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Transfer Learning Empowered Bone Fracture Detection

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ABSTRACT

Detection of bone fractures using modern technology has significant implications in medical analysis and artificial intelligence. This importance is especially pronounced in the realm of deep learning. Deep learning techniques find extensive application in the field of medicine and disease classification. The early identification of bone fractures is crucial for efficient treatment planning and patient care. Our research proposes a transfer learning-based model for predicting bone fractures using a dataset of bone X-ray images. These images will be classified into two categories: normal and bone fracture, based on extracted features. Our proposed model, the Bone Fracture Detection Transfer Learning Algorithm (BFDTLA), achieved an average accuracy of 97% on the dataset. The BFDTLA model demonstrated superior performance when compared to previous quantitative and qualitative research studies. This research focuses on the early detection of bone fractures using transfer learning algorithms, emphasizing the significance of accurate and timely diagnosis.

1. Introduction

Bone diseases and disorders encompass a broad spectrum of medical conditions that impact the structural integrity and overall health of the skeletal system. These conditions range from common issues such as fractures and osteoporosis to more rare and complex diseases like osteosarcoma and Paget's disease. Early and accurate detection of bone diseases is paramount for effective clinical intervention, treatment planning, and patient management. In recent years, there has been a growing interest in leveraging advanced machine learning techniques, particularly transfer learning, to enhance the accuracy and efficiency of bone disease detection. The human skeleton serves as the foundational framework for our bodies, providing support, protection, and mobility. Any disruption or ailment within this intricate system can have profound consequences for an individual's quality of life. Bone fractures, for instance, are among the most common injuries encountered in clinical

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practice. Timely diagnosis and appropriate management are essential to facilitate the healing process and minimize complications. On the other hand, chronic conditions like osteoporosis, characterized by the weakening of bones, can lead to an increased risk of fractures and pose significant challenges to the affected individuals. Moreover, rare bone diseases, although less prevalent, can be devastating and often require specialized expertise for accurate diagnosis and treatment. Traditional diagnostic methods for bone diseases involve clinical evaluation, medical imaging, and laboratory tests. X-ray imaging, in particular, has been a cornerstone in bone disease diagnosis due to its non-invasive nature and the ability to visualize bone structures. However, interpreting X-ray images, especially in cases of complex or subtle bone diseases, can be challenging and relies heavily on the expertise of radiologists.

The advent of deep learning, a subset of machine learning, has revolutionized the field of medical image analysis. Convolutional neural networks (CNNs), a type of deep learning architecture, have demonstrated remarkable success in various image recognition tasks, including medical image analysis. Transfer learning, a technique within deep learning, enables models to leverage pre-trained knowledge from large datasets, typically unrelated to the specific task at hand, and adapt it to new, domain-specific tasks with relatively small datasets. This capability has opened up exciting opportunities for improving the accuracy and efficiency of bone disease detection.

This research paper explores the application of transfer learning and deep learning techniques in the realm of bone disease detection. We aim to investigate how transfer learning can be effectively employed to enhance the accuracy of bone disease classification using X-ray images. The paper will delve into the existing literature on bone disease detection, highlighting the challenges and opportunities in this field. It will also present the methodology and architecture design of our bone disease detection model based on transfer learning principles. Furthermore, the paper will discuss the dataset used in our research and present the performance evaluation of the proposed Bone Disease Detection Transfer Learning Algorithm (BDDTLA). Finally, we will consider potential avenues for further research and the broader implications of applying transfer learning to bone disease detection in clinical practice.

The subsequent sections of this paper follow a structured framework. In the second section, we delve into an exploration of prior work related to the detection of bone fractures, focusing on the utilization of machine learning and deep learning techniques. Moving forward to the third section, we examine the components and the design architecture. The fourth section is dedicated to a comprehensive discussion of the research dataset and the evaluation of performance.

2. Related Works

The detection of bone fractures is crucial for medical diagnosis and patient care, with recent advancements driven by developments in medical imaging and machine learning [1]. Meena & Roy [2] introduced a significant shift in bone fracture detection using deep supervised learning from radiological images, highlighting the potential of deep learning models for automating the detection process. Yadav et al. [3] presented a hybrid SFNet model, combining machine learning and deep learning, showcasing the effectiveness of hybrid approaches in improving detection accuracy. Samothai et al. [4] explored the use of you only look once (YOLO) series models for real-time detection in clinical applications. Santos et al. [5] took an innovative approach by investigating bone fracture detection using microwave imaging. In the context of artificial intelligence, AlGhaithi & al Maskari [6] discussed the application of AI in bone fracture detection, emphasizing its potential to enhance diagnostic precision. Yadav & Rathor [7] focused on deep learning approaches for bone fracture detection and classification, illustrating the role of deep learning in medical image analysis.

Basha et al. [8] proposed an enhanced computer-aided technique employing the Harris Corner technique, highlighting the significance of feature extraction in fracture detection. Sahin [9] explored image processing and machine learning-based detection using X-ray images. Ma and Luo introduced a two-stage system of Crack-Sensitive CNN for fracture detection, emphasizing the advantages of multi-stage models [10]. Abbas et al. [11] used Faster RCNN for lower leg bone fracture detection, showcasing the utility of object detection methods. Zhang et al. [12] introduced a new window loss function for fracture detection and localization, enhancing localization accuracy. Boger et al. [13] explored induced acoustic resonance for noninvasive fracture detection, introducing a unique non-imaging technique.

Rao et al. [14]employed bag-of-visual-words with SIFT-based feature extraction, emphasizing feature engineering's role in accurate detection. Yang & Cheng [15] proposed an artificial neural network-based approach for long-bone fracture detection, showcasing the power of neural networks in medical image analysis. Basha et al. [16] presented an effective computer-automated technique, underscoring the potential of automation in clinical settings. Sinthura et al. [17] developed a bone fracture detection system using CNN algorithms, contributing to the development of deep learning-based diagnostic tools. Thinzar & Myint [18] implemented a lower leg bone fracture detection system from X-ray images, demonstrating practical applications in diagnosing specific fracture types.

These studies collectively illustrate diverse methodologies and techniques, highlighting the promising role of innovative imaging approaches in enhancing diagnostic accuracy and patient outcomes as technology continues to advance. The adoption of transfer learning emerges as a promising strategy to enhance the precision and effectiveness of fracture detection techniques relying on X-rays, as highlighted in the aforementioned studies. This approach places a critical emphasis on precise image segmentation as a means to isolate and accurately identify fracture regions. The use of morphological gradient techniques, known for their ability to enhance edge information in images, holds the potential to aid in fracture localization.

These investigations collectively portray the ever-evolving landscape of bone fracture detection. Researchers actively explore a broad range of methodologies, encompassing image processing, geometric analysis, and the integration of intelligent systems. This diverse array of approaches contributes to the continual improvement of fracture diagnosis accuracy and efficiency, showcasing the dynamic and promising nature of this field. Conclusively, the adoption of transfer learning emerges as a promising strategy to enhance the precision and effectiveness of fracture detection techniques relying on X-rays. The aforementioned studies highlight the efficacy of transfer learning in refining pre-existing CNN models, elevating their performance in fracture detection tasks. Future research endeavors should delve into exploring the potential of transfer learning across various modalities and expanding its application to real-world clinical settings.

2.1 Limitations and Contributions

The examination of bone fractures through CT X-rays has undergone a thorough investigation. Earlier approaches exhibit the following limitations:

i. The majority of studies on pneumonia utilize conventional CNNs.
ii. The dataset is characterized by a restricted number of classes, providing insufficient images for comprehensive analysis.
iii. The accuracy of the trained models in previous studies is inferior to ours, accompanied by a high loss rate.

The main contributions towards solving those limitations include:

i. Creating a comparative analysis with previously known research to improve the prediction system.
ii. Increased precision and accuracy.
iii. Keeping the threshold criteria high.

3. Materials and Methods

Deep learning and machine learning have catalyzed a transformative wave in the field of medicine and medical diagnostics. The computational prowess of modern high-capability graphics cards enables the rapid training and testing of substantial datasets. Artificial intelligence has found application in various domains, spanning fraud detection, image prediction, and object classification. These technologies empower the analysis and classification of copious amounts of data based on distinctive features. Early detection of bone fractures stands as a crucial endeavor for medical practitioners, aiming to mitigate delays in diagnosis and expedite tailored treatment plans for individual patients [19]. While multiple algorithms have been deployed for quantitative data analysis, much of the existing research in the medical domain pertains to machine learning [20]. The adoption of deep learning remains limited in various medical applications due to the considerable resource demands associated with graphics processing units (GPUs). In the context of bone fracture detection, the primary source of information for feature extraction resides in image datasets, particularly Chest X-ray-based images.

Our approach involves the utilization of a modified version of AlexNet, CNN renowned for its image feature extraction capabilities. AlexNet comes pre-trained with a wealth of knowledge from diverse image datasets, and this prior knowledge is leveraged during training with new images from our dataset. The motivation behind this research endeavor is to develop an efficient system that can ultimately transition into an application-level solution with real-world implementation. The architectural representation of the application-level system is depicted in Figure 1.

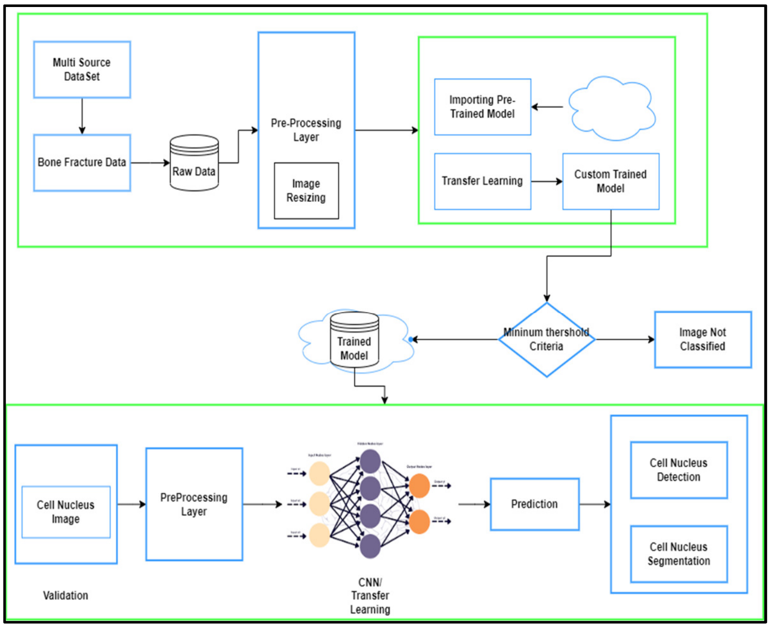

Fig. 1. Diagram of the proposed PDTLA model

The devised system model for bone fracture detection (BFDTLA) consists of two fundamental layers: the pre-processing layer and the application layer. The pre-trained AlexNet model, utilized for image classification, is a key component in the adaptation of the second layer.

For the bone fracture detection task, we sourced our dataset from the Kaggle repository, initially in raw format. In the pre-processing layer, we standardized the dataset images to a consistent size of 227 x 227 x 1 pixel to ensure uniform dimensions across all images. Following this, the pre-trained AlexNet model was incorporated into the second layer and fine-tuned to meet the specifications of our binary classification problem, distinguishing between normal bone conditions and those indicative of fractures (Figure 2).

Fig. 2. Chest X-ray samples representing normal and fractures

Data analysis and predictive modeling utilize a range of algorithms to uncover valuable insights and make quantitative predictions. In the context of predictions derived from images and videos, sophisticated techniques, including feature map extraction, focal loss, and intersection over union (IoU) loss, are employed to enhance the accuracy and effectiveness of the models. There exists a plethora of methods tailored to image and video detection tasks, and in today's era, image and video-based predictions are integral. This marks the juncture where deep learning asserts its utility, particularly in the domain of biomedical disease-based classification. Notably, pre-trained models such as YOLOv4, AlexNet, and ResNet have gained prominence in transfer learning applications for novel problems. A pre-trained model's familiarity with the foundational principles of object classification equips it to swiftly and efficiently perform detections.

3.1 Preprocessing

The steps included in preprocessing are:

i. *Conversion to grayscale* – Bone X-ray images are conventionally captured in grayscale due to the nature of the information being conveyed. Converting these images to grayscale simplifies the analysis process and reduces computational complexity while preserving the crucial structural details.
ii. *Resizing* –Bone X-ray images may exhibit varying dimensions depending on the imaging equipment and settings used. To ensure uniformity and compatibility with the analysis, it is essential to resize these images to a standard size. This standardization simplifies the subsequent processing steps.
iii. *Intensity normalization* – Adjusting the pixel intensities of bone X-ray images can enhance the visibility of relevant details and improve contrast. This normalization process ensures

that critical bone structures and potential fractures are more readily discernible by the algorithms.

iv. *Denoising* – Like chest X-rays, bone X-ray images can also suffer from noise, which may obscure vital information. Applying denoising techniques to bone X-ray images helps eliminate or reduce this noise, ensuring that the algorithms can accurately identify fractures and other abnormalities.

v. *Segmentation* – In bone fracture detection, the focus is primarily on the bones themselves. To isolate and highlight the bone structures from the surrounding tissues and background, a segmentation step can be employed. This segmentation aids in pinpointing potential fractures with greater precision.

vi. *Data augmentation* – To augment the dataset and account for variations in the positioning, orientation, and scale of bone X-ray images, data augmentation techniques are invaluable. These techniques, such as rotation, flipping, scaling, and translation, help diversify the dataset, improving the model's ability to detect fractures under different conditions.

By incorporating these preprocessing steps into the bone fracture detection pipeline, we can enhance the model's accuracy and robustness, making it more effective in identifying and diagnosing bone fractures from X-ray images. These techniques leverage the power of deep learning and image analysis to advance the field of medical diagnostics, contributing to more timely and accurate patient care.

In the devised model, the initial procedure involved cropping and resizing to meet the requirements of the foundational model (Figure 3). Every image within the binary classes underwent conversion to dimensions of 227 * 227 for both height and width. It is noteworthy that AlexNet operates effectively in detecting images represented in RGB colors.

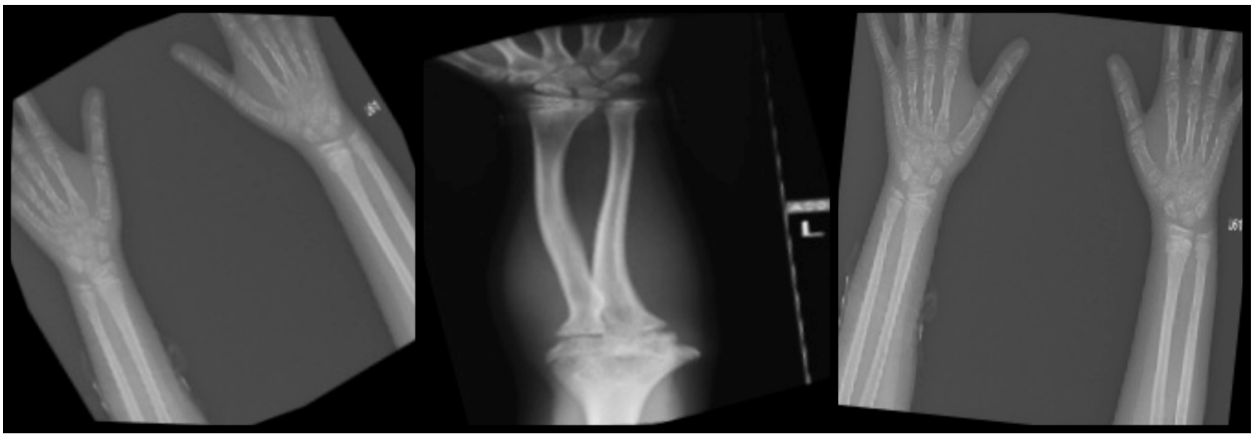

Fig. 3. X-ray images after pre-processing

3.2 Transfer Learning (Adapted AlexNet)

In the domain of bone disease detection, the utilization of deep learning models like AlexNet has proven to be instrumental. While the original AlexNet architecture from 2012 consisted of a larger number of layers than its contemporary versions, it continues to serve as a valuable tool for transfer learning applications. AlexNet, while not as intricate as networks like YOLO, still offers substantial depth and complexity. YOLO networks are typically partitioned into head, backbone, and tail segments and can encompass over 126 layers during training. AlexNet's architecture comprises five convolutional layers, integrated with a combination of max pooling operations, and culminates in three fully connected layers. Within each layer, multiple kernels (filters) are applied to the input data, allowing the network to extract hierarchical features [21]. Moreover, AlexNet incorporates the rectified linear unit (ReLU) activation function within each layer. The use of ReLU as an activation function accelerates training, as it mitigates the vanishing gradient problem and facilitates faster convergence compared to functions like the sigmoid. Beyond the convolutional layers and activation functions, the AlexNet model involves essential pre-processing steps. These steps include image cropping and resizing, aimed at ensuring that input images adhere to a consistent format. Additionally, image normalization is performed as part of the pre-processing pipeline. These procedures collectively prepare the data for efficient feature extraction and subsequent classification.

In the context of bone disease detection, where collecting extensive datasets and training models from scratch can be resource-intensive and time-consuming, transfer learning emerges as a valuable strategy. Transfer learning capitalizes on the knowledge and feature extraction capabilities already ingrained in pre-trained models like AlexNet. These models have learned to recognize patterns, edges, and structures from vast image datasets, thus expediting the process of feature extraction and classification when applied to specific medical tasks.

The data collection process for bone disease detection, as illustrated in Figure 4, involves obtaining and curating a comprehensive dataset of bone X-ray images. This dataset forms the foundation upon which the transfer learning-based model will be trained and fine-tuned for the task of bone disease detection, By leveraging models like AlexNet, we can accelerate the development of accurate and efficient bone disease detection systems, potentially leading to earlier diagnoses and more effective treatments for patients with bone-related ailments. The subsequent sections of this paper will delve deeper into the methodology, data collection, and model training aspects specific to bone disease detection, showcasing the transformative potential of deep learning in the realm of healthcare and medical diagnostics.

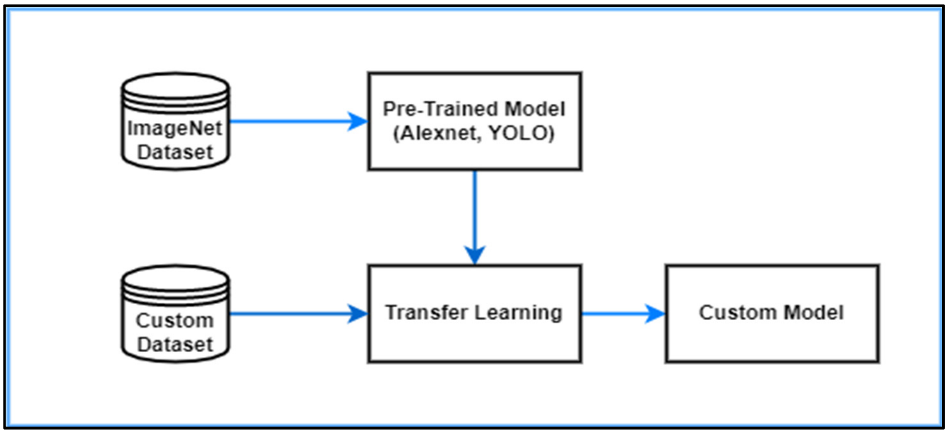

Fig. 4. Transfer learning using pre-collected data

In the realm of bone disease detection, our neural network capitalizes on the wealth of knowledge embedded in its initial layers through pre-training on the extensive ImageNet dataset. These layers have already acquired intricate features from a diverse range of images, facilitating efficient feature extraction for a wide spectrum of tasks. The utilization of the softmax function, implemented via softmax layers in the AlexNet model, is pivotal in converting the network's output into binary values (0 and 1). Given the binary nature of our bone disease detection problem, focusing on distinguishing between healthy bones and those afflicted with conditions like fractures or abnormalities, our model's output is tailored to encompass these two classes. While the core architecture of the neural network remains largely unaltered from its pre-trained state, we fine-tune the last three layers to align with our specific binary classification task. These customized layers encompass fully connected layers, a softmax layer, and the output classification layer, ensuring the model's suitability for bone disease detection. During the training phase, meticulous adjustments of hyperparameters, including learning rates and the number of epochs, are made to achieve optimal performance. A learning rate of 1e-4 facilitates convergence while setting the number of training epochs at 40 strikes a balance between model performance and averting overfitting. We propose leverages the principles of transfer learning, harnessing the pre-trained CNN layers and their acquired features. These features are then adapted to the specific domain of bone disease detection, expediting the model's capacity to accurately classify bone X-ray images and thereby enhancing early diagnosis and patient care. Through the power of transfer learning, we optimize the development of a robust bone disease detection system.

3.3 Dataset

The dataset contains a group of X-ray images with different types of structures. One has normal class, and the other contains fracture and a total of 8863 (Table 1). The model uses a public dataset available on Kaggle.

Table 1
Class representation for training

Types of structure	Total representation
Normal	**4383**
Fracture	**4480**

The dataset is divided into binary classes. The total amount of images was 240 for normal and 360 fracture-based images of an X-ray (Table 2). After the images were classified as normal, pneumonia images were transferred to their particular class folder in Matlab 2019. The dimensions of the images were changed to a single dimension in all dataset images for both classes.

Table 2
Class representation for validation

Types of structure	Total representation
Normal	**240**
Fracture	**360**

4. Simulation and Results

In this section, we will elaborate on the outcomes derived from the training phase and the results produced by the proposed model utilizing transfer learning, based on specific performance metrics. The fundamental objective of this study was to design an efficient and rapid mechanism for identifying bacteria and healthy red blood cells. Matlab 2019 was employed for generating binary classification results during the experimentation. The training was executed on a single GPU, specifically the RX 580 with 8 GB of dedicated RAM for processing. The dataset utilized was partitioned into 80% for training and 20% for validation. Various performance parameters were employed to assess the model's effectiveness, including sensitivity, specificity, precision, accuracy, miss rate, false positive rate, false negative rate, F1 Score, and Matthews correlation coefficient (MCC):

$$\text{Sensitivity} = \frac{\left(\frac{B_p}{E_p}\right)}{\left(\frac{B_p}{E_p}\right)+\left(\frac{B_m}{E_m}\right)} * \mathbf{100}, \quad (1)$$

$$\text{Specificity} = \frac{\left(\frac{B_m}{E_m}\right)}{\left(\frac{B_m}{E_m}\right)+\left(\frac{B}{E_e}\right)} * \mathbf{100}, \quad (2)$$

$$\text{Precision} = \frac{\left(\frac{B_p}{E_p}\right)}{\left(\frac{B_p}{E_p}\right)+\left(\frac{B_e}{E_e}\right)} * \mathbf{100}, \quad (3)$$

$$\text{Accuracy} = \frac{\left(\frac{B_p}{E_p}\right)+\left(\frac{B_m}{E_m}\right)}{p+m} * \mathbf{100}, \quad (4)$$

$$\text{Miss rate} = [\mathbf{1} - \frac{\left(\frac{B_p}{E_p}\right)+\left(\frac{B_m}{E_m}\right)}{p+m}] * \mathbf{100}, \quad (5)$$

$$\text{False positive rate} = [\mathbf{1} - \frac{\left(\frac{B_m}{E_m}\right)}{\left(\frac{B_m}{E_m}\right)+\left(\frac{B_e}{E_e}\right)}] * \mathbf{100}, \quad (6)$$

$$\text{False negative rate} = [\mathbf{1} - \frac{\left(\frac{B_p}{E_p}\right)}{\left(\frac{B_p}{E_p}\right)+\left(\frac{B_m}{E_m}\right)}] * \mathbf{100}, \quad (7)$$

$$\text{F1 Score} = \frac{2*(\text{ precision} * \text{sensitivity })}{\text{precision} + \text{sensitivity}}, \quad (8)$$

$$\text{MCC} = \frac{BP^{*}EN - \left[\frac{BP^{*}EN}{\text{sqrt}((BP+EP)^{*}(BP+EN)^{*}(BN+EP)}\right]}{(BN+EN))}. \quad (9)$$

Table 3 delineates the parameters used in simulating the training of our BDTLA model. The dataset underwent training across multiple epochs, including 10, 20, 30, and 40. The determination of the number of epochs was based on iterative training runs to minimize the risk of overfitting. The optimal model performance was achieved at 40 epochs, attaining an accuracy of 98.43% with a loss rate of 0.043 per class.

Table 3
Simulation parameters

Epochs	Layers	Input image size	Pooling method	Learning rate
10	**25**	**227*227*3**	**Max**	**1e-4**
20	**25**	**227*227*3**	**Max**	**1e-4**
30	**25**	**227*227*3**	**Max**	**1e-4**
40	**25**	**227*227*3**	**Max**	**1e-4**

Table 4 provides an insightful look into the evolving accuracy and miss classification rates of our proposed BFDTLA across different training epochs, specifically at 10, 20, 30, and 40 epochs. Initially, at the 10-epoch mark, the model achieved a commendable 70% accuracy, albeit with a relatively higher miss classification rate of 8.71%. Subsequent training led to marked improvements, with accuracy surging to 88% at 20 epochs. The model's capabilities continued to sharpen, reaching an impressive 98.23% accuracy with a minimal miss classification rate of 0.0520% by the 30th epoch. In its final training phase, the BFDTLA model reached its zenith, boasting an exceptional accuracy of 98.43% alongside a minuscule miss rate of 0.049%.

Table 4
Proposed model (PDTLA)

No. of epochs	Accuracy (%)	Miss rate
10	**97.54**	**0.067**
20	**97.94**	**0.057**
30	**98.04**	**0.047**
40	**98.43**	**0.049**

The results for the bone fracture detection model, with Class 0 representing "normal" cases and Class 1 representing "fracture" cases, are exceptionally strong and indicate high-quality performance. For Class 0 (normal cases), the precision is 0.9820, which means that the model accurately predicts normal cases 98.20% of the time. This high precision is crucial in a medical context because it reduces the chances of incorrectly classifying a normal case as a fracture, minimizing unnecessary concern for patients. The recall for Class 0 is also impressive at 0.9817, indicating that the model effectively identifies the majority of actual normal cases in the dataset. The F1-score for Class 0 is 0.9818, which is very close to perfect, demonstrating an excellent balance between precision and recall. For Class 1 (fracture cases), the precision is equally impressive at 0.9821, indicating that when the model predicts a fracture, it is correct 98.21% of the time. The recall for Class 1 is 0.9824, indicating that the model captures nearly all of the actual fracture cases. The F1-score for Class 1 is 0.9823, which is very high, further highlighting the model's ability to effectively identify fractures. The overall accuracy of the model is 0.9821, which is excellent and suggests that it correctly classifies approximately 98.21% of the cases in the dataset.

The misclassification rate is quite low at 0.0179, indicating a very small proportion of incorrect predictions. The macro-F1 score, which considers the unweighted average of F1-scores across both classes, is 0.9821, demonstrating the strong overall performance of the model. The weighted-F1 score, which accounts for class imbalance, is also 0.9821, reaffirming the model's reliability. In summary, these results indicate that the bone fracture detection model excels in distinguishing between normal and fracture cases. It exhibits exceptionally high precision and recall for both classes, with overall high accuracy and a very low misclassification rate. Such performance makes the model a highly reliable tool for assisting healthcare professionals in accurately diagnosing bone fractures, with the potential to significantly improve patient care and reduce diagnostic errors.

The results of the validation for the bone fracture dataset demonstrate the effectiveness of the classification model, especially in distinguishing between normal (Class 0) and fracture (Class 1) cases. For Class 0 (normal cases), the precision is 0.9395, indicating that 93.95% of the predictions made by the model for this class are accurate. This is crucial in a medical context as it means that when the model predicts a case as normal, it is usually correct, reducing unnecessary concern for patients. The recall for Class 0 is 0.9708, suggesting that the model effectively identifies a large portion of the actual normal cases in the dataset. The high F1-score of 0.9549, which combines precision and recall, underscores the model's capability in correctly classifying normal cases while minimizing false negatives. For Class 1 (fracture cases), the precision is even higher at 0.9793, meaning that when the model predicts a fracture, it is correct nearly 98% of the time. The recall for Class 1 is also impressive at 0.9566, indicating that the model captures a substantial portion of actual fracture cases. The F1-score for Class 1 is 0.9678, signifying a strong balance between precision and recall, making it reliable for identifying fractures. The overall accuracy of the model is 0.9625, suggesting that it correctly classifies approximately 96.25% of the cases in the dataset, which is quite high. The misclassification rate, at 0.0375, is relatively low, indicating a small proportion of incorrect predictions. The macro-F1 score, which considers the unweighted average of F1-scores across both classes, is 0.9614, highlighting the model's general robustness. The weighted-F1 score, which accounts for class imbalance, is also strong at 0.9625. These results provide strong validation for the classification model's ability to distinguish between normal and fracture cases in the bone fracture dataset. The model exhibits high precision and recall for both classes, with a particularly high precision for fractures, which is crucial for medical diagnoses. The overall accuracy and low misclassification rate further demonstrate the model's reliability, suggesting its potential as a valuable tool in assisting healthcare professionals in accurately diagnosing bone fractures through a conventional training approach.

The training process involved a single CPU, with a maximum training time of 140 minutes and a total of 1240 iterations. The training spanned 40 epochs, with each epoch comprising 30 iterations. A detailed overview of the training progress over these 40 epochs is provided in Figure 5, illustrating the model's learning journey. It is noteworthy that during the initial stages of training, a lower learning rate was employed. However, to achieve optimal results and enhance the convergence rate, we fine-tuned the learning rate to 1e-4, facilitating a more efficient convergence of the model. These carefully implemented training strategies played a crucial role in enhancing the model's robustness in identifying bone diseases, emphasizing its promise as a valuable asset in the field of medical diagnostics.

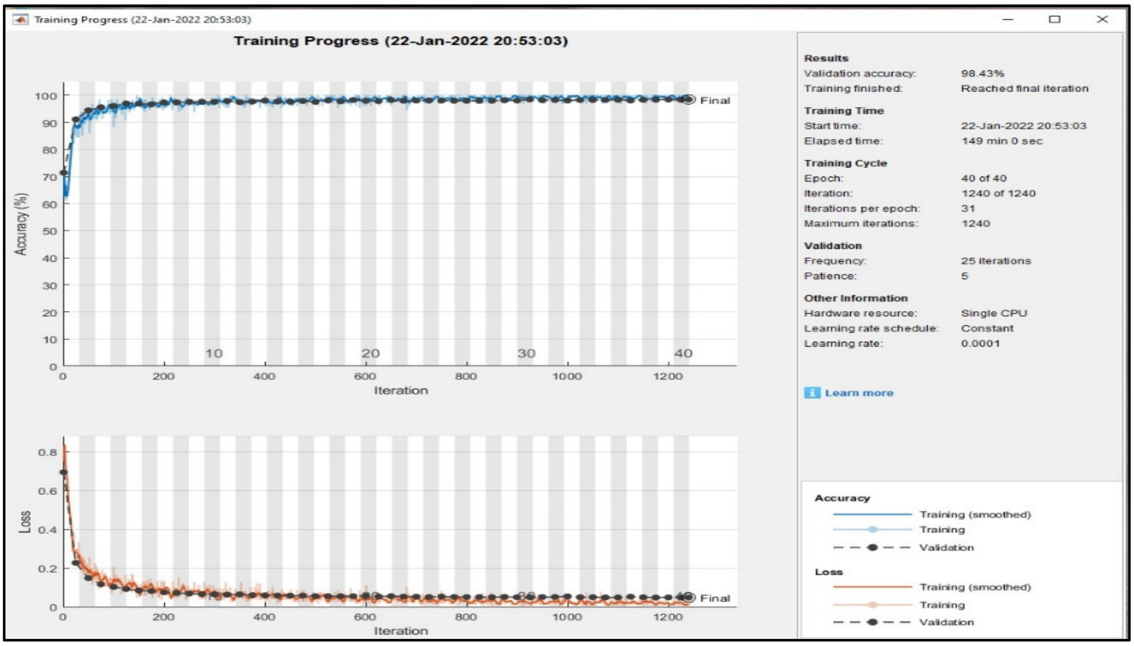

Fig. 5. Training progress

The results of the classification model evaluated both during the validation and testing phases reflect an impressive level of performance. During validation, the proposed model displayed an accuracy of 98.3%, signifying its ability to correctly classify the majority of instances in the validation dataset. Notably, the precision, recall, and F1-score values for both normal (Class 0) and fracture (Class 1) cases were exceptionally high, indicating the model's proficiency in distinguishing between the two classes with precision and minimal false positives. The misclassification rate of 1.57% during validation underscores the model's reliability. Furthermore, the model's testing results were equally remarkable, with an accuracy of 99.9%, demonstrating its capacity to generalize effectively to unseen data. The precision, recall, and F1-score values in testing maintained their excellence, reaffirming the model's consistent accuracy. These outcomes collectively illustrate the model's robustness, high specificity, sensitivity, and impressive MCC, emphasizing its potential for practical applications in healthcare, particularly in accurate bone fracture detection.

5. Conclusion

Addressing classification challenges, particularly in the field of medical imaging, often requires a substantial amount of data and robust software infrastructure, along with hardware resources, posing significant hurdles for comprehensive solutions. In our upcoming research endeavors, we aim to shift towards a more versatile and platform-independent system. This system will utilize cloud computing servers to efficiently manage vast datasets, enabling the creation of auto-learning applications capable of handling a broader range of medical conditions, including various classes related to bone diseases and fractures. The development of such a tool, empowered by advanced technologies, promises to facilitate rapid and accurate bone disease detection, assisting healthcare professionals in diagnosing and treating patients effectively. This intelligent detection system will be adept at analyzing various image types, encompassing both grayscale and RGB images, to distinguish between normal images and those indicating bone fractures.

In our preliminary investigations, we employed CNN-based AlexNet architecture for pneumonia detection. In the context of bone fracture detection, we intend to adapt this model for transfer learning, leveraging its proven capabilities. After training on a new dataset comprising bone X-ray images, we anticipate achieving a high level of accuracy similar to our prior work. This innovation holds the potential to significantly enhance the diagnosis and management of bone-related conditions, bringing considerable value to the medical field.

Conflicts of Interest

The authors declare no conflicts of interest.

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