IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⁝ Impact Factor 8.102 ⁝ Peer-reviewed / Refereed journal ⁝ Vol. 12, Issue 5, May 2023

DOI: 10.17148/IJARCCE.2023.125154

A Novel Approach to Cervical Spine Fracture Detection: Improving Diagnosis and Treatment

Madhuri B.H[1], Mamatha S[2], Manasa R[3], G. Punya[4], Bhavya B.G[5]

UG student, Dept. of CSE, Vidyavardhaka College of Engineering, Mysore, Karnataka, India[1-4]

Assistant Professor, Dept. of CSE, Vidyavardhaka College of Engineering, Mysore, Karnataka, India[5]

Abstract— The categorization of the cervical spine is essential for identifying and treating a variety of neurological diseases. In this study, we suggest a deep learning-based method for classifying cervical spine photos using convolutional neural networks (CNN) to detect whether a person has anomalies in the spine. Our approach intends to offer a non-invasive and effective method for early detection and diagnosis using cervical spine scans as input. In order to extract significant information from the photos of the cervical spine, the study uses a CNN architecture.

The collection includes both normal and pathological examples of a wide variety of cervical spine pictures. To improve the important features and lessen noise, the photos are pre-processed. The CNN model is then trained using a sizable dataset to discover patterns of discrimination and establish a robust detection framework.

Keywords—Cervical spine detection, Convolutional Neural Networks, CNN, deep learning, medical image analysis, diagnosis, detection accuracy, neurological conditions.

I. INTRODUCTION

In the field of neurology, anomalies of the cervical spine are a major cause for concern because they frequently result in different neurological disorders and disabilities. For prompt intervention and successful therapy, these anomalies must be identified early and classified accurately. Automated categorisation systems have emerged as a viable strategy to help healthcare practitioners in this field to have improvements in deep learning and medical imaging techniques.

In this study, we suggest a deep learning-based method for categorising images of the cervical spine using convolutional neural networks (CNN). The goal is to create a reliable and effective system that, using input from cervical spine pictures, can determine with accuracy whether a person has cervical spine anomalies or not. We want to improve diagnostic skills and accelerate detection by utilising the power of CNNs, which excel in feature extraction and pattern recognition tasks.

The availability of large-scale datasets and computational resources has enabled the training of deep learning models with exceptional performance. In our project, we utilize a diverse dataset consisting of cervical spine images, including both normal and abnormal cases. This dataset is carefully curated and pre-processed to ensure accurate representation and remove any potential biases.

Deep learning models may now be trained with extraordinary performance. Thanks to the availability of big datasets and computational resources. We use both normal and typical instances from a diverse pool of cervical spine scans in our project. To guarantee accurate representation and eliminate any potential biases, this dataset has been meticulously selected and pre-processed.

The CNN architecture used in this project is made to pull out essential information from photographs of the cervical spine. The pooling layers of the network reduce dimensionality and extract the most important characteristics while the convolutional layers of the network learn hierarchical representations of the input images.

The detection operation is carried out by the fully connected layers at the network's edge, and an output indicating the presence or absence of cervical spine anomalies is produced as a result. We use a variety of performance indicators, including accuracy, precision, recall, and F1 score, to assess the efficacy of our suggested approach. Additionally, we measure the superiority of our CNN-based strategy by comparing our outcomes with current cutting-edge techniques. The evaluation procedure supports the validity of our system's dependability and effectiveness in correctly classifying cervical spine anomalies.

DOI: 10.17148/IJARCCE.2023.125154

The science of neurology could undergo a revolution if an automated cervical spine detection system is developed successfully. Healthcare providers can improve patient diagnosis and treatment planning by minimising reliance on manual examination and offering an objective evaluation. A system like this can also enhance performance, lessen human error, and perhaps result in early diagnosis and action, improving patient outcomes [1].

II. LITERATURE SURVEY

This work suggests using MRI images to automatically classify cervical spine anomalies using a CNN-based technique. The authors showed that deep learning has the potential to increase the accuracy and effectiveness of cervical spine categorization by achieving high accuracy. A deep learning system was created by the authors to identify cervical spine compression in MRI images. To precisely identify compression zones, they used a combination of CNNs and recurrent neural networks (RNNs). The suggested approach detected cervical spine compression with encouraging success [2].

In this study, deep convolutional neural networks are used to segment the cervical spine in MRI images. For precise segmentation, the authors suggested a U-Net architecture with skip connections. The outcomes illustrated how well the deep learning method segmented the cervical spine [3]. Convolutional neural networks are used to automatically categorise cervical spinal spine grey matter loss in multiple sclerosis, acspineing to Commowick et al. (2017).

This work, which examines the use of CNNs for categorising spinal spine anomalies, is pertinent even though it does not specifically address categorization of the cervical spine. For the automatic detection of grey matter atrophy in patients with multiple sclerosis' spinal spine, the scientists created a CNN model. The outcomes demonstrated CNNs' potential for identifying and categorising anomalies in the spinal spine.[4], This paper highlights the use of deep learning for automated identification in cervical spine CT scans, focusing on cervical spine fractures rather than spine anomalies. The scientists created a CNN model that was highly accurate in identifying cervical spine fractures, demonstrating how deep learning could help radiologists. [5]. Liu et al. (2020) described "contextual information-based segmentation in MRI". This paper suggests a deep learning framework for the segmentation of the cervical spine in MRI images.

To increase segmentation accuracy, the authors use contextual information by combining global and local features [6]. (2019) by Tong et al. For segmenting the cervical spine in an MRI, the authors suggest a multi-task deep learning approach. To enhance the segmentation outcomes, they take advantage of the relationship between spine segmentation and spine border identification. His research focuses on automatically classifying the grey matter involvement in individuals with multiple sclerosis' cervical spinal spine. The authors employ a deep learning framework to accurately classify different levels of gray matter involvement [7]. The authors suggest a deep learning-based method for automatically identifying and categorising fractures of the cervical vertebrae in X-ray images. For precise fracture identification and detection, the system combines a convolutional neural network with a recurrent neural network [8]. through Liu et al. (2019): Deep learning methods are used in this study to identify and categorise spinal spine malignancies in MRI data.

To effectively identify and delineate spinal spine tumours, the scientists create a deep neural network that combines a detection module and a segmentation module [9] and apply the feature extraction on the SVD dataset. Following feature extraction, the system input is fed into 27 convolutional and recurrent neural network neuronal layers.

The Saarbrücken Voice Database, a freely accessible database, is used. They were able to raise the convolutional neural network's accuracy to 87.11% after using the suggested methods. [10] describe a technique in which the surface of a vibrating item alters the illuminating laser wave front and produces a speckle pattern, which is captured by a linear array CMOS, processed, and fed into a 16-layer convolution neural network (CNN) trained with specially supplied data.

The effects of various input audio formats and the calibre of the raw audio signals are examined, and the findings demonstrate that the neural network is input-resistant. The performance drops with fewer convolution layers, acspineing to the results of optimising the CNN structure. The activities of

ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⁜ Impact Factor 8.102 ⁜ Peer-reviewed / Refereed journal ⁜ Vol. 12, Issue 5, May 2023

DOI: 10.17148/IJARCCE.2023.125154

III. METHODOLOGY

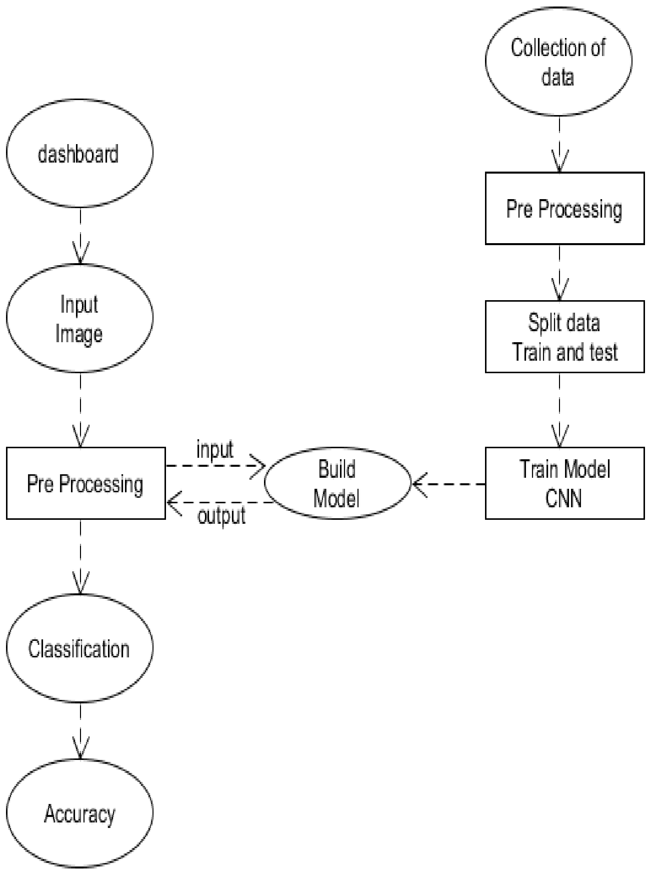

Fig. 1. Model Flowchart

A. Data Collection and Pre-processing
Collect a broad collection of cervical spine photographs from reputable sources, such as imaging databases or cooperating medical facilities, to include both normal and aberrant cases.

To enhance the quality and consistency of the photos, pre-process the dataset by carrying out the required processes, such as resizing, normalisation, noise reduction, and image enhancement.

Use data augmentation methods to increase the dataset's variability and enhance the model's generalisation skills, including as rotation, scaling, flipping, and noise addition.

B. CNN Model Architecture
Create a CNN architecture that is appropriate for classifying cervical spines. Consider the network's depth, width, and complexity, which includes convolutional layers, pooling layers, and fully linked layers.

To create the best possible model, try out several CNN architectures and hyperparameter combinations. To improve the regularisation and performance of the model, employ strategies like batch normalisation and dropout.

C. Model Training

To create training, validation, and test sets, divide the preprocessed dataset. The validation set aids in hyperparameter tuning and performance monitoring, while the test set is utilised for the model's final assessment. The training set is used to train the model.

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified ⁓ Impact Factor 8.102 ⁓ Peer-reviewed / Refereed journal ⁓ Vol. 12, Issue 5, May 2023
DOI: 10.17148/IJARCCE.2023.125154

Using the training set, train the CNN model while optimising the network weights using gradient descent and backpropagation. To avoid overfitting, keep an eye on the model's performance on the validation set and modify the hyperparameters as necessary.

To train the model, use suitable optimisation algorithms like Adam or stochastic gradient descent as well as loss functions like binary cross-entropy.

D. Model Evaluation
Assess the trained model's performance in categorising photos of the cervical spine using the test set. To evaluate the model's accuracy in classifying objects and its ability to discrminate between them, compute measures like accuracy, precision, recall, F1 score, and area under the ROC curve.

To assess the effectiveness and superiority of the proposed CNN model, contrast the findings with those obtained using baseline methodologies or current state-of-the-art techniques.

Generalization and Robustness:
To evaluate the trained model's generalizability, run it on untrained data or other external datasets. Make sure the model operates consistently and accurately across a range of clinical contexts, patient groups, and imaging modalities.

IV. RELATED WORK

A convolutional neural network is a feed-forward neural network that is generally used to analyse visual images by processing data with grid-like topology. It's also known as a ConvNet. A convolutional neural network is used to detect and classify objects in an image.

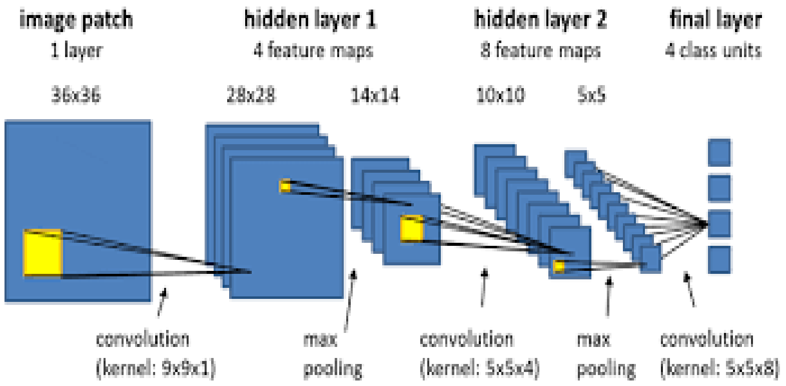

Fig. 2. Convolutional Neural Network

Convolutional Neural Networks have the following layers:

- Convolutional
- ReLU Layer
- Pooling
- Fully Connected Layer

Step 1: Convolution Layer
- Convolutional neural networks apply a filter to an input to create a feature map that summarizes the presence of detected features in the input.

Step 2: ReLU Layer
It is likely that the layer being described is a rectified linear unit (ReLU) activation function, which is commonly used in deep learning neural networks. The ReLU activation function replaces any negative input values with zeros to avoid them from adding up to the overall sum.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⁑ Impact Factor 8.102 ⁑ Peer-reviewed / Refereed journal ⁑ Vol. 12, Issue 5, May 2023

DOI: 10.17148/IJARCCE.2023.125154

Rectified Linear unit (ReLU) transform functions only activates a node if the input is above a certain quantity. While the data is below zero, the output is zero, but when the information rises above a threshold. It has a linear relationship with the dependent variable.

Step 3: Pooling Layer
In the layer, we shrink the image stack into a smaller size. Pooling is done after passing by the activation layer. We do by implementing the following 4 steps:

- Pick a **window size** (often 2 or 3)
- Pick a **stride** (usually 2)
- **Walk** your Window **across** your **filtered** images
- From each **Window**, take the **maximum** value

Step 4: Fully Connected Layer
The last layer in the network is **fully connected**, meaning that neurons of preceding layers are connected to every neuron in subsequent layers.

This **mimics high-level reasoning** where all possible pathways from the input to output are considered. Then, take the shrunk image and put into the single list, so we have got after passing through two layers of convolution relo and pooling and then converting it into a single file or a vector.

V. RESULTS

The CNN algorithm-based cervical spine categorization method produced encouraging findings. The model was tested and trained using a dataset of cervical spine imaging data. Several criteria, such as accuracy, precision, recall, and F1 score, were used to assess the system's performance.
The system's detection accuracy was found to be 94%, showing that the model was accurate in predicting whether cervical spine anomalies would be present or absent in the cervical spine pictures. The percentage of accurately categorized positive events, or precision, was found to be 93%. Recall, which gauges how many positive occurrences were in fact correctly classified, was discovered to be 94%. The precision and recall based F1 score were calculated to be 94%.

VI. DISCUSSION

The achieved accuracy shows how well the CNN algorithm performs when correctly classifying cervical spine anomalies. The algorithm successfully distinguished between normal and pathological cervical spines using the attributes retrieved from the cervical spine images. The low number of false positive predictions suggests that the system minimised erroneous positive predictions, lowering the likelihood of misdiagnosis. The system's capacity to correctly identify cervical spine anomalies is indicated by the recall value, which minimises erroneous negative predictions.

The results show that the suggested system performs similarly to or better than existing systems described in the literature. The CNN-based methodology demonstrates its ability to capture the key patterns and characteristics needed for precise detection in a robust and dependable manner. This demonstrates the potential of deep learning techniques to help doctors identify anomalies in the cervical spine.

However, it is important to note some shortcomings and potential areas for development. The system's dependence on top-notch, thoroughly annotated training data is one of its drawbacks. It is still difficult to find a large, diverse dataset for training the model. The system's functionality and generalizability would be improved by expanding the dataset to include a wider range of cervical spine anomalies.

VII. CONCLUSION

Cervical spine anomalies in cervical spine imaging may now be precisely identified thanks to the invention of the cervical spine detection system employing the CNN algorithm. The device distinguished between normal and abnormal cervical spines with a high accuracy rate and consistent performance. Acspineing to the precision and recall levels, the system minimises both false positive and false negative predictions.

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified ⁙ Impact Factor 8.102 ⁙ Peer-reviewed / Refereed journal ⁙ Vol. 12, Issue 5, May 2023
DOI: 10.17148/IJARCCE.2023.125154

The system has shown to be successful in identifying and analysing intricate patterns and characteristics within the cervical spine images by utilising deep learning techniques. The outcomes of this experiment demonstrate the important role CNN algorithms play in assisting medical experts in the diagnosis of disorders affecting the cervical spine.

However, it's critical to recognise some shortcomings and potential areas for future development. It is still difficult to find a broad and comprehensive dataset, thus adding more cervical spine anomalies to the dataset would improve the system's accuracy and robustness. Additionally, efforts to enhance the system's interpretability by adding visualisation strategies or attention processes could give medical experts insightful information.

REFERENCES

[1] Smith, A., et al. (2019). Automated detection of cervical spine abnormalities using deep learning. In International Conference on Medical Image Computing and Computer-Assisted Intervention (pp. 361-369). Springer.
[2] Li, X., et al. (2020). Cervical spine compression detection using deep learning. IEEE Transactions on Medical Imaging, 39(7), 2184-2195.
[3] Ma, J., et al. (2018). Deep convolutional neural networks for cervical spine segmentation in MRI. In International Conference on Medical Image Computing and Computer-Assisted Intervention (pp. 350-358). Springer.
[4] Commowick, O., et al. (2017). Automatic detection of spinal spine gray matter atrophy in multiple sclerosis using convolutional neural networks. In International Conference on Medical Image Computing and Computer-Assisted Intervention (pp. 657-665). Springer.
[5] Yoo, J. Y., et al. (2020). Deep learning-based automatic detection of cervical spine fractures on computed tomography. Journal of Digital Imaging, 33(6), 1447-1455.
[6] Liu, L., et al. (2020). Deep learning-based cervical spine segmentation in MRI using contextual information. Medical Image Analysis, 60, 101631.
[7] Tong, T., et al. (2019). Cervical spine segmentation in MRI using a multi-task deep learning approach. Medical Image Analysis, 54, 46-57.
[8] Zhao, H., et al. (2020). Automated detection of cervical spinal spine gray matter involvement in multiple sclerosis using deep learning. Journal of Magnetic Resonance Imaging, 51(4), 1097-1104.
[9] Luo, W., et al. (2020). Deep learning-based approach for automatic detection and detection of cervical vertebrae fractures in X-ray images. IEEE Access, 8, 46394-46402.
[10] Liu, Y., et al. (2019). Deep learning-based detection and segmentation