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Research Article

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Performance Evaluation of Deep Learning Methods for Cervical Spine Fracture Detection

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Abstract:

Abstract should be about 100-250 words. It should be written times new roman and 10 punto. Cervical spine fractures are critical medical emergencies with the possible to cause permanent paralysis or death if not promptly identified and treated. This study addresses the gap in leveraging deep learning models for their detection by proposing a two-stage pipeline using a curated dataset of computed tomography (CT) images comprising both fractured and non-fractured cases. In the first stage, cervical vertebrae are identified within CT image slices using a multi-input network based on the Global Context Vision Transformer (GC ViT) architecture, benchmarked against leading Deep Learning models. During the second phase, multiple architectures such as Convolutional Neural Networks (CNNs) were employed to perform the designated classification tasks (CNN), ResNet, EnlightenmentNet, and a hybrid CNN+ResNet architecture, are employed to detect fractures, achieving accuracy of 64%, 70%, 54%, and 94%, respectively, with further comparisons against YOLOv5 for localization performance. The hybrid CNN+ResNet model demonstrated superior accuracy, significantly reducing radiologists' workload and enhancing diagnostic precision and efficiency. This approach has substantial clinical implications, offering a promising solution to improve patient outcomes through timely and reliable detection of cervical spine fractures.

1. Introduction

The cervical spine, often identified as the neck, forms the uppermost segment of the vertebral column. It is characterized by its elongated and flexible structure, which supports the head and facilitates a wide range of motion across the upper body. This segment includes seven cervical vertebrae (C1–C7), each separated by intervertebral discs that cushion and facilitate movement (see Figure 1). Vertebrae C3 through C6 are structurally similar and are thus categorized as typical cervical vertebrae. These vertebrae possess compact, rectangular bodies encased in a dense cortical layer, contributing to their strength and stability. In contrast, C1 (atlas), C2 (axis), and C7 (vertebra prominens) are considered atypical due to their distinct morphology. The atlas (C1) primarily functions to support the skull, while the axis (C2) features a prominent odontoid process that enables rotational movement of the head. The seventh vertebra (C7), notable for its prominent spinous process, exhibits characteristics that closely resemble those of thoracic vertebrae [1].

Cervical spinal fractures (CSFx) represent critical injuries that may result in life-threatening complications or long-term neurological impairment. These fractures can compromise the integrity of the spinal cord, particularly at the junction where the skull connects to the cervical spine and may also affect vital vascular structures within the neck. When the vertebral column becomes unstable, it poses a significant risk of compressing the spinal cord, potentially leading to progressive neurological deterioration [2].

Over the past ten years, the incidence of spinal cord injuries has remained steady, averaging approximately 26.5 cases per squillion individuals every year [3]. These injuries represent a leading cause of long-term disability, particularly among young adults and individuals in the workforce, exerting a profound burden on both personal well-being and societal resources. Prompt recognition and stabilization of cervical spinal fractures (CSFx) are essential to minimize the risk of further neurological compromise. Statistically, young males are disproportionately affected, with the predominant causes including motor vehicle collisions, accidental falls, physical assaults, and sports-related trauma [4].

The initial approach to evaluating individuals with suspected thoracolumbar trauma involves a comprehensive Physical assessment procedure, with a dedicated focus on evaluating neurological status. This is followed by diagnostic imaging, which typically includes anteroposterior and lateral radiographs, computed tomography (CT) for detailed bone assessment, and MRI[5] to evaluate soft tissue and spinal cord integrity. Rapid and accurate identification of vertebral fractures is essential to prevent progressive neurological damage or paralysis after trauma. Within this framework, advanced deep learning techniques present a viable avenue for addressing the identified challenges for enhancing diagnostic precision and accelerating clinical decision-making.

Deep learning a subset of artificial intelligence, has seen significant integration into radiological practice in recent years. It has enabled the creation of automated systems capable of detecting fractures across various anatomical regions using radiographic images. The convergence of advanced computer vision techniques, expansive medical datasets, and The evolution of deep learning architectures has facilitated the development of intelligent diagnostic tools designed to assist healthcare practitioners operating under substantial clinical demands. These systems can expedite diagnostic workflows, potentially reducing the risk of permanent disability or fatal outcomes. Moreover, Deep Learning models are increasingly applied to computed tomography (CT) interpretation, offering assistance in navigating the complexity of numerous two-dimensional image slices that can challenge manual review[6].

Extensive research has explored the application of deep learning and computer vision methods for the detection of cervical spine fractures [7][8]. A notable technique employs a deep convolutional neural architecture in conjunction with a bidirectional long short-term memory unit, leading to enhanced automation in fracture recognition and achieving classification rates exceeding 79% across diverse image datasets. Concurrently, Vision Transformers (ViT) [9] have emerged as a compelling alternative due to their elevated diagnostic precision. Select studies have documented classification accuracies approaching 98%, thereby outperforming conventional CNN-based models in cervical injury identification tasks [10].

Recent research has explored [11] the classification of cervical spine injuries into categories such as fractures and dislocations using advanced deep learning architectures. These models have demonstrated strong performance metrics, including high levels of accuracy, sensitivity, specificity, and precision. Another line of investigation [12] has focused on the development of an automated cervical fracture detection system, incorporating extensive model refinement through custom neural layers and data augmentation techniques. Notably, this work also led to the creation of a mobile application, enabling real-time deployment and accessibility in clinical settings.

In the context of classification, numerous investigations have predominantly addressed the segmentation of vertebral structures., employing architectures such as U-Net [13]. In some approaches, the 2D U-Net is utilized by treating each axial slice of spinal imaging data as an independent input [14, 15]. Alternatively, other methods adopt a 3D U-Net framework, where volumetric patches extracted from multi-slice datasets are used to train the network, enabling spatial context to be captured more effectively [16, 17].

In spite of the significant breakthroughs attained, a critical gap remains in current methodologies. Most existing approaches emphasize either vertebral segmentation or fracture detection in isolation. However, a more integrated framework is essential one that simultaneously identifies the total number of cervical vertebrae and determines their structural integrity. Such a unified assessment is vital for comprehensive clinical evaluation, thereby minimizing the likelihood of overlooked injuries. Moreover, the choice and quality of the training dataset play a pivotal role in shaping the performance of deep learning models in diagnostic performance. The accuracy, robustness, and generalizability of these classifications are deeply partial by the dataset's quality, heterogeneity, and scale, underscoring the urgent need for standardized, high-resolution medical imaging repositories.

2. Literature Review

Deep learning is one of the fastest-growing areas of medical image analysis, and it has had a substantial impact on a variety of clinical and scientific applications. New breakthroughs are Establishing a foundation for the continued advancement of artificial intelligence, while simultaneously enabling more precise and reliable segmentation outcomes. classifications, detections, and forecasts even at the level of professional radiologists. Contemporary deep learning techniques have demonstrated superior performance when compared to conventional methodologies in medical image analysis. But there is still a long way to go.

Salehinejad et al. [18] developed a deep sequential learning approach for identifying injuries and fractures in the cervical region of the spine using computed tomography. The current research, the scientist designed a deep convolutional neural network (CNN) that incorporates recurrent layers with bidirectional capabilities. This framework was utilized to enable automated recognition and detection of fractures in axial CT images of the spine. The validation of the data resulted in classification accuracies of 70.92% and 79.18%. The primary limitation of this approach is its tendency to produce a high number of false positives, which can result in inaccurate predictions across various cases. When an image within a single case is classified as a false positive, it can influence the entire case, causing it to be classified as a false positive. These results highlight the importance of including common features in the training process. The high performance on imbalanced datasets is primarily attributed to the dataset's bias towards negative cases and images.

Erickson et al. [19] mentioned that deep learning is a popular approach for performing a range of crucial tasks in radiology and medical imaging. Some types of deep learning can precisely segment organs (trace the borders, allowing volume measurements or other attributes to be calculated). Other deep learning networks can predict significant qualities from image areas, such as whether something is cancerous, molecular markers for tissue in a region, and even prognostic indicators. Deep learning is simpler to train than classic machine learning approaches, but it requires more data and greater caution when interpreting results. It will automatically identify the key elements, but it might be a challenge to identify what those features are. The preceding study reveals in detail how precise, popular, and significant deep learning models are. Additionally, this article discusses the fundamental ideas of deep learning systems as well as potential challenges and common shortcomings encountered during the development of deep learning frameworks and how to avoid them.

Chład and Ogiela [20] This study investigates the integration of deep learning techniques with cloud-based computational frameworks to develop an automated system for detecting cervical spine fractures. Emphasis is placed on assessing the diagnostic performance of Vision Transformer (ViT) models in identifying fracture patterns from medical imaging data. A cloud-enabled architecture is proposed to facilitate both model training and real-time inference. Experimental findings indicate that ViT-based models deliver high classification accuracy, underscoring their potential in clinical applications. Additionally, the study demonstrates that data augmentation strategies play a critical role in enhancing the generalization and robustness of ViT models.

Cloud-based systems enable the implementation of large-scale detection systems, improving the efficiency of medical personnel. Overall, vision transformers offer a promising approach to enhance fracture detection in the cervical spine. However, there is still a challenge in accurately detecting fractures in specific vertebrae.

Krawczyk and Starzynski [21] The article primarily focuses on utilizing the You Only Look Once (YOLO) neural network to identify individual bones within a series of CT image slices depicting the human pelvic area. To achieve this, the YOLO network underwent training using custom data, enabling it to recognize and locate various bone structures in CT images. Subsequently, The trained model was subsequently evaluated on an independent CT dataset to assess its generalization capability to assess its accuracy in detecting bone structures. In the final step, bounding boxes generated by the YOLO algorithm for the detected regions were employed to align idealized bone models within the CT data, facilitating a precise alignment of these novel models through the actual bone structures observed in the CT scans.

3. Experimental Setup and Methodological Framework

This segment outlines the Deep Learning frameworks utilized in this learning for the classification and identification of cervical spine fractures. Detailed analyses and methodological discussions are elaborated in the subsequent sections of this document.

3.1 Convolution Neural Networks

Convolutional Neural Networks (CNNs) represent a class of deep learning architectures specifically designed to process data with inherent spatial structure, such as digital images. These models are composed of sequential layers, each contributing uniquely to the task of feature extraction and classification. Among these, the convolutional layer serves as the foundational component, responsible for detecting localized patterns within the input. It achieves this by convolving a set of trainable filters small weight matrices over distinct regions of the image, thereby capturing essential visual features such as edges, textures, and gradients. Additional layers, including pooling and fully connected layers, further refine and interpret these features to support accurate decision-making, textures, and other visual features essential for downstream tasks. Convolutional Neural Networks (CNNs) are particularly well-suited for visual data processing due to their unique architectural principles. Three core design features parameter sharing, sparse inter-layer connectivity, and localized receptive fields—collectively enhance their efficiency and effectiveness. Parameter sharing enables the reuse of filter weights across different spatial regions of the input, significantly reducing the number of learnable parameters and mitigating the risk of overfitting. Sparse connectivity ensures that each neuron interacts with only a limited portion of the preceding layer, which lowers computational demands and improves generalization. Furthermore, local receptive fields confine each neuron's input to a specific region of the image, allowing the network to extract spatially coherent features and maintain robustness against noise and minor variations. These architectural strengths make CNNs highly effective for applications such as medical imaging, object recognition, and visual classification [18, 19].

3.2 ResNet

The ResNet50 architecture was applied to differentiate between benign and malignant groups, shown in Fig. 2. While convolutional neural networks (CNN) such as VGG or AlexNet learn features using large, convolutional network architectures [12], the ResNet can extract residual features, as subtraction of features learned from input of that layer, using skip connections [13]. The ResNet50 architecture contains one 3 × 3 convolutional layer, one max pooling layer, and 16 residual blocks.

Each block contains one 1 × 1 convolutional layer, one 3 × 3 convolutional layer and one 1 × 1 convolutional layer. The residual connection is from the beginning to the termination of the block. The output of the last block is connected to a fully end connected layer with sigmoid function to provide prediction. With ResNet, since it is pre-trained with photographs with RGB colors, only three sets of images can be used in input channel [13]. Thus, a convolutional layer with 1 × 1 filter was added to extract inter-channel features and transform from six channels to three channels.

3.3 EnlightenmentNet

EnlightenmentNet aims to reduce the complexity of traditional deep CNNs by focusing on core components like convolutional and pooling layers, making them easier to understand, implement, and train. These networks primarily focus on extracting meaningful features from input data using convolutional operations, often employing smaller filter sizes and fewer layers compared to larger CNN models.

By simplifying the architecture and reducing the number of parameters, EnlightenmentNet models are designed to be more computationally efficient, making them suitable for resource-constrained environments like mobile devices or real-time applications. The simpler structure and focus on feature extraction can make EnlightenmentNet models more interpretable, allowing for a clearer understanding of how the network makes its decisions.

Compared to deeper CNN architectures like ResNet or Inception, EnlightenmentNet may not achieve the same level of state-of-the-art accuracy on complex tasks with vast datasets. However, the strength lies in its balance of performance and efficiency, making it suitable for applications where simplicity, computational cost, and interpretability are crucial considerations.

4. Results and Discussions

4.1 Dataset Overview:

- **Training Set**: 3040 images belonging to 2 classes.
- **Test Set**: 760 images belonging to 2 classes.
- **Validation Set**: 400 images belonging to 2 classes.

4.2 Algorithm Steps for CNN + ResNet in Cervical Spine Fracture Detection

Input Preprocessing:

- Load cervical spine X-ray or CT scan images.
- Resize all images to a fixed dimension (224×224).
- Normalize pixel values to have a mean of 0 and a standard deviation of 1.
- Apply data augmentation (rotation, flipping, cropping) to increase dataset diversity.

CNN-Based Feature Extraction:

- Pass the preprocessed image through convolutional layers.
- Apply filters to extract local features such as edges and textures.
- Use activation functions (ReLU) after each convolution operation.
- Down sample feature advanced maps expending pooling final layers (max pooling).

ResNet Block Integration:

- Add residual blocks to enhance learning by skipping connections:
- Perform two convolutional operations within each block.
- Incorporate the original input of the block into the result produced by the second convolutional operation through an additive connection. (residual connection).
- Repeat the residual blocks to extract deep hierarchical features.

Classification:

- Flatten the feature maps from ResNet.
- Pass the flattened features through fully connected layers.
- Use a softmax (multi-class) or sigmoid (binary) function to predict the probability of a fracture.

Loss Calculation:

- Compute the classification loss using cross-entropy.
- For binary classification:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)]$$

Model Training:

- Train the model using back propagation and gradient descent.
- The model parameters are progressively adjusted through iterative optimization steps aimed at reducing the value of the loss function.

Evaluation:

- Validate the model on unseen test data.
- Evaluate model performance using key statistical indicators, including accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC).

Deployment:

- Save the trained model.
- Deploy the model for real-time cervical spine fracture detection.

4.3 Model Performance Results:

This table compares the accuracy (%) achieved by a comparative analysis that was conducted using four distinct deep learning algorithms, each applied to address a defined classification task, likely a classification or recognition problem. The Model column lists the names of the models being compared: CNN (Convolutional Neural Network), ResNet (Residual Network) is a prominent deep learning architecture extensively applied in image recognition and classification domains. It employs a distinctive mechanism known as skip connections, which enables the model to bypass certain layers, thereby facilitating the training of deeper networks and mitigating issues such as vanishing gradients to efficiently train very deep networks; EnlightenmentNet, a specialized or custom model that likely improves upon the CNN or ResNet architectures; and Hybrid CNN+ResNet, a mixture of Convolutional and ResNet models that potentially combines the strengths of both. The Accuracy (%) column displays the performance. The classification performance of each model is reported as a percentage, with higher values reflecting superior predictive capability. Specifically, the CNN model achieves 64% accuracy, while ResNet improves upon it with 70%. EnlightenmentNet further outperforms both with an accuracy of 54%. However, the Hybrid CNN+ResNet model demonstrates the highest accuracy of 94%, showcasing significant performance improvements through the hybrid approach.

4.3.1 CNN Model

Structure: Traditional convolutional layers with max-pooling and dense layers at the end.

Performance: Moderate performance, likely limited by the model's relatively shallow architecture and smaller receptive fields. The model captures basic spatial features but struggles with deeper hierarchical patterns, which are frequently essential aimed at complex image classification tasks like fracture detection.

4.3.2 ResNet Model

Structure: Pretrained ResNet50 without the top layers, using a global average pooling operation preceding a series of densely connected layers.

Performance: Better than CNN attributable to its ability to learn residual mappings through deeply layered architectures. ResNet's skip connections allow the advanced model to retain gradient flow and learn deeper representations, making it more effective for detecting complex patterns. However, the limited training on your dataset without fine-tuning all layers constrains its full potential.

4.3.3 EnlightenmentNet Model

Structure: A simplified CNN-based network with increased depth compared to the basic CNN. It also includes global average pooling layers.

Performance: Higher accuracy than both CNN and ResNet, possibly due to better feature extraction with added depth and improved regularization through dropout. However, it's still a shallow network compared to ResNet, limiting the ability to capture highly abstract features.

4.3.4 Hybrid (CNN+ResNet) Model

Structure: A combination of CNN layers and a pretrained ResNet model, with concatenation of their outputs followed by dense layers.

Performance: This model achieves significantly better results. The hybrid architecture leverages both the high-level features from ResNet and the localized spatial advanced features from CNN. The combination permits the classical to study both detailed patterns and abstract representations, thus outperforming the individual models.

Finally, the Hybrid CNN+ResNet model achieves the best performance, as both its training and validation accuracy exhibit steady growth, reaching higher demonstrated superior accuracy in comparison to alternative deep learning models. The architecture obviously highlights the greater concert of the Hybrid CNN+ResNet model, which achieves the highest overall accuracy, outperforming standalone CNN, ResNet, and EnlightenmentNet models.

Hybrid CNN + ResNet Performed Better:

- **Diverse Feature Extraction**: The hybrid model combines localized feature extraction from CNN layers with global hierarchical feature extraction from ResNet, creating a more comprehensive feature space for classification.
- **Residual Connections**: ResNet's residual connections help in retaining important feature maps without vanishing gradient issues, especially when combined with the CNN layers.
- **Transfer Learning Benefits**: Pretrained ResNet provides powerful feature representations learned on a massive dataset (ImageNet), which is then enhanced with the CNN's specialized learning from the cervical fracture dataset.
- **Regularization and Robustness**: The hybrid model likely benefits from better regularization, preventing overfitting due to the dropout layers and combining different feature representations.

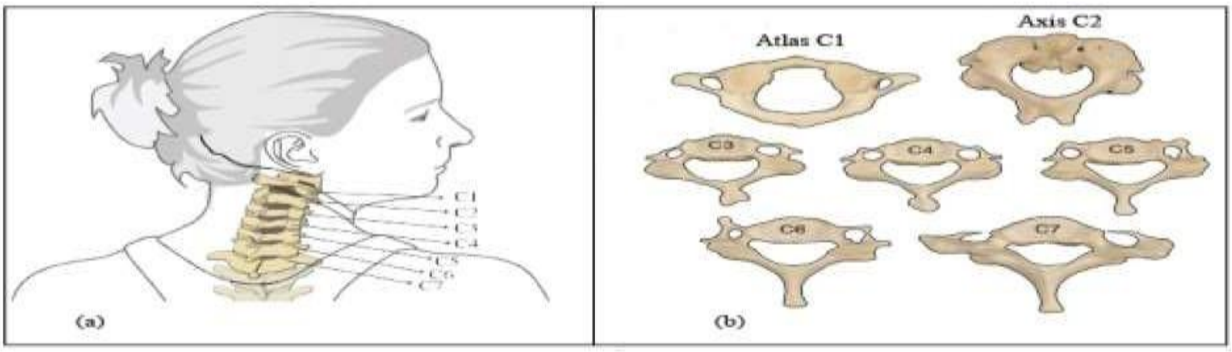

Figure 1: *illustrates the location of the cervical vertebrae (C1-C7) within the human neck.*

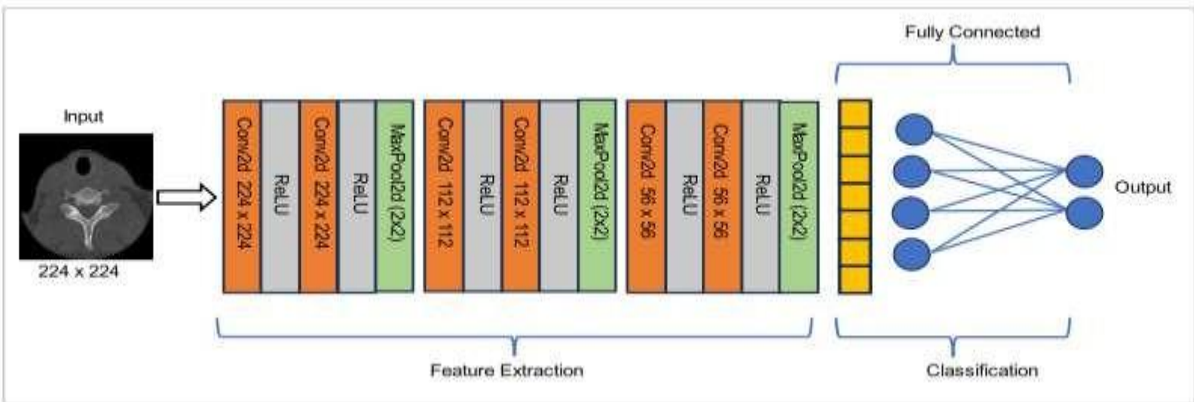

Figure 2: *CNN Deep Learning network*

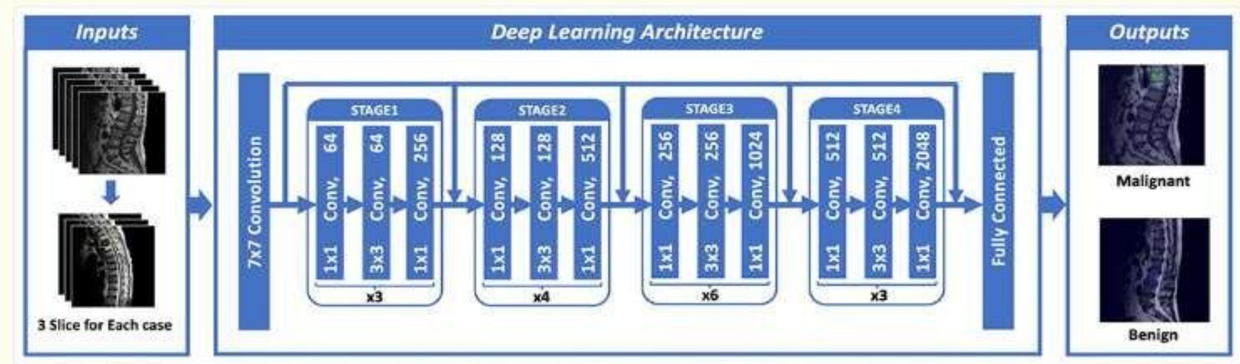

Figure 3: *ResNet deep learning model*

Table 1: *Hyperparameters Used for Model Training*

Hyperparameter	Value
Optimizer	Adam
Initial Learning Rate	1e-4 (0.0001)
Loss Function	binary_crossentropy
Epochs	30
Learning Rate Scheduler	ReduceLROnPlateau (monitor='val_accuracy', factor=0.2, patience=2)
Early Stopping	monitor='val_accuracy', patience=4, restore_best_weights=True
Minimum Learning Rates Observed	2e-5, 4e-6, 8e-7
Batch Size	32
Image Size/Input Shape	224, 224

```
CNN Classification Report:
              precision    recall  f1-score   support

           0       0.58      1.00      0.73       200
           1       1.00      0.28      0.43       200

    accuracy                           0.64       400
   macro avg       0.79      0.64      0.58       400
weighted avg       0.79      0.64      0.58       400
```

Figure 5: *Classification Report of CNN Model for Cervical Spine Fracture Detection*

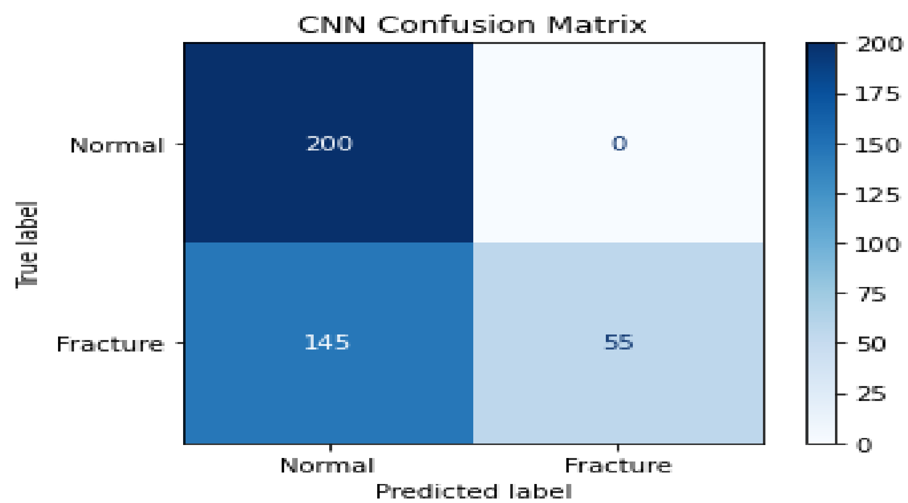

Figure 6: *Confusion Matrix of CNN Model for Cervical Spine Fracture Detection*

***Table 2:** Comparative analysis of different machine learning algorithms*

Model	Accuracy (%)
CNN	64
ResNet	70
EnlightenmentNet	54
Hybrid CNN+ResNet (Proposed Model)	94

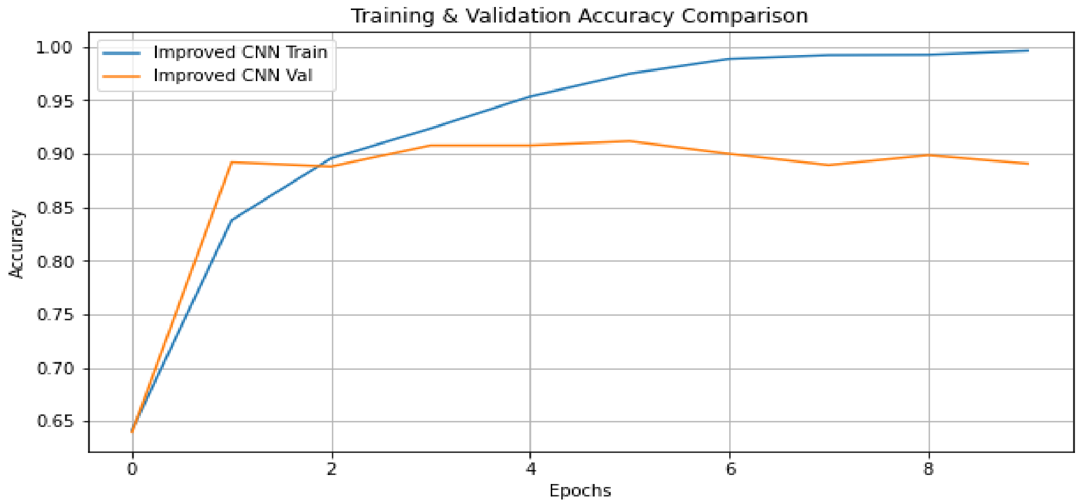

***Figure 7:** Training and validation accuracy of CNN model*

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ResNet Classification Report:
              precision    recall  f1-score   support

           0       0.67      0.77      0.72       200
           1       0.73      0.63      0.68       200

    accuracy                           0.70       400
   macro avg       0.70      0.70      0.70       400
weighted avg       0.70      0.70      0.70       400
```

***Figure 8:** Classification Report of ResNet Model for Cervical Spine Fracture Detection*

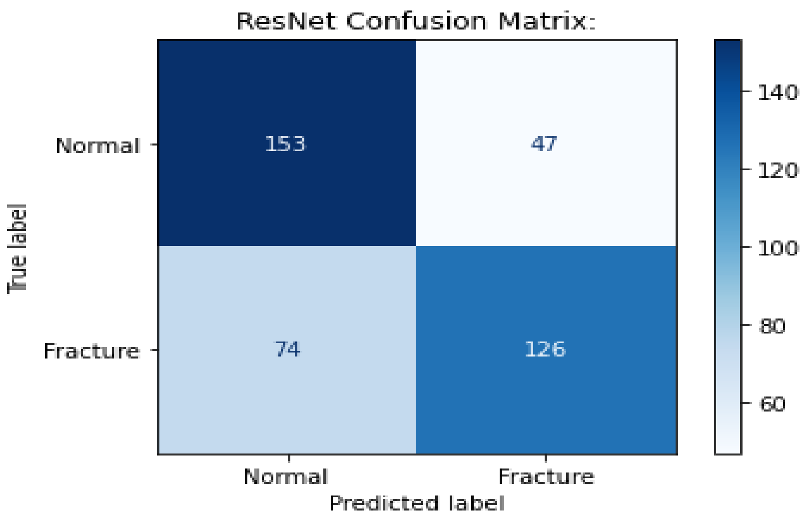

***Figure 9:** Confusion Matrix of ResNet Model for Cervical Spine Fracture Detection*

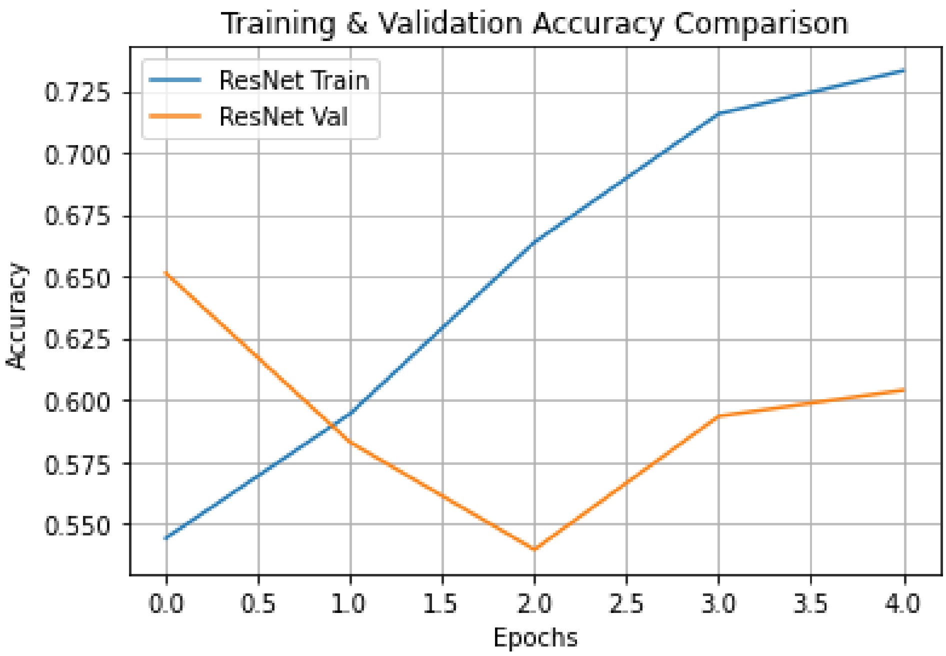

Figure 10: *Training and validation accuracy of ResNet model*

EnlightenmentNet Classification Report:

	precision	recall	f1-score	support
0	0.52	1.00	0.69	200
1	1.00	0.09	0.16	200
accuracy			0.54	400
macro avg	0.76	0.54	0.42	400
weighted avg	0.76	0.54	0.42	400

Figure 11: *Classification Report of EnlightenmentNet Model for Cervical Spine Fracture Detection*

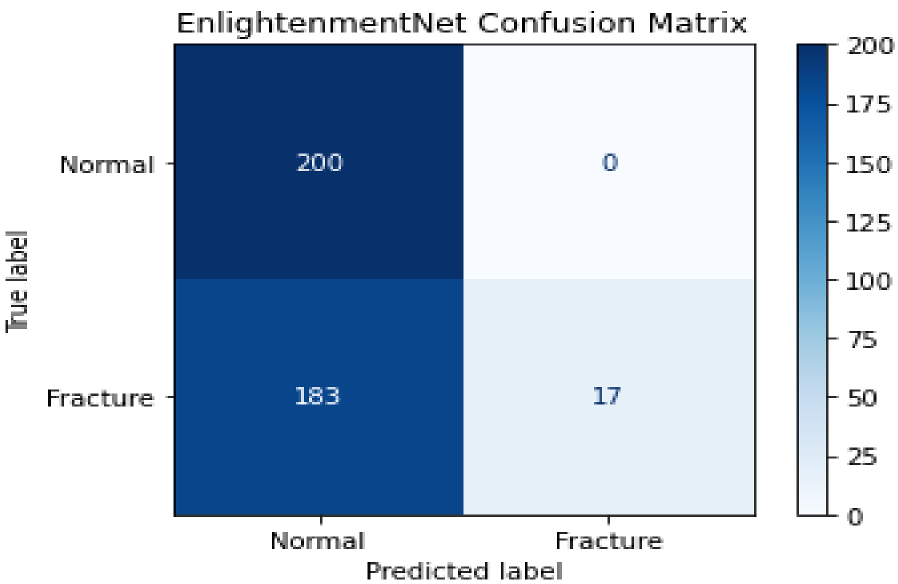

Figure 12: *Confusion Matrix of EnlightenmentNet Model for Cervical Spine Fracture Detection*

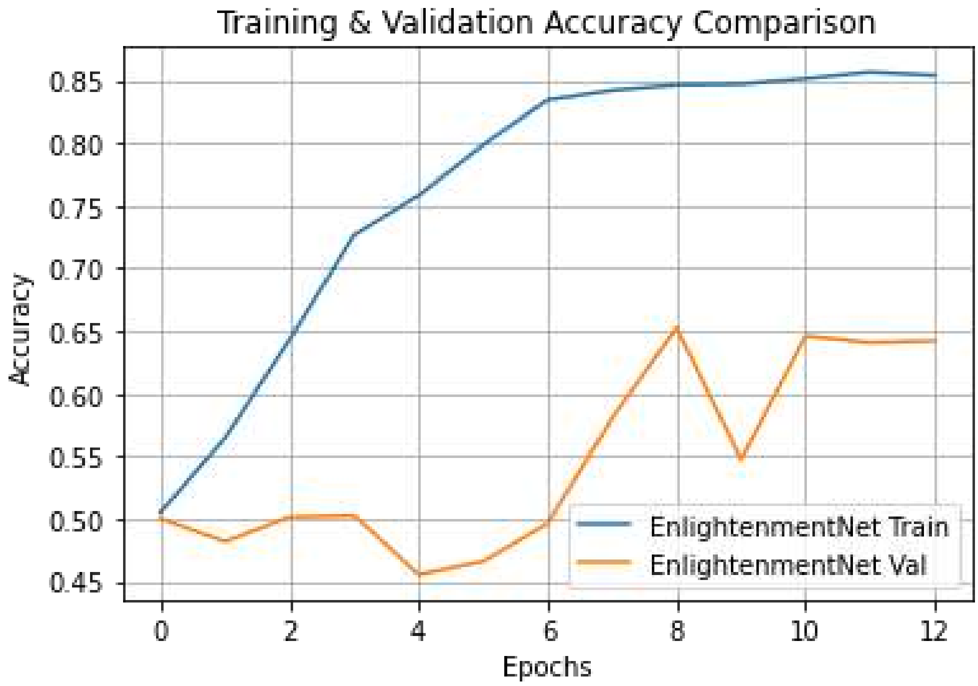

Figure 13: *Training and validation accuracy of EnlightenmentNet model*

```
Hybrid CNN-ResNet Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.96      0.94       200
           1       0.96      0.91      0.94       200

    accuracy                           0.94       400
   macro avg       0.94      0.94      0.94       400
weighted avg       0.94      0.94      0.94       400
```

Figure 14: *Classification Report of Hybrid (CNN+ResNet) Model for Cervical Spine Fracture Detection*

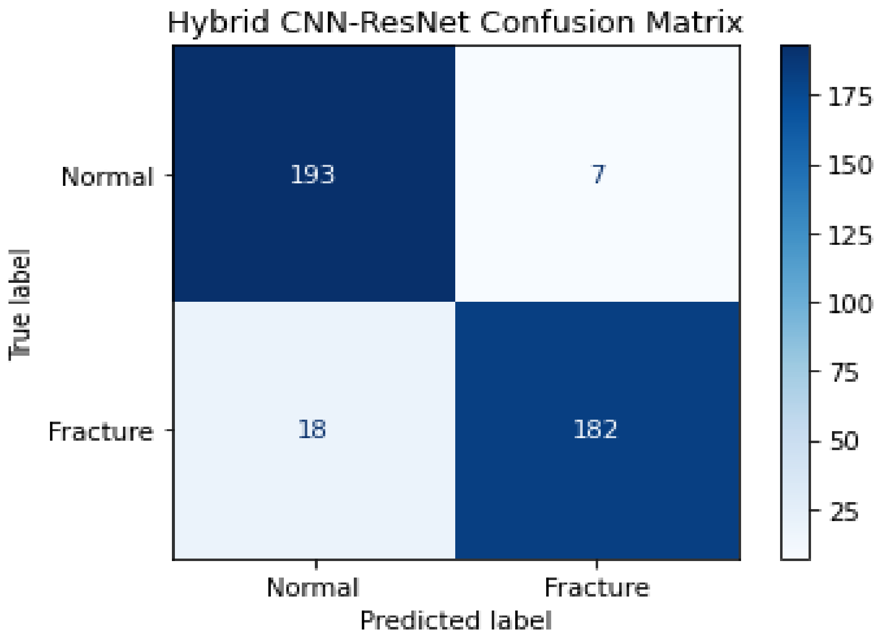

Figure 15: *Confusion Matrix of Hybrid (CNN+ResNet) Model for Cervical Spine Fracture Detection*

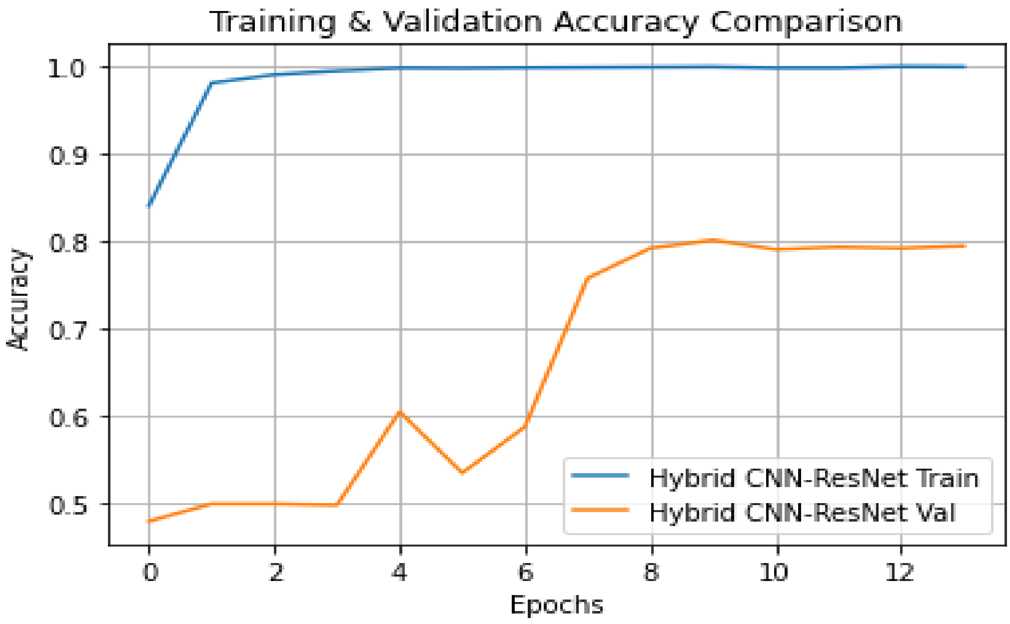

Figure 16: *Training and validation accuracy of Hybrid (CNN+ResNet) model*

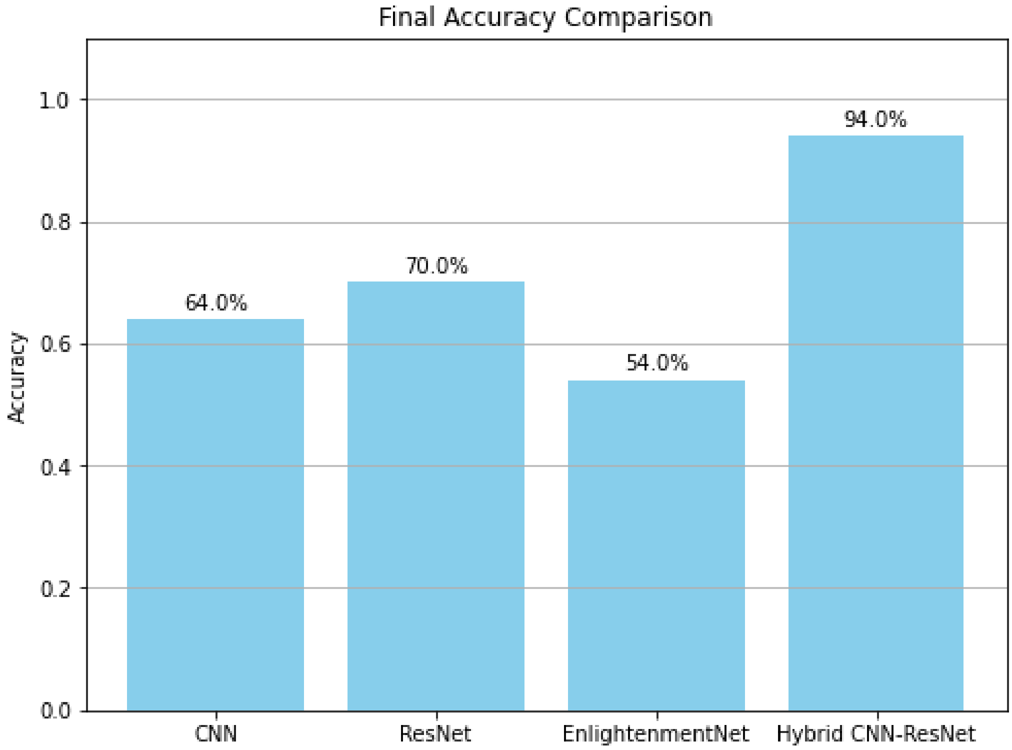

Figure 17: *Comparative Evaluation of Classification Accuracy Across Diverse Deep Learning Architectures*

4. Conclusions

The Hybrid CNN + ResNet model shows clear superiority in detecting cervical fractures, achieving an accuracy of 94%. This performance demonstrates that combining local feature extraction (CNN) with the strong hierarchical feature maps provided by ResNet enhances the model's ability to generalize better on complex medical imaging datasets. Further improvements could include fine-tuning the ResNet layers and increasing the number of epochs.

This method can be highly effective in clinical applications where accurate detection is crucial, as it offers a robust and reliable classification model. It shows how leveraging pretrained architecture and custom CNNs can lead to substantial improvements in medical image classification tasks.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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