A COMPARATIVE ANALYSIS OF DEEP LEARNING MODELS AND CONVENTIONAL APPROACHES FOR OSTEOPOROSIS DETECTION IN HIP X- RAY IMAGES

Abstract

Osteoporosis is a common bone disease characterized by a reduced bone mass and bone structure degradation that poses a huge risk to fractures, especially among elders. Deep learning models for osteoporosis detection using hip X-ray images. A dataset of 117 images was carefully crafted, annotated and augmented to the highest level of quality. Initially, three state-of-the-art deep learning models, i.e., ResNet—50, Inception Net, and YOLOv7, were utilized, and later, the latest Ultralytics YOLOv8 model.

ResNet-50 obtained an accuracy of 80% which indicated a promising performance in osteoporosis detection. The improved performance of Inception Net is attributed to its novelty in design, which achieved an accuracy of 85.2%. YOLOv7, a fast and effective object detection model, gave an accuracy of 90.9%. Lastly, the study presented the Ultralytics YOLOv8 model that achieved a remarkable precision of 98.8% mAP@0.5.

Comparative analysis showed that the YOLOv8 model had higher sensitivity which was attributed to its real time object detection capabilities and architectural enhancements. Its high resistance to scale changes and occlusions, coupled with its efficiency and effectiveness at handling the limited training data, make YOLOv8 a preferred option for the accurate osteoporosis detection. It is concluded that deep learning models, particularly YOLOv8, represent better alternatives to traditional diagnostic systems and that they may offer an approach to osteoporosis screening for wider accessibility.

Keywords: Artificial intelligence, X- Ray, Ultralytics

Authors

Vedant Naikwade
GH Raisoni Institute of Engineering and Technology, (GHREITN)
Maharashtra, India.

Virja Kawade
GH Raisoni Institute of Engineering and Technology, (GHREITN)
Maharashtra, India.

Dr. Sakshi Sadhwani
GH Raisoni Institute of Engineering and Technology (GHREITN)
Maharashtra, India.

I. INTRODUCTION

Osteoporosis is a common bone complaint characterized by low bone mass and structural deterioration of bone towel, leading to increased bone fragility and a advanced threat of fractures. It primarily affects aged individualities, particularly women after menopause, but can also do in men and youngish individualities.

Prevention and operation of osteoporosis involve a multifaceted approach. Acceptable input of calcium and vitamin D, regular weight- bearing and muscle- strengthening exercises, avoidance of tobacco and inordinate alcohol, and fall forestalment strategies are essential for maintaining bone health. In some cases, specifics may be specified to decelerate bone loss or promote bone conformation.

Early discovery of osteoporosis is pivotal to initiate applicable interventions. Binary-energy X-ray absorptiometry (DXA or DEXA) is the most generally used test to measure bone mineral viscosity and assess fracture threat. Webbing guidelines vary, but generally, women over 65 and men over 70 should suffer DXA testing.

II. DATASET EMPLOYED

Data drawing is an essential step in the data medication process, icing that datasets are accurate, harmonious, and dependable for analysis. It involves relating and amending crimes, inconsistencies, and inaccuracies in data, ranging from missing values and indistinguishable entries to formatting issues and outliers. The process frequently starts with data profiling and exploratory analysis to gain perceptivity into the quality and structure of the data. Also, colourful ways are applied to handle different types of issues, similar as insinuation styles for missing values, deduplication algorithms for removing duplicates, and data metamorphosis approaches for homogenizing formats. Confirmation checks and quality assurance measures are also performed to insure that the gutted data meets the predefined criteria or constraints. Through effective data cleaning, associations can enhance data integrity, reduce impulses, and ameliorate the delicacy and trust ability of posterior data analysis and modelling tasks.

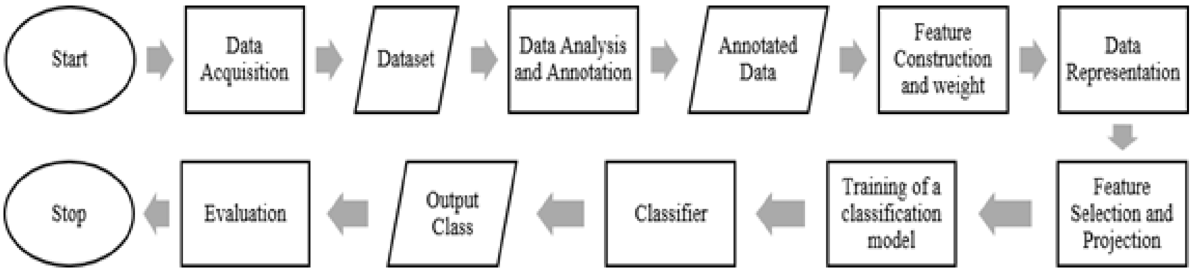
The data used in the model was collected from colourful sources like Kaggle, Roboflow, etc. The data comported of 49 hipsterismX-Ray images of males and ladies. Latterly the data was gutted and annotated with the help of Roboflow under the supervision of Orthopedic surgeons from Lata Mangeshkar Hospital, Nagpur. Next, the data was anatomized. The following parcels were kept as dereliction for all images

1. **Auto-Orient:** Applied and
2. **Resize:** Stretch to 640X640.

Finally, the data was applied with the following list of augmentations after which the data increased to 117 images:

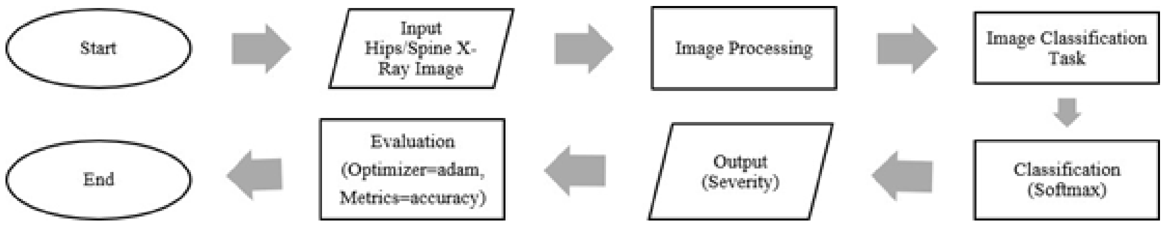
1. **Flip:** Horizontal,
2. **Minimum Zoom:** 40%
3. **Rotation:** Between -15° and +15°

III. FLOW CHART & BLOCK DIAGRAM FLOWCHART



Flow chart for the working of Osteoporosis Detection using Deep Learning Models

Block Diagram



Block diagram depicting the workflow of the program for Osteoporosis Detection using Deep Learning Model

IV. RESULTS

The "skip connections" function of ResNet presents an innovative solution to the vanishing gradient issue. Convolutional layers that were initially inactive are stacked, bypassed, and then activated again from the prior layer (many identity mappings; ResNet). Skipping quickens early training by lowering the network's layer count. When the ResNet model was trained on the hip X-Ray dataset, an accuracy of 80% was observed. Table I displays the accuracy, precision, recall, and F1-score values acquired on the testing dataset, as well as the confusion matrix generated during the evaluation of ResNet-50 on the Hips X-Ray Dataset.

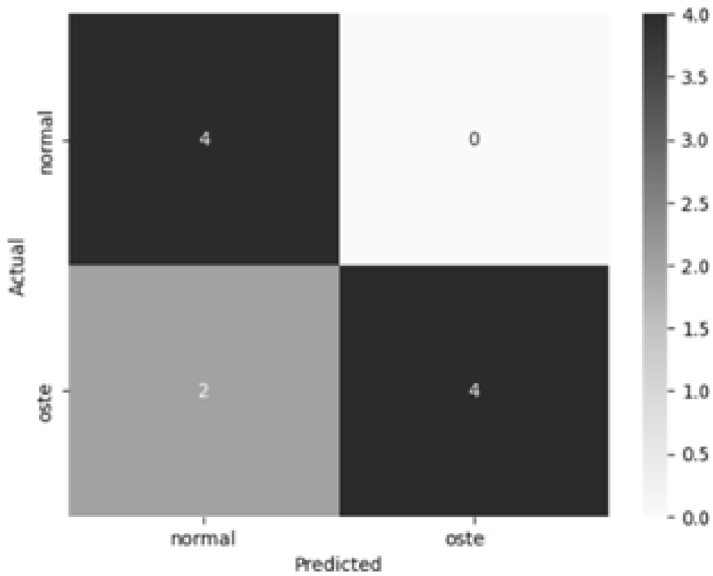


Figure 1: Confusion matrix for ResNet model on X-Ray data of hips consisting of 10 images belonging to two classes: a) Normal, b) Osteoporosis.

Classes	**Evaluation Metrics**			
	Accuracy	**Precision**	**Recall**	**F1-Score**
All Classes	0.80	1.00	0.67	0.80
Normal	0.67	0.67	1.00	0.80
Osteoporotic	0.80	1.00	0.67	0.85

Table 1: Precision, Recall, And Mean Average Precision Values of Resnet-50 on Hip X-Ray Dataset

1. **Inception Net:** Large networks are more prone to over fitting, and the network's processing cost rises when numerous convolutional processes are coupled together. Researchers created simple Convnet designs in order to realize the Inception network and module. A deep neural network with repeated architectural elements known as Inception modules is an inception network. A 1x1 convolution layer for feature reduction, 3x3 and 5x5 convolutional layers for learning various spatial features at various scales, and a max pooling layer make up the Inception module.

   Once CNN's Inception Net architecture was used to detect osteoporosis using the Hips X- Ray dataset, 85.2% accuracy was reached. The confusion matrix and accompanying accuracy and precision show the outcomes of the Inception Net model, recall and F1-score values are depicted in Table II.

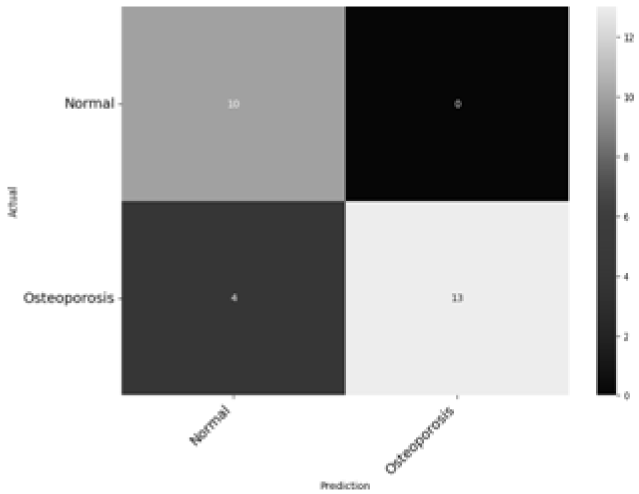


Figure 2: Confusion matrix for X-Ray data of hips consisting of 27 images belonging to two classes: a) Normal, and b) Osteoporosis, trained on the InceptionNet model.

Classes	Evaluation Metrics			
	Accuracy	**Precision**	**Recall**	**F1-Score**
All Classes	0.851	1.000	0.714	0.833
Normal	0.851	0.714	1.000	0.851
Osteoporotic	0.851	1.000	0.714	0.750

Table 2: Precision, Recall, and Mean Average Precision Values Of Inception Net On Hip X-Ray Dataset

2. **YOLO v7:** Before doing object detection in a single step, YOLO (You Only Look Once) first divides the image into N grids. These grids all measure 5 by 5. Any objects that might be present in any of these locations are found and located using it. Each grid predicts the bounding box coordinates,

   B, of any potential objects together with their item labels and a likelihood score for their presence.

   Following the publication of YOLOv7 in 2022 by Chien-Yao Wang et al., it was the best object detection algorithm on the market. As shown in Table III, the accuracy on the YOLOv7 model for this particular application was 90.9% for mAP@0.5 (mean average precision).

   The various losses as well as the evaluation metrics are plotted for training and validation sets.

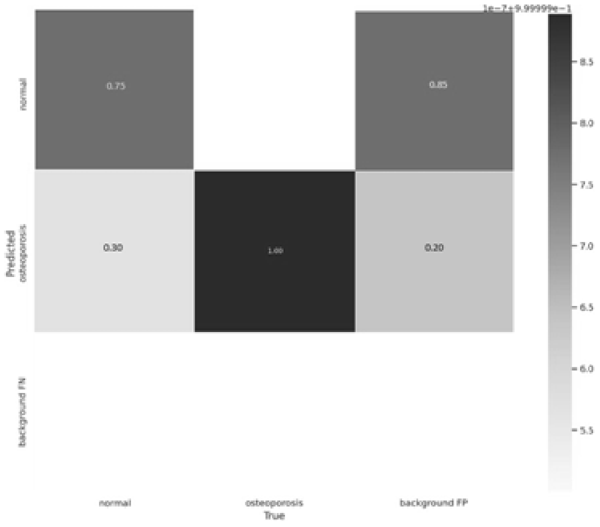


Figure 3: Confusion matrix for X-Ray data of hips two classes: a) Normal, and b) Osteoporosis, along with an additional background class trained on the YOLO v7 model.

Classes	Evaluation Metrics			
	Precision	**Recall**	**mAP @0.5**	**mAP @0.5:0.95**
All	0.820	0.788	0.909	0.822
Normal	0.939	0.700	0.908	0.849
Osteoporotic	0.700	0.875	0.910	0.795

Table 3: Precision, Recall, and Mean Average Precision Values Of Yolov7 On Hip X-Ray Dataset

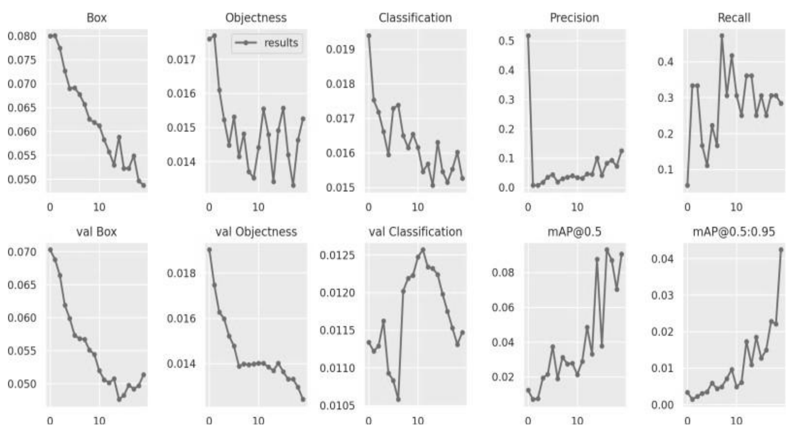


Figure 4: Graphs for box loss, objectness loss, classification loss, precision, recall and mean average precision (mAP@0.5 & mAP@0.95) over training and validation sets on YOLO v7

3. **Ultralytics YOLO v8:** The most recent iteration of the well-known real-time object detection and image segmentation model is called Ultralytics YOLOv8. Modern advancements in computer vision and deep learning allow YOLOv8 to provide unmatched speed and accuracy. Due to its simple engineering, it is excellent for many applications and effectively adaptable to various equipment stages, including edge devices and cloud APIs.

   The hips X-ray dataset was used to train the YOLOv8 model, and the precision acquired afterward was 98.8% mAP@0.5, the greatest accuracy attained throughout the study. Table IV displays the findings for the evaluation measures employed in this study, along with the related graphs for losses and evaluation metrics.

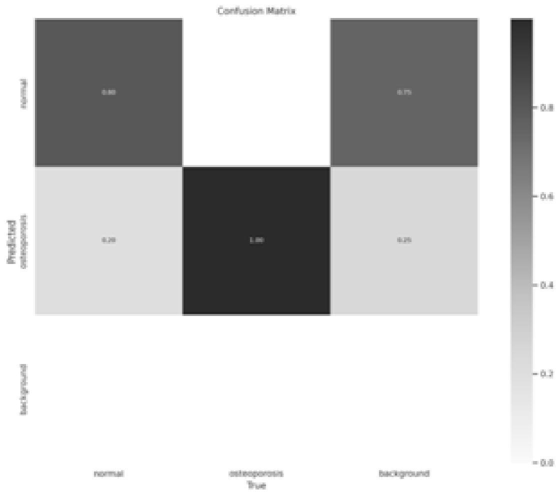


Figure 5: Confusion matrix for X-Ray data of hips two classes: a) Normal, and b) Osteoporosis, along with an additional background class trained on the YOLO v8 model.

Classes	**Evaluation Metrics**			
	Precision	**Recall**	**mAP @0.5**	**mAP @0.5:0.95**
All	0.929	0.904	0.988	0.888
Normal	1.000	0.807	0.995	0.889
Osteoporotic	0.858	1.000	0.982	0.887

Table 4: Precision, Recall, And Mean Average Precision Values Of Yolov8 Ultralytics On Hip X-Ray Dataset

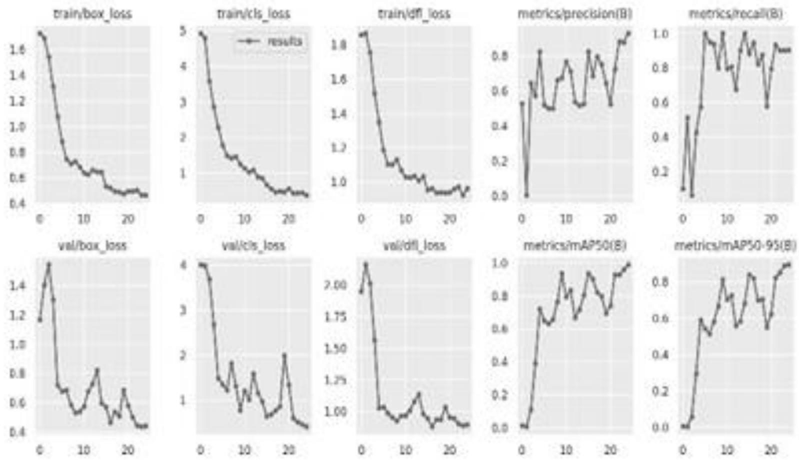


Figure 6: Graphs for box loss, objectness loss, classification loss, precision, recall and mean average precision (mAP@0.5 & mAP@0.95) over training and validation sets on YOLO v8

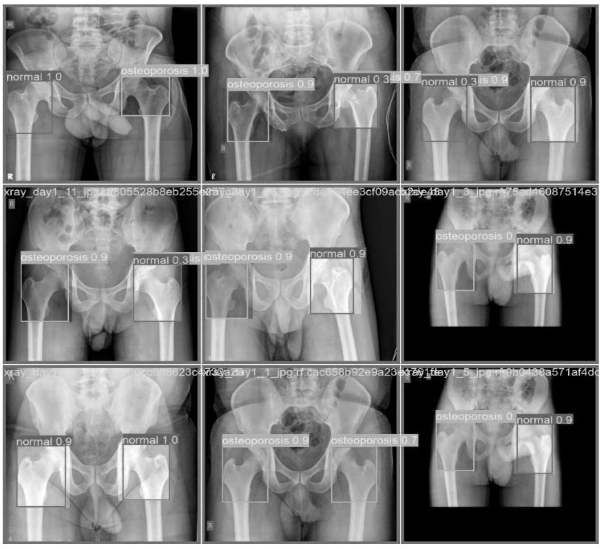


Figure 7: Ultralytics YOLOv8.0.20 prediction results on the validation set of hip X-Ray dataset labeling the confidence on the bone being predicted as normal or osteoporotic.

V. CONCLUSION

The bone complaint called osteoporosis is characterized by dropped bone mineral viscosity (BMD) and an increased threat of fracture. The Binary- Energy X-Ray Absorptiometry (DXA) check-up, one of the most recent ways for diagnosing and treating osteoporosis, has come the gold standard for dependable osteoporosis discovery. The sole disadvantage of this procedure is that it's precious and out of reach for individualities in lower socioeconomic classes. The authors, thus, suggest using deep literacy ways on X-ray film land in place of DEXA by conducting this study. On an X-Ray dataset of hips conforming of 117 images after addition, the paper summarises and compares four deep literacy algorithms used for the same task ResNet- 50, Inception Net, YOLOv7, and Ultralytics YOLO v8 models.

Among the four algorithms estimated, the YOLO v8 model demonstrated the loftiest delicacy in the conducted study. This superior performance can be attributed to several crucial factors essential to the YOLO v8 armature. Originally, the YOLO (You Only Look formerly) model family is known for its real- time object discovery capabilities. YOLO v8, in particular, leverages a single unified neural network armature that predicts bounding boxes and class chances directly on a thick grid, thereby enabling faster conclusion speed compared to other object discovery models. Also, YOLO v8 incorporates multitudinous architectural advancements and advancements over its forerunners, similar as the addition of point aggregate networks, anchor- grounded prognostications, and point emulsion ways. These advancements grease more accurate localization and bracket of objects within images. Considering these factors, the YOLO v8 model's superior delicacy can be attributed to its real- time object discovery capabilities, architectural advancements, robustness against scale variations and occlusions, and the vacuity of comprehensive training data. These advantages inclusively contribute to its remarkable performance and make it a favoured choice for accurate object discovery tasks.