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A Deep Learning-Based Approach for Cervical Spine Fractures Classification

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Nadin Hossam El-Din Moustafa*[1], Abed Nasr [2], Wessam Fathy [3], Ahmed Saleh [4]

[1] Department of Electronics and Communications Engineering - Faculty of Engineering - Horus University – Egypt.
[2] Mathematics and Engineering Physics Department, Faculty of Engineering, Mansoura University - Mansoura, Egypt, fldp7@mans.edu.eg
[3] Neurosurgery Department, Faculty of Medicine, Mansoura University, Mansoura, Egypt, wesam010@mans.edu.eg
[4] Computers Engineering and Control Systems Department, Faculty of Engineering, Mansoura University, Mansoura, Egypt, aisaleh@mans.edu.eg
* Correspondence: Mohamed Maher Ata, nadine.hossameldin1@gmail.com

Abstract: Cervical spine fractures are a critical medical emergency that can lead to severe complications, including permanent disability or death if not diagnosed promptly. A cervical spine fracture may be detected by using computed tomography (CT). This study presents a deep learning-based approach for the classification of cervical spine fractures using a dataset containing computed tomography (CT) images of fractured and normal cervical spines. The proposed methodology incorporates transfer learning models, including DenseNet121, VGG16, and MobileNet, to achieve high accuracy in distinguishing between normal and fractured cervical spines. The study evaluates model accuracy, precision, recall, and F1-score to determine the most effective architecture. Experimental results indicate that the VGG16 model optimized with the Nadam optimizer achieves the highest classification accuracy of 98.37%, outperforming other models or the same model with another optimizer. The findings highlight the potential of deep learning in assisting radiologists with faster and more reliable cervical spine fracture detection, ultimately improving patient care and reducing diagnostic delays.

Keywords: Cervical Spine Fracture, Deep Learning, Convolutional Neural Networks, Classification, Transfer Learning, Medical Imaging, Optimizers, Healthcare

1. Introduction

Cervical spine, an essential component of the human skeletal system, is made up of seven interconnected vertebrae, designated C1, C2, C3, C4, C5, C6, and C7 in Figure 1. Intervertebral discs divide these vertebrae, and ligaments bind them together. The cervical spine links up to the skull at its higher end and the thoracic spine at its lower end [1]. Cervical spine fractures can occur at any age but are more common in men. Falling is the most common cause of cervical spine fracture, followed by car accidents, motorcycling, and diving, all of which result in 5-10% immediate death [2] Moreover, cervical spine fractures are induced by abnormal motion or a collection of improper movements, including hyper-flexion, rotation, hyperextension, lateral bending, and axial loading of the spinal column [3]. Traumatic incidents that impact the cervical spine led to a high number of emergency department visits, with over one million cases recorded each year in North America [4].

Neck pain is a common indication of cervical spine fracture, and it may extend to the head, jaw, and shoulders. Patients with such injuries might additionally have numbness and weakness throughout their bodies [5].
A cervical spine injury is expected to be associated with an elevated mortality and morbidity rate, and a delay in detecting an unstable fracture that triggers insufficient immobilization may result in a severe deterioration in neurologic function with catastrophic repercussions [6].
Patients involved in accidents may be in fragile state in some cases, necessitating immediate medical care and close monitoring to prevent delays in critical procedures. Rapid and straightforward detection of fractures or injuries in the cervical spine might significantly accelerate therapy for these injured patients [7]. Medical imaging is critical for the diagnosis and management of spinal injuries [8]. throughout the last few decades, there has been a substantial rise in spine imaging procedures because of the growing rate of spinal disease related to an aging population and the widely available use of computed tomography (CT), which is recognized as the standard of care imaging technique for examining cervical spine injuries [9].
By utilizing deep neural networks to extract features from CT scan images, researchers can enable early and precise diagnosis of cervical spine fractures, enhancing diagnostic accuracy and the ability to differentiate between normal and fractured neck conditions.
The lack of a dependable and efficient system for detecting cervical spine fractures presents a major challenge in radiology. Current reliance on manual image analysis often leads to delays in diagnosis, higher healthcare expenses, and potential complications for patients. Therefore, there is an urgent need for an automated, accurate solution to assist healthcare professionals in promptly identifying cervical spine fractures and ensuring timely medical intervention, thereby safeguarding patient well-being and preventing further complications.
This study focuses on creating deep learning models designed to diagnose and detect cervical spine fractures with greater accuracy and speed compared to conventional radiological approaches. The primary objective is to develop a robust and efficient tool that supports healthcare professionals in delivering precise and timely diagnoses. In this paper, a computer-aided system utilizing deep learning techniques will be presented for the diagnosis of cervical spine fractures. The study employs DenseNet201, VGG16, and MobileNet models to classify cervical spine CT images into two categories: normal and fractured usings Adam and Nadam optimizers.

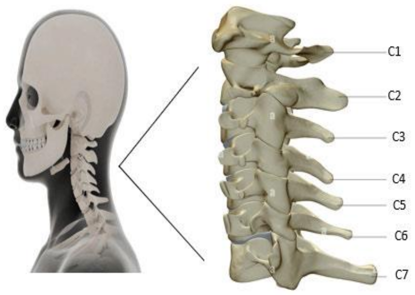


Figure 1. Anatomy of cervical spine.

2. Literature Review

Deep learning, specifically convolutional neural networks (CNNs), has drastically altered medical image processing, providing more accuracy and efficiency in illness identification. In the case of cervical spine injuries, immediate and exact classification is essential for appropriate intervention and treatment. Deep learning has shown significant promise in improving diagnostic accuracy, speed, and reliability for cervical spine fractures and other orthopedic injuries, and its role in clinical management is expected to grow further.

M. Yaseen et al [1], used DenseNet121 architecture that produces an accuracy of 94.2%. Gaikwad et al [10], used YOLO v5 model and reached an accuracy of 89%. For classification. Liawrungrueang et al [11] offered a detection and classification system and achieved an accuracy of 92.14%. Showmick et al [12] utilized ResNet50 and the accuracy was 92.75%. Nicolaes et al [13] proposed a CNN-based framework and achieved 92% accuracy. Small JE et al [14] implemented another CNN architecture, which yielded an accuracy of 92% in their classification experiments. K Murata et al [15] introduced a deep convolutional neural network (DCNN) approach, attaining an accuracy of 86%. Table 1 summarizes the most related state-of-the-art methodologies for classifying cervical spine fracture.

The related work has two major limitations: the limited dataset size and the lack of high accuracy. In the following sections, a proposed methodology will be provided to overcome these limitations

Table 1. Related studies in cervical spine fracture classification

Author	Dataset	Method	Test Accuracy	Year
M. Yaseen [1]	The RSNA 2022 Cervical Spine Fracture Detection Challenge dataset	CNN Pretrained model (DenseNet121)	94.2%	2024
Gaikwad [10]	3,000 CT studies	CNN Pretrained model (YOLO v5)	89%	2024
Liawrungrueang [11]	500 X-Rays Images	CNN	92.14%	2024
Showmick [12]	**Spine fracture prediction from C.T**	CNN Pretrained model (ResNet50)	92.75%	2023
Nicolaes et al [13]	Private dataset of 1011 CT scans	CNN	92%	2023
Small JE [14]	Multiple collection	CNN	92%	2021
K Murata [15]	Private dataset of Radiograph of 300 patients	Deep convolutional neural network (DCNN)	86%	2020

Although the studies listed in Table 1 have demonstrated promising results using various deep learning architectures for cervical spine fracture detection, they often rely on relatively small or private datasets, which limits their applicability across broader patient populations. In most cases, the datasets used lack diversity in terms of imaging conditions, scanner types, demographics, and anatomical variability, which are critical factors in clinical practice.

3. Material and Methodology

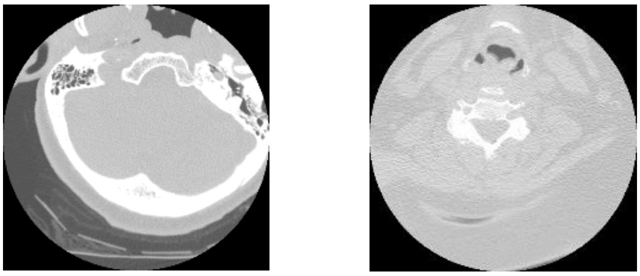
The conventional approach of detecting cervical spine fractures is primarily reliant on the skill of radiologists and orthopedic experts who manually interpret imaging procedures such as X-rays, CT scans, and MRIs. This procedure entails a thorough visual examination of the cervical spine to detect fractures, but it is typically time-consuming, delaying essential decision-making, particularly in emergency situations. Furthermore, the subjective nature of manual interpretation might result in diversity in diagnosis, with the possibility of human error or missing fractures. Clinician exhaustion, particularly in high-volume settings, worsens these difficulties, emphasizing the need for more efficient and trustworthy diagnostic approaches.

When treating a cervical spine fracture, several critical factors must be carefully considered to ensure effective management and optimal recovery. The stability of the fracture is a primary concern, as unstable fractures involving misaligned vertebrae or spinal cord compression often require surgical intervention, such as stabilization with rods, screws, or decompression procedures. Additionally, the patient's overall health, including age, bone density (e.g., osteoporosis), and underlying conditions, must be evaluated to tailor the treatment plan. Early identification allows for immediate intervention, which is critical to preventing further damage to the spinal cord, nerves, and surrounding structures. also enables healthcare providers to stabilize the spine effectively, whether through immobilization with a cervical collar or surgical intervention, reducing the risk of long-term complications like chronic pain, spinal instability, or neurological deficits also guiding appropriate treatment plans. Beyond the physical benefits, early diagnosis provides psychological reassurance to the patient and their family, allowing them to focus on recovery. In trauma cases, a high index of suspicion and immediate action are essential to save lives, preserve function, and optimize outcomes.

Computed Tomography (CT) is the gold standard for detecting cervical spine fractures, particularly in trauma settings where rapid and accurate diagnosis is critical. CT scans provide detailed cross-sectional images of the cervical spine, allowing for the identification of even subtle fractures that may be missed on conventional X-rays. The high resolution and ability to reconstruct images in multiple planes (axial, sagittal, and coronal) make CT exceptionally effective for evaluating complex fractures, dislocations, and bony abnormalities.

Distinguishing between a normal cervical spine and a fractured one on imaging can be challenging, particularly in cases of subtle or non-displaced fractures. In a normal cervical spine, the vertebrae appear well-aligned with smooth, continuous cortical margins, uniform intervertebral spaces, and no evidence of abnormal angulation. The prevertebral soft tissues should also appear normal in thickness, and the spinal canal should maintain its integrity without encroachment. However, in a fractured cervical spine, these features may be disrupted.

Fractures can manifest cortical breaks, misalignment of vertebrae, compression or collapse of vertebral bodies, or abnormal spacing between structures. Subtle fractures, such as hairline cracks or non-displaced fractures, may be difficult to detect, overlapping structures or poor image quality can obscure findings. Additionally, soft tissue swelling or hematoma visible on imaging can be an indirect sign of injury, even if the fracture itself is not immediately apparent. The difficulty lies in differentiating normal anatomical variants or degenerative changes from true fractures, particularly in older patients or those with pre-existing spinal conditions. Figure 2 shows a representation of two CT Imaging Findings: Fractured vs. Normal Cervical Vertebrae.



(a) (b)

Figure 2. Samples from "spine fracture prediction from C.T" dataset: (a) Fractured cervical spine (b) Normal cervical spine [16]

Thus, The development of a deep learning model to assist doctors in distinguishing between normal and fractured cervical spine images holds significant potential to revolutionize clinical practice. Cervical spine fractures, particularly subtle or non-displaced ones, can be challenging to detect, especially in high-pressure trauma settings where time is critical. A deep learning model can analyze imaging studies with remarkable speed and precision, identifying patterns and abnormalities that may be missed by the human eye. This capability not only enhances diagnostic accuracy but also reduces the risk of overlooking critical injuries, which can lead to severe complications such as spinal cord damage. Additionally, by acting as a first-pass screening tool, the model can alleviate the workload of radiologists, allowing them to focus on complex cases and treatment planning.

For less experienced clinicians, the model can serve as a valuable decision-support tool, improving diagnostic confidence and reducing errors.

3.1 Pretrained Models

Pretrained convolutional neural network (CNN) architectures—VGG16, DenseNet121, and MobileNet—are utilized to establish the classification models. Each of these models consists of a series of convolutional layers followed by pooling layers and fully connected (dense) layers with ReLU activation functions, dropout layers (with dropout rates ranging from 0.3 to 0.5 to reduce overfitting).

In this approach, pretrained CNN models are employed through transfer learning, where the base layers—trained on large-scale datasets like ImageNet—are reused to capture low-level image features. These layers were either frozen or partially fine-tuned, and custom dense layers were added on top for task-specific learning (binary classification of cervical spine fractures).

I. VGG16

The Visual Geometry Group (VGG) is a research group associated to Oxford University's Department of Science and Engineering. Beginning with VGG16 and continuing through VGG19, VGG has created a number of convolutional network models that are frequently utilized for pattern classification modules. Investigating how network depth affects the accuracy classification and detection efficacy of large-scale datasets was the initial goal of VGG's research. In order to accomplish this, the VGG researchers used a technique called deep-16 CNN, in which they used a compact 3x3 convolution kernel in each layer to increase the number of network layers while reducing the number of parameters [17].

- **The Network Structure**

The VGG architecture accepts an RGB image with dimensions of 224x224 pixels. Before the image is input into the VGG convolutional network, the average RGB value is calculated across all training images to normalize the input. The convolutional operations within VGG utilize either 3x3 or 1x1 filters, with a fixed convolution step. VGG comprises three fully connected layers, with the total number varying according to the specific variant, which ranges from VGG11 to VGG19. The minimum configuration, VGG11, consists of 8 convolutional layers and 3 fully connected layers, whereas the maximum configuration, VGG19, includes 16 convolutional layers along with 3 fully connected layers. It is important to highlight that VGG does not utilize a pooling layer following each convolutional layer; instead, it features a total of five pooling layers that are strategically placed at various points within the convolutional layers. A depiction of the VGG16 architecture is presented in Figure 3 [18].

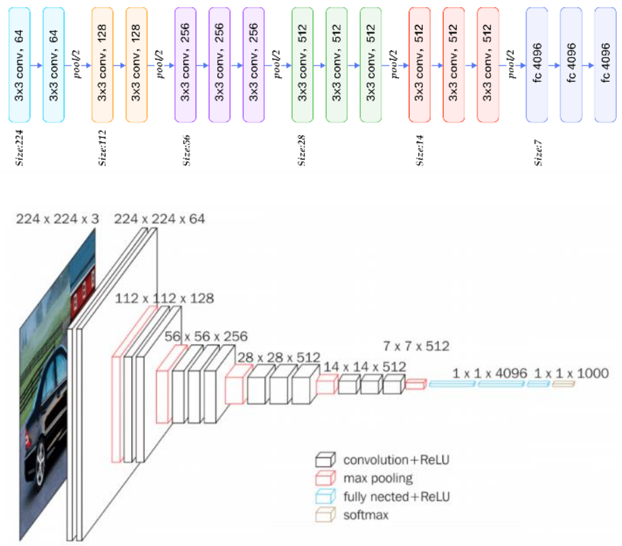


Figure 3. VGG16 neural network architecture

II. DenseNet

DenseNet architecture represents an adaptation of conventional CNN architecture, as illustrated in Figure 4. In a DenseNet, every layer forms connections with all preceding layers, which is the reason it is referred to as a "Densely Connected Convolutional Network." Overall, for L layers, there are L(L+1)/2 direct connections established. Within this framework, the input for each layer comprises the feature maps from all prior layers, and the feature maps generated by each layer serve as input for the layers that follow [19].

To put it simply, DenseNet connects every layer to every other layer, which is the core concept behind its remarkable power. Inside a DenseNet, the input of a layer is formed by combining the feature maps from previous layers through concatenation. By reusing features learned by earlier layers, DenseNets can reduce the number of parameters required to represent the model, while still achieving high levels of accuracy on a variety of tasks.

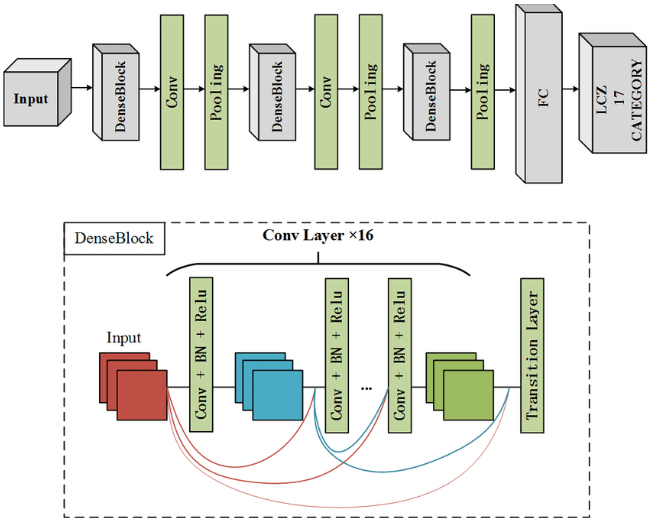


Figure 4. DenseNet architecture

III. MobileNet

The foundation of MobileNet is depthwise separable convolutions, which are made up of two central layers: depthwise and pointwise convolutions. The process of filtering input without making new features is called depthwise convolution. As a result, pointwise convolution—a method for creating new features—was integrated. Ultimately, the two-layer combination was dubbed depthwise separable convolution. This model applied a single filter to each input channel using depthwise convolutions, and then it created a linear combination of outputs from the depthwise layer using 1x1 convolution (pointwise). Following each convolution, the Rectified Linear Unit (ReLU) and Batch Normalization (BN) were applied. The depthwise and pointwise convolution steps are displayed in Figure 5.

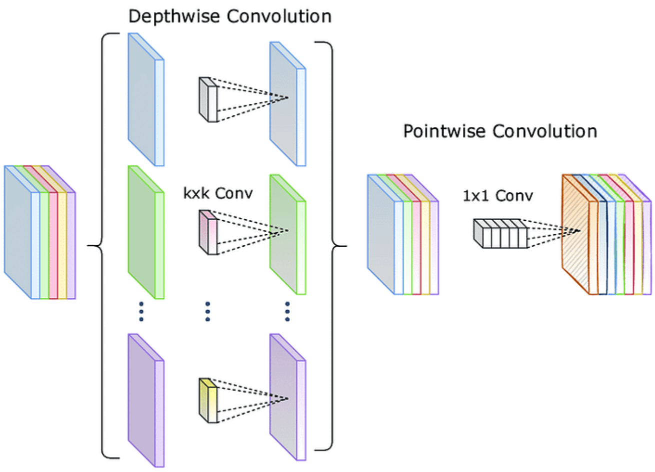


Figure 5. MobileNet architecture

3.2 Optimizers

I. Adam Optimizer

The Adam optimizer (Adaptive Moment Estimation) is a powerful optimization technique widely used in deep learning. It combines the benefits of the Momentum and RMSprop algorithms by adaptively modifying the learning rate for each parameter. Adam maintains moving averages of the gradients' first moment (mean)

and second moment (uncentered variance), allowing for efficient and reliable convergence. It is especially effective for training deep neural networks since it can handle sparse gradients and noisy updates.
Adam (adaptable Moment Estimation) is commonly employed in classification applications because of its adaptable learning rate, rapid convergence, and capacity to handle noisy or sparse gradients. Unlike classic stochastic gradient descent (SGD), Adam dynamically adjusts the learning rate for each parameter, resulting in more efficient updates and avoiding problems like overshooting and sluggish convergence. Adam combines the benefits of Momentum and RMSprop to help deep neural networks train faster and stabilize optimization, making it especially effective for large-scale classification tasks in computer vision and natural language processing. Its default hyperparameters perform well across multiple datasets, minimizing the necessity for major tuning, making it a popular choice among deep learning operators.

II. Nadam Optimizer

The Nadam optimizer (Nesterov-accelerated Adaptive Moment Estimation) is a powerful optimization technique that combines the advantages of Adam and Nesterov momentum. It improves on Adam by including Nesterov momentum, which aids in parameter prediction and increases convergence speed. Nadam, like Adam, dynamically modifies the learning rate for each parameter using first and second moment estimates, but using Nesterov momentum, it can update parameters more effectively by looking ahead. This leads to smoother optimization and often higher generalization in deep learning models, making Nadam an excellent choice for training neural networks in classification, NLP, and image recognition problems.

The next section explains in detail the proposed DenseNet121, VGG-16, and MobileNet - based models and their implementation. Figure 6 shows a flowchart of the suggested technique.

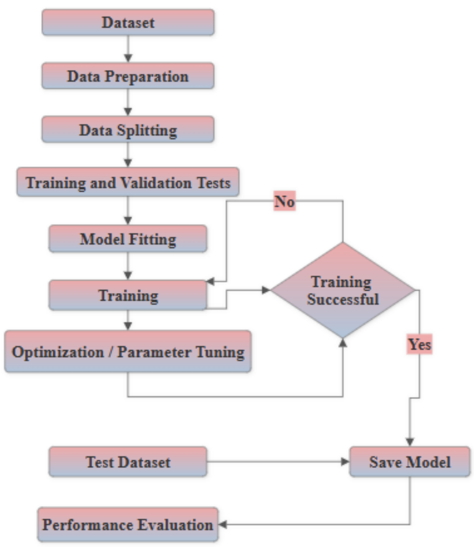


Figure 6. The proposed methodology

3.3 Dataset

Labeled data is a crucial input to deep learning classification problems [20]. The study was carried out using the "spine fracture prediction from C.T." dataset [16]. Using cervical spine fracture C.T. images, There are two classes of images in the dataset: normal cervical spine images and fractured cervical spine images. The original

dataset is separated into two sections: a "train" folder and a "Val" (validation) folder. 4200 images make up the dataset, while 1900 fracture and 1900 normal images are included in the train folder. The test dataset contains 400 images, 200 for each class.
The dataset was edited to be separated to 1700 fracture and 1700 normal images in the train folder and 800 images in the Val folder, 400 for each class to have better results.

3.4 Data Preprocessing

Data augemntation is implemented into the training of a model using the Keras deep learning library. This feature can be made by using the ImageDataGenerator class. To get started, an instance of this class can be constructed, and the necessary data augmentation strategies are specified by arguments given to the constructor. The class covers a variety of techniques, such as image shifts (by width and height shift ranges), image flips (both horizontally and vertically), image rotations (clockwise and counterclockwise), shearing transformation (distorts the image along an axis by up to 20%), and image zoom (zoom in and zoom out). These approaches aid increasing the size of the dataset to an appropriate level that is more suitable for deep learning applications. This created a larger and more diversified dataset, hence improving the accuracy and robustness of the proposed deep learning models.
Rescaling is a preprocessing step taken to standardize pixel values to a fixed range (0 to 1). This helps with numerical stability during training.
Fill Mode is also a preprocessing step that determines how new pixels are filled when transformations (like rotation, shifting, or zooming) introduce empty areas in the image.

3.5 Holdout Cross-Validation

The holdout validation technique is used to partition the dataset randomly into two subsets: training and validation sets. The training set consists of 80% of the total data, while the validation set contains 20% of the training data while the remaining 20% of the original data was kept as a test set.
The training set is used to train the deep learning models and the validation set to evaluate their performance on unseen data and tune their hyperparameters. Using a separate validation set, the generalization ability of the models can be assessed, and overfitting is prevented.

3.6 The Deep Learning Models

Transfer learning techniques have been utilized to create the model. Three pre-trained CNN models were employed, VGG-16, DenseNet-201, and MobileNet as proposed models for classification. Transfer learning is the process of using the pre-trained weights of a pre-existing model as a starting point for training a new model on an associated task. By reusing the pre-trained models' learned features, the quantity of required training data was greatly decreased and the training process became more efficient and improved. Fine tuning was performed in the pre-trained VGG-16, DenseNet-201 and MobileNet models by freezing some layers initially to retain learned features, training only the custom classification head additional layers. The final architecture consisted of the pre-trained base model, followed by fully connected layers for classification.

To prevent overfitting, besides data augmentation, several techniques have been applied such as freezing the pre-trained model layers, as this prevents the model from overfitting by avoiding excessive training on the small dataset. Additionally, adding a Dropout(0.3) layer in the custom classification head, which randomly disables 30% of the neurons during training. This helps prevent the model from becoming too reliant on specific neurons, promoting better generalization. Also, using a smaller learning rate (0.0001), which can prevent the models from making large updates to weights and overfitting to noisy or unrepresentative parts of the training data.

3.7 Performance Metrics

It is necesseary to use multiple assessment criteria to choose the best model that research presents. Assessing the level performance of the prediction model on testing data, which contains unfamiliar variables, is crucial once it has been trained on the training dataset [21]. Five of the most common performance metrics were utilized for cervical fracture classification problem. These are namely accuracy (A), precision (P), recall (R), F1 score (F1), and confusion matrix [22].

4. Experimental Results

The analysis of the proposed model's training and validation accuracy and loss, based on VGG-16 as the base model, is represented in Figure 7. The results demonstrate that the proposed model achieves notably higher accuracy and loss values converging at an impressive rate, yielding a training accuracy of 99.94% using Nadam Optimizer.

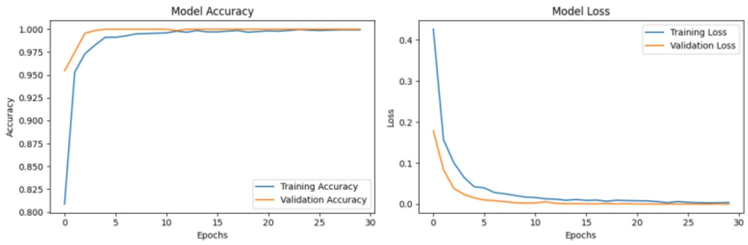


Figure 7. VGG16 model training and validation analysis – Nadam Optimizer: (a) Accuracy analysis (b) Loss analysis

The proposed model has achieved a test accuracy of 98.37%. The number of false positive and false negative cases is illustrated in the confusion matrix shown in Figure 8.

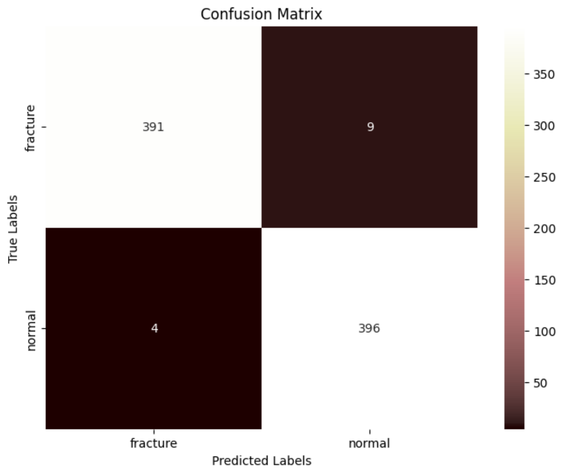


Figure 8. Confusion matrix using VGG-16 – Nadam Optimizer

Figure 9 illustrates the training and validation accuracy and loss of another proposed model, which utilizes VGG-16. The results indicate that the model attains high accuracy, with loss values stabilizing efficiently. Notably, the model achieves a training accuracy of 99.17% using the Adam optimizer.

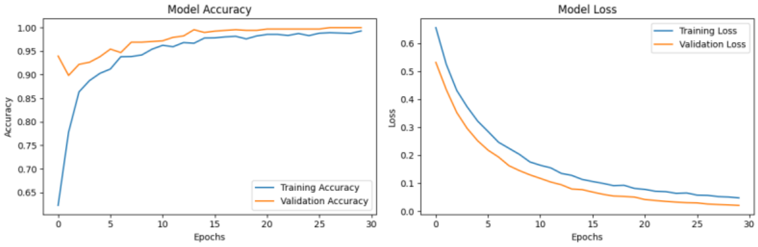


Figure 9. VGG16 model training and validation analysis – Adam Optimizer : (a) Accuracy analysis (b) Loss analysis

This model has achieved a test accuracy of 96.88%. The confusion matrix is shown in Figure 10.

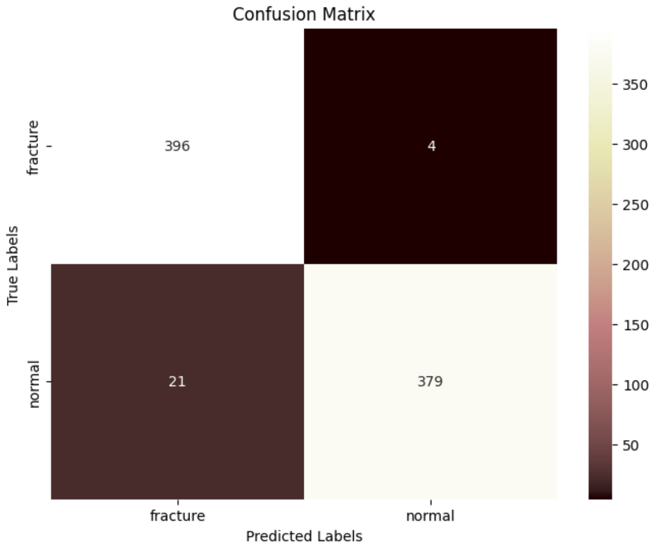


Figure 10. Confusion Matrix using VGG-16 – Adam Optimizer

The analysis of the DenseNet121 model's training and validation accuracy and loss, utilizing Nadam Optimizer is presented in Figure 11 reaching 99.75% training accuracy.

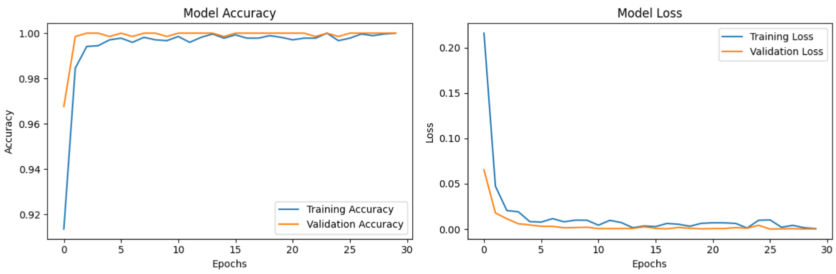


Figure 11. DenseNet-121 model training and validation analysis – Nadam Optimizer: (a) Accuracy analysis (b) Loss analysis

This model has achieved a test accuracy of 95.63%. The number of false positive and false negative cases is indicated in the confusion matrix shown in Figure 12.

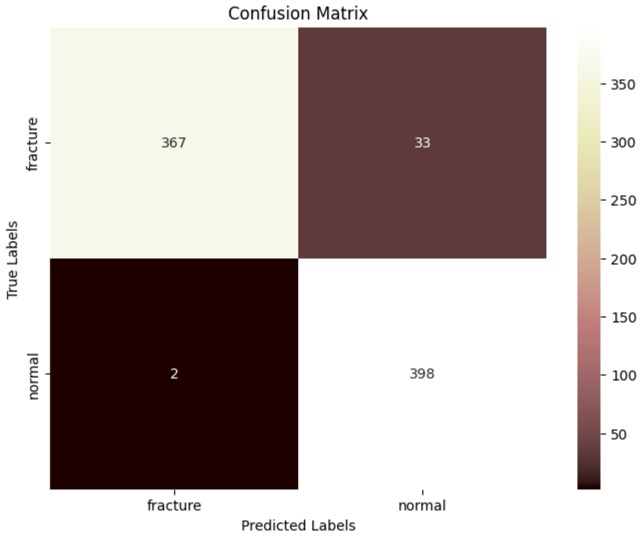


Figure 12. Confusion Matrix using DenseNet-121 – Nadam Optimizer

While using Adam optimizer showed slightly better results with DenseNet121 model as the test accuracy was 97.62%. Training and validation accuracy and loss graphs are represented in Figure 13.

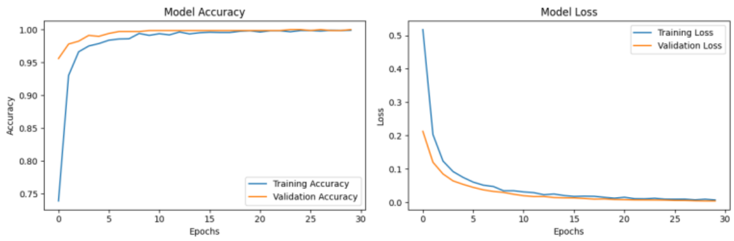


Figure 13. Model training and validation analysis using DenseNet-121 – Adam Optimizer: (a) Accuracy analysis (b) Loss analysis

The number of false positive and false negative cases is indicated in the confusion matrix shown in Figure 14.

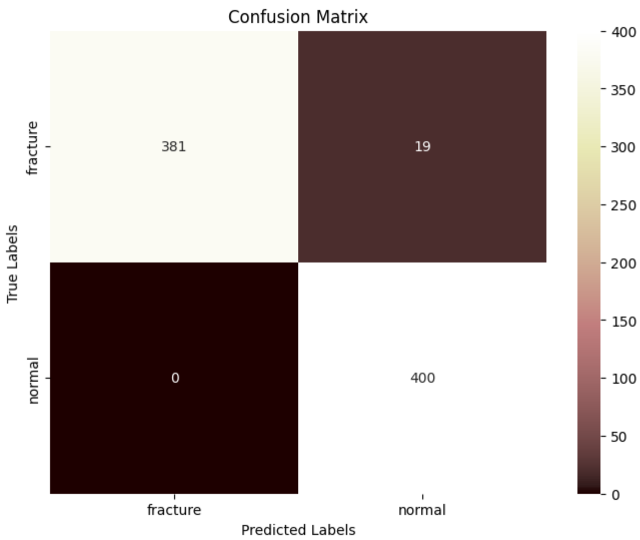


Figure 14. Confusion Matrix of DenseNet-121 model – Adam Optimizer

Figure 15 illustrates the training and validation accuracy and loss analysis of the MobileNet model using the Nadam Optimizer.

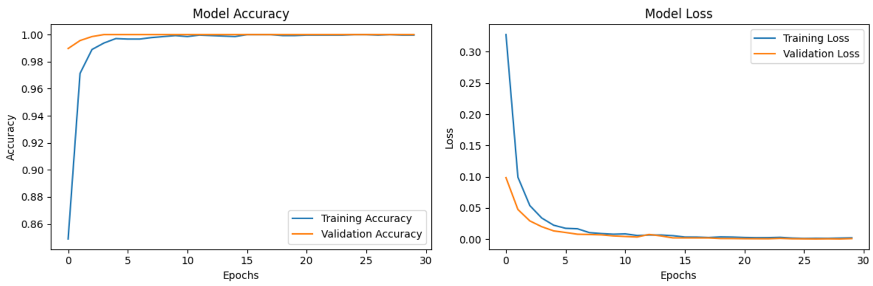


Figure 15. MobileNet model training and validation analysis – Nadam Optimizer: (a) Accuracy analysis (b) Loss analysis

Figure 16 presents the confusion matrix of the model, reaching accuracy of 95.50%. While applying Adam optimizer with MobileNet model showed 93.37% test accuracy. Figure 17 represents training and validation training accuracy and loss. Figure 18 presents the confusion matrix of the model, and Table 2 shows the results summary of the proposed models.

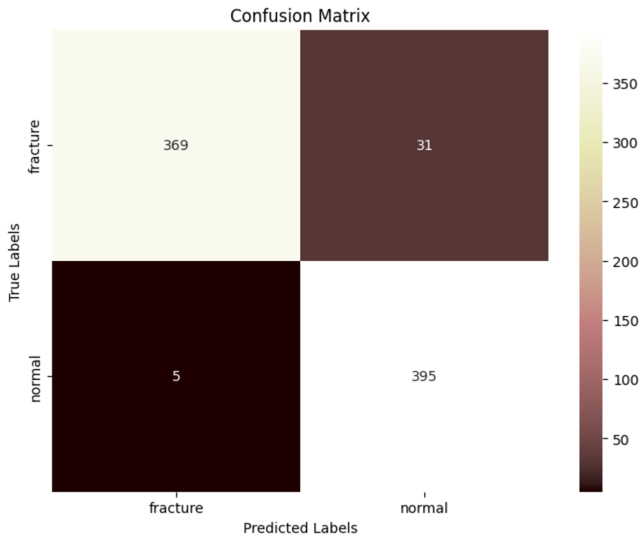


Figure 16. MobileNet model Confusion Matrix – Nadam Optimizer

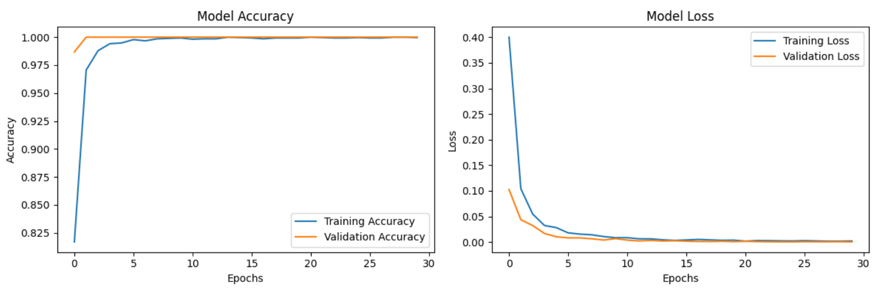


Figure 17. MobileNet model training and validation analysis – Adam Optimizer: (a) Accuracy analysis (b) Loss analysis

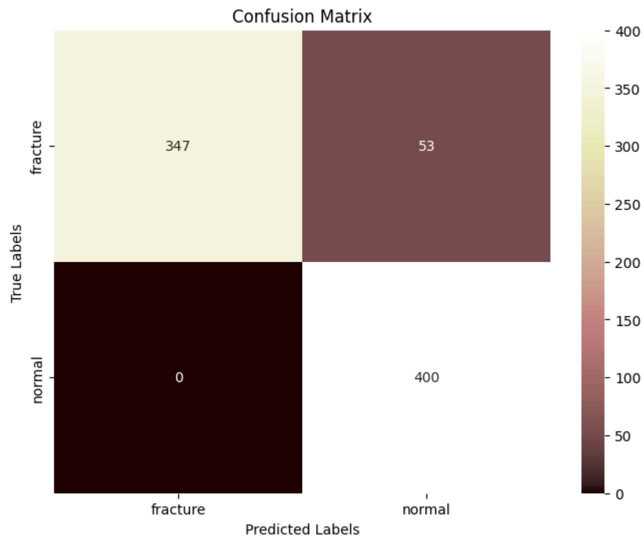


Figure 18. MobileNet model Confusion Matrix – Adam Optimizer

Table 2. Related studies in cervical spine fracture classification.

Model	Optimizer	Accuracy	Precision	Recall	F1 score
VGG-16	Nadam	**98.37%**	99.01%	97.75%	98.35%
	Adam	96.88%	94.96%	99.00%	96.94%
DenseNet-121	Nadam	95.63%	99.46%	91.75%	95.45%
	Adam	**97.62%**	100%	95.25%	97.57%
MobileNet	Nadam	**95.50%**	98.66%	92.25%	95.35%
	Adam	93.37%	100%	86.75%	92.90%

5. Discussion

The study has provided significant insights and advances. It is known that Adam optimizer is the most widely used optimization technique in deep learning tasks, especially in the medical field as it is applied in medical image analysis, disease prediction, segmentation, and classification tasks because of its adaptability and efficiency. Researchers are used to utilizing Adam optimizer with every pretrained model used. However, the Nadam optimizer is less common than Adam but, in some cases, it can provide better accuracy and better performance.

The results are optimizer model dependent, the VGG-16 model with Nadam optimizer achieved 98.37% accuracy, making it the best-performing model.

Comparing this study's results with related studies, the proposed study illustrates a remarkable improvement in accuracy. The proposed models have exceeded the prior studies, which usually faced limitations such as small sample sizes and reduced accuracies.

While the overall performance of the proposed models is strong, special attention was given to minimizing false negatives due to their critical impact in medical diagnosis, to not misclassify any patient which may lead physicians to wrong treatment decisions. The number of false positives may lead to excessive intense disruption. Both types of false results had been avoided as much as possible using the proposed models to obtain accurate results. The best-performing model (VGG16 with Nadam) achieved a recall of 97.75%, indicating a low rate of missed fracture cases. This is notably higher than many comparable studies in the literature, where recall often ranges between 91% and 94%. To help reduce false negatives, a balanced dataset was used, applied data augmentation, and introduced dropout layers to improve generalization.

While the proposed model demonstrates a low false negative rate, integration into clinical workflows should be accompanied by human oversight and risk-aware systems to ensure no critical injuries are overlooked. Additional strategies such as ensemble modeling, threshold tuning, and uncertainty-aware classification may be explored to further minimize false negatives and enhance clinical safety.

Cervical spine fracture diagnosing models can be beneficial for several reasons:

1. Faster and more accurate diagnosis: Deep learning models can analyze thousands of CT scans in seconds, making it useful in emergency settings. This can assist in accelerating the diagnosis process and guarantee that patients get the appropriate treatment as DL reduces the risk of human error in fracture detection, especially for subtle or complex cases leading to earlier treatment, reducing the risk of spinal cord injury and long-term disability.

2. Consistency in diagnosis: compared to human radiologists, who may give different interpretations, deep learning models produce reliable and reproducible results, also DL models reduce inter-observer variability among doctors.

3. Improved Sensitivity for Subtle Fractures: some cervical spine fractures are difficult to detect. Deep learning can diagnose subtle abnormalities that may be missed by radiologists.

4. Reducing Workload for Radiologists: DL models can function as an AI-assisted second opinion, allowing radiologists to focus on complex cases.

5. Integration with AI-Assisted Decision Support: deep learning models can be integrated with hospital PACS (Picture Archiving and Communication Systems) and can provide automated reports with fracture classification.

Moreover, this study's models can aid researchers in detecting several other medical conditions. Since cervical spine fractures are considered as medical emergency, these proposed study outcomes offer a critical lifeline by allowing faster more accurate diagnoses that can actually save lives and improve patient care as it is the main goal of biomedical engineering field.

For the future work, the studies will focus on enhancing the generalizability and clinical applicability of the proposed models. First, evaluating the models on additional datasets from diverse sources, also, exploring real-time deployment and validation of the models in clinical environments, particularly in emergency and trauma care settings, to test their effectiveness under real-world, time-sensitive conditions.

Additionally, exploring cross-disease analysis by adapting the proposed models to classify other spinal conditions or musculoskeletal abnormalities visible in CT scans, such as disc degeneration, vertebral tumors, or lumbar fractures. This would help assess the generalizability of the model architecture and training pipeline beyond a single diagnosis and could contribute to the development of comprehensive AI-assisted diagnostic systems capable of identifying multiple spine-related conditions from a unified framework.

6. Conclusions

This study demonstrates the effectiveness of deep learning techniques in detecting cervical spine fractures using CT images. The proposed approach significantly enhances classification accuracy compared to conventional radiological methods. Among the tested models VGG16, MobileNet, and VGG16, the VGG16 model with Nadam optimization exhibited superior performance, achieving an accuracy of 98.37%. The results indicate that model performance is heavily influenced not just by the pretrained model used, but also by the optimizer technique employed. Deep learning can serve as a valuable tool for automating and improving the efficiency of cervical spine fracture diagnosis. Future research should focus on expanding dataset diversity and integrating real-time diagnostic applications. The findings of this study contribute to the advancement of AI-driven medical imaging solutions, potentially reducing misdiagnosis rates and improving patient outcomes.

7. References

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