Bone Fracture Detection using Deep Learning Techniques

Rimjhim Singh[1], J. Sri Sai Samhitha[2], K. Adarsh Sagar[3], Nemaladdinne Abdul Khadar Jilani[4]
Dept. of Computer Science and Engineering, Amrita School of Computing, Bengaluru, Amrita Vishwa Vidyapeetham, India.
[1] ps_rimjhim@blr.amrita.edu, [2]bl.en.u4cse21072@bl.students.amrita.edu, [3]bl.en.u4cse21075@bl.students.amrita.edu,
[4]bl.en.u4cse21135@bl.students.amrita.edu,

***Abstract*—Bone fractures have emerged as prevalent issue in the medical field, and accurate, timely diagnosis of bone fractures is very important for effective treatment. Traditional methods for detection of bone fractures are subjective and time-consuming as they are dependent upon the expertise of radiologists. Application of deep learning techniques for automated bone fracture detection helps us to overcome these challenges. A comparative analysis of several Deep Learning algorithms, including GoogleNet, Xception, ResNet, DenseNet, Perceiver, and VGG16 models has been performed to identify fractured bones. Among the all models analysed,DenseNet displayed notable potential in effective detection of bone fractures due to its unique ability to effectively utilize features through dense connectivity. Additionally, a novel DenseNet-based model is proposed which enhances performance and aids in improved and efficient detection. The results obtained clearly demonstrates that proposed DenseNet model outperforms the traditional DenseNet architectures by achieving superior accuracy, precision, recall, and F1-scores.The performance of the models has been further analysed by plotting accuracy plots and loss plots for each of the studied models.**

***Index Terms*—Deep Learning, Health sector, DenseNet, ResNet, Xception, GoogleNet, VGG16, Perceiver.**

I. Introduction

There are total 206 bones in the human body, and all the bones are different from each other concerning their size, shape, and strength. The smallest of these are the cranial, which are found in the auditory canal while the largest and most colossal are the femora. It is evident that human beings experience a number of fractures particularly in the lower leg region of the bones. Deep learning is a form of artificial intelligence that has gradually been adopted for identifying patterns from medical imaging over the recent years. Sharpened to assist physicians in diagnosing illnesses that affect human beings and determining the right course of action in reference to their patients.However, the cases of bone fractures are rising all over the world and it is not only the third world countries but even the developed countries are being affected as well. Diagnostic images are shared by using a protocol called Digital Imaging and Communications in Medicine (DICOM). Among several instruments that are needed in construction of the biological image, X-rays are preferred more for identifying the presence of a fracture in the bone since they are quick, affordable and easy to apply. Medical imaging was discovered in the year 1895 by Wilhelm Roentgen through using x rays and it has formed a great part of clinical practice today. Conventional screen-film systems, fluorescent image-enhancement machines, computerised X-ray image processors, and portable X-ray machines have ensured that digital X-ray imaging plays a role in many fields of medicine. Unquestionable, deep learning approaches should be significant for medical data analysis nowadays. To facilitate the detection and identify specific anomaly areas in Medical image of human skeletal system, the complicated formula is needed.

Bones that have been broken might be because of several diseases and or injuries. Thus, diagnosis is the initial but significant stage of the process, and it has to be carried out correctly and at the proper phase. For instance, a doctor or radiologist who suspects that a patient has a fracture is likely to set the patient for an X-ray as a means of being certain of how severe the breakage is and the type of breakage is. The detection of fracture is inconsequential when it is done manually or by using the conventional method, which is the X-ray technique. Due to the fact that this set was intermingled with otherwise ordinary picture, one day a radiologist became too exhausted to realize one of them pointed to the fracture. They include a computer vision system that assists in analyzing the X-ray images for any form of deviation to send an alert to the resulting doctor for the patient. However, deep learning techniques have been regarded as very effective especially in the detection of bone fractures. Neural networks are powerful tool used in deep learning to process data. Our work encompasses deep learning models which in turn propagate information through different layers to make a prediction. They are also able to detect more complex patters in the data making them quite effective in the detection of bone fractures.

In this our work mainly focuses on detecting bone fracture and Deep Learning and we have considered the dataset from Kaggle website ensuring a comprehensive and diverse set of MRI images for model training and evaluation the deep learning models we have considered are GoogleNet,VGG16, Xception model,ResNet, DenseNet, and Perceiver model.The comparative analysis showcases that the DenseNet outperforms all the other models in bone fracture detection. Additionally a model with improvements to the DenseNet model architecture is proposed which aids in enhancing the performance further.

II. Literature Survey

N.Umadevi et al.[1] An automatic system for detecting leg bone fractures from X-rays is the main focus of this study. The system uses ensemble models with texture and shape features to classify the fractures, and experimental results show a significant improvement in fracture identification with the fusion of SVM, BPNN, and KNN classifiers ranking first in detecting the fractures by analysis the given X-ray images.

Yu Cao et al. [2] A method for detecting bone fractures of various types and structures using stacked random forests feature fusion. The proposed method improves fracture detection performance, capturing 81.2% of fracture findings with a precision of 24.7%. It was evaluated on 145 X-ray images with top ranking fracture bounding-boxes, using feature types such as Schmid texture, Gabor texture, and Contextual-Intensity.

G Kitamura et al. [3] researched on detection of Ankle fractures using a CNN ensemble with multiple views. Training is done on small dataset and includes several data augmentation techniques. Models were built using Tensorflow, including Inception V3, Resnet, and Xception. Dataset collection, image processing, de-identification, and pixel value extraction were performed. Training included data augmentation, standardization, and convergence monitoring. Five CNN models were built, including Inception V3, Resnet, and Xception. Accuracy, PPV, NPV, sensitivity, and specificity were measured. An ensemble of five models achieved 76% accuracy for one view, while an ensemble of five models with three views achieved 81% accuracy. Overall, 81% accuracy was achieved with a small dataset using ensemble models.

PHS Kalmet et al. [4] focused on the use of various deep learning algorithms like VGG16, Inception V3, ResNet and others in diagnosing bone fractures. These algorithms learned from thousands of images, which enables them to classify fracture types accurately. They ensured that these algorithms were trained without overfitting, and had demonstrated impressive performance on tasks like fracture detection in radiographs and CT scans. These algorithms, has the potential to diagnose fractures in emergency situations without the need for immediate access to radiologists.

Justin Krogue et al. [5] conducted studies in diagnosing Hip fracture using deep learning techniques where researchers have used DenseNet and utilized a dataset obtained from their radiology report database, consisting of hip and pelvic radiographs and pre-processed using Python Pydicom package. The model demonstrated an impressive binary accuracy of 93.7 percentage for fracture detection and a sub-classification accuracy of 90.8 percentage. Performance metrics such as sensitivity, specificity, and area under the curve (AUC) were used for evaluation and this model showed remarkable accuracy in detecting and classifying hip fractures, suggesting its potential as a valuable tool in clinical settings for improved diagnostic outcomes.

Rebecca M. Jones et al. [6] have focused on determining fractures in radiographs of patients across hospitals using deep learning techniques. The data is split in the ratio of 80:10:10 for training, tuning, and testing purposes, and a combination of ten Convolutional Neural Networks based on the Dilated Residual Network Architecture has been tested on the dataset. Metrics such as AUC, sensitivity, specificity, NPV, and PPV have been evaluated, and the model reported impressive values for these metrics. The algorithm illustrates the development of a robust and very effective fracture detection system.

W Abbas et al. [7] researched on an automatic system for detecting and classifying lower leg bone fractures using the Faster-RCNN model. The VGG-16 architecture was chosen for generating feature maps and to detect bone fractures. The dataset was normalized using the min-max method. The CNN network stage used a Faster-RCNN deep neural network consisting of three networks: Region Proposal Network, Detection Network, and Feature Network. Anchor boxes are used for training bounding boxes of different shapes and sizes. Non-Maximum Suppression is applied to eliminate overlapping boxes. In the evaluation stage, the model is evaluated for detection and classification performance using Mean Average Precision and performance matrices. The proposed model shows promising results in detecting and classifying lower leg bone fractures.

DP Yadav et al. [8] developed a CNN model. consisting of convolution, pooling, flatten, and dense layers, which automatically extract features from the input image. The CNN architecture includes multiple convolution layers with different feature maps and filter sizes. Max-pooling layers are used to reduce the dimension of the filtered image. The activation function relu is implemented in each layer. The system's performance is evaluated using training and test data, measuring accuracy and loss. The proposed model achieved a high accuracy of 92.44% in classifying bone fractures. The model outperformed previous models that had accuracies of 84.7% and 86%.

L Tanzi et al. [9] utilized Deep learning approaches were tested for bone fracture detection. Successful transfer learning was utilized to classify wrist fractures. A neural network system was utilized to identify fractures in X-rays. Various assessment measures were employed. High accuracy was achieved for classification using cropped images. The device achieved 94.3% accuracy. Transfer learning was successful on X-ray pictures. Specialists' expertise is critical for appropriate categorization.

HP Nguyen et al. [10] proposed an approach for arm fracture detection using YOLACT++ for instance segmentation and YOLOv4 for object detection and X-ray images were segmented for enhancing speed and efficiency and the processed data then entered YOLOv4, in predicting arm fractures. Data augmentation techniques and the CLAHE algorithm were employed to enhance model performance. Evaluation results revealed impressive performance, with YOLOv4 achieving an AP of 81.91%. The combination of segmentation and CLAHE demonstrated superior results, showcasing a 4.5% improvement. Their results and work demonstrated significant improvements in fracture detection accuracy, which helps in enhancing medical image analysis for arm fractures.

NE Regnard et al. [11] conducted research based on AI identified fractures, dislocations, elbow effusions, and focal bone lesions. The study involved 4774 exams, where AI outperformed radiologists in detection. AI was compared to radiologists in detecting fractures, dislocations, effusions, and lesions. NPV, PPV, and F1-score were utilized to evaluate the reports of AI and radiologists. Specificity and sensitivity metrics were compared for fractures, dislocations, effusions, and FBL. AI outperformed radiologists in detecting fractures, dislocations, effusions, and lesions. AI exhibited a high sensitivity (90) and specificity (88) for all lesions. AI detected missed lesions, thereby reducing diagnostic errors in radiologists' reports. AI had higher sensitivity but lower specificity compared to radiologists.

T Meena et al. [12] researched on the use of various deep learning algorithms for fracture detection in which one of them had used Inception V3 model, initially designed for non-radiographical images, and re-trained its top layer for binary classification on a dataset of 1389 wrist radiographs. The performance metrics, including AUC, sensitivity, and specificity, indicated high accuracy with values around 0.95, 0.90, and 0.88 respectively another researcher had usedResNet-152 model applied to 1891 plain shoulder radiographs and this model outperformed orthopaedic surgeons, general physicians, and shoulder-specialized orthopaedic surgeons, achieving an accuracy of approximately 96 percentage and an AUC of 0.996. These algorithms, has the potential in accurately detecting fractures from radiographs and CT scans.

F Hardalaç et al. [13] explored Deep learning techniques to identify wrist fractures in X-ray pictures. Achieved great accuracy in the ensemble model. Deep learning models with varying backbones. Transfer learning is applied in all models. The evaluation criteria include AP, AR, precision-recall curve, and LRP error. The WFD-C model produced a high AP50 for wrist fracture identification. The WFD-C model outperformed the YOLO model across many datasets. Ensemble models enhanced fracture detection accuracy. DCNv2 with Faster R-CNN and ResNet50 were employed for detection. The developed WFD-C model earned the highest AP score. Fracture detection was improved by utilizing 26 distinct deep learning models. Achieved a 10% gain above the top AP result in literature.

I Khatik et al. [14] conducted a review of bone fracture detection models utilizing the CNN technique. Machine learning and neural networks are utilized to automate bone fracture diagnosis. CNN and transfer learning are used to identify bone fractures. Deep learning techniques such as R-CNN, DCNN, and DCFPN were used. Data gathering included web searches, filtering, and analysis of pertinent publications. Accuracy, sensitivity, specificity, and F1 score are popular measurements. Precision, recall, ROC curve, and AUC are all utilized measures. Different CNN techniques to bone fracture detection lack universality. The integration of CNN techniques into a hybrid pipeline is proposed.

AMA Barhoom et al. [15] A deep learning VGG16 model is used to detect and classify bone abnormalities. Multilabel classification is done with 14 classes of bone abnormalities. The VGG16 deep learning algorithm is applied to detect bone abnormalities. The VGG16 model achieved a precision of 85.96%, a recall of 85.82%, and an F1-Score of 85.77%. Deep learning helps accurately detect bone abnormalities from X-rays.

S Beyraghi et al. [16] conducted a study on deep neural networks for diagnosing bone fractures. Microwave imaging was used to diagnose fractures without X-rays. The system avoids issues with labeling and data collection by using S-parameters profiles. Commercial dipole antennas connected to a portable VNA were used. Instead of X-ray images, S-parameters were used for DNN training. The successful training of the DNN without overfitting was verified by numerical simulations. The model accurately classifies fracture types and estimates crack dimensions. DNN accurately categorizes bone fractures and estimates the crack size with low error. Mean regression error on the test dataset is 0.91 mm. DNN evaluation utilizes precision, recall, and F1-score.

K Thaiyalnayaki et al. [17] proposed an automated system using Convolutional Neural Network for bone fracture detection, which improves accuracy and reduces diagnosis time. The system focuses on classifying normal vs. fractured bones by utilizing image processing, feature extraction, and classification techniques. It incorporates a Crack-Sensitive Convolutional Neural Network and achieves 99.5 percentage classification accuracy. Pre-processing, segmentation, classification, feature extraction, and statistical values are conducted for bone fracture detection. The model proposed using CNN achieves 99.5 percentage accuracy, which is an improvement compared to the FAMO model.

N Vasker et al. [18] utilized AI to detect fractures using deep learning for accurate diagnosis. Data augmentation improves model performance with 5-fold cross-validation. 32 feature maps and 3x3 filter size used for feature extraction. Experimented with 90% training data and 10% testing data. A CNN model developed to classify bone fractures. It consists of convolutional layers, pooling layers, flattened layers, and dense layers. Convolutional and pooling layers capture patterns present in the images. 92.44% accuracy in distinguishing healthy and fractured bones. Accuracy exceeds 95% and 93% on 10% and 20% of data. The model achieved 92.44% accuracy in bone fracture classification. Model surpasses 95% and 93% accuracy on subsets of data.

I Wali et al. [19] implemented a bone fracture detection system is on an embedded platform through the utilization of deep learning techniques. In order to assess the diagnostic accuracy, a comparison is made between convolutional neural networks (CNNs) and medical professionals. The evaluation of the models is conducted based on two metrics: loss and accuracy. By employing a deep learning model, bone fractures can be identified accurately. The introduction of a deep learning model leads to an improvement in accuracy accompanied by a reduction in loss. The diagnostic performance of VGG16 CNN architecture exhibits promising results.

Sriram R et al. [20] conducted many studies in predicting

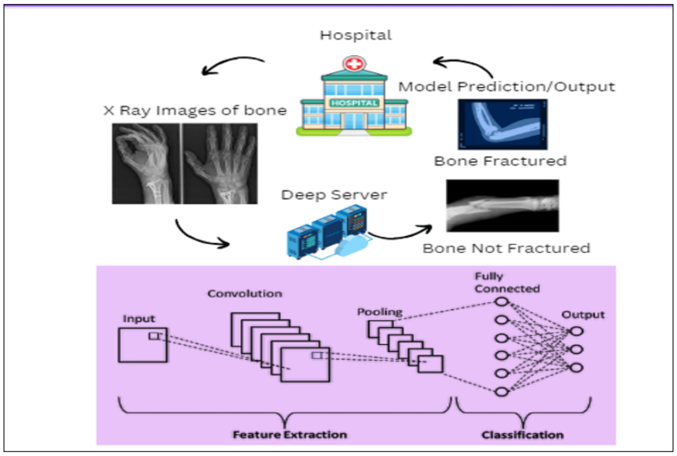

Fig. 1. Architecture flow of the proposed methodology

bone fracture using deep learning and their dataset consist of 40,000 fracture images. They used TensorFlow for model evaluation, implementing transfer learning and fine-tuning techniques to optimize network layers and their results showed an impressive accuracy of over 89% and a loss of 29% after 50 epochs. Evaluation metrics like recall, accuracy, F1-score, precision, and AUC ROC score were used, for evaluating the model's performance. Their work demonstrated effectiveness in bone fracture prediction, emphasizing its potential as a valuable tool in medical image analysis for fracture detection.

III. Methodology

A. Dataset Description

This section provides an overall description of the dataset utilized for the project. The dataset considered is the musculoskeletal radiographs (MURA) dataset, which comprises 20,335 X-ray images of three bone parts - elbows, shoulders, and hands - categorized as fractured or normal. The X-ray images in the musculoskeletal radiographs dataset include various types, such as an uninjured hand bone, a fractured elbow, and various other X-rays of the patients. Multiple images of each patient's bones are considered to train the model for accurate predictions. The count of the X-ray images of the bone parts falling under the categories of fractured or normal are summarized in TABLE I.

Bone Part	**Count of X-ray images**		
	Normal	***Fractured***	***Total***
Elbow	3160	2236	5396
Shoulder	4496	4440	8936
Hand	4330	1673	6003

TABLE I
Dataset Description

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B. Deep Learning Models

1) Perceiver Model: The Perceiver architecture is based on the combination of the inherent features of transformers and CNNs, resulting as a powerful tool which uses less computing power and works better with complex problems. Unlike conventional architectures, the Perceiver employs a two-stage process: consisting an attention operation to input data processing into the low-dimensional space and a cross-attention operation to encode the low-dimensional representation into the output space. Through its ability be adroitly filtering on what is relevant from the input and using the shared weights across modalities, the Perceiver is capable of achieving outstanding results across numerous tasks, such as image classification, language modeling, and reinforcement learning thus showing its widespread applicability and adaptability as a scalable model for multimodal tasks.

2) Xception Model: The Xception model is another successive model based on the Inception model and it has the name Xception is derived from "Extreme Inception.". These convolutions factorize the standard convolution process into two simpler steps: There are two major methods called pointwisewise convolution and depthwisewise convolution that are effectively used for designing efficient Convolutional neural architectures. This highly reduce down the parameters and computational overheads, but there is not much of loss in terms of speed and performance, because Xception is specifically designed to work on image classification and other vision based applications.

3) VGG16 Model: VGG16 is a type of deep learning model in the family of convolutional neural network with 16 weight layers or parameters that make it work efficiently in recognizing images. VGG16 was set up by the Visual Geometry Group (VGG) at Oxford University and the plainness of the architecture established in the model is noteworthy; no other dimension different from the 3×3 convolutional filters. This design is highly useful in computer vision applications where there is need to capture detail features in an image hence used a lot.

4) GoogleNet Model: Inception v1 or GoogleNet is a deep learning model developed by Google, which made use of the inception module. This would enhance the efficiency and effectiveness of the network since it can pull out several hierarchical characteristics of the same data and regulate the depth of the layers. By using these smaller convolution filters and praying that number of parameters does not increase as heavily, The GoogleNet identify higher parameters than Siamese Network but with fewer computations making it ideal for large-scale image recognition.

5) DenseNet121 Model: The DenseNet has distinct architecture that goes by the name of dense connection and involves in each layer to surpass inputs from prior layers, so leading to a reusage of features that is rich and flowing gradients. The architecture that is defined is a growth rate that prescribes the number of new feature maps that are created by the layer, and ensures that the size of the networks does not get out hand. The bottleneck layers are more pragmatic where 1×1 convolutions to vary the number of input feature maps before the 3×3 convolutions are performed. Although, the dense blocks are succeeded by transition layers to reduce the feature maps, and the dimensional volume of the spatial information to prevent it from getting bulky and complex. This results into the achievement of connectivity, the reusability of the features as well as handling of parameters in an appropriate manner hence developing a good model neural network.

6) ResNet50 Model: ResNet is shorthand for Residual network and the network is composed of residual connections that connect an input to any layer in an attempt to consciously bypass the gradient computed at the output layer that is important in addressing the vanishing gradient problem. This architecture indeed implements residual blocks concept which suggests that an operation is stacked with another exact operation and inputs and their outputs are added to the identity mapping. In these blocks, identities shortcuts are used for activation so as to work directly whereby tempted pathways of signal are provided to flow and help in maintaining information at various layers. Additionally, other complexities associated with deeper ResNet versions include: Bottleneck layers; these are the 1x1, 3x3, and 1x1 layers of convolution, aimed at the reduction of density in the computational work and at the same time enhancing the network depth. This is because the residuals connections and the identity mappings enable ResNet to train deeper neural networks, which has in fact made ResNet to deliver unbelievably high performance in deep learning tasks.

7) Proposed Model: The model which is proposed has showed improved accuracy and performance compared to the DenseNet121 model. The proposed model has several improvements included into the base model of DenseNet121. Learning rate scheduler and fine tuning is also incorporated. The self-attention layers added after each dense layer aids the model in focusing on important features while processing the data which helps in improving its ability to capture long-range dependencies between different parts of the input.Instead of using the ReLu activation function, swish activation function is used in the dense layers that can provide better performance.A learning rate scheduler is added into the model that gradually reduces the learning rate during training the model , which leads to better convergence and increased accuracy. Fine-tuning allows us to further adjust the model's parameters, particularly in the later layers, to better suit the specific task or dataset at hand in turn enhancing the models performance.

IV. Results and Discussions

This section describes the evaluation metrics obtained for each of the model and provides a understanding regarding the performance of the models. It also provides an understanding of the accuracy plots and loss plots obtained while evaluating the models. The proposed model has self attention layers added into between the dense layers, and the activation function used in the dense layers is been upgraded to Swish Activation function. Fig. 2. represents the accuracy plot and loss plot of GoogleNet model which depicts how the training and validation accuracy and loss changes over the epochs. The accuracy of GoogleNet model is 91.23%.Fig. 3. represents the accuracy plot and loss plot of VGG16 model through which we

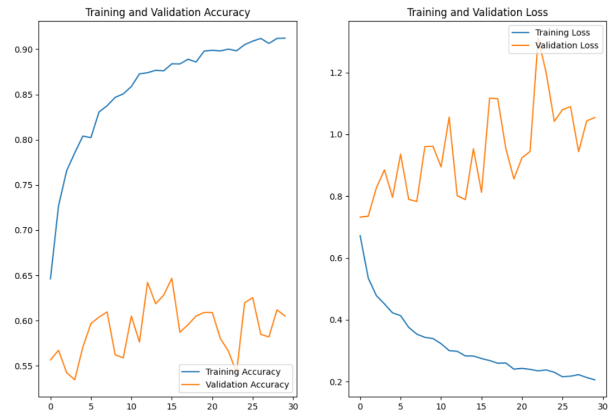

Fig. 2. Accuracy Plot and Loss Plot of GoogleNet

can obtain the accuracy of VGG16 as 95.81%. Table 1 depicts a comparison between the metrics of all the deep learning models evaluated to figure out the best models suitable to detect bone fractures.

TABLE II
Evaluation Metrics Comparison Table

Model	Precision (%)	Recall (%)	F1 Score (%)	Accuracy (%)
ResNet	49.5	50	49.5	60.72
DenseNet	49.5	49.5	49	97.84
GoogleNet	50.5	50	50	91.23
VGG16	54	49.5	49.5	95.81
Perceiver	49	66	56	70.48
Xception	50.5	50.5	50.5	95.67
Proposed Model	50.5	50.5	50.5	98.82

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Fig. 3. represents the accuracy plot and loss plot of VGG16 model through which we can obtain the accuracy of VGG16 as 95.81%. the accuracy and loss curves variations of the Xception model is plotted in Fig. 4. The ResNet50 model accuracy and loss plots obtained are as shown in Fig. 5.Similarly the plot obtained for Perceiver model and DenseNet are as captured in Fig.6 and Fig.7 respectively. The best performing model, which is the proposed architecture models accuracy and loss plots is as shown in Fig. 8. with a very high accuracy of 98.8% and a minimal loss of 0.39 by which is outperforms all the other deep learning models considered.

The proposed model shows better accuracy in detecting bone fractures than other deep models, including DenseNet121. It includes improvements like self-attention layers and Swish activation function. A learning rate scheduler and fine-tuning parameters enhance model performance. These enhancements establish the proposed model as the top performer in bone fracture detection among evaluated deep models.

V. Conclusion

Comparative analysis of the deep learning models including DenseNet121, ResNet50, GoogleNet, Perceiver model,

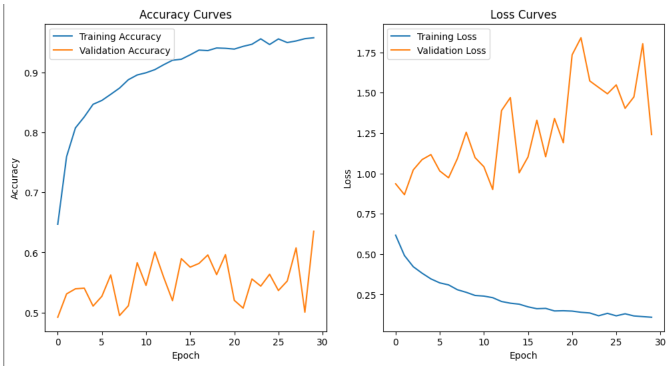

Fig. 3. Accuracy Plot and Loss Plot of VGG16

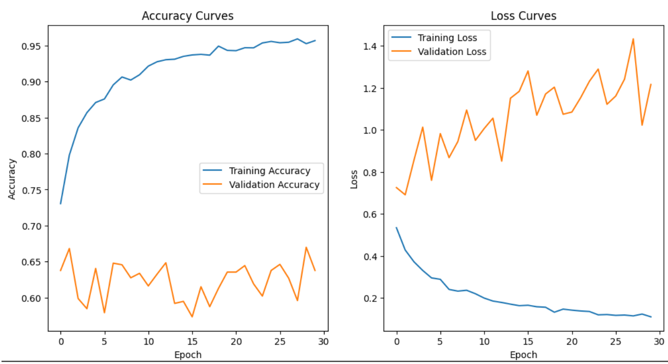

Fig. 4. Accuracy Plot and Loss Plot of Xception

VGG16, Xception model and the proposed model has been done based on the evaluation parameters including accuracy, precision, recall , F1 score and the loss obtained . The proposed model to detect the bone fractures is an advanced version of DenseNet model with inclusions of self attention layers, Swiss activation function, Learning rate scheduler and fine tuning which overall helped in improving the performance of the model. Out of the all the models the proposed architecture showcased the best performance in detecting the bone fractures with 98% accuracy..

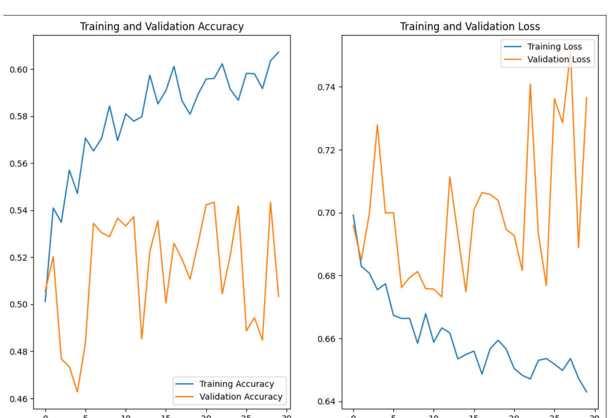

Fig. 5. Accuracy Plot and Loss Plot of ResNet50

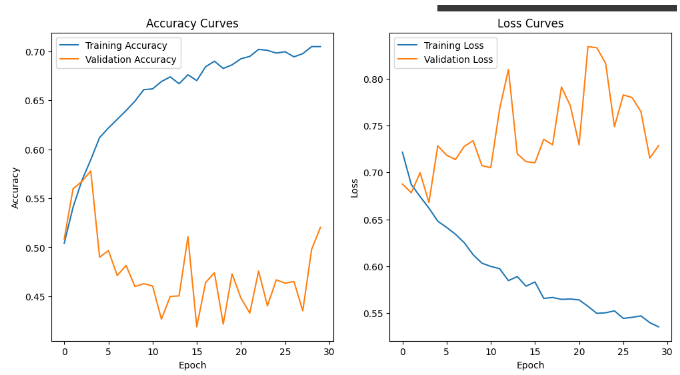

Fig. 6. Accuracy Plot and Loss Plot of Perceiver

Fig. 7. Accuracy Plot and Loss Plot of DenseNet121

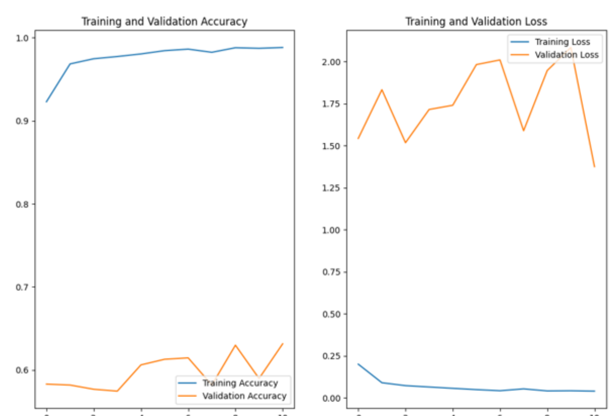

Fig. 8. Accuracy plot and loss plot of proposed model

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