Testing Dataset: Splits the labeled dataset into training and testing subsets for model evaluation. Partitions the dataset into separate sets for training the model (to learn patterns) and testing the model's performance (to assess accuracy).
7. U-Net Model Generation: Implements the U-Net architecture to train a deep neural network for fracture segmentation. Constructs the U-Net model using convolutional layers and performs training using the labeled training dataset to learn to identify fractures and vertebral classes.
8. Transfer Learning: During U-Net model generation, applies transfer learning with the InceptionResNetV2 architecture. Fine-tunes a pre-trained InceptionResNetV2 model acting as encoder whose output is feeded into the U-Net model's decoder, enhancing the model's ability to classify fractures by leveraging knowledge from the pre-trained network.
9. Deploy Model: Deploys the trained model for real-time fracture detection.
Integrates the trained model into a deployable application environment, ready for user interaction.
10. Flask Framework Integration: Integrates the trained model with the Flask web framework to create a user-friendly interface. Sets up endpoints for user authentication, image uploading, and

prediction result retrieval using Flask routes.

The methodology combines data preprocessing, model training, and deployment, leveraging deep learning techniques to automate cervical spine fracture detection. Each module plays a crucial role in the overall workflow, contributing to the system's accuracy and efficiency in clinical settings.

Used Algorithms

1. U-Net Architecture: The U-Net architecture is a convolutional neural network (CNN) designed for semantic segmentation tasks, known for its effectiveness in medical image analysis. U-Net consists of an encoder-decoder structure with skip connections that allow the network to capture both high-level features and detailed spatial information. The encoder downsamples the input image to extract features, while the decoder upsamples the features to generate the segmentation mask. Skip connections concatenate feature maps from the encoder to the decoder, facilitating precise localization.

- **Encoder:**
  zi = Conv(ReLU(Conv$i-1$($zi-1$)))
- **Decoder:**
  yi=Conv(ReLU(Conv$i-1$(Concat($zi-1$,$yi-1$)))

2. InceptionResNetV2 for Transfer Learning: InceptionResNetV2 is a CNN architecture characterized by dense connections between layers, allowing each layer to directly receive input from all its preceding layers. In transfer learning, a pre-trained InceptionResNetV2 model, trained on a large dataset like ImageNet, is fine-tuned on the specific task of cervical spine fracture detection. The dense connections facilitate feature reuse and enable the model to learn discriminative features from the limited medical imaging dataset.
x_{l+1} = H_l([x_0, x_1, ..., x_l]), where (x_{l+1}\) represents the output feature maps of the (l+1)th layer, (H_l\) denotes the layer function, and ([x_0, x_1, ..., x_l]\) denotes the concatenation of feature maps from all preceding layers.

3. Binary Cross-Entropy Loss Function:
Description: Binary cross-entropy is a loss function commonly used for binary classification tasks, such as fracture detection, where each pixel is classified as fractured or intact.
Explanation: Binary cross-entropy measures the dissimilarity between the predicted probability distribution and the ground truth labels. It penalizes deviations from the true labels, encouraging the model to produce accurate predictions.
$L(y,y^\wedge)=-N1\sum i=1N[yi\log(y^\wedge i)+(1-yi)\log(1-y^\wedge i)]$, where (y) represents the ground truth labels, (hat{y}) represents the predicted probability distribution, and (N) denotes the number of pixels.
4. Stochastic Gradient Descent (SGD) Optimization: SGD is an optimization algorithm commonly used to minimize the loss function during model training. SGD updates the model parameters iteratively by computing the gradient of the loss function with respect to the parameters and adjusting the parameters in the opposite direction of the gradient. It aims to find the optimal set of parameters that minimize the loss.
Mathematical Equation:
$\theta t+1=\theta t-\eta\nabla L(\theta t)$, where $\theta t\theta t$ represents the model parameters at iteration tt, $\eta\eta$ denotes the learning rate, and $\nabla L(\theta t)\nabla L(\theta t)$ represents the gradient of the loss function with respect to the parameters.

IV. Results

The U-Net model deployed alongwith InceptionResNetV2 model as transfer library achieved an accuracy of 96% in cervical spine fracture segmentation.
The implementation of the cervical spine fracture detection system yielded promising outcomes, as depicted by the user interface screenshots and prediction results. This section elaborates on the system's functionalities and the interpretation of its outputs.

Training Phase Results: The training phase of the system involved data processing and modeling, as illustrated in Figures-2 and 3, respectively. These screenshots demonstrate the system's capability to preprocess medical imaging data and develop a model for fracture detection.

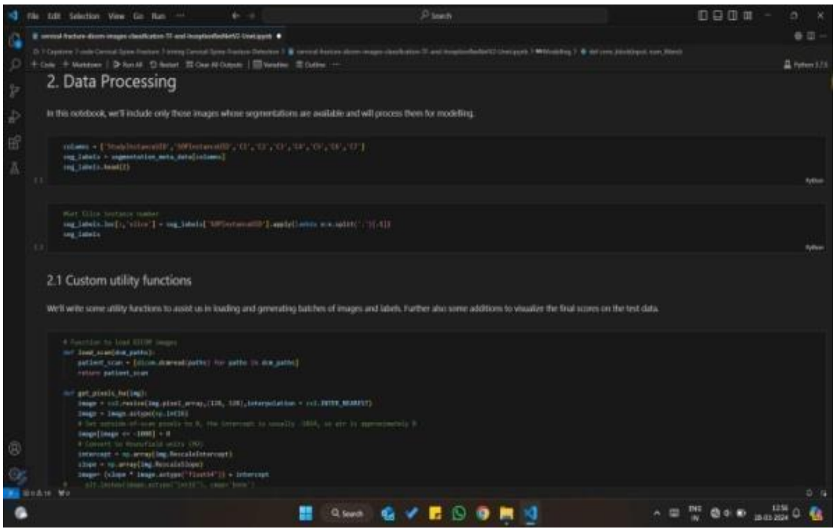

Fig-2: Data Processing

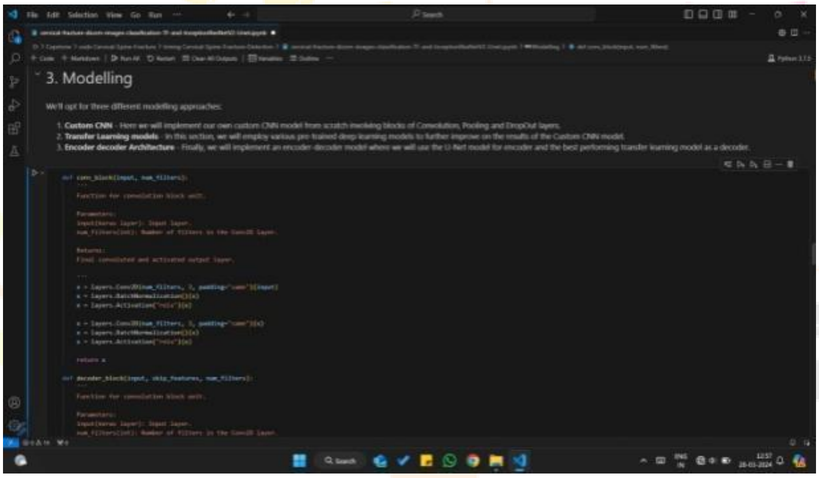

Fig-3: Model generation

Prediction Phase Results: During the prediction phase, users interact with the system through an upload page, as depicted in Figure 4. This feature enables users to input cervical spine images for fracture detection conveniently. Subsequently, the system generates prediction results, indicating whether a fracture is detected or not, as illustrated in Figures 5 and 6.

Interpretation of Prediction Results

The prediction results provide valuable insights into the system's performance by predicting the spine class of the input image. When a fracture is detected (Figure 5), it signifies the system's ability to accurately identify pathological abnormalities in the cervical spine images. Conversely, when no fracture is detected (Figure 6), it suggests the absence of evident abnormalities, thereby reinforcing the system's specificity and reliability.

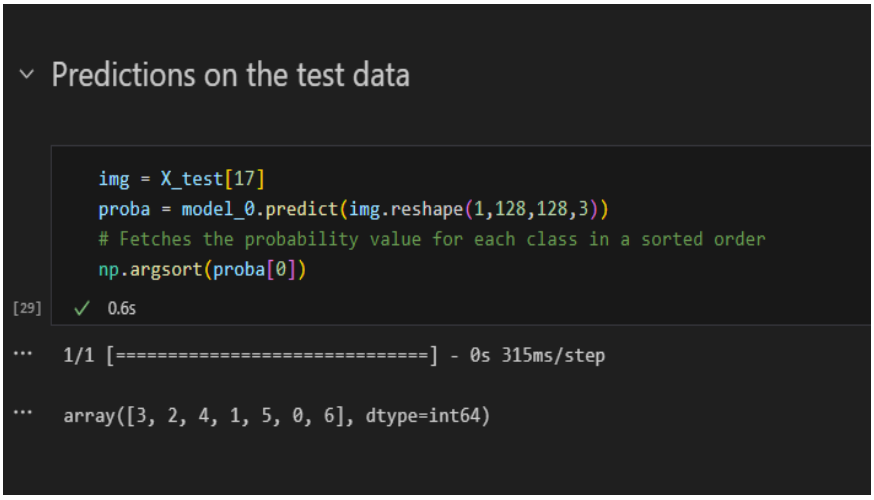

Fig-4: Prediction

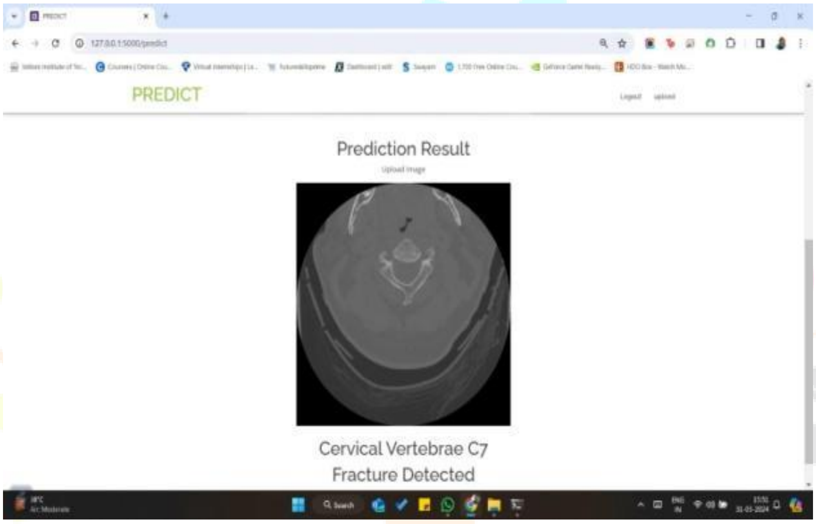

Fig-5: Fracture is detected

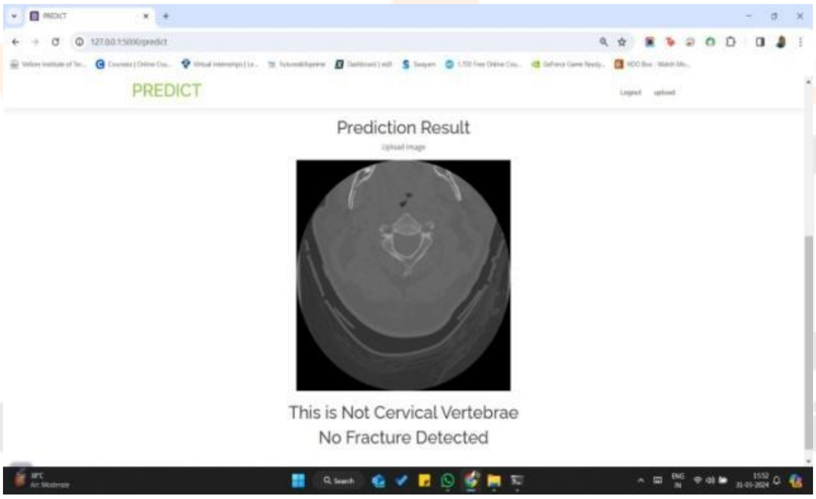

Fig-6: No Fracture is detected

V. CONCLUSION & FUTURE SCOPE

Conclusion: The automated cervical spine fracture detection system, employing deep neural networks and transfer learning, marks a substantial leap forward in medical imaging. By accurately delineating vertebrae boundaries and discerning fractures in CT images, it significantly improves diagnosis efficiency. Integration with Flask ensures user-friendly interaction. Minimizing human error, it enables timely interventions, potentially transforming fracture diagnosis and patient care. Further advancements in technology promise continued refinement, driving improvements in fracture detection and patient outcomes.

Future Scope: Future enhancements for "Cervical Spine Fracture Detection Using Deep Neural Networks" aim to bolster model performance, expand capabilities, and integrate seamlessly into clinical workflows. Key areas for development include leveraging advanced deep learning architectures like Vision Transformers and Graph Neural Networks for improved spatial understanding. Multi-modal fusion, incorporating clinical data, and enhancing interpretability with Explainable AI (XAI) techniques can enhance diagnostic accuracy and clinical decision-making. Real-time applications require optimizing model efficiency for rapid analysis in emergency settings. Continuous learning approaches and collaborative research partnerships can ensure the model stays current and effective in diverse healthcare settings. Regulatory approval and commercialization pathways are essential for translating research findings into tangible clinical solutions, ensuring widespread adoption and impact on patient care.

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