Detection of Bone Fractures in Upper Extremities Using XceptionNet and Comparing the Accuracy with Convolutional Neural Network

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Keywords: Bone Fractures, Convolutional Neural Networks, Deep Learning, Health, Novel XceptionNet Model, Upper Extremity.

Abstract: Goal of this study is to differentiate an unique XceptionNet model deep learning (DL) model to Convolutional neural networks (CNN) in order to recognize bone fracture at the upper extremities of hands with considerably higher accuracy. Materials and Methods: To enhance the accuracy metric of bone fracture recognition in the upper extremity areas of hands, deep learning techniques such as the novel XceptionNet model (N=10) and Convolutional Neural Networks (N=10) were iterated. In this work, bone fracture detection using x-rays images dataset was used which was acquired via Kaggle. The dataset, which has a total of 9463 x-ray images, is 181 MB in size. The Train and Val datasets were separated. There are 633 photos in the val dataset and 8987 images in the train dataset which were used to calculate accuracy for the two groups with an 80% of G power. Results and Discussion: The classification accuracy of the novel XceptionNet model is 88.74%, which is significantly greater than the accuracy of the CNN model, which is 72.50% for Bone fracture detection using x-rays images dataset. It is discovered that the novel XceptionNet model and convolutional neural networks differed statistically with a notable difference of $p<0.001$ ($p<0.05$) (2-tailed). Conclusion: The methodology used in this paper with two deep learning models namely novel XceptionNet and convolutional neural networks. The results reveal the usefulness of the latest methods in identifying bone fracture detection in the upper extremities and show their value for fracture prediction at an early stage.

1 INTRODUCTION

As we are all aware, bones act as the body's framework and as points where muscles can attach. As society advances, people's propensity for bone fractures increases. Broken bones can impair blood supply to the bones and result in additional complications, but they can also hurt the wounded limbs as well as the surrounding soft tissues. Delays in the diagnosis and medical management of injuries can potentially lead to complications with fractures. Because broken bones can seriously harm a person's body, it is vital for people to have a clear-cut and efficient diagnosis of injuries (Pranata et al., 2019). The analysis and remedial measures of many diseases have advanced thanks to new trends and technology in radiology (Sa, Mohammed and Hefny, 2020). However, there are 7.5 times as many patients and radiological scans each year as there are radiologists. The procedure for detection is required to be completed in the very brief period of time possible because each of these images needs to be analyzed (Li et al., 2020). In order to alleviate the frequency of these issues and intensify the diagnosis effectiveness, computer-aided diagnosis (CAD) has been recommended recently. They may serve as an alternative perspective for doctors to support and assist their decisions. Numerous research has been conducted to develop CADs for use at a range of medical contexts, including the identification of cancer, breast lesions, cognitive tumors, and particularly cracks and fractures of upper extremity (Lee and Fujita, 2020). In contrast to traditional approaches, deep learning can automatically discover strong, complicated features eliminating the need for feature development using unprocessed information. Utilization of advanced machine learning in genetics, electronic health records, and images for medicine and pharmaceutical discovery are said to have evident advantages in maximizing the employment in biomedicine data and boosting health. (S. Yang et al., 2021).

The topic of detecting bone fractures in the upper extremity areas were covered in 4 articles published

Y., T. and Pramila, P.
Detection of Bone Fractures in Upper Extremities Using XceptionNet and Comparing the Accuracy with Convolutional Neural.
DOI: 10.5220/0012772300003739

In *Proceedings of the 1st International Conference on Artificial Intelligence for Internet of Things: Accelerating Innovation in Industry and Consumer Electronics (AI4IoT 2023)*, pages 360-366
ISBN: 978-989-758-661-3

by IEEE and over 16,800 papers according to Google Scholar over the past five years. The study by (Agarwal et al., 2022) concentrates on the classification of photographs from X-rays and assessment of lower limb broken bones using a variety of mechanisms for undertaking, such as approach to envision refining, unsharp masking and harris corner recognition for features extraction, and classification methods, such as decision tree(DT) for determining whether a bone is fractured or unfractured and KNN algorithm for determining a particular type of cracked bone, with an accuracy of 92% and 83%, independently. Region Proposal Network (RPN) accelerated Region-based Convolutional Neural Networks (R-CNN) Deep learning (DL) model for cracked bone diagnosis and categorization was proposed by (Abbas et al. 2020) Additionally, the model's topmost layer was retaught through 50 x-rays and the Inception v2 (version 2) network blueprint. They assessed the effectiveness of the suggested framework when it comes to both category and determination. Overall accuracy of their system in terms of classification and detection is 94%. Because bone fractures result in various mechanical vibration responses, the research by (Yoon et al., 2021) investigates the transverse vibration responses of bones. The technique of modal guarantee to evaluate the longitudinal resonance remarks of both solid and damaged joints criteria was developed and utilized to detect bone fractures. In the work by (Raisuddin et al., 2021), For the purpose of diagnosing wrist fractures, they established and evaluated a cutting-edge DL-based source dubbed DeepWrist, and they evaluated it against two test sets: one for the general population and one difficult test set that only included instances that needed CT confirmation. Their findings show that while a widely used and effective method, such as DeepWrist, performs almost perfectly on the hard test set, it does far worse on the general independent sets of test typical precision is 0.99 (0.99-0.99) Vs 0.64. (0.46–0.83). The study "Bone fracture detection in X-ray images using convolutional neural networks" (Bagaria, Wadhwani, 2022) is in my opinion the finest one.

Convolutional neural networks (CNN) do remarkably well when classifying images that are highly similar to the dataset. Convolutional Neural Networks, on the other hand, typically struggle to categorize images if there is even a slight tilt or rotation. This problem was examined in this work, and it was resolved by training the system using a method known as data augmentation, or image augmentation. The research's primary objective is to determine the efficiency of two novel DL (deep learning) models XceptionNet and CNN in predicting the upper extremity bone fractures.

2 MATERIALS AND METHOD

Proposed experiment took place in the programming lab of the Saveetha School of Engineering, SIMATS. Convolutional neural networks and XceptionNet are the two deep learning methods selected for this research. The experiment was repeated using the aforementioned algorithms 10 times. The iteration's sample size is 10. The G-power for the available data samples was calculated to be 80%, and Alpha was adjusted to 0.05.

The testing environment for the planned study was a Lenovo ideapad FLEX 15 IWL with 8.00 GB RAM, an Intel i7 8th gen processor, 475 GB of storage capacity, and Windows 11OS.

Bone fracture detection using x-rays images is the open source dataset used in this research project, which was acquired via Kaggle (Sairam 2022). Multiple joints in the upper extremity regions of hands are included in this dataset. The dataset, which has a total of 9463 x-ray images, is 181 MB in size. The Train and Val datasets were separated. There are 633 photos in the val dataset and 8987 images in the train dataset.The Train set of data was further divided into subcategories for fractured and not-fractured data. The not fractured set of data included x-ray images of healthy bone while the fractured subcategory included images of bone fractures in the upper extremities.

2.1 XceptionNet

Depth Wise Separable Convolutions are used in the XceptionNet deep convolutional neural network architecture. Researchers at Google created it. Convolutional neural networks' Inception modules, according to Google, act as a transitional stage between the regular convolution process and the depthwise separable convolution process (a depthwise convolution followed by a pointwise convolution).

2.2 Convolutional Neural Networks (CNN)

A CNN (Convolutional Neural Network) is a kind of ANN employed in deep learning that is often applied to image, text, object, and recognition categorization. Convolutional neural networks, usually referred to as convnets or CNN, are a well-known technique in computer vision applications. The class of deep neural networks that are employed in the evaluation of visual imagery. To identify objects from picture and video data, this kind of architecture is studied. NLP (neural language processing), video or image recognition, and other applications utilize it.

2.3 Statistical Analysis

Statistical Package for the Social Sciences (SPSS) version 26 has been used to do the crucial statistical calculations. SPSS was developed to undertake statistical analysis for the data collected. It currently offers an extensive library of AI statistics, open source scalability, and the capability to compare the average accuracy of various algorithms. The independent variable is the accuracy of the novel XceptionNet model, while the dependent variable is adequacy. To ascertain the fact that empirical proof exists that demonstrates the ability of the corresponding populations to be substantially different, the Independent Samples T-test was utilized to gauge the pair of independent groups, XceptionNet and Convolutional Neural Networks.

Table 1: This table displays the Pseudocode and steps performed.

S.No	Model	Pseudocode
1.	XceptionNet	Input: Training and Testing data Output: PerformanceAccuracy 1. Import dataset and required packages 2. Pre-process the data 3. Divide the dataset into train and test data 4. Define the model 5. Fit the model on the training and testing dataset 6. Train and test the model 7. Evaluate the model 8. Plot the graph using matplotlib 9. Derive the confusion matrix for the model's metrics 10. Report performance
2.	CNN	Input: Data from Training and Testing Output: Value of accuracy 1. Importing dataset and required packages 2. Pre-process the data 3. Divide the dataset into Training and Testing sets 4. Fit the CNN model on the training and testing dataset 5. Evaluate the CNN model 6. Plot the graph using matplotlib 7. Derive Confusion matrix 8. Calculate the accuracy score

Table 2: Sample values for the groups i.e, CNN and novel XceptionNet model.

S.NO	**ACCURACY**	
	CNN	**XceptionNet**
1	59.38	78.45
2	63.00	84.40
3	64.44	87.52
4	64.13	88.11
5	67.56	88.31
6	65.33	88.45
7	67.62	88.49
8	68.94	88.60
9	69.25	88.38
10	72.50	88.74
Average	66.21	86.94

Table 3: Performance metrics of XceptionNet and Convolutional neural network.

S.NO	METRICS	XCEPTION	CNN
1	Accuracy	88.74%	72.50%
2	Precision	88.45%	88.82%
4	F1-score	89.68%	89.11%
5	Sensitivity	90.94%	89.4%
6	Specificity	87.86%	89.73%

Table 4: Statistical analysis of diverse samples examined between novel XceptionNet and CNN deep learning models. The mean accuracy of XceptionNet is 88.74% and CNN is 72.50% Standard Deviation(SD) of XceptionNet is 3.24 and CNN is 3.73. The T-test for comparison for XceptionNet standard error mean (std. mean) is 1.02 and CNN is 1.17.

	Group	N	Mean	Std. Deviation	Std. Error Mean
Accuracy	XceptionNet	10	86.94	3.24	1.02
	CNN	10	66.21	3.73	1.17
Loss	XceptionNet	10	30.15	6.57	2.07
	CNN	10	60.26	3.40	1.07

Table 5: The data set is subjected to an Isolated Sample T-Test, with the confidence interval set at 95% and the corresponding significance level set to p<0.001 (p<0.05) (2-tailed), groups are statistically significant.

		Leven's Test of Equality of Variances		T-test for Equality of Means					95% Confidence Interval of the Difference	
		F	**Sig**	**t**	**df**	**Sig (2-tailed)**	**Mean Difference**	**Std Error difference**	**Lower**	**Upper**
Accuracy	Equal Variance assumed	0.606	0.004	13.25	18	<.001	20.73	1.56	17.44	24.01
	Equal Variance not assumed			13.25	17.66	<.001	20.73	1.56	17.43	24.02
Loss	Equal Variance assumed	1.150	0.298	-12.86	18	<.001	-30.10	2.34	-35.02	-25.19
	Equal Variance not assumed			-12.86	13.51	<.001	-30.10	2.34	-35.14	-25.07

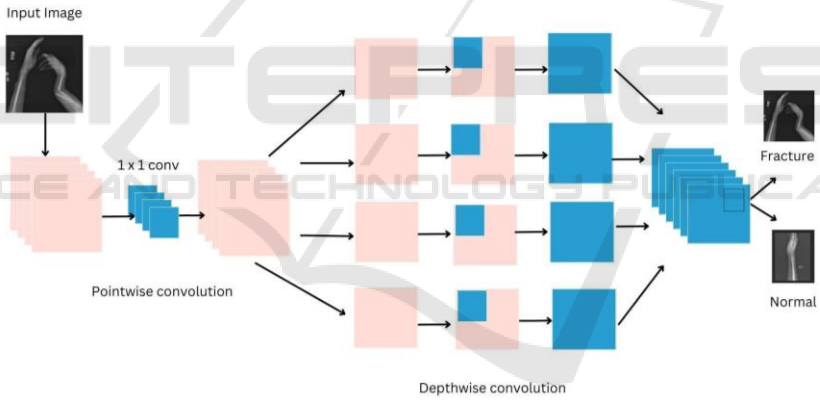

Figure 1: Conceptual representation of XceptionNet Deep learning model's architecture.

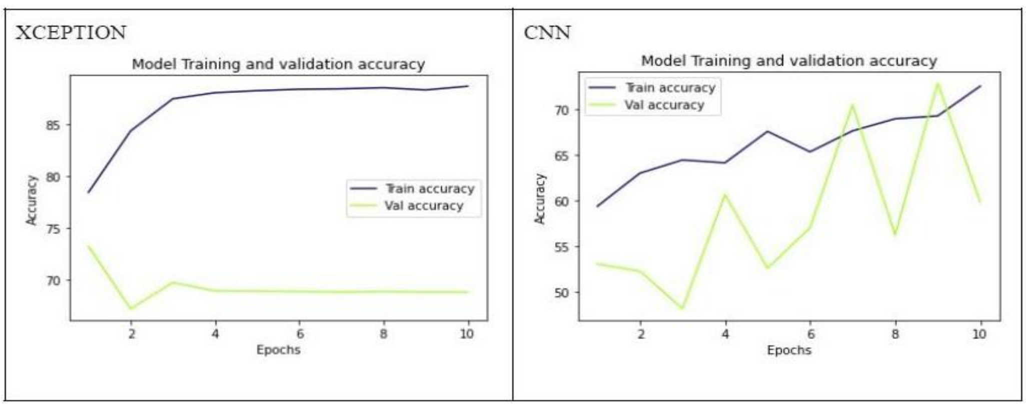

Figure 2: Novel XceptionNet and CNN - training accuracy as well as validation accuracy.

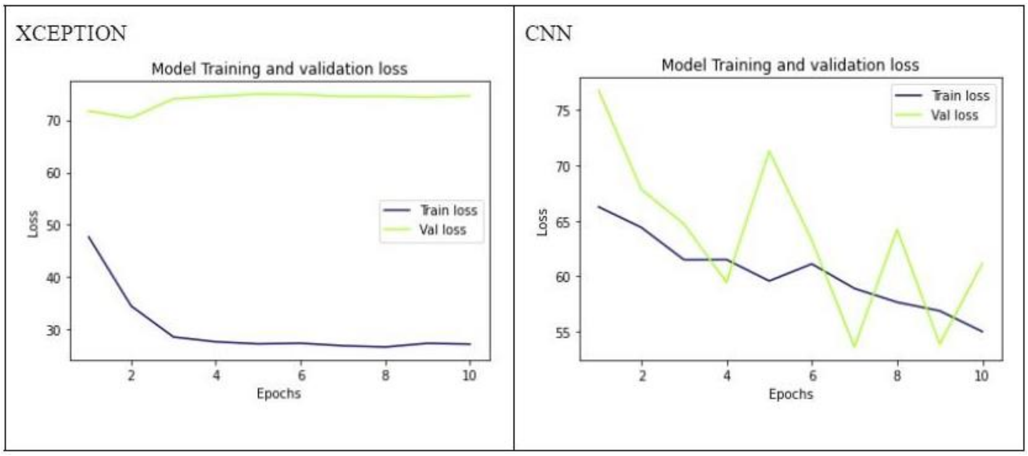

Figure 3: Novel XceptionNet and CNN - training loss and validation loss.

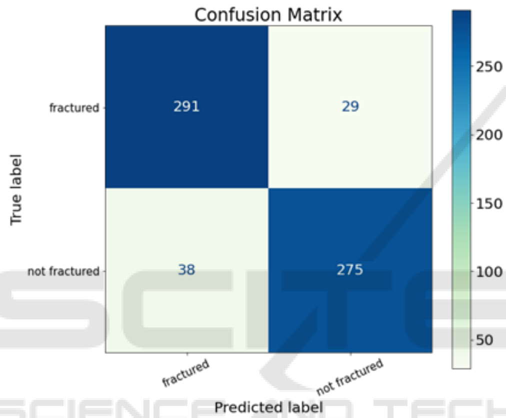

Figure 4: Confusion matrix (CM) for XceptionNet deep learning model.

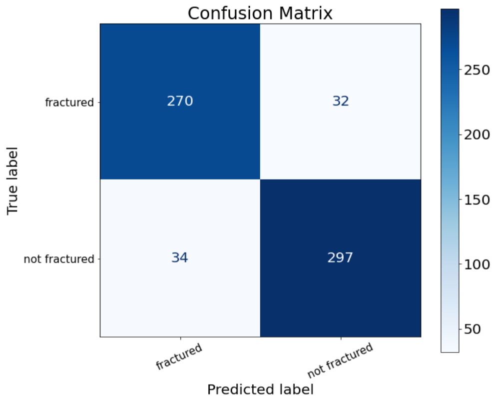

Figure 5: Confusion matrix (CM) of CNN deep learning model.

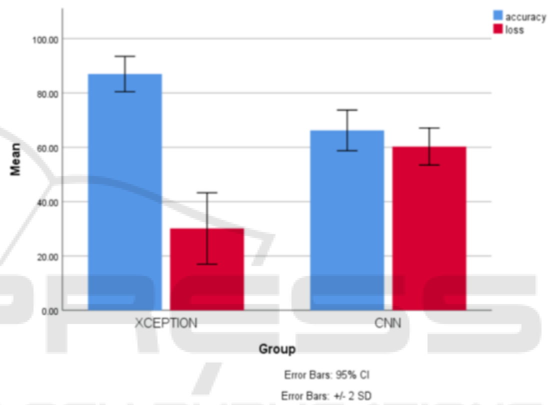

Figure 6: Bar graph presents the contrast between Mean accuracy of novel XceptionNet and Convolutional neural network (CNN) deep learning model in bone fracture detection using x-rays dataset. XceptionNet does produce better results with standard deviation (SD). X Axis: XceptionNet vs Convolutional neural network and Y axis: Mean Accuracy of detection SD = ±2 and confidence interval of 95%.

3 RESULTS

The experimental results are based on the recital of Novel XceptionNet and CNN DL models, which are both measured in terms of accuracy. The XceptionNet has a 89.44 percent accuracy, whereas the CNN has a 54.44 percent accuracy. Table 1represents the steps of the pseudocode performed for XceptionNet and CNN models. The innovative XceptionNet and Convolutional neural networks, two deep learning models, are contrasted for accuracy in Table 2. In the third or Table 3 the metrics of XceptionNet and Convolutional neural network models are shown. Precision, F1 score, specificity and sensitivity values obtained for XceptionNet are 88.45%, 99.68%, 87.86% and 90.94%. Table 4 examines the summary statistics from separate samples utilizing the cutting-edge CNN and XceptionNet deep learning models. The novel XceptionNet model has a mean accuracy of 88.74% compared to the CNN model's 72.50%. Relating the XceptionNet to convolutional neural networks, the XceptionNet has a standard deviation of 3.24. The CNN standard error mean is 1.17, whereas the XceptionNet standard error mean is 1.02, according to the T-test. Table 5 demonstrates a statistical independent sample t-test comparing the novel XceptionNet and CNN (Convolutional Neural Network), of a 95% confidence interval(CI). $p<0.001$ ($p<0.05$) (2-tailed) has been calculated as the significant value for accuracy and groups are statistically significant.

Fig. 1 displays the conceptual representation of XceptionNet deep learning model's architecture. The training and validation accuracy of the innovative XceptionNet and CNN deep learning models are shown in Fig. 2, where x is the axis that represents the epochs and y-axis displays accuracy performance. Fig. 3 depicts training and validation loss of the XceptionNet and CNN (Convolutional Neural Networks) deep learning models. Fig. 4 and Fig. 5 shows the pictorial representation of confusion matrices for XceptionNet and Convolutional neural networks deep learning models. A vertical bar chart depicting the average accuracy of the novel XceptionNet and CNN models for identifying bone fractures in upper extremity areas of hands using x-ray images dataset can be observed in Fig. 6. Novel XceptionNet appears to get better results with standard deviation. Mean of Detection SD = ±2 and X Axis: XceptionNet Vs. Convolutional Neural Network (CNN).

4 DISCUSSIONS

The novel XceptionNet and Convolutional Neural Networks (CNN) approaches are used and contrasted to be able to improve the accuracy rate of bone fracture detection in the upper extremity regions of hands. In the proposed research, observations revealed that the unique XceptionNet deep learning model worked substantially better than the Convolutional Neural Networks Technique at detecting bone fractures in x-ray datasets. The novel XceptionNet model has an accuracy rate of 88.74% for recognizing fractures in the upper extremity regions compared to Convolutional Neural Networks Technique's accuracy rate of 72.50%. The outcomes demonstrate that Novel XceptionNet performs more accurately than Convolutional Neural Networks in terms of accuracy.

According to a research, categorizing broken and healthy bone with a block attention module, convolutional neural network (CNN), faster R-CNN, and FPN provided recall, precision, accuracy, sensitivity, and specificity values of 0.789, 0.894, 0.853, 0.789, and an AUC of 0.920 (T.-H. Yang et al. 2022). In another study, "You Look Only Once" (YOLO) models served as algorithms for skeletal segmentation and lesion diagnosis and an accuracy of 90% was reported for bone fracture diagnosis (Faghani et al. 2023). A convolutional neural network (CNN) was used to locate the fracture ROI, and a second CNN was used to identify and segment different types of fragments within the ROI. This deep learning model was implemented into this cascaded architecture. For segmenting CT images, this model produced average dice coefficients of 90.5% and average mean accuracy value of 89.40% for identifying individual fragments (L. Yang et al. 2022). On the MobileNet network, a two-step categorization technique was found to have a 73.42% accuracy rate for bone fracture prediction. (El-Saadawy et al. 2020). The accuracy of the AC-BiFPN detection methods and modified Ada-ResNeSt backbone network was reported to be 68.4% in another study (Lu, Wang, and Wang 2022).

Sometimes, the mistake that occurred in the train set of data and the error that occurred in the testing data set are very different. It happens in complicated models when there are too many parameters in comparison to the quantity of observations. Future research can assess a model's effectiveness based on how well it performs on a test data set rather than how well it performs on the training data that was provided to it.

5 CONCLUSION

In this paper, computer diagnostic methods for X-ray image-based bone detection in upper extremities were demonstrated. The dataset was initially trained using the XceptionNet deep learning model. The fracture's position is determined after the initial stage. Patterns tested on a set of images and the results were evaluated according to the characteristics. In comparison to convolutional neural networks (CNN), which had an accuracy rate of 72.50%, the analysis revealed that the results were satisfactory and that the XceptionNet technique had a high accuracy of 88.74%.

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