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SPINE-EDL NET: ENSEMBLE APPROACH FOR CERVICAL SPINAL FRACTURE DETECTION

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ABSTRACT
Deep learning algorithms have shown significant potential for early disease identification and prevention, becoming increasingly popular in recent years. Cervical spine injuries require immediate diagnosis to ensure adequate treatment. Numerous methods have been projected; but, they repeatedly lack accurateness in detecting minor fractures and may surge the false positive rate due to the limitations of single network-based classifiers. Moreover, the shortage of publicly obtainable spine data makes automated cervical spine fracture detection ominously more challenging to attain. To address these issues, we suggest a new and vigorous method called the Spine-Ensemble Deep Learning Network (Spine-EDLNet). Ensemble learning subsidises a vital role in extracting powerful features from image data. Our model harnesses the strengths of three pretrained deep learning networks: EfficientNetV2, InceptionNetV3, and VGG16, united with a majority voting mechanism. Tailored layers are combined into each model to improve fracture classification. Besides, comprehensive data augmentation and preprocessing practices are applied to the dataset before training, successfully overcoming the dataset obtainability challenge. Investigational results validate that Spine-EDLNet outperforms previous models, attaining a maximum accuracy of 99.6%. This methodology purposes to optimize diagnostic accuracy, robustness, and generalization.

Keywords: Ensemble Method, Cervical Spine Fractures, Deep Learning, Transfer Learning, Binary Classification

1. INTRODUCTION
Globally, Eight million spinal fractures occur annually, with a notable prevalence in the cervical spine, making it one of the most frequently impacted regions [1]. In North America, injuries to the cervical spine cause more than 1 million admissions to hospitals for emergency treatment annually [2]. Seven stacked vertebrae, or stacks of bones, make up the cervical portion of the spine and are designated C1, C2, C3, C4, C5, C6, and C7. Injuries to the Cervical spine affect the neck , discs located amongst vertebrae, the joint muscles, and the ligaments [3]. Fractures or dislocations of the cervical spine can happen as a result of intense strain from car crashes, trips and falls, and sports-related injuries [4].

The elderly generation has a much higher rate of spinal fractures caused by osteoporosis and deteriorating health conditions [5].Cervical spine fractures can have serious neurological effects. These injuries have the potential to cause instability and compression of the spinal cord underneath, thereby worsening the potential complications [6-8]. A significant rate of illness and mortality has been associated to cervical spine injuries [9]. As a result, primary detection and treatment of cervical spine fractures (CSFx) is essential to prevent additional impairments [10, 11].

Deep learning techniques have become essential in healthcare for locating fractured and distressed regions in any part of the body. The efficacy of deep learning algorithms is evident in image classification, object detection, pattern recognition, and medical image analysis. Diverse methodologies have been suggested to identify cervical spinal fractures. Certain algorithms make use of machine learning approaches, which conventionally depend on time-intensive manual feature extraction. However, a variety of deep learning techniques have emerged with the advances in convolutional neural networks. These CNN-based techniques greatly increase the accuracy and effectiveness of fracture identification as compared to conventional methods through automatically extracting information from medical image data. Cervical spine fracture classification in images is an intricate process that usually requires specialized medical expertise. Moreover, the unavailability of diverse public datasets for training deep learning models presents a significant challenge.

Despite extensive research on detecting cervical spine fractures, very little attention has been given to ensemble approaches. To the best of our knowledge our proposed work is novel, which performs data augmentation techniques along with ensemble method for the effective detection. The main offerings of this research is as follows:

Our Proposed Model's contribution

- The paper introduced an improved deep learning model called Spine-Ensemble Deep Learning Network (Spine- EDLNet), which utilizes transfer learning and ensemble learning approaches to identify cervical spine fractures from CT scans.
- This work implemented a cutting-edge cervical fracture CT scans dataset sourced from the RSNA Cervical Spine Fracture Detection Challenge 2022.
- Our Model employed ensemble learning by combining three TL-based deep learning models: VGG16, EfficientNetV2, and InceptionNetV3, along with our customized layers. This approach integrated the strengths of multiple models, resulting in improved performance in detecting cervical spine fracture due to enriched feature extraction.
- Ensemble learning helped overcome the deficiencies of individual models, leading to more reliable results. By aggregating the predictions of multiple models through majority voting scheme, our proposed model achieved enhanced accuracy and robustness in classifying cervical spinal fractures.
- Our suggested approach has been validated by comprehensive experiments that proved the superiority of Spine-EDLNet over existing methods.

The remaining paper is organized as: section 2 describes related studies, section 3 demonstrates methodology, section 4 explains the results, and section 5 describes the conclusion and future work.

2. LITERATURE REVIEW

Artificial intelligence (AI) has been widely applied in healthcare in recent years. It has frolicked a vigorous role in saving uncountable lives by, for example, diagnosing cancer in its initial stages or distinguishing benign and malignant tumors [12]. The consequences of AI are sometimes more precise compared to those of trained professionals, henceforth assuring an immediate investigation. AI offers quick detection, and in certain circumstances, its deductions are far more exact compared to the findings of professionals [12].

Numerous inquiries have been done to decide how well AI performs in identifying fractures [13]. It has been used to find fractures in many anatomical regions such as the humerus, hip, distal radius, hand, wrist, and ankle using radiographs [14-21]. Moreover, it has also been applied in diagnosing thoracic and lumbar spine injuries with dual-energy x-ray absorptiometry (DXA) [22]. Also, AI has also been successful in sensing calcaneal fractures and fractures in the vertebral bodies of the thoracic and lumbar regions through computed tomography scans [23-26].

In emergency conditions, plain cervical spine capturing is a crucial and often-used method for diagnosing cervical spinal fractures. Anteroposterior and lateral cervical spine radiographs are frequently collected in severely injured patients, facilitating quicker diagnosis and management of numerous serious ailment [27, 28]. However, a complementary CT scan is recommended since plain scans are unable to accurately observe the cervical spine following significant damage [29, 30].Computed tomography scan is one of the most advantageous and commonly used imaging techniques for detecting fractures [31].

Computed tomography rather than traditional radiography is constantly employed for imaging diagnosis of adult spine fractures [32] nowadays. Nevertheless despite improvements in artificial machine learning (ML), very few techniques are available for identifying fractures in CT images of the cervical spine [31]. In [2], authors employed a three-dimensional ResNet-101 Deep CNN [33], trained on 222 fractured and 990 healthy instances. This method performed well in terms of AURPC and AUROC metrics on the validation dataset which contained 37 fractured and 98 healthy instances. The model attained an AUPRC of 0.52 and AUROC of 0.87 in terms of image-level evaluation. The AUPRC and AUROC were both 0.82 when assessed at the case level. In [31] authors proposed a ResNet-50[33] combined with a Bidirectional LSTM [34] Machine learning model, encompassing the properties of a Deep neural network, for automated categorization of cervical spine fractures. The network is trained and validated employing a labelled dataset of 3,666 computed tomography (CT) images containing 729 positive and 2,937 negative samples. The model showed a categorization accuracy of 70.92% on the balanced (104= Positive and 104=Negative) and 79.18% on the imbalanced (Positive =104 and Negative = 419) test dataset, respectively.

The suggested model integrated both spatial and temporal features to categorize fractures of the cervical spine. In [35] authors employed a two-stage pipeline for fracture detection. In the first phase, segmentation was carried out using UNet-EfficientNet, and in the second stage, detection was performed using CrackNet-LSTM. The overall accuracy of this approach reached 94.9 %. To lessen serious outcomes, [36] emphasized on the urgent early diagnosis of upper cervical spine fractures, especially in segment C1. This study involved Efficient Net DNN models from B0 to B7 and a dataset containing over 350 image slices, where EfficientNet B6 demonstrated the highest accuracy. It attained a training accuracy of 98.25%, a testing accuracy of 99.25%, and a validation accuracy of 99.4%.

3. Proposed Methodology

This section describes all stages of the proposed method, namely Spine-EDLNet, from acquiring data to assessing the resultant outcome. The suggested methodology includes several key phases, such as data preprocessing, which involves image cropping, noise elimination, data augmentation, and data rescaling. To classify cervical spine fractures into normal and fractured classes, preprocessed data is fed into our chosen pre-trained models, EfficientNetV2, InceptionV3, and VGG16, combined in an ensemble fashion. Additionally, for improved classification performance, customized layers such as Max Pooling, Global Average Pooling, Batch Normalization, Dropout, Dense, and finally Sigmoid layers are added to each pretrained model separately. Furthermore, a majority voting block is added to combine the outcomes of the three customized pretrained models, enhancing the model's accuracy and generalizability. Figure 1 shows a general flow of our proposed framework.

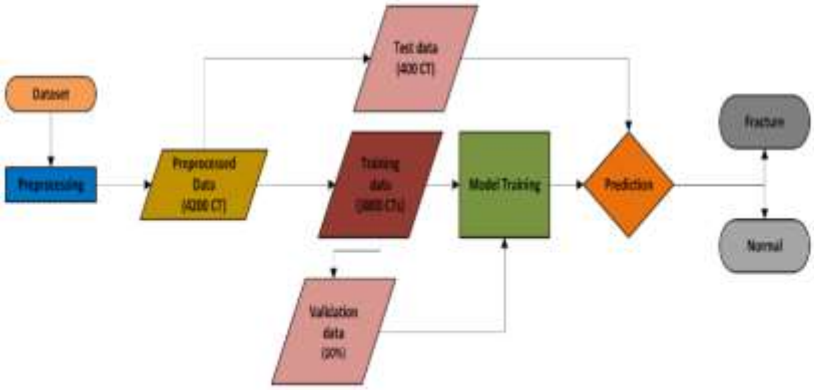

Figure 1: Generel flow of Proposed Method

The key motivation for selecting these deep learning models lies in their extensive features extraction, employing architecture adaptability, transfer learning advantages, design flexibility, and strong support from the DL communities [37]. These techniques excel at extracting and understanding complex characteristics and patterns from scans, which is essential for accurately identifying cervical spine fractures. Additionally, we evaluated pre-trained models depending on validation accuracy, validation loss, and overall performance. The detection performance of these pretrained deep learning models was extensively evaluated both individually and in ensemble configuration. The flow diagram of the proposed model is shown in Figure 2.

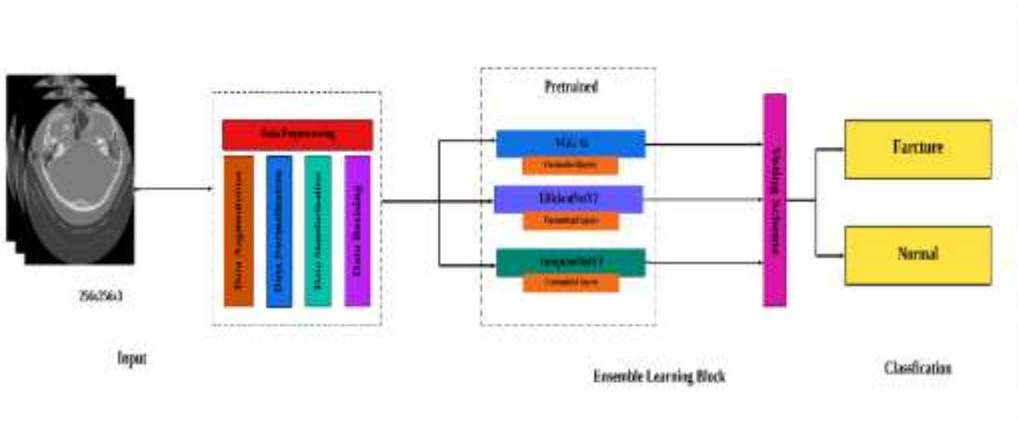

Figure 2: Flow Diagram for the Proposed System

3.1. Data preprocessing

Data Prepossessing improves model performance and reduces computational time. We have employed several preprocessing techniques to prepare our dataset [38]. we have resized all input images to a standardized dimension of (224x224). The process of rescaling images aids in reducing training time and computing overhead for models. It also ensures uniformity in input image sizes for model, reducing complexity and accelerating the training process. Moreover, data standardization has been instrumental to ensure that our dataset is used for optimal learning. We have converted CT images to grayscale, applied histogram equalization to enhance contrast, normalized pixel values using mean and standard deviation, and rescaled pixel values to the range [0-255]. These normalization steps have standardized our input data, making it suitable for training our model. The pre-processed data is displayed in Figure 3

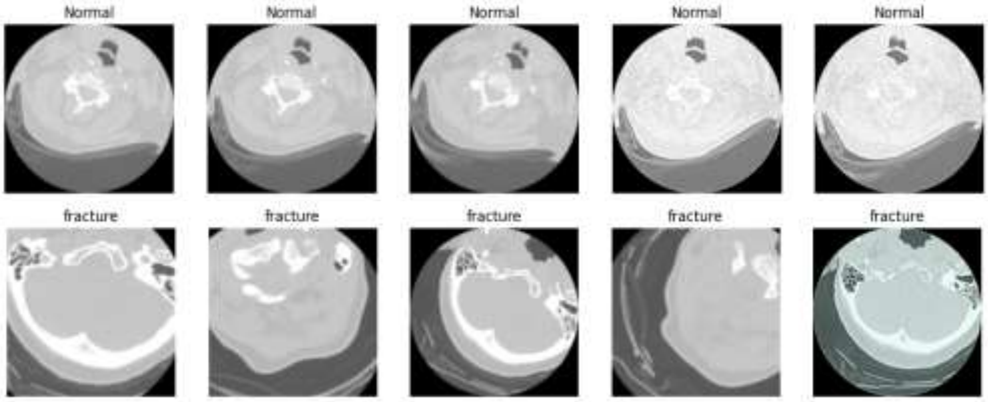

Figure 3: Samples from Preprocessed Data

3.2 Data Augmentation

Data augmentation enhances dataset diversity and eventually model efficacy. In our study, we employed several data augmentation techniques. These techniques include zooming (0.2), rotation (15 degree), horizontal (0.1) and vertical (0.1) shifting, shear transformations (0.2), horizontal flipping, and fill mode adjustment. Figure 4 displays a selection of augmented images.

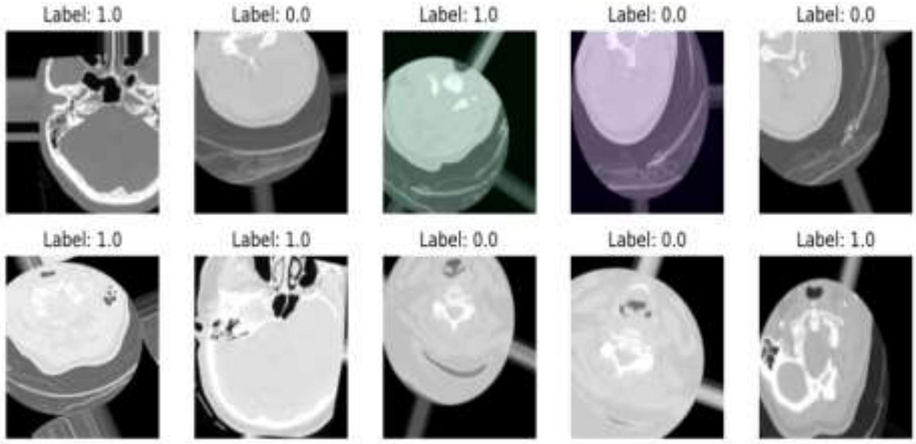

Figure 4: Samples from Augmented Data

3.3. Pretrained- DL models

Transfer learning, a highly popular approach, significantly improves model performance. This method involves employing knowledge gained from completing one task to enhance performance on another associated task. The following pre-trained base DL networks were chosen for the work: InceptionNetV3, VGG16, and EfficientNetV2. Each of these models will be discussed in detail below.

3.3.1 VGG16

Our proposed framework involves utilizing a pretrained VGG16 [39] model followed by a series of customized layers .VGG16 was released in 2014 at the University of Oxford by the Visual Geometry Group. With its 16 layers, VGG16 follows an established architecture. Following pre-processing, the collected features are sent into a stacked Convolution layer with a constant stride of 1 and 3x3 receptive-field filters. Next, 5 max-pooling layers, each having 2x2 filter and a stride of 2, are used to apply spatial pooling. The architecture is completed with a SoftMax layer for the result and two fully connected layers after the final convolutional layer.

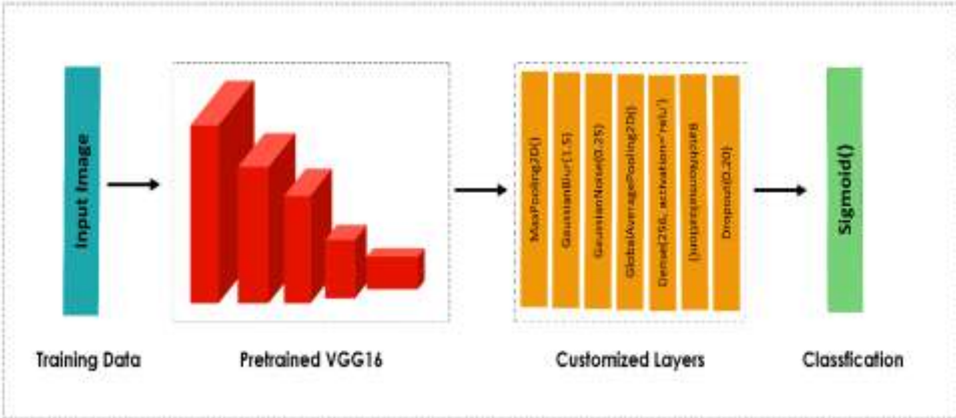

Figure 5: Detailed Architecture of VGG16 with Customized Layers.

3.3.2 InceptionNetV3

InceptionNetV3[40] is a CNN considered for classification tasks. It is pretrained using the ImageNet dataset and contains 48 deep layers. It is an improved version of inception architecture and employs label smoothing. It was designed to provide efficient network without requiring an unnecessary number of training parameters. The InceptionV3 model uses batch normalization and label propagation through factorized 7×7 convolutions with an auxiliary classifier. In addition to its present design, numerous other modified layers have been incorporated. The InceptionV3 network has 525,313 trainable parameters and a total of 22,328,609 parameters.

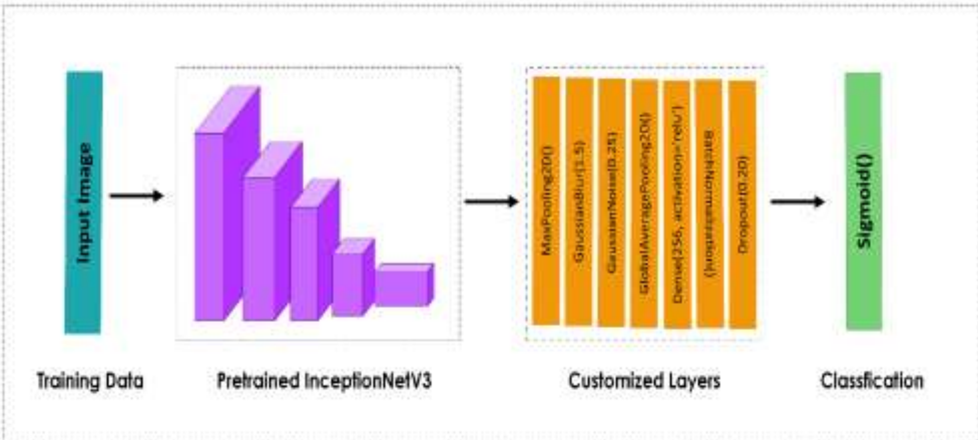

Figure 6: Detailed Architecture of InceptionNetv3 with Customized layers

3.3.3. EfficeintNetV2

EfficientNetV2 [41] is a erudite convolutional neural network architecture famous for its high performance and computational efficacy. It stimuluses advanced techniques such as progressive learning, which vigorously regulates image sizes through training, and an improved compound scaling method to balance model resolution, depth, and width professionally. This design surpasses in both precision and speed, applying fewer parameters and smaller convolutions while keeping outstanding performance. Its elastic design makes it well-suited for transfer learning, garnering noteworthy support from the deep learning communal.

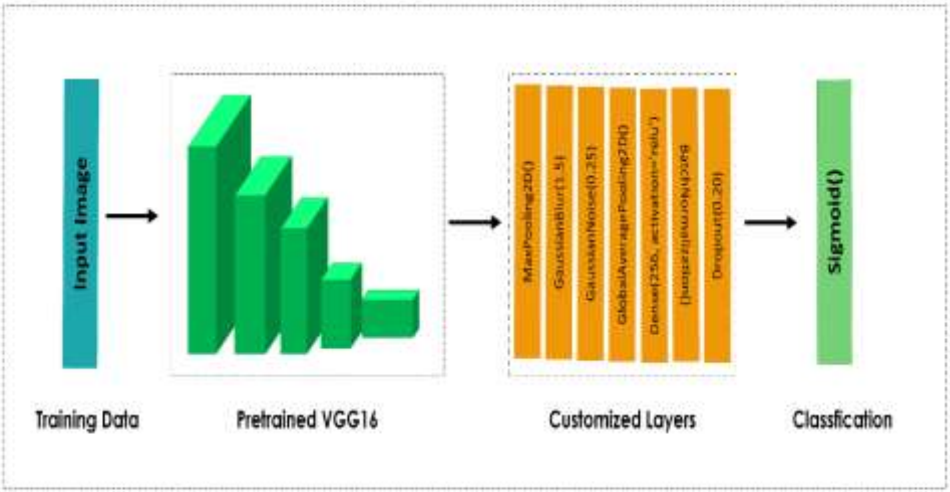

Figure 7: Detailed architecture of EfficientNetV2 with Customized layers

3.3.4. Our customized Layers

We involved pre-trained deep learning models, authorising their weights remain frozen to hold their learned features. This method halts re-training of the base models, allowing them to practise on their current knowledge while focusing on learning novel features from employed data. Complementary, tailored layers are added to enlarge the models' classification performance

These additional layers are strategically chosen such as: MaxPooling2D was utilized to excerpt essential features from input images expertly, minimalizing computational complexity. Gaussian blur (1.5) and Gaussian noise (0.25) were applied for regularization, efficiently dropping image noise and enhancing data clarity. Also, GlobalAveragePooling2D aggregated features largely across the spatial dimensions of the input sample. Dense layers equipped with ReLU activation function allowed comprehensive feature extraction, familiarizing non-linearity. Batch normalization was utilized to soothe learning, while additional noise regularization layers additionally refined the noise reduction process.

Dropout layers were employed to alleviate overfitting, promoting generalizability in classification tasks. Lastly, a sigmoid layer was added to guarantee exact classification of fractures grounded on the extracted features. Henceforth, these customized layers were applied independently to each model, enhancing their classification performance.

3.4. Ensemble Deep learning (EDL)

Due to its non-linear nature, deep Learning (DL) networks provide a high degree of flexibility when working with small training datasets. However, due to fine-tuning, which uses random methods and changes in weight settings during training, they might demonstrate some variance [41].

The model therefore generates inconsistent predictions as a result of this variance. EL method, which train several Deep Learning models rather than just one, have become popular as a solution to this problem [42]. The final output is obtained by summing up the predictions made by each of these individual models. Through the usage of several model’s predictions, EL captures more detailed characteristics from images and yields reliable classification results. EL improves the overall model’s output through leveraging the combined knowledge of numerous models. Existing literature primarily employs a single CNN for spinal fracture detection. However, there has been minimal attention given to the use of EL approaches for cervical spinal fracture detection and classification.

In this research, we investigate the use of ensemble Deep Learning approach. We proposed an ensemble method that combines three pre-trained deep learning models to mine comprehensive features while enhancing overall working, as shown in Figure 8.

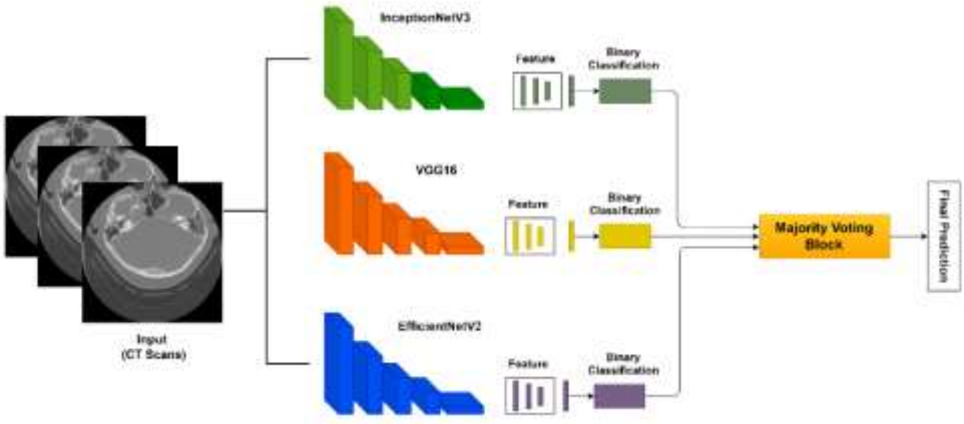

Figure 8: The Process of Ensemble learning and Majority Voting Scheme

3.5. Voting Scheme

Following the acquisition of predictions from three pre-trained deep learning models, we implemented a majority voting scheme. This technique is commonly employed in classification tasks based on ensemble learning [43]. The three pre-trained models: EfficientNetV2, VGG16, and InceptionNetV3 categorized cervical spine data as either normal or fracture based on their respective features. The class with the maximum number of votes is then selected as the output class.

4. Experimental Result

4.1. Experimental Protocols

The research was performed utilizing the Python, and the Google Collaboratory code editor. Experiments were performed on a machine equipped with an Intel(R) Core (TM) i7-4700HQ processor and 8 GB of RAM.

4.2. Dataset

This research utilized the 'spine fracture detection from CT scans obtained from Kaggle. The dataset is separated into 'Train' and 'Validation' sets, each containing both normal and fractured cervical spine images. It comprises in total 4200 images, evenly distributed with 1900 fractured images and 1900 normal images within the train folder, as show in Table 1.

Table 1. Data Distribution

Dataset	Normal	Fracture	Total Images
Training	1900	1900	3800
Testing	200	200	400

Simultaneously, the test dataset consists of 400 photos, with 200 belonging to each class, namely fractured and normal. Moreover, 10 percent of the training images are randomly selected for validation process.

4.3 Evaluation Metrices

A number of metrics, comprising F1-score, Precision, Recall, and Accuracy, are utilized to evaluate the usefulness of our suggested model. The equations of all metrices are given below.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}, \quad (1)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}, \quad (2)$$

$$Recall = \frac{TP}{TP+FN}, \quad (3)$$

$$F1\ score = 2 * \frac{Precision*Recall}{Precision+Recall}, \quad (4)$$

Where TP denotes the count of correctly classified fracture cases, FP signifies the number of incorrectly identified fracture cases, TN indicates the accurately categorized non-fracture cases, and FN represents the erroneously classified non-fracture cases.

4.4 Results

In this section, we explain the outcomes by our proposed model. We trained and tested our model Spine-EDLNet by first training individual networks such as VGG16, EfficientNetV2, and InceptionNetV3. We merged the predictions of these individual models to form our ensemble approach. The outcomes showed significant improvements over the individual models. Results are shown in Table 2. Among all individual models, our proposed Spine-EDLNet performed the best in spinal fracture identification, achieving the highest precision (99.8%), accuracy (99.5%), recall (99.9%), and F1-score (99.7%), as shown in Figure 9. This highlights how ensemble learning effectively utilizes the various characteristics of individual models to improve accuracy and reliability in detection tasks.

TABLE 2: PERFORMANCE EVALUATION OF OUR MODEL

Techniques	*Accuracy*	*Precision*	*Recall*	*F1 Score*
VGG16	96.9%	97.5%	98.9%	97.3%
EffiecientNetV2	97.6%	99.6%	99.6%	99.6%
InceptionNetV3	98.6%	98.3%	98.7%	98.6%
Proposed Spine-EDLNet	99.5%	99.8%	99.9%	99.7%

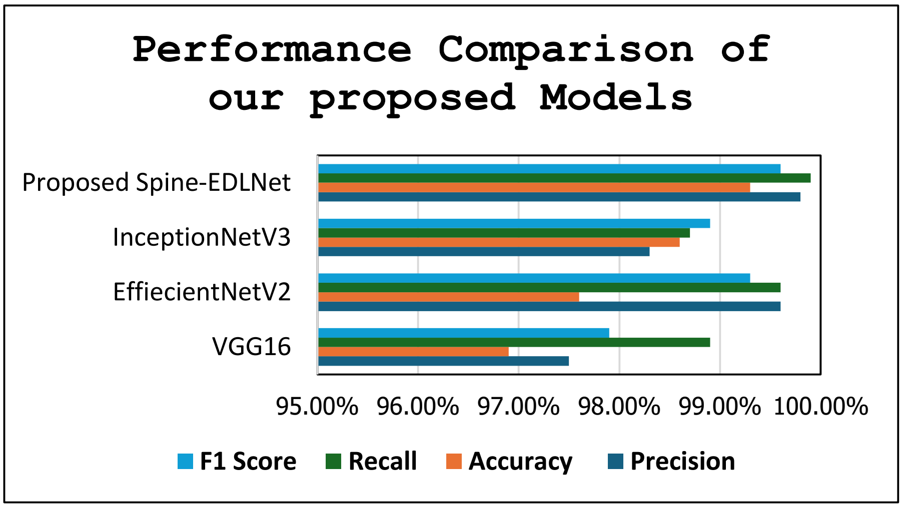

Figure 9. Performance Analysis of our Models

4.5 Comparison with existing techniques

In this section, a comparative study is performed for cervical spine fracture detection with our proposed model Spine-EDLNet. The statistics are reported in Table 3. Researchers for the spine fracture detection have proposed several approaches attaining considerable outcomes. For example, RESNet50-LSTM [31] achieved an accuracy of 79.18% on the 3666CT dataset, indicating its capability but having room for improvement. Another model CrackNet-LSTM [36] confirmed significant performance, achieving an accuracy of 94.9% on the 2019 CT dataset. Then, DeIT-T16 [44] showcased significant performance, providing a robust accuracy of 98% on the 2019 CT dataset, suggesting its suitability for fracture detection tasks.

TABLE 3: PERFORMANCE EVALUATION AGAINST EXISTING MODELS

Model	*Accuracy*	*Dataset*
RESNet50-LSTM[31]	79.18%	3666CT
CrackNet-LSTM[36]	94.9%	2019 CT
DeIT-T16[44]	98%	2019 CT
EfficientNet B6 [45]	99.2%	2019 CT
GoogleNet [46]	99.56%	2009 x-ray
Proposed Spine-EDLNet	99.6%	4200 CT

However, our proposed Spine-EDLNet model outperforms all existing models, achieving a considerable accuracy of 99.6% on an extensive 4200 CT dataset. This remarkable performance confirms the efficacy and reliability of our model in accurately identifying cervical spine fractures, indicating its potential for advancement in medical imaging diagnostics. Figure 7. depicts the performance comparison with existing deep learning techniques. It is evident that our model surpassed all detectors in terms of accuracy.

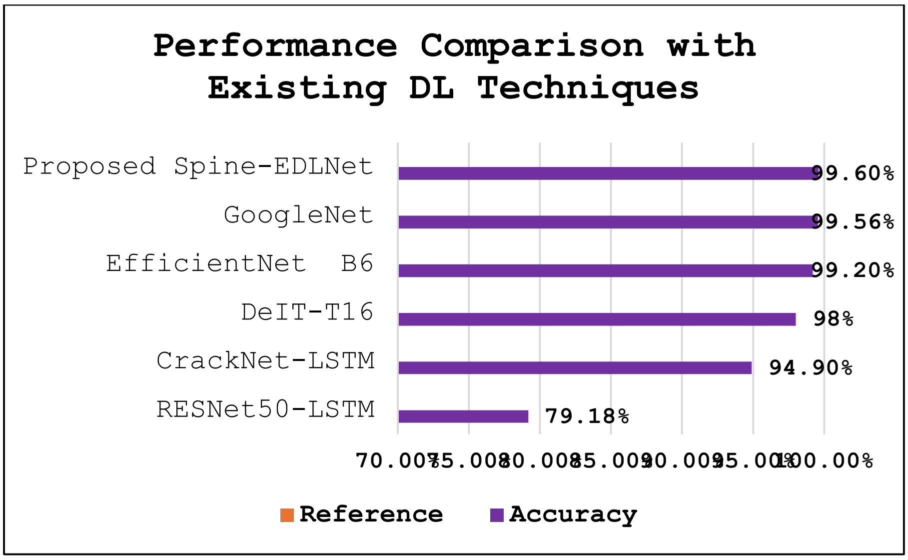

Figure 10. Camparative Anlysis among Existing Techniques

5. Conclusion

Cervical spine injuries necessitate immediate diagnosis to ensure adequate treatment. Therefore, in this work, we propose a novel and robust method called the Spine-Ensemble Deep Learning Network (Spine-EDLNet). The proposed model contributes an essential role in extracting powerful features from image data due to ensemble learning approach. More specifically, model harnesses the strengths of three pre-trained deep learning networks: EfficientNetV2, InceptionNetV3, and VGG16, combined with a majority voting mechanism. Moreover, customized layers are attached into each model to enhance fracture classification. Furthermore, comprehensive data augmentation and pre-processing techniques are employed to the dataset before training, effectively overcoming the dataset availability challenge. Experimental results demonstrate that Spine-EDLNet outperforms previous models, achieving a maximum accuracy of 99.6%. This methodology aims to optimize diagnostic accuracy, robustness, and generalization. However, we noticed that when we fed blurry scans, the performance of the proposed model was degraded. Therefore, in future we aim to improve the performance on unseen samples by leveraging new datasets and fine-tuning the model.

References

1. Dong, Y., et al., Global incidence, prevalence, and disability of vertebral fractures: a systematic analysis of the global burden of disease study 2019. The Spine Journal, 2022. **22**(5): p. 857-868.

2. Dunsker, S.B., et al. Deep-learning artificial intelligence model for automated detection of cervical spine fracture on computed tomography (ct) imaging. in Journal of Neurosurgery. 2019. AMER ASSOC NEUROLOGICAL SURGEONS 5550 MEADOWBROOK DRIVE, ROLLING MEADOWS, IL.
3. Bhavya, M.B.S., M.V. Pujitha, and G.L. Supraja. Cervical Spine Fracture Detection Using Pytorch. in 2022 IEEE 2nd International Conference on Mobile Networks and Wireless Communications (ICMNWC). 2022. IEEE.
4. Bland, J.H. and D.R. Boushey. Anatomy and physiology of the cervical spine. in Seminars in arthritis and rheumatism. 1990. Elsevier.
5. Aguirre, M.F.I., A.I. Tsirikos, and A. Clarke, Spinal injuries in the elderly population. Orthopaedics and Trauma, 2020. **34**(5): p. 272-277.
6. Dreizin, D., et al., Multidetector CT of blunt cervical spine trauma in adults. Radiographics, 2014. **34**(7): p. 1842-1865.
7. Sugandhavesa, N., et al., A multilevel noncontiguous spinal fracture with cervical and thoracic spinal cord injury. International Journal of Surgery Case Reports, 2021. **88**: p. 106529.
8. Phonthee, S., et al., Incidence and factors associated with falls in independent ambulatory individuals with spinal cord injury: a 6-month prospective study. Physical therapy, 2013. **93**(8): p. 1061-1072.
9. Inaba, K., et al., Cervical spinal clearance: a prospective Western trauma association multi-institutional trial. The journal of trauma and acute care surgery, 2016. **81**(6): p. 1122.
10. Copley, P., V. Tilliridou, and A. Jamjoom, Traumatic cervical spine fractures in the adult. British Journal of Hospital Medicine, 2016. **77**(9): p. 530-535.
11. Fischer, P.E., et al., Spinal motion restriction in the trauma patient–a joint position statement. Prehospital Emergency Care, 2018. **22**(6): p. 659-661.
12. Landais, A., Cervical Spine Fracture Detection by Computer Vision. 2023.
13. Small, J., et al., Ct cervical spine fracture detection using a convolutional neural network. American Journal of Neuroradiology, 2021. **42**(7): p. 1341-1347.
14. Adams, M., et al., Computer vs human: deep learning versus perceptual training for the detection of neck of femur fractures. Journal of medical imaging and radiation oncology, 2019. **63**(1): p. 27-32.
15. Urakawa, T., et al., Detecting intertrochanteric hip fractures with orthopedist-level accuracy using a deep convolutional neural network. Skeletal radiology, 2019. **48**: p. 239-244.
16. Cheng, C.-T., et al., Application of a deep learning algorithm for detection and visualization of hip fractures on plain pelvic radiographs. European radiology, 2019. **29**(10): p. 5469-5477.
17. Chung, S.W., et al., Automated detection and classification of the proximal humerus fracture by using deep learning algorithm. Acta orthopaedica, 2018. **89**(4): p. 468-473.
18. Gan, K., et al., Artificial intelligence detection of distal radius fractures: a comparison between the convolutional neural network and professional assessments. Acta orthopaedica, 2019. **90**(4): p. 394-400.
19. Kim, D. and T. MacKinnon, Artificial intelligence in fracture detection: transfer learning from deep convolutional neural networks. Clinical radiology, 2018. **73**(5): p. 439-445.
20. Lindsey, R., et al., Deep neural network improves fracture detection by clinicians. Proceedings of the National Academy of Sciences, 2018. **115**(45): p. 11591-11596.
21. Olczak, J., et al., Artificial intelligence for analyzing orthopedic trauma radiographs: deep learning algorithms—are they on par with humans for diagnosing fractures? Acta orthopaedica, 2017. **88**(6): p. 581-586.
22. Derkatch, S., et al., Identification of vertebral fractures by convolutional neural networks to predict nonvertebral and hip fractures: a registry-based cohort study of dual X-ray absorptiometry. Radiology, 2019. **293**(2): p. 405-411.
23. Pranata, Y.D., et al., Deep learning and SURF for automated classification and detection of calcaneus fractures in CT images. Computer methods and programs in biomedicine, 2019. **171**: p. 27-37.

24.Burns, J.E., J. Yao, and R.M. Summers, Vertebral body compression fractures and bone density: automated detection and classification on CT images. Radiology, 2017. **284**(3): p. 788-797.
25.Tomita, N., Y.Y. Cheung, and S. Hassanpour, Deep neural networks for automatic detection of osteoporotic vertebral fractures on CT scans. Computers in biology and medicine, 2018. **98**: p. 8-15.
26.Muehlematter, U.J., et al., Vertebral body insufficiency fractures: detection of vertebrae at risk on standard CT images using texture analysis and machine learning. European radiology, 2019. **29**: p. 2207-2217.
27.Griffith, B., et al., Screening cervical spine CT in a level I trauma center: overutilization? American Journal of Roentgenology, 2011. **197**(2): p. 463-467.
28.Athinartrattanapong, N., et al., Prediction score for cervical spine fracture in patients with traumatic neck injury. Neurology research international, 2021. **2021**.
29.Gale, S.C., et al., The inefficiency of plain radiography to evaluate the cervical spine after blunt trauma. Journal of Trauma and Acute Care Surgery, 2005. **59**(5): p. 1121-1125.
30.Schenarts, P.J., et al., Prospective comparison of admission computed tomographic scan and plain films of the upper cervical spine in trauma patients with altered mental status. Journal of Trauma and Acute Care Surgery, 2001. **51**(4): p. 663-669.
31.Salehinejad, H., et al. Deep sequential learning for cervical spine fracture detection on computed tomography imaging. in 2021 IEEE 18th International Symposium on Biomedical Imaging (ISBI). 2021. IEEE.
32.Adam Flanders, C.C., Errol Colak, Felipe Kitamura, Hui Ming Lin, Jeff Rudie, John Mongan, Katherine Andriole, Luciano Prevedello, Michelle Riopel, Robyn Ball, Sohier Dane RSNA 2022 Cervical Spine Fracture Detection. 2022.
33.He, K., et al. Deep residual learning for image recognition. in Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.
34.Salehinejad, H., et al., Recent advances in recurrent neural networks. arXiv preprint arXiv:1801.01078, 2017.
35.Kim, D., et al. Cervical Spine Fracture Detection Through Two-Stage Approach of Mask Segmentation and Windowing Based on Convolutional Neural Network. in 2023 International Conference on Platform Technology and Service (PlatCon). 2023. IEEE.
36.Bayangkari Karno, A.S., et al., Classification of cervical spine fractures using 8 variants EfficientNet with transfer learning. International Journal of Electrical & Computer Engineering (2088-8708), 2023. **13**(6).
37.Khushi, H.M.T., et al., Improved Multiclass Brain Tumor Detection via Customized Pretrained EfficientNetB7 Model. IEEE Access, 2023.
38.https://www.kaggle.com/datasets/vuppalaadithyasairam/spine-fracture-prediction-from-xrays/data.
39.Belaid, O.N. and M. Loudini, Classification of brain tumor by combination of pre-trained vgg16 cnn. Journal of Information Technology Management, 2020. **12**(2): p. 13-25.
40.Sam, S.M., et al., Offline signature verification using deep learning convolutional neural network (CNN) architectures GoogLeNet inception-v1 and inception-v3. Procedia Computer Science, 2019. **161**: p. 475-483.
41.Liu, S., et al., Recent progress in the cuhk dysarthric speech recognition system. IEEE/ACM Transactions on Audio, Speech, and Language Processing, 2021. **29**: p. 2267-2281.
42.Zhang, Q.-L. and Y.-B. Yang. Sa-net: Shuffle attention for deep convolutional neural networks. in ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). 2021. IEEE.
43.Mahum, R., et al., Tran-DSR: A hybrid model for dysarthric speech recognition using transformer encoder and ensemble learning. Applied Acoustics, 2024. **222**: p. 110019.
44.Chłąd, P. and M.R. Ogiela, Deep learning and cloud-based computation for cervical spine fracture detection system. Electronics, 2023. **12**(9): p. 2056.

45.Karno, A.B., et al., Classification of cervical spine fractures using 8 variants EfficientNet with transfer learning. International Journal of Electrical and Computer Engineering (IJECE), 2023. **13**(6): p. 7065-7077.
46.Naguib, S.M., et al., Classification of cervical spine fracture and dislocation using refined pre-trained deep model and saliency map. Diagnostics, 2023. **13**(7): p. 1273.