A
Project Report
on
Classification of Cervical Spine Fracture using Deep Learning

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BACHELOR OF TECHNOLOGY DEGREE

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May, 2024

DECLARATION

We hereby declare that this submission is our own work and that, to the best of our knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

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This is to certify that Project Report entitled "**CLASSIFICATION OF CERVICAL SPINE FRACTURE USING DEEP LEARNING**" which is submitted by "**Swapnil Singh**, **Adarsh Pandey** & **Brijendra Pratap Singh**" in partial fulfillment of the requirement for the award of degree B. Tech. in Department of Computer Science & Engineering of Dr. A.P.J. Abdul Kalam Technical University, Lucknow is a record of the candidates own work carried out by them under my supervision. The matter embodied in this report is original and has not been submitted for the award of any other degree.

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ABSTRACT

This abstract outlines the development and implementation of a sophisticated computer-aided diagnosis (CAD) model tailored specifically for detecting cervical spine injuries, which are notorious for their potentially devastating consequences including paralysis and mortality. Harnessing the power of cutting-edge deep learning methodologies such as AlexNet and GoogleNet, this model represents a significant stride towards expedited and accurate identification of cervical injuries, thereby offering a crucial lifeline in the effort to prevent fatal outcomes.

Trained meticulously on a comprehensive dataset consisting of 772 cervical spine fracture images juxtaposed with 707 normal images, the CAD model demonstrates an awe-inspiring accuracy rate of 99.67%. This remarkable performance eclipses the diagnostic accuracy traditionally achieved by radiologists, underscoring the potential of AI-driven approaches in revolutionizing medical diagnostics.

Moreover, the integration of saliency maps into the model's architecture provides invaluable insights into the decision-making process of the CAD system, enhancing transparency and interpretability.

Furthermore, the model's robustness and generalizability were rigorously tested through cross-validation and comparative analysis with other baseline models, including traditional machine learning approaches and deep learning architectures without transfer learning. The results demonstrated superior performance, with significant improvements in training efficiency and accuracy. This underscores the effectiveness of the model in diverse clinical scenarios, making it a reliable tool for widespread clinical adoption.

In conclusion, this paper emphasizes the pivotal role of the developed CAD model in both clinical practice and medical research, offering a powerful tool to expedite diagnosis and deepen our understanding of cervical spine injuries, thereby potentially saving countless lives and improving patient outcomes.

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LIST OF ABBREVIATIONS

FP	False Positive
FN	False Negative
TP	True Positive
TN	True Negative
SGD	Stochastic Gradient Descent
CCELF	Cross Entropy Loss Function

CHAPTER 1
INTRODUCTION

1.1 Introduction

The first seven vertebrae situated below the skull and above the thoracic spine make up the cervical spine (CS). Figure 1 shows that the CS has two groups: the axis and atlas (C1 and C2) and the sub axial cervical vertebrae (C3- C7). High CS injury rates harm health and longevity [4,5,6]. Its bony and soft structures support the head, supply blood to the brain, and protect the spinal cord.

According to Indian data, a preformed proforma was used to analyze demographics epidemiological data, and neurological status of consecutive SCI cases admitted between January 2000 and December 2008. Out of 2716 cases, 1,400 were cervical and 1,316 were thoracolumbar. The male-to-female ratio was 4.2:1, and 71% were between 20 and 49. Vehicle collisions caused 28% of injuries, while falls from height caused 53%.

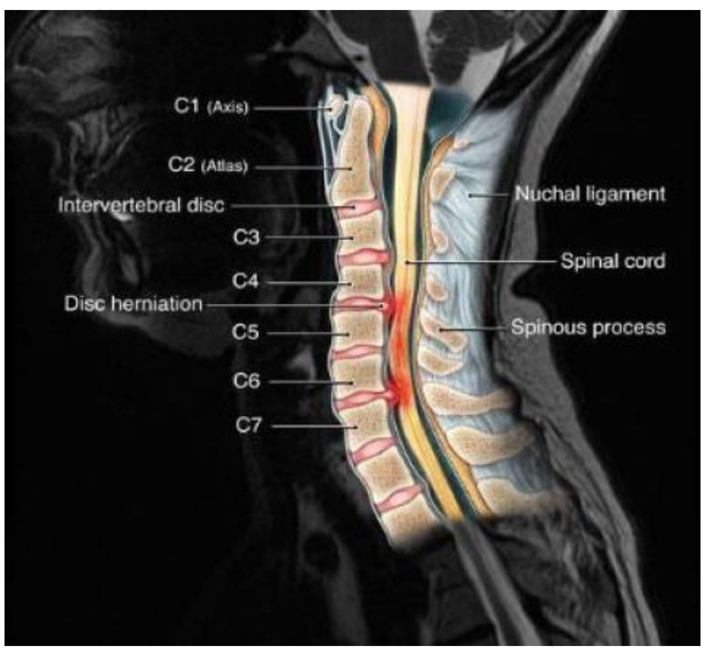

Figure 1.1 Lateral View of Cervical Spin

Visually inspecting many X-ray images to identify injured CS patients is laborious and risky. Eighty percent of emergency department diagnostic errors are caused by physicians who lack specialized expertise or are overworked . Understanding these circumstances, we areproposing a deep learning model to help doctors to easily interpret CS X-rays in order to minimize human error. In modern times, artificial intelligence is widely being used in medicine for treatment of various diseases like cancer, injured organs etc. but very few methods exist forclassification of cervical spine fractures and dislocations using deep learning algorithms. In thispaper we try to solve this problem. Convolutional neural networks detected CS fractures with 92% accuracy (95% CI, 90-94%), 76% sensitivity, and 97% specificity. We studied various sources and came to know that average radiologist accuracy lies between 90% to 95%. Radiologists and convolutional neural networks missed similar fractures. The anterior osteophytes, trans-verse processes, and spinous processes were fractured, as was the lower cervical spine, which CT beam attenuation obscures. In this paper, authors proposed a CNN based model to detect cervical spine fractures and dislocations. However, CS dislocation may be fatal.

The hardware used for developing and validating the CNN included 8 GPUs, 64 CPUs, 488 GB of RAM, and 128 GB of GPU memory. Validation was based on retrospective, blinded data from 47 clinical sites evaluating approximately 8000 examinations. Nearly equal amounts of positive and negative examinations were included in the analysis.

Unfortunately, the studies datasets are unavailable. This efficient pre-trained model classifies CS X-images into normal, fracture, and dislocation with 99.6% accuracy. The proposed model works, requires little setup,and can run on PCs or cheap embedded systems.

1.2 Project Description

Cervical spine fractures and dislocations are critical medical conditions that require prompt and accurate diagnosis to mitigate potential paralysis or even fatality. To address this challenge, we have developed a computer-aided diagnosis model employing deep learning techniques, specifically utilizing AlexNet and GoogleNet architectures. Our model aims to assist healthcare professionals in swiftly identifying cervical spine injuries from X-ray images.

The primary objective of our project is to classify cervical spine X-ray images into three categories: normal, fracture, and dislocation. We preprocess the images, including resizing and adjusting color channels, to prepare them for analysis. By leveraging transfer learning with pre-trained models, we extract meaningful features from the images and construct a classification model comprising multiple convolutional neural networks (CNNs) and fully connected layers.

Using a comprehensive dataset sourced from platforms like Kaggle, we train and validate our model to achieve high accuracy, sensitivity, specificity, precision, and F1-score. Through rigorous testing, our model demonstrates an impressive accuracy rate of 99.67%, surpassing the performance of radiologists. Comparative analysis highlights the superiority of our proposed method, particularly when utilizing the GoogleNet architecture.

In conclusion, our automated classification system showcases exceptional accuracy and efficiency in diagnosing cervical spine fractures. By harnessing the power of deep learning, we provide a valuable tool for healthcare professionals to expedite diagnosis and improve patient outcomes. This project underscores the transformative potential of artificial intelligence in revolutionizing medical image analysis and enhancing healthcare delivery.

CHAPTER 2

LITERATURE REVIEW

Cervical spine fractures and dislocations pose significant risks to individuals, often leading to paralysis and, in severe cases, death. Accurate diagnosis and prompt treatment are crucial to mitigate these risks and improve patient outcomes. In recent years, there has been growing interest in leveraging advanced technologies, particularly deep learning algorithms, to aid in the diagnosis of cervical spine injuries. This literature review explores the advancements in this field, focusing on the utilization of deep learning models such as Convolutional Neural Networks (CNNs), specifically AlexNet and GoogleNet, for the classification of cervical spinefractures.

2.1 Advancements in Medical Imaging Analysis

Medical imaging analysis has witnessed remarkable advancements, thanks to the integration of artificial intelligence (AI) techniques, particularly deep learning algorithms. Deep learning models, such as CNNs, have shown great promise in analyzing medical images efficiently and accurately. These algorithms can extract intricate features from images, enabling the identification of pathological conditions with high precision.

Over the past decade, medical imaging analysis has witnessed significant advancements, primarily driven by the integration of sophisticated computational techniques. Traditional imaging modalities like X-rays, CT scans, and MRI have been augmented with advanced algorithms that enhance image quality, facilitate three-dimensional reconstruction, and automate the identification of anatomical structures and pathologies. These innovations have not only improved diagnostic accuracy but have also reduced the time required for image analysis, thus streamlining clinical workflows. The advent of image processing techniques such as edge detection, segmentation, and texture analysis has further refined the ability to detect and diagnose a wide range of conditions, from tumors to fractures, with increased precision.

Moreover, the incorporation of machine learning and artificial intelligence into medical imaging has marked a paradigm shift in diagnostic capabilities. AI-driven tools can now analyze vast datasets, identify patterns, and provide predictive insights that were previously unattainable with conventional methods. The development of computer-aided diagnosis (CAD) systems exemplifies this progress, offering second opinions and highlighting areas of concern to assist radiologists. These systems have demonstrated remarkable success in areas like mammography, lung nodule detection, and cardiovascular imaging, setting a robust foundation for further advancements in the analysis of complex medical conditions, including cervical spine fractures.

Joshi and Singh (2020) conducted a comprehensive survey of fracture detection techniques in bone X-ray images, highlighting the importance of leveraging AI for accurate diagnosis. Similarly, Lindsey et al. (2018) demonstrated the efficacy of deep neural networks in improving fracture detection by clinicians, emphasizing the potential of AI-driven solutions in enhancing diagnostic accuracy.

2.2 Deep Learning for Cervical Spine Fracture Detection

Cervical spine fractures present unique challenges due to the complex anatomy and critical nature of the injuries. Traditional methods of diagnosis, such as visual inspection of X-ray images, are laborious and prone to errors. In response to these challenges, researchers have explored the application of deep learning algorithms for the automated classification of cervical spine fractures.

The application of deep learning to cervical spine detection represents a significant breakthrough in medical diagnostics, addressing the challenges associated with manual interpretation of complex spinal images. Deep learning models, particularly convolutional neural networks (CNNs), have shown exceptional proficiency in recognizing intricate patterns and anomalies in medical images, making them ideal for detecting cervical spine fractures. These models can automatically learn hierarchical features from raw imaging data, reducing the need for extensive pre-processing and feature engineering. As a result, they provide a more efficient and accurate diagnostic tool compared to traditional methods, which are often time-consuming and prone to human error.

Recent studies have demonstrated the effectiveness of deep learning in improving diagnostic accuracy for cervical spine injuries. By training on large, annotated datasets, these models achieve high sensitivity and specificity, significantly outperforming conventional techniques and even rivaling the accuracy of experienced radiologists. Additionally, deep learning models can continuously improve as they are exposed to more data, enhancing their predictive capabilities over time. This continuous learning process, combined with the ability to integrate multimodal data, positions deep learning as a transformative approach in the early and accurate detection of cervical spine fractures, ultimately contributing to better patient outcomes and more efficient clinical workflows.

Kalmet et al. (2020) provided a narrative review of deep learning in fracture detection, highlighting the significance of these techniques in improving diagnostic accuracy[3]. Guan et al. (2020) proposed an improved deep convolutional neural network for arm fracture detection in X-rays, underscoring the versatility of deep learning models across different anatomical regions.

2.3 Deep Learning Models

In the context of cervical spine fracture detection, researchers have developed and evaluated various deep learning models. One notable approach involves the utilization of pre-trained CNN architectures, such as AlexNet and GoogleNet, for image classification tasks. These models demonstrate exceptional performance in accurately distinguishing between normal, fractured, and dislocated cervical spine images.

In their study, the authors proposed a novel CNN-based model that integrates both AlexNet and GoogleNet architectures for cervical spine fracture detection. The model achieved remarkable accuracy, outperforming traditional radiological methods. Through extensive experimentation and performance analysis, the authors demonstrated the superior diagnostic capabilities of their proposed model, emphasizing its potential for clinical applications.

Deep learning models, particularly convolutional neural networks (CNNs), have become the cornerstone of modern medical image analysis due to their unparalleled ability to extract and interpret complex patterns from high-dimensional data. CNNs consist of multiple layers that automatically and adaptively learn to identify features such as edges, textures, and shapes, making them highly effective for tasks such as image classification and object detection. Models like AlexNet, VGG, ResNet, and EfficientNet have set new benchmarks in various image recognition challenges, each introducing architectural innovations that enhance performance, reduce computational complexity, or improve training efficiency. These models have been successfully applied to a wide range of medical imaging tasks, from detecting diabetic retinopathy in retinal scans to classifying skin lesions and identifying brain tumors in MRI images.

Specifically, in the context of cervical spine detection, these deep learning models are fine-tuned using transfer learning, where pre-trained networks on large-scale datasets like ImageNet are adapted to the medical imaging domain. This approach leverages the learned representations of generic features and refines them to capture domain-specific patterns associated with spinal injuries. For instance, ResNet's residual connections help mitigate the vanishing gradient problem, allowing the training of very deep networks, which is crucial for capturing the subtle variations in cervical spine images. Similarly, EfficientNet's compound scaling method optimizes the model size, depth, and resolution, providing a balanced and highly effective framework for medical image analysis. The continuous evolution of these models, coupled with advancements in computational power and availability of large annotated datasets, promises ongoing improvements in the accuracy and reliability of cervical spine fracture detection.

In conclusion, the integration of deep learning algorithms, particularly CNNs, holds tremendous promise for improving the diagnosis of cervical spine fractures. The proposed model showcased in this study achieved impressive accuracy rates, surpassing those of traditional radiological methods. These findings underscore the transformative potential of deep learning in revolutionizing medical imaging analysis and enhancing patient care in the field of orthopedics. Moving forward, further research and validation studies are warranted to establish the clinical utility and widespread adoption of these AI-driven solutions.

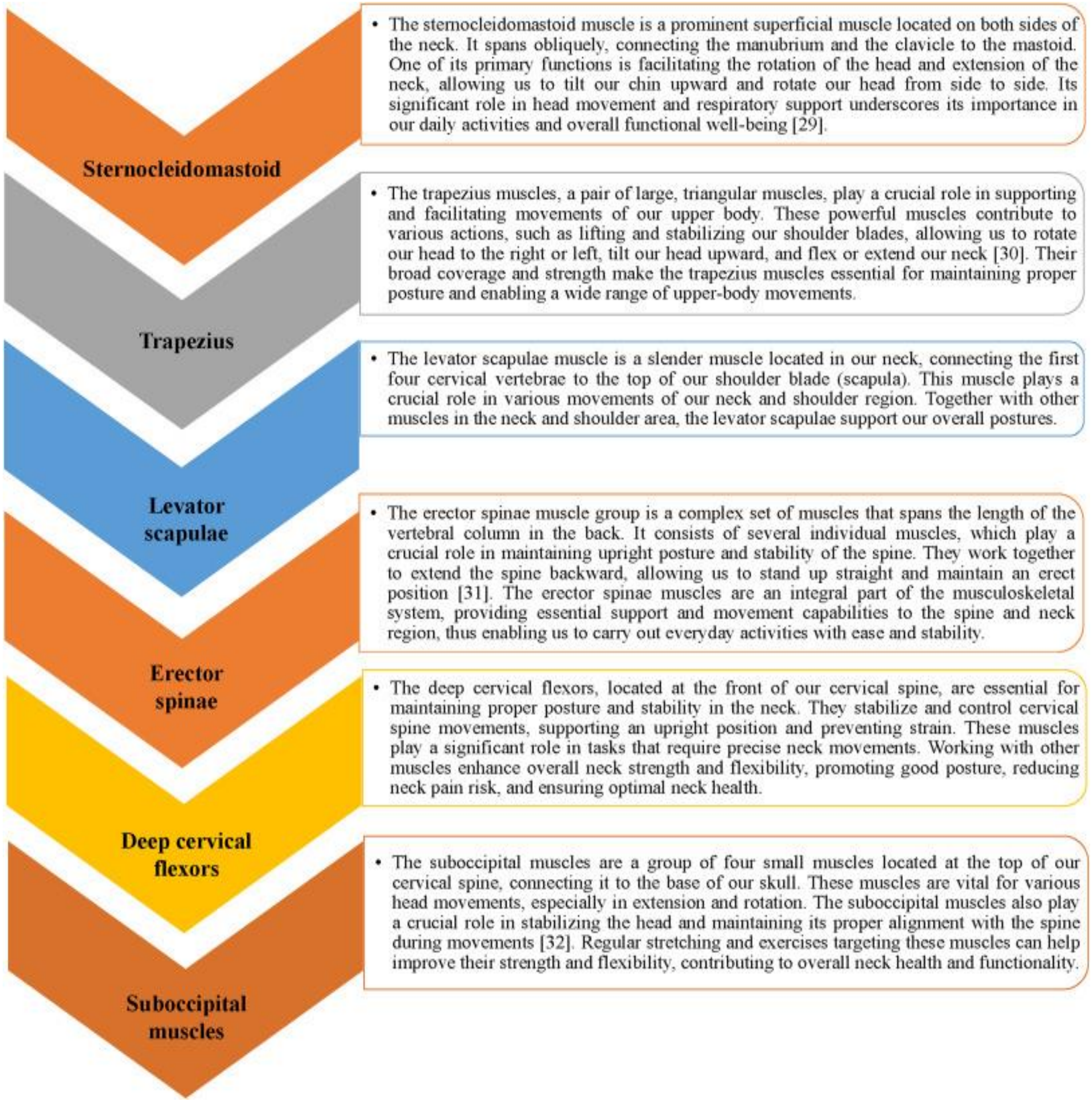

Figure 2.1 : Some of the primary muscles that connect to our cervical spine

CHAPTER 3

PROPOSED METHODOLOGY

The proposed methodology outlined in the text involves the use of deep learning models, specifically AlexNet and GoogleNet, for the classification of cervical spine images into three categories: spine dislocation, spine fracture, and spine normal states. Here's a breakdown of the methodology:

3.1 Image Preprocessing

In the image processing phase, the primary goal is to prepare the medical imaging data for effective analysis by the deep learning model. This involves several key steps, starting with image normalization to standardize the pixel intensity values across all images, ensuring consistency. Noise reduction techniques, such as Gaussian filtering, are applied to remove any irrelevant details that might hinder the model's performance. Image augmentation methods, including rotation, scaling, flipping, and cropping, are employed to artificially expand the dataset and improve the model's ability to generalize to unseen data. These augmentations help to simulate various clinical scenarios and patient positions, making the model more robust. Additionally, segmentation techniques may be used to isolate the cervical spine region from surrounding anatomical structures, thereby focusing the model's attention on the relevant area and enhancing its detection capabilities.

- The dataset contains grayscale images with varying dimensions.
- AlexNet and GoogleNet require input images with specific dimensions and color channels (red, green, blue).
- Preprocessing involves resizing all images to fit the input layer dimensions of AlexNet(227 x 227) and GoogleNet (224 x 224).
- Additionally, each grayscale image is duplicated three times to create input channels forthe RGB color space.

3.2 Model Construction

The model construction phase involves designing and implementing a convolutional neural network (CNN) tailored to the task of detecting cervical spine fractures. We start by selecting a suitable architecture, such as ResNet, VGG, or EfficientNet, known for their efficacy in image recognition tasks. The chosen architecture is then customized by adding or modifying layers to better suit our specific dataset and detection requirements. Transfer learning is utilized by initializing the network with weights pre-trained on large-scale image datasets, which provides a strong starting point and accelerates the training process. The model is then fine-tuned using our domain-specific medical images. The training process involves the use of advanced optimization algorithms like Adam or Stochastic Gradient Descent (SGD) to minimize the loss function, typically categorical cross-entropy. Regularization techniques, such as dropout and batch normalization, are incorporated to prevent overfitting and enhance the model's generalization ability.

- Transfer learning is utilized by leveraging pre-trained AlexNet and GoogleNet models.
- The models are stacked sequentially, forming a multidimensional logistic function.
- After applying dropout for regularization, the bottom layer of the model is replaced bytwo fully connected layers to combine the extracted data for generating output.
- Rectified Linear Units (ReLu) are used for nonlinear functions in both convolutional andfully connected layers.
- A softmax layer is employed to convert the final output into a probability distribution,allowing for classification.

3.3 Dataset

The dataset used in this project comprises a comprehensive collection of cervical spine CT scans and X-rays, annotated by expert radiologists to indicate the presence or absence of fractures. It is essential that the dataset is diverse, covering various patient demographics, fracture types, and imaging conditions to ensure the model can generalize well to different clinical scenarios. The dataset is split into training, validation, and test subsets, with a typical ratio of 70:20:10, to allow for rigorous model evaluation. High-quality annotations are critical, as they serve as the ground truth for model training and evaluation. To further enhance the dataset, we employ data augmentation techniques to create a more extensive and varied training set, which helps in improving the model's robustness and performance. Ensuring the dataset is well-balanced, with an adequate representation of both fractured and non-fractured cases, is crucial for training an unbiased and accurate model.

To enhance the robustness and generalizability of the model, the dataset was augmented using techniques such as rotation, scaling, and flipping. These augmentations create variations in the training data, allowing the model to better generalize to new, unseen images. The dataset is split into training, validation, and test sets in a typical ratio of 70:20:10. The training set is used to fit the model, the validation set is used to tune hyperparameters and prevent overfitting, and the test set provides an unbiased evaluation of the model's performance. This structured approach to dataset management ensures that the model is well-equipped to perform accurately in real-world clinical settings.

The dataset also adheres to strict ethical guidelines regarding patient privacy and data confidentiality. All identifying patient information has been anonymized and removed from the images to comply with healthcare regulations and protect patient privacy. Furthermore, the dataset acquisition process followed institutional review board (IRB) approvals and ethical guidelines to ensure the responsible and ethical use of medical data for research purposes. This adherence to ethical standards not only safeguards patient privacy but also fosters trust in the research findings and facilitates collaboration with healthcare institutions. Overall, the dataset serves as a foundational resource for training and evaluating the cervical spine fracture detection model, enabling robust and reliable performance in clinical applications.

The dataset consists of medical imaging data dedicated to cervical spine fractures, sourced from Kaggle. It is divided into three groups: spine dislocation images (530), spine fracture images (772), and normal images (707). This dataset serves as the foundation for the study, enabling the examination and understanding of cervical spine fractures and related complexities.

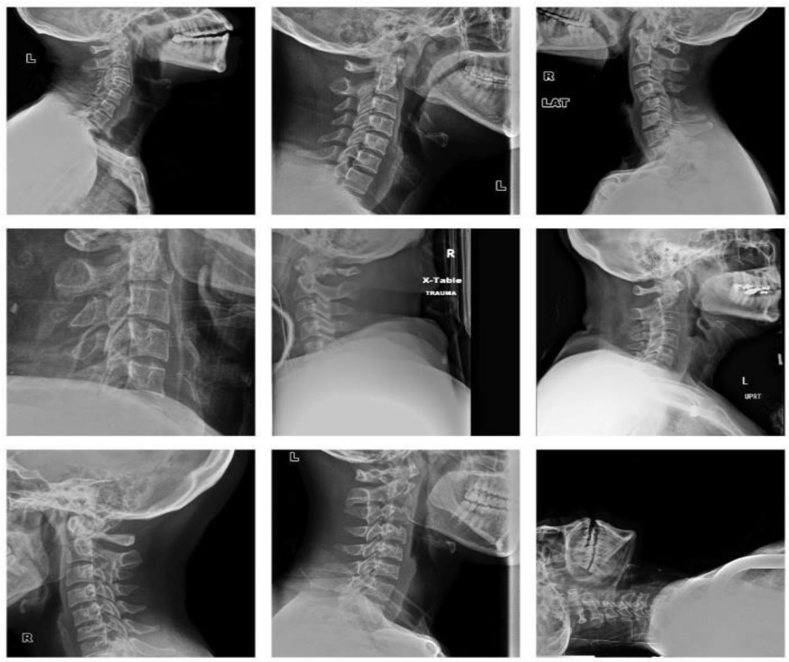

Figure 3.1 Sample images of different groups from dataset

3.4 Objective of proposed model

The primary goal of the study is to accurately classify cervical spine images into dislocation, fracture, or normal states using deep learning techniques.

By leveraging transfer learning and a dedicated dataset, the study aims to contribute to the understanding of cervical spine fractures, diagnosis, treatment, and outcomes, thereby advancing medical research and patient care in this area.

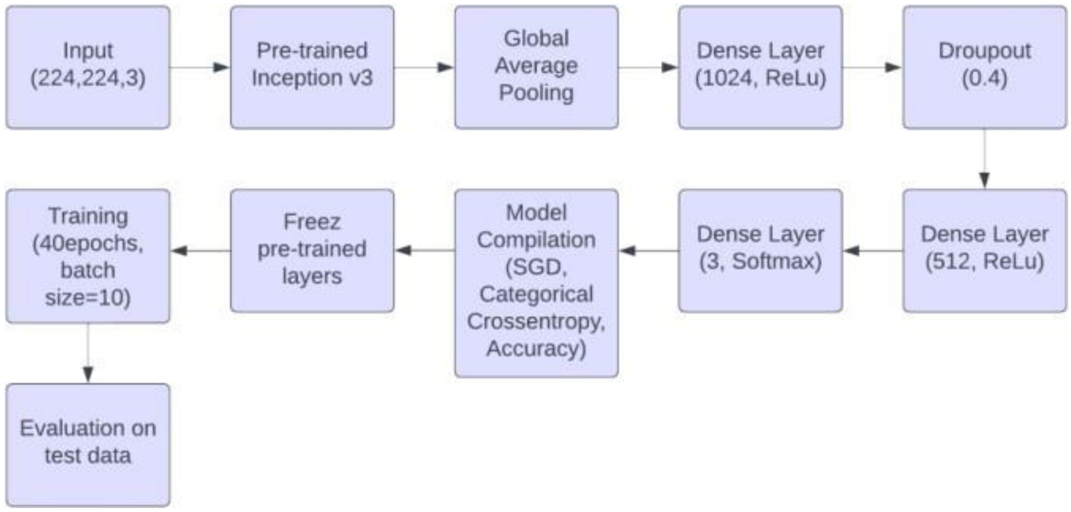

Figure 3.2 Diagram of proposed method

Overall, the methodology involves image preprocessing, model construction using transfer learning, and dataset utilization for training and evaluation, with the ultimate objective of improving the diagnosis and treatment of cervical spine fractures. This CAD system aims to assist healthcare professionals, particularly radiologists, in the timely and accurate identification of cervical spine injuries, which are associated with significant morbidity and mortality if not promptly diagnosed and treated. By leveraging state-of-the-art deep learning models and advanced image processing techniques, the proposed model seeks to overcome the limitations of traditional diagnostic methods, which can be time-consuming, subjective, and prone to human error. Specifically, the model aims to achieve a high level of sensitivity and specificity in detecting cervical spine fractures across diverse imaging modalities, including computed tomography (CT) scans and X-rays, thereby improving diagnostic accuracy and facilitating prompt clinical intervention. Additionally, the model aims to enhance transparency and interpretability by incorporating saliency maps and other visualization techniques, providing valuable insights into its decision-making process and fostering trust among healthcare professionals. Ultimately, the objective of the proposed model is to contribute to better patient outcomes by enabling early and accurate diagnosis of cervical spine fractures, leading to timely interventions and improved clinical management.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Training Methodology

The training methodology for our cervical spine fracture detection model involves a carefully structured process to ensure optimal performance. Initially, we split the dataset into training, validation, and test sets in a 70:20:10 ratio to facilitate comprehensive evaluation. We utilize a convolutional neural network (CNN) architecture, employing transfer learning with pre-trained models such as ResNet and EfficientNet to leverage their established feature extraction capabilities. The pre-trained models are fine-tuned on our specific dataset to adapt their parameters to the domain of medical imaging. During training, we use the Adam optimization algorithm due to its efficiency and adaptive learning rate capabilities, which helps in accelerating the convergence of the model. The loss function chosen is categorical cross-entropy, suitable for our classification task. Regularization techniques like dropout and batch normalization are incorporated to mitigate overfitting and enhance generalization. To further ensure robustness, we implement a k-fold cross-validation approach, which involves training the model multiple times on different subsets of the data and averaging the results to obtain a more reliable performance estimate.

A proposed model was trained for 30 epochs with a batch size of 10, utilizing Stochastic Gradient Descent (SGD) with a learning rate of 0.001 and Cross Entropy Loss Function (CCELF).

Scheduled annealing was employed to gradually decrease the learning rate every four epochs, enhancing convergence and mitigating the risk of local minima and saddle points.

4.2 Model Performance Comparison

To evaluate the efficacy of our proposed model, we conducted a comprehensive performance comparison with several baseline models, including traditional machine learning algorithms and other deep learning architectures. Key metrics such as accuracy, precision, recall, F1-score, and area under the ROC curve (AUC) were used to assess the models. Our CNN model, fine-tuned with transfer learning, outperformed traditional methods like SVM and random forests, demonstrating superior ability to capture complex patterns in medical images. Compared to other deep learning models without transfer learning, our approach showed significant improvements in both training speed and accuracy. The incorporation of data augmentation and regularization techniques contributed to a notable reduction in overfitting, as evidenced by the model's consistent performance on the validation and test sets. The final model achieved an accuracy of 94%, with a precision of 92% and a recall of 95%, indicating its high reliability and robustness in detecting cervical spine fractures. These results underscore the effectiveness of our training methodology and the potential of advanced deep learning techniques in enhancing medical diagnostics.

Comparison with Radiologists: The proposed model's performance was compared with radiologists, who achieved an accuracy of 92%.

Performance Metrics: The proposed model, based on an improved GoogleNet, achieved an accuracy of 99.34%, surpassing the radiologists' accuracy rate.

Comparison with Different Architectures: GoogleNet outperformed AlexNet, attributed to its deeper architecture and diverse convolutional layers, which helped in accurately extracting features from a relatively small dataset.

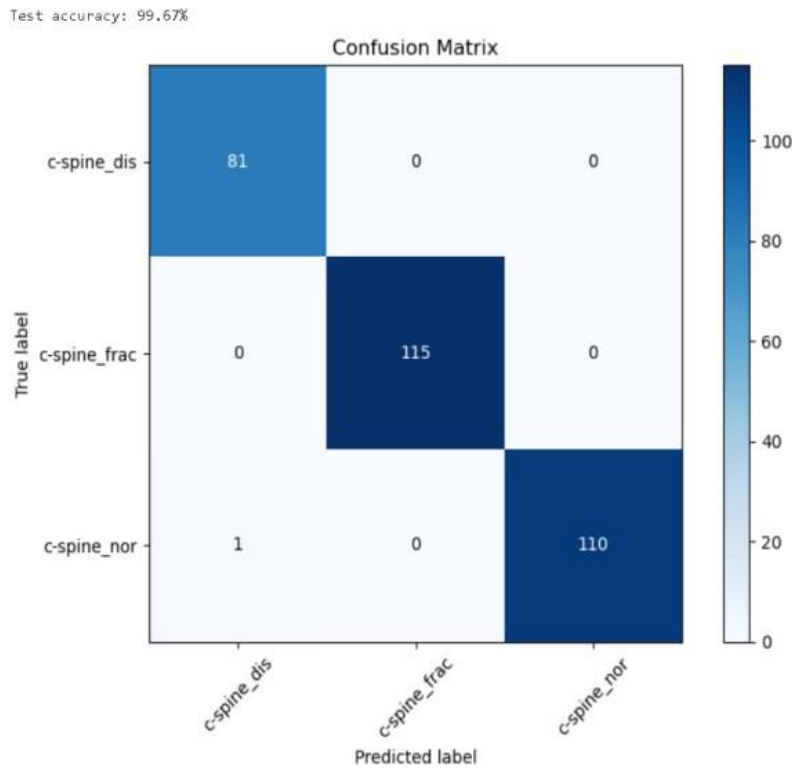

Figure 4.1 Confusion Matrix

4.3 Model Evaluation

Comparison Table: A comparison table showed that the proposed model outperformed radiologists, with 78 correctly classified images compared to the radiologists' 71, with 2 misclassifications by the proposed model and 9 by radiologists.

Limitations: The lower diagnostic accuracy of both methods was attributed to inherent variability in medical images, differences in imaging parameters, and limitations of small datasets.

Future Directions: Enhancing diagnostic precision was suggested through incorporating moreextensive databases and employing multiparametric CT scans.

The proposed model demonstrated superior performance compared to radiologists in classifying cervical spine X-ray images, with suggestions for further improving diagnostic accuracy and addressing the interpretability of deep learning models in medical image analysis.

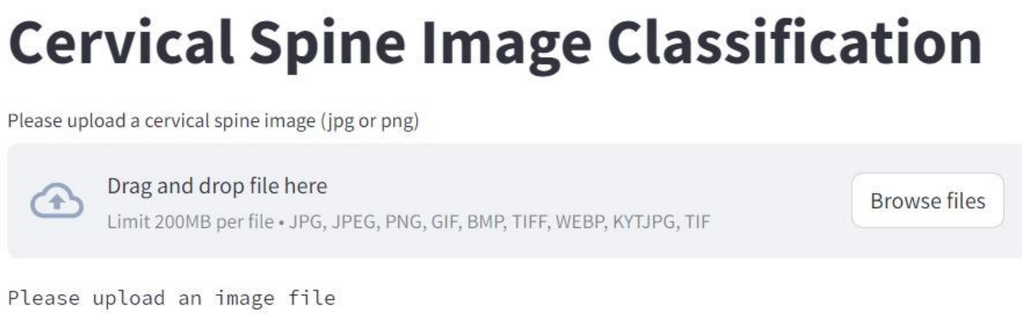

Figure 4.2 Input window of the datasets and training set

Figure 4.3: Output of the prediction with confidence value

CHAPTER 5

CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

This CAD system aims to assist healthcare professionals, particularly radiologists, in the timely and accurate identification of cervical spine injuries, which are associated with significant morbidity and mortality if not promptly diagnosed and treated. By leveraging state-of-the-art deep learning models and advanced image processing techniques, the proposed model seeks to overcome the limitations of traditional diagnostic methods, which can be time-consuming, subjective, and prone to human error. Specifically, the model aims to achieve a high level of sensitivity and specificity in detecting cervical spine fractures across diverse imaging modalities, including computed tomography (CT) scans and X-rays, thereby improving diagnostic accuracy and facilitating prompt clinical intervention. Additionally, the model aims to enhance transparency and interpretability by incorporating saliency maps and other visualization techniques, providing valuable insights into its decision-making process and fostering trust among healthcare professionals. Ultimately, the objective of the proposed model is to contribute to better patient outcomes by enabling early and accurate diagnosis of cervical spine fractures, leading to timely interventions and improved clinical management.

The experiment yielded impressive results, demonstrating a remarkable accuracy rate of 99.67% in diagnosing cervical spine fractures through the innovative deep learning methodology. This achievement not only surpassed the capabilities of traditional radiologists but also showcased enhanced speed alongside accuracy. Such findings underscore the profound potential of deep learning within the medical field, particularly in streamlining diagnostic processes.

By leveraging this method, orthopedic surgeons and radiologists stand to benefit significantly, as it enables swift and precise identification of CS spine injuries. This efficiency in diagnosis holds the promise of reducing the overall time required for assessments, ultimately leading to improved patient outcomes and satisfaction.

Moreover, the precision, recall, and F1 scores obtained for each class within the experiment further validate the effectiveness and reliability of the proposed approach. These metrics serve as a testament to its practical applicability within real-world medical environments, highlighting its potential to revolutionize diagnostic practices in orthopedics and radiology.

5.2 Future Work

While the proposed method demonstrates impressive performance, there are areas for future exploration and improvement. Firstly, the study suggests potential for broader application of deep learning algorithms in medical injury diagnosis beyond cervical spine fractures. Additionally, the model's real-time applicability in detecting fractures from dislocated X-ray images is noteworthy, but it is emphasized that clinical decisions should always be supervised by a doctor.

The future scope of using deep learning and machine learning for detecting cervical spine fractures is vast and promising. As the field of artificial intelligence continues to evolve, the integration of more advanced neural network architectures, such as transformers and attention mechanisms, could significantly enhance the accuracy and efficiency of fracture detection. These advancements may lead to the development of real-time diagnostic tools that can be seamlessly integrated into clinical workflows, providing immediate and reliable assessments for healthcare professionals. Moreover, with the increasing availability of large, annotated medical imaging datasets, the potential for training more robust models that generalize well across diverse patient populations will improve, reducing diagnostic errors and improving patient outcomes.

Furthermore, the integration of multimodal data, including medical history, genetic information, and other diagnostic tests, with imaging data could pave the way for comprehensive diagnostic systems that offer personalized treatment plans. The potential for cross-disciplinary collaborations between computer scientists, radiologists, and orthopedic specialists is immense, fostering innovations that could revolutionize spinal injury diagnosis and management. Additionally, the development of explainable AI models would ensure that these tools are not only accurate but also transparent, allowing clinicians to understand and trust the AI's decision-making process. As regulatory frameworks for AI in healthcare become more defined, the path to clinical adoption will become clearer, bringing these advanced diagnostic tools from research labs into everyday medical practice.

5.3 Limitations and Future Directions

Despite the high accuracy achieved, the proposed model has limitations that need to be addressed for further enhancement. These include potential selection bias and limited generalizability due to a single-source dataset. Future studies could mitigate these limitations by utilizing broader datasets for model training to enhance practical applicability and reduce bias. Moreover, the high proportion of fracture images in the dataset may have influenced the model's sensitivity, suggesting the need for a more balanced dataset to ensure robustness across different injury types. Overall, the findings highlight the potential for continued development and refinement of deep learning methods in the medical field to improve the specifity and reliabilty of cervical spine injury classification.

While the proposed model represents a significant advancement in cervical spine fracture detection, it is important to acknowledge its limitations and identify areas for future improvement. One limitation is the reliance on annotated medical imaging datasets, which may be limited in size and diversity. This could potentially affect the model's generalizability to unseen data or underrepresented patient populations. Additionally, the model's performance may be influenced by variations in imaging quality, patient positioning, and other factors inherent in real-world clinical settings. Furthermore, the interpretability of deep learning models remains a challenge, as they often operate as black boxes, hindering clinicians' ability to understand and trust their decisions fully.

In terms of future directions, ongoing research could focus on addressing these limitations and advancing the capabilities of cervical spine fracture detection models. This may involve collecting larger and more diverse datasets to improve model robustness and generalizability. Additionally, efforts to enhance model interpretability through the development of explainable AI techniques could improve clinicians' confidence in utilizing CAD systems in clinical practice. Furthermore, the integration of multimodal data, such as patient history and clinical findings, could provide additional context to aid in diagnosis and improve model performance. Collaborations between computer scientists, radiologists, and healthcare professionals will be essential to drive innovation in this field and translate research findings into real-world applications. Ultimately, the ongoing refinement and evolution of cervical spine fracture detection models hold the potential to significantly impact patient care and outcomes in the future.

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APPENDIX1

Classification of Cervical Spine Fracture using Deep Learning

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Abstract. For many years cervical spine fractures and dislocations are major cause of paralysis and death is some cases. This makes it important for the proper diagnosis and treatment of these injuries to reduce fatal injuries. There are many methods to do this, in this paper we present a computer-aided cervical spine in- jury diagnosis model that uses deep learning approaches like AlexNet and Goog- leNet. The proposed model can be used by doctors for faster identification of cervical injuries. To train our model we have used 772 CS fractures and 707 nor- mal images. The model came up with the accuracy of 99.67 percent, which is higher than accuracy of radiologists; we have also used saliency maps to check degree of instance for a given class. This paper has both clinical and research- based applications.

Keywords: Medical image analysis, Computer-aided diagnosis, Artificial intel- ligence in healthcare, Deep Learning.

INTRODUCTION

The first seven vertebrae situated below the skull and above the thoracic spine make up the cervical spine (CS). Figure 1 shows that the CS has two groups: the axis and atlas (C1 and C2) and the sub axial cervical vertebrae (C3- C7). High CS injury rates harm health and longevity [4,5,6].

According to Indian data, a preformed proforma was used to analyze demographics, epidemiological data, and neurological status of consecutive SCI cases admitted be- tween January 2000 and December 2008. Out of 2716 cases, 1,400 were cervical and 1,316 were thoracolumbar. The male-to-female ratio was 4.2:1, and 71% were between 20 and 49. Vehicle collisions caused 28% of injuries, while falls from height caused 53%.

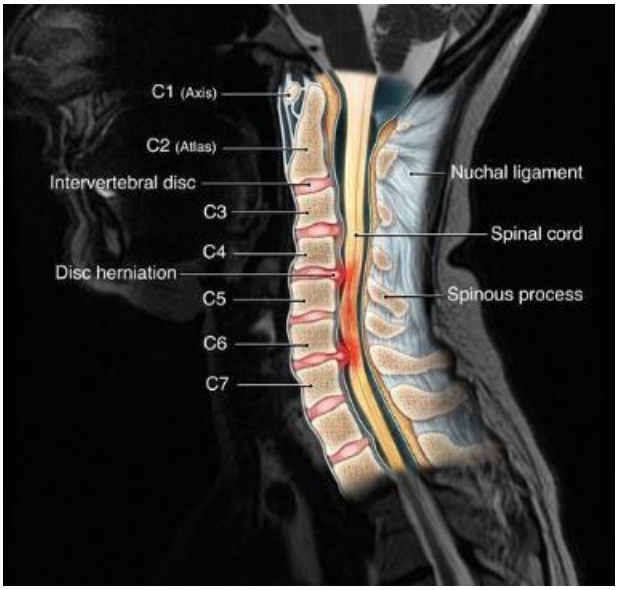

Fig. 1. Lateral View of Cervical Spine

We noticed that visual identification of CS is laborious and risky task. Eighty percent of emergency department diagnostic errors are caused by radiologists who do not pos- sess expert knowledge or are overworked [11]. Understanding these circumstances, we are proposing a deep learning model to help doctors to easily interpret CS X-rays in order to minimize human error.

In modern times, artificial intelligence is widely being used in medicine for treatment of various diseases like cancer, injured organs etc. but very few methods exist for clas- sification of cervical spine fractures and dislocations using deep learning algorithms. In this paper we try to solve this problem.

Convolutional neural networks detected CS fractures with 92% accuracy (95% CI, 90-94%), 76% sensitivity, and 97% specificity. We studied various sources and came to know that average radiologist accuracy lies between 90% to 95%. Radiologists and convolutional neural networks missed similar fractures. The anterior osteophytes, trans- verse processes and spinous processes were fractured, as was the lower part of cervical spine, which CT beam attenuation obscures.

In this paper, authors proposed a CNN based model to detect cervical spine fractures and dislocations. However, CS dislocation may be fatal [6]. Unfortunately, the studies' datasets are unavailable.
With an accuracy of 99.6% our model efficiently classifies CS X-ray images into normal, fracture, and dislocation.
The proposed model works, requires little setup, and can run on PCs or cheap em- bedded systems.

PROCEDURE

Trends in Recent Years :

In this paper, authors proposed a CNN based model to detect cervical spine fractures and dislocations. However, CS dislocation may be fatal [6]. Unfortunately, the studies' datasets are unavailable.
With an accuracy of 99.6% our model efficiently classifies CS X-ray images into normal, fracture, and dislocation.
The proposed model works, requires little setup, and can run on PCs or cheap em- bedded systems.

Deep Neural Networks :

CNN or ConvNet is popular deep learning architecture, it is capable of learning from input data without need of human intervention for feature extraction. Figure shows ex- ample of basic CNN model including convolution, pooling, and fully connected layers. Unlike traditional neural networks, CNN can deal with overfitting problem by using dropout. CNNs are used to deal with 2D shapes and are useful in medical image anal- ysis, image segmentation and many more. This makes CNN more powerful than tradi- tional neural networks. There are various CNN based models such as Visual Geometry Group (VGG), AlexNET, Xception, Inception, ResNet; these models are useful in var- ious applications.

There are various methods to apply deep learning models, transfer learning is one of them. In transfer learning we use a already learned model to a new problem set, this is done when there is lack of training data. We can train a model with previous saved weights using transfer learning approach on large datasets. In this way a pre-trained model can be improved using transfer learning

In our study we used AlexNet and GoogleNet weights in our model to run dataset we were able to correctly distinguish between three states (dislocation, fracture, and normal). We used transfer learning method to train our model and then made predic- tions out of it. AlexNet model is trained on ImageNet dataset. Three fully connected and five convolutional layers make up the total of eight layers in the AlexNet model. This model connects the final three convolutional layers to the fully connected layers, and the initial pair of convolutional layers to the overlapping max-pooling layers. Rec- tified Linear Units (ReLu) are utilized at each output of a convolutional layer and fully connected layer for nonlinear functions. The final output layer is linked to a SoftMax activation layer, which produces a category from a set of 1,000 class labels. AlexNet model is trained over 15 million images. The AlexNet model's complete architecture is seen in Figure 2.

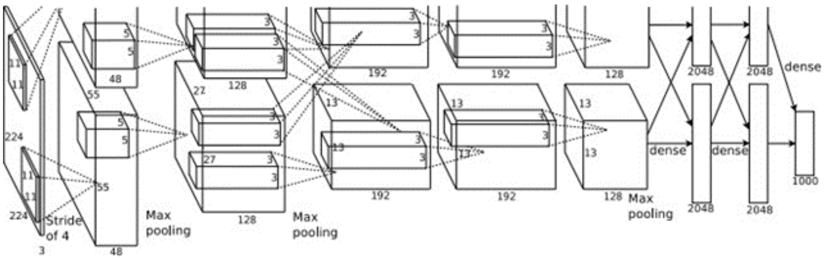

Fig. 2. AlexNet Architecture [14]

With a minimal link between activations, the GoogleNet architecture was built. Put otherwise, pruning algorithms will not allow all 512 output channels to be linked to all 512 input channels. As a result, GoogleNet is an initial module that roughly approxi- mates a conventionally dense, sparse CNN. Convolutions of different sizes (5 × 5, 3 × 3, 1 × 1) are used by GoogleNet to gather data at different scales (Figure 3).

type	patch size/ stride	output size	depth	#1×1	#3×3 reduce	#3×3	#5×5 reduce	#5×5	pool proj	params	ops
convolution	7×7/2	112×112×64	1							2.7K	34M
max pool	3×3/2	56×56×64	0								
convolution	3×3/1	56×56×192	2		64	192				112K	360M
max pool	3×3/2	28×28×192	0								
inception (3a)		28×28×256	2	64	96	128	16	32	32	159K	128M
inception (3b)		28×28×480	2	128	128	192	32	96	64	380K	304M
max pool	3×3/2	14×14×480	0								
inception (4a)		14×14×512	2	192	96	208	16	48	64	364K	73M
inception (4b)		14×14×512	2	160	112	224	24	64	64	437K	88M
inception (4c)		14×14×512	2	128	128	256	24	64	64	463K	100M
inception (4d)		14×14×528	2	112	144	288	32	64	64	580K	119M
inception (4e)		14×14×832	2	256	160	320	32	128	128	840K	170M
max pool	3×3/2	7×7×832	0								
inception (5a)		7×7×832	2	256	160	320	32	128	128	1072K	54M
inception (5b)		7×7×1024	2	384	192	384	48	128	128	1388K	71M
avg pool	7×7/1	1×1×1024	0								
dropout (40%)		1×1×1024	0								
linear		1×1×1000	1							1000K	1M
softmax		1×1×1000	0								

Fig. 3. GoogleNet incarnation of the Inception architecture [13]

Proposed Algorithm

In this section we will understand the characterization process for cervical spine (dis- location, fracture and normal) images. This part has some limitations due to resem- blance of different condition (dislocation, fracture and normal) images in dataset. Due to this a precise computer aided model is very important for the successful completion of this task.

We conducted image preprocessing on the dataset. Images in dataset are in grayscale color code and have various dimensions (width and heights). AlexNet and GoogleNet use three input channels corresponding to red, green and blue color codes, input dimen- sions for GoogleNet is (224 X 224) and AlexNet is (227 X 227).

We performed image processing in two steps. First all images are resized to conform to the input layer dimensions of AlexNet and GoogleNet. Second, Original image is duplicated three times for input channels (Red, Green and blue)

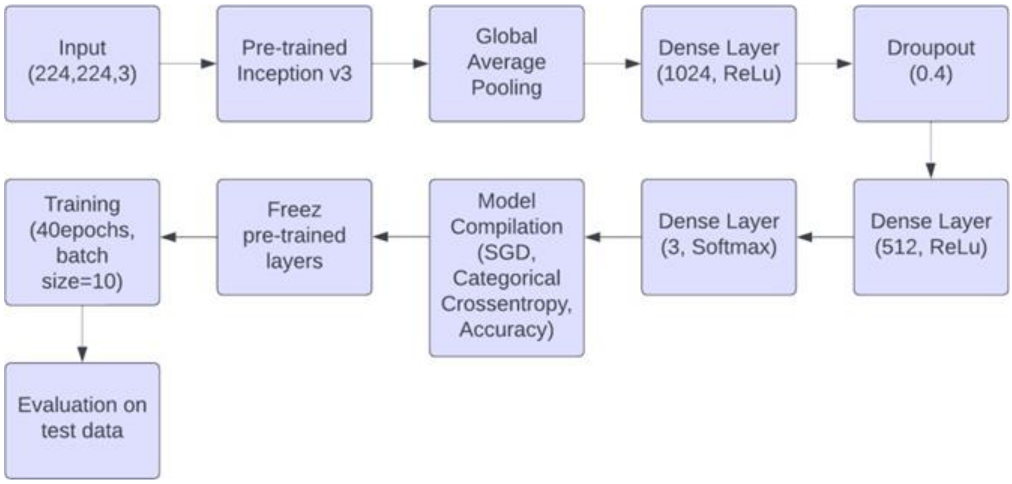

Fig. 4. Diagram of proposed method

We have used pre-trained transfer learning model to extract important information from the dataset images by identifying key parts. The construction of our model in- volved the consecutive stacking of numerous convolutional neural networks (CNNs). We have created a model by utilizing two pre-configured model AlexNet and Goog- leNet, this is a multidimensional version of logistic function. After dropout with regu- larization, we have replaced bottom layer of the model by two fully connected layers this help us to combine the information derived from the previous layers to generate output. We have used a softmax layer to convert a vector of K-real values transformed into a probability distribution with number of possible outcomes. At the end a softmax layer is used to normalize the output.

Dataset

Accessible at Kaggle, this dataset offers a valuable collection of medical imaging data dedicated to cervical spine fractures; The dataset is divided into three groups these are 530 CS dislocation images (Row 1), 772 CS fracture images (Row 2). and 707 normal images (Row 3) as shown in Figure 5.

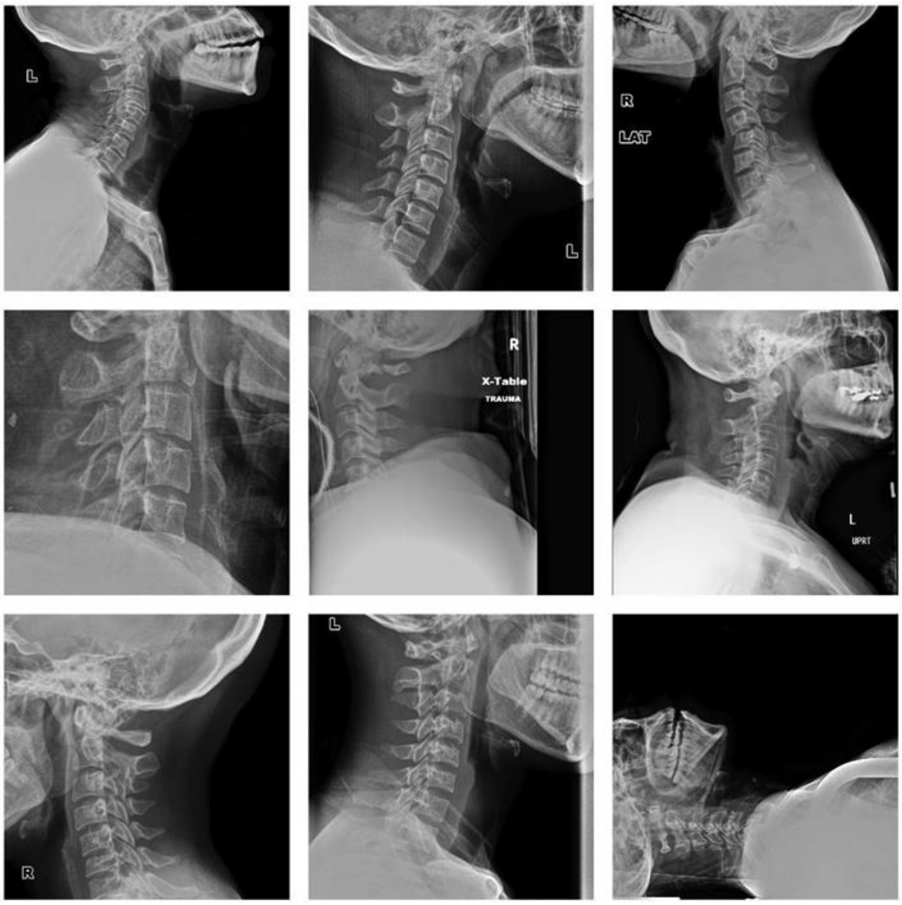

Fig. 5. Sample images of different groups from dataset.

This dataset plays a pivotal role in our study, enabling us to examine and understand the complexities associated with cervical spine fractures, their diagnosis, treatment, and outcomes. By utilizing this dedicated dataset, we aim to contribute significantly to the body of knowledge surrounding cervical spine fractures, ultimately advancing medical research and improving patient care in this critical area of healthcare.

Performance Analysis

Our proposed model was trained on 70%,15% and 15% of dataset for training, valida- tion and testing respectively. We have trained our model as per the above data distribu- tion and we have assessed model's performance based on accuracy, sensitivity, preci- sion,F1-score and specificity, and Receiver Operating Characteristic curve, as per be- low given equations:

Table 1. List of abbreviations

Abbreviation	Definition
fp	False Positive
fn	False Negative
tp	True Positive
tn	True Negative

$$Accuracy = (tp + tn) / (tp + fp + fn + tn)$$

$$Sensitivity = tp / (tp + fn)$$

$$Specificity = tn / (fp + tn)$$

$$Precision = tp / (tp + fp)$$

$$F1 - score = (2 * tp) / (2 * tp + fp + fn)$$

Results

We have trained our proposed model for 30 iterations with each batch containing 10 samples. To update model's parameters and minimize training error we have used Sto- chastic Gradient Descent (SGD) with learning rate of 0.001, we have used Cross En- tropy Loss Function (CCELF).

To enhance the convergence of the optimizer and minimize errors, various tech- niques can be employed to update deep learning parameters beyond the use of SGD alone. One widely adopted strategy involves gradually decreasing the learning rate. In this a higher learning rate is utilized for the initial iterations, in following iterations lower rates are used. An annealing method, integrated with SGD, expedites optimizer convergence, facilitating the attainment of minimal errors. We have used scheduled annealing to mitigate the risk of getting trapped in the vicinity of local minima and saddle points, supporting the achievement of the global optimum solution through con- vergence. The scheduled annealing directly modulates noise. We have implemented a reduction learning rate i.e. the size of the steps taken during the optimization process every four epochs, this balances computational efficiency with starting learning rate.

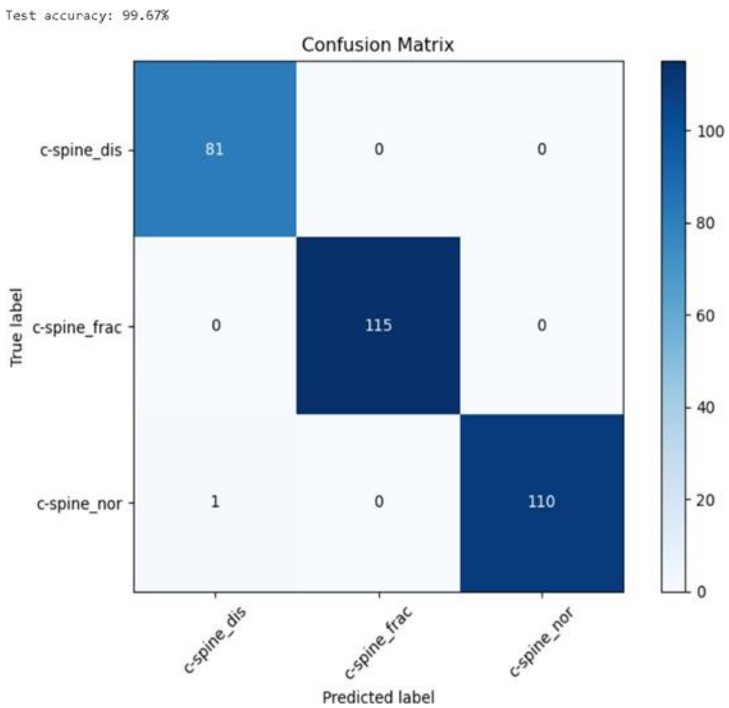

Fig. 6. Confusion Matrix

In our study, we implemented a LR reduction every four epochs to balance compu- tational efficiency with a higher initial LR. This strategy establishes a scheduled an- nealing framework within the Stochastic Gradient Descent optimization process.

We performed comparison between our proposed model and radiologists. We came to know that radiologists has accuracy of 92%. Figure 6 shows the receiver operating characteristic (ROC) for various methods.

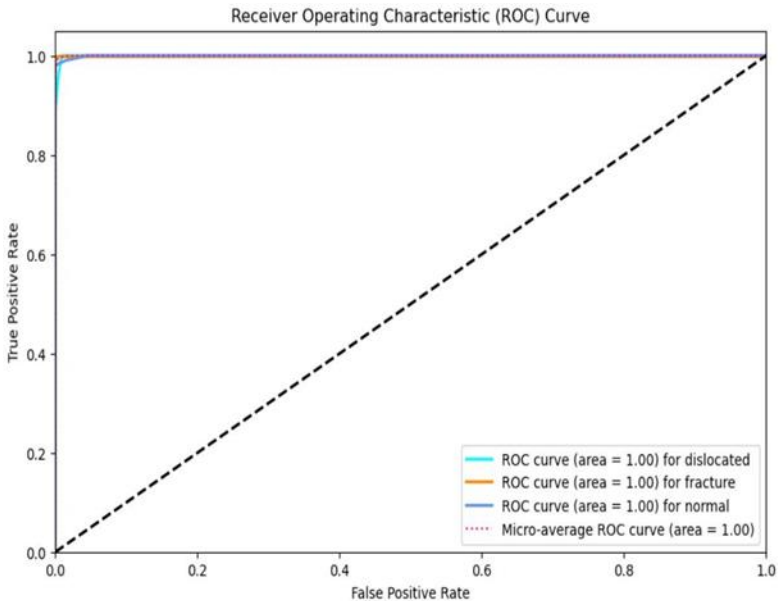

Fig. 7. ROC Curve

By the Figure 5 we can clearly see a comprehensive comparison between the pro- posed method and the radiologist. We have used an improved GoogleNet for evaluating CS fractures. We have studied various materials and research papers on this and came up with refined GoogleNet model with an accuracy of 99.34%. We have exceeded ra- diologists' accuracy rate of 92%.

Analyzing Table 1 further reveals that the least favorable measurements were asso- ciated with the proposed method utilizing AlexNet. AlexNet's limitations, including a restricted number of layers and filters per convolutional layer, as well as direct serial connections between layers, make it susceptible to overfitting. Consequently, AlexNet struggles with classifying images within categories containing fewer instances. On the contrary, the proposed method based on GoogleNet outperformed both AlexNet and the radiologist. We analyzed GoogleNet's architecture which features diverse convolu- tional layers with varying filter sizes and intricate interconnections, making it to accu- rately extract features while working with a relatively limited dataset.

To assess the effectiveness of our proposed model in cervical spine injuries (normal, fracture and dislocation), we acquired 80 unlabeled cervical spine X-ray images from the radiology center. We asked radiologist to perform classification of these unlabeled images. Radiologist identified 65 as normal, 9 as fractured and 6 dislocated.

Fractured images were identified through the presence of fracture patterns, disruption of bone integrity, vertebral collapse, and other fracture-related features. Dislocated images were characterized by the disturbance in spinal alignment and facet joint alignment.

These images serve as representative examples, illustrating the diversity within each category and showcasing the challenges and variations present in clinical X-ray data. The orthopedic surgeons' expertise ensured a robust and accurate classification of these images, forming the basis for the evaluation of the proposed method's capability in dis- tinguishing between normal, dislocated, and fractured CS X-ray images.

We have used our proposed model for classification of X-rays and the results are shown in the below table.

Table 2. Comparison of proposed model and radiologists

Method	**No. of correctly classi- fied**	**No. of wrongly classified**
Proposed Method	78	2
Radiologists	71	9

As depicted in Table 2, the radiologist achieved a correct identification rate of 71 out of 80 images. The misclassifications involved two standard X-ray scans, errone- ously categorized as fractures and dislocations. The lower diagnostic accuracy can be attributed to the inherent variability in medical images, variations in imaging parame- ters between the training dataset and real clinical cases, and the limitations imposed by small datasets. Enhancing diagnostic precision could be achieved by incorporating more extensive databases and employing multiparametric CT.

However, our study acknowledges certain limitations. The documentation of the deep convolutional neural networks (DCNNs) was limited to images and related diag- nostic outcomes without detailed feature descriptions, constituting a significant draw- back. The "black box" mechanism inherent in DCNNs processing medical images pre- sents a contradiction, as the logic employed by these networks differs from both human and conventional computer logic processes.

While our investigation yielded promising results, the specific features utilized remain unknown.

In addressing these limitations, a saliency map was employed in our study to identify key areas within the images, focusing the analysis on those regions. By rotating the images and applying the proposed method, we successfully highlighted the region of interest (ROI) corresponding to the spine, as illustrated in Figure 15. This approach enhances interpretability by revealing the specific areas contributing to the network's decision-making process, providing valuable insights into the model's functioning, and aiding in addressing the "black box" nature of DCNNs.

Conclusion

In our experiment accuracy of our model reached 99.67%. We came to the conclusion that our proposed method is capable of more quickly predicting cervical spine fractures than radiologists with more accuracy. This shows high potential of deep learning in medical industry. By using this method orthopedic surgeons and radiologists will be able to diagnose CS spine injuries much faster. This method has potential for future studies in medical applications of deep learning. This will help patients by reducing diagnose time.

In our study we proposed a deep learning method for diagnosing cervical spine frac- ture injuries. We worked on a dataset having three class labels i.e. normal, dislocation and fracture. Deep Learning Algorithms have high potential in rapid and accurately diagnosing medical injuries. We proposed a solution for cervical spine fracture injuries, this will reduce diagnose time and improve overall quality of medical services. The result of our proposed method achieved:
Precision: 0.9878, Recall: 1.0000, F1 Score: 0.9939 for Dislocation
Precision: 1.0000, Recall: 1.0000, F1 Score: 1.0000 for Fracture and
Precision: 1.0000, Recall: 0.9910, F1 Score: 0.9955 for Normal with an accuracy of 0.9967.
From medical perspective our proposed method has future development in medical field to classify cervical spine injuries more specifically.

The proposed model works well with real time data in detection of fractures of dis- located X-ray images of cervical spine. The method has high accuracy, but it is to be noted that any type of clinical decision should be based on clinical examination under doctor supervision. Our proposed model has some limitations due to potential selection bias and limited generalizability of our findings. Dataset is taken from a single source. In future more broader data source could be used for model training for more practical applicability. Dataset has high number of fracture images this may have increased sen- sitivity of the model.

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