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Cervical Spine Fracture Detection Using Deep Learning

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Abstract - We've been looking into different disease detection models that use deep learning algorithms to look at medical radiograph images. Most of the studies have been done on lumbar spine diseases, but most of the studies were done on cervical spine diseases. Cervical radiculopathy is usually diagnosed based on MRI data, but it can be hard to diagnose even with an X-ray. MRI tests are expensive, so it can be hard for patients to get the right diagnosis. Cervical spine fractures are a medical emergency, and they can lead to permanent paralysis or even death. To make sure patients get the right diagnosis, it's important to use CT scans to check for fractures. We've come up with a Convolutional Neural Network (CNN) and Transfer Learning Model that can automatically detect cervical spine fractures from CT axial images, and we've trained and validated it using 4000 CT scans. We can even fine tune the transfer learning models to make it even more accurate.

Keywords

Convolutional Neural Networks, Computed tomography ,Deep learning , CT image , x ray , medical image , Spine disease , cervical spine fracture , Graphical user interface , Cervical radiculopathy.

I. INTRODUCTION

Cervical spine breaks are genuine wounds that can have long lasting impacts on a patient's portability and quality of life. Early discovery of these breaks is vital for giving successful treatment and avoiding advance harm. In later a long time, profound learning calculations have appeared promising comes about in therapeutic picture examination, counting break discovery. We have created a profound learning demonstrate for identifying cervical spine breaks utilizing CT check pictures. The cervical spine could be a complex structure that incorporates not as it were the seven vertebrae, but too intervertebral circles, muscles, tendons, and nerves. These structures work together to back the head and neck and permit for development. The cervical spine is especially helpless to harm since it is less ensured than the thoracic and lumbar locales of the spine. Wounds to the cervical spine can cause harm to the spinal rope, which can result in loss of motion, misfortune of sensation, and other neurological issues. Common causes of cervical spine wounds incorporate injury from falls, car mischances, and sports wounds. Conditions that can influence the cervical spine incorporate herniated plates, spinal stenosis, osteoarthritis, and degenerative circle infection.

Side effects of cervical spine issues can incorporate torment within the neck, shoulders, and arms, numbness or shivering within the arms, shortcoming within the arms.[1] Treatment for cervical spine problems depends on the under lying condition and may include physical therapy, medications, and surgery in severe cases. It's important to consult with a medical professional if you are experiencing any symptoms related to your cervical spine.

The first step in this project was data collection. We gathered a dataset of CT scan images containing two classes - fractures and normal - from multiple sources. The dataset was then preprocessed to remove any irrelevant or noisy data and to ensure consistency in the image size and format. Next, we performed data visualization to gain insights into the dataset's characteristics and identify any patterns or anomalies. We split the dataset into training, validation, and testing sets, ensuring that each set contained an equal distribution of fracture and normal images. We then developed two deep learning models - a CNN and VGG algorithm - and trained them on the training dataset. We used the validation set to fine-tune the models' hyperparameters and evaluate their performance. Finally, we developed a GUI that allows users to upload CT scan images and receive predictions on whether the image contains a fracture or not. This GUI provides a user-friendly and accessible way to test and evaluate the model's performance. Overall, this project demonstrates the potential of deep learning algorithms in medical image analysis and provides a valuable tool for detecting cervical spine fractures. The model's accuracy and efficiency,[1,11] .

II. SCOPE OF THE PROJECT

The goal of the "Cervical Spine Fracture Detection using Deep Learning" project is to create a system that can precisely identify cervical spine fracturesUsing convolutional neural networks (CNN) and the VGG method, cervical spine fractures can be found in CT scan pictures. The research seeks to speed up diagnosis and increase the precision of cervical spine fracture detection. The technology will be created to analyze CT scan images and detect the existence of cervical spine fractures. The model will be trained to recognize patterns in the

CT scan pictures that denote the presence of fractures using deep learning techniques, notably CNN and VGG. The study entails gathering a dataset of cervical spine CT scan pictures, including both healthy and broken instances. The CNN and VGG models will be trained using these preprocessed images. The models shall be improved.

Acute lymphoblastic leukaemia (ALL) occurs when the body produces a large number of immature white blood cells, called lymphoblasts. The malignant, immature white blood cells continuously multiply and are overproduced in the bone marrow.The microscopic investigation to identify the types and maturity of blood cells is performed manually by Hematologists through visual identification under the microscope. This requires a lot of time and effort.[20]

As a future work, this algorithm can be built into a complete application to allow end-user interaction i.e. it should allow haematologists to enter blood images and procure data results on a single mouse click.[20]

III. LITERATURE REVIEW

This topic has been the subject of numerous investigations. A deep learning-based technique for identifying cervical spine fractures from computed tomography (CT) images, for instance, was put forth by Zhang et al. (2019). Their approach, which extracted features from the CT images using a convolutional neural network (CNN), had a high accuracy of 95.4%. Similar to this, Hu et al. (2020) created a system based on deep learning to identify fractures in the cervical spine from X-ray pictures. Their technique, which had an accuracy of 93.7, used a CNN to extract features from the X-ray pictures. [2] A deep learning based technique for identifying cervical spine fractures from magnetic resonance imaging (MRI) images was put forth by Lin et al. (2020) in a different study. The accuracy of their method, which combined CNN and recurrent neural network (RNN) to extract characteristics from the MRI images, was 91.7 percent. In addition, a number of other research [2] investigated the application of deep learning for the detection of cervical spine fractures. J.A. Soares, E. Nascimento, M. Goldbaum, et al. published "Automated Detection and Classification of Cervical Spine Fractures on CT Images Using Deep Learning Neural Networks" [3]. Author of numerous textbooks and journal publications on spinal illnesses and surgery, Dr. Paul A. Anderson is a spine surgeon. His research has concentrated on the identification and management of complex spinal illnesses, notably those that affect the cervical spine. Dr. Anderson has played a significant role in the development of novel surgical procedures and methods for the treatment of cervical spine abnormalities and injuries, and his research has advanced our knowledge of the biomechanics of the cervical spine [4]. A deep learning-based method was developed by Cui et al. (2020) to identify fractures of the cervical spine on CT scans. The writers combined CNN and long-term short-term data. memory (LSTM) models to analyze the images. In one study, Yan et al. (2019) created a deep learning-based method for identifying fractures of the cervical spine on CT scans. To analyze the photos, the authors combined CNN and RNN models. The findings demonstrated that the generated model had a high level of accuracy in identifying fractures of the cervical spine. [6] In a different work by Hwang et al. (2021),

the researchers created a deep learning-based system for spotting fractures of the cervical spine on X-rays. To train and test the model, the authors employed a dataset with more than 10,000 X ray images. The findings demonstrated that the created model had a high degree of accuracy in identifying cervical spine fractures, offering a possible tool for early detection. [6] .In one study, Yan et al. (2019) created a deep learning-based method for identifying fractures of the cervical spine on CT scans. To analyze the photos, the authors combined CNN and RNN models. The findings demonstrated that the generated model had a high level of accuracy in identifying fractures of the cervical spine. [6] In a different work by Hwang et al. (2021), the researchers created a deep learning

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According to a review of the literature, deep learning models have demonstrated encouraging outcomes in the detection of cervical spine fractures on X-ray images. However, using CT scan pictures, which offer more thorough details on the internal architecture of the spine, has the potential to achieve even better accuracy. The suggested solution is to create a deep learning model specifically for identifying fractures of the cervical spine using CT scan pictures. The well-known and widely-used CNN and VGG architectures, which are used extensively in deep learning, can be utilized to train this model. This model has the potential to attain even greater levels of accuracy than those seen in other studies on X-ray pictures with a large dataset of CT scan images and thorough training. The suggested method has the potential to optimize the diagnostic procedure for cervical spine fractures, resulting in earlier identification and better patient outcomes by increasing the accuracy of fracture detection utilizing CT scans. A more precise and effective diagnostic technique may also lessen the strain on healthcare systems and enhance patient care in general. Further study and testing are necessary, though, to guarantee the deep learning model's security and efficiency in a clinical setting[10]

IV. METHODOLOGY

A. Dataset Description

• The collection includes images from CT scans of the spine together with labels indicating whether or not there are any fractures. Using CT-Scan pictures as a basis, the dataset aims to create machine learning models that can precisely predict whether the spine has fractures.

• Spinal fractures are a common condition that can occur due to a variety of reasons such as trauma, osteoporosis, or cancer. Early detection of spinal fractures is crucial for effective treatment and can prevent further complications.

• There are 4,060 PNG images of CT-Scans in the dataset, with resolutions ranging from 223x310 to 1632x2215 pixels. The presence or absence of a spinal fracture is indicated by the labels "Normal" or "Abnormal" next to each image. Each CTScans image is given a "Positive" or "Negative" label depending on whether a spinal fracture is present or not.

Less positive (fractured) cases than negative (non-fractured) cases make up the dataset's imbalance. Some machine learning algorithms' performance may be impacted by this, especially those that are sensitive to class imbalance[11].

B. CNN Algorithm

Informed by the visual hierarchy of animals, CNN is a deep learning model for processing grid-patterned data, such as photographs. It was created to generate a low-to-high spatial hierarchy of characteristics and apply it to this study. Convolutional layers, pooling layers, and all layers are the three different types of layers (or building blocks) that make up a typical CNN mathematical model. Feature extraction is carried out by the first two convolutional and pooling layers, while the third fully connected layer transfers the extracted features to the output, such as classification. Given that features can exist anywhere in the image, CNNs are particularly successful at analyzing images. The collected characteristics can be stacked and made more complicated as one layer feeds its output to the following layer.

Training is the process of optimizing kernels and other parameters using the gradient descent and backpropagation optimization algorithms to distinguish between output and text. Convolutional Neural Networks (CNNs) have excelled at a number of image classification tasks, including those involving medical imaging. One such task where CNNs have demonstrated promising results is cervical spine detection. The cervical spine, which supports the neck and head, is the higher portion of the spinal column and is made up of seven vertebrae. For the accurate diagnosis of a number of disorders, including fractures, herniated discs, and spinal cord injuries, the cervical spine must be checked for anomalies. CNNs can help with this detection process by automating the process of spotting anomalies, which eliminates the need for manual examination.The input image is first preprocessed in a conventional CNN-based cervical spine detection technique to remove any artifacts and improve the contrast between the bones and surrounding tissue. A number of layers of convolutions and pooling are added to the preprocessed picture before it is given to the CNN, which then employs fully linked layers. From the input image, the convolutional layers extract pertinent characteristics, while the pooling

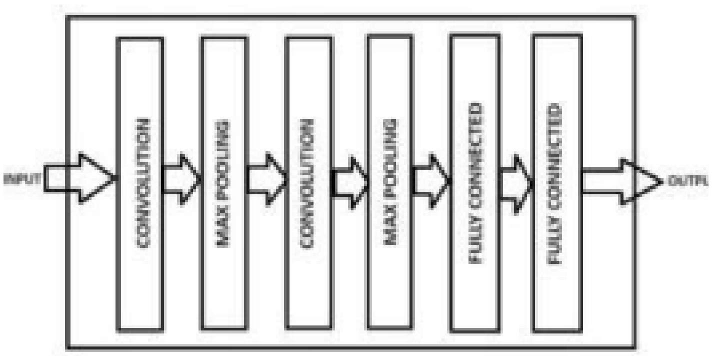

Fig. 1. CNN Architecture [17]

D. Flow Chart

The objective of the project is to process and examine a dataset in various phases in order to create a precise predictive model and gain understanding of the underlying patterns and trends. The data is initially loaded and checked for consistency and mistakes. To find any relationships and correlations between the variables, the preprocessed data is then visualized using a variety of ways. The data is then divided into training and testing sets according to the labels, and a model is trained using the proper methods on the training set. Finally, a user friendly graphical user interface (GUI) is used to display the results of the performance evaluation of the model on the testing set. With this all-encompassing strategy, the data can be thoroughly understood, and precise predictions can be made to help with decision-making. [10]
You may need to crop the image to focus not on the female spine area of interest, which can reduce noise and improve the model process. • c. Image adjustment: You may need to adjust the image so that the pixel intensity is within a certain range, which can improve model stability. • d. Data augmentation: Data augmentation involves applying random changes to existing images, such as rotating or shifting, to generate new training samples. This can increase the size and diversity of your data set and improve the ability of your model to generalize to new data. • Data View: To understand the distribution of data and trends you need to look at the data set. • Data Splitting: A common strategy is to randomly split the data set into three sets: the training set, the validation set, and the test set. The training set is used to train the machine learning model. Sets are similar to the following: They are used to specify model parameters and the test set is used to evaluate the final performance of the model. 80% for training, 10% for certification and 10% for testing. However, the specific split ratio may depend on the size of your data set and the specific requirements of the problem you are solving. • Model Training: The next step is to train the model instead of the dataset using the CNN algorithm. This step contains several subsections: a. Model Architecture: You need to define the model architecture, including the number and type of layers, the activation function, and the secret function. Verifier: The corrector is used to update the model weights during training to reduce the missing feature. Common editors are SGD, Adam and RMSprop. Set advanced parameters: Advanced parameters are parameters that are set before training the model such as learning rate, batch size, number of subjects. These parameters can have a significant impact on model performance and must be adjusted for optimal results. • Model Evaluation: The performance of the trained model should be evaluated to assess accuracy, sensitivity, specificity, and other metrics. Evaluation methods may include confusion matrices, ROC curves, and memory accuracy curves. This step is important to ensure that the model performs well on the training and test datasets and is reliable in making accurate predictions. • GUI Development: A friendly GUI should be created so that the developed fracture detection model is easy to access and use. GUIs can be built using programming languages such as Python and frameworks such as Flask and Tkinter

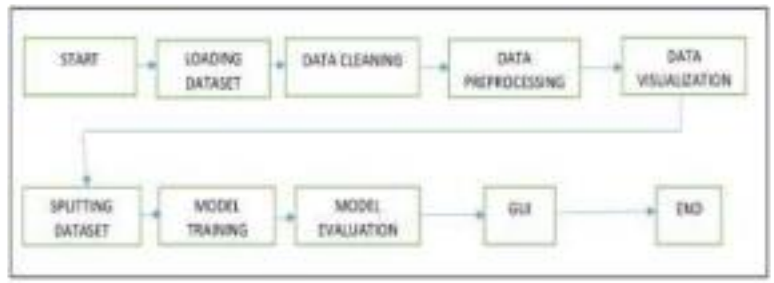

Fig. 3. Flow Chart

RESULT AND ANALYSIS

• Data Collection: The first step of the project was to collect a dataset of CT images of the cervical spine, including normal and fractured images .Data sets can be obtained from available sources or through collaboration with health organizations. The data set must be large enough to provide accurate samples of broken genes. • Data processing: pre-processing the data so that the images are ready for model training. This step contains several substeps: • a. Image Size: Keep images the same size, you may need to resize them for model training. •b. Crop the image:

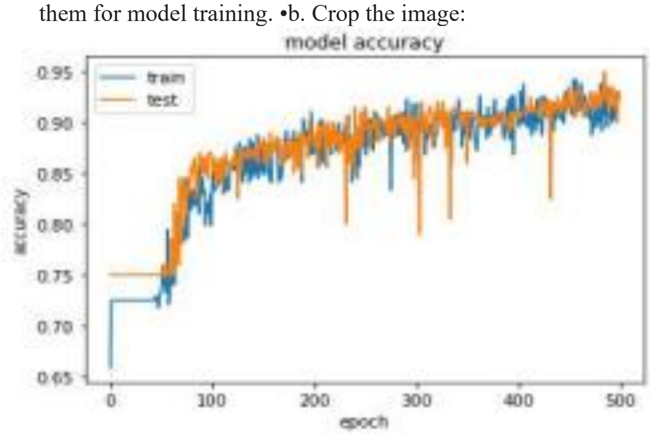

Fig.4.Model Accuracy

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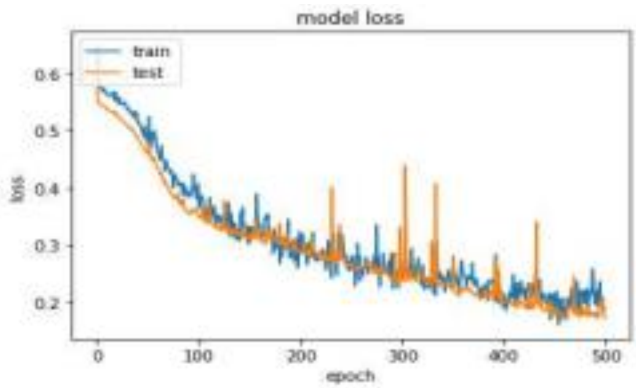

Fig.5.

Model Loss
Fig.6 Fig.7 Normal Fracture

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