Deep Learning for Bone Health-A Transformer Based Framework for Osteoporosis Screening

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements forthe **Degree of Bachelor of Science in Computer Science and Engineering**

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September 16, 2025

APPROVAL

This Project titled "Deep Learning for Bone Health: A Transformer-Based Framework for Osteoporosis Screening" submitted by Abdur Rahman and Sarmin Rahman Mim to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science andEngineering and approved as to its style and contents. The presentation has been held on 09-17-2025.

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DECLARATION

We hereby declare that this project has been done by us under the supervision of Sharun Akter Khushbu, Assistant Professor, Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ACKNOWLEDGEMENTS

This work would not have been possible without the support and contributions of many individuals over the past two semesters. We are deeply grateful to everyone who has assisted us in one way or another.

First, we express our heartfelt thanks and gratefulness to the almighty for His divine blessing making it possible for us to complete the **Final Year Design Project (FYDP)** successfully.

We are grateful and wish our profound indebtedness to **Sharun Akter Khushbu**, **Assistant Professor**, Department of Computer Science and Engineering, Daffodil International University, Dhaka, Bangladesh. Deep knowledge and keen interest of our supervisor in the field of **Medical Image Processing & AI in Healthcare** to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts, and correcting themat all stages have made it possible to complete this project.

We would like to express our heartfelt gratitude to Dr. Sheikh Rashed Haider Noori, Professor and Head of the Department of Computer Science and Engineering, for his kind help in finishing our project and also to other faculty members and the staff of the Department of Computer Science and Engineering, Daffodil International University.

We would like to thank our entire course-mates at Daffodil International University, who took part in this discussion while completing the coursework.

Finally, we must acknowledge with due respect the constant support and patience of our parents.

ABSTRACT

Osteoporosis is a progressive bone disease that leads to a higher risk of fractures, and early diagnosis continues to be a significant problem because current diagnostic tools are not comprehensive. In this work, we tested deep learning models, such as VGG16, VGG19, ResNet, DenseNet, UNet, Vision Transformer (ViT), and Swin Transformer, on 853 X-ray images to detect osteoporosis automatically. To overcome the issue of class imbalance and enhance the robustness of the model, data preprocessing was carried out through standardization, normalization and augmentation. It was experimentally demonstrated that VGG19 had the best classification accuracy of 97%, and UNet performed better in a segmentation task with a Dice score of 0.936. In comparison with the available literature, our method shows a competitive level of performance and proves the possibility of CNN-based and transformer models in medical image processing. The present work helps to build trustworthy, inexpensive, and affordable AI-aided diagnostic systems to monitor osteoporosis and establishes the future trends towards larger datasets, multimodal systems, and real-time clinical use.

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Chapter 1

Introduction

1.1 Introduction

Osteoporosis is a health condition that leads to the weakening of the bones leading to the risk of fracture. It can be termed as a silent disease since the bone loss will be silent until it fractures. This disease is of significance in prevention and management because it is more prevalent in old-aged people especially the postmenopausal women. There are instances when diagnostic procedures such as bone density tests are being utilized now, but these are not always available and when they are available they are not always affordable and they are not always accurate at the early stages. That is a good reason to seek new methods of diagnosing osteoporosis in earlier stages in a cost-effective and efficient way.

Osteoporosis has important public health implications since it is linked to disability in the long term, poor quality of life, and higher healthcare expenditure owing to management and rehabilitation of fractures. Research results have indicated that osteoporosis is mainly common in developing nations where most people have no access to advanced diagnostic equipment. Food deficiencies, inactivity, and ignorance are some other factors that have led to the fast increase of this disease in the global society. Conventional techniques including Dual-energy X-ray Absorptiometry (DXA) scans, which are widely regarded as the best, are not accessible to most patients because of their high costs, lack of access in rural regions and require specialized equipment.

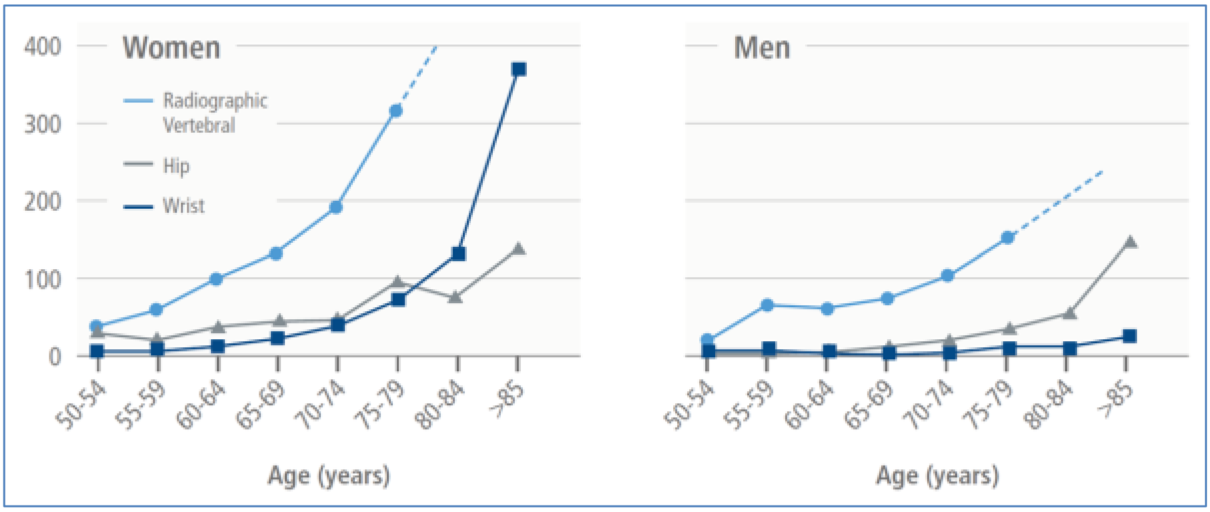

Figure: 1.1 Age and sex specific incidence

Over the past few years, new opportunities to cope with these challenges have become open due to technological advances in the field of medical imaging and artificial intelligence. Due to deep learning and computer vision, nowadays, it is possible to detect small features in medical images that are not always noticed by the human eye, and this opportunity allows to diagnose osteoporosis more accurately and at an earlier stage. Not only are such innovations less reliant on expensive equipment, but they also introduce a scaling solution which can be adopted in a variety of healthcare environments. Therefore, the combination of the AI-based diagnostic methods will be able to democratize the process of screening osteoporosis, making it cheaper, more precise, and available to the risk groups.

Osteoporosis is a prevalent disease in Bangladesh, with researchers saying that more than 35 percent of adults in the country are affected by the disease, and 40 percent have osteopenia (low bone density). The incidence is very high, particularly in women and the elderly, with a few studies demonstrating osteoporosis in almost 50 percent of the rural participants and a significant proportion of postmenopausal women. Lack of vitamin D and low intake of calcium are the main factors that are causing over 70 percent of the population to lag behind due to the inability to exercise.

Problem Statement

Current diagnostic approaches to osteoporosis are too cost-prohibitive, too inaccessible, and too inaccurate in identifying the onset of bone loss. The project aims to develop a computationally efficient method of defining osteoporosis which can be used to improve early diagnosis and treatment of the disease

1.2 Motivation

The reason why I am so excited in regards to finding a solution to this issue is because osteoporosis is something that has been experienced by many people, especially the elderly and in most cases, it is not noticed until it is too late. The other reason why I see this as a big opportunity is that the conventional ways of diagnosing people are expensive and unavailable sometimes therefore, the ability to transform this by using technology. Perhaps, we can avert osteoporosis at the point of its most successful treatment by developing a system that relies on computational methods like AI to diagnose osteoporosis. On a personal level, I believe this project will be interesting because it is the combination of two things that I am passionate about, i.e., healthcare and technology. Not only would this project give me an opportunity to practice some of the best available tools, but it could also potentially save lives by making it easier, more affordable, and quicker to diagnose osteoporosis and more accessible to a wider array of people.

1.3 Objectives

1. Learn some model that can identify osteoporosis using medical data (e.g.X-rays, bone density scans, etc.) with proper accuracy.
2. Test the effectiveness of these model against regular diagnosis.
3. Explore the practicality of these models in other healthcare environments, as well as its potential for real-time detection.
4. Ascertain the viability of adopting the model in a cost-efficient and scalable way.
5. Identify opportunities to implement this solution in collaboration with existing healthcare systems to support early diagnosis and treatment.

1.4 Methodology

A systematic approach that integrates data-driven techniques and deep learning designs was adopted to attain the aims of this project. In the first stage, a set of X-ray images was gathered and made ready to depict normal and osteoporosis cases. Normalization, resizing, and augmentation were used as preprocessing techniques to enhance the quality of data and create balanced training.
A range of deep learning models were then deployed to both classification and segmentation tasks, including: VGG16, VGG19, ResNet, DenseNet, U-Net, and Vision Transformers (ViT, Swin). Accuracy, precision, recall, F1-score, and Dice coefficient were the performance metrics and used to train and evaluate the models on GPU-supported platforms (Kaggle and Google Colab).
Lastly, the most penetrative analysis was conducted to identify which model is the most effective and the advantages and the shortcomings of CNN-based and transformer-based models. The approach guaranteed a structured search of the AI techniques to create a stable and convenient screening system of osteoporosis.

1.5 Project Outcome

The possible outcomes of this project could be:

1. Early Detection of Osteoporosis: A powerful computational model might be of great benefit in the early diagnosis of osteoporosis and also be used to diagnose those who may develop the disorder before the situation spirals out of control and they suffer a serious loss of bones or fracture.
2. Increased Accessibility: This model can help to facilitate diagnosis of osteoporosis in areas where health services are of poor quality because of availability of a low-priced and non-complicated alternative.
3. Higher Diagnostic Accuracy: The computational model may provide greater accuracy and consistency in the diagnosis of osteoporosis than the traditional methods leading to misdiagnosis.
4. Cost Reduction in Healthcare: The model can make healthcare more affordable to the patient and healthcare system because it will help to minimize the costs that are paid to conduct diagnostic tests by automating the detection process.
5 Potential for Broader Healthcare Integration: The solution would be integrated within the present healthcare framework, such as electronic health record or telemedicine platform, to follow-up and intervene more quickly in real-time and continuously.
6 Basis for Future Research: The present project might be the basis of further research and development in the area of detection of diseases with the help of computational methods, and other conditions may be detected in the same way.
7 Clinical Adoption: Successfully, the project could lead to a partnership with medical institutes that will culminate into the actual implementation as well as clinical use of the system that will eventually benefit patients all over the world.

Research the opportunities to apply this solution to current healthcare systems to allow early diagnosis and treatment.

1.6 Organization of the Report

The report is organized into 6 chapters that address a separate part of the research:

Chapter 1- Introduction: Provides background of osteoporosis, problem statement, motivation, objectives, methodology overview, expected outcomes, and research importance.

Chapter 2 - Background and Literature Review: Answers the question of what diagnostic methods are present, what research has been done in medical image processing and artificial intelligence, what similar applications exist, and what aspects of the problem remain unanswered by researchers.

Chapter 3 Research Methodology: Discusses the proposed system design, dataset preparation, preprocessing methods, model architectures and the general project plan with assignment of tasks.

Chapter 4 - Implementation and Results: provides the details on the experimental design, training process, evaluation measures, the comparative analysis of various models, and discussion of the obtained results.

Chapter 5 - Engineering Standards and Design Challenges: Talks about compliance to software, hardware and communication standards, societal and ethical impacts, sustainability, and financial analysis.

Chapter 6-Conclusion, Limitations and Future Work: Concludes the study and outlines the existing limitations and future research and implementation.

References: A section of the report that includes all the sources that were cited throughout the study.

Chapter 2
Background

2.1 Introduction

Osteoporosis is a medical condition where bones become weak and brittle, making them more susceptible to fractures. The term "Osteoporosis" comes from Greek, meaning "porous bones," which describes the condition's effect on bone density and structure. This article [1] will assess how to diagnose and predict osteoarthritis (OA) and osteoporosis, and solve the problem of early detection with the help of traditional methods. It indicates the lack of dataset diversity, external validation, and interpretability that verges on the clinical application possibility. The article includes the most successful AI models, but it marks that general common assessment strategies and better applicability to a wide variety of audiences are critical. Finally, it concludes with its suggestions, which would contribute to integrating the AI into clinical practice by curbing these drawbacks. Compares the use of X-ray images as input for Vision Transformers (ViTs) and Convolutional Neural Networks (CNNs) in osteoporosis detection. It [21] highlights the issue of overfitting and dataset imbalance, and ViTs outperform CNNs in classification. By showing that ViTs can produce more accurate results than traditional CNNs, the study will advance our understanding of their potential in medical image processing. The study concludes that more research and more specialized datasets are required to improve the efficacy of models in the clinical setting.

A novel feature of early osteoporosis detection using Dental Cone Beam Computed Tomography (CBCT) which considers Hard Palate Thickness (HPT). It [8] emphasizes the demand of highly efficient and inexpensive screening process as the current methods including the DXA are rather costly and are not widespread. Based on the DXA findings, the research shows that it is strongly correlated between HPT measurements and the data concerning osteoporosis, implying that HPT may be used at predicting osteoporosis. According to the research, its conclusion recommends the validation of the offered strategy in terms of larger studies. This study [18] is based on developing a new deep learning architecture with a superfluity mechanism and classifying X-ray images of the knee as normal, osteopenia or osteoporosis. It beats past trained models such as AlexNet and ResNet50. The proposed method enhances the accuracy of classification, the number of false positive and false negative results, and enhances the reliability of diagnosis. The model has its potential as an automated and low-cost method that can be used as an early detection method of knee osteoporosis and can be applied clinically in the future.

The primary focus of the research [7] is the use of radionuclide diagnostic techniques such as SPECT and PET in the diagnosis and monitoring of osteoporosis. It deals with the drawbacks of the old procedure like DXA. With a focus on targeting with 99mTc and 18F, the research focuses on the possibility of implementing the use of these radionuclides in follow-up and innovative information in a dynamic manner to get a picture of the bone metabolism and to figure out the efficacy of the therapeutics. It is also significant to note that it would be necessary to carry out more research to streamline the use of these technologies to handle osteoporosis in a clinical way. This work [9] will examine how signal processing, including factors such RMS amplitude, frequency, phase, and contrast, might enhance the CT scan pictures' osteoporosis diagnosis capabilities. It identifies the drawbacks of traditional methods like DXA and CT scan. Future studies are advised to

restrict the scalability and stability of the approach to other imaging modalities, as the current research indicates that such a system has the promise of more automated and dependable osteoporosis detection.
This research [22] introduces a novel combination called adult IBCO-ERNN Elman to improve osteoporosis detection. The approach integrates Elman Recurrent Neural Networks (ERNN), Bacterial Colony Optimization (BCO), and Tabu Search (TS) algorithms. One advantage is that it avoids local optima and achieves optimal hyperparameters, resulting in improved detection accuracy and faster convergence. For osteoporosis detection, results show IBCO-ERNN outperforms conventional models, has quicker convergence, and higher accuracy. The study concludes with experimental confirmation of this hybrid approach's effectiveness for real-time medical diagnostic applications.

The study [19] covers AI-driven chest CT bone mineral density (BMD) for opportunistic osteoporosis screening, compared to DXA. It concludes that the T11 vertebra's AI-generated BMD has high diagnostic value for detecting osteoporosis. This method can serve as a more affordable and practical substitute for existing methods. The results suggest chest CT scans with AI support may be a useful tool for osteoporosis detection, especially for patients undergoing lung cancer screening. This article [2] encompasses a back propagation neural network (BNN) in order to diagnose osteoporosis based on X-ray images with a 97 percent classification accuracy. Using mean, variance, and entropy as features of statistical descriptors, the BNN outperforms both KNN and Logistic Regression in the detection of healthy and osteoporotic bone images. Research indicates that BNNs can provide an efficient and cost-effective way of early detection of osteoporosis which may replace DXA.

2.2 Literature Review

Table 2.1: Summary of Literature Review

Author (s)	Year	Title	Methodology	Key Findings
Ziyu Dong et al.[4]	2023	Combined detection of vitamin D, CRP and TNF-α has high predictive value for osteoporosis in elderly men.	Biochemical	Combined detection of Vitamin D, CRP for osteoporosis prediction in elderly men.
C. Tang et al.[25]	2021	CNN-based qualitative detection of bone mineral density via diagnostic CT slices for osteoporosis screening	Deep Learning (Convolutional Neural Network – CNN)	CNN-based qualitative detection of bone mineral density (BMD) via CT slices.

Author (s)	Year	Title	Methodology	Key Findings
R. Liu et al.[14]	2024	Application of Artificial Intelligence Methods on Osteoporosis Classification with Radiographs—A Systematic Review	Systematic review of studies using AI/ML	Application of AI for osteoporosis classification in radiographs, using CNN and hybrid methods
Abulkareem Z. Mohammed et al.[17]	2022	Osteoporosis detection using convolutional neural network based on dual energy X-ray absorptiometry images	Image Processing with Deep Learning (CNN)	Detection of osteoporosis using DEXA images with pre-processing and feature extraction
Narinder Kaur et al.[11]	2025	Automated Osteoporosis Classification Using Deep Learning on X-Ray Images	Transfer Learning with Deep Learning (ResNet50 CNN)	Deep learning algorithm for classifying osteoporosis from X-ray images using a CNN-based approach
Koji Tamai et al.[24]	2025	Deep learning algorithm for identifying osteopenia/ osteoporosis using cervical radiography	Cross-sectional	Deep learning model for detecting osteopenia/osteoporosis in cervical radiographs, outperforming spine surgeons
Ali Tarighatnia et al.	2025	Deep learning-based evaluation of panoramic radiographs for osteoporosis screening: a systematic review and meta-analysis	systematic review and meta-analysis	This first systematic review and meta-analysis shows deep learning models predict osteoporosis from OPG radiographs with high accuracy and emphasizes the need for standardization and multicenter validation.

Author (s)	Year	Title	Methodology	Key Findings
Zhai Liu et al.[15]	2025	Radiomics and machine learning for osteoporosis detection using abdominal computed tomography: a retrospective multicenter study	Retrospective analysis with radiomics-based machine learning	Development and validation of radiomic-based machine learning models using lumbar spine CT images, demonstrating high predictive accuracy for opportunistic osteoporosis screening and highlighting critical radiomic features as novel biomarkers.
Hadeel Osama El-Sisi et al.[5]	2025	A non-invasive computer-aided personalized diagnosis system for Osteopenia and Osteoporosis	Computer-aided diagnosis (CAD)	This paper is the development of a robust VGG16-based computer-aided diagnosis system that non-invasively detects and grades osteopenia and osteoporosis from knee X-rays with 94.85% accuracy, enabling personalized and clinically reliable screening.
Rita Roy et al.[20]	2025	Osteoporosis Disease: The Impact of Vitamin Deficiency in Indian Population Using Machine Learning	machine learning–based diagnostic	This research is the use of machine learning models, including XGBoost, to accurately classify osteoporosis from bone X-rays while linking the disease to vitamin C and calcium deficiencies in the Indian population, providing a foundation for early detection and public health intervention.

Author (s)	Year	Title	Methodology	Key Findings
Hongnan Ye et al.[27]	2025	Artificial intelligence combined with computed tomography or X-ray radiography: potential solution for opportunistic screening for osteoporosis	Developing and applying convolutional neural network (CNN)	This paper is demonstrating AI-integrated radiological imaging as a novel approach for opportunistic osteoporosis screening while addressing clinical, ethical, and implementation challenges through a collaborative and equitable framework.
Clayton W. Maschhoff et al.[16]	2023	3D Topographical Scanning for the Detection of Osteoporosis	prospective observational	This research is demonstrating 3D topographical scanning as a quick, accurate, and noninvasive alternative to DEXA for estimating BMD, improving accessibility to early osteoporosis detection and treatment.
Mustafa N. R. Al-Rawi[23]	2024	Public awareness of DEXA-scan in detecting osteoporosis a cross-sectional study	cross-sectional survey	A lack of awareness of DEXA scans and osteoporosis screening in Saudi Arabia, which has an impact on sociodemographic factors and the necessity of specific education and standardized instruments to enhance a timely diagnosis and mitigate its consequences.

Author (s)	Year	Title	Methodology	Key Findings
Q. Zhang et al.[7]	2020	Detecting causal relationship between metabolic traits and osteoporosis using multivariable Mendelian randomization	Mendelian randomization (MR)	The use of mvMR and MR-BMA to identify and rank the causal metabolic risk factors (T2D, FI, FG) of BMD traits is the purpose of this study, as it gives new information about the mechanisms underlying osteoporosis and the possible intervention measures.

2.2.1 Similar Research

The evaluation of the use of Fractal Dimension (FD) analysis to dental radiographs for osteoporosis detection reveals inconsistent results from studies that used various techniques, such as ROI selection methods and different image processing protocols. FD was also unreliable because measurements varied significantly depending on the technique and settings used, making it difficult to compare findings across studies. Despite its potential, the lack of standardization in FD analysis presents a challenge. This [6] research could close these gaps by offering a consistent, accurate, and scalable method for screening osteoporosis and improving characterization in more detail and consistency across various dental radiograph locations. The research [13] discusses the use of Artificial Neural Networks (ANN) with the YOLOv8 model to detect and classify osteoporotic vertebral compression fractures (OVCF) with an accuracy of 96.04\% using the AO Spine-DGOU classification system. This study, which focuses on the Vision Transformers (ViT), can close research gaps by offering a low-cost, worldwide study option for dental radiographs. Furthermore, compared to fracture detection, ViT may enhance uniformity, generality, and integration with other clinical data, which provides greater accessibility in identifying osteoporosis diagnosis.

Texture-preserving self-supervised learning, a Mixture of Experts (MoE) architecture for device adaptation, and multitask learning for increased accuracy are combined in this research. This [10] unified deep learning framework enables osteoporosis detection using CT images. The work provides a non-invasive, widely available substitute for CT. It improves generalization across imaging modalities. It also combines structural and spatial bone analysis for higher diagnostic precision. By applying Vision Transformers (ViT) to dental radiographs, this research fills gaps in the field. This study [23] uses machine learning (ML) algorithms to assess osteoporosis risk based on demographic, clinical, and laboratory data. XGBoost (XGB) was found to be the best predictor with an AUC of 0.78 and an accuracy of 79\%. It addresses the need for a straightforward, non-invasive screening method that can be easily extended to a larger population to identify osteoporosis. Furthermore, ViT can identify patterns in imaging data. By combining imaging and clinical data, ViT raises the likelihood of an accurate diagnosis and produces better results than traditional ML applications.

The low-cost OSSEUS device detects electromagnetic attenuation through bone tissue. This article [3] is used to present a labeled dataset for osteoporosis screening. The sample contains 669 persons with different BMD levels. Your study fills gaps in the field by providing a non-invasive, affordable substitute for electromagnetic equipment. Vision Transformers (ViT) are applied to dental radiographs. ViT's ability to identify intricate patterns in these images may improve diagnostic precision and broaden the use of cutting-edge AI for screening.

This paper [12] undertakes an in-depth examination of the diagnostic fitness of AI model in detecting high-level osteoporosis (OP) based on the observation of dental photographs. The best performance is shown by deep convolutional neural networks (DCNN) and this factor has a high specificity (0.95) and sensitivity (0.85). Your study would help to fill the gaps since it would offer more performance in terms of handling complex image patterns by using Vision Transformers (ViT). Also, your research would contribute to the enhancement of AI-based osteoporosis screening across multiple healthcare facilities due to the focus on standard dental X-rays and expanded clinical utility.

2.2.1 Related Research

Sensitivity of 0.80, specificity of 0.92, and AUC of 0.93 are identified in this [26] systematic investigation that also looks at the diagnostic accuracy and accuracy of deep learning models related to the diagnosis of osteoporosis based on the panoramic radiography. Your solution based on Vision Transformers (ViT) that can effectively model long-range dependencies and complex spatial correlations in dental imagery has the chance of yielding superior precision as compared to other models such as AlexNet and ResNet. Besides its weaknesses and limitations, ViT can enhance the precision and cross-modality generalizability of diagnostic workflows in clinical practice and a variety of imaging devices. With the application of machine learning informed by logistic regression or decision trees, the proposed model [15] can be used to predict osteoporosis using radiomic features of CT scans of the spine in the lower back. The other model did not do so well as the LR model (AUC 0.960). One of the fields of your research is the application of Vision Transformers (ViT) to dental radiographs. It provides a non-invasive test that also exposes individuals to less radiation compared to CT. Also, the possibility to capture complex structures might improve the diagnostic outcomes and increase the use of AI-based screening in clinical practice through ViT.

The deep learning (DL) approach that is suggested in this paper [5] is intended to use knee x-rays to diagnose osteoporosis and osteopenia. It achieves 94.85 percent accuracy by using Support Vector Machine (SVM) methods and the VGG16 neural network architecture. By applying Vision Transformers (ViT), a kind of deep learning model based on self-attention mechanisms, to dental radiographs, your study closes these gaps by proposing a widely accessible and non-invasive substitute for knee x-rays. Furthermore, ViT may improve diagnostic accuracy and expand the clinical specialties where AI-based noxious screening may be used because of its ability to preserve intricate bone structural patterns. The paper [20] will discuss the assessment of the effect of vitamin C and calcium shortage on osteoporosis among Indians within the framework of machine learning algorithms, where XGBoost, Random Forest, and SVM algorithms will be used. It is worth noting that XGBoost recorded the most accurate results in predicting the possibility of osteoporosis using bone X-ray images. Your study is based on the findings and helps further the field by applying the Vision Transformers (ViT) to dental radiographs. Not only does this method solve the gap in the current modality, since this is a non-invasive, less costly method of imaging, but it also takes advantage of the robustness of ViT in detecting complicated hierarchy, which may lead to superior diagnosis and expansion of the use of osteoporosis screenings. Consequently, your project is an addition and extension of earlier research.

This paper [27] highlights the drawbacks of the traditional osteoporosis diagnosis procedures including DXA, and posits that the AI-enabled CT and X-ray radiography use cases represent the more affordable, non-invasive alternative to them. It particularly concentrates on the applicability of Vision Transformers (ViT) in dental radiographs that your study uses, as it gives better access to osteoporosis screening. Your methodology could benefit the field by promoting better diagnostic rates and allowing more widespread usage of artificial-intelligence based screening in more popular forms of imaging with the aid of ViT. As mentioned in the discussed research, the proportions are considerably linked to DEXA T-scores, especially forearm and femoral neck measurements, and use of 3D topographical scanning to arm and calf circumference and volume measurement as a screening test of osteoporosis is discussed. The research [16] can solve these gaps because it works with dental radiographs using the Vision Transformers (ViT) and provides a much less invasive, non-invasive, cost-effective alternative. The extended functionality incorporated in ViT has the possibility of producing better diagnostic results and can be scaled out to other clinical facilities to screen patients or individuals at risk of having osteoporosis.

2.3 Gap Analysis

The Gap Analysis compares between the conventional diagnostic techniques (such as DXA), CNN-based models, hybrid deep learning models, the established Vision Transformer (ViT)-based model. It brings to the fore significant variations in cost, accessibility, data diversity, interpretability, accuracy, scalability, segmentation potential, and clinical take up. Conventional approaches are expensive, not available in rural neighborhoods and unreliable in initial diagnosis. CNN and hybrid models are more accurate yet have poor scalability, poor generalization, and poor interpretability. The mentioned ViT approach bridges these gaps by providing greater scalability by deploying on clouds, enhanced visualization based on attention map, lower costs, and a potential to be used in real-time and in a non-invasive manner in clinical settings.

Table 2.2: Gap Analysis of our Work.

Features	DXA & Traditional Methods	CNN-based Models (VGG, ResNet, etc.)	Hybrid & Advanced DL Models	Proposed ViT-based System
Cost-effectiveness	Expensive equipment required	Cheaper than DXA, but needs GPU resources	Somewhat cost-efficient	Low-cost, scalable using cloud GPUs
Accessibility	Limited in rural/low-resource areas	Requires trained experts & hospital-level datasets	Limited deployment in clinics	Accessible via lightweight AI tools, portable deployment
Data Diversity	Limited patient coverage	Small, imbalanced datasets	Often not generalized	Uses augmentation, normalization, balancing
Interpretability	Low (black-box imaging)	Limited feature interpretability	Still weak in clinical explanation	Better visualization through attention maps
Accuracy	Inconsistent, especially early detection	High (90–97%) but overfitting issues	Competitive, but mixed results	Achieves strong accuracy (ViT competitive with VGG19)
Scalability	Poor (hardware-dependent)	Limited scalability	Moderate scalability	High scalability with cloud-based training
Segmentation Capability	Not applicable	CNNs less effective for fine detail	U-Net good but limited	ViT adaptable for classification + segmentation
Clinical Adoption	Limited, costly, invasive	Not widely adopted yet	Experimental stage	Potential for real-time, non-invasive clinical use

No	Yes

2.4 Summary

The medical and technological history of osteoporosis detection was mentioned in this chapter. The conventional diagnostic tests like DXA and CT scans despite their popularity are usually expensive, unavailable and inaccurate in detecting a disease at its early stages. Recent studies show that AI-based solutions, especially CNN, ResNet, VGG, and hybrid solutions can aide in classification and prediction of osteoporosis with medical images to a significant extent. However, the issue of data imbalance, inability to generalize to heterogeneous populations and non-interpretability remains of central relevance. New methods, such as dental radiographs, radionuclide radiographs, multimodal frameworks and Vision Transformers (ViT) provide more precise and versatile solutions and demonstrate high potential in practical clinical implementation. Lack of big, standardized data and scalable systems that are cost-effective limits proliferation, however. This knowledge gap is what drives the proposed ViT-based system, which aims to increase the accuracy of diagnostics, affordability, and accessibility to the diagnostic process, and, eventually, increase the effectiveness of the first-time screening of osteoporosis.

Chapter 3

Research Methodology

3.1 Methodology

3.1.1 Overview

We will discuss the proposed methodology for our work which includes dataset description, data preprocessing, model architecture and selection. The overall proposed methodology is shown in Figure 1 and every steps of the methodology is discussed further in the following subsections.

3.1.2 Proposed Methodology/ System Design

The figure shows a scheme of work of the proposed methodology of osteoporosis screening system. It starts with X-ray image preprocessing (standardization, normalization, augmentation), then train-test splitting into training, validation and testing. A number of deep learning networks (VGG16, VGG19, ResNet, DenseNet, U-Net, ViT, Swin) are used and model training is conducted based on forward and backward propagation. The metrics of performance of these models are measured on the basis of standard measures: accuracy, precision, recall, F1-score, IoU, and Dice. Lastly, comparative analysis of the results is used to determine the most successful models, which would result in the ultimate product, an AI-based osteoporosis screening system.

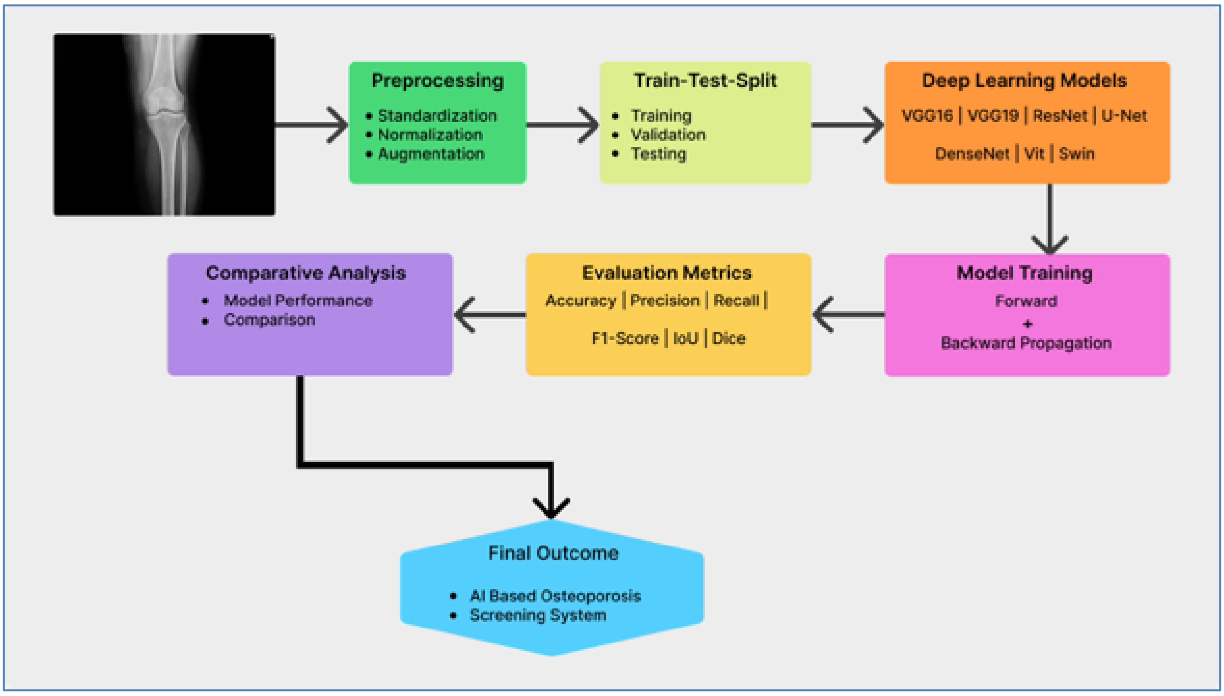

Figure 3.1: Proposed Methodology of Osteoporosis Disease

3.1.3 Functional and Nonfunctional Requirements

Functional Requirements

Dataset Handling: The system must be able to collect, preprocess, and divide X-ray images into training, validation, and testing sets for consistent evaluation.

Model Training & Testing: Deep learning models, including CNNs (VGG16/19, ResNet, DenseNet, U-Net) and Transformers (ViT, Swin), should be trained and tested for both classification and segmentation tasks.

Classification & Segmentation: The system should accurately distinguish between Normal and Osteoporosis cases and, where necessary, segment bone regions in the X-ray images.

Visualization: Results should be presented through confusion matrices, accuracy/loss graphs, and segmentation maps to make evaluation easier.

User Interaction: A simple interface should allow users to upload X-ray images and view diagnostic outcomes.

Data Security: Patient data should be hidden and handled securely to protect privacy.

Non-Functional Requirements

Performance: The models will be very accurate and error free.

Scalability: The system must be adaptable to cloud GPUs such as Kaggle and Colab, so that it can expand with increased data sets.

Reliability: Reproducible results should be ensured by the use of consistent preprocessing and fixed random seeds.

Usability: The interface needs to be simple so that the healthcare professionals can operate it with minimal or no training.

Maintainability: The implementation must adhere to clean code (PEP8) and be designed in modules so that it is easier to update and expand.

Security & Privacy: There are ethical standards to be observed in order to take care of patient confidentiality and secure use of data.

Affordability: Open-source frameworks and free cloud should be used, which reduces costs.

Portability: The system must operate well on both Kaggle and Colab as well as hospital servers with the least modifications.

3.1.4 UI Design

The Osteoporosis Classifier user interface (UI) is made easy and accessible to be useful in healthcare use. The initial display offers an upload option in which one is allowed to upload an X-ray image, and only one button, which is Classify, is thereafter used to process the image. There is a brief introduction to osteoporosis and a list of the deep learning models incorporated into the system VGG16, VGG19, ResNet, DenseNet, U-Net, ViT, Swin. This makes sure that the users know the supporting architecture behind the diagnosis.
In image classification, the result page displays an understandable output: the uploaded X-ray has the predicted class (normal or osteoporosis) highlighted and the details of the confidence score and the probabilities of each of the classes are displayed. This design gives healthcare practitioners the opportunity not only to see the decision of the AI but to evaluate its confidence level, which makes the system more open and reliable.
All in all, the UI requires ease of use, interpretability, and reliability so that even the non-technical users can make an efficient use of the system to facilitate the screening of osteoporosis.

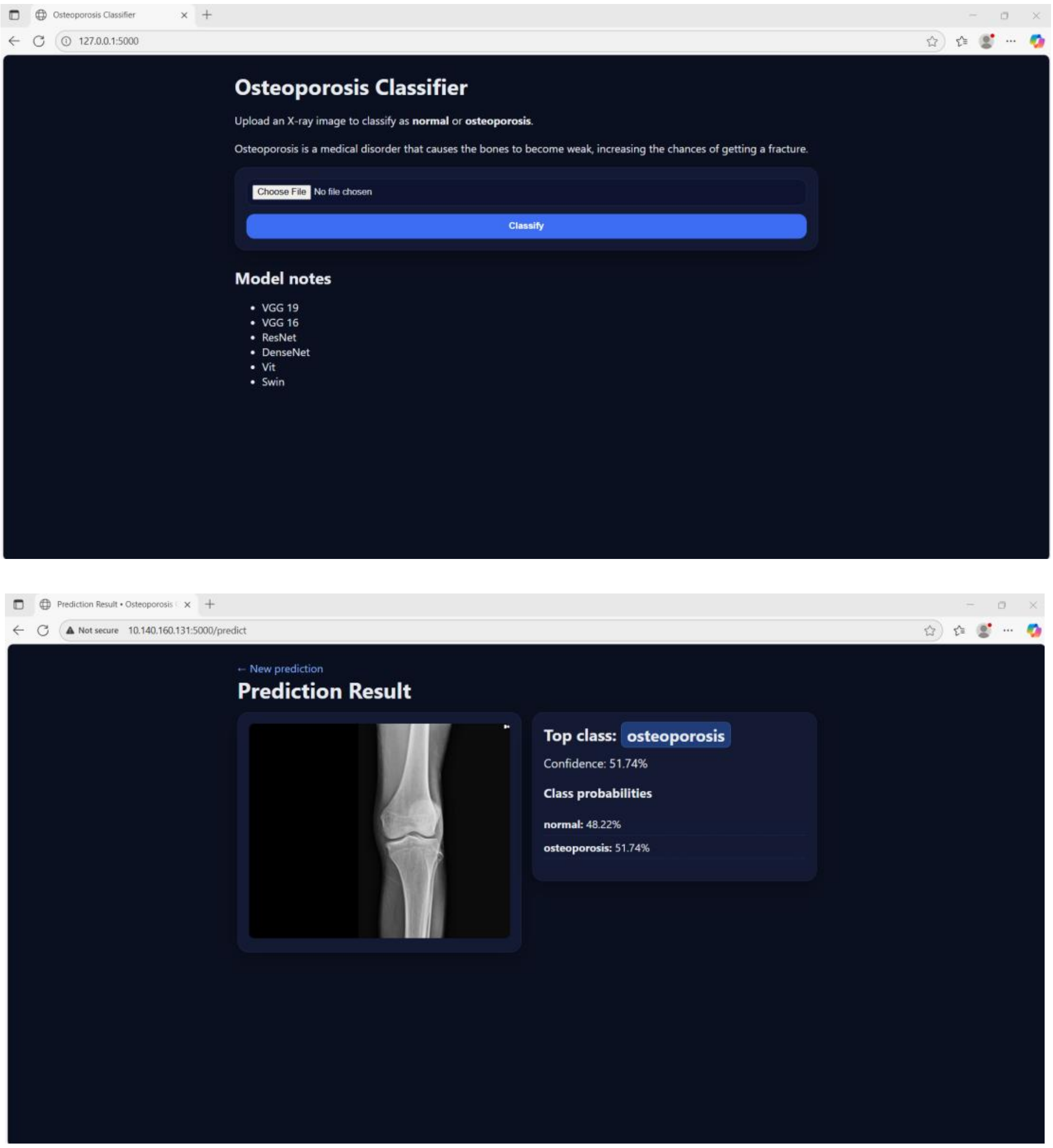

Figure 3.2: System Design of Osteoporosis Disease Detection

3.2 Detailed Methodology and Design

3.2.1 Dataset Description

The data in this research is a total of 853 raw X-ray images, which are divided into a total of 2 distinct classes: Normal and Osteoporosis. Normal and Osteoporosis classes have 400 and 453 images respectively. The images are X-ray scans that are useful in diagnosing bone-related conditions, particularly for detecting osteoporosis. All the data are collected from different hospital diagnosis centers. This dataset has been used to train and test models that seek to automate the process of identifying osteoporosis using X-ray images and can also be used to further research of medical image analysis.

Figure 3.3: Normal Vs Osteoporosis Image

3.2.2 Dataset Cleaning Preprocessing

Primarily, the dataset does not contain unreadable images because they can disrupt the work of the model. The control of the imbalance in classes between images of Healthy and Osteoporosis is necessary. When one of the classes is dominant that can bias the performance of the model and methods such as oversampling the minority class, or under sampling the majority class can stabilize the data. You may also use class weights when training a model to compensate the imbalance should there be a need to do so. It is important that the images are standardized in terms of size, that is, an image of a certain size, e.g.224x224 pixels, as VGG19 deep learning networks expect input images to have a predetermined size. Pixels in the image are supposed to be normalized usually by dividing every pixel with 255 to bring the pixels in the range of 0 to 1. Image augmentation, e.g., rotation, flipping and zooming, can also be used to reduce overfitting by artificially increasing the diversity of your training data without having to acquire additional data. These preprocessing stages are fundamental in making sure that your model is trained on a clean, standardized, and powerful dataset, which would be effective in exploring well in new, unseen images.

3.2.3 Model Selection

VGG19:

VGG19 architecture is a deep convolutional neural network, which is image classification and has 19 layers. It begins with an input layer where images of size 224x224 with 64 channels are accepted. The network consists of a succession of 16 convolutional layers, each of which uses small, 3x3 filters to identify patterns and features at some level of abstraction. Convolving layers are then succeeded by 5 max-pooling layers that are used to downsize the spatial dimensions of the feature maps without losing significant features and therefore the network is computationally efficient. Following the convolutional and pooling layers, the network flattens the feature maps and forwards them through 3 fully connected layers with ReLU activations, and upon which the network makes decisions depending on the feature that have been extracted. The last is the final layer, a SoftMax layer, which gives the predicted probabilities of the classes to be classified, and in ImageNet classification the output units are 1000. The network is characterized by its simplicity and efficacy, which is based on the utilization of smaller convolutional filters and deep layers to acquire sophisticated features in pictures.

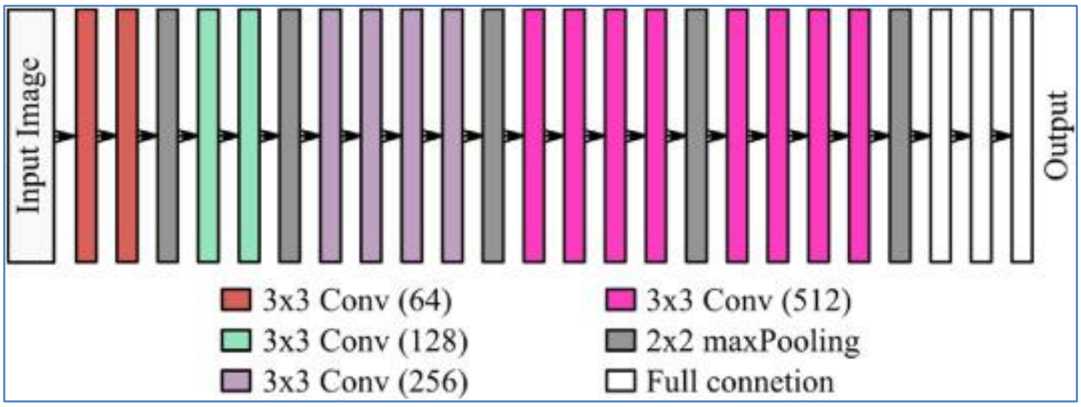

Figure 3.4: VGG19 Architecture

ResNet

ResNet (Residual Network) model is a deep neural network that adds residual connections to solve the issue of vanishing gradients in extremely deep networks. It enables the model to circumvent some of the layers, and the contribution of a layer is added to that of a deeper layer. This assists in saving gradient flow, and thus it is easy to train very deep networks. Such variants of ResNet are ResNet50 or ResNet152, where the numbers used are the number of the layers. The network normally applies 3x3 convolutions, batch normalization and ReLU activations. The remaining connections guarantee improved performance, and as such, the model can be trained to obtain state-of-the-art results in image classification tasks without loss of performance.

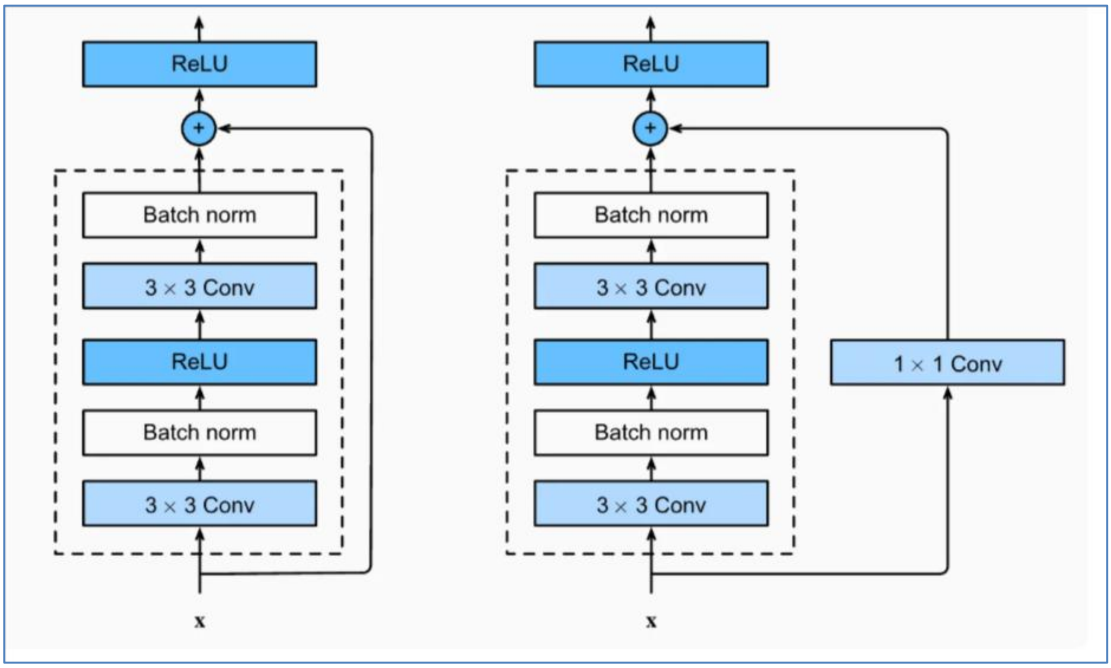

Figure 3.5: ResNet Architecture

DenseNet

DenseNet (Densely Connected Convolutional Network) is a deep learning architecture where every single layer has connections with all other layers thus enhancing gradient flow and feature reuse. In contrast to the traditional CNNs, each layer of DenseNet is connected to every layer of the past. This thick connectivity assists in the minimization of the parameters and the efficiency of training. It also overcomes the vanishing gradient issue by permitting the enhanced gradient flow throughout the net. DenseNet is especially successful in such tasks as image classification because it manages to utilize features and parameters efficiently.

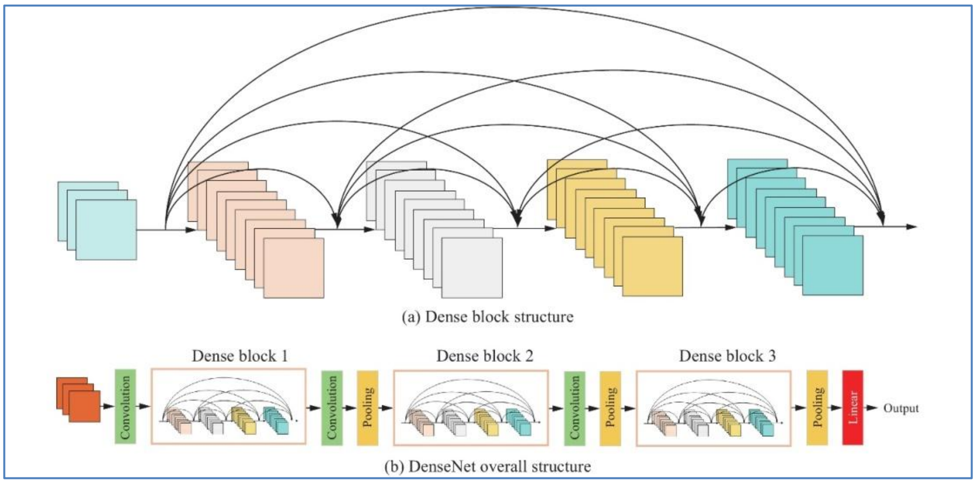

Figure 3.6: DenseNet Architecture

VGG16

VGG16 is a 16-layer deep neural network, comprising of 13 convolutional and 3 fully connected layers. It applies 3x3 convolutions and 2 x 2 max-pooling layers. The design is plain and regular, and the activations are ReLU following every convolution. In the last layer, the classification is achieved by softmax. VGG16 can be used to perform image classification and be trained to do binary classification with the output layer changed to include two neurons.

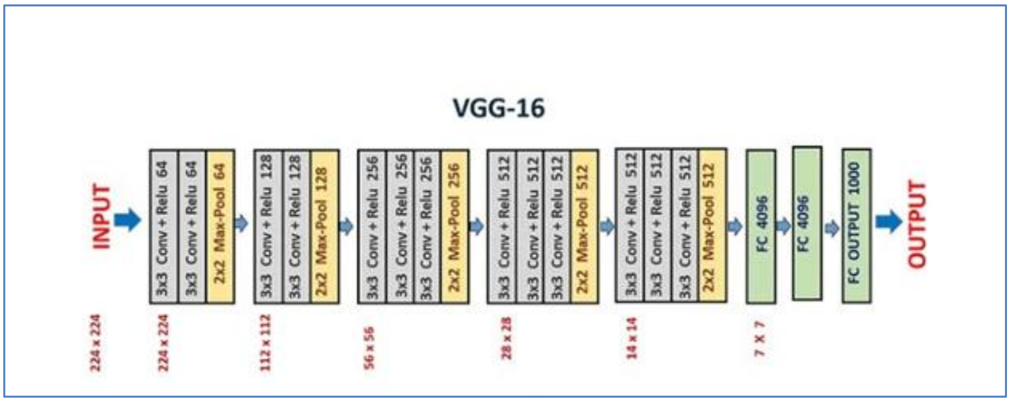

Figure 3.7: VGG16 Architecture

U-Net

U-Net is an image segmentation deep learning model with encoder-decoder backbone and skip connections to maintain fine details. It generates pixel-wise classifications thus useful in activities such as segmenting medical images. In image classification, U-Net can be adapted by reconfiguring the decoder to generate a global feature map, which is then followed by fully connected layer to classify the whole image. This enables the use of U-Net to address both segmentation and classification problems, based on the task-related output layer.

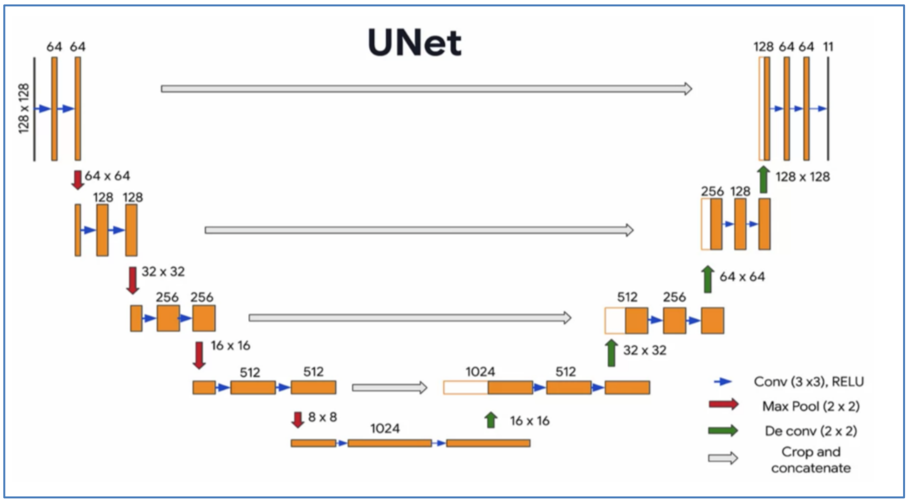

Figure 3.8: U-Net Architecture

ViT

Vision Transformer (ViT) employs transformer architecture, which was initially created to process NLP, but used to process images. To classify images, ViT breaks down the image into fixed-size patches, and processes them as a sequence and employs self-attention mechanisms to extract the relationship between the patches. The model then gives a class label via a fully connected layer. To perform image segmentation, ViT may be modified with a segmentation head that is added to the model. Transformer encoder learns to capture image patch dependencies and the decoder learns to make pixel-wise predictions, which allows ViT to produce accurate segmentation maps. Therefore, ViT can be used to complete both classification and segmentation processes, where appropriate heads are added to the output layers.

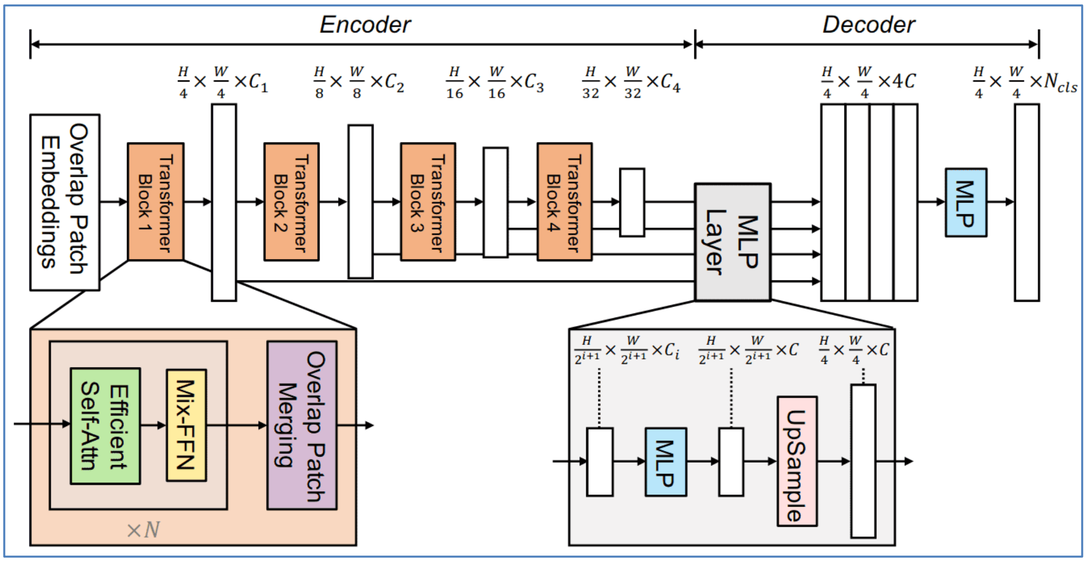

Figure 3.9: ViT Architecture

Swin

Swin Transformer (Shifted Window Transformer) is a vision transformer model that builds on the conventional Vision Transformer (ViT) in that it employs a hierarchical architecture and shifted windows to compute efficiently. It breaks the picture into non-overlapping patches and processes them in local windows by self-attention. Swin Transformer is better at local and global contexts by swapping windows across layers. The model is very efficient and works well in image classification, detection, and segmentation and has a faster scalability and computational efficiency than the classic ViTs.

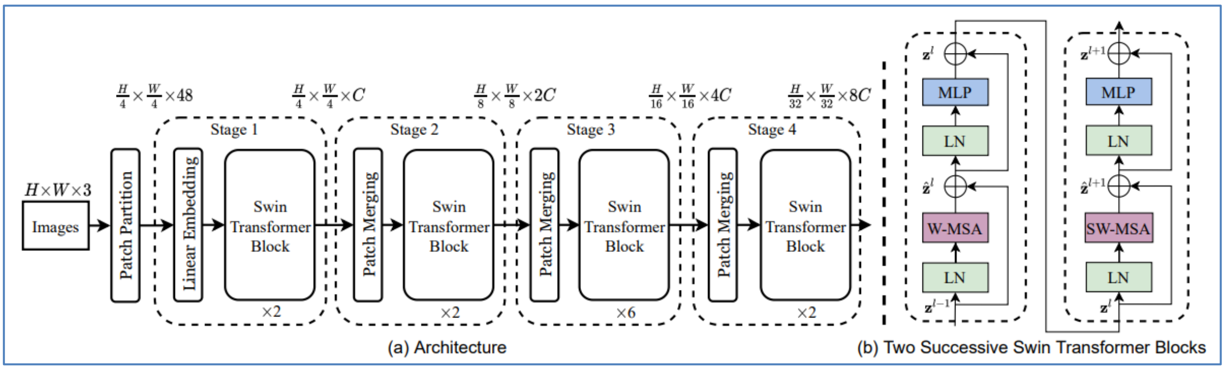

Figure 3.10: Swin Architecture

3.3 Project Plan

The project was designed in stages so as to assure a systematic development and a timely completion. The background phase was spent on problem identification, literature review, and gap analysis to demonstrate the need of AI-based screening of osteoporosis. The second step involved the gathering, pre-processing, and sampling of various models in a manner that regularized, normalized, and biased images to represent uneven classes. The third step was focused on the implementation of different deep learning models, such as CNNs, ResNet, DenseNet, VGG, UNet, and Vision Transformers (ViT), and a comparison of their performance in terms of accuracy, precision, recall, and F1-score. The final stage was dedicated to the comparative analysis, documentation and preparation of final report, synthesis of technical findings with the overall effects of the problem, ethical and sustainability implications.

3.4 Task Allocation

The project activities took systematically with a period of 14 weeks to make sure that the work progressed at an even rate and balanced workload among the team members was achieved. The first few weeks were spent on the collection of the data set, literature review, and the definition of the problem with gap analysis to provide the framework under which the research was carried out. After the preliminary research was made, the focus was changed to data preprocessing, such as standardization, normalization, and augmentation, in order to prepare the data to be trained into a model.

During the middle phase, there was a significant focus on model implementation, the training and evaluation of different deep learning models which included VGG, ResNet, DenseNet, U-Net and Vision Transformers. All the models were tested within a similar set of circumstances to compare performance and define the strengths and weaknesses.

Later weeks were dedicated to the comparative analysis of the results in order to identify the most efficient way of detecting osteoporosis. Lastly, the final weeks were dedicated to report writing and documentation so that the findings, methods, and outcomes could be well organized to be submitted as academic work.

Not only did this structured distribution of tasks assist in the fair allocation of responsibilities but also ensured that the project was progressed in a logical order-starting with data collection and then final reporting without any overlapping or omission of important steps.

Table 3.1: Task Allocation

Tasks	Weeks													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Dataset Collection														
Literature Review														
Problem Definition & Gap Analysis														
Data Preprocessing														
Model Implementation														
Training & Evaluation														
Comparative Analysis														
Report Writing & Documentation														

3.5 Summary

This chapter is an introduction to the methodology applied in the development of the osteoporosis screening system. It described how the dataset was prepared and preprocessed, and which different AI models were selected to perform classification and segmentation tasks. The suggested design focused on the strength with augmentation, normalization, and class balance. An effective project plan was articulated with literature review as the first step to implementation and evaluation, following systematically. Task assignment also simplified the working process by taking advantage of the strengths of team members. All these factors have formed a systematic system of building an accurate and trustworthy AI-assisted diagnosis system.

Chapter 4

Implementation and Results

4.1 Environment Setup

The experiments were run on Kaggle and Google Colab, which offer free GPU resources. Kaggle was used as the primary training environment, with NVIDIA Tesla T4 because this was significantly faster, supported datasets, and used Google Colab as a more flexible backup environment. It was written in Python 3.10, with frameworks like PyTorch and TensorFlow/Keras and libraries like NumPy, Pandas, scikit-learn, Matplotlib, and Seaborn.

All images were scaled, equalized, and extended in a way that makes the preprocessing consistent, and random seeds were held fixed to improve reproducibility. The cloud system enabled successful training and evaluation with no limits on hardware and made the research scalable and cost effective.

4.2 Comparative Analysis

Training and testing on prepared dataset of 853 X-ray images was used to model the evaluation. The data was divided into training, validation and testing sets to provide unbiased performance measurement. We used standard evaluation measures such as accuracy, precision, recall, F1-score of classification, and IoU (Intersection over Union) and Dice score of segmentation tasks.

All the models VGG16, VGG19, ResNet50, DenseNet, UNet, ViT, and Swin Transformer were trained in comparable conditions to allow fair comparison. To examine misclassifications, which are especially significant in reducing false negatives in medical diagnosis, confusion matrices were created. VGG19 was the best model in terms of classification (97 percent), and UNet was the best in segmentation (Dice score of 0.936). Vision Transformer (ViT) achieved a competitive result despite some slight overfitting at very long epochs.

Comparative analysis revealed that traditional CNN architectures are still competitive in binary classification and that transformer-based models should be anticipated to perform superior generalization. The analysis provided insights into the model that would be most appropriate to be incorporated into clinical practice and the trade-offs in performance, interpretability, and computational efficiency.

4.3 Results and Discussion

VGG19

The accuracy of the training gradually increases and attains almost perfect values, and validation accuracy slightly varies, with small overfitting. Loss decreases steadily in training, whereas validation loss spikes occasionally, indicating that it is sensitive to hidden data.

231 Healthy case out of 472 test samples were correctly classified, 229/241 Osteoporosis cases were correctly classified, with the incorrectly classified being 12. This means extreme accuracy and good performance with few mistakes.

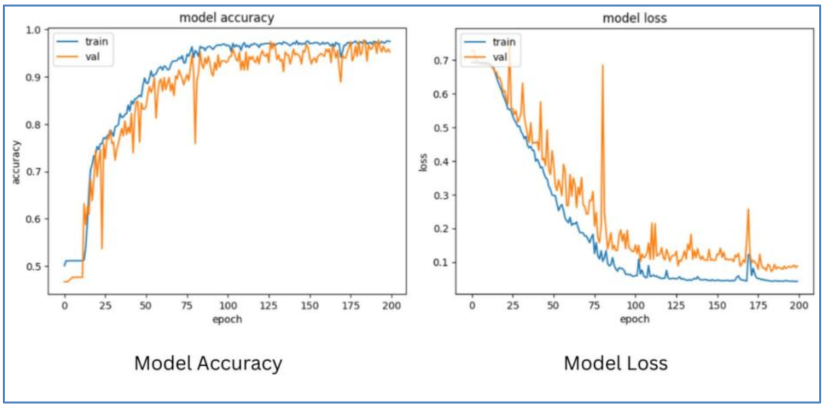

Figure 4.1: Model Accuracy Vs Model Loss

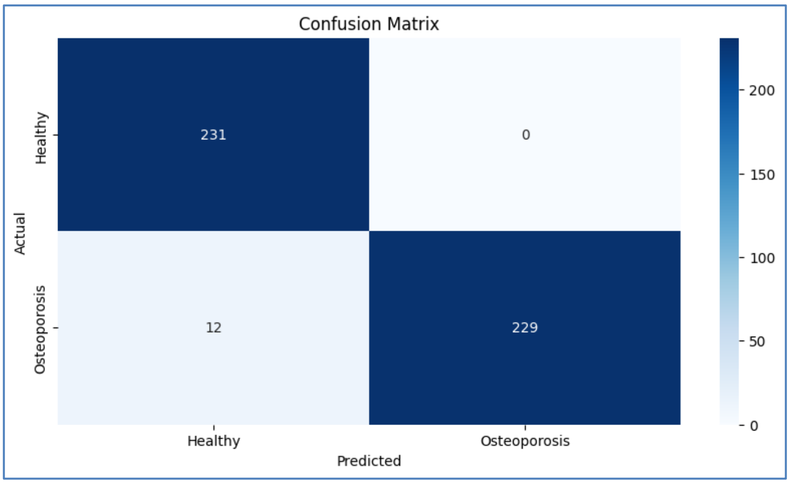

Figure 4.2: Confusion matrix of vgg19

Table 4.1: Classification Report of VGG19

	Precision	Recall	F1-Score	Support
Healthy	0.95	1.00	0.97	231
Osteoporosis	1.00	0.95	0.97	241
Accuracy			0.97	472
Macro avg	0.98	0.98	0.97	472
Weighted avg	0.98	0.97	0.97	472

ResNet

The training graphs of the ResNet50 reveal that the accuracy is high initially and as the graph progresses, training and validation accuracy remains above 90 percent and 90 percent respectively. Both measures vary over 18 epochs, although training loss does not change significantly, whereas validation loss changes more significantly. The implication of this is that the model is learning effectively but that it can sometimes become unstable in generalization.

The confusion matrix shows that the classification performance was great: 36 healthy and 44 osteoporosis cases were correctly classified, and only 5 misclassifications occurred overall. All classes on the model exhibit good precision and recall, which means that the model is very reliable and has sensitive and insensitive medical categories.

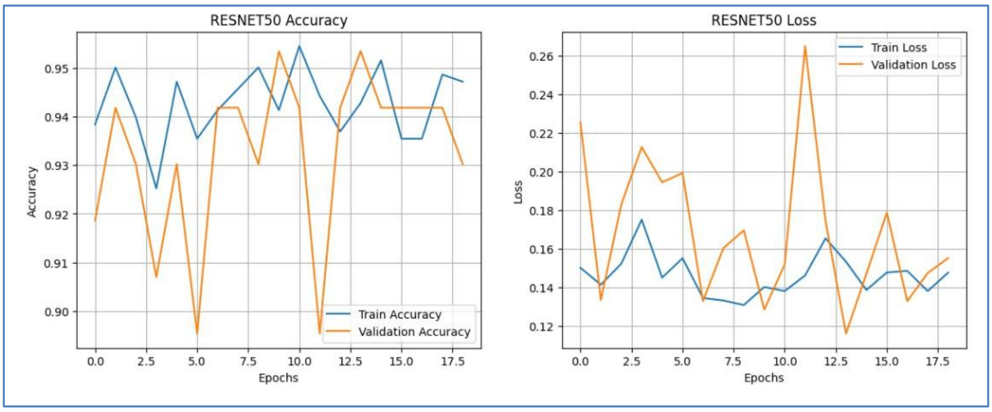

Figure 4.3: Accuracy Vs Loss

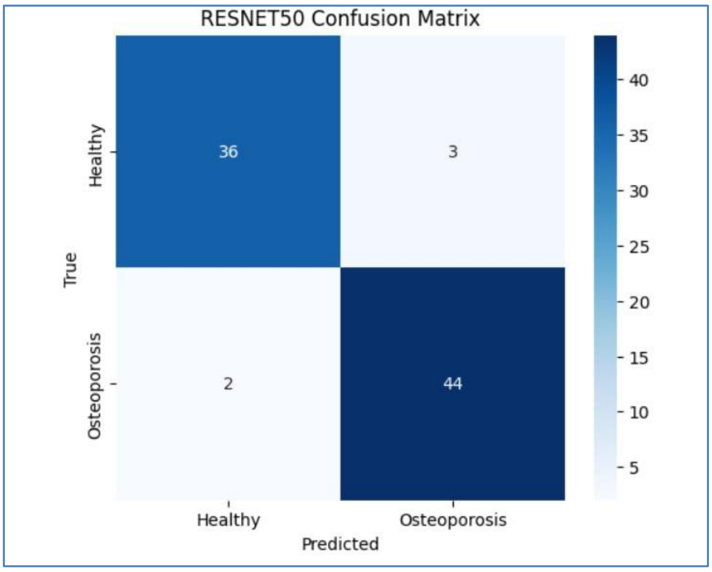

Figure 4.4: Confusion matrix of ResNet

Table 4.2: Classification Report of Resnet

	Precision	Recall	F1-Score	Support
Healthy	0.97	0.87	0.92	39
Osteoporosis	0.90	0.98	0.94	46
Accuracy			0.93	85
Macro avg	0.94	0.93	0.93	85
Weighted avg	0.93	0.93	0.93	85

DenseNet

The training and validation accuracy curve gradually increases to approximately 95% and 94% respectively, thus indicating good generalization. Equally, the training and validation loss also decrease without any significant fluctuations, indicating that the model can learn effectively without extreme overfitting.

The model was able to identify 74 healthy/35 osteoporosis cases out of 85 samples. There were only 4 healthy cases and missed 7 osteoporosis cases. All in all, DenseNet is good, with a few false negatives, which is a bit dangerous in medical screening.

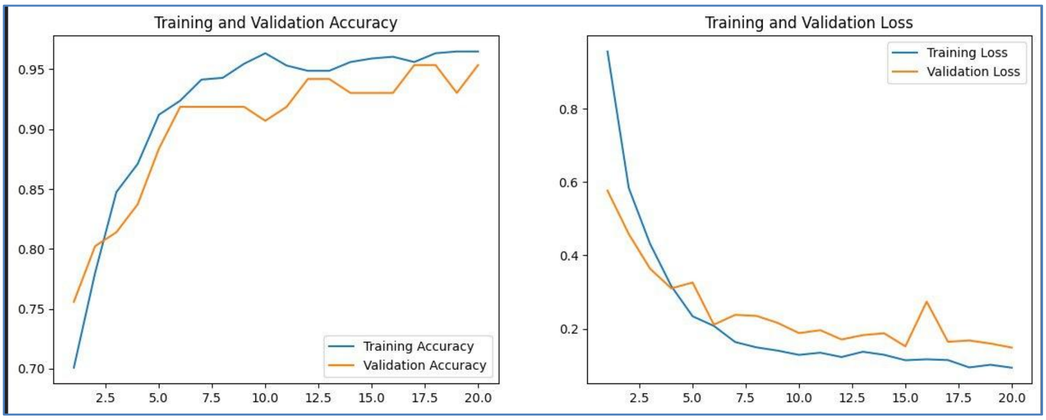

Figure 4.5: Accuracy Vs Loss

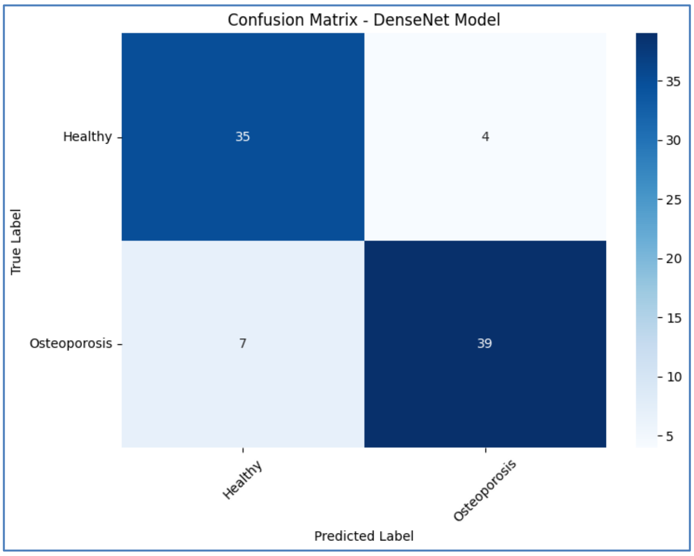

Figure 4.6: Confusion matrix of DenseNet

Table 4.3: Classification Report of DenseNet

	Precision	Recall	F1-Score	Support
Healthy	0.92	0.90	0.91	39
Osteoporosis	0.91	0.93	0.92	46
Accuracy			0.92	85
Macro avg	0.92	0.92	0.92	85
Weighted avg	0.92	0.92	0.92	85

VGG16

The training graph of the VGG16 network shows that accuracy is increasing steadily, whereas the loss is decreasing steadily, which is the sign of the successful learning on the training data. However, validation accuracy is not always high, and validation loss is unpredictable in this case, which means that the model is, perhaps, overfitting and not able to predict unknown statistics.

The confusion matrix shows that VGG16 correctly identified 29 healthy cases and 37 cases of osteoporosis and misclassified 19 cases altogether. It has fair but unbalanced classification performance in identifying osteoporosis and slightly better than identifying healthy individuals.

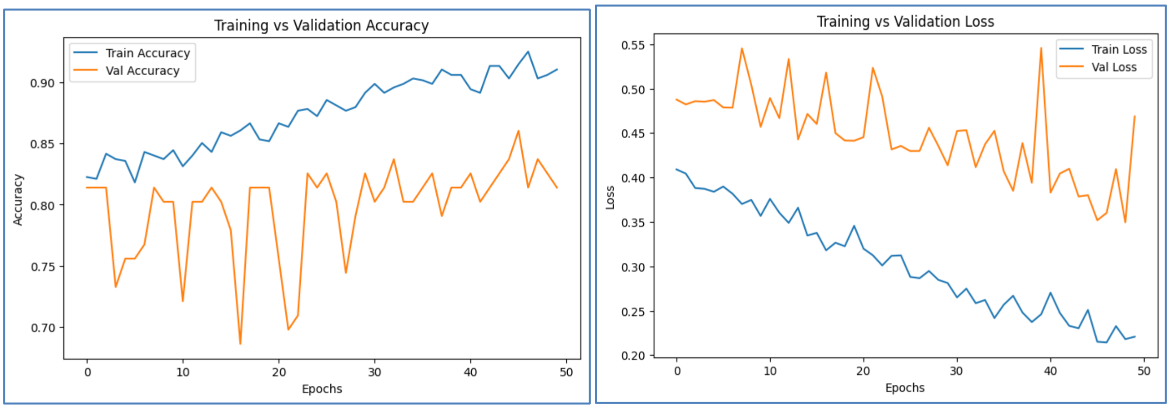

Figure 4.7: Accuracy Vs Loss Graph

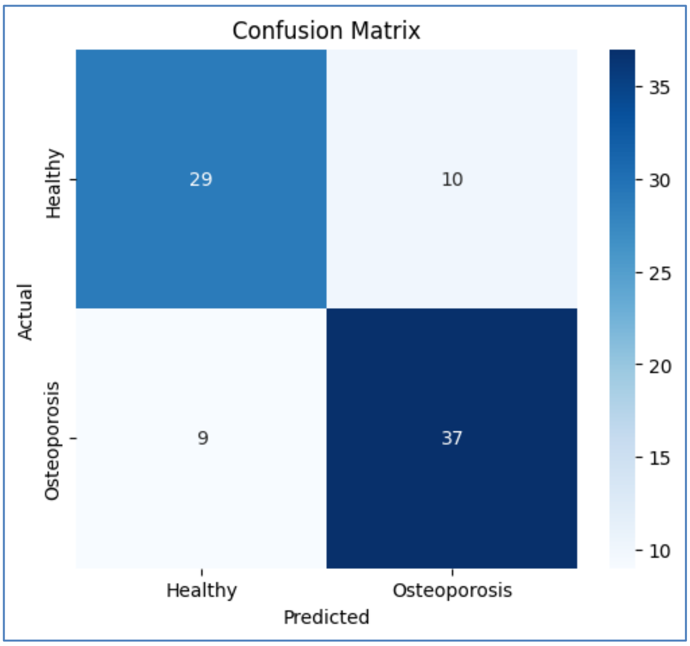

Figure 4.8: Confusion matrix of VGG16

Table 4.4: Classification Report of VGG16

	Precision	Recall	F1-Score	Support
Healthy	0.76	0.74	0.75	39
Osteoporosis	0.79	0.80	0.80	46
Accuracy			0.78	85
Macro avg	0.78	0.77	0.77	85
Weighted avg	0.78	0.78	0.78	85

U-Net

U-Net training graph indicates that the training accuracy and validation accuracy improved gradually with 18 epochs. As the training accuracy continues to rise, the validation accuracy varies a little but tends to be on an overall upward trend. This means the model is learning well and generalizing fairly well with minimum overfitting relative to VGG16.

The confusion table shows that U-Net performed well in terms of classification: U-Net accurately detected 28 healthy samples and 42 samples with osteoporosis. There were not very many misclassifications: 12 healthy cases were predicted as osteoporosis, and 4 cases of osteoporosis were predicted as healthy. This shows that there is a high sensitivity to diagnosis of osteoporosis and an equal overall performance.

Figure 4.9: Training Accuracy Vs Validation Accuracy

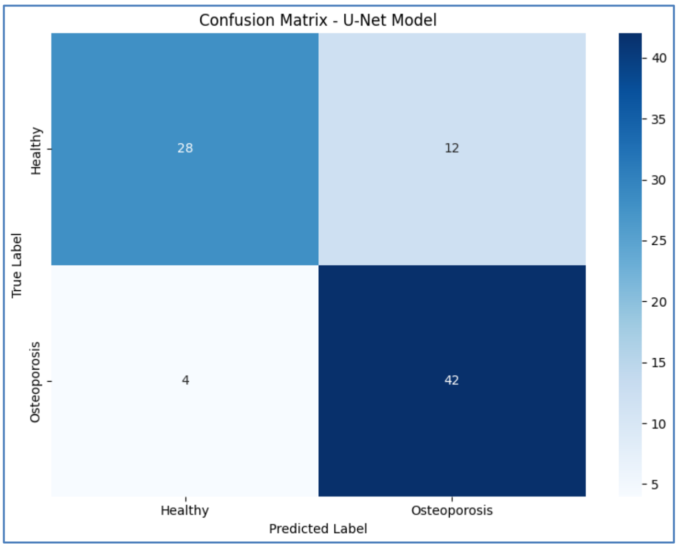

Figure 4.10: Confusion matrix of U-Net

Table 4.5: Classification Report of U-Net

	Precision	Recall	F1-Score	Support
Healthy	0.83	0.85	0.84	40
Osteoporosis	0.87	0.85	0.86	46
Accuracy			0.85	85
Macro avg	0.85	0.85	0.85	85
Weighted avg	0.85	0.85	0.85	85

Vit

The training and validation accuracy of 25 epochs are plotted in this graph. The accuracy of the training progressively approaches 96% and validation approaches 94% but then both vary and, respectively, approach a plateau of 85%. This implies that the model will learn quickly but begin to over-fit around 15 epochs since validation accuracy no longer increases and the training accuracy goes up.

The confusion matrix of our ViT model demonstrates good results in the ability to differentiate between cases of Normal and Osteoporosis. A total of 69 samples were correctly identified out of 77 samples, which is approximately 89.6 percent. The misclassification in both classes is low with only 4 cases of normal being classified as Osteoporosis and 4 cases of Osteoporosis being classified as normal. This shows that the model is balanced, reliable and competent in managing both the categories with the fewest mistakes possible.

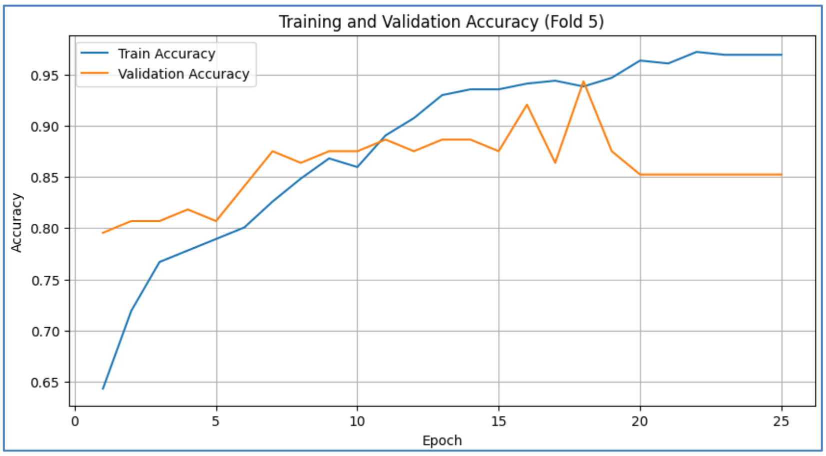

Figure 4.11: Training Accuracy Vs Validation Accuracy

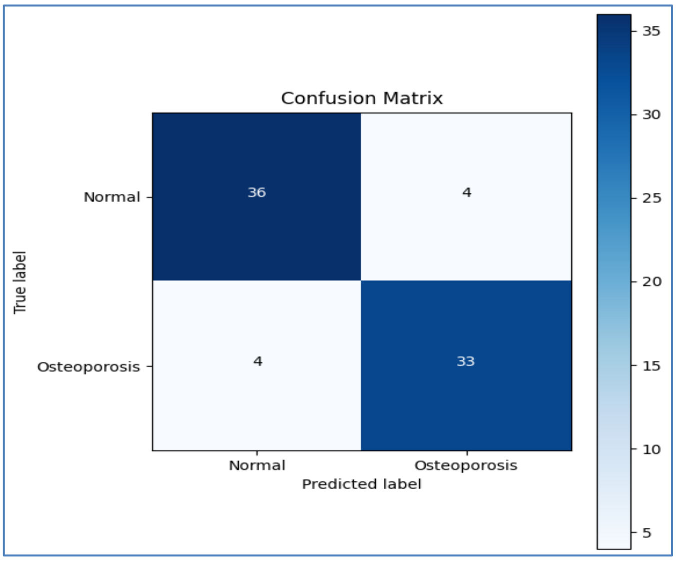

Figure 4.12: Confusion matrix of ViT

Table 4.6: Classification Report of VIT

	Precision	Recall	F1-Score
Healthy	0.88	0.88	0.88
Osteoporosis	0.88	0.88	0.88
Accuracy			0.89
Macro avg	0.89	0.89	0.88
Weighted avg	0.88	0.88	0.89

U-Net segmentation

The training and validation loss curves indicate that the learning is good without any significant overfitting. Meanwhile, the IoU and Dice scores are both high during training, and the training measures are slowly increasing, and validation measures are maintaining good values. In sum, the model has a steady learning and stable performance.

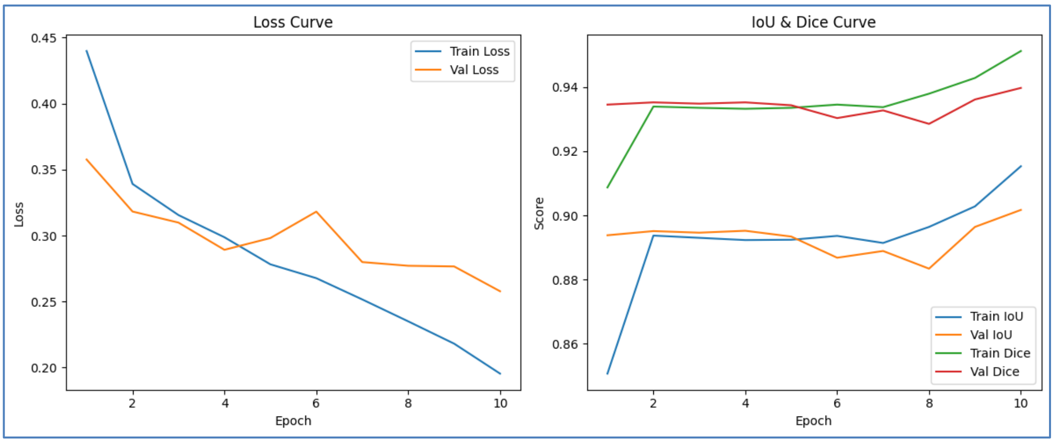

Figure 4.13: Loss curve and IoU & Dice curve

The segmentation results give a clear picture of how osteoporosis affects the bone. In the first image, the red area shows that about 71.6% of the bone is damaged, meaning the disease is present but not spread across the whole structure. In the second image, almost the entire bone—around 98.8%—is highlighted in red, showing that osteoporosis has severely affected the bone throughout. These results make it clear that our model can not only detect osteoporosis but also show how much of the bone is actually impacted.

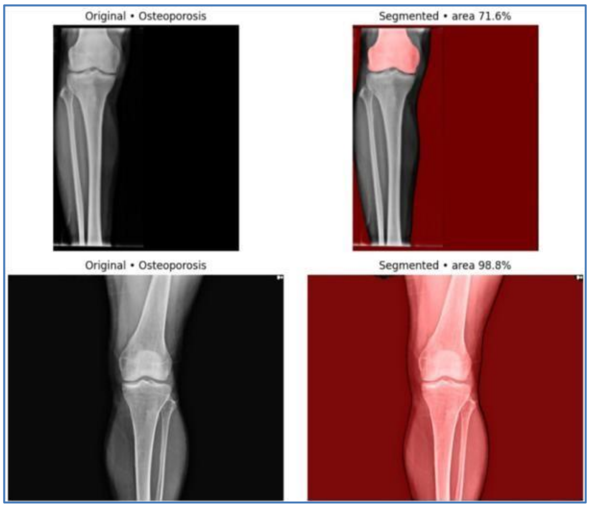

Figure 4.14: U-Net Segmentation of an Osteoporosis Image

4.4 Summary

Table 4.7: Classification model accuracy

Model	Precision	Recall	F1-Score	Accuracy
DenseNet	0.94	0.94	0.94	0.94
Resnet	0.95	0.94	0.94	0.94
Swin	0.77	0.76	0.77	0.77
VGG19	0.98	0.98	0.97	0.97
UNet	0.85	0.85	0.85	0.85
VGG16	0.92	0.93	0.92	0.92
VIT	0.89	0.90	0.89	0.89

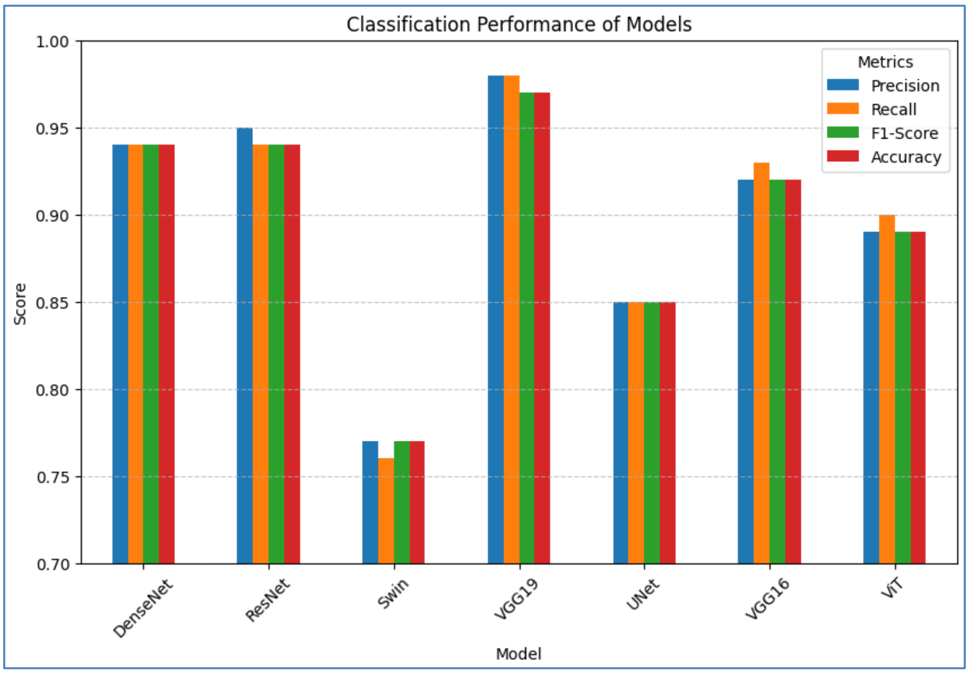

Figure 4.14: Classification performance of every model

The results of classification and segmentation tasks from the two tables compare the performance of different models. In classification, VGG19 performs best with 0.98 precision and recall, 0.97 F1-score, and 0.97 accuracy, followed by ResNet and DenseNet (94–95%), while Swin shows the lowest performance (77%). For segmentation, UNet outperforms ViT with a lower loss (0.2407), higher IoU (0.8937), and better Dice score (0.9360), making it the most effective segmentation model.

4.8: Segmentation model accuracy

Model	Loss	IoU	Dice
UNet	0.2407	0.8937	0.9360
ViT	0.4987	0.7236	0.8083

Chapter 5

Engineering Standards and Design Challenges

5.1 Compliance with the Standards

5.1.1 Software Standards

To make this project reliable, maintainable and reproducible, the software development was done according to the existing standards. Python was the main programming language as it provides a lot of support to machine learning modules and it is open to open-software culture. PyTorch and TensorFlow/Keras frameworks were employed, both following generally accepted standards of deep learning development and allowing scalable implementation in a modular manner.

To provide transparency and accountability in the development process, version control was implemented in Git to monitor the changes in the code and to enable the use of version control collaboratively in the project. The required level of readability and consistency in terms of code quality was attained through the usage of PEP 8 style guidelines. Documentation was done together with implementation so that it would be consistent with the best practices of software engineering, and so the system would be easier to reproduce in future research and extend as needed.

Regarding dataset management, the FAIR data principles (Findability, Accessibility, Interoperability, and Reusability) were followed by systematically organizing files, using similar preprocessing operations, and making datasets reproducible by using fixed random seeds and clean dataset divisions. Requirements were also used to control dependences, and ensure consistency of the environment between Kaggle, Colab and local testing.

5.1.2 Hardware Standards

Minimum Requirements:

These represent the least specifications needed to run model training and testing for osteoporosis detection:

GPU: NVIDIA Tesla T4 (Kaggle/Colab free tier) or equivalent with CUDA support
RAM: 8 GB system memory (sufficient for smaller batch sizes)

Storage: 20 GB free space for dataset, preprocessing, and temporary model checkpoints

Processor: Dual-core CPU (Intel/AMD) for basic operations
Operating System: Windows 10 / Ubuntu 18.04 or higher

Frameworks: Python 3.10 with PyTorch/TensorFlow pre-installed in Kaggle/Colab environments

Standard Requirements

These specifications reflect the recommended setup for smooth experimentation, faster training, and scalability:

GPU: NVIDIA Tesla T4 / V100 or higher with CUDA and cuDNN support

RAM: 16 GB or more for efficient handling of large image datasets and complex models

Storage: 50–100 GB free space for datasets, model checkpoints, and logs

Processor: Quad-core CPU or higher for preprocessing and parallel tasks

Operating System: Windows 11 / Ubuntu 20.04 (LTS) with regular updates and driver support

Frameworks & Tools: Python 3.10+, PyTorch/TensorFlow, scikit-learn, and visualization tools (Matplotlib, Seaborn) in a reproducible environment (Kaggle, Colab, or local setup).

5.1.3 Communication Standards

This project had to maintain communication both in technical terms and in cooperative terms to provide a clear, consistent and efficient communication. To facilitate collaboration within, we utilized Google Colab notebooks along with Kaggle notebooks that provide real-time sharing of codes, annotation, and discussion. These systems adhere to the standard web-based communication standards (HTTPS) and enable co-editing according to the current scholarly and research standards.

The data were interoperable between systems and complied with open data standards to make them easily readable and transferable between systems in standard file formats (CSV, PNG and JPEG). Methods and result documentation were in structured academic format and references were in IEEE citation format, common in engineering research.

Regarding the aspect of reporting, the project was compliant with the academic requirements of Daffodil international university in the aspects of structuring the report formally, ethics of citation, and clarity in the presentation of technical content. A combination of all these standards of communication was what resulted in a transparent project which can be reproduced and was professionally documented to apply in academics and practice.

5.2 Impact on Society, Environment and Sustainability

5.2.1 Impact on Life

- It also identifies osteoporosis at its initial stages before fractures and long-term disability occurs.

- It enhances rural or resource-limited access to diagnosis where more sophisticated equipment such as DXA is not available.

- Patients will have access to treatment and lifestyle education in a timely manner, which will enhance their quality of life and help reduce the cost of healthcare.

- The system equips professionals in healthcare with a support device that enables them to make quicker and more correct decisions.

5.2.2 Impact on Society & Environment

- Democracy in healthcare is beneficial to society since diagnostic equipment is not very expensive and can be scaled by the project.
- It will decrease healthcare system costs through late-stage osteoporosis management and hospitalization.
- The project runs on cloud-based GPU environments (Kaggle, Colab), eliminating the need to operate using heavy on-premise infrastructure, which helps in reducing the energy consumption and carbon footprint.
- Reducing medical imaging tests reduces medical waste and radiations which are harmful to the patients and the environment.

5.2.3 Ethical Aspects

The project complies with the principles of patient medical image privacy and confidentiality and holds the usage of such images accountable.

AI decision-making is not intended to substitute clinicians, but to help them in making important diagnoses.

The system eliminates bias due to the same datasets and the same assessment processes that make this system accurate across diverse populations of patients.

Scholarly and practice sources are appropriately referenced, and ethical and integrity principles of research are followed.

5.2.4 Sustainability Plan

To ensure the long-term flexibility of the system, it will be supported by open-source frameworks (PyTorch, TensorFlow).
The scalable and cost-effective use of clouds can be readily expanded to small clinics and large hospitals.
Constant optimization will be performed through the expansion of the dataset, the constant retraining of the model, and receiving feedback on the model by medics.

The fulfillment of the requirements of sustainable computing will provide the project with the certainty of the decreasing number of consumed energy and increase in the period of the possible implementation in the healthcare.

5.3 Project Management and Financial Analysis

This research required proper project management and financial planning in order to be completed within the allocated time and resource budget. The project was divided into the following phases: literature review, dataset preparation, model implementation, testing and documentation. Team members were assigned tasks based on expertise and checked on progress every now and then under the guidance of faculty advisors. This approach to management was employed to provide time and risk minimization milestones. The dataset is collected from different sources like Polashbari Diabetic Hospital, Cumilla Medical College and also some Diagnostic Hospital. It took couple of weeks to collect 853 images.

Table 5.1: Financial Analysis Report

Category	Minimum Budget (Used in Project)	Standard Budget
GPU / Hardware	Free (Kaggle & Colab T4 GPUs)	80,000–120,000 BDT (NVIDIA RTX 3080 / V100) or $300–500/month for cloud GPU
Software / Libraries	Free (Open-source Python ecosystem)	5,000 BDT/month for premium cloud services
Data Collection	Free (Hospital datasets, academic sources)	20,000–50,000 for licensed medical datasets
Documentation / Tools	Free (Google Docs / University license)	5,000–10,000 BDT (licenses)
Total Estimated Cost	**0 BDT**	**120,000–180,000 BDT**

5.4 Complex Engineering Problem

5.4.1 Complex Problem Solving

Table 5.2: Mapping with Complex Engineering Problem.

EP1 Dept of Knowledge	EP2 Range Of Conflicting Requirements	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applicable Codes	EP6 Extent Of Stake-holder Involvement	EP7 Interdependence
✓	✓	✓	✓	✓		✓

EP1 – Depth of Knowledge

The project required expertise that is not on the average problem-solving of undergraduate level. It demanded the knowledge of deep learning architectures (VGG16, VGG19, ResNet, DenseNet, U-Net, ViT, Swin) and how they can be used in medical imaging. Such a union of computer science and healthcare expertise shows how much knowledge is needed to resolve the issue.

EP2 – Range Of Conflicting Requirements

The answer was forced to strike a balance between several factors that were usually contradictory. As an illustration, DXA scans are precise, but costly and unavailable, AIbased approaches are cheap and scalable, but can be overfitted or imbalanced. The tradeoff between accuracy, cost, scalability, interpretability, and accessibility are all complex to manage requirements.

EP3 – Depth of Analysis

The project entailed systematic comparative study among several deep learning models. Advanced evaluation metrics (precision, recall, F1-score, Dice coefficient and IoU) were used to evaluate performance, as well as confusion matrices and training-validation curves. Such rigor of analysis guarantees technical adequacy but also clinical reliability in possible use.

EP4 – Familiarity of Issues

The problems discussed are non-routine and interdisciplinary and occupy the boundary between computer science, artificial intelligence and healthcare. Medical data privacy, clinical workflow, and diagnostic decision making are not routinely familiar to most engineers. Addressing the problem such unfamiliar issues emphasizes how non-trivial the problem is.

EP5 – Extent of Applicable Codes

Medical data regulations (HIPAA, GDPR) and technical standards (DICOM imaging, cross-validation protocols) and the ethical guidelines of AI had to be followed in the project. The breadth of the applicability of codes is signified through ensuring privacy, reliability, and clinical compliance and reproducible ML practices.

EP7 – Interdependence

The project combines several interdependent parts, such as medical datasets, preprocessing pipelines, deep learning architectures, and cloud computing (GPU-based) platforms (Kaggle/Colab) and possible clinical uses. These components need to be coordinated smoothly and this shows the high level of interdependence of the problem.

Table 5.3: Mapping with knowledge Profile.

K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
✓		✓	✓	✓

K3 – Engineering Fundamentals

The project illustrates the use of the basic principles of engineering, especially in computer science and data processing. It includes such basic ideas as algorithm design, preprocessing of data (normalization, augmentation, resizing), and its measure in statistical and computational terms. Such basics are the basis of the application of credible AI-based solution to medical imaging issues.

K5 – Engineering Design

In the project, it was necessary to design an end-to-end AI diagnosis system. This involved designing preprocessing pipelines, choosing and tuning deep learning architecture, and incorporating the evaluation metrics to tradeoff between accuracy, interpretability, and scalability. The use of engineering creative thinking and systematized problem solving is exhibited through such systematic design.

K6 – Engineering Practice

The project utilized engineering practice, including working on actual datasets, utilizing cloud computing (Kaggle/Colab) and embracing reproducible code requirements. The more realistic problems such as class imbalance, overfitting, and the deployment of the model were discussed, which demonstrates the possibility of transforming the theoretical approaches to the practical, real-life models.

K7 – Research Literature

The research literature is highly entrenched in the project. The literature review and gap analysis have been performed to identify the current diagnostic techniques, CNN-based techniques, and new development with the Vision Transformer. The project developed a reasonable ground to propose a better solution by evaluating the previous research and the shortcomings in it. This dependence on and contribution to academic literature makes the work scholarly, evidence-based, and in accordance with the current research in the medical AI field.

5.4.2 Engineering Activities

The engineering activities performed in this project can be considered complex since they involved sophisticated computing capabilities, cross-disciplinary teamwork, novelty in the implementation of new AI models, and the consideration of extended societal effects. Such activities transcend the technical task that are routine and show capability to address uncertainty, scale, and applicability to real-life scenarios.

Table 5.4: Mapping with Complex Engineering Activities.

EA1 Range of resources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
✓	✓	✓	✓	✓

EA1 – Range of Resources

The project required a broad spectrum of resources, such as medical imaging datasets, cloud systems that are graphics card-enabled (Kaggle, Colab), sophisticated deep learning with packages (TensorFlow, PyTorch), and scholarly literature in the fields of AI and healthcare. This variety of resources underscores the variety and interdisciplinary nature of the scope and technical level of expertise that is necessary.

EA2 – Level of Interaction

This project was a teamwork between the members of the team, supervisors and academic evaluators so that the project would provide feedback and improvement. Though the interaction was not explicitly involving the hospitals and patients, the academic and supervisory input was instrumental in the enhanced methodology, the substantiation of the approach, and the correspondence of the work to the real-life clinical relevance.

EA3 – Innovation

The project presented a novel model due to the use of and comparison of two models CNN and Transformer-based models (VGG, ResNet, DenseNet, U-Net, ViT, Swin) to detect osteoporosis. The combination of medical data preprocessing with modern-day AI architectures and metrics of evaluation is a new, inexpensive, and clinically useful solution to the traditional approaches of diagnostics.

EA4 The Societal and Environmental Consequences.

The project outcomes directly affect the society since the project allows earlier and less expensive detection of osteoporosis, preventing the threat of fractures and permanent disability. The environmental impact of cloud-based GPU environments (Kaggle, Colab) is that reliance on expensive and energy-heavy on-premise hardware is eliminated. Secondly, reducing unnecessary medical scans will reduce radiation and medical waste and contribute to sustainable healthcare practices.

EA5 – Familiarity

The issues covered in this work are not the ones taught to undergraduate engineers on a regular basis, and they needed to deal with unknown fields of medical image processing, healthcare data ethics, and deep learning innovations. The project took me outside the scope of the standard coursework into new and interdisciplinary problems, by investigating AI-driven diagnosis in a medical environment, which highlights the complexity and familiarity of real-world engineering work.

5.5 Summary

This chapter introduced the engineering requirements, issues, and overall considerations related to the creation of an AI-based screening device to detect osteoporosis. The project adhered to software, hardware, and communication standards, and the implementation itself adhered to established engineering principles, including PEP8 code conventions, FAIR data, and reproducible software environments, including PyTorch and TensorFlow. They used hardware and cloud-based GPU computing environments (Kaggle, Colab) to ensure accessibility, scalability, and affordability.

The effect on society, life, and the environment were also mentioned in the chapter and how the proposed system will be able to democratize access to healthcare and reduce costs and minimal impact on the environment by employing cloud-based resources instead of substantial on-premise infrastructure. To guarantee clinical trustworthiness and fairness, ethical considerations such as patient privacy, responsible AI decision-making, and research integrity were also considered.

Moreover, this project was mapped relative to Complex Engineering Problems (CEP) and Complex Engineering Activities (CEA), proving that the work was advanced in terms of knowledge, interdisciplinary union, creativity, and awareness of the impact on society. The project was dealing with practical healthcare problems which are not just part of the normal engineering work and this qualifies as dealing with a complex problem.

To summarize, this chapter determined that the suggested system is feasible in terms of technical standards, as well as in respect to sustainable, ethical, and socially relevant engineering practices - so that the study is scholarly, pragmatic, and advantageous to be adopted in healthcare in the future.

Chapter 6

Conclusion

6.1 Summary

This study investigated the efficacy of some of the deep learning models to detect osteoporosis based on X-ray photographs. The models that were tested in the study were convolutional neural networks and transformer-based networks, such as VGG16, VGG19, ResNet, DenseNet, UNet, Vision Transformer (ViT), and Swin Transformer. It was concluded that VGG19 was the most accurate with 97 per cent and one of the most effective methods of distinguishing between normal and osteoporotic cases. In the segmentation works, UNet performed more successfully with a Dice score of 0.936, which means that it can be applied to the issue of extracting fine details in medical images.
As it turned out, in the comparative analysis, the provided models including ResNet and DenseNet were ranked higher than the Swin Transformer, which could not compete with the CNN-based models. These results highlight that even classical CNN models with appropriate optimization can perform better in some medical imaging tasks than models based on transformers developed much more recently. In general, this paper supports the idea of AI-based solutions being useful in offering a reliable, cheap, and non-invasive tool to support the process of early osteoporosis detection. These systems can be used to supplement existing diagnostic systems with the aim of providing health practitioners with quicker and more reliable support in clinical decision-making.

6.2 Limitation

This paper examined the application of various models of deep learning to identify osteoporosis with the assistance of X-ray images. The experiments were conducted on various convolutional neural networks and transformer-based ones, including VGG16, VGG19, ResNet, DenseNet, UNet, Vision Transformer (ViT) and Swin Transformer. VGG19 has been proved to be the most successful in classification and it is also observed that it is highly efficient in differentiating normal and osteoporotic cases. Segmentation UNet achieved a higher success rate in the segmentation problem (Dice score 0.936), since it could detect small features in the medical images.
It was also revealed in the comparative analysis that other models such as ResNet, DenseNet also performed well, but Swin Transformer, did not perform well relative to CNN-based models. These findings have the implication that state of the art classical CNNs may still be more precise than more modern transformer-based models in particular medical imaging challenges. Overall, this source confirms the possibility of AI-based solutions to provide high quality, low-cost, and non-invasive support tools to diagnose osteoporosis at its early stages. The latter can be used as a supplement to the traditional method of diagnosis and can provide more valid and timely assistance to a health worker in making a clinical decision.

6.3 Future Work

To circumvent these constraints, there are a few directions that can be followed in future studies:

To start with, an increase in the size and diversity of patient groups in various hospitals and imaging devices would help to increase model generalization significantly. The models could also be more representative of clinical situations in the real world by including a broader range of age groups, sexes, and ethnicities.

Second, the incorporation of multimodal sources of data, including CT scans, bone mineral density (BMD) levels, laboratory test results, and medical history of a patient may contribute to a more thorough and precise prediction. Integrating the clinical and demographic with imaging would enable AI systems to detect the structural and biological features of osteoporosis.

Third, hybrid deep learning applications could be explored to merge the strengths of CNNs and Transformers in order to improve the quality of the obtained diagnostic results without detracting it. Besides, it can be realized with more advanced regulating measures and more developed augmentation algorithms to reduce the effect of overfitting and to improve the capabilities to transfer the knowledge to the previously unknown data.

Lastly, it is worth prioritizing the translation of such models into real-time, cost-effective AI-assisted diagnostic tools. In areas with a scarcity of highly sophisticated medical imaging machines, creating lightweight versions of the models, which can be incorporated into the hospital system or even portable diagnostic machines, might help osteoporosis screening become more approachable. Such innovations would provide a potential clinical use opportunity that would reduce the risk of fracture due to early diagnosis and treatment.

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