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Wrist Bone Fracture Classification using Least Entropy Combiner for Ensemble Learning

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Abstract

The human body comprises 206 bones of varying sizes, shapes, complexities, and biological characteristics. This research presents a novel approach for wrist bone fracture detection, utilizing a custom Convolutional Neural Network (CNN) in conjunction with pre-trained networks to form an ensemble learning model enhanced by the Least Entropy Combiner (LEC) method. Bones are composed of four types of cells osteoblasts, osteocytes, osteoclasts, and bone lining cells that play crucial roles in the healing process following a fracture. Upon fracturing, a hard callus forms to bridge the gap and initiate healing. Artificial Intelligence (AI) and Machine Learning (ML) are revolutionizing medical imaging by assisting physicians in diagnosing diseases and developing optimal treatment plans, significantly benefiting the healthcare industry. Bone fractures can result from accidents, natural conditions, aging, and other factors. Automated fracture detection accelerates the diagnostic process, reducing the risk of misdiagnosis and improving outcomes. Our custom CNN model achieves 70% accuracy, while the LEC-enhanced ensemble model attains an impressive 97% accuracy, demonstrating substantial advancements in fracture detection accuracy.

Keywords: Wrist X-ray, custom CNN, Ensemble Learning, Bone Fracture Detection, Transfer Learning, Least Entropy Combiner, Neural Networks

1. Introduction

The human skeletal system plays a crucial role in day-to-day life while working with regular tasks and activities. Detecting bone fractures using the naked eye is an error-prone and time-consuming task. In big health organizations like hospitals and colleges, the diagnosis process will be difficult if we consider the number of end users. As a solution to this critical challenge, the development of an automated system for diagnosing bone fractures has been developed already and it has remarkable results in real time. Fractures can happen in any bone within the human body [1], including the wrist, hip, heel, ankle, ribs, legs, chest, shoulders, and more. Digital imaging is a field where a different form of images like X-ray images, CT images, mammograms, angiograms, and MRI is used to find solutions to medical problems and conditions. Mostly fractured images are in the form of X-rays and CT images and it called Radiographs. X-Ray is an old technology that is used today for capturing radiographs from a human body [2]. Sometimes, an artificial part is present in the bone as a replacement or as a support to a bone as a part of treatment, this part is known as a prosthetic. This prosthetic can be of any material like metal, fiber, polymer, glass, or ceramics. The wrong position of the prosthetic in the bone may lead to another fracture, poison in the body, or serious trauma. To ensure the correct position of the prosthetic, the system needs wrist radiographs [3] images for further medical evaluation. The next important step is radiograph interpretation to classify the image in fractured and non-fractured type and this is done using peer review support.

Traditional machine learning techniques are a common approach to diagnosing fractures which include pre-processing, feature extraction, and classification. Recent years have shown remarkable growth in machine learning algorithms and its application. Several noise removal techniques are available to handle the noise present in the image. The next stage is to extract features or properties from the image and use it as an input for the next step which is classification. Earlier studies focused on detecting a fracture region where a fracture line is observed.

2. Related Work

The body of research encompasses a range of significant studies that enhance the identification of bone fractures through various techniques and algorithms. The existing models used for the studies use open-source image datasets collected from various sources of devices. One of the open-source datasets is MURA first introduced in the Open-review platform announced at the conference held in Amsterdam in 2018 [4]. MURA is the largest public radiographic image dataset and it contains 40,561 total X-ray images which consist of fractures of different parts of the body including shoulder, wrist, elbow, finger, forearm, hand, and humerus. In this research study conducted by Rajpurkar et al. Using DenseNet169, the AUC score was 0.929 and Cohen's Kappa score was 0.705 [5]. In the classification carried out by Harini et al., the highest accuracy achieved was 56.30% for wrist image data with DenseNet169 [6]. Shao and Wang developed a two-staged system and the highest accuracy achieved on humerus bone images with Densenet201 was 90.94% [7]. ResNet18 and GoogLeNet pre-trained networks were used by Story et al. To detect wrist bone fractures [8]. In the classification study carried out by Fatih et al., an ensemble approach was used on shoulder X-ray images and

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experimented with different 26 ensemble models along with 2 different ensemble models which enhanced the overall accuracy of 84.55% and 84.72% [9]. Similarly, In [10] the authors identify fractures from shoulder X-ray images with NasNet trained on well known imageNet model and the highest accuracy achieved was 80.4%. Abu Mohammed Raisuddin et al [11] developed a neural network model for the detection of distal radius wrist fractures, in line with contemporary advancements in deep learning and medical imaging analysis. The approach underwent benchmarking against recent methodologies in wrist fracture detection to evaluate its effectiveness and potential advantages [12]. This comparative evaluation contributes to the advancement of fracture detection techniques, ultimately enhancing diagnostic accuracy and patient care in clinical practice. As a result of the classification made by Rajesh et al., the highest accuracy obtained was 85% with the help of Meta classifier consisting of a decision tree random forest and neural network [13]. A 90% accuracy was achieved along with 91.67% precision with the proposed method and classification performed by R. Kapse on the Kaggle dataset [14]. The bone fracture detection process performed by E Susmitha et al. With machine learning based on GLCM [15-16] achieved 85% classification accuracy [17]. A GUI-based application was developed by Siva S. et al. which uses discrete wavelet transformation as a segmentation method used with spatial fuzzy C- means method gives the highest accuracy of 78% after applying pre-processing techniques such as canny edge detection [18]. A comprehensive study of different bones and bone fractures is done using MATLAB [19] and using different operations like dilation, erosion, and histogram the clarity and quality of images are being improved [20-21]. The 84.7% accuracy was achieved in the study conducted by A. M. Tripathi et al. on femur bone images, and these images are pre-processed with noise removal (median and average filter), Logarithmic operator [22], and Sobel edge detection technique. One study performed fracture detection on Ankle [23] radiographs using an ensemble model which consists of five CNN models giving 76% test accuracy which is more compared to this research conducted on wrist radiographs. Anupama bhan et al. conducted a study [24] on Osteoporosis Detection with the help of pre-trained CNN models and an ensemble of those three base models gives 91.3% training accuracy and 87.1% test accuracy. A study conducted on the chest and abdomen used ensemble techniques like voting with CNN and outperformed with 96.97% on abdomen scans [30]. Sachin et al. [25] conducted research on the wrist radiograph dataset from Kaggle and used the SimCLR approach of transfer learning and achieved 94.10% accuracy which is less as compared to the proposed model in this research. The ensemble model proposed in the research [26] consists of YOLO and EfficientNet-B3 achieving 81% highest accuracy as compared to another ensemble model. Transfer learning is also being used in wrist fracture prediction and obtains 98.45% accuracy with the help of ResNet101 [27] which is the highest compared to other approaches. A more recent study [28] uses a deep convolutional neural network to enhance the fracture diagnosing process in X-ray images captured from different parts of the body.

The most common types of fractures include oblique fracture, transverse fracture, stress fracture (hairline fracture), and metacarpal fracture (Wrist fracture) are challenging to diagnose correctly because of their visibility on the bone on an X-ray radiograph. Considering MURA there are different datasets available publicly but the reason behind using the MURA dataset for this research is it has a balanced number of both fractured (abnormal) and non-fractured (normal) sample images. In this study, only wrist bone X-ray images are used for the classification of fractures. MURA has 7 different types of bone fractures and out of these types reason behind choosing a single type which is the wrist dataset is to develop a stable model for the detection of this type of fracture using different deep-learning models and approaches associated with it.

Based on recent studies [29-36] it is observed that images obtained from different sources like CT, MRI, and X-ray devices are classified by traditional machine learning such as NB, SVM, and random forest as well as deep learning techniques such as ResNet or DenseNet. In this literature, the classification of wrist bone X-ray images was performed on both fractured and non-fractured images from the MURA dataset. Also, custom CNN is developed and experimented with different numbers of layers, number of filters, number of filter sizes, activation function, and optimizer. The main reason for building a custom CNN approach and transfer learning on built CNN models followed by ensemble learning is to contribute to the performance of deep learning models proposed in the classification of wrist bone X-ray images. In this study, different approaches from baseline CNN traditional models to the state-of-the-art method studied to enhance the model performance.

3. Proposed Method

The proposed method aims to enhance Wrist Bone Fracture Detection by introducing a novel approach that leverages the ensemble model in conjunction with the Least Entropy Combiner approach. Also, a custom CNN is developed to check the performance of custom CNN with layers, filters, and other hyperparameters on the MURA wrist image dataset. This literature focuses on two different models:

3.1 Custom CNN

Recent studies have already proven that pre-trained network performs well on MURA datasets or any publicly available image dataset. Studies demonstrated that hyper tune of feasible parameters results in better accuracy but the concern is its difficult to tune all the hyper-parameters from pre-trained deep learning models such as DenseNet, ResNet, MobileNet, etc. In the below custom CNN model, there are 5 convolutional layers, 5 max-pooling layers followed by 4 fully connected layers. Also, it comprises batch normalization, L2 regularization, and dropout layers in between to enhance the overall performance of the proposed CNN model.

3.1.1 Convolution Layer

This is the core of CNN and it extracts the feature by applying different filters to the input image and the model learns the filters using techniques like backpropagation and gradient descent.

3.1.2 MaxPooling Layer

Pooling is a downsampling method that takes a maximum value from the window precisely called a kernel.

3.1.3 FC layer

Fully connected layer where each neuron is associated with some weight and each neuron is connected to every neuron in the next FC layer.

3.1.4 Batch Normalization
During backpropagation, the internal parameters get updated automatically and this leads to a slow training process and requires a lower learning rate. To overcome this situation batch normalization is required. Also, it makes the training process fast and stable.

3.1.5 L2-Regularization
This is known as Ridge regularization. It introduces a penalty term to the model's cost function. This helps to reduce overfitting and evenly distributes the weights across all features.

3.1.6 DropOut Layer
It is a technique to prevent overfitting where some neurons are randomly dropped or deactivated during the training process.

Below Figure 1 represents the architecture of proposed custom CNN and it's respective layers along with input and output.

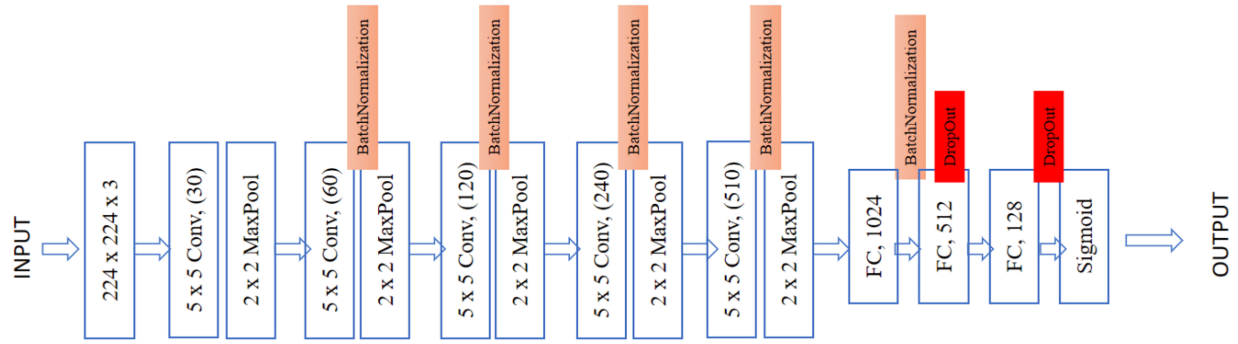

Fig. 1. Custom CNN Architecture

3.2 LEC Approach for Ensemble Learning
LEC model stands for Least Entropy Combiner and it is used in combination with ensemble models of different DNNs [7]. The proposed ensemble learning approach comprises of two DNN models known as DenseNet121 and MobileNetV2 and a custom CNN architecture as explained in section 3.1. The training of the proposed model is conducted in two different phases.

3.2.1 Ensemble Model
In the first phase, each model including custom CNN is trained independently on the training dataset, and their individual scores are obtained. These individual confidence scores are then concatenated and passed to the LEC model for the calculation of entropy and weights.

3.2.2 LEC Approach
The LEC model aims to minimize the entropy of concatenated output by updating the weights of the LEC layer during the training process. The generalized formulae to calculate entropy are:

$$H(S) = -\text{sum}\ (p(i) * \log_2(p(i)))$$

where,

p_i is simply the probability of class i in the data,
H(S) is the entropy of a given class

Entropy is calculated for a set of combined predictions and optimization algorithms like gradient descent, Adam is used for the same. A Fully connected layer helps to learn complex patterns from combined features extracted by the previous layer. ReLu activation function is used to add non-linearity into the model. The final output or prediction is with minimum entropy value which indicates higher confidence in the respective class.

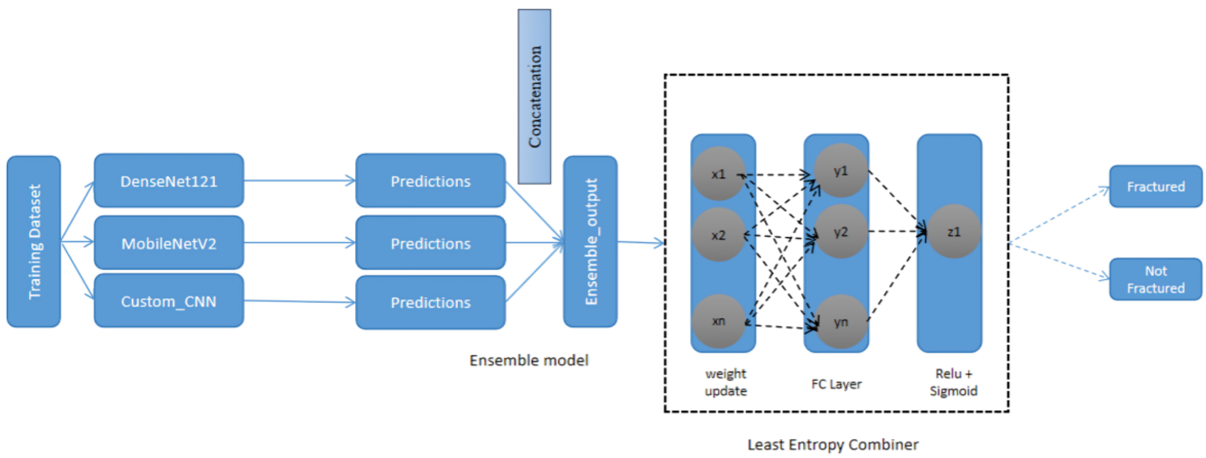

Fig. 2. LEC approach for ensemble learning

Figure 2 gives an overview of the proposed LEC model and how it predicts the final class. Below is a detailed explanation of the same is given:

3.2.2.1 Training Dataset
The training dataset has a set of X-ray images and provides it as input to the base models. For dataset details please refer a section 4.

3.2.2.2 Base Models: Base
Models like DenseNet, MobileNet, and Custom CNN are needed for a meta-model and those base models were trained independently on the same training dataset and generated output for each base classifier.

3.2.2.3 Ensemble Model
This ensemble model is called a Blender which is nothing but a simpler CNN architecture that takes the concatenated output of base learners and trains the model by treating this output as a feature vector.

3.2.2.4 LEC Model
The weights are updated such that the entropy cost of the classification is reduced. The predictions generated by the ensemble model need weights to be assigned, so for that purpose entropy is calculated and class scores are weighted and combined using the below function:

$$x = \sum_{i=1}^{N=3} a_i W_i \tag{1}$$

where,
a = scores obtained from each individual model,
w = weights are determined according to their individual performance

Next, the combined softmax scores x are fed into a dense layer resulting in a vector y which is then finally given to a ReLU activation followed by a sigmoid layer resulting in the class confidence score z is given by Equation (2)

$$z(i) = \frac{exp(y(i))}{\sum_i exp(y(i))} \tag{2}$$

Further, the LEC model weights are updated using the Adam optimizer which minimizes the entropy loss given as

$$loss(z, \bar{z}) = -\sum_{i=1}^{C} z(i) log(z(i)) \tag{3}$$

where,

$\bar{z}$ is the class probability,
$\bar{z}(i) = 1$ indicates that the particular example belongs to the fractured class and 0 to the non-fractured class.

Thus, the proposed combiner minimizes the entropy loss with the help of Equation (3) and that is the reason it is called as least entropy combiner. Ensemble models take advantage of each base model and enhance the performance. Taking one step further LEC approach updates weights according to calculated entropy after training each base classifier separately, to give importance to the specific model that outperforms the rest. Thus, the performance of the LEC approach performs better as compared to other ensemble approaches.

4. Results and Discussions

The MURA dataset [35] used for this research is an open-source radiographic image dataset that contains 40,561 X-ray images for different types of fracture. The musculoskeletal radiographs(MURA) images were collected by conducting studies on 12,173 patients. It has a total 40561 number of images categorized into 7 types of fractured and non-fractured images which include forearm, shoulder, finger, hand, humerus, elbow, and wrist. The wrist dataset has 9756 images in the training dataset and 1198 images in the validation dataset. All the images have different sizes and the dataset is well organized. These images are divided into two classes as Positive (Fractured) and Negative (Not Fractured).

Table 1. Dataset Details:

Dataset	Fractured	Not-Fractured	Total
Training Images	3987	5769	9756
Testing Images	661	537	1198

In table 1, the details about the wrist dataset are given and the same set of images is used for the research. The wrist dataset has more radiograph images as compared to other body parts.

Pre-processing is the key step to enhance the quality of raw input images. Original input images have some sort of noise present in the X-ray.

A Custom CNN has been created after performing many trials and errors, and it has 70% training accuracy and 61 % validation accuracy which is comparatively much less than pre-trained models. Fig. 3 shows the gradual improvement in model accuracy over the number of epochs.

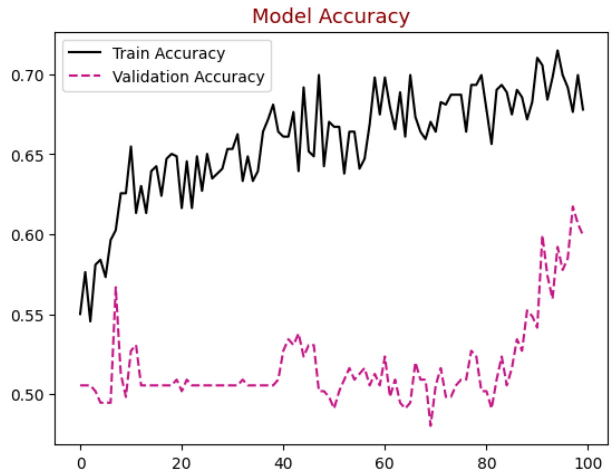

Fig. 3. Custom CNN Accuracy vs Epochs

The performance of the model is evaluated with different methods. The loss estimates the error produced by the CNN model. A higher loss value represents the erroneous model. The purpose of plotting the training loss and validation loss on a graph is to analyze the model's behavior and which aspect needs a tunning to stabilize it.

The combined features are explored with an ensemble approach, DenseNet121, MobileNet, and Custom CNN were employed as a base estimator and the individual confidence score of the individual model is password as an input feature to the LEC model and then the final prediction is generated.

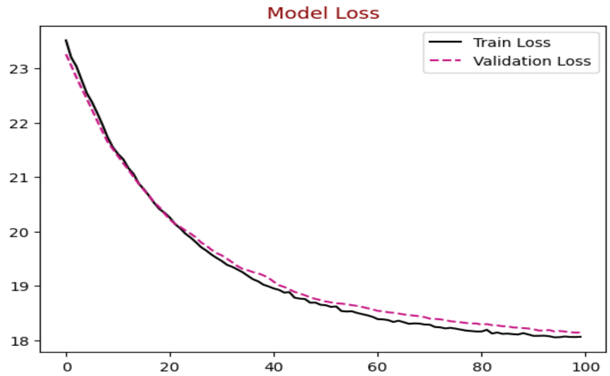

Fig. 4. Custom CNN Loss vs Epochs

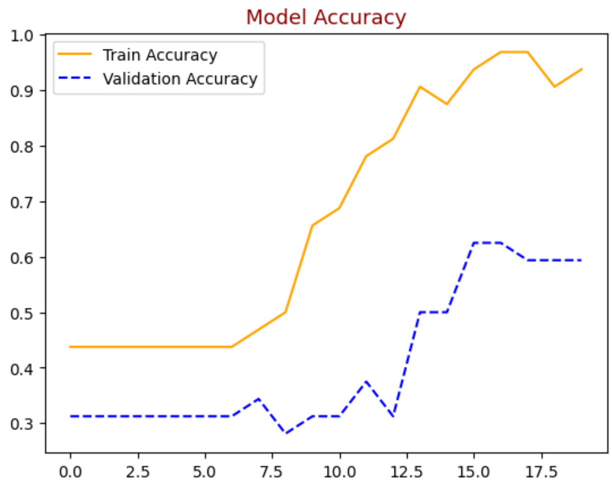

Fig. 5. LEC model Accuracy vs Epochs

Fig 5 and 6. shows the significant improvement in training performance over the number of epochs.

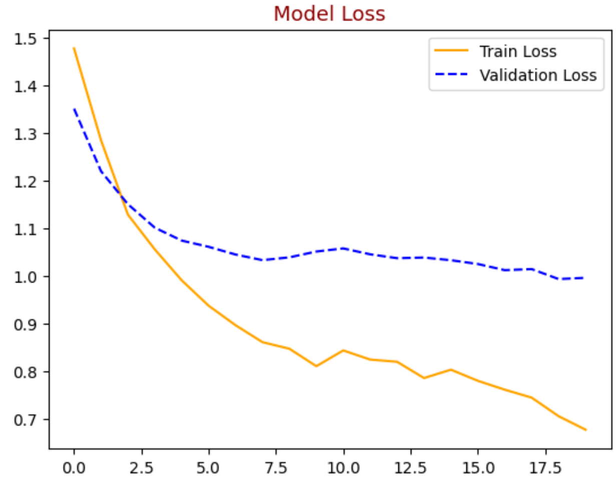

Fig. 6. LEC model Loss vs Epochs

The ensemble approach aims to take the benefit of individual classifiers to achieve a better performance in terms of accuracy. The experiments done with custom CNN do not give better accuracy than pre-trained models but the proposed LEC method which works with ensemble learning achieves a remarkable accuracy of 97%. This performance improvement over individual classifiers highlights the effectiveness of the LEC approach for ensemble learning and mitigating the limitations associated with individual classifiers.

Table 2. Comparative analysis of the proposed method with the relevant existing methods

References	Technique	Dataset Used	Accuracy (%)
Yang et al. [18]	AlexNet, PCA, SVM, Rand om Forest	MURA dataset (Shoulder, forearm, finger, humerus, elbo w, hand and wrist)	78.04
Urban et al. [23]	NasNet	MURA shoulder implants, 597 X-ray images	80.4
Yadav D. P. et al. [22]	Hybrid SFNet	The Diagnostic Imaging Dataset (DID)	99.12
Kosrat et al. [24]	SVM	270 X-ray images	92.85
Anupama Bhan et al. [34]	Resnet-50, MobileNetV2, ResNeXt-50, Ensemble	MURA wrist dataset	91.3
Jeong et al. [36]	Deep learning	CT images	100% sensitivity and 77% specificity
Li-Wei Cheng et al. [35]	ResUNet, YOLOv4	X-ray images	94
Proposed Me thod	Custom CNN	MURA wrist X-ray images	70
Proposed Me thod	Least Entropy Combiner	MURA wrist X-ray images	97

The integration of medical images with state-of-the-art deep learning techniques has shown promising results in performance and fracture diagnosis. The proposed LEC model contributes to the collective study of how deep learning techniques can further enhance bone fracture diagnosis, ultimately improving patient care and outcomes. State-of-the-art displays with 94% accuracy were achieved which enhanced the performance of the model. The LEC approach is an advancement in the deep learning approach and it has 97% highest accuracy. It improves the learning capability of the proposed CNN architecture by calculating entropy and weight updates within a network.

The computational Complexity of the CNN model is calculated in terms of FLOPs (Floating Point Operations) required by a model to perform an overall computations. Table 3 gives an oversight on the computational complexity of different CNN models implied in current research:

Table 3. Comparative Analysis of Computational Complexity

Sr. No.	CNN Approach	FLOPs
1	MobileNetV2	613382337
2	Custom CNN	3121052033
3	DenseNet121	5700422209
4	Stacking Model	7405514161
5	LEC Model	9387517004

From the above observations, it proves that as the model gets more complex architecture then it has a higher number of FLOPs and it leads to higher computational complexity. The LEC model has a more complex architecture in terms of several total parameters so it has 9.39 billion FLOPs.

The LEC model has a 2 minutes of execution time on GPU and 16 minutes on CPU as the base models are trained independently and saved to pass the output of it as an input to the LEC model. It uses a T4 Google Colab GPU which runs more quickly as compared to traditional CPU. As GPU is expensive in cost as compared to CPU, so this will not be the best fit for real-time applications where speed is a critical factor from request response time perspective.

5. Conclusion and Future Work

The proposed work involves customizing a CNN model by tuning various hyperparameters and evaluating its performance. An LEC approach for ensemble learning is employed to enhance the overall performance of the proposed model. While tuning different hyperparameters and exploring various factors can potentially improve the CNN model's performance, the custom CNN in this study achieved an accuracy of 70%, which is lower than that of individual pre-trained CNN models. For the MURA wrist image dataset, DenseNet121 achieved an accuracy of 87%, and MobileNet reached 84%, both outperforming other pre-trained models. An ensemble model built from individual base classifiers achieved a training accuracy of 93% on the same dataset. By incorporating the LEC model with the ensemble, the proposed method demonstrated a significant improvement in accuracy, reaching an impressive 97%.

In summary, this work provides valuable insights into the application of custom CNNs and the LEC approach for ensemble learning in wrist bone fracture detection. An open-source, web-based tool could be developed to detect fractures in real-time by marking the fracture regions on provided X-ray images, which would greatly assist physicians in large hospitals and emergency services. Additionally, incorporating bone scintigraphy images, which provide clearer fracture visuals, could further enhance research outcomes. Future work could integrate various types of medical data, such as clinical notes, disease registries, health surveys, and clinical trial data, to expand the scope of research. Larger and more diverse datasets would allow for a more comprehensive investigation of different ensemble strategies and CNN approaches. Furthermore, incorporating Explainable AI (XAI) techniques would improve feature extraction and the interpretability of the proposed model, making it more accessible and trustworthy for clinical use.

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