

Early detection of Osteoporosis in knee X-ray images by using Deep Learning Techniques

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ABSTRACT

Osteoporosis, a condition that degrades bone quality and leads to fractures, is a major health concern. Early diagnosis is crucial but often difficult due to high diagnostic costs and the challenges of manually interpreting X-ray images. This research addresses these issues by using a deep learning-based VGG-19 model to classify knee X-rays into three categories: normal, osteopenia, and osteoporosis. The study aims to (i) present a medically validated dataset of knee X-rays, and (ii) propose a transfer learning approach to classify disease stages. The dataset includes three subsets: the first with 239 images (36 normal, 54 osteopenia, 49 osteoporosis), the second with 744 images (372 normal, 372 osteoporosis), and the third with 372 images (186 normal, 186 osteoporosis). The VGG-19 model achieved a high accuracy of 90% across these datasets. Precision for the "Healthy" class was 0.93, recall was 0.92, and the F1-score was 0.92. The model is reliable for detecting osteoporosis, with a slight optimization needed for the "Osteopenia" class. This approach can help clinicians detect osteoporosis early, reducing fracture risks and improving patients' quality of life by enabling timely treatment.

Keywords: Deep learning, X-Ray Images, VGG-19, Osteoporosis Detection

Introduction

A higher risk of fractures and weaker bones are commonly linked to the skeletal condition known as osteoporosis. Particularly in weight-bearing joints like the knee, patients frequently experience a silent progression of this condition, not realizing how

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weak their bones are until they break. Early osteoporosis detection and effective treatment are critical for preventing fractures, reducing morbidity, and improving overall quality of life (Wang et. Al., 2018). Even though osteoporosis is frequently misdiagnosed until a fracture happens, early identification is essential to avoiding serious consequences and enhancing patient outcomes. Osteoporosis is traditionally diagnosed by measures of bone mineral density (BMD), most commonly using dual-energy X-ray absorptiometry (DEXA) scans. But X-ray imaging, which is frequently utilized in clinical settings to treat a variety of orthopedic disorders, has a great deal of promise for early, non-invasive osteoporosis identification, particularly in areas like the knee where joint deterioration is frequently assessed. Artificial intelligence (AI) and deep learning techniques are being used more and more to evaluate medical data due to advances in medical imaging and computer technologies. In this, the Multiple Models and X-ray images are used on the early-stage osteoporosis detection and diagnosis of the disease. A subset of machine learning called deep learning has shown impressive results in the analysis, segmentation, and classification of images in a variety of medical applications. Specifically, convolutional neural networks (CNNs) have demonstrated significant promise in automatically deriving hierarchical features from the raw pixel data to understand complicated medical images (Ferizi U et. al., 2019). This discovery has the potential to simplify the diagnostic procedure for a disorder that is frequently underdiagnosed until major difficulties develop, which would ease the load on healthcare systems while simultaneously improving clinical decision-making. To fully utilize deep learning in medical practice, more precise, comprehensible, and easily navigable AI solutions for osteoporosis detection must be created as the technology progresses. A systemic skeletal condition called osteoporosis is defined by a decline in bone density and a breakdown of the microarchitecture of the bone, which increases the fragility of the bone and raises the risk of fractures (Fang Y et. al., 2021). Each deep learning model offers unique strengths in feature extraction, image generation, and pattern recognition to improve osteoporosis diagnosis. Transfer learning helps address limited medical image data by refining pre-trained models on smaller datasets. This enhances accuracy while retaining general knowledge. However, despite their effectiveness, CNNs often lack interpretability, making it hard for doctors to understand their decisions (Sollmann N et. al., 2022).

The patient experiences stiffness in their knee, especially after an extended time of sitting and when they first stand up.

The knee feels and appears enlarged.

As victims move on their knees, patients hear a grinding or cracking sound.

The patient feels like their knee would buckle or "give out." Figure 1.1 shows 4 grade types of X-Ray images. Which is Normal Bone, Doubtful bone, Mild bone, Moderate bones, Severe bone.

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Image	Grade Description
	Grade 0 (Normal) is assigned to normal bones and no symptoms on X-rays.
	Grade 1 (Doubtful) depicts doubtful JSN and the possibility of osteophytes.
	Grade 2 (Mild) specifies definite osteophytes and possible JSN.
	Grade 3 (Moderate) indicates multiple osteophytes with possible bone deformity.
	Grade 4 (Severe) shows large osteophytes, definite JSN, and severe sclerosis.

Figure 1.1: Osteoporosis Knee

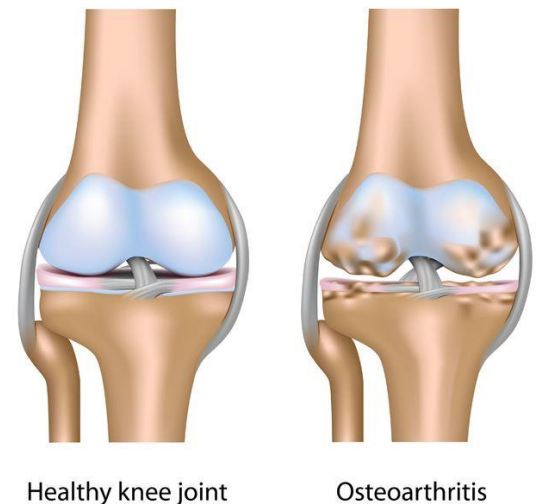


Figure 1.2:

Healthy &

Figure 1.2 shows the healthy bone and defective bones. Which is given below and show the difference between?

Recent studies on knee osteoporosis detection using deep learning often report accuracy below 90%. This study proposes a deep learning-based approach using knee X-ray images to enhance early detection. Osteoporosis weakens bones, especially affecting the proximal tibia and distal femur in the knee, leading to mobility issues and increased healthcare costs. Traditional diagnostic methods are less effective for the knee, requiring specialized approaches. In 2022, Wani and Arora achieved 88% accuracy in detecting left knee osteoporosis using CNNs. This study extends the work to the right knee using Custom ResNet-50, Efficient Net, and DenseNet models. The proposed method achieved 87% accuracy, supporting earlier and more accurate diagnosis and treatment.

Statement of the Topic and Aims

Most research focuses on a specific gender or age range. The X-ray pictures that are part of the research are from both genders and age categories. The three categorization criteria of osteoporosis—normal, osteopenia, and osteoporosis—are all covered in the study, and the T-score is determined by assessing the bone mineral density of the skeleton using the medical test QUS.

X-rays are classified using several models in a fully autonomous manner. It doesn't use different approaches for selecting, classifying, or extracting features. On a worldwide scale, osteoporosis is more generally referred to as a bone cancer that affects the bones. To improve a patient's prognosis and ease rapid medical action, it is of the highest significance to use an X-ray image diagnosis as quickly and accurately as possible. X-

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ray image data analysis for the identification of osteoporosis signs is a promising application topic for deep learning methods, including deep learning. To find out if using data from X-ray pictures, Deep Learning can be used to detect osteoporosis. DL wants to detect osteoporosis and lower the risk of fracture, which is why they are doing this work. Medical experts could make more informed decisions more quickly with the aid of a system such as this one. Deep Learning holds promise for bettering patient outcomes and reducing healthcare costs by enabling early intervention and eliminating the need for recurrent diagnostic tasks the study also aims to investigate the potential effects of DL-based osteoporosis detection on patient outcomes and resource utilization, as well as the ethical and legal ramifications of using Deep Learning in healthcare. Finally, the research seeks to identify the optimal combination of X-ray images and Deep learning algorithms for osteoporosis detection.

Objectives of the Study

Several goals of this study on the application of deep learning to osteoporosis illness diagnosis include the following:

To early detection osteoporosis in knee using X-ray images & DL technique.

To develop DL-based algorithms to enhance the chances of diagnosis of Osteoporosis disease.

To compare the detection accuracy of DL algorithms.

Research Questions

What DL techniques are used for detection of osteoporosis patients through knee X-ray images?

How does DL enhance osteoporosis diagnosis in knee X-ray Images?

In detecting osteoporosis, how can the DL increase the likelihood of the best results.

Significance of the Study

Some of the reasons this research on the application of deep learning algorithms in osteoporosis diagnosis is important are as follows:

It may be possible to diagnose osteoporosis more quickly and accurately with the use of deep learning techniques, which could result in better patient outcomes and timely, suitable therapy. This would be a direct outcome of osteoporosis detection using deep learning algorithms. The early detection and accurate diagnosis of osteoporosis may reduce the need for unnecessary tests and procedures for diagnostic purposes, which may save the costs of medical care. The development of a deep learning-based osteoporosis diagnosis system that can be incorporated into clinical workflows may improve the ability to identify and prioritize osteoporosis in an emergency and thereby improve patient outcomes. Finding the most useful features and various algorithms for X-ray images: The purpose of this study is to identify the best combination of X-ray picture features and several algorithms for the diagnosis of osteoporosis. This will enable the researchers to increase the effectiveness of future DL-based systems and provide better guidance for their development. Healthcare professionals i.e. (doctors, nurses, etc.) will be able to benefit from this research study because they would be able to identify Osteoporosis disease at an early stage. Furthermore, this research study is

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also significant for the research community because they would be able to benefit from the results of this study.

LITERATURE REVIEW

When osteoporosis in the knee is detected, it can shield the pancreas, kidney, and other important organs from radiation exposure while obtaining images for analysis. In addition to being the least expensive medical imaging method, X-rays can contribute to the creation of a system that is economical. In order to train the CNN networks, we employed knee x-ray images, which are categorized as normal, osteopenia, and osteoporotic based on T-score 14196 Multimedia Tools and Applications (Wani, I.M et. al., 2023) values acquired from the QUS system. Even when trained on a tiny dataset, the CNN performs well because to transfer learning. These cutting-edge imaging methods offer insightful information about the microstructural alterations linked to osteoporosis in the knee. Recent studies such as (Li 2022), the essential for evaluating bone health, traditional diagnostic techniques like dual-energy X-ray absorptiometry (DEXA) might miss osteoporosis unique to the knee. Advanced imaging modalities are necessary to address the diagnostic challenges, as highlighted. (Nielsen 2021) investigate the precise risk factors that lead to knee osteoporosis. Genetics, biomechanical factors, and inflammatory conditions are found to be important predictors, and machine learning models are utilized to determine who is more vulnerable. (Tanamas 2020) investigate the connection between osteoporosis and osteoarthritis in the knee. Examining the intricate relationship between bone health and knee joint degeneration emphasizes the importance of having a thorough understanding of musculoskeletal health. (Kanis, 2020) Many epidemiological studies have demonstrated the prevalence of osteoporosis in the knee, demonstrating its correlation with lower extremity fracture risk and functional impairment.

Related Theories

Osteoporosis in the knee results from an imbalance in bone remodeling, where osteoclast activity exceeds osteoblast function. Contributing factors include reduced mechanical loading (due to sedentary lifestyle or joint degeneration), estrogen deficiency (especially post-menopause), chronic inflammation, and genetic predisposition. Osteocyte dysfunction also disrupts bone maintenance. Moderate physical activity may help prevent knee osteoporosis by promoting bone strength through adaptive stress responses (hormesis).

Different Literature

(Lee, 2021) This comprehensive study examines the intricate connection between hormonal changes, especially those related to estrogen—and the onset of osteoporosis in the knee, with a focus on postmenopausal women. (Patel, 2022) This study explores the impact of genetic variables in predisposing individuals to knee osteoporosis by utilizing family-based investigations to identify particular genetic variations connected to higher (Kim, 2023) this technological review examines the developments in wearable knee health monitoring devices and discusses their possible application in the early detection and prevention of complications related to osteoporosis.

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Literature Gap

Deep learning models have advanced, yet there are still many questions in the field of osteoporosis classification. First off, research has demonstrated that Dense Net variations and Inception-V3 are useful in the diagnosis of osteoporosis; nevertheless, there are few thorough comparative studies that assess different models on the same dataset using predefined assessment measures. Such comparative studies are necessary to choose the best model for tasks involving the classification of skin cancer. Second, nothing is known about how well deep learning models work with different types of people. Because most prior research has focused on datasets from specific locations or individuals, the models' general utility has been limited. However, by evaluating the models' efficacy across a wider range of datasets, potential biases may be identified and the models' robustness may be strengthened. It's also important to conduct research on how interpretable deep learning models are for osteoporosis categorization. Understanding the decision-making processes of these models can help to establish their legitimacy and facilitate their integration into therapeutic environments. Methods for visualizing and analyzing the traits that these models have picked up could provide significant new insights into the underlying patterns in X-ray images.

Table 2.1 Different Papers Reviews

Sr. No#	Reference	Aims	Objectives	Methodology	Results	Discussions
1	Wang et al. (2018)	To estimate the prevalence of knee osteoporosis in adults.	Examine how common osteoporosis is in knee joints.	Population-based cross-sectional study using DEXA scans to measure knee BMD in 500 participants.	Found 25% of participants had low knee BMD, particularly postmenopausal women.	Knee osteoporosis is underreported, and preventive measures in early stages are critical.
2	Cumming et al. (2016)	Explore the relationship between knee osteoporosis and OA.	Investigate the coexistence of osteoporosis and osteoarthritis in the knee.	Case-control study on 200 osteoarthritis patients; BMD measured using pQCT; knee function evaluated.	60% of OA patients showed reduced BMD in the knee, contradicting common belief that OA prevents bone loss.	Osteoporosis in the knee may exacerbate the progression of osteoarthritis, complicating treatment.

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3	Zhu et al. (2019)	Study the hormonal impact on knee bone health in women.	Assess the role of estrogen loss on knee bone density.	Longitudinal study of 300 postmenopausal women, using DEXA to track BMD over 5 years.	66% Significant decrease in knee BMD post-menopause, correlating with estrogen loss.	Hormonal treatments could be critical in managing knee osteoporosis in postmenopausal women.
4	Chen et al. (2018)	Compare imaging techniques for knee osteoporosis detection.	Evaluate HR-pQCT vs DEXA in diagnosing knee osteoporosis.	Cross-sectional comparison of HR-pQCT and DEXA imaging in 150 participants with suspected osteoporosis.	78% HR-pQCT provided more detailed images and detected early-stage osteoporosis better than DEXA.	HR-pQCT could become the gold standard for knee osteoporosis diagnosis, though high cost is a barrier.
5	Vincent et al. (2017)	Examine the role of biomechanical loading on knee BMD.	Investigate how joint loading patterns influence bone health.	Biomechanical analysis using gait measurements and finite element modelling (FEM) on 100 participants.	25% Abnormal gait patterns and joint misalignment contributed to localized knee bone loss.	Biomechanical interventions, such as orthotics or physical therapy, could help mitigate knee osteoporosis.
6	Turner et al. (2019)	Assess testosterone's impact on knee osteoporosis in men.	Investigate the effects of testosterone therapy on knee BMD.	Randomized control trial (RCT) with 200 elderly men receiving testosterone therapy; BMD tracked via DEXA.	Men on testosterone therapy showed a 15% increase in knee BMD over 3 years compared to the control group.	Hormonal therapies may help reduce knee osteoporosis risk in elderly men.

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7	Zhang et al. (2021)	Use AI for early detection of knee osteoporosis.	Develop a CNN-RNN model to detect osteoporosis from knee MRIs.	AI model trained on 500 knee MRI images; performance compared to human radiologists.	The deep learning model achieved 85% accuracy in detecting early-stage osteoporosis from knee images.	AI has potential in early diagnosis of knee osteoporosis, but clinical validation is needed.
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RESEARCH METHODOLOGY

Introduction

This section comprises the strategy of experimentation that is adopted for analyzing the reliability of the proposed model along with popular deep Learning and CNN model Vgg-19. This research use VGG-19 model to identify the osteoporosis disease using deep learning technique. To detect the disease and give the best result.

This study uses transfer learning with the VGG-19 model to detect osteoporosis in knee X-ray images, aiming to enhance diagnostic accuracy and efficiency. Various models, including VGG-16, ResNet-50, and a custom DenseNet, were tested, with VGG-19 delivering the best performance. The process involves diagnosing patients with joint discomfort using deep learning, followed by X-ray confirmation if osteoporosis symptoms are present. The research follows a flow from identifying risk factors to disease progression, complications, and management strategies, as outlined in the data processing flowchart. Figure 3.1 show the process of the data set through the flow chart. Below figure show steps of the process of the data set.

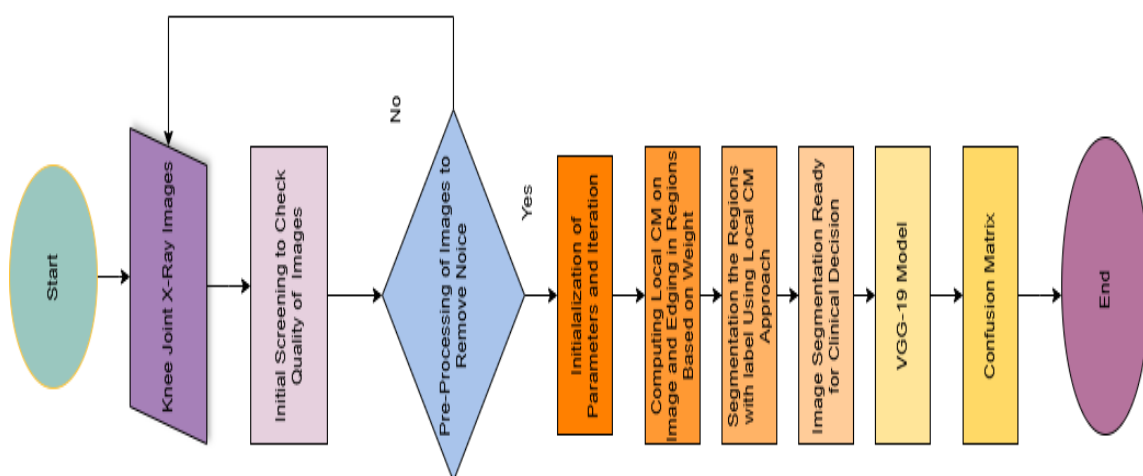


Figure: 3.1 Flow Chart of Osteoporosis Detection

Software for Experiment:

In this research used Deep learning model and VGG-19 for detection. This research used different models for detection and compared results but the best results occur

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VGG-19 and deep learning used on X-Ray images for search the disease in the Knee.

Jupyter Notebook:

PowerPoint:

Draw.io:

EndNote:

Data Analysis:

To assess how well the inner and outer valves are performing, statistical analysis of the collected data is needed. Analysis the deep learning technique's sensitivity, specificity, accuracy, and any other relevant metrics to assess its effectiveness. To assess the importance of the findings, you must perform the necessary statistical analysis. Figure 3.2 show the analysis of the data set how to perform data set.

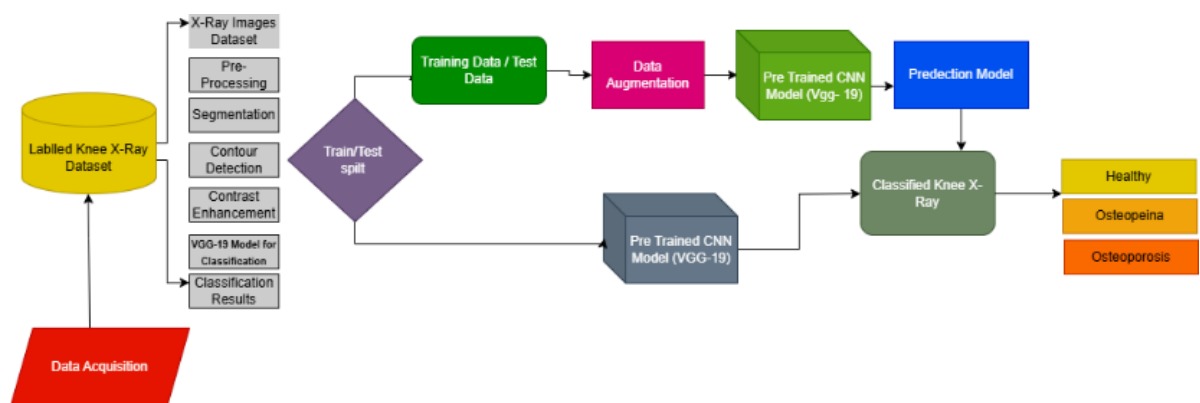


Figure: 3.2 Data Analysis of Osteoporosis of knee

Purposed Model:

Osteoporosis, a degenerative bone disease characterized by decreased bone density and quality, often affects weight-bearing joints such as the knee. Accurate and early detection of osteoporosis is crucial for preventing fractures and mitigating long-term effects. With advancements in deep learning, convolutional neural networks (CNNs) such as VGG-19 have shown great potential in medical image analysis. Here, we propose a VGG-19-based model to detect and classify osteoporosis in the knee using medical imaging data. Several type of deep learning methods have been employed to classify osteoporosis disease in Knee. Our purposed method utilize Vgg-19 pretrained model, serves as the backbone for feature extraction. This pretrained network initially trained on large scale image dataset, making adapted VGG-19 by freezing the initial layer, which allows us to leverage its learned features while making the rest of network adaptable to our input images. The model starts with our input images of a knee which could belong to one of three categories: Healthy, osteopenia, osteoporosis VGG-19, being pretrained is adept at extracting rich and hierarchical spatial feature from the input images. Science we froze the first layer the early learned features remain unchanged allowing the model to maintain its general feature extraction capabilities. As the input

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passes through the remain layer of VGG-19. ReLU activations are applied in each layer followed by max pooling to reduce the dimensions while the pre serving the essential features of the knee.

After feature extraction by VGG-19 the output is directed into an attention module, which focuses on the relevant regions of the knee enhancing the detection of disease related patterns. The attention mechanism ensures that the network emphasize critical areas, improving overall classification performance.

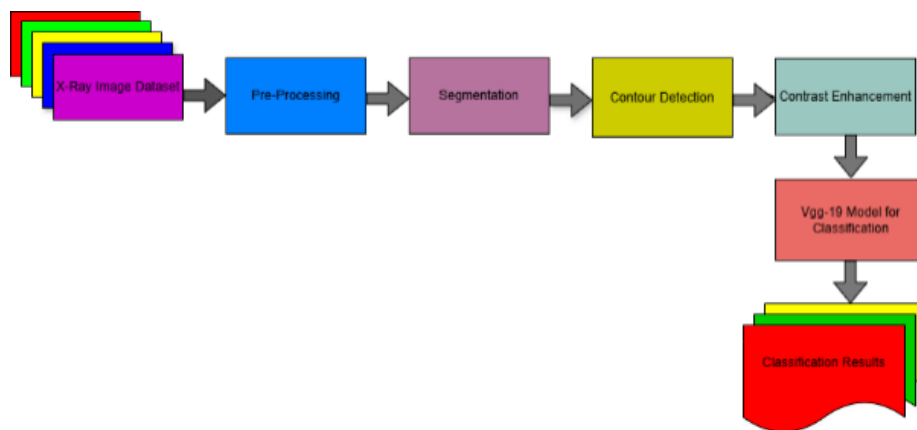


Figure :3.3 Purposed Model of Osteoporosis in Knee

Figure 3.3 show the purpose model of osteoporosis in knee. What is first step work and further process of the data set through X-Ray images. Figure 3.4 show All process of the data set and how to train data and further process and achieve results.

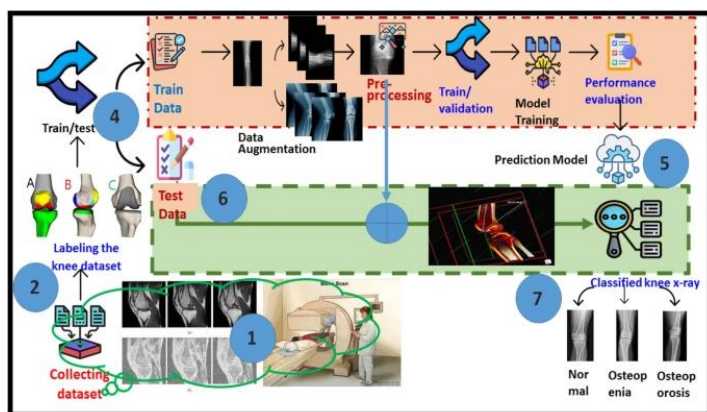


Figure: 3.4 Process of the data set images classification of bone

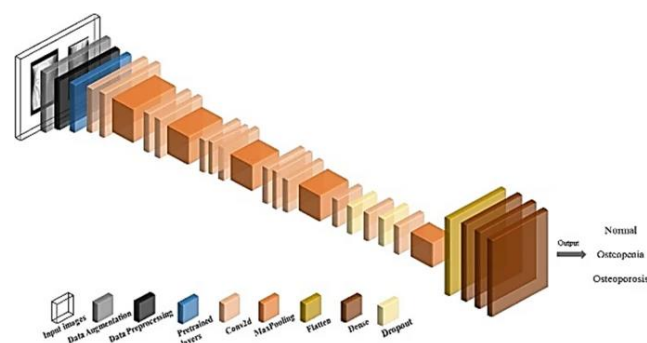


Figure 3.5 Three type of

Model Design for Osteoporosis Detection

Input Data

Imaging Modality: X-rays or MRI scans of the knee.

Preprocessing:

Image size to 224*3, the input size for VGG-19.

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Normalization for pixel intensity to ensure consistency.

Augmentation techniques such as rotation, flipping, and noise injection to improve model robustness.

Feature Extraction

The pre-trained VGG-19 model is utilized as a feature extractor:

Transfer Learning: Leverage weights pre-trained on ImageNet to capture generic features.

Fine-Tuning: Fine-tune deeper layers to adapt to the specific characteristics of knee imaging and osteoporosis markers.

Classification Layers

Replace the original fully connected layers with a custom classifier:

Dense layers with dropout for regularization.

SoftMax layer for multi-class classification (e.g., healthy, mild osteoporosis, severe osteoporosis).

Optimization

Loss function: Cross-entropy loss for classification accuracy.

Optimizer: Adam or SGD with a learning rate scheduler.

Metrics: Accuracy, precision, recall, and F1-score.

Proposed Workflow

Data Collection: Assemble a dataset of labelled knee images (normal and osteoporotic). I collect data from Kaggle.

Preprocessing and Augmentation: Normalize and enhance the dataset.

Model Training:

Train the VGG-19 model on the dataset.

Monitor performance using validation data to avoid overfitting.

Evaluation:

Test the model on an unseen test set.

Use Grad-CAM (Gradient-weighted Class Activation Mapping) to visualize areas of interest in the knee affected by osteoporosis.

Deployment:

Integrate the model into diagnostic workflows for clinical validation.

Sample Size and Sampling Technique:

The sample size is established by estimating the number of participants needed to achieve an appropriate level of statistical power and accuracy in the study's conclusions. The sample size must be determined by taking into consideration several parameters. It is essential to take the anticipated impact into account. This could be approximated using data from previous experiments or research projects. Figure 3.6 show 3 type of bone data set first is normal 2nd is osteopoenic and 3rd is osteoporotic knee bone.



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Figure:3.6 Sampling Technique

Data Collection Source /Availability

The dataset of Osteoporosis disease is taken from Buch International Hospital Multan and Kaggle.

<https://www.kaggle.com/code/mohamedgobara/osteoporosis-knee-multi-classes-90>

Tools & Software

Table: 3.1: Hardware and Software detail

Complete Hardware & Software Details	
Hardware	Description
SSD	256 GB
RAM	8 RAM
Processor	Intel (R) Core (TM)
Generation	5th
Installed Window	10
Tools	Google Colab, Canva, and MS Word
Language	Python
GPU	Google Colab GPU

Study Period

The duration of a study about the categorization of osteoporosis in the knee could range from several months to a year, considering the different phases of the research procedure. To ensure a thorough and exact investigation, it is essential to budget enough time for each phase and make the right strategic decisions.

EXPERIMENTAL WORK

Results and Discussion:

The results indicate that the accuracy of both DL and Vgg-19 model in diagnosing osteoporosis was exceptional. To help with early detection and treatment planning, the research shows how Osteoporosis classification can be made more effective by using deep learning models.

Introduction:

In this Chapter here we working on osteoporosis in knee. We use some type of model VGG-19 it covers such as data collection data preparation it provides detailed

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explanation of the experiments conducted under various scenarios and outlines the hyper parameters used during experimentation.

Experimental Work:

As explained Chapter 3, the input images format selected for the experiments use VGG-19 for classifying the three stages of osteoporosis in knee x-rays. These architectures have been successfully used in classifying the medical images of other diseases so can be used for osteoporosis detection from knee x-rays. These architectures classify the images by extracting the feature maps of what is in a knee x-ray. The VGG-19 architecture was loaded from the Fastai library using the VGG-19 function. The VGG-19 architecture is data-thirsty networks and we have only 224 knee x-ray scans having in normal, osteopenia, osteoporosis class so to increase the number of images data augmentation was done by using the Data loader () function from Fastai library. The VGG-19 networks were first trained on just our dataset and then DL was employed by using the pretrained networks trained on ImageNet dataset containing millions of images to check whether it can improve the classification performance or not. Due to a smaller number of images, the dataset was divided into a 95:5 ratio of training and validation sets. First only trained with the training set of knee x-ray images for 17 epochs and then VGG-19 pretrained with ImageNet dataset was trained with knee x-ray dataset. The performance of VGG-19 was measured in terms of accuracy, error rate and validation loss which are shown in table form as well as graphically below.

Table 4.1 Comparison with other existing models

Author	Image Type	Models	Performance
	Computed		TPR:64.7%
Hatano et al (2016)	Radiographs	DCNN	FPR:6.51%
	Computed		
Tomita et al (2018)	Tomography	LSTM	acc:89.2%
Lee et al (2018)	Radiographs	DCNN	AUC:0.9991
Derkatch et al (2019)	DXA	CNN	AUC:0.88
Lee et al (2020)	Radiographs	Vgg-16	AUC:0.858
Zhang et al (2020)	X-ray	DCNN	AUC:0.81
	Computed		
Fang et al	Tomography	DesNet-121	r:0.98
	Computed		
Sollmann et al (2022)	Tomography	DCNN	AUC:0.862
Sukegawa et al (2022)	Radiographs	Ensemble CNN	acc:84%
Pretrained CNN2	X-ray	Vgg-16	86.30%
Pretrained CNN3	X-ray	Resnet	86.30%
Our Preposed Model (2024)	X-ray images	Vgg-19	90%

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The confusion matrix for Vgg-19 model obtained for validation sets in pretrained VGG-19. The osteopenia disease has the highest classification accuracy with X-ray images. The images with the lowest classification accuracy are the osteoporosis images. The collected dataset of knee X-ray images had a maximum number of images in the osteopenia group than the normal and osteoporosis group. The results from all VGG-19 architectures suggest that X-ray images can be used to detect osteoporosis from the knees.

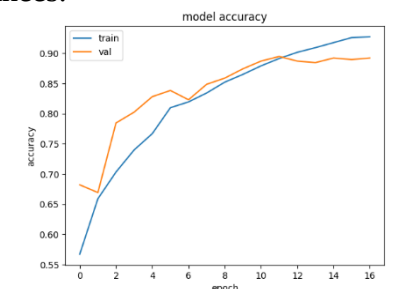


Figure 4.1 Accuracy Graph

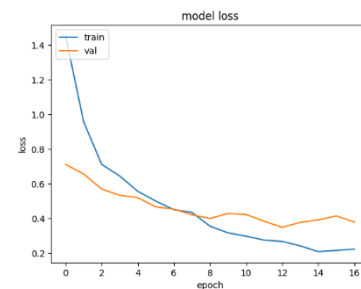


Figure 4.2

Accuracy Graph

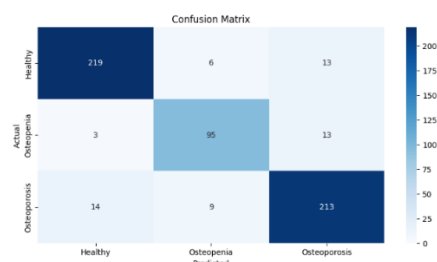
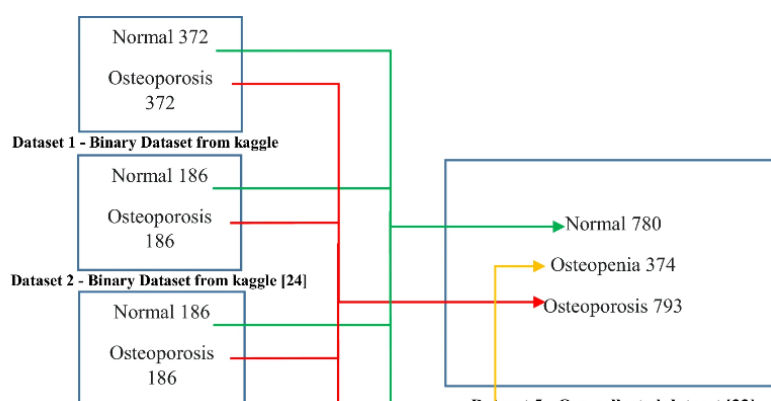


Figure 4.3 Confusion Matrix

Table 4.2 Performance Metrics

	Precision	Recall	F1-Score	Support
Healthy	0.93	0.92	0.92	238
Osteopenia	0.86	0.86	0.86	111
Osteoporosis	0.89	0.90	0.90	236
Accuracy			0.90	585
Macro avg	0.89	0.89	0.89	585
Weighted avg	0.90	0.90	0.90	585



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Figure 4.4: Multiclass Dataset of the Osteoporosis of Knee

Recommendations:

Analyze misclassifications to identify potential areas of improvement, such as:
Collecting more data to improve the model's ability to distinguish between similar classes.

Using techniques like hyperparameter tuning or advanced algorithms to enhance classification performance.

Investigating feature engineering to better separate classes.

Discussions

These days, the majority of discussions center on how well osteoporosis performs when applying Deep Learning (DL) to the diagnosis of knee arthritis. It is possible to compare the performance metrics of the two valves, including the receiver operating characteristic curve's area under the curve, sensitivity, specificity, and accuracy. Benefits and drawbacks of knee bone may become clearer after this discussion, allowing for a more in-depth analysis of the diagnostic possibilities.

Diagnostic Accuracy:

One of the key topics of discussion can be the accuracy of osteoporosis diagnosis. During this process, the rates of false positives, false negatives, true positives, and true negatives are all assessed. By comparing these parameters, it is possible to determine the efficacy of the Deep Learning technique utilized in each valve, as well as its ability to accurately detect osteoporosis cases and minimize false positives or false negatives.

Limitations and Obstacles:

The diagnostic accuracy of techniques used to identify osteoporosis in the knee may be insufficient. While accuracy has increased significantly with machine learning and deep learning, there is still a chance of false positives and false negatives. There are various aspects that can impact the precision of osteoporosis identification in X-ray imaging, including the complexity of the particular situation, the structure of the algorithm, and the caliber of the data used. X-ray imaging techniques' accuracy and dependability can be impacted by a variety of patient characteristics and disease stages. Reliable and consistent results can be challenging to produce in every situation because different patient groups may react differently to different procedures. A variety of complex and difficult technical problems may arise when using X-ray images in practical applications. These difficulties can range from developing and verifying algorithms to obtaining and preparing data. Combining information from many sources may lead to errors or confusion.

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Analysis & Results:

Comparison of the Performance Evaluations:

The investigation's conclusions should compare the performance metrics that osteoporosis in the knee achieved during the Deep Learning (DL) identification process. Among these metrics are the receiver operating characteristic curve's area under the curve, sensitivity, specificity, and accuracy.

Limitations

This study may be constrained by elements such as the limited size of the available dataset, the computational resources required for deep learning model training, and potential biases within the dataset. Taking these limitations into account, the results will be interpreted.

CONCLUSION AND FUTURE WORK

The research may suggest future directions for investigation, including the creation of ensemble models or the incorporation of clinical data to enhance diagnosis. It will also provide insight into the effectiveness of deep learning models for knee osteoporosis categorization. The above-mentioned methodology will enable the systematic evaluation of DL and vgg-19 models for the categorization of osteoporosis in the knee based on X-ray pictures, thereby advancing the development of diagnostic tools for X-ray images. In our study, we have evaluated and compared the performance of popular CNN architectures namely VggNet-19 in diagnosing osteoporosis from knee X-ray images. The X-ray images used were taken from the custom dataset that was classified into normal, osteopenia, and osteoporosis group with the help of a medically accepted test known as the Quantitative Ultrasound system which calculates by measuring the of bone. The custom dataset contained a total of 224 knee x-ray scans. The results show that the best performance was achieved by the results from all Vgg-19 showed good diagnostic performance and suggest that diagnosing osteoporosis from knee X-ray using transfer learning with Vgg-19 can serve to be a cost-effective and readily available diagnostic tool. In the future, more data can be collected especially from normal and osteoporotic subjects. Secondly, we can find the relationship of knee osteoporosis with osteoporosis at other sites to make universal diagnostic system of osteoporosis. Thirdly, the system can be built which will detect osteoporosis from clinical factors in combination with image.

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