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WRIST FRACTURE PREDICTION USING TRANSFER LEARNING, A CASE STUDY

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Abstract
Patients regularly present to emergency rooms with suspected fractures, which frequently results in delayed treatment and poor recovery because fractures in images from X-rays are missed. Sometimes emergency care professionals who lack orthopaedic knowledge interpret these images incorrectly. Convolutional neural networks (CNNs), in particular, have attained human-level accuracy in classifying bone fractures. A deep learning model might reduce time wastage and incorrect diagnosis if it is created effectively. ResNet-101, a cutting-edge deep convolutional neural network frequently utilized in computer vision applications like object detection, image classification, and image segmentation, is used in our suggested framework, a WFP-TL model, which achieves 98.45% accuracy. Res Net-101, sporting 101 layers, regularly produces better results on benchmark datasets, MATLAB2020a is used for results and simulations. By teaching generalist medical practitioners on the front lines of healthcare, transfer learning improves patient care. The study demonstrates the potential of DL-based wrist fracture diagnosis on clinical radiographs, will serve as a foundation for future studies incorporating multi-view data for fracture classification.

Keywords: Wrist Fracture, Deep Learning, Transfer Learning, X-rays

Introduction
An orthopedic X-ray records images of the bones as well as the surrounding muscle and flesh. Segmenting the bone component with a precise contour is a challenging procedure because the pixels in the flesh and bone portions typically have overlapping intensity ranges [1]. Bone fractures that go untreated or have the wrong diagnosis are one of the biggest issues in orthopedics. Patients may end up with the wrong diagnosis or course of treatment as a result, lengthening their recovery time [2], bone fractures' because bones can only tolerate so much stress before breaking, which is the main

cause of fractures. Accordingly, falls, trauma, or a direct punch or kick to the body can result in bone fracture. Stress fractures, which are caused by overuse or repetitive motions that wear down the muscles and increase pressure on the bone, are common among athletes. Additionally, conditions like osteoporosis or bone cancer that make the bone brittle can also result in fractures. Bone fractures can be identified by sudden pain, bruising, swelling, apparent deformity, warmth, or redness [3]. The most frequent type of fractures is wrist fractures [4], which often signify fractures in the ulna bones. According to recent data, there were over 18 million hand and wrist fracture incidences worldwide, and wrist fractures are very common [5]. Figure 1 represents a wrist fracture.

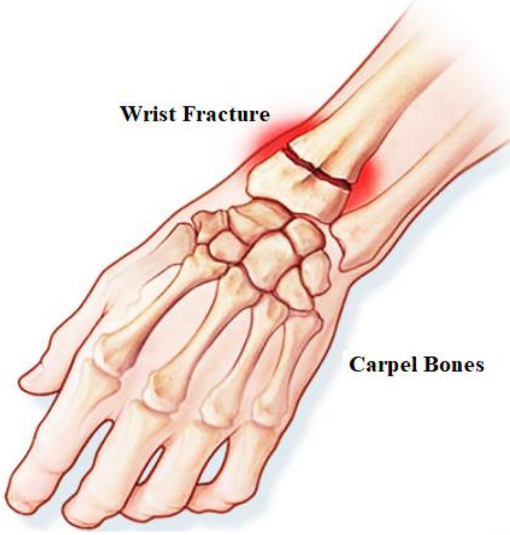


Figure 1. Wrist Fracture [6]

Radiologists use visual inspection to evaluate X-ray samples to determine whether fractures in particular bones are present. The manual inspection of fractures involved in radiograph interpretation takes a lot of time and effort. Additionally, a lack of medical professionals in locations with inadequate medical resources, a shortage of specialist radiologists in busy clinical settings, or exhaustion brought on by heavy workloads could result in a high likelihood of false detection and poor fracture healing [7]. Recent years have seen a sharp rise in the demand for radiological services, placing a significant burden on the workforce. Between 2012 and 2015, the UK had a 29% growth in computed tomography (CT) exams, while recruiting lagged, leaving 9% of consultant radiology positions unfilled [8]. On the other hand, there is a lack of radiologists as a result of a slow hiring process and the high number of radiologists who are nearing retirement. Additionally, deciphering healthcare images can frequently be a challenging and time taking task. When diagnosing wrist fractures, conventional radiography or X-ray imaging is frequently utilized as the initial method [9]. Machine learning employs methods and algorithms that iteratively enhance, or learn, in response to training data to provide predictions on their own [10]. One subtype of supervised machine learning requires the delivery of pre-labeled training data. Deep learning is now the most effective machine learning tool, in the fields of general imaging and computer vision [11]. Artificial neural network advancements that add additional network layers to boost performance and abstraction levels are known as deep learning techniques. [12]

It is necessary to pay particular attention to challenging situations in order to develop a fully automatic wrist image evaluation system in a clinical scenario. Having a trustworthy diagnostic method for these uncommon circumstances, therefore, significantly affects patient care.

IMAGE PROCESSING

The techniques used in image processing include those that work with arrays of pixels to create changed images in which some information is necessarily hidden and some other information is boosted in visibility. It is assumed that this is done because the user can infer from the image's intended usage which information is currently crucial.

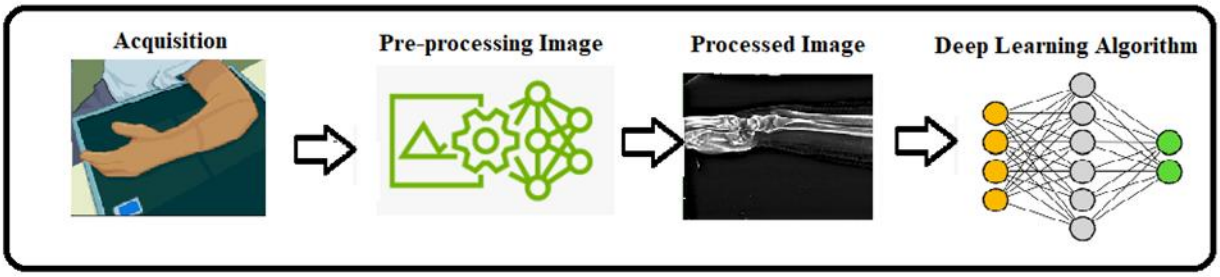


Figure 2. Image processing

Objectives

Different processing may be applied in other circumstances to draw out additional information from the image. [13], which enhances the visibility of the disorder. Figure 2 represents the processing of the image.

The main contributions of the papers are as follows:

- Wrist fractures are predicted in two categories, fracture and normal
- A novel WFP-TL model is being proposed with the goal of predicting wrist fracture
- Transfer learning approach is being employed to leverage the knowledge from ResNet-101, which is a deep convolutional neural network, used as the model's foundational architecture.
- By incorporating prospective factors, the suggested model enhances the capacity to predict wrist fracture.
- The significance of the suggested model and the algorithm's efficiency were demonstrated by experimental results using real data.

The main objective of the study under consideration is to increase medical knowledge by creating a cutting-edge, deep learning-based wrist fracture prediction tool. Our goal is to revolutionize the early identification and treatment of wrist fractures by utilizing the most recent developments in medical imaging technology and artificial intelligence. We strive to offer healthcare practitioners a holistic solution that gives quick and highly accurate diagnostic information by smoothly blending cutting-edge technology with established medical practices.

The rest of the breakdown of the paper's structure is as follows; The most recent developments in bone fracture monitoring and detection are highlighted in Section 2 of the literature. Section 3 covers the research methods, our cutting-edge proposed wrist fracture model, and deep learning techniques. It provides a brief glimpse of the ResNet101 architecture used in our study. Section 4 covers the dataset selection and data details. Section 5 covers the outcomes of experiments and results. Section 6 provides the performance evaluation of the proposed model and its comparison with traditional algorithms. Section 7 covers the conclusion, and Section 8 includes references.

LITERATURE REVIEW / RELATED WORKS

Deepa et al. [14] created two datasets, The Surface Crack Dataset and Wrist Fracture Dataset for automatic detection and segmentation of wrist bone fracture. The Surface Crack Dataset was used to improve models generalizations. They proposed a mask RNN modified architecture. Modification is done at two levels Level 1 and level 2 then both of these are combined to get better results. They achieved 92.278% average precision for fracture detection.

Kethu et al. [15] introduced a framework consisting 5 pre trained CNNs. Dataset of medical images taken from MURA was used. In the proposed architecture, DenseNet169-with-random-forest was able to discriminate between fractures of various body parts with a 90.3% accuracy, InceptionV3- and Xception-with-random-forest could only distinguish between fractured and non-fractured bones with an accuracy of 86%.

An artificial intelligence (AI) system was proposed [16], and they tested it against five expert musculoskeletal radiologists to determine how well it could diagnose scaphoid fractures on standard multi-view radiographs. They compare the proposed system results and the feedback from the radiologists. For detecting scaphoid fractures, The algorithm had an Aera under the curve of 0.88, sensitivity of 72%, and specificity of 93%.

Üreten et al. [17] used the transfer learning method with convolutional neural networks (CNN). The raw dataset contained 270 radiographs of normal hands, 257 radiographs of fractured phalanx, and 275 radiographs of broken wrists. In this investigation, CNN, a deep learning technique, was applied. To enhance the performance of the model, transfer learning was applied to the pre-trained VGG-16, GoogLeNet, and ResNet-50 networks.

Hržić et al. [18] suggested a machine-learning model using the YOLOv4 strategy. They performed thorough testing on three levels and the model built upon YOLOv4 architecture outperformed the most recent method based on the U-Net model by a wide margin. The YOLO 512 Anchor model-AIand YOLOv4-based model, outperformed four radiologists and five radiologists in terms of ROC (AI ROC 0.96 and Radiologist average ROC 0.83). Furthermore, they demonstrated that the AI model considerably enhanced the performance.

Kim et al. [19] proposed a model to examine the potential for automated fracture detection on standard radiographs using transfer learning from deep convolutional neural networks (CNNs) with non-medical images as training data. The model was trained on a total of 11,112 images from an initial set of 1,389 radiographs, 695 of which had fractures and 694 of which did not. This was done using an eight-fold data augmentation approach. The training, validation, and test groups were each given an equal share of the training data set (80:10:10). For statistical analysis and final testing, 50 fracture images and 50 non-fracture images totaling 100 wrist radiographs were employed. This test's AUC was 0.954.

Olczak et al. [20] Collected 256000 wrist, hand, and ankle radiographs from Danderyd's Hospital, and identified four classes. They then selected five specially tailored deep learning networks, including the BVLC Reference CaffeNet network, the VGG CNN S network, the VGG CNN, and Network-in-Network. The effectiveness of the network was then contrasted with that of two skilled orthopedic surgeons who looked at visualizations with the same resolution identical to that of the network. It revealed that all networks were at least 90% accurate at identifying laterality, body part, and exam view. The ultimate assessment of fracture accuracy was 83%.

Singh et al. [21] created a deep-learning model for the simple wrist radiograph-based detection of both non-apparent occult scaphoid fractures and visible fractures. 525 X-ray pictures altogether were used, including 250 normal scaphoids, 219 fractured scaphoids, and 56 occult fracture X-rays. Gradient-weighted class activation mapping (Grad-CAM) was then used for fracture localization, which is a deep learning model built on CNN for two classes normal and fracture, and three classes normal, fracture, and occult. The sensitivity, specificity, accuracy, and AUC of the proposed CNN model for two-class classification were 92%, 88%, 90%, and 0.95, respectively.

Yoon et al. [22] presented DCNN models that were trained in this work to recognize scaphoid fractures. Scaphoid fractures are not obvious to human viewers. In separating scaphoids with fractures from those without fractures, With an AUROC of 0.955, DCNN showed overall sensitivity and specificity of 87.1% and 92.1%, respectively. Grafted class activation mapping closely matched the locations of the observed fractures.

Ebsim et al. [23] suggested a model that analyses lateral and posterioanterior radiographs to identify wrist fractures (distal radius fractures) using convolutional neural networks (CNNs). The suggested method automatically segments the radius using a limited local model with random forest regression voting. Using the automatic annotation that results, the object is registered throughout the dataset and crop patches. For each view independently, a CNN is trained on the registered patches. It showed an AUC of 96.

Table 1. presents a summary of the literature review.

Ref	DATASET	Contribution	LIMITATIONS
Hendrix et al. [16]	Dataset 1 (12,990 radiographs, taken at Radboudumc between 2003 and 2019), and Dataset 2 (1117 radiographs, taken at JBZ between 2018 and 2019). Datasets 3 and 4 (4316 radiographs obtained between 2003 and 2019 at Radboudumc and 688 from 2011 to 2018 at JBZ, respectively)	AI program for detecting scaphoid fractures on multi-view radiographs.	By using all information in the PACS and EHR system instead of only studies that require a further CT or MRI scan for testing, they intended to reduce selection bias in test set. Therefore, occult scaphoid fractures may have been classified as negative instances if the patient left the hospital without returning. By training different CNNs for each view, model performance may be enhanced much more
Üreten et al. [17]	275 wrist fractures, 257 phalanx fractures, and 270 radiographs of normal hands were included in the data set, which was compiled from emergency departments at Nevşehir State Hospital and Krkkale University's faculty of medicine.	The study utilized transfer learning with convolutional neural networks (CNN) on a dataset of radiographs of normal hands, fractured phalanx, and broken wrists to enhance model performance.	The data set was limited
Hržić et al. [18]	The Division of Paediatric Radiology, Department of Radiology, Medical University of Graz, Austria, collected the dataset between 2008 and 2018. It consists of 5997 distinct paediatric patients' 10,150 unique studies worth 19,700 8-bit paediatric wrist X-ray images.	They presented a fracture recognition YOLOv4-based machine learning model, which outperformed the U-Net model	Instead of 1024 x 512, the image's input size was set to 512 x 512. 8 was chosen as the batch size. The model was trained for 500 epochs with an early stopping threshold of 6 epochs, but the validation set showed no improvement.
Kim et al. [19]	After using an eightfold data augmentation technique, the initial batch of 1,389 radiographs of which 695 had fractures and 694 did not was expanded to a total of 11,112 pictures. They got anonymous lateral wrist radiographs from the Royal Devon & Exeter Hospital.	They utilized transfer learning from deep convolutional neural networks (CNNs) trained on non-medical pictures for automatic fracture detection on plain radiographs.	In studies of machine learning, sample size is frequently a limiting factor. The evaluation of a human radiologist served as the foundation for the reference standard, or ground proof, used for the training and testing images. This meant that the model could never outperform a human in this scenario.
Olczak et al. [20]	256,000 wrist, hand, and ankle radiographs from	They used human-level artificial	The quality of picture labels is a critical restriction because

	Danderyd's Hospital make up the dataset.	intelligence, deep learning techniques, and orthopedic radiography.	the neural networks rely on them as input. The classification process in the present networks only utilized one image.
Singh et al. [21]	The dataset consists total of 525 X-rays taken, of which 250 showed normal scaphoids, 219 showed broken scaphoids, and 56 showed concealed fractures collected from The Department of Orthopaedics at Kasturba Medical College (KMC), Manipal, provided these X-ray images.	Standard wrist radiographs were used to create a CNN-based deep-learning model that can recognize both obvious and occult scaphoid fractures.	-
Yoon et al. [22]	Between January 2001 and December 2019, CGMH Hospital and Michigan Medicine hand radiographs in the DICOM format were collected; 4183 DICOM images from 2176 patients treated at MM and 13 339 DICOM images from 5553 patients treated at CGMH.	They trained DCNN models to accurately identify scaphoid fractures, demonstrating their potential for detecting minor bone fractures and occult scaphoid fractures that are not easily visible to humans.	Radiographs from patients with a high chance of scaphoid fracture were included in the training set, indication bias is a potential limitation of the study.
Ebsim et al. [23]	The dataset consists of 1010 patients in total, with 50 percent having fractures. for 787 patients' images Two local emergency departments (EDs) provided 378 of the patients, while the remaining patients were obtained via the MURA dataset.	They presented a method for detecting wrist fractures in radiographs using convolutional neural networks (CNNs).	-

MATERIALS AND METHODS

Machine learning techniques are used to analyze and forecast the attributes of medical images, filling in any gaps in medical image processing or other domains. Deep learning also plays a crucial part in the effective early detection of medical images. Therefore, deep learning is particularly beneficial to both patients and doctors in detecting bone fractures. As deep learning is a very powerful method for detecting fractures we proposed the wrist fracture prediction using the transfer learning (WFP-TL) model which uses ResNet 101. By allowing for the reuse of previously trained models and representations, transfer learning has completely changed the way that high-performance models are created. Particularly for challenging computer vision applications and medical imaging, transfer learning with ResNet-101 can result in significant training time and resource savings. In the model's earliest layers, it makes use of features discovered from a sizable dataset while tailoring the subsequent layers to the details of the target task. Proper detection of wrist fracture, enables doctors to treat patients with treatments that are beneficial to their health and allows people to easily maintain their health before any serious complications develop.

Artificial Neural Networks (ANN)

In addition to helping doctors recognize patterns more quickly and precisely, neural networks also let patients independently evaluate images to take charge of their health. It should be highlighted that algorithms used by patients to recognize patterns on their own progress far more slowly than those employed by doctors.

Neural networks are expected to be used in software in the future to analyze vast amounts of data rapidly and accurately as well as do tasks that are beyond the capabilities of humans. This reduces the impact of the human component [24].

ResNet 101

ResNet-101 is a deep neural network design that can learn incredibly powerful feature representations. It has been widely used for a variety of tasks and represents a significant achievement in the field of computer vision. is incredibly good at extracting hierarchical features from images. It can extract pertinent information from medical pictures like X-rays, CT scans, MRIs, or histopathology slides in the context of disease prediction. These characteristics could include patterns, textures, and shapes that are crucial for spotting disease-related trends. The capacity of ResNet-101 to use transfer learning is one of its main benefits, huge datasets are used to train ResNet-101 models.

The multi-scale feature extraction module and the depth feature extraction module are introduced in ResNet101 [25]. The residual network, or ResNet, plays a big role in computer vision problems.

ResNet101 has 104 convolutional layers made up of 33 layers-blocks, and 29 of these squares are used directly in earlier layers-blocks [26].

Figure 3 from dataset selection to prediction.

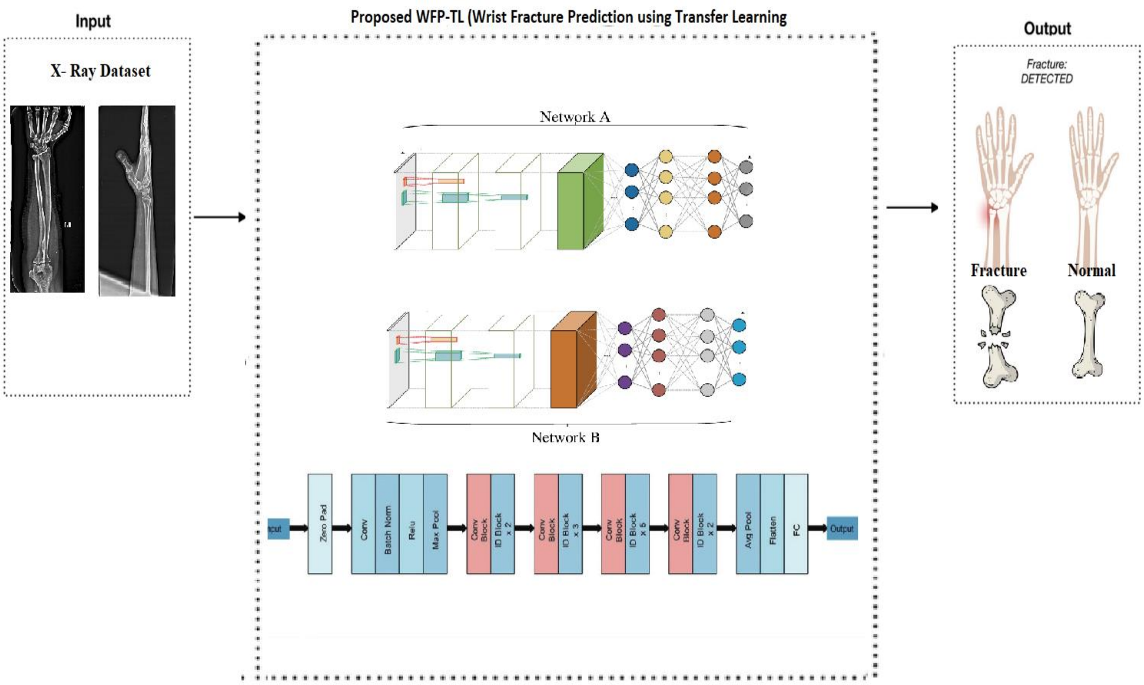


Figure 3. Proposed model for the detection of Wrist fracture

1. DATASET

Table 1. Detail of X-ray Images

Wrist Fracture State	Number of Images
Normal	82
Fracture	111
Total	193

We made use of the Wrist Fracture - X-rays dataset [27], online available at Mendely. X-ray Images are included in this collection. It has 111 images of fractured wrists and 82 images of normal wrists. This dataset, which we got from Mendeley, probably contains the information on each image that is listed in Table 2. Figure 4 is used as a representation of the image categories in your dataset. This image could serve as a visual representation of the two main categories: healthy wrists and fractured wrists. This type of visualization can assist in giving a brief summary of the dataset.

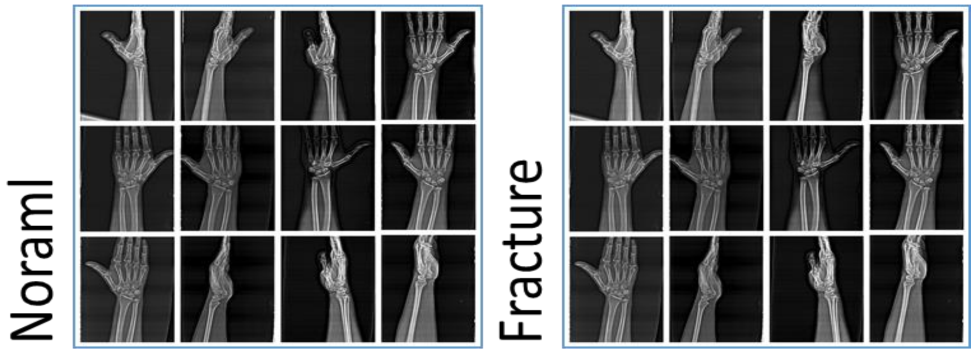


Figure 4. Normal Vs Fracture X-ray Images

EXPERIMENTS AND RESULTS

Details of the experiment results used to forecast wrist fracture using the suggested strategy are provided in this section. The study uses a detailed method of experimentation to accurately predict wrist fractures. There are two crucial sections in it: validation and training. The creation of the predictive model must go through these phases. Ten epochs are completed by the model during the training phase. A full traverse across the entire training dataset constitutes one epoch. There are 10 iterations in every epoch. These incremental phases, or iterations, show how the model modifies its internal parameters in response to the data it is exposed to. These epochs and iterations work together to help the model learn. During the training procedure, a learning rate of 0.01 is taken into consideration. The step size at which the model changes its parameters is determined by the learning rate, a hyper parameter. Controlling how quickly or slowly the model learns is essential. Better outcomes and faster convergence can arise from a well-balanced learning rate.

Visualizations are utilized to get a better understanding of how the model is doing throughout training and validation, as shown in Figure 5. The main depiction is a graph that contrasts accuracy and loss. This graph shows how the loss (a measure of error) fluctuates and how the model's accuracy increases or decreases during training. Growing accuracy and declining loss show that the model is improving its prediction abilities.

PERFORMANCE OF MODEL

In general, our methodology is a well-organized approach to developing and evaluating a predictive model for the identification of wrist fractures. In order to develop and evaluate machine learning models efficiently, it is essential to specify the number of training iterations, and the learning rate, and use visualizations to track the model's progress.

Figure 5 graphically displays the model's performance during the training and validation phases. In the training phase, achieving 100% accuracy was the main goal of this analysis. In machine learning, a model is said to have fully learned a set of training data when it achieves 100% accuracy on that set of data. The validation phase, however, is where the model's performance on fresh, untested data must also be assessed. It demonstrates that the model's excellent accuracy during the validation phase was 98.45%. This shows that, when given new data, the model is very proficient at correctly identifying wrist X-ray pictures as either normal or fractured.

Table 2 Variables & Symbols for Algorithm

Variables and Symbols	Description
R	A set to store the predicted labels (Fracture or Normal).
Preprocessing_completed	A boolean variable to track whether preprocessing is completed
Transfer_learning_completed	A boolean variable to track whether transfer learning is completed

Table 3 Algorithm of WFP-TL

Algorithm: Wrist Prediction using Transfer Learning WFP-TL

Input:
X-ray dataset (images) represented as T
Configuration options C = {preprocessing, transfer_learning}
Output:
Predicted labels for each image, represented as R

BEGIN
R ← Empty set
Preprocessing_completed ← False
Transfer_learning_completed ← False

if C includes preprocessing then
Apply preprocessing steps (e.g., resizing, normalization) to the X-ray images.
Set Preprocessing_completed to True

if C includes transfer_learning then
Load a pre-trained model (e.g., ResNet101) for image classification.
Fine-tune the model on the preprocessed X-ray dataset.
Set Transfer_learning_completed to True

for each image t in T
Make a prediction using the trained model:
if the model predicts fracture then
Add "Fracture" to R
else
Add "Normal" to R
end for
return R (Predicted labels for each image)

END

The notational symbols used in Algorithm are displayed in Table 3, and Table 4, represents the algorithm of the proposed WFP-TL.
Confusion matrix can be used to assess the performance of the classifier in making predictions. As shown in Table 5, the confusion matrix has two categories to analyze the performance, such as accuracy.

Table 4 Confusion Matrix

	Fracture	**Normal**
Fracture	TN (True Negatives)	FN (False Negatives)
Normal	FP (False Positives)	TP (True Positives)

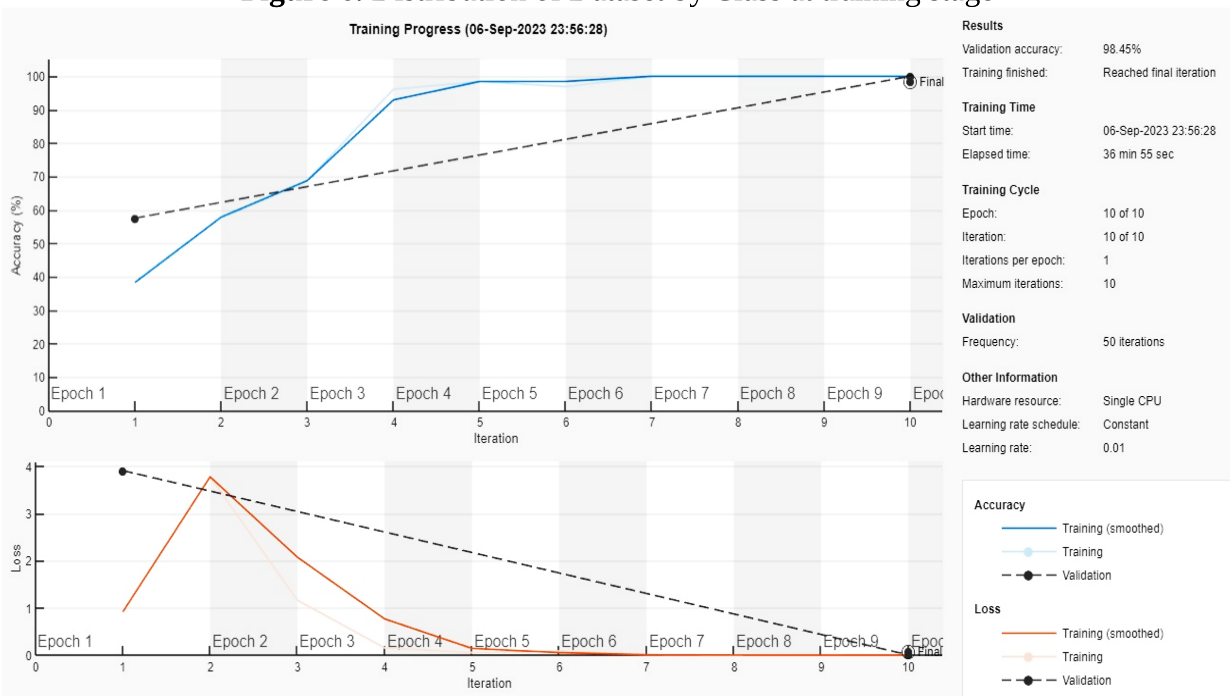
$$Acc = tp + tn /(tp + tn + fp + fn) \qquad (1)$$

Equation (1) represents the accuracy calculation of the proposed WFP-TL model
Figure 6 appears to offer a more in-depth look at the training results. The results appear to be divided

into two categories: "normal" and "fractured." This visualization most likely demonstrates how, during training, the model's predictions and the actual labels for these two classes agree. For the model to be useful in identifying wrist fractures, it must be able to distinguish between cases that are normal and those that are broken.

Figure 5. Proposed wrist Fracture Prediction system using Transfer Learning WFP-TL System

Figure 6. Distribution of Dataset by Class at training stage



Tools and Environment

Table 6. presents the tools and environments under which study is being conducted. The deep learning model (ResNet-101) was implemented, and trained, the performance of the model was visualized and examined using MATLAB 2020a, which is a robust and well-liked tool in the disciplines of machine learning, image processing, and scientific research.

Table 5. Tools & environment

Tool Device Name	Description
System	DESKTOP-OEA1KN4 Window 10 pro
Processor	Intel(R) Core(TM) i7-7700HQ CPU @ 2.80GHz 2.80 GHz
RAM	16.0 GB
Tool	MATLAB 2020a

COMPARISON OF PERFORMANCE OF WFP-TL AND TRADITIONAL METHODS

Table 7. presents a comparison between the recent studies, which shows that our state-of-the-art model outperformed the others in terms of accuracy

Table 6 Comparison of Performance of Traditional ML Algorithms and Proposed WFP-TL

Studies	Model	Results	Year
Hendrix et al. [16]	AI Algorithm	AUC 88%	2023
Üreten et al. [17]	CNN with TL	Accuracy 93.3%	2022
Hržić et al. [18]	U-Net NN	AUC 96%	2022
Kim et al. [19]	DCNN	AUC 95%	2018
Olczak et al. [20]	CNN	Accuracy 83%	2017
Singh et al. [21]	CNN with Grad-CAM	Accuracy 90% AUC 95%	2022
Yoon et al. [22]	DCNN	AUC 95%	2021
Ebsim et al. [23]	CNN	AUC 96%	2019
Our Proposed WFP-TL method	Transfer Learning	Accuracy 98.45%	2023

Conclusion and Future Work

Within the realm of medical imaging, machine learning is crucial for the diagnosis of wrist fractures. It can help healthcare professionals to increase the precision and effectiveness of fracture diagnosis. In order to provide optimal care, reduce pain and problems, and promote quicker and more thorough recovery, early fracture detection is crucial. A highly effective system wrist fracture prediction using transfer learning (WFP-TL) is being proposed, that's based on ResNet-101 architecture and transfer learning, for wrist fracture prediction. The suggested model uses the features collected from the X-rays of the healthy wrist bone and the fractured wrist bone, to detect wrist fracture. The simulation and results have been accomplished using the MATLAB 2020a tool. Transfer learning is used in the proposed wrist fracture prediction (WFP-TL) system for training and validating wrist fracture prediction. Deep learning, specifically the convolutional neural network (CNN) model ResNet-101, enables the precise detection and categorization of bone fractures from X-ray images. The proposed system's accuracy result of 98.45% is higher than that of the state-of-the-art reported approaches. This study will help patients and doctors by enabling them to quickly predict wrist fractures. To sum up, careful consideration should be given to the integration of AI into clinical practice. Future versions of this study will incorporate multiclass categorization of fractures, which would be very beneficial to the healthcare sector. It may be improved upon and refined further. This could entail optimizing hyper parameters, testing various neural network topologies, investigating further cutting-edge deep learning methods for medical image processing, and analyzing the model's performance across a larger range of patient demographics and fracture kinds.

DATA AVAILABILITY

The corresponding author can provide the data used in this paper upon request.

CONFLICTS OF INTEREST

The authors declare that there are no conflicts of interest.

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