A Joint Fracture Detection Using Ensemble Deep Learning Methods

Abstract

Accurate detection of bone fracture is an important task for medical experts in order to hinder long term complications and helps to give early cure for the patients that have a bone fracture risk. Bone fractures can be detected by medical experts manually which can be time consuming and subjective. It is preferable to detect human bone fractures fast, accurately and automatically which can be a feedback measure for medical experts. Here, we propose a deep learning based approach to automatically detect bone fractures using X-ray images. This paper proposes a deep ensemble learning method which combines four distinctive deep learning networks; CNN, InceptionV3, MobileNetV2, and ResNet-151 to detect bone fractures automatically using images. The proposed algorithm is trained and tested on the public dataset named Bone Fracture Dataset from Kaggle. A stacking-based ensemble deep learning based approach has been developed that integrates outputs of four distinctive networks which allows the model to leverage their complementary feature extraction capacity. We include experimental results, they have shown that the proposed model accurately detects bone fractures with the 100 percent classification accuracy which outperforms deep learning networks individually. By ensembling deep learning models, the ensemble model produces a robust method to noise and image variations, enabling a computer aided feedback (CAF) tool for medical imaging.

Keywords: Ensemble deep learning model, Transfer learning, Bone fracture detection, InceptionV3, MobileNetV2, ResNet-151, Medical imaging, X-ray image.

1 Introduction

In modern healthcare systems, there is an increasing need for artificial intelligence (AI)-driven technologies that enable accurate, automated, and noninvasive disease detection to enhance patient care and diagnostic efficiency [1–3]. Human bones are the main part of the skeletal system that provide body movement and fractures at bone seriously limit the life quality of humans. Bone fractures are among the most prevalent musculoskeletal injuries that can be caused by strikes, osteoporosis, or repetitive stress on laborers, sportsmen, elderly people etc. Statistics indicate that more than 1.7 billion people suffer from musculoskeletal diseases such as bone fractures [4] and humans have a potential to suffer from bone related problems. Medical experts use various imaging scans such as X-ray images, Computed Tomography (CT) scans, and Magnetic Resonance Imaging (MRI) to estimate bone fractures. Bone fractures can be understood by manual inspections from medical experts which can be time consuming, subjective, and detection can be challenging due to complex bone geometries, partial bone images and varying image qualities that can lead to incorrect detections. Therefore, accurate detection of bone fractures is critical to early and appropriate cure of the problem. Recent developments in deep learning methods presented generalizable, automatic, enhanced medical image analysis options. Convolutional Neural Networks (CNNs) are effective methods for medical image processing that can extract spatial and textured image features and learn from labeled image dataset, presenting automatic detection methods. Despite advances in CNN networks, an individual CNN network can produce incorrect matches which can be upgraded further using individual network outputs. To solve false classification detections, individual deep learning networks can be integrated to enhance classification accuracy. In this context, this research introduces a multi-network ensemble framework that combines CNN, InceptionV3, MobileNetV2, and ResNet-151 architectures. By integrating deep learning methods, the proposed approach upgrades a single network that enhances prediction results, presents a robust detection method. In this research work, we have explored ensemble based deep learning approaches that integrate multiple deep architectures to upgrade detection accuracy to a higher level. Such ensemble approaches improve accuracy and robustness of the detection system. This research fills that gap by applying a diverse four-network ensemble method to a real-world data, Bone Fracture dataset which is publicly available at Kaggle. The proposed algorithm achieves superior generalization and reliability across the stand alone networks. This research paper is organized with five main sections as follows: Section 1 introduces the bone fraction problem and gives insights for deep learning approaches. The previous work and algorithms related to bone fracture detection which is the next are explained in Section 2. Meanwhile, we explained the public dataset used in this research and details of the proposed bone fracture detection algorithm in Section 3. Section 4 presents results and discussion for baseline models and the proposed algorithm while Section 5 explains future directions of this research and concludes the paper. The main contributions of this work are: Firstly, Development of a heterogeneous ensemble integrating both lightweight and deep feature extraction networks. Secondly, Implementation of a stacking-based fusion strategy to combine predictions from CNN, InceptionV3, MobileNetV2, and ResNet-151. Thirdly, Comprehensive evaluation on the Bone Fracture Dataset (Kaggle), demonstrating state-of-the-art accuracy and stability.

2 Related Study

Machine learning techniques present computer-aided fracture detection which is based on handcrafted image feature extractions and classifiers such as SVM, LDA, Random Forests are trained to seek for true detection. Machine learning networks extracts features and processes images for fracture detection [5]. Bashra et al. proposed a machine learning model for diagnosis of bone fractures [6], they used image filtering methods to enhance X-ray images, used edge detectors, and feature matching is used to detect fractured bone locations which detected bone fractures with 92 percent accuracy.Image preprocessing is an important part of bone fracture identification, filtering techniques, point projection, and tuning image pixel intensity can enhance bone fractured areas and detection accuracy increases [7]. Deep learning based methods present more accurate and automatic fracture detection. Lin et al. proposed a Convolutional Neural Networks (CNNs) for regions, their proposed method automatically detects skull bone fractures [8]. Object detection algorithms can be trained with fracture datasets, transfer learning based approaches also proposed. Choi et a. Used YOLO algorithm for bone fracture detection, found 91.7 percent accuracy [9]. Haider et al. developed FracNet which is developed on a deep learning model, using feature fusion and selection mechanisms that improves the performance of the proposed network accuracy [10]. The number of samples is important for successful training of the networks. However, patient data can be hard to find due to data collection limitations and patient permissions, so researchers tried alternative ways. Parvin et al. used a pretrained object detector (YOLOv8), trained the YOLOv8 with a bone fracture dataset, and enhanced detection accuracy with data augmentation techniques [11]. Neural networks can be used to extract planar image features and hyperparameter tuning can optimize performance of the model. Alam et al. developed MobLG-Net for feature engineering which uses X-ray images to extract features; a tree based classifier detected fractured bones [12]. Deep learning methods can be cascade connected and the performance can be enhanced with using multiple networks. Jia et al. used ResNet for feature extraction from X-ray images and pyramid network for collecting different scales of features; their proposed cascade network performed 0.71 mean average precision [13]. Wei et al. proposed a multi task learning framework, they used YOLOv11 to detect and classify bone fractures giving real time fracture localization [14]. Bone fractures not only can be detected with X-ray imagery, but also can be detected with CT scans. Chen et al. proposed a pelvic trauma severity score system from bone fracture detections by using RCNN to detect features and Bayesian Inference scores the severity of trauma using CT scan images [15]. Zhang et al. [16] conducted a study involving patients with acute thoracic trauma who underwent thin-slice CT imaging. Their CT scans were categorized into three groups: one evaluated with radiologist assistance, another with deep learning (DL) serving as a concurrent reader, and a third with DL functioning as a secondary reader. The findings demonstrated that the proposed DL as a concurrent reader presented significant enhancement for the rib fracture detection. Bevers et al. [17] investigated the relationship between statistical shape model (SSM)-derived morphological features and fracture occurrence in the patients with clinically suspected scaphoid fractures. Their proposed SSM model was constructed using MATLAB and a template mesh, with a set of meshes undergoing rigid and non rigid registrations. Their statistical analysis has shown that the first shape mode accounted for 72.1 percent of the total variance, whereas the second and the third modes accounted for 6.3 percent and 4.2 percent, respectively. Hybrid deep learning networks are also proposed for biomedical research, Yadav et al. [18] proposed a hybrid SFNet network, the SFNet is developed for automated bone fracture detection and bone image classification using the SoftMax activation function. Their proposed algorithm was trained on a dataset comprising 34,000 radiographic images. Based on precision metrics, their proposed algorithm showed a minimum accuracy of 45 percent when adding to MobileNetV2 and a maximum of 100 percent with the proposed hybrid SFNet network. Ma et al. [19] proposed a bone classification system that categorizes the human skeletal structure into 20 distinct anatomical types. For fracture detection, they used the Faster R-CNN algorithm and compared the proposed algorithm performance with several algorithms. Their experiments indicated that the proposed model demonstrated superior performance in terms of recall and specificity, achieving an overall accuracy of 88.39 percent, so outperforming other proposed bone fracture detection algorithms. Li et al. [20] investigated the diagnostic utility of ultrasound imaging for the assessment and detection of various bone fractures. The risk of bias and the relevance of the included studies were evaluated across the several metrics based on performance and time. The quality assessment was conducted using the QUADAS-2 framework. Their findings showed that, compared to conventional radiography, ultrasound imaging exhibited a high level of accuracy in detecting bone fractures, supporting its potential as a reliable diagnostic tool. Ahmed et al. [21] conducted research using a bone fracture dataset that consists of 270 leg radiographic images. The dataset passed through a series of pre-processing steps that included noise suppression, contrast increase, and edge detection to improve radiographic image quality. Their method extracts texture features using the Gray-Level Co-occurrence Matrix (GLCM) method, considering five statistical descriptors; correlation, dissimilarity, energy, contrast, and homogeneity; across four interpixel distances and seven angular orientations. This procedure produced a total of 140 features per image. They used various machine learning techniques and the Support Vector Machine (SVM) achieved the best performance, yielding a maximum classification accuracy of 92.85 percent. In addition to image based detection methods, bone fractures can also be detected by antenna based systems that enable non-invasive, remote, non-ionizing, low cost, radio frequency based detection. Additionally, Antenna based bone fracture detection enables detection without depending on operator expertise. Wolynski et al. proposed a novel method that is based on an antenna sensor system designed on a flexible substrate [22]. Their proposed system enables remote and continuous monitoring of the bone healing process in patients by detecting physiological and structural changes associated with the bone fracture recovery process. This proposed system demonstrates the potential of integrating flexible antenna technology into bone fracture diagnostics to enhance real time evaluation and improve patient needs. Kaiwanto et al. investigated microwave antenna based detection methods with various antennas [23]. Based on their experiments, they found that fractures responded to high variations in responses for S11 and S21 for their test antennas.

3 Material and Method

3.1 Dataset and Data Augmentation

The publicly available dataset includes 4800 hand labeled X-ray bone images, sized 224 by 224 pixels from various human body sections in JPEG format, half of the images labeled as "fractured" and other half of the dataset is labeled as "normal" [24]. In our experiments, data is splitted to three categories: training set for 3360, validation set for 720 and test set for 720 images.

In our experiments, we normalized the dataset to hold data in [0,1]. Since medical image data is limited with 4800 images we applied data augmentation techniques which helps to capture more variations on samples and enhances prediction accuracy of the decision system. Therefore, we applied rotation, translation, flip, shearing and scale changes to the dataset. After that, base learners are trained with the augmented dataset.

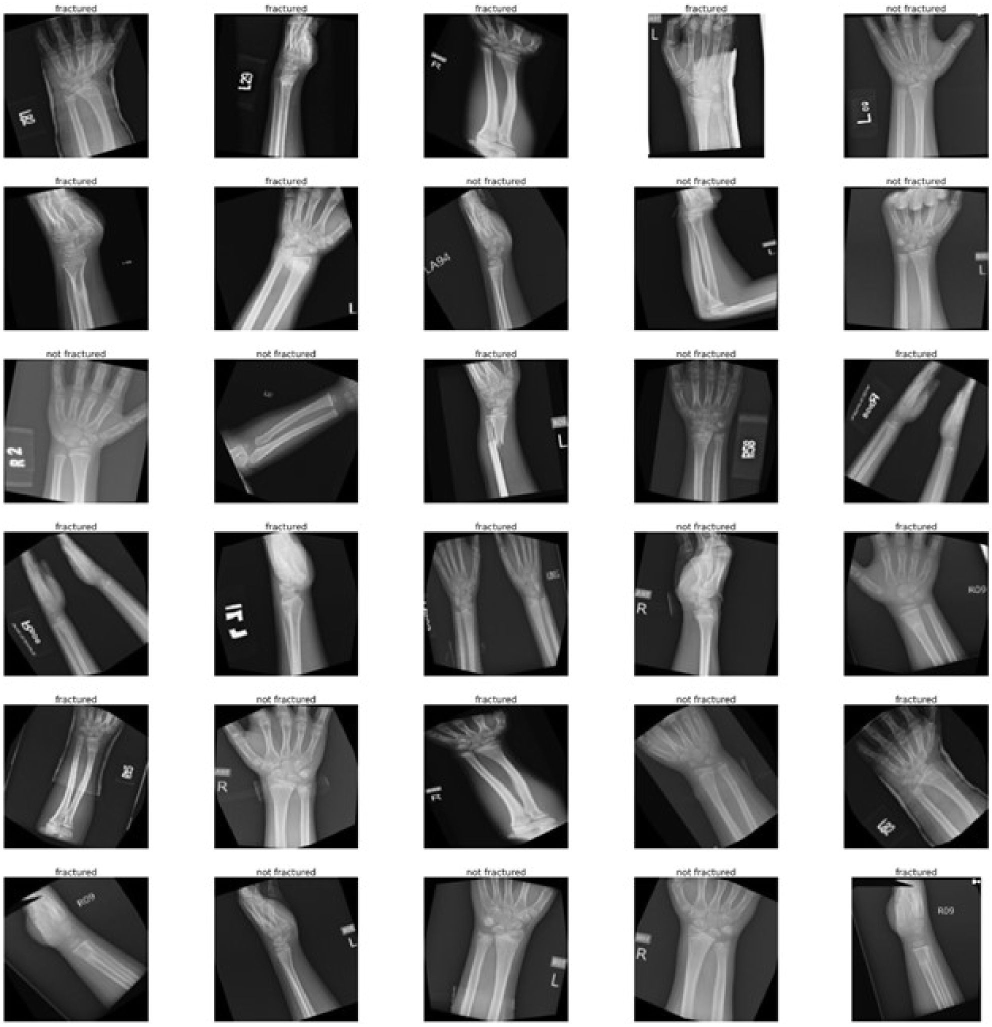

Fig. 1: Random samples and labels are given from the dataset which includes fractured and not fractured bone X-ray images

3.2 Proposed Ensemble Architecture

Ensemble machine learning technique aggregates multiple base models to upgrade prediction accuracy to a higher level with respect to base models. Ensemble learning presents several advantages to artificial intelligence. Combining multiple artificial neural networks improves the accuracy of the decision system. The variance of the predictions is reduced since estimations of several models are averaged that gives reduced error and variance for the new prediction system. The ensemble model includes reduced noise and outliers due to averaged prediction results; this improves the robustness of the decision system. In some cases, a single machine learning model can not detect complex relationships of the data. Instead of using a single model, ensemble models can better identify complex data and present reliable models. In this context, the proposed ensemble learning method combines four deep learning models: CNN, InceptionV3, MobileNetV2, and ResNet-151 to detect bone fractures. Each deep learning method captures distinctive bone image features and patterns from radiographic imagery. Then, the proposed algorithm aimed to enhance detection accuracy of the bone fractures. Since the number of layers in the neural networks increased, the performance of neural networks can increase with using more data and computation. However, limits of the public datasets hinder training cycles, so transfer learning methods can accelerate the time for proper training of the deep learning models. Therefore, we used transfer learning techniques to improve performance of the base learners which improves the performance and accuracy of the proposed ensemble algorithm. Here, we used a soft voting approach which takes into consideration the probability scores of base learners. Then, soft voting calculates weighted average of calculated probabilities to make an estimation based on deciding the highest probability in predictions. In order to train deep learning models, deep learning models needed a labeled dataset, so we used a publicly available dataset for bone fractures which is freely available here by clicking. We wanted to improve the performance of the deep learning models, so we used data augmentation techniques that rotate, shift and scale the images at the dataset which increases the number of the samples and detection accuracy. Then, we partitioned the dataset in three as follows: training set, validation set, and test set. We selected deep learning models which can extract image features, patterns and variation from image samples, so four base learners trained with the training set. Then, the proposed ensemble model fused the detections from base learners. In doing so, the proposed ensemble model gives the best performance by combining four base learners. All experiments were executed on a NVIDIA AGX ORIN that has 64 cores, computation time for the proposed algorithm takes 3 minutes 13 seconds. Each model independently outputs a probability for detecting bone fractures. These predictions are then fused using an ensemble classifier that calculates weighted average of the base learner predictions. Then, the highest probability found based on predictions from the base models. Each deep learning model has advantages and the properties of deep learning models explained in the next.

3.2.1 CNN

A convolutional neural network is a type of network that learns through convolving images through kernel filters and backpropagation structure. CNNs can provide improved detection accuracy on image based problems such as object recognition, including image classification, detection, and segmentation since convolution filters can extract image textures, patterns automatically. CNNs include several layers: convolutional layer, pooling layer, activation function, and fully connected layer to predict from image data. Convolutional layers filter images and capture variations and features on the image. The pooling layer generally comes after the convolution layer, reducing the dimension of the input data. Activation functions transmit data from input to output and the input and decide the neuron active or passive state. Fully connected layer is a type of layer in the CNN where all the input neurons of the former layer are connected to the output for the final classification task. Based on processing image data through several layers, CNNs can better extract and identify fine grained edge data and image features. The custom CNN trained with 20 epoch, 0.3 percent dropout rate, Adam optimizer with cross entropy loss function.

3.2.2 InceptionV3

InceptionV3 is a deep multi branch architecture that includes 48 layers. InceptionV3 has a modular architecture and parallel processing design which combines multiple parallel convolutional filters and pooling layers to extract image features; decreases the computational time and complexity for training step due to one dimensional convolutions. Therefore, InceptionV3 is known as an efficient method for extracting information from complex and textured image data. Therefore, InceptionV3 is able to perform high accuracy to detect bone fractures. The InceptionV3 trained with 20 epoch, 0.5 percent dropout rate, Adam optimizer with 0.0001 learning rate, and weights transferred from imagenet.

3.2.3 MobileNetV2

MobileNetV2 includes inverted residuals which enables a computationally efficient deep learning model and efficient feature extraction method using depthwise convolutions and selu activation function which is modified from relu and the selu hinders negative input values at the certain value for proper training mechanism. MobileNetV2 presents a computationally efficient deep learning network due to its architecture of reduced depth which makes it an appropriate model for mobile applications. The MobileNetV2 upscales the input using depthwise separable convolutions with different scales which enables improved feature extraction and performance of the deep learning model. Feature maps are normalized with batch normalization. At the final layer the fully connected layer predicts the bone fracture images. The MobileNetV2 trained with 20 epoch, 0.5 percent dropout rate, and weights transferred from imagenet.

3.2.4 ResNet-151

ResNet-151 is a part of deep residual networks that includes a different number of convolutional layers and is able to extract complex image patterns. ResNets include

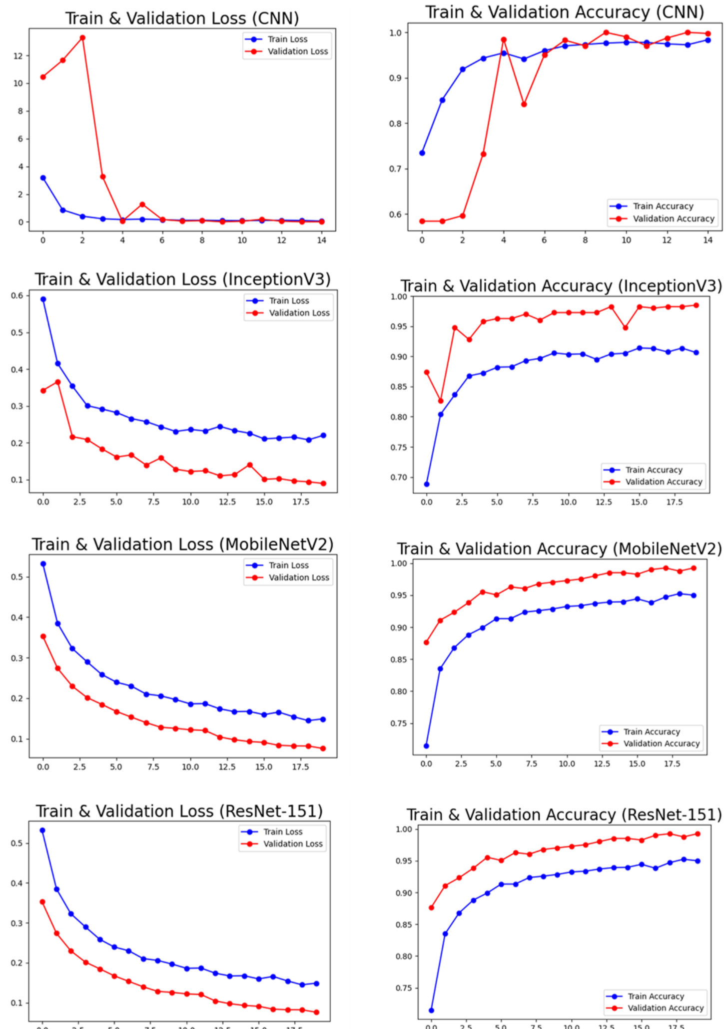

Fig. 2: Loss and accuracy graph given for base models during training and validation step.

squeeze block which aggregates feature maps that generate a channel descriptor. Additionally ResNets include an Excitation block that uses the previous channel descriptors that updates the weights through the fully connected layer. ResNets presents a residual learning method by skipping connections. Therefore, the ResNet-151 can skip connecting layers, preventing gradients that are going to very low values. In doing so, ResNet-151 hinders the vanishing gradients that enable deep contextual learning and proper training of the network. The ResNet-151 trained with 20 epoch, 0.5 percent dropout rate, Adam optimizer with 0.0001 learning rate, and the weights are transferred from imagenet.

3.3 Evaluation Metrics

In order to evaluate the performance of the models, we employed several metrics that emphasize different aspects of classification quality, such as accuracy, sensitivity, and the area under the ROC curve (AUC). Accuracy (ACC) is a measure of how often a model correctly predicts the class labels. It is the ratio of the number of correct predictions to the total number of predictions made. Sensitivity (S) measures how well a model identifies actual positive cases. S shows the proportion of real positives that were correctly predicted by the model. Area Under Curve (AUC) refers to the area under the Receiver Operating Characteristic (ROC) curve. The ROC curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at various classification thresholds.

$$\text{Accuracy (ACC)} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Sensitivity (S)} = \frac{TP}{TP + FN}$$

$$\text{Area Under Curve (AUC)} = \int_0^1 TPR(FPR)\, d(FPR)$$

Table 1: Performance metric comparison of models used in this research

Model	**Accuracy (%)**	**Sensitivity (%)**	**AUC (%)**
CNN	97.99	98.00	98.00
MobileNetV2	97.24	96.09	97.27
InceptionV3	96.49	93.00	96.50
ResNet-151	98.75	98.00	98.75
The Proposed (Ensemble)	100.00	100.00	100.00

4 Experimental Results

The experimental results prove that the proposed ensemble learning significantly improves the performance of deep learning models in medical image classification specifically classifying bone fractures from radiographic imagery. While base deep learning models are able to detect various fractures, they are poor as a single base model. Loss and accuracy plots are given in Fig. The custom CNN gives 97.99 percent accuracy; the MobileNetV2 gives 97.24 percent accuracy; the InceptionV3 gives 96.49 percent accuracy; the ResNet-151 gives 98.75 percent accuracy. The confusion matrix gives a simple insight about classification performance of the model, the confusion matrix shows number of detections for each class. Though base learners were able to perform true detection in most of the samples, the proposed ensemble model fused four base learners outperformed those base models, yielded superior classification performance, and gave 100 percent accuracy and precision. The experimental results confirm that ensemble learning substantially enhances the performance of deep models in medical image classification. While individual networks captured different structural and textural features, their integration yielded superior generalization and robustness. The perfect accuracy and precision of the ensemble indicate its potential for real-world diagnostic applications, where reliability and interpretability are paramount.

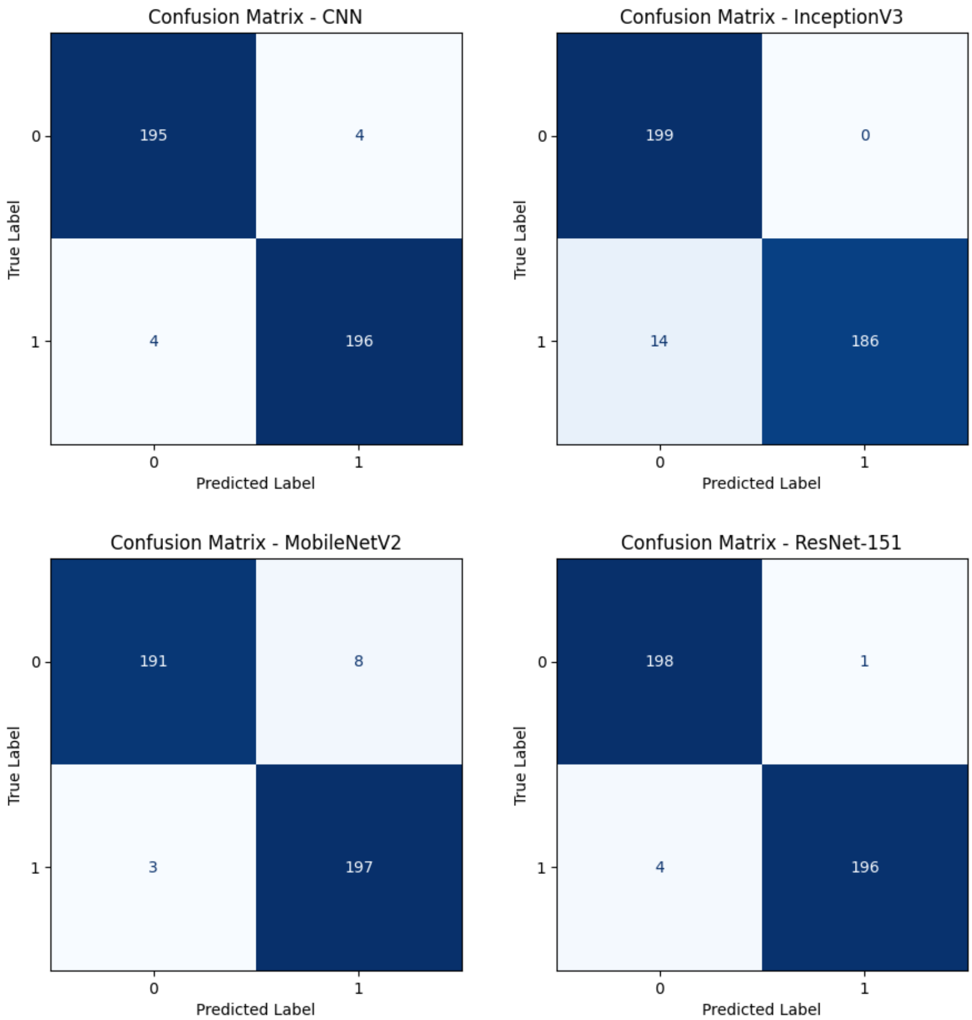

Fig. 3: Confusion matrixes are given for base models, they show true and false predictions regarding test samples.

Additionally, the proposed ensemble model proves that integration of heterogeneous architectures can reduce the overfitting problem and improve accuracy of the decision making system to subtle fracture cues.

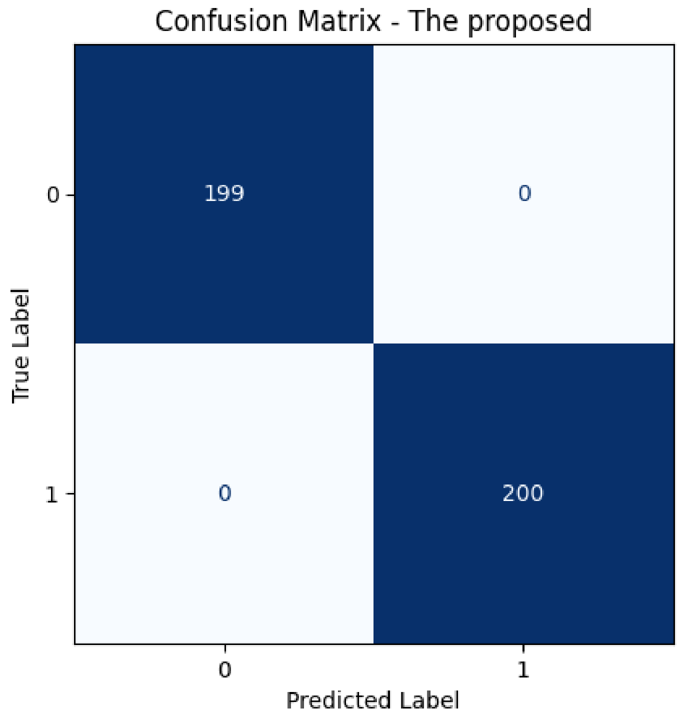

Fig. 4: The confusion matrix for the proposed ensemble model is given, confusion matrix shows perfect prediction results for each classes.

5 Discussion

The performance comparison of different deep learning architectures for joint fracture detection is given at Table 1. Among the base learner models, The ResNet-151 performed the highest accuracy (98.75 percent), followed by CNN (97.99 percent), MobileNetV2 (97.24 percent), and InceptionV3 (96.49 percent). Even though these base deep learning models demonstrated strong classification to detect bone fractures, their performance is still inconsistent across sensitivity and AUC metrics due to false detections. For instance, InceptionV3 performed the lowest sensitivity (93.00 percent) which indicated its limited ability to correctly identify all the bone fracture samples from X-ray imaging. In contrast, the proposed ensemble model significantly outperformed all the base deep learning models, by achieving 100 percent accuracy, sensitivity, and AUC. This superior performance proves the effectiveness of combining complementary feature representations from multiple deep learning architectures. The ensemble model benefited from the diversity of feature extraction patterns ResNet-151's deep residual learning, MobileNetV2's lightweight depthwise separable convolutions, and InceptionV3's multi-scale feature analysis resulting in enhanced generalization and robustness against data variability. The remarkable performance improvement of the ensemble method indicates that single deep learning models can

(a) Not Fractured bone 1

(b) Fractured bone 2

(c) Fractured bone 3

(d) Not fractured bone 1

(e) Fractured bone 2

(f) Fractured bone 3

Fig. 5: Random X-ray samples from the dataset and detection results are given for the proposed ensemble model. The proposed model finds not fractured bones (a,d) and fractured ones (b,c,e,f). The proposed model even detects small fractures (e,f).

struggle to capture all discriminative features required for accurate bone fracture detection. The fusion strategy effectively eliminates stand alone model bias and variance, leading to a more accurate and reliable fracture detection method. The results also suggest that ensemble learning can overcome overfitting issues often observed in stand alone deep learning models, particularly when dealing with limited medical imaging datasets. Based on our research on the dataset, our findings demonstrate that while individual CNN-based models provide competitive detection accuracy, the proposed ensemble framework presents a new benchmark in bone fracture identification, achieving flawless diagnostic metrics and underscoring its potential for real world clinical application.

6 Conclusion

In this research work, we specifically studied detection of joint fractures with various deep learning models respectively: CNN, MobileNetV2, InceptionV3, and ResNet-151. Additionally we investigated ensemble deep learning techniques. We proposed an ensemble deep learning model with soft voting. While each individual deep learning model exhibited good detection, their detection accuracy and sensitivity remained slightly inconsistent. Among them, ResNet-151 gives the highest individual performance (98.75 percent accuracy), demonstrating its strong feature extraction capacity. However, the proposed ensemble model surpassed all standalone architectures, achieving 100 percent accuracy, sensitivity, and AUC, confirming the robustness and efficiency of the ensemble learning approach.

The exceptional results of the ensemble framework highlight the benefits of integrating multiple feature extraction strategies, which significantly enhance generalization and minimize the risk of false detection. This demonstrates that combining complementary model strengths can effectively capture subtle fracture characteristics that individual networks might overlook.

For future research, several directions can be pursued to strengthen the clinical relevance of the proposed method. First, the model can be validated on larger, multi-institutional, and heterogeneous datasets to ensure its robustness across diverse imaging conditions. Second, fusing with additional models could improve interpretability and clinician trust by highlighting critical regions associated with fractures. Third, optimizing the model for real-time deployment on edge or mobile medical imaging systems would enhance accessibility in clinical and remote healthcare settings. Lastly, integrating the ensemble framework with 3D imaging modalities such as CT or MRI could further improve diagnostic precision. Overall, the proposed ensemble model demonstrates remarkable potential as a highly accurate, reliable, and scalable solution for automatic joint fracture detection in radiographic imaging.

Appendix A Section title of first appendix

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