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Automated Bone Fracture Detection with a Weighted Ensemble Learning Approach

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Abstract

Bone fracture is the most common problem existing in the field of medical emergencies. In Bone fracture detection, conventional approaches typically depend on the expertise of radiologists to interpret radiographic images. However, due to high volume of data and variations among fractures, there is a risk of misinterpretation.

Deep learning, particularly convolutional neural networks (CNNs), has transmuted fracture diagnosis through automating this process. In this research, a novel ensemble learning method is introduced, a robust fracture detection model that utilizes an ensemble strategy with added weights to accurately differentiate between normal and fractured bone conditions Through extensive experimentation and validation against few cutting-edge CNN-rooted models adapting transfer learning techniques, the proposed model demonstrates superior performance, exceeding the capabilities of existing methods by a significant margin. A key perspective of this study is the significant impact of base classifier selection on ensemble model performance.

Keywords Artificial Intelligence, bone fracture detection, convolution neural network, deep learning model, ensemble learning, transfer learning

1. Introduction

Bone fractures ensue when external forces surpass the structural integrity of bone, especially traumatic occurrences such as falls, vehicular accidents, and sports-related incidents precipitate fractures [1]. Moreover, osteoporosis, a condition characterized by diminished bone density, heightens susceptibility to fractures even from trivial trauma[2]. Prolonged or repetitive mechanical stress on specific skeletal sites may incite stress fractures, evolving insidiously due to incremental microstructural compromise[3]. Furthermore, pathological etiologies such as neoplastic processes or metabolic aberrations can undermine osseous robustness, culminating in fractures termed pathological in nature[4]. Within contemporary healthcare practices, the identification and categorization of bone fractures[5] entail collaborative endeavors among healthcare professionals, utilizing a spectrum of imaging modalities such as X-rays, computed tomography (CT), and magnetic resonance imaging (MRI). Of these modalities, X-ray imaging emerges as a pivotal tool renowned for its cost-effectiveness and widespread availability[6]. The convolutional neural network (CNN) is essential in deep learning for automatic image feature extraction, widely used in disease detection[7-8]. Despite the success of CNN-based models in medical image classification, they face significant challenges[9], particularly the need for large amounts of labeled data, which is difficult and expensive to obtain in the medical field. In response, researchers have introduced the concept of transfer learning[10]. This paradigm involves retraining a CNN, initially trained on a large dataset, on a novel problem with a smaller dataset, leveraging the knowledge gleaned from the former to swiftly acquire features from the latter[11]. Transfer learning proves particularly advantageous when data are scant for achieving specific tasks, as the pre-trained model furnishes a superior starting point, circumventing the need to retrain an extensive model from scratch. This, in turn, facilitates efficacious resolution of various image-classification challenges. Despite the commendable performance exhibited by numerous methodologies in classifying bone fractures, inherent limitations persist in these proposed methods. Specifically, extant methodologies demonstrate superior performance during the training phase; however, their accuracy markedly declines during validation and testing phases. Within the realm of automated healthcare, testing accuracy assumes paramount importance, as even a marginal enhancement in accuracy can precipitate more precise and expeditious diagnoses, thereby ameliorating patient outcomes and treatment strategies[12]. To overcome these predicaments and alleviate the variability while using individual models, this paper introduces a novel innovative technique for building a weighted ensemble model utilizing transfer-learning principles for bone fracture diagnosis[13]. Encouragingly, this has demonstrated commendable outcomes relative to extant strategies.

The contributions of this study are delineated as follows: Mainly, the inception of the envisaged model, adeptly harmonizing the virtues of DenseNet201 and MobileNetV2 through a nuanced weighted ensemble methodology, thus enabling flexible feature learning and portrayal. Additionally, a comprehensive evaluation encompassing various CNN models like ResNet152, Inception V3, and the proposed ensemble model, was undertaken, with meticulous analysis of their respective performance metrics. Furthermore, a thorough evaluation of diverse weight configurations was conducted to ascertain optimal coefficients that elevate performance metrics.

2. Literature Review

The utilization of artificial intelligence (AI) in diagnostic imaging has marked a groundbreaking period in diagnosis of fractures, revolutionizing traditional methods by offering automated and precise fracture detection and categorization from various imaging facilities[14]. Through deep learning algorithms, AI systems[15] can swiftly and accurately identify fractures, aiding radiologists in timely diagnosis and treatment planning while reducing the risk of oversight or misdiagnosis.

Yubin Qi *et al*. [16] , used an anchor based Faster RCNN method for fracture detection supported by ResNet50 for locating fracture regions and classification for the type of fracture in femoral shaft fractures. Additionally, researchers like Chung *et al*. employ ResNet-152 to categorize fractures into five distinct groups. [17].kim*et al*. made use of pre-trained algorithm Inception V3 for classification of wrist fractures by retraining its last layer with their current dataset of wrist radiographs[18]. AnupKhanal*et al*. in [19] created and tested an ensemble model with DCNNs' VGG19, Inception, MobileNet, DenseNet169 and ResNet152, for the analysis of fractured limbs and eradicate the generalization errors and the dataset used was CT image dataset . In the study [20] three different model VGG16, MobileNetV2 and Inception V3 were ensembled for acquiring the best accuracy on training humerus dataset from MURA dataset. The images were augmented for the best results. The ensemble model was compared on a whole with the above trained models. Riel Castro *et al.*in[21] evaluated the trade-offs between speed and accuracy and the overall effectiveness of four broadly used transferred learning convolution neural networks InceptionV3, ResNet50, MobileNetV2, and VGG16 in classifying rib fractures. Kim *et al.* and his team constructed a transfer learning ensemble models which comprises of six models which also includes MobileNetV2 which gave highest accuracy[22]. Six pre-trained deep convolutional neural network (DCNN) architectures with diverse levels of depth were utilized for detecting osteoporosis using CT images of spine in [23]. The VGG16 model demonstrated the most promising outcome. Zeng, Zhigao, *et al.* in [24] addressed a solution for musculoskeletal abnormality detection using light weighted network MobileNetV2 fused with EfficientNet-B2 which resulted in subjected recognition of bone abnormalities with decent accuracy.A novel lightweight network architecture termed MobileNetV2 was introduced by Sandler, Mark, et al. designed to uphold high accuracy in image classification while ensuring computational efficiency, particularly on small devices with limited resources[25]. This study [26] elaborates about the light weighted architecture of MobileNetV2 and understand the proposed SSD(single shot multi box detector) algorithm and how it enhanced the detection performance. To understand the characteristics and underlying architecture of MobileNetV2, the study [27] was examined and comprehended the working of the same. Researchers in [28] comprehend that DenseNet and VGG19 CNN architectures to discern fractures in the images of X-rays. The research [29] describes a new architecture for segmentation of skull images using DenseNet and U-Net resulting in 87% specificity. The paper [30] introduced IDNet, a network combining perception and DenseNet, achieving 92% accuracy in classifying upper limb bone injuries. This research [31] uses a deep learning method to analyze X-ray images of the humerus, first standardizing their size, then employing DenseNet-169 to distinguish between normal and abnormal scans.

Based on the literature survey, improving accuracy and other metrics is possible. A large dataset with simple models increases computational cost, while a small dataset with complex models risks over fitting. From previous research, one can derive suggestions, conclusions, and further improvements. Systematic examination of model accuracies, dataset size, model complexity, and implementation steps is essential.

Paper organization-Section III explicates the proposed model architecture, while Section IV elaborates on the characteristics of the dataset(s). Section V delves into the results and engages in discussions. Sections VI and VII encapsulate the conclusions and references, respectively.

3. Proposed Model Architecture

In the proposed research, the opted dataset was carried out for training with ResNet152, MobileNetV2, Inception V3 and DenseNet201. The existing pre trained models were analyzed meticulously for their individual performance on the select fracture dataset.

3.1. Transfer Learning and Fine Tuning

These four models were previously trained on large ImageNet dataset which contained 1000 classes. So, the transfer-learning approach was subsequently employed to structure the four existing CNN models for training. In the process of training , the models were trained by freezing all the layers from their existing structure but the top layer was made “false” and replaced by the customized dense layer which was added. Subsequently these models were fine-tuned by selecting weights from pre-training ensues. Talking about the workflow of the proposed project elucidated in Figure 1, the input dataset is split into training's and testing's in the ratio of 0.8 and 0.2. Then the pre-processing and batch normalization steps transpire. During preprocessing, images are resized to 224x224 pixels, aligning with default input dimensions of many pre trained deep learning models. Rescaling the images with a rate of 1/255 optimizes training and computational efficiency. These steps enhance model performance and reduce computational cost. In scrutinizing the efficacies of four DCNN models MobileNetV2[33] and DenseNet201[34] showed unmatched competence on the dataset used for the proposed system in terms of accuracy.

In optimizing the models, the Adam optimizer was employed in conjunction with fine-tuned learning rates. Binary Cross Entropy function served as the loss function to gauge model performance and refine parameters accordingly. Delving into the mathematical modeling of the selected optimal models, MobileNetV2 follows a simple single shot detecting mechanism with a light weighted architecture using a depth wise separable convolution strategy formulated in Equations 1-4 where X is the input tensor which is used for expanded point wise in (1), depth wise in (2) and projected point wise convolution in (3). Y_r denoted the output tensor from residual connection , W represented weights and b represented bias values.

$$X_p = ReLU6(X * W_1 + b_1) \quad (1)$$

$$X_d = ReLU6\left(X_p \cdot W_d + b_d\right) \quad (2)$$

$$\mathrm{Xpr} = X_p * W_2 + b_2 \quad (3)$$

$$Y_r = X_{pr} \quad (4)$$

Another model DenseNet201 which consists of convolution dense blocks represented in Equation 5 where I is the inpiut image vector and K is the kernel filter with dimension (m,n) and (x,y) represented input image dimensions and transition blocks layer wise with a mechanism of global average pooling broadly represented in the Equation 6 where $d^{[L]}$ is the collected output value from all the layers and $d^{[1]}$ to $d^{[L-1]}$ denoted the individual layer outputs. $d^{[1]}$ will be the input value for the 2nd dense block and $d^{[2]}$ will be its output value.

$$(I * K)_{(x,y)} = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} I_{(x+m,y+n)} K_{(m,n)} \quad (5)$$

$$d^{[l]} = g(d^{[1]}, d^{[2]}, d^{[3]}, \dots d^{[l-1]}) \qquad (6)$$

In the construction of DenseNet201, the dropout value of 0.5 was implemented, while MobileNetV2 incorporated a similar dropout ratio.

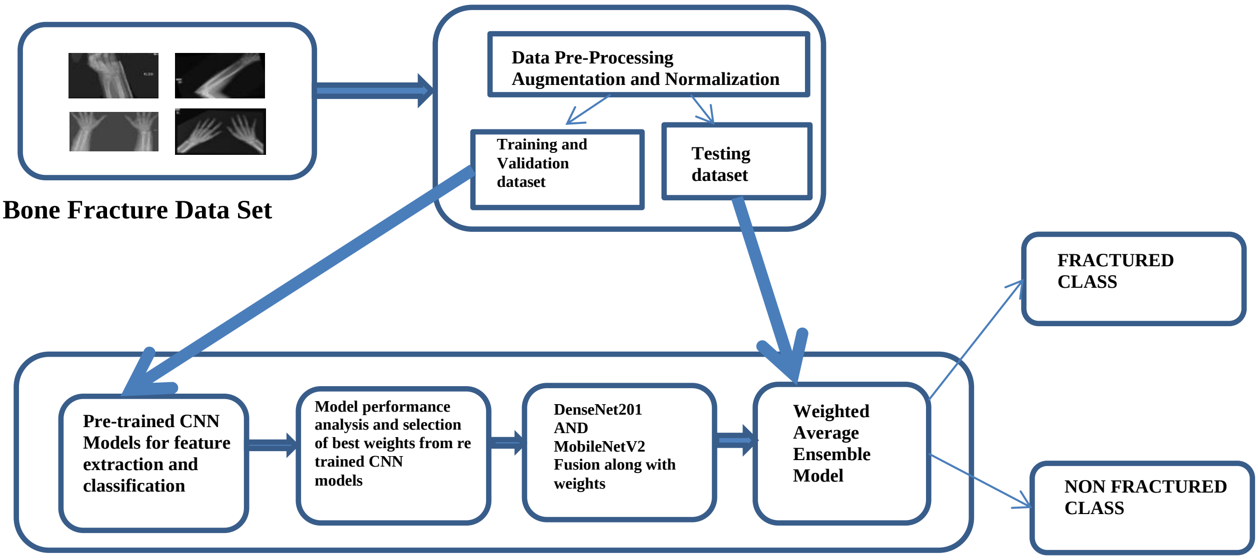


Figure 1. Block diagram of project flow

3.2 Weighted Ensemble Approach

In this study, a novel ensemble methodology was introduced in which the input data underwent parallel processing through select architectures - MobileNetV2 (M_m) and DenseNet201 (M_d) and the predicted outputs were amalgamated .The output value of the model was illustrated in Equation 7 where N represents the no.of models used for the ensemble. In the ensemble approach, a meticulously calibrated weighted average technique delineated in Equation 8 was used where W_m is the best possible added weight for MobileNetV2 and W_d for DenseNet201 respectively. The added weights (W_m & W_d) were chosen only after an iterative exploration of grid combination of different weight ratios to govern the influence of each model's contribution, favoring superior accuracy whereas M_m & M_d were the yielded individual predictions of the models in testing phase. M_m and M_d here refer to the difference between the true values and the predicted values of MobileNetV2 and DenseNet201 models respectively as elucidated in Equations 9 and 10. Throughout the individual model training and testing, a notable prevalence of false positives and false negatives was identified. Nevertheless, the ensemble approach effectively resolved these issues, showcasing its prowess in improving predictive accuracy.T he illustrated architecture diagram of the proposed system is depicted in Figure 2.

$$Ensemble\_output = \frac{1}{N}\sum_{i=1}^{N} Model_i\,(Input) \qquad (7)$$

$$Ensemble\_Preds = (W_m.M_m + W_d.M_d)/2 \qquad (8)$$

$$M_m = y_m - \widehat{y_m} \qquad (3)$$
$$M_d = y_d - \widehat{y_d} \qquad (4)$$

This technique served to mitigate the over fitting conundrum by introducing stochasticity during training, thus enhancing model generalization and robustness.

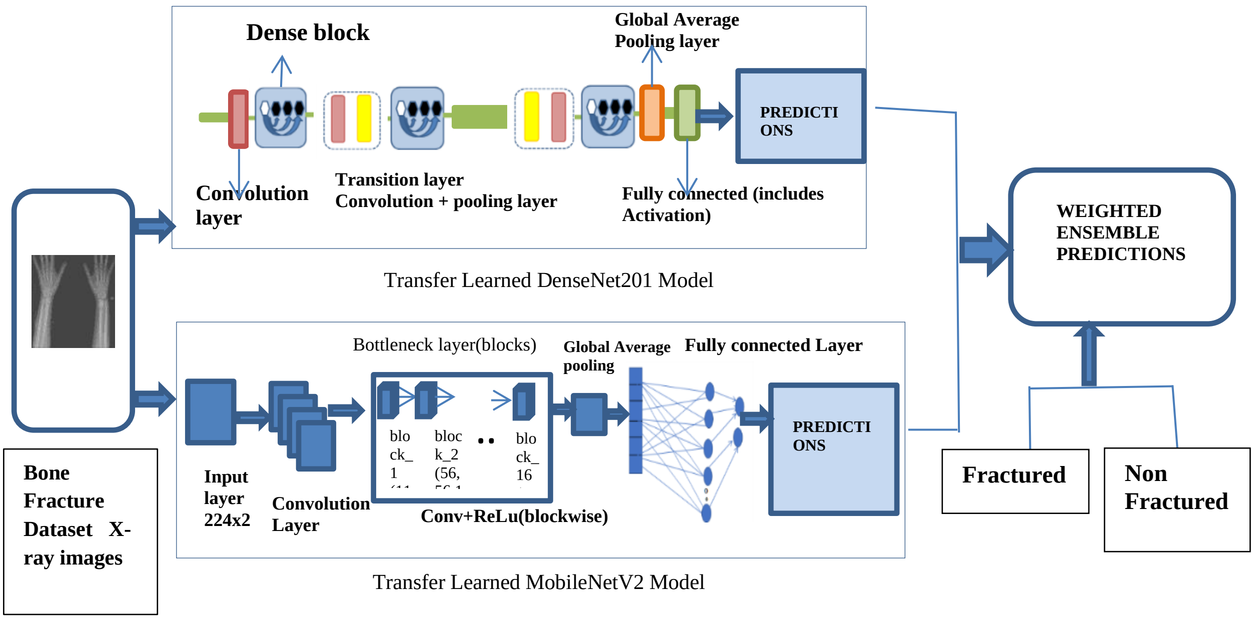


Figure 2. Illustrated architecture diagram of the proposed ensemble model

4. Dataset Description and Preprocessing

The fracture dataset of hands, wrist and fingers from Kaggle [32] consisted of 7096 X-ray images, comprising 3669 depicting fractures and 3442 representing non-fractures for training, with an additional 1772 image reserved for testing. Each image was tagged with either class 0 for non-fractured or class 1 for fractured during the training phase. The sample distribution of fracture dataset of images for training and testing phase were elucidated in Table 1. Upon model evaluation, random X-ray images, portraying either fractures or non-fractures, were submitted for prediction. The study was conducted using the Keras framework in the Colab Pro environment, leveraging a Tesla T4 GPU for computational processing. Employing Keras offered extensive support for deep learning tasks, featuring an intuitive interface and access to a rich library of pre-implemented neural network architectures and optimization techniques. Figure 3 showed the sample X-ray images from the opted fractured dataset in which (a) represented fractured X-ray and (b) represented non-fractured image of X-ray.

Table 1. Dataset description table

Class Label	**Total no.of images**	**Training samples**	**Testing samples**
Class 0 Non Fractured class	4382	3506	876
Class 1 Fractured class	4480	3584	896

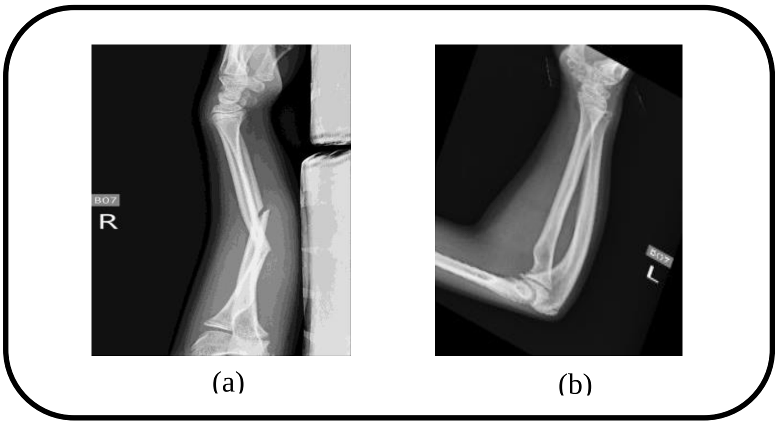
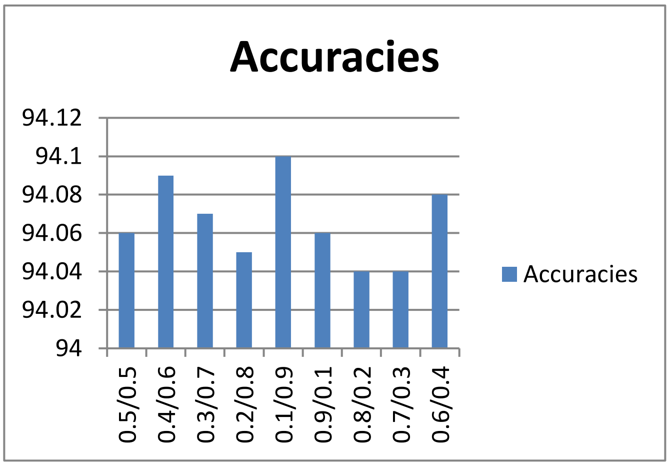


Figure 3. Sample images from X-ray dataset

5. Results and Discussion This section elaborates the outcomes derived from scrutinizing class wise results, incorporating labels, performance metrics from diverse models employed in training, and contrasting the findings with the weighted ensemble method. Figure 4 elucidated the performance trends cross diverse weight ratios, further illustrating the efficacy of the identified optimal combination. The synergistic fusion of DenseNet201 and MobileNetV2, with weights of 0.9 and 0.1 respectively, represents an optimal amalgamation. This approach harnesses the robust feature extraction capabilities of DenseNet201 while embracing the inherent computational efficiency of MobileNetV2. When juxtaposing the performance measures of the four CNN architectures with the proposed ensemble model, a discernible trend emerges: the ensemble model unequivocally surpasses its predecessors. The culmination of our research endeavors is encapsulated within Table 1, wherein the discerning metrics of training's accuracy, validation's accuracy, training's loss and validation's loss are meticulously documented alongside the cardinal parameters of trainable and total model parameters. Upon meticulous scrutiny, our proposed model emerges as the preeminent contender, boasting the loftiest testing accuracy amongst its peers and the ensemble counterpart. This unequivocally underscores the efficacy and supremacy of the proposed model in predictive performance over the gamut of models scrutinized in this study.

Figure 4. Weighted Ensemble Accuracy values for different weight ratios

Pursuant to Table 2, DenseNet201 exhibited superior training accuracy compared to the proposed model, albeit at the expense of higher loss. However, upon scrutinizing validation accuracies, the proposed model emerged as the frontrunner, achieving the highest values with minimal loss. InceptionV3, renowned for its complexity, demands substantial computational



resources during training, whereas ResNet152 encountered challenges due to its skip connection property, necessitating prolonged training durations.

Table 2. Deep comparative analysis of accuracies during training the models

Model	Tr_A	Tr_L	Val_A	Val_L	Prec	Rec	FS
ResNet152	0.84	0.34	0.83	0.41	0.67	0.98	0.79
InceptionV3	0.809	0.41	0.903	0.25	0.8	0.83	0.87

DenseNet201	0.96	0.12	0.92	0.23	0.91	0.91	0.92
MobileNetV2	0.93	0.21	0.93	0.2	0.9	0.9	0.93
Proposed Ensemble Model	**0.94**	**0.1**	**0.94**	**0.09**	**0.98**	**0.98**	**0.94**

Conversely, MobileNetV2's lightweight architecture and single-shot detection mechanism facilitated commendable performance. DenseNet201's prowess stems from its adept feature selection capability. Remarkably, the proposed model surpasses all pre- trained counterparts by a noteworthy 1% margin in validation accuracy while exhibiting a favorable parameter count.

Despite DenseNet201 exhibiting superior competence on the training set compared to the proposed model, it yielded a higher number of false positives, consequently leading to diminished specificity and sensitivity.

The analysis of class-wise metrics revealed that the judicious allocation of weights between model predictions and ensemble averages yields peak performance across all classes, epitomizing the efficacy of nuanced ensemble optimization. This underscored the indispensability of meticulous weight tuning in enhancing predictive efficacy, particularly in contexts marked by class disparities or heterogeneous class complexities. Table 3 delineated the parameters explained in Table 2. Furthermore, the proposed model underwent rigorous testing on numerous images, showcasing exemplary performance. Four select results from the test dataset are presented, featuring two images per designated class effectively discerned by the model in accordance with ground truth labels. Figure 5 delineated the categorized predicted outputs, aligning them with the corresponding ground truth categories.

Table 3. Parameters of Table 2

Parameter Abbreviation	Parameter Explained
Tr_A	Accuracy in training
Tr_L	Loss in training
Val_A	Accuracy in validation
Val_L	Loss in validation
Prec	Precision value of the model
Rec	Recall value of the model
FS	F1 Score of the model

A comparative analysis conducted against prior literature elucidates the limitations therein, highlighting the advancements achieved by the proposed model in Table 4.

Table 4. Analysis of previous literature for different bone fracture classifications

This table demonstrated the consummate performance of the proposed model, surpassing the constraints inherent in previous approaches. The apparent dissonance between DenseNet's commendable accuracy, as delineated in Table 2, and its lackluster specificity and sensitivity underscores the nuanced nature of its performance evaluation. While accuracy serves as a fundamental metric gauging overall correctness, it may obscure finer intricacies inherent in classification tasks. Specificity and sensitivity, encapsulating the model's aptitude in discerning true negatives and true positives respectively, offer critical insights into its discriminatory prowess. The incongruity between high accuracy and deficient

Literature	Method	Accuracy achieved
[17]	InceptionV3	0.93
[20]	MobileNetV2	0.92
[22]	Six pre trained algorithms were used in which InceptionResNetV2 got highest accuracy	0.89
[29]	Perception and DenseNet121(IDNet)	0.92
Proposed DenseNet	Transfer Learning of Pre trained DenseNet201	0.96
Proposed MobileNet	Transfer Learning of Pre trained MobileNetV2	0.93
Proposed Weighted Ensemble Method	Fusion of pre trained models DenseNet201 and MobileNetV2 with Fine tuning of weights	0.94

specificity/sensitivity implies potential shortcomings in correctly identifying certain classes or an elevated propensity for false positives/negatives. This necessitates a judicious balance of evaluation metrics to comprehensively appraise the model's efficacy, particularly in domains where precise classification holds paramount significance, such as medical diagnostics. Upon comparing the proposed model with prior literature, it becomes evident that the weighted ensemble average method, integrating two superior models within the proposed architecture, surpasses previous endeavors across various bone fracture datasets pertaining to distinct skeletal regions. Table 2 underscores that InceptionV3, owing to its intricacy, fails to deliver optimal performance, whereas InceptionResNetV2 architecture exhibits potential for enhancement to augment accuracy. Although MobileNetV2 offers lightweight architecture, instances of misclassifications are noted, while DenseNet121 exhibits suboptimal performance in isolation. Consequently, the proposed fused weighted ensemble average model emerges as the premier choice for bone fracture classification in hands, wrists, and fingers, as evidenced by the trained dataset.

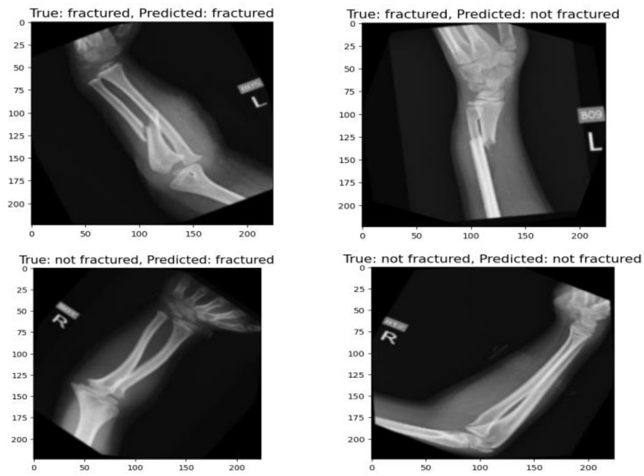


Figure 5. Prediction of test images by proposed ensemble model

6. Conclusion and Future work

The proposed model has showcased superior efficacy in the realm of bone fracture classification, achieved through the amalgamation of MobileNetV2 and DenseNet201 models. This fusion, coupled with weighted averaging, strategically capitalizes on the strengths of each model while alleviating innate constraints and provides invaluable perspectives on the potential advantages of employing an ensemble approach with weights to bolster accuracy and reduce false positives in bone fracture classification. A primary constraint of this study lies in the heightened parameter utilization compared to amalgamated models. It is recommended that forthcoming investigations explore alternative methodologies for parameter reduction without giving up on efficacies. This system can be enhanced with optimistic features which can make it identify multiple fractures and it can be embedded into mobile devices as an android application which makes this “bone fracture detection” system highly available and accessible by more no.of medical practioners.

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