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Detection of Osteoporosis and Osteoarthritis Using Deep Learning Algorithms

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***Abstract* -- Osteoporosis and osteoarthritis in the knee are common musculoskeletal conditions that have significant consequences for healthcare. The possibility of deep learning techniques to automate the detection of these circumstances is investigated in this work. For the analysis of medical images (such as X-rays and CT scans) and clinical data, we implement and compare the performance of various deep learning architectures, including Convolutional Neural Networks (CNNs), Artificial Neural Networks (ANNs), Multilayer Perceptrons (MLPs), and Long Short-Term Memory (LSTM) networks. Important performance indicators like accuracy, loss, sensitivity, Receiver Operating Characteristics (ROC), Area Under the Curve (AUC), and Scalability, are utilized to assess each approach's effectiveness. The results were impressive, with CNN demonstrating exceptional accuracy in both diagnoses. For osteoporosis detection, CNN achieved a remarkable 94.3% accuracy, significantly outperforming ANN (87%), MLP (80%), and LSTM (74%). In osteoarthritis detection, CNN again displayed dominance with a 99% accuracy rate, followed by ANN (88.7%), MLP (87%), and LSTM (80.3%). This comprehensive study strongly suggests that deep learning holds immense promise for revolutionizing the diagnosis of Osteoporosis and Osteoarthritis.**

***Index terms* -- ANN, CNN, Deep Learning, Knee Osteoporosis, Knee Osteoarthritis, LSTM, Medical Image Analysis, MLP**

I. INTRODUCTION

Musculoskeletal conditions pose a substantial worldwide health burden, particularly when they impact our joints and bones. Osteoporosis and osteoarthritis are two significant players in this field that impact millions of people worldwide and reduce mobility and quality of life. Loss of bone mass and density is the outcome of a condition known as osteoporosis. It gradually weakens bones and increases the risk of fractures, especially those of the wrist, knee hip, and spine. On the other hand, osteoarthritis is a degenerative condition that causes the cartilage that shields our joints from harm to break down. Pain, stiffness, and decreased flexibility are common complaints affecting the hands, hips, and knees [1]. Worldwide, osteoporosis affects about 34 million people, and the World Health Organization estimates that a fracture happens every three seconds. More than 350 million people worldwide suffer from osteoarthritis, which is far more common. As the population ages, it is anticipated that these figures will rise even higher, putting further pressure on healthcare systems and individual wellbeing. Conventionally, the diagnosis of these disorders has been made by radiography, physical examinations, and bone density scans (DXA) for osteoporosis [2]. Though these methods yield important information, they have limitations in that they only identify severe joint degradation in osteoarthritis and overlook early-stage osteoporosis. Physical tests may overlook minor changes since DXA is expensive. The need for more impartial, trustworthy, and precise diagnostic tools is highlighted by these concerns.

II. RELATED WORKS

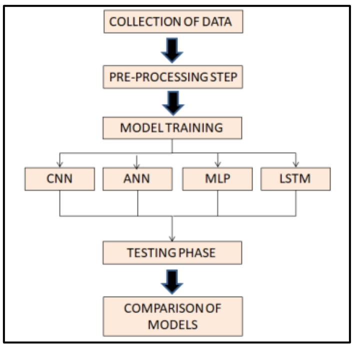
IM Wani et al (2023) proposed a method for detecting osteoporosis in knee X-rays using transfer learning with Convolutional Neural Networks (CNNs). They trained and compared different pre-trained CNN architectures (Alex Net, VGG-16, Res Net, VGG-19) on a dataset of 381 knee X-rays categorized as normal, osteopenia, and osteoporosis. The best performance achieved an accuracy of 91.1% with Alex Net, suggesting that transfer learning based CNNs can be effective tools for early-stage osteoporosis detection [1].

T.-S. Yang et al (2022) The study aimed to identify knee diseases (osteoarthritis and osteoporosis) in X-ray images using deep learning. They compared two methods: VGG16 (a CNN architecture) for osteoporosis and Late-Fusion (combining models) for osteoarthritis. VGG16 achieved 82% accuracy for osteoporosis detection, demonstrating its potential for this under-researched area, while Late-Fusion achieved 77% accuracy for osteoarthritis [2].

Pingjun Chen et al (2022) proposed a two-stage deep learning approach for knee OA severity assessment using X-rays. First, a customized YOLOv2 network locates the knee joint. Then, fine-tuned CNNs (Res Net, VGG, Dense Net, InceptionV3) with a new ordinal loss function classify the KL grade of the detected knee joint. This method achieved state-of-the-art performance with 85.8% accuracy in knee joint detection and 69.7% accuracy in KL grade classification [6].

III. MATERIALS AND METHODS

In this proposed work we focus on four deep learning algorithms for the detection of both the diseases. Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), Multilayer Perceptron (MLP), and Long Short-Term Memory networks (LSTM)[3]. Each model will be trained on the pre-processed image data. Followed by testing and evaluation step where rigorous testing will be conducted using validation data to assess the performance of each model. Key metrics, such as model accuracy, model loss, sensitivity, ROC, Area Under the Curve (AUC) and scalability, will be employed for comprehensive evaluation [4]. The performance of each model will then be compared and contrasted to identify the algorithm with the most efficient and accurate detection capabilities for both osteoporosis and osteoarthritis [6]



A. *Collection of Data*

For this research, we leveraged the power of open-source data by acquiring a curated image dataset from Kaggle [5]. This dataset encompasses a total of 1110 medical images, specifically divided into two categories; osteoporosis with 545 images and osteoarthritis with 565 images.

B. *Dataset Pre-processing*

After acquiring the dataset from Kaggle, we employed several preprocessing techniques to ensure the data's quality and consistency for our deep learning models. The scan images were subjected to pre-processes such as image format standardization and image resizing [7]. The dataset contained images in both PNG and JPG formats. ensure compatibility and avoid potential processing errors, we converted all images to a single format, PNG in this case. PNG offers advantages like lossless compression, which is crucial for preserving image details in medical data. Deep learning models typically require a fixed image size as input. The original images in the dataset might have varied.

pixel values. To address this, we normalized all images to the range (0,1) . This ensures that each image contributes equally to the training process and simplifies computational efficiency within the model. The pre-processed images are then split into learning and validation sets in the ratio of 7:3.

C. *Model Training*

- ***Convolutional Neural Networks (CNN)***

Firstly, both the datasets are loaded and pre-processed. The code iterates through the classes of “yes/” and “no/”. A sequential convolutional neural network is constructed from Keras with alternating convolutional and max pooling layers, followed by fully connected layers. Three convolutional layers are added with 32, 64, and 128 filters respectively, each with a kernel size of (3, 3) and ReLU activation. After each convolutional layer, a max pooling layer with a pool size of (2, 2) is added for down sampling [15]. The feature maps from the last convolutional layer are flattened into a single vector using the flatten layer. Two fully connected layers are added with 128 neurons each and ReLU activation. A dropout layer with a rate of 0.5 is included for regularization. The final layer has the same number of neurons as the number of classes (2) and uses soft max activation for multi-class classification. The model is then compiled and trained using loss, optimizer, accuracy, The model is trained for 100 epochs with a batch size of 16. Training progress is monitored and stored.

- ***Artificial Neural Networks (ANN) and Multi-Layer Perceptron (MLP)***

The loaded, pre-processed images are converted into NumPy arrays and splitted. Then we perform data flattening where the data originally in 3D format (representing image width, height, and colour channels) is flattened into a single 1D array for each image. The model consists of three fully connected layers: The first layer has 256 neurons with Re LU activation for non-linearity. A dropout layer with a rate of 0.5 is added for regularization to prevent overfitting [8]. The following layer has 128 neurons with Re LU activation. Another dropout layer with a rate of 0.5 is included. The final layer has the same number of neurons as the number of classes (2) and uses soft max activation for multi-class classification. The model is compiled with Sparse categorical crossentropy loss for multi-class classification and Adam optimizer with a learning rate of 0.0001. The model is trained for 100 epochs with a batch size of 16. Then the model is evaluated in testing set for validation and predictions are made. The key metrics are then generated [16].

- ***Long Short Term Memory (LSTM)***

Unlike ANN and MLP, which handle the entire image as a single input, LSTMs are designed to process sequential data. Here, each image is reshaped into a 3D tensor with dimensions time steps, features. This reshaping transforms the data into a sequence of feature vectors, suitable for LSTM processing. The model architecture consists of an LSTM layer with 64 units and Re LU activation for processing the sequential data. A dense layer with 128 units and Re LU activation for further feature extraction. A dropout layer with a rate of 0.5 for regularization. A flattening layer to convert the 2D output from the previous layer into a 1D vector before feeding it to the final layer [9]. The final dense layer with the same number of neurons contains the number of classes (2) and soft max activation for multi-class classification. The model is then compiled with Sparse categorical crossentropy loss and Adam optimizer. The model is then trained on the training dataset for 100 epochs.

D. Testing Phase

After training, the model is evaluated on the testing set and predictions are made. The predictions can either be osteoporosis is detected or not detected and osteoarthritis is detected or not detected [14]. Finally based on the predictions made by the model the key metrics accuracy, loss, sensitivity, ROC, AUC and scalability are generated to evaluate the efficiency and performance of the models [10].

E. Comparison of Models

The results of the parameter of all the model are then compared. Depending on the parameters model accuracy, model loss, sensitivity, ROC, Area Under the Curve (AUC), and scalability of the models CNN, ANN, MLP and LSTM the best deep learning model is suggested for real- time application in healthcare.

IV. RESULTS AND DISCUSSIONS

In order to determine the efficient model for real-time detections the models are tested for their performance on the basis of Accuracy, Loss, Sensitivity, Scalability, ROC and AUC. Here we have presented the results obtained as graphs [12]. The accuracy, loss, scalability, ROC, AUC, sensitivity, confusion matrix graphs of the CNN, ANN, MLP, LSTM model for osteoporosis and osteoarthritis detection shown in Figure 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25 respectively.

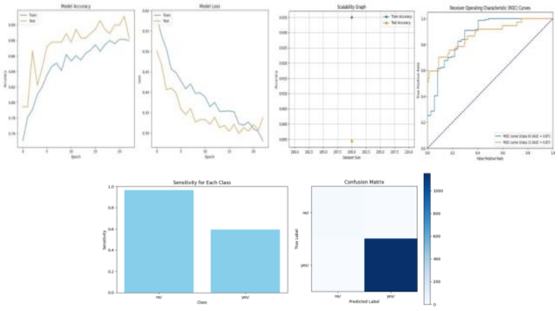


Fig 2 CNN Osteoporosis accuracy and loss graph, Fig 3 Scalability, ROC, AUC, Fig 4 Sensitivity and Confusion Matrix

The CNN model reached 94.3% accuracy for osteoporosis on testing data after 20 epochs as shown in fig 2. The model loss also decreases in a continuous fashion from 60% to 20% in training set and 50% to 30% in testing sets under 20 epochs in fig 2. Fig 3 shows ROC, AUC is 0.87, which means that the model is performing well. The CNN model is scalable. The confusion matrix in fig 4 shows that correct predictions were (143 osteoporosis, 20 non-osteoporosis) and wrong predictions were (17 osteoporosis, 2 non-osteoporosis cases). The formula used to derive sensitivity graph is denoted below in equation (1). The model has achieved sensitivity of 0.89 for osteoporosis detection shown in fig 4.

Sensitivity = True Positives / (True Positive + False Negatives ... (1)

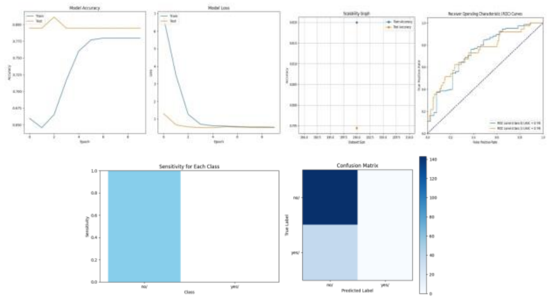


Fig 5 ANN Osteoporosis accuracy and loss graph, Fig 6 Scalability, ROC, AUC, Fig 7 Sensitivity and Confusion Matrix

The graph in fig 5 shows that the accuracy of the training and testing, it seems to rise with the number of epochs, ending with 87% accuracy on validation for osteoporosis detection using ANN. The y-axis on the fig 5 right graph shows the model's loss; lower values, starting at 10%, denote greater performance. This graph shows that as the number of epochs rises, the training and testing losses seem to go down. Fig 6 shows that ANN model is not scalable. The AUC (Area Under Curve) in the ROC graph in fig 6 is 0.74. The graph in figure 7 shows the sensitivity is calculated using the equation (1) is high in no class as 100% and 0% in yes class. The ANN correctly classified 143 negatives (no osteoporosis) and 0 positives (osteoporosis). It also incorrectly classified 37 positives and 0 negatives as shown in fig 7.

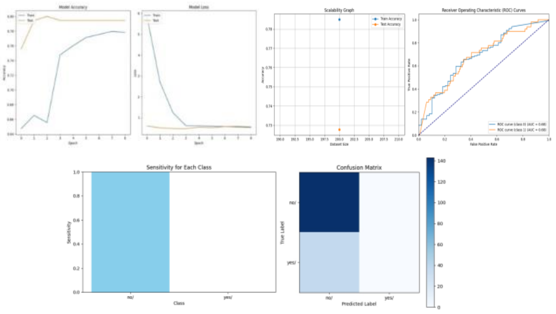


Fig 8 MLP Osteoporosis accuracy and loss graph, Fig 9 Scalability, ROC, AUC, Fig 10 Sensitivity and Confusion Matrix

The accuracy graph in fig 8 shows that the MLP model's performance improved during eight epochs, rising from 76% to 80% for osteoporosis detection [10]. In eight epochs, the model's loss drops from six to one in fig 8. Fig 9 shows the MLP model is scalable and the area under the curve (AUC) for the ROC curve is 0.68. It achieved sensitivity same as ANN by (1) and 143 negatives (no osteoporosis) and 0 positives (osteoporosis) were accurately categorized by the MLP as shown in fig 10. Additionally, it misclassified 0 negatives and 37 positives. This performance indicates a critical issue where the model is completely missing all positive cases.

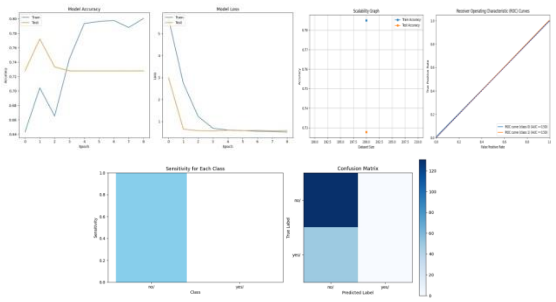


Fig 11 LSTM Osteoporosis accuracy and loss graph, Fig 12 Scalability, ROC, AUC, Fig 13 Sensitivity and Confusion Matrix

The accuracy on the testing set is 74% for osteoporosis detection by LSTM model. The loss graph shows that the training loss decreases to 1 by the end of training whereas the loss in testing set appears to be decreasing at a faster rate in fig 11. The accuracy and loss graphs suggest that the LSTM model might be under fitting the data. Fig 12 illustrates that LSTM model is not scalable. The AUC value for this model is 0.50 as shown in fig 12. The sensitivity of no classes is 99%. This suggests the model might be biased towards predicting negative cases, even when osteoporosis is present. The figure 13 confusion matrix of LSTM model correctly classified 131 negatives (no osteoporosis) and 0 positives (osteoporosis). It also incorrectly classified 49 positives and 0 negatives.

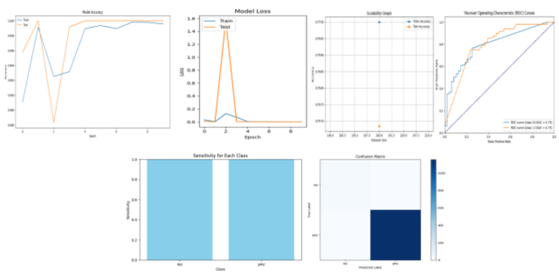


Fig 14 CNN Osteoarthritis accuracy and loss graph, Fig 15 Scalability, ROC, AUC, Fig 16 Sensitivity and Confusion Matrix

The highest accuracy of 99.8% is displayed by the CNN model for osteoarthritis detection in fig 14. The loss indicates that the model is learning since it begins at a high value of 30% and decreases throughout the course of the epochs as given in fig 14. Fig 15 shows that CNN model is highly scalable and derived AUC value for the ROC curve in the graph is 0.6. The sensitivity is 0.99 in both the classes from (1) in fig 16. CNN model correctly classified 16 negative cases (no osteoarthritis) and 154 positive cases (osteoarthritis). It also incorrectly classified 0 negative cases and 0 positive cases. This implies that the model may be more adept at extrapolating its findings to data from future epochs. Overall, the graph shows that the CNN is a promising approach for osteoarthritis detection.

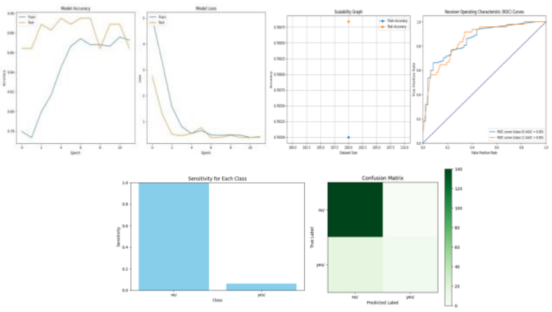


Fig 17 ANN Osteoarthritis Accuracy and loss graph, Fig 18 Scalability, ROC, AUC, Fig 19 Sensitivity and Confusion Matrix

The accuracy of ANN model for osteoarthritis detection starts at 87% and increases to about 88.7% by 10 epochs in fig 17. The graph in the right side of fig 17 represents the model loss. In both the accuracy and loss graphs, the training data (blue line) shows a steeper improvement than the testing data (orange line). Fig 18 infers that ANN model is not scalable and AUC value under ROC is 0.85. From figure 19 we infer that the sensitivity is high in no class. ANN model correctly classified 140 negative cases (no osteoarthritis) and 5 positive cases (osteoarthritis). It also incorrectly classified 17 positive cases and 0 negative cases. This suggests the ANN model might be biased towards predicting negative cases, even when osteoarthritis is present. This suggests that the model may be overfitting the training data.

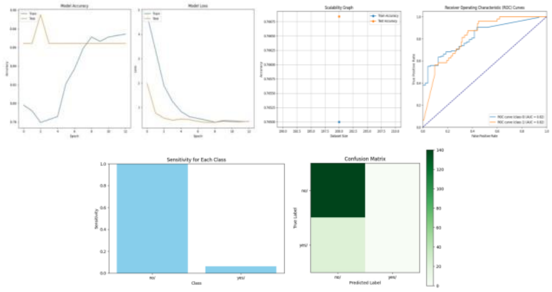


Fig 20 MLP Osteoarthritis Accuracy and loss graph Fig 21 Scalability, ROC, AUC, Fig 22 Sensitivity and Confusion Matrix

On the testing data of osteoarthritis detection using MLP, the accuracy is 87% from figure 20 it is evident that the MLP model starts at around 4 on the training data and trends downwards to about 1 by the end of training. From fig 21 we see that the model is not scalable. The AUC value for the ROC curve in the fig 21 for class 0 is 0.82 and the sensitivity on Yes class is 10% and no class is 98%. MLP model correctly classified 140 negatives (no osteoarthritis) and 0 positives (osteoarthritis) as illustrated in fig 22. It also incorrectly classified 22 positives and 0 negatives.

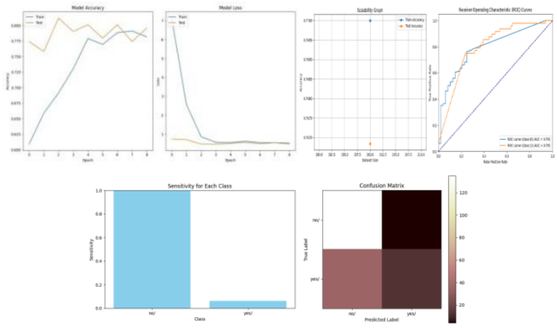


Fig 23 LSTM Osteoarthritis Accuracy and loss graph Fig 24 Scalability, ROC, AUC, Fig 25 Sensitivity and Confusion Matrix

The testing accuracy curve for osteoarthritis detection using LSTM starts at around 75% and increases to about 80.3% on the y-axis over the course of the epochs It is important to note that the testing accuracy is lower than the training accuracy in fig 23. The accuracy and loss graphs suggest that the LSTM model might be underfitting the data. The AUC value for the ROC curve in the fig 24 for class 0 is 0.79 and the sensitivity of this model is 99% in no class and 10 % in yes class. The confusion matrix in figure 25 proves that LSTM model correctly classified 135 negative cases (no osteoarthritis) and 12 positive cases (osteoarthritis). It also incorrectly classified 35 positive cases and 4 negative cases. This suggests LSTM model possesses some difficulty correctly identifying osteoarthritis, particularly when there is actually osteoarthritis present (positive cases).

TABLE 1. COMPARISON OF MODELS FOR OSTEOPOROSIS DETECTION

MODEL	ACCURACY	LOSS	SENSITIVITY	ROC	AUC
CNN	94.3%	30%	0.89	0.87	0.87
ANN	87%	10%	0.90	0.74	0.74
MLP	80%	6-1%	0.99	0.68	0.68
LSTM	74%	3-1%	0.99	0.50	0.50

The study in table 1 compared four algorithms for osteoporosis detection: CNN, ANN, MLP, and LSTM. CNN achieved the highest accuracy (94.3%) with the least training iterations (20). ANN and MLP showed promise but reached lower accuracy (87% and 80% respectively) and suffered from overfitting. LSTM might be under fitting the data (77% training accuracy, 74% testing accuracy). Overall, CNN is the best option for now, but further research is needed on the other algorithms.

TABLE 2 COMPARISON OF MODELS FOR OSTEOARTHRITIS DETECTION

MODEL	ACCURACY	LOSS	SENSITIVITY	ROC	AUC
CNN	99%	30%	0.99	0.6	0.6
ANN	88%	3%	0.99	0.85	0.85
MLP	87%	3%	0.98	0.82	0.82
LSTM	80.3%	6%	0.79	0.85	0.85

The comparison shown in table 2 compares algorithms for osteoarthritis detection reveals interesting insights. CNN reigns supreme with an impressive 99.98% accuracy and low loss (30%) after just 20 training epochs, suggesting its efficiency and strong generalization capabilities. ANN and MLP, while showing improvement with training, reach lower peak accuracies (88.7% and 87% respectively). However, ANN might be overfitting due to its significant gap between training and testing performance. Conversely, MLP offers 87% accuracy which is lesser than CNN but shows potential with further training. Finally, LSTM achieves accuracy (80.3%) and seems to be underfitting as training data performs better than testing data, potentially requiring additional training or data augmentation. Overall, while all methods hold promise, CNN stands out for its exceptional accuracy, efficiency, and good generalization, making it a strong contender for osteoarthritis detection.

V. CONCLUSIONS

The novelty of this project lies in its exploration of various deep learning algorithms for the detection of both osteoporosis and osteoarthritis using medical images. While prior research has focused on using individual algorithms like CNNs or LSTMs for either osteoporosis or osteoarthritis detection, this project comprehensively compares the performance of CNN, ANN, MLP, and LSTM for both diseases [17]. This comparative analysis not only reveals the most suitable algorithm for each disease but also highlights the strengths and weaknesses of each method. CNN emerges as the best model, achieving an outstanding accuracy of 94.3% for osteoporosis and osteoarthritis with efficient training, indicating its ability to generalize well to unseen data [18]. While ANN and MLP show improvement with training, they reach lower peak accuracies and raise concerns about overfitting in the case of ANN. LSTM, while achieving reasonable accuracy, exhibits signs of under fitting, suggesting the need for further training or data augmentation [19]. Therefore, based on the analysis, CNN stands out as the most promising approach for accurate and efficient osteoarthritis detection, although further research in advanced machine learning techniques might be necessary to refine the other methods and explore their potential [20].

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