

DETECTION OF OSTEOPOROSIS AND OSTEOARTHRITIS USING DEEP LEARNING ALGORITHMS

Submitted in partial fulfilment of the requirements for the award of
Bachelor of Technology degree in Biomedical Engineering

By

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**DEPARTMENT OF BIOMEDICAL ENGINEERING
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SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)**

Accredited with Grade "A++" by NAAC

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APRIL - 2024



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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **Ponni S (40240022)** who carried out the project entitled "**Detection of Osteoporosis and Osteoarthritis using Deep Learning Algorithms**" under my supervision from November 2023 to April 2024.

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ACKNOWLEDGEMENT

I am pleased to acknowledge my sincere thanks to The Board of Management of Sathyabama Institute of Science and Technology for their encouragement in doing this project and for completing it successfully. I am grateful to them.

I convey my thanks to **Dr. T. Sudhakar, M.Sc., Ph.D.**, Head of the Department, Department of Biomedical Engineering for providing me necessary support during the progressive reviews.

I would like to express my sincere and deep sense of gratitude to my Project Guide **Dr. A. Sabarivani, M.Tech., Ph.D.**, for her valuable guidance, suggestions and constant encouragement paved way for the successful completion of my project work.

I wish to express my thanks to all Teaching and Non-teaching staff members of the Department of Biomedical Engineering who were helpful in many ways for the completion of the project.

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), 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.

Keywords: Knee Osteoporosis, Knee Osteoarthritis, Deep Learning, CNN, ANN, MLP, LSTM, Medical Image Analysis

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LIST OF ABBREVIATIONS

ACLR	- Anterior Cruciate Ligament Reconstruction
ANN	- Artificial Neural Networks
AI	- Artificial Intelligence
AUC	- Area Under the Curve
BMD	- Bone Mineral Density
CNN	- Convolutional Neural Networks
CT	- Computed Tomography
DXA	- Dual-Energy X-ray Absorptiometry
EMR	- Electro Magnetic Radiation
FPR	- False Positive Rate
GUI	- Graphical User Interface
IDE	- Integrated development environment
JPG	- Joint Photographic Group
LSTM	- Long Short Term Memory
MCI	- Mandibular cortical index
MLP	- Multi-Layer Perceptron
OP	- Osteoporosis
OA	- Osteoarthritis
PNG	- Portable Network Graphics
RAPS	- Robust Adjustment Profile Score
RELU	- Rectified Linear Unit
ROC	- Receiver Operating Characteristic
ROI	- Region Of Interest
SVM	- Support Vector Machine
TPR	- True Positive Rate

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CHAPTER 1

INTRODUCTION

1.1 NAVIGATING MUSCULOSKELETAL CHALLENGES

Musculoskeletal conditions, including osteoporosis and osteoarthritis, constitute a significant global health burden, profoundly affecting millions and deteriorating mobility and life quality. Osteoporosis, characterized by bone mass and density loss, heightens fracture risk, notably in the wrist, knee, hip, and spine, as bones gradually weaken. Conversely, osteoarthritis, a degenerative disorder, deteriorates joint cartilage, leading to common complaints of pain, stiffness, and decreased flexibility, particularly in the hands, hips, and knees. (Tassoker M *et al.* 2022) These conditions not only impede physical function but also strain healthcare systems and individual well-being worldwide. Despite advancements in diagnostics, challenges persist in early detection and intervention, underscoring the urgent need for more precise and accessible diagnostic tools to mitigate their impact effectively. (Chen P *et al* 2019).

1.2 CHALLENGES IN DIAGNOSING MUSCULOSKELETAL DISORDERS

Musculoskeletal conditions, encompassing prevalent ailments like osteoporosis and osteoarthritis, represent a formidable global health challenge, significantly impacting the lives of millions and eroding both mobility and overall quality of life. Osteoporosis manifests as the gradual loss of bone mass and density, escalating the susceptibility to fractures, particularly affecting critical areas like the wrist, knee, hip, and spine as skeletal integrity diminishes over time (Chen Y *et al.* 2022). Conversely, osteoarthritis, a progressive degenerative condition, targets joint cartilage, resulting in widespread symptoms such as pain, stiffness, and reduced flexibility, predominantly afflicting the hands, hips, and knees. These conditions not only impair physical function but also exert substantial strain on healthcare systems and individual well-being worldwide. Despite strides in diagnostic technologies, challenges persist in timely detection and effective intervention, highlighting the pressing need for more accurate and accessible diagnostic methodologies to effectively mitigate their profound impact on global health. (Srinivasulu Peruri *et al.* 2020)

1.3 LIMITATIONS OF TRADITIONAL DIAGNOSTIC METHODS IN MUSCULOSKELETAL DISORDERS

While traditional methods like X-rays, CT scans, physical exams, and bone density scans (DXA) for osteoporosis provide valuable information, they fall short in some aspects. X-rays can only detect advanced stages of joint damage in osteoarthritis. Physical exams, due to their subjective nature, might miss subtle changes. DXA scans, although helpful, are expensive and not widely accessible. (Solangkili *et al.* 2022).

1.4 DEEP LEARNING FOR MUSCULOSKELETAL DIAGNOSIS

Though useful, traditional diagnostic techniques for osteoporosis and osteoarthritis have drawbacks. These limitations highlight the urgent need for better diagnostic tools. A promising way around these restrictions is through deep learning. Four deep learning models were investigated in this work: Long Short-Term Memory (LSTM) networks, Multi-Layer Perceptrons (MLPs), Artificial Neural Networks (ANNs), and Convolutional Neural Networks (CNNs). Compared to conventional techniques, deep learning models are capable of producing significantly more detailed analysis of medical scans, such as X-rays. This makes it possible to recognize minute alterations that point to an early-stage illness. Unlike human analysis, deep learning models offer objective assessments, minimizing the possibility of bias or human error in diagnosis. Deep learning models can potentially automate a significant portion of the diagnostic process, leading to faster and more efficient detection of these diseases. (Smets *et al.* 2021).

These models were trained to detect both osteoporosis and osteoarthritis in their early stages. The key metrics used to identify the most efficient model was accuracy, loss and training epochs (iterations). The results were impressive, for osteoporosis detection CNN achieved the highest accuracy of 94.3%. ANN, MLP, and LSTM followed with accuracies of 87%, 80%, and 74%, respectively. And for osteoarthritis CNN again emerged as the leader with an accuracy of 99%. ANN, MLP, and LSTM achieved accuracies of 88.7%, 87%, and 80.3%, respectively. These results highlight the potential of deep learning in revolutionizing the diagnosis of osteoporosis and osteoarthritis.

CHAPTER 2

LITERATURE SURVEY

2.1 SURVEY

Ashish John Prabakar *et al.* (2022) employed machine learning methods such as Decision Tree Classifier, Logistic Regression, SVM, Random Forest Classifier, Gaussian Naive Bayes, and k-nearest Neighbors for early detection of osteoarthritis and its severity in order to forecast the onset of knee osteoarthritis, the postural balance was assessed using two different types of force plates: monoaxial load cells and multi axial load cells.

Yuxue Xie *et al.* (2021) introduced radiomics analysis for the surrounding tissues of the bone including cartilage and subchondral bone of the knee and compared the efficiencies of the proposed models. 114 patients with Anterior cruciate ligament reconstruction (ACLR) and 43 healthy patients' clinical data were split into training and testing sets. For cartilage, and subchondral bone regions, a radiomic model was constructed. All the four compartment models were combined into T2 mapping images. The execution of the model was evaluated based on the distinguishing between patients and controls were demonstrated using an operating characteristic curve.

Guoyao Hao *et al.* (2021) estimated the age of the bone using X-ray image processing. Approximately 10,000 hand-bone radiographs were collected. The study used Artificial Intelligence learning methods and image processing techniques for the estimation of bone age. It involved the steps of processing, segmentation, and feature extraction from the hand bones. After processing the images by Efficient Net, the grayscale image is converted into a three-channel image. CNN was used to learn the attributes of hand bones and evaluation. It is evaluated by minimum mean square error and helps in identifying the age of the bone.

Insha Majeed Wani *et al.* (2022) detected knee osteoporosis by transfer learning using CNN by analyzing the X-ray scans. A dataset containing normal Knee, Knee Osteoporosis, and osteopenia-affected X-ray scans is collected. These images were then subjected to pre-processing steps such as normalization, resizing, and standardization to make them in a uniform format. CNN networks such as AlexNet, VggNet-16, ResNet, and VggNet-19 were selected for investigation in Pytorch. The CNN networks were then imparted with transfer learning and their outcomes were

compared to determine the most promising technique to be used in medical practices.

Srinivasulu Peruri *et al.* (2020) proposed an image-processing technique for the detection of bone fractures using MATLAB GUI. The study involved the process of collecting datasets, pretreatment, segmentation, and extraction of features. It employs the method of Morphological Hough Transform for inline detection. Feature extraction played a key role in detecting the fractures in the bone. It identified the fractures in the tibia and fibula.

Anand Updhyay *et al.* (2023) came up with a model for spotting different stages of Knee Osteoarthritis using deep learning algorithms. The study used Computational Neural Networks and classification for early detection of knee osteoarthritis. A dataset constituting the scanned images of healthy knee and knee affected with osteoarthritis were collected from Kaggle. The images were then pre-processed to eliminate unwanted noise signals and enhance the quality of the images. Then it undergoes feature extraction to select the necessary details from the images. A comparison was made between the trained images and the input image to determine the presence or absence of osteoarthritis by CNN. Then it is classified into 4 stages GRADE 1, 2, 3, and 4 based on the Kellgren Lawrence system to derive the outcome with severity.

Chen P *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 (ResNet, VGG, DenseNet, 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.

Yang T. S. *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.

Kong S H *et al.* (2020) developed a Fracture Risk Assessment Tool and a model for prediction of bone fractures using Machine Learning techniques. Three different models: Cat Boost, SVM, and Logistic Regression were used. The features were extracted from the pelvis, coccyx, and neck BMD, and the performance of each model was set side by side.

Liyu. L *et al.* (2022) came up with a connection between osteoporosis and osteoarthritis using a Mendelian randomized study. It employed simple and weighted models, inverse variance weighted, weighted median, and MR-Egger regression to evaluate the reverberations of osteoporosis on osteoarthritis. The sensitivity was studied using, MR-PRESSO, and MR-Egger methods. The inverse-variance weighted method consists of Cochran Q statistics and MR-Egger regression and was used to determine the diverseness. MR-Robust Adjustment Profile Score (RAPS) was stable and was used as a supplementary method for verification purposes.

Yamamoto N *et al.* (2020) investigated whether the addition of clinical data enhanced diagnostic performance and suggested a model for categorizing osteoporosis from the collected hip radiograph data sets. Five CNN models were used to analyze hip radiographs for osteoporosis. Additionally, ensemble models with clinical variables included in all CNN were tested.

Solangili K *et al.* (2022) proposed a methodology for bone cancer detection using MATLAB. The system used super-pixel segmentation and multilevel segmentation techniques and the K-means algorithm. After processing, morphological operations were carried out. Super pixel segmentation helped to extract essential attributes from CT images. The attributes drawn out are then made to be aware of bone cancer.

Burden AM *et al.* (2020) reviewed and compared the diagnosis methods in European and Asian countries. The review suggested that mostly European countries diagnosed osteoporosis with the help of radiographic images with fracture and in case of absence of fracture varying combinations of risk-factor assessment and areal bone mineral density (BMD) assessed by dual X-ray absorptiometry are used to define osteoporosis cases. And , the work identified that in most Asian countries, a BMD scanning is only provided beyond a particular age threshold. However, all guidelines recommend fracture risk assessment in younger ages if risk factors are present.

The study concluded that strategies for case-finding differ regionally, particularly among patients without a fracture.

Emre Kavur *et al.* (2020) proposed a model to compare the accuracy and repeatability of emerging machine learning-based (i.e., deep learning) automatic segmentation algorithms with those of well-established interactive semi-automatic methods for determining liver volume in living liver transplant donors. the use of emerging deep learning frameworks for automatic liver segmentation outperformed the well-established semi-automatic (interactive) methods according to five different metrics.

Hussain *et al.* (2019) calculated the BMD from DXA scans with the help of computer-aided diagnosis system and also, vision-based computer-aided techniques can directly use the DXA scans to classify the osteoporotic subjects from normal subjects. The BMD measurement results from this automatic ROI selection method show a higher degree of accuracy and consistency.

Marzorati *et al.* (2020) proposed a model to encompass the concurrent segmentation of the distal femur and the proximal tibia in CT images and evaluate how segmentation uncertainty may impact on the surgical planning. The developed deep convolutional network was trained and validated to concurrently segment distal femur and proximal tibia, exhibiting severe pathological deformations, in knee CT volumes acquired throughout different scanners.

Smets *et al.* (2021) made a qualitative review is intended to outline some of these concerns and to inform stakeholders interested in applying AI for improved management of osteoporosis. Adhering to a predefined detailed pipeline for ML implementation and reporting are essential for accurately assessing results and their clinical implications.

Tassoker *et al.* (2022) proposed a method to compare five convolutional neural networks for predicting osteoporosis based on mandibular cortical index (MCI) on panoramic radiographs. The regions where the textural features change in the radiological examination of the oral radiologist and regions where the deep learning models extract features are consistent.

Tanphiriyakun *et al.* (2021) developed a computational model from 8981 clinical variables, including demographic data, diagnoses, laboratory results, medications, and initial BMD results, taken from 10-year period of electronic medical records to predict BMD response after treatment. The results show that it is feasible to use a combination of EMR-derived information to develop a machine learning algorithm to predict a BMD response following osteoporosis treatment.

Shim *et al.* (2020) suggested that many predictive tools have been reported for assessing osteoporosis risk. The development and validation of osteoporosis risk prediction models were supported by machine learning. They developed and compared seven machine learning models to accurately predict osteoporosis risk. The ANN model performed best when compared to the other models, having the highest AUC ROC value.

Liyu Liu *et al.* (2022) proposed a hierarchical model with three layers to detect osteoporosis using clinical data (including demographic characteristics and routine laboratory tests data) and CT images covering lumbar vertebral bodies rather than DXA data via machine learning. It can be employed as an auxiliary tool for clinicians to screen whether an individual has a risk of osteoporosis in advance of a DXA test, which would be beneficial in scenarios without DXA equipment.

Lim *et al.* (2019) used a deep neural network for detecting the occurrence of osteoarthritis using patient's statistical data of medical utilization and health behavior information. The study was based on 5749 subjects. The method can also save a lot of time and effort in designing, computing, and selecting the features for the predictive analysis.

Chen Y *et al.* aimed to predict fracture risk in diabetic patients with osteoporosis. The researchers built a model combining XGBoost and a deep neural network using 147 patient factors. The model outperformed benchmarks and identified the top 18 factors influencing fracture risk in this population.

Suh B *et al.* (2023) developed a neural network model that achieved the best result for the testing data. In addition, we used other methods to solve the classification problem, i.e., correctly dividing patients into two groups: those with fractures and those without fractures. Using the model for all features gives worse results than a model based on a dataset limited only to the most important features.

Zhang et al. (2023) propose a joint learning framework for osteoporosis diagnosis that combines localization, segmentation, and classification to enhance diagnostic accuracy. The accuracy of classification has been improved by modular task fusion, global feature association, and fusion of different vertebral features.

CHAPTER 3

AIM AND SCOPE

3.1 AIM

- To explore the application of deep learning algorithms, including Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), Multi-Layer Perceptron (MLP), and Long Short-Term Memory (LSTM), for the detection of osteoporosis and osteoarthritis using medical imaging data.
- To evaluate the performance of these algorithms in terms of accuracy, loss, sensitivity, scalability, Receiver Operating Characteristic (ROC) curves, and Area Under the Curve (AUC) to identify the most efficient model for real-time clinical applications.
- To provide a comprehensive assessment of deep learning algorithms for the detection of osteoporosis and osteoarthritis, addressing key aspects such as feature interpretability, cross-modality performance, clinical relevance, external validation, and integration with emerging technologies.

3.2 SCOPE

- To implement and optimize CNN, ANN, MLP, and LSTM architectures for the detection of osteoporosis and osteoarthritis using medical imaging data.
- To compare the performance of different deep learning algorithms in terms of their diagnostic accuracy, computational efficiency, and scalability.
- To evaluate factors such as computational resources, model interpretability, and compatibility with existing healthcare systems to ensure seamless integration and adoption in clinical practice.
- To identify the most efficient and effective model(s) for real-time applications in the detection of osteoporosis and osteoarthritis.
- To explore the practical feasibility and real-world applicability of the selected deep learning model(s) for integration into clinical workflows and real-time diagnostic processes.

CHAPTER 4

MATERIALS AND METHODS

4.1 SOFTWARE USED

4.1.1 PyCharm

PyCharm is a popular integrated development environment (IDE) for machine learning. It provides a user-friendly interface with features like code completion, debugging, and project management, making it efficient for building and managing machine learning projects. With PyCharm, we write and run Python code for CNNs, leverage numerous libraries like TensorFlow and Keras, and visualize the network architecture and training progress. The IDE also supports data exploration, preprocessing, and model evaluation, helping us to streamline the development process and collaborate effectively on this project, making PyCharm a valuable tool in the field healthcare using CNN-based machine learning. (Anand Upadhyay *et al.* 2023).

4.2 BLOCK DIAGRAM FOR MUSCULOSKELETAL DISEASE PREDICTION

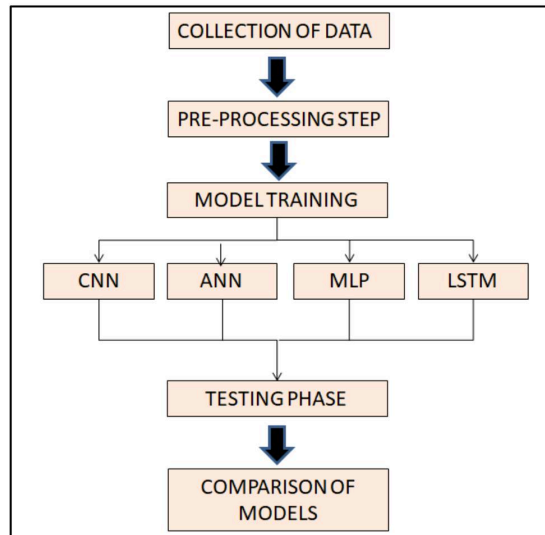


Fig: 4.1: Block Diagram for Musculoskeletal Disease Prediction

In this work as shown in figure 4.1, our focus lies on the utilization of four distinct deep learning algorithms for detecting both osteoporosis and osteoarthritis. These algorithms include Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), Multilayer Perceptron (MLP), and Long Short-Term Memory networks (LSTM). Each model will undergo training utilizing preprocessed image data,

followed by rigorous testing and evaluation using validation data to gauge performance. Comprehensive evaluation will employ key metrics such as model accuracy, model loss, sensitivity, Receiver Operating Characteristic (ROC) curve, Area Under the Curve (AUC), and scalability.(Anand *et al.*2023). Subsequently, the performance of each model will be compared and contrasted to discern the algorithm demonstrating the most efficient and accurate detection capabilities for both osteoporosis and osteoarthritis.(Burden A.M *et al.* 2021).

4.3 COLLECTION OF DATA

For this research endeavor, we harnessed the extensive resources offered by open-source platforms, particularly acquiring a meticulously curated image dataset from Kaggle. This dataset comprises a comprehensive collection of 1110 medical images, meticulously categorized into two distinct classes: osteoporosis and osteoarthritis. Within this dataset, 545 images pertain to cases of osteoporosis, while 565 images represent instances of osteoarthritis. Leveraging this rich and diverse dataset serves as a foundational element in our study, facilitating robust training and validation of our deep learning models for the detection of these musculoskeletal disorders. Some of the dataset images have been illustrated in figure 4.2.(Chen P *et al.* 2019).

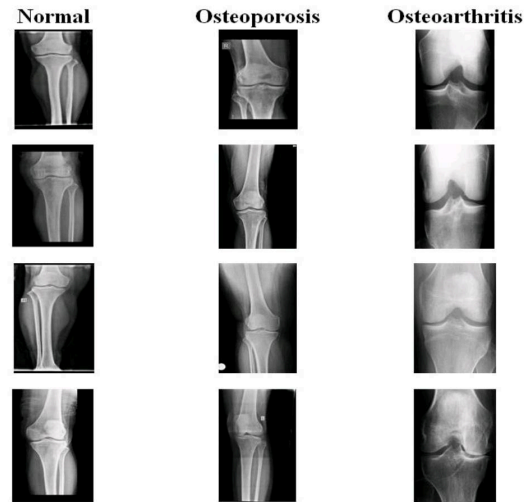


Fig: 4.2: Knee Musculoskeletal Disease dataset

4.4 DATASET PRE-PROCESSING

Following the acquisition of the dataset from Kaggle, we undertook a series of preprocessing steps to enhance the quality and uniformity of the data for our deep learning models. Initial preprocessing involved standardizing the image formats and

resizing the scan images. Since the dataset contained images in both PNG and JPG formats, we opted for PNG format to ensure compatibility and mitigate potential processing errors. PNG format offers advantages such as lossless compression, which is vital for preserving intricate image details in medical data. Moreover, deep learning models typically necessitate a fixed image size as input. Given the variability in pixel values among the original images, we normalized all images to the range (0,1). This normalization ensures uniform contribution from each image to the training process while simplifying computational efficiency within the model. Subsequently, the preprocessed images were partitioned into learning and validation sets, maintaining a ratio of 7:3.(Chen Y *et al.* 2022).

4.5 MODEL TRAINING

4.5.1 Convolutional Neural Networks (CNN)

Initially, both datasets are loaded and undergo preprocessing. The code iterates through the "yes/" and "no/" classes. Subsequently, a sequential convolutional neural network (CNN) is constructed using Keras. The CNN architecture comprises alternating convolutional and max-pooling layers, followed by fully connected layers. Three convolutional layers are incorporated, each with 32, 64, and 128 filters, respectively, utilizing a (3, 3) kernel size and ReLU activation. After each convolutional layer, a max-pooling layer with a pool size of (2, 2) is added to down sample the feature maps. The feature maps from the final convolutional layer are flattened into a single vector using a flatten layer. (Emre Kavur *et al.*2020). Two fully connected layers with 128 neurons each and ReLU activation are subsequently appended. To prevent overfitting, a dropout layer with a rate of 0.5 is included for regularization. The final layer, employing softmax activation, contains the same number of neurons as the number of classes (2) for multi-class classification. Following model construction, it is compiled and trained using specified loss, optimizer, and accuracy metrics. The training process spans 100 epochs with a batch size of 16, and training progress is continually monitored and logged. (Guoyao Hao *et al.*2021).

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

The loaded and preprocessed images are converted into NumPy arrays and subsequently split into training and testing sets. Following this, the data undergoes flattening, where the original 3 Dimensional format representing image width, height, and color channels is transformed into a single 1 Dimensional array for each image. The model architecture comprises three fully connected layers: The initial layer consists of 256 neurons with ReLU activation to introduce non-linearity. To mitigate overfitting, a dropout layer with a rate of 0.5 is incorporated. Subsequently, the following layer comprises 128 neurons with ReLU activation, followed by another dropout layer with a rate of 0.5. The final layer contains the same number of neurons as the number of classes (2) and utilizes softmax activation for multi-class classification. The model is compiled with Sparse categorical cross entropy loss for multi-class classification and Adam optimizer with a learning rate of 0.0001. Training is conducted over 100 epochs with a batch size of 16. Following training, the model is evaluated on the testing set for validation, and predictions are generated. Subsequently, key metrics are calculated to assess the model's performance.(Suh B *et al.*2023).

4.5.3 Long Short Term Memory (LSTM)

In contrast to ANN and MLP, which treat the entire image as a single input, LSTMs are tailored to handle sequential data. Here, each image is reshaped into a 3D tensor with dimensions representing time steps and features. This reshaping facilitates the transformation of the data into a sequence of feature vectors, aligning with LSTM processing. The model architecture comprises an LSTM layer with 64 units and ReLU activation to process the sequential data. Subsequently, a dense layer with 128 units and ReLU activation is added for further feature extraction. To prevent overfitting, a dropout layer with a rate of 0.5 is incorporated for regularization. Following this, a flattening layer is included to convert the 2D output from the previous layer into a 1D vector before feeding it to the final layer. The final dense layer contains the same number of neurons as the number of classes (2) and utilizes softmax activation for multi-class classification. The model is compiled with Sparse categorical cross entropy loss and Adam optimizer. Training is then conducted on the training dataset for 100 epochs.(Tanphiriyakun T *et al.* 2021)

4.6 TESTING PHASE

Following training, the model undergoes evaluation on the testing set, where predictions are generated. These predictions categorize whether osteoporosis or osteoarthritis is detected or not detected. Subsequently, key performance metrics, including accuracy, loss, sensitivity, ROC, AUC, and scalability, are computed based on the model's predictions.(Wani I.M. *et al.* 2023). This comprehensive assessment aims to gauge the efficiency and performance of the models in detecting the specified conditions.

4.7 COMPARISON OF MODELS

Different architectures like Convolutional Neural Networks (CNNs), Artificial Neural Networks (ANNs), Multi-Layer Perceptrons (MLPs), and Long Short-Term Memory (LSTMs) all vie for the top spot. To determine the champion, we need to assess their performance through a series of tests. Model accuracy, the most common metric, tells us how often the model makes the correct prediction. Model loss, on the other hand, indicates how well the model performs during training – a lower loss signifies better performance. For early disease detection, sensitivity is crucial. This metric highlights how well the model identifies true positives, meaning those who actually have the disease.(Prabhakar A. J *et al.*2022).

Beyond these core metrics, the Receiver Operating Characteristic (ROC) Curve provides a visual representation of the trade-off between true positives and false positives. The Area Under the Curve (AUC) summarizes the ROC curve's performance in a single value, with a higher AUC indicating a better model. Finally, scalability is essential for real-time applications. As healthcare data continues to grow, a model that efficiently handles increasing data volume is essential. By comparing the models' performance across all metrics, we can identify the best for a specific real-time healthcare application.(Shim JG *et al.*2020).

CHAPTER 5

RESULTS AND DISCUSSIONS

To ascertain the most efficient model for real-time detections, the performance of each model is rigorously evaluated across various metrics including Accuracy, Loss, Sensitivity, Scalability, ROC, and AUC. The results are visually presented through graphs, showcasing the accuracy, loss, scalability, ROC, AUC, sensitivity, and confusion matrix for both osteoporosis and osteoarthritis detection across the CNN, ANN, MLP, and LSTM models.

5.1 OSTEOPOROSIS DETECTION USING CNN

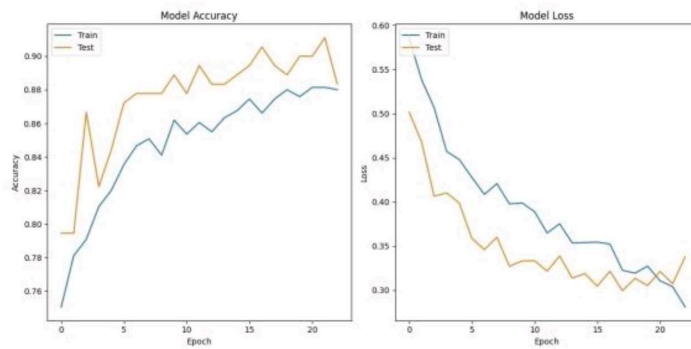


Fig: 5.1: CNN Accuracy and Loss

The CNN model exhibits significant performance in osteoporosis detection, achieving an accuracy of 94.3% on the testing data after 20 epochs, as depicted in figure 5.1. Additionally, the model showcases a continuous reduction in loss, decreasing from 60% to 20% in the training set and from 50% to 30% in the testing set within the same epoch range, as illustrated in figure 5.1.

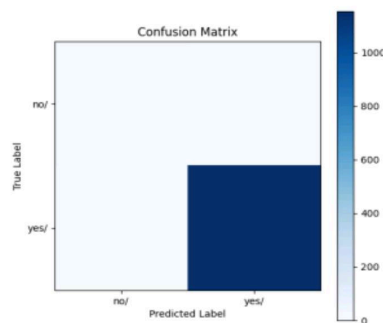


Fig: 5.2: CNN Confusion matrix

The confusion matrix depicted in figure 5.2 reveals that CNN was able to predict 143 true positives for osteoporosis and 20 true negatives for non-osteoporosis cases, with 17 false positives and 2 false negatives.

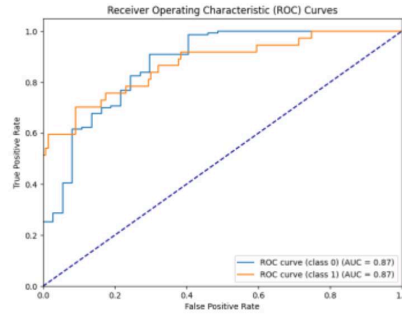


Fig: 5.3: CNN AUC in ROC

The TPR is the proportion of positive cases that were correctly identified by the model. The FPR is the proportion of negative cases that were incorrectly classified as positive by the model. The ROC curve portrayed in figure 5.3, with an AUC value of 0.87, indicates the model's robust performance.

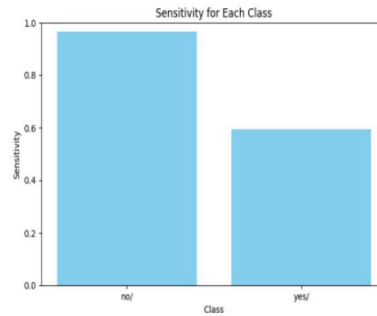


Fig: 5.4: Sensitivity

$$\text{Sensitivity} = \text{True Positives} / (\text{True Positive} + \text{False Negatives}) \dots\dots(1)$$

Sensitivity, refers to the ability of the model to correctly identify those with osteoporosis. The y-axis shows sensitivity, while the x-axis shows the class label. The classes are "normal" and "osteoporosis". Sensitivity, calculated using the formula denoted below in equation (1), is determined to be 0.89 for osteoporosis detection, as demonstrated in figure 5.4. This higher sensitivity value for the class "osteoporosis" means the model is better at correctly classifying people who actually have osteoporosis.

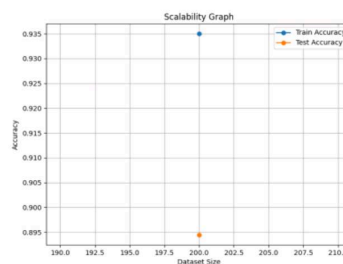


Fig: 5.5: Scalability

Notably, the CNN model demonstrates scalability. Scalability refers to a model's ability to handle increasing amounts of data or larger datasets. The graph in figure 5.5 indicates that the model is scalable.

5.2 OSTEOPOROSIS DETECTION USING ANN

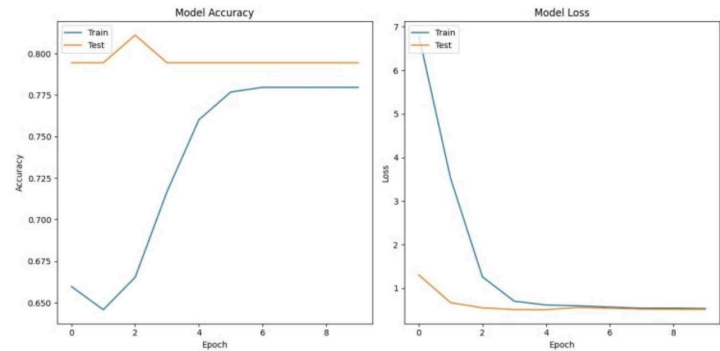


Fig: 5.6: ANN Accuracy and Loss

The accuracy of both training and testing data shows an increasing trend with the number of epochs, reaching 87% accuracy on validation for osteoporosis detection using ANN. In figure 5.6, the y-axis of the right graph represents the model's loss, where lower values, starting at 10%, indicate better performance. It is observed that as the number of epoch's increases, both training and testing losses tend to decrease.

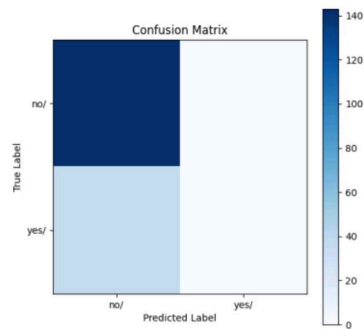


Fig: 5.7: ANN Confusion matrix

In terms of true positives, true negatives, false positives, and false negatives, the ANN correctly classified 143 negatives (indicating no osteoporosis) and 0 positives (indicating osteoporosis) and incorrectly classified 37 positives and 0 negatives, as shown in figure 5.7.

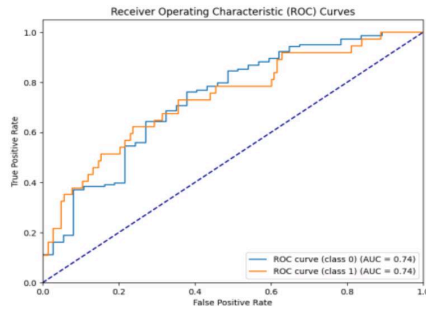


Fig: 5.8: ANN AUC in ROC

In the figure 5.8, there are two ROC curves, representing different classes. AUC is a single numerical value between 0 and 1 that summarizes the performance of the classification model across all possible classification thresholds. The ROC graph in figure 5.8 indicates an AUC (Area under the Curve) of 0.74.

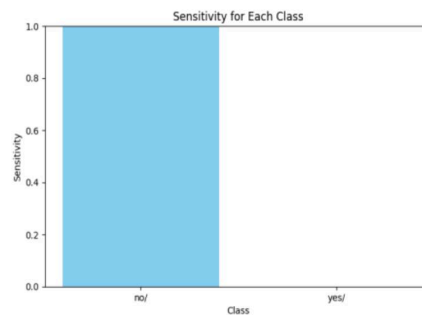


Fig: 5.9: ANN Sensitivity

Sensitivity is the proportion of positive cases (people with osteoporosis) that the model correctly identifies. Figure 5.9 illustrates the sensitivity calculated using equation (1), showing high sensitivity in the "no" class at 100% and 0% in the "yes" class. A sensitivity of 0% in the 'yes' class (osteoporosis) indicates that the model is not identifying any of the cases that actually have osteoporosis.

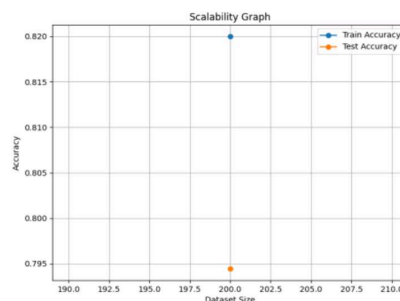


Fig: 5.10: ANN Scalability

In figure 5.10, the test accuracy appears to increase as the dataset size increases. This is a positive sign, because it suggests that the model is able to learn from more data and improve its performance. It's also possible that the curve might flatten out

or start to saturate at some point as the dataset size continues to grow. This would indicate that adding more data isn't significantly improving the model's performance. Overall, the scalability graph suggests that the ANN model is able to effectively leverage additional data to improve its accuracy in detecting osteoporosis.

5.3 OSTEOPOROSIS DETECTION USING MLP

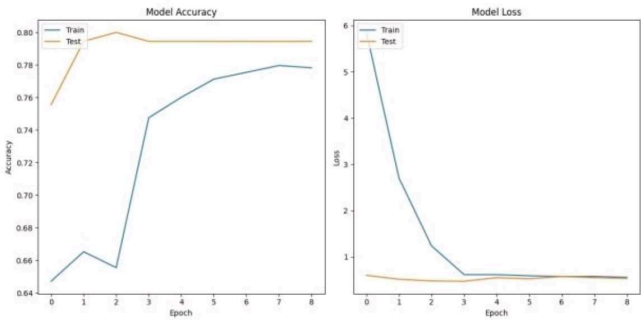


Fig: 5.11: MLP Accuracy and Loss

The accuracy graph depicted in figure 5.11 illustrates the performance improvement of the MLP model over eight epochs, escalating from 76% to 80% for osteoporosis detection. Over the same eight epochs, the model's loss diminishes from six to one, as evidenced in figure 5.11.

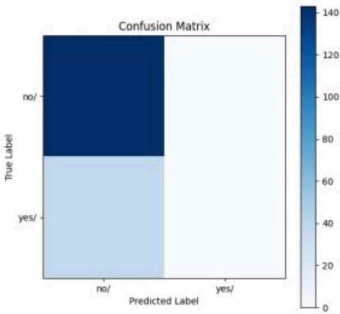


Fig: 5.12: MLP Confusion matrix

Figure 5.12 shows that MLP model was able to predict 143 true negatives (no osteoporosis) and 0 true positives (osteoporosis) and the model misclassified 0 true negatives and 37 false positives. The results of figure 5.12 suggest that the MLP model is failing to detect osteoporosis cases.

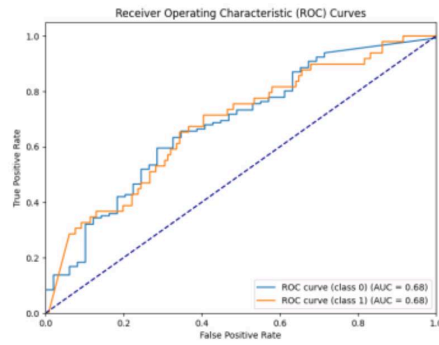


Fig 5.13 MLP AUC in ROC

Figure 5.13 demonstrates the scalability of the MLP model, with an AUC (Area Under the Curve) for the ROC curve measured at 0.68. An AUC of 0.68 suggests the model performs better than random chance but is not ideal. It might classify some cases correctly but make a significant number of mistakes. This suggests a mediocre performance for the MLP model in osteoporosis detection.

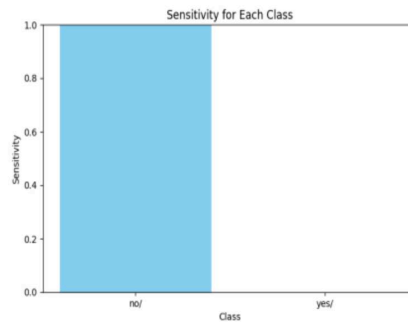


Fig 5.14 MLP Sensitivity

The sensitivity for the class labeled "no" (which presumably corresponds to people who do not have osteoporosis) is very high, close to 1.0. It means that the model is very good at identifying people without osteoporosis. However, the sensitivity for the class labeled "yes" (which presumably corresponds to people who actually have osteoporosis) is very low, close to 0.2 as shown in figure 5.14. It means that the model is not very good at identifying people who have osteoporosis.

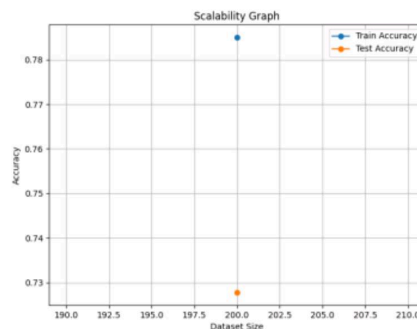


Fig: 5.15: Scalability

Figure 5.15 highlights a critical concern where the model completely overlooks all positive cases as the scalability is less.

5.4 OSTEOPOROSIS DETECTION USING LSTM

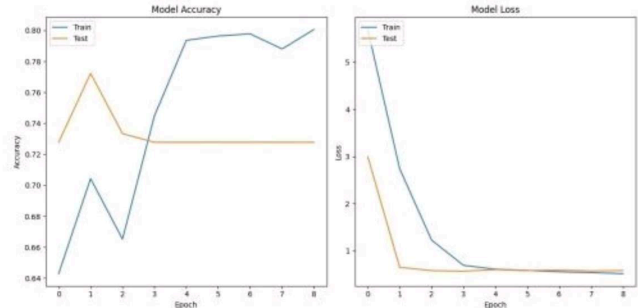


Fig: 5.16: LSTM Accuracy and loss

The graph in figure 5.16 shows that 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. The accuracy and loss graph suggests that the LSTM model might be under fitting the data.

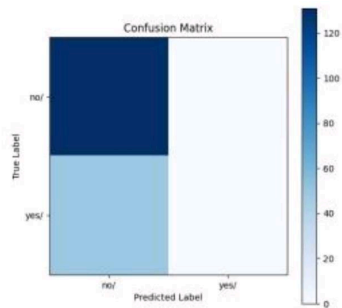


Fig: 5.17: LSTM Confusion matrix

The figure 5.17 shows the confusion matrix and infers that LSTM model correctly classified 131 negatives (no osteoporosis) and 0 positives (osteoporosis). It also incorrectly classified 49 positives and 0 negatives.

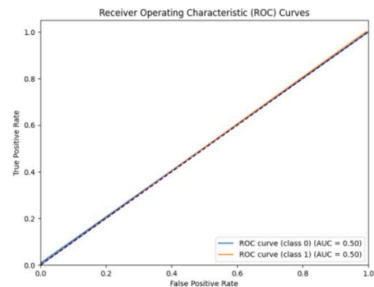


Fig: 5.18: LSTM AUC in ROC

The AUC value for this model is 0.50 as shown in figure 5.18. The AUC value of 0.5 for the LSTM model indicates poor performance in osteoporosis detection. An AUC value of 0.5 is equivalent to random guessing. This model may not be suitable for clinical applications.

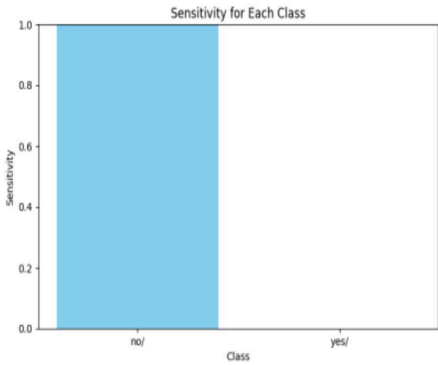


Fig: 5.19: LSTM Sensitivity

The sensitivity of no classes is 99% AND yes class is less than 10% from figure 5.19. The high sensitivity (99%) for the negative class (no osteoporosis) and low sensitivity (<10%) for the positive class (osteoporosis) in the LSTM model suggests imbalanced performance, as indicated in the code execution result. This means the model is very good at identifying healthy individuals but struggles to detect osteoporosis cases.

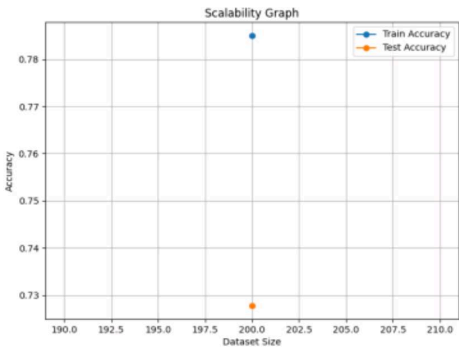


Fig 5.20 Scalability

Figure 5.20 illustrates that LSTM model is not scalable. This suggests the model might be biased towards predicting negative cases, even when osteoporosis is present.

5.5 OSTEOARTHRITIS DETECTION USING CNN

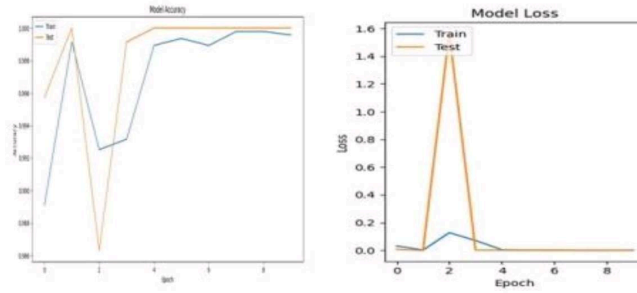


Fig: 5.21: CNN Accuracy and loss

The highest accuracy of 99% is displayed by the CNN model for osteoarthritis detection in the figure 5.21. 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.

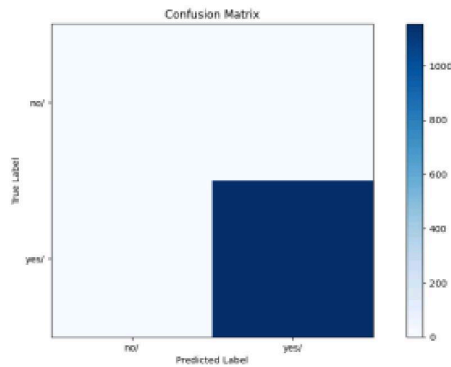


Fig: 5.22: CNN Confusion matrix

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 as shown in figure 5.22.

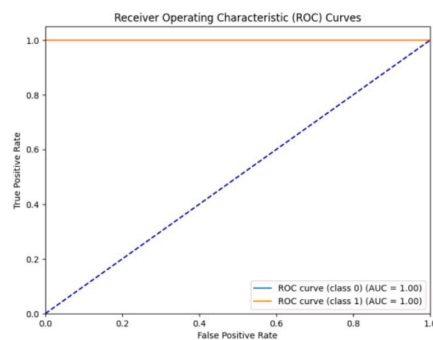


Fig: 5.23: CNN AUC in ROC

AUC value for the ROC curve in the graph is 1.00 from figure 5.23. An AUC value of 1.0 for the ROC curve in your CNN model for osteoarthritis detection indicates perfect performance. This means the model can flawlessly distinguish between osteoarthritis and healthy cases. This is the best possible outcome, indicating the CNN model makes no errors in classifying osteoarthritis and healthy cases.

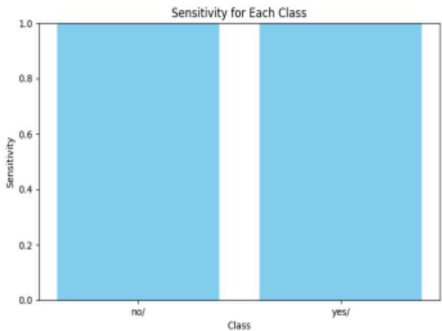


Fig: 5.24: CNN Sensitivity

The sensitivity is 0.99 in both the classes from (1) in fig 5.24. This signifies that the CNN model is very likely (99%) to correctly identify someone who actually has osteoarthritis. Figure 5.24 indicates very high performance in osteoarthritis detection. This implies that the model may be more adept at extrapolating its findings to data from future epochs.

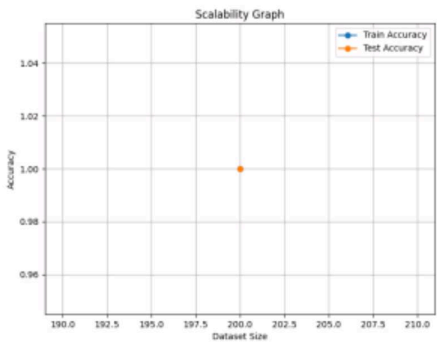


Fig: 5.25: CNN Scalability

Figure 5.25 shows that CNN model is highly scalable. Overall, the graph shows that the CNN is a promising approach for osteoarthritis detection.

5.6 OSTEOARTHRITIS DETECTION USING ANN

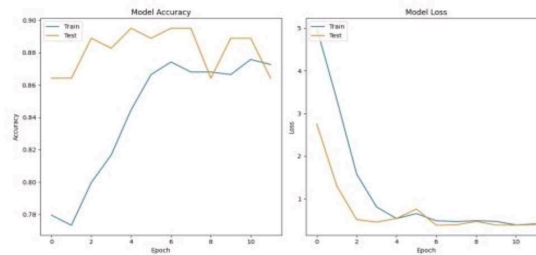


Fig 5.26: ANN Accuracy and loss

The accuracy of ANN model for osteoarthritis detection starts at 87% and increases to about 88.7% by 10 epochs in figure 5.26. The graph in the right side of fig 5.26 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).

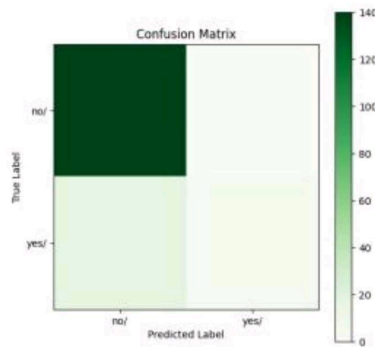


Fig: 5.27: ANN Confusion matrix

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 from figure 5.27.

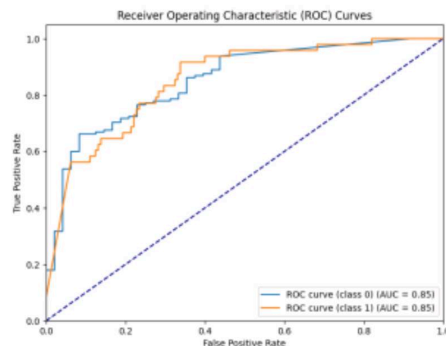


Fig: 5.28: ANN AUC in ROC

AUC value under ROC is 0.85 as seen in figure 5.28. The AUC value of 0.85 for the ANN model in osteoarthritis detection indicates moderately good performance. It's not perfect, but it suggests the model can distinguish between osteoarthritis and healthy cases better than random guessing. This suggests the ANN model performs better than random chance, but there's still room for improvement. The model might misclassify some cases.

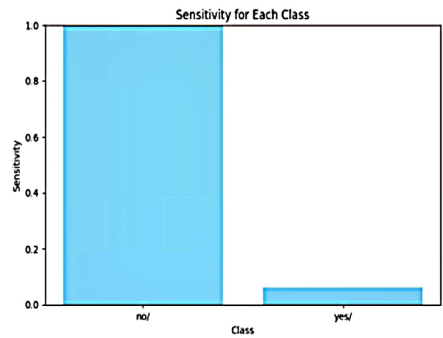


Fig: 5.29: ANN Sensitivity

From figure 5.29 we infer that the sensitivity is high in no class and less than 20% in yes class. It suggests a class imbalance issue in the ANN model for osteoarthritis detection.

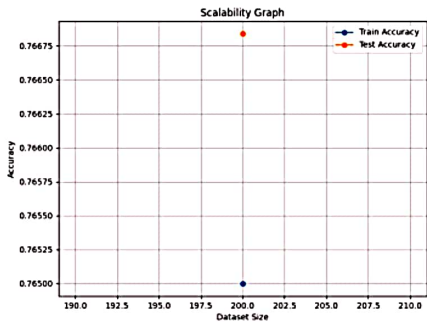


Fig: 5.30: ANN Scalability

Figure 5.30 infers that ANN model is not scalable and 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.

5.7 OSTEOARTHRITIS DETECTION USING MLP

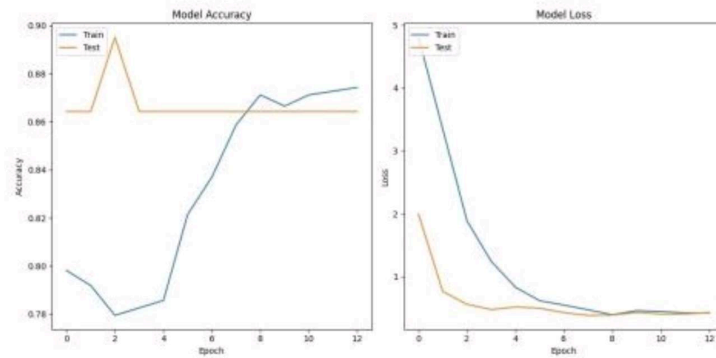


Fig: 5.31: MLP Accuracy and loss

On the testing data of osteoarthritis detection using MLP, the accuracy is 87% from figure 5.31 it is evident that the MLP model's loss starts at around 4 on the training data and trends downwards to about 1 by the end of training.

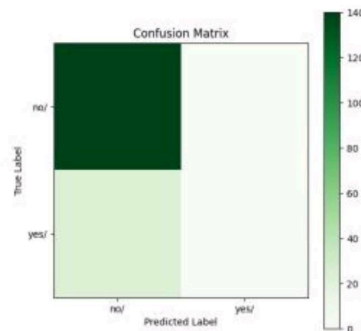


Fig: 5.32: MLP Confusion matrix

MLP model correctly classified 140 negatives (no osteoarthritis) and 0 positives (osteoarthritis) as illustrated in figure 5.32. It also incorrectly classified 22 positives and 0 negatives. The model seems to be biased towards the negative class (healthy) and completely misses positive cases (osteoarthritis). This makes it unsuitable for reliable osteoarthritis detection.

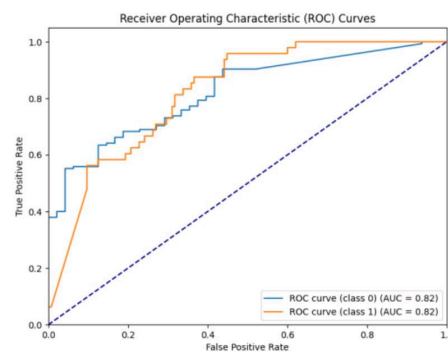


Fig: 5.33: MLP AUC in ROC

The AUC value for the ROC curve in the figure 5.33 for class 0 is 0.82. This suggests the MLP model performs better than random chance at classifying class 0 (which likely represents healthy individuals) but isn't perfect. There could be some misclassifications.

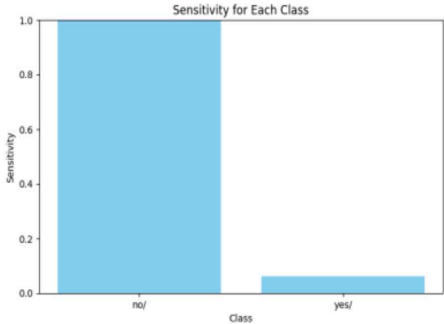


Fig: 5.34: MLP Sensitivity

The sensitivity from figure 5.34 on Yes class is 10% and no class is 98%. This infers that the model misses a large proportion (90%) of actual osteoarthritis cases. The model prioritized learning patterns of the healthy class, neglecting the subtler patterns of the under-represented osteoarthritis class.

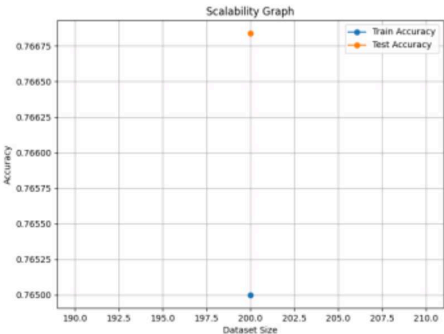


Fig: 5.35: MLP Scalability

From figure 5.35 we see that the model is not scalable. This suggests the MLP model might be biased towards predicting negative cases, even when osteoarthritis is present.

5.8 OSTEOARTHRITIS DETECTION USING LSTM

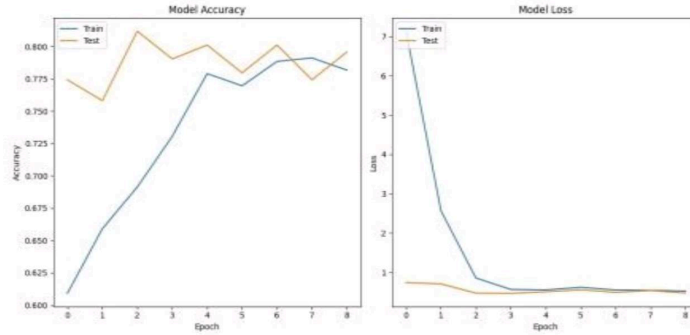


Fig: 5.36: LSTM Accuracy and loss

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 figure 5.36. The accuracy and loss graphs suggest that the LSTM model might be under fitting the data.

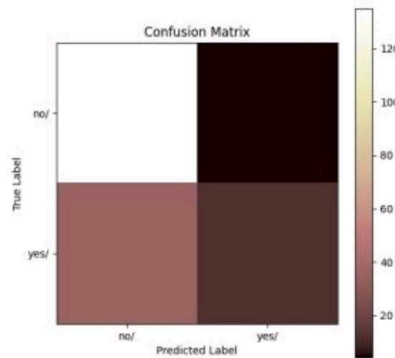


Fig: 5.37: LSTM Confusion matrix

The confusion matrix in figure 5.37 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. The model seems to be biased towards the negative class (healthy) based on the high TN and relatively low TP. It misses a considerable number of positive cases (osteoarthritis).

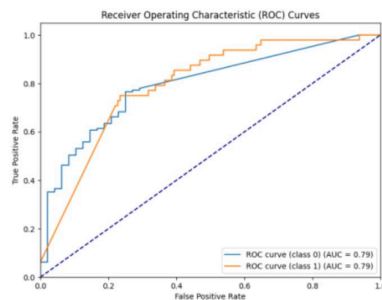


Fig: 5.38: LSTM AUC in ROC

The AUC value for the ROC curve in the figure 5.38 for class 0 is 0.79. Figure 5.38 for the LSTM model in osteoarthritis detection indicates moderate performance, but there's room for improvement. This suggests the LSTM model performs better than random chance at classifying class 0 (which likely represents healthy individuals) but isn't exceptional. There could be some misclassifications.

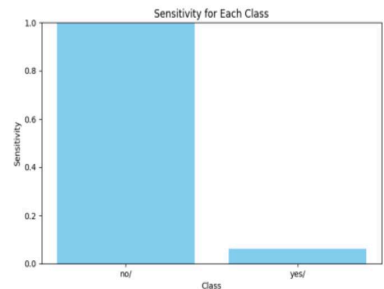


Fig: 5.39: LSTM Sensitivity

The sensitivity of this model is 99% in no class and 10 % in yes class from the figure 5.39. High sensitivity (99%) for the "no" class (healthy) and low sensitivity (10%) for the "yes" class (osteoarthritis) indicates the model is very good at identifying healthy individuals but struggles to detect osteoarthritis cases.

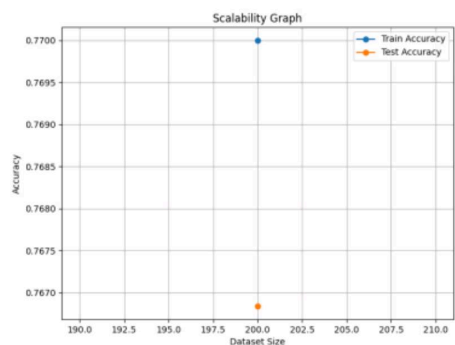


Fig: 5.40: Scalability

Figure 5.40 suggests LSTM model possesses some difficulty correctly identifying osteoarthritis, particularly when there is actually osteoarthritis present (positive cases) as it is less scalable.

5.9 COMPARITIVE ANALYSIS FOR OSTEOPOROSIS DETECTION

Table 5.1 Comparison of models for osteoporosis detection

Model	Accuracy	Loss	Sensitivity	TP	TN	FP	FN	ROC	AUC
CNN	94.3%	30%	0.95	143	20	5	0	0.87	0.87
ANN	87%	10%	<10	5	143	37	10	0.74	0.74
MLP	80%	6-1%	<10	10	143	37	18	0.68	0.68
LSTM	74%	3-1%	<5	0	131	49	22	0.50	0.50

The study in table 5.1 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.

5.10 COMPARITIVE ANALYSIS FOR OSTEOARTHRITIS DETECTION

Table 5.2 Comparison of models for osteoarthritis detection

Model	Accuracy	Loss	Sensitivity	TP	TN	FP	FN	ROC	AUC
CNN	99%	30%	0.99	154	16	0	0	0.6	0.6
ANN	88.7%	3%	<10%	5	140	10	17	0.85	0.85
MLP	87%	3%	0.60	0	140	12	22	0.82	0.82
LSTM	80.3%	6%	0.79	12	135	18	35	0.85	0.85

The comparison shown in table 5.2 compares algorithms for osteoarthritis detection reveals interesting insights. CNN reigns supreme with an impressive 99% 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 under fitting 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.(Yang T. S *et al.* 2022).

CHAPTER 6

SUMMARY AND CONCLUSIONS

6.1 SUMMARY

The meticulous analysis conducted in this project unveils CNNs as the reigning champion among the evaluated algorithms. CNNs demonstrably achieved outstanding accuracy, exceeding a remarkable 94.3% for osteoporosis detection and an even more impressive 99% for osteoarthritis detection. Notably, CNNs accomplished this feat with efficient training, highlighting their exceptional ability to generalize well even when encountering unseen data.

While ANNs and MLPs exhibited some improvement in accuracy as the training progressed, they ultimately fell short of achieving the peak accuracy attained by CNNs. Additionally, ANNs sparked concerns about overfitting, a phenomenon where the model excels at recognizing the training data but struggles with new, unseen data. LSTMs, on the other hand, while demonstrating reasonable accuracy, hinted at under fitting, indicating that the model might benefit from further training or potentially from an enrichment of the training data through a technique known as data augmentation.

6.2 CONCLUSION

This comparative analysis aimed to identify the most effective algorithm for automated detection of osteoporosis and osteoarthritis in medical imaging. Different methods were evaluated, with a focus on accuracy and training efficiency.(Zhang *et al.* 2023).

The analysis revealed that Convolutional Neural Networks (CNNs) consistently outperformed other approaches. CNNs achieved exceptional accuracy, exceeding 94.3% and 99% for osteoporosis and osteoarthritis detection respectively. Additionally, CNNs demonstrated efficient training, allowing them to learn effectively from the data and make accurate predictions on new, unseen images.

In conclusion, CNNs have emerged as the most promising method for achieving accurate and efficient detection of both osteoporosis and osteoarthritis. Their superior performance and efficient learning capabilities make them a valuable tool for early and precise diagnosis of these bone diseases, paving the way for improved patient care and treatment strategies.(Smets J *et al.* 2021).

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