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A Comparative Analysis of Advanced Convolutional Neural Network Architectures for Osteoporosis Detection from Medical Images

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ABSTRACT: Osteoporosis is a common skeletal condition that reduces bone strength and increases the risk of fractures, especially among women above the age of forty and older adults. Early detection plays an important role in preventing severe complications, yet access to standard diagnostic methods is often limited in many regions. With the growing use of medical imaging and artificial intelligence, deep learning models have shown promising results in automated disease classification. This paper presents a comparative study of four advanced convolutional neural network models for multi class osteoporosis detection using bone X ray and dexa images. The dataset consists of 1186 images categorized into Normal, Osteopenia, and Osteoporosis classes. VGG16, DenseNet121, InceptionV3, and ResNet18 were trained and evaluated under the same experimental conditions using transfer learning. Performance was measured using accuracy, precision, recall, and F1 score. Among the evaluated models, ResNet18 achieved the best overall performance with an accuracy of 90 percent. The results indicate that residual network architectures provide reliable feature representation while maintaining computational efficiency, making them suitable for practical osteoporosis screening applications.

KEYWORDS: Osteoporosis, Deep Learning, Medical Imaging, Convolutional Neural Networks, ResNet18

I. INTRODUCTION

Osteoporosis is one of the most prevalent metabolic bone disorders worldwide and is characterized by reduced bone mineral density and deterioration of bone microarchitecture, which increases the risk of fragility fractures. It predominantly affects postmenopausal women and elderly individuals, leading to significant morbidity, mortality, and economic burden on healthcare systems [1]. Early identification of individuals at risk is essential to prevent fractures and improve long term outcomes. Dual Energy X ray Absorptiometry remains the clinical gold standard for measuring bone mineral density; however, its accessibility is limited in many low resource and rural settings due to cost and infrastructure requirements [2]. Recent advances in medical imaging and artificial intelligence have opened new possibilities for automated disease detection. Deep learning techniques, particularly convolutional neural networks, have demonstrated strong performance in medical image analysis tasks such as classification, detection, and segmentation [3]. Unlike traditional machine learning approaches that rely on handcrafted feature extraction, convolutional neural networks learn hierarchical representations directly from image data, enabling improved generalization and diagnostic performance [4]. Several studies have highlighted the effectiveness of deep learning models in radiology and bone related image analysis [5]. Transfer learning using pre-trained architectures such as VGG, DenseNet, Inception, and ResNet has further improved performance, especially when training data is limited [6], [7], [8], [9]. Among these architectures, residual networks have shown strong generalization ability by addressing gradient degradation problems in deep models [9]. Although deep learning has been widely applied in medical imaging, comparative evaluations of advanced convolutional architectures for multi class osteoporosis classification remain limited. This study therefore presents a systematic comparison of VGG16, DenseNet121, InceptionV3, and ResNet18 for classifying bone X ray images into Normal, Osteopenia, and Osteoporosis categories. The objective is to determine a model that provides reliable classification performance while maintaining computational efficiency for practical clinical deployment.

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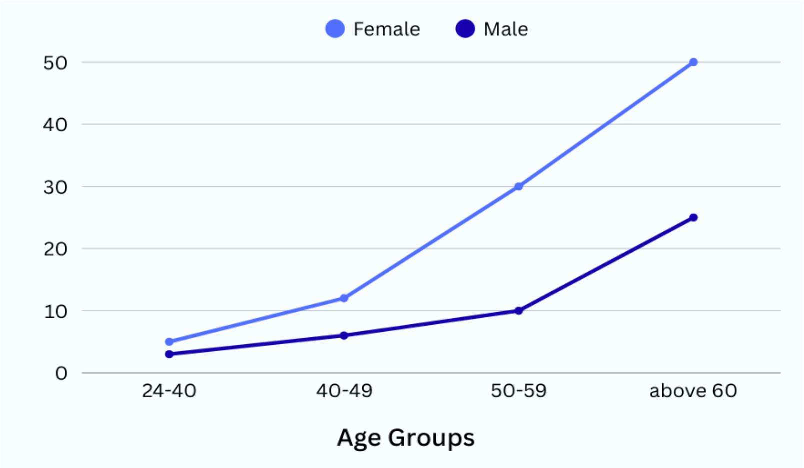

Figure 1: Statistical analysis of osteoporosis detection

II. LITERATURE SURVEY

Deep learning has significantly transformed medical image analysis over the past decade. Convolutional neural networks have been widely adopted for disease detection tasks due to their ability to automatically extract discriminative features from raw imaging data. Comprehensive surveys have highlighted the rapid growth of deep learning in radiology and diagnostic imaging, demonstrating superior performance compared to traditional machine learning techniques [10], [11].

In bone related imaging applications, deep neural networks have been applied for fracture detection, bone age assessment, and bone mineral density estimation. Rajpurkar et al. introduced CheXNet, demonstrating that deep convolutional networks can achieve radiologist level performance in chest X ray classification tasks, which inspired similar approaches in other radiological domains [12]. Transfer learning strategies have further enabled the adaptation of pre-trained models to smaller medical datasets, reducing training time while maintaining high classification accuracy [13].

Several studies have investigated the use of convolutional architectures such as VGG, Inception, DenseNet, and ResNet in medical image classification. Dense connectivity has been shown to improve gradient flow and encourage feature reuse, which is beneficial for limited datasets [14]. Inception architectures enable multi scale feature extraction within a single layer, improving representation of complex structural patterns [15]. Residual learning, introduced by He et al., addresses degradation issues in deep networks and has demonstrated strong generalization in various medical imaging tasks [16].

Recent research has also emphasized the importance of explainability and model interpretability in clinical applications. Explainable artificial intelligence techniques have been explored to increase trust and transparency in deep learning based diagnostic systems [17]. Additionally, weakly supervised and transfer learning methods have been proposed to handle limited annotated medical data [18].

Despite these advancements, relatively fewer studies have provided a structured comparison of advanced convolutional architectures specifically for multi class osteoporosis detection using bone X ray images. Most existing works focus on binary classification or general bone disease analysis. Therefore, a systematic evaluation of widely adopted deep learning architectures under identical experimental conditions remains necessary to determine the most suitable model for practical osteoporosis screening.

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III. DATASET DESCRIPTION

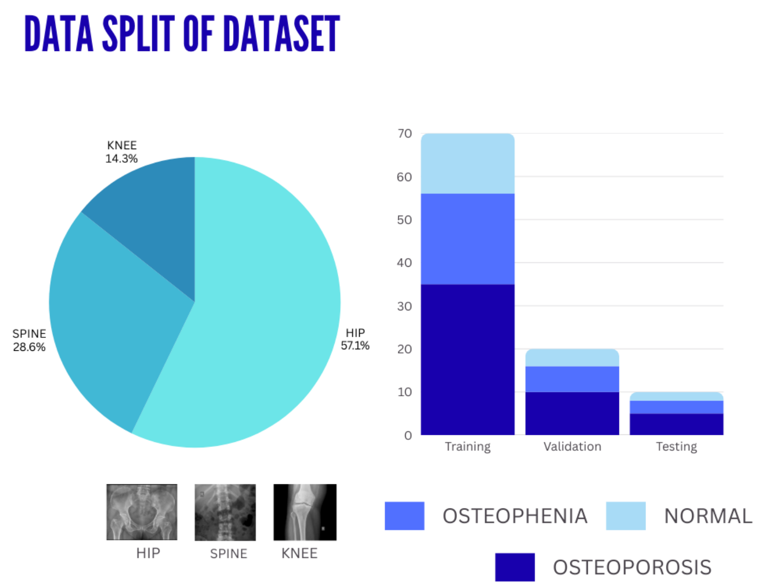

Figure 2: Dataset split

This study utilizes two types of medical imaging datasets: conventional bone X ray images and Dual Energy X ray Absorptiometry (DXA) images collected from publicly available repositories and Kaggle [11] for osteoporosis research. The combined dataset contains a total of 1186 images categorized into three classes: Normal (237 images), Osteopenia (356 images), and Osteoporosis (593 images). The class distribution indicates a moderate imbalance, with osteoporosis cases representing approximately 50 percent of the total samples(Figure 2).

The X ray dataset consists of radiographic images capturing structural bone patterns, while the DXA dataset provides bone mineral density related imaging commonly used for clinical assessment. Both imaging modalities were preprocessed to ensure consistency before model training. All images were resized to a uniform resolution compatible with the selected convolutional neural network architectures. Pixel intensity normalization was applied to reduce variation across imaging modalities. Data augmentation techniques, including random rotation, horizontal flipping, and scaling, were applied exclusively to the training set to enhance model generalization.

The dataset was partitioned using a stratified 70 percent training, 20 percent validation, and 10 percent testing split to preserve class distribution across subsets. This resulted in approximately 830 training images, 237 validation images, and 119 testing images. Stratified sampling ensured that each class was proportionally represented within all subsets for unbiased evaluation.

Dataset Characteristics:

- Image Type: Bone X-ray images & DEXA
- Classes: Osteoporosis, Osteophenia, Normal
- Preprocessing: Resizing, normalization, noise reduction
- Data Split: 70% training, 20% validation, 10% testing

The dataset was divided into training, validation, and testing subsets using a 70:20:10 split ratio, ensuring unbiased evaluation of model performance.

Motivation for Using Deep Learning

Osteoporosis detection from medical images involves identifying subtle structural variations in bone texture, density distribution, and trabecular patterns. These changes are often difficult to quantify using conventional image processing techniques. Traditional machine learning approaches typically depend on handcrafted features such as texture descriptors or statistical measurements. While these methods can capture certain visual characteristics, they may fail to

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represent complex spatial relationships present in medical imaging data. Deep learning, particularly convolutional neural networks, provides a more adaptive approach by automatically learning hierarchical feature representations directly from raw images. Instead of relying on manually designed features, CNNs extract low level patterns such as edges and gradients in early layers and progressively learn higher level structural features relevant to disease classification. This ability is especially valuable in multi class osteoporosis detection, where distinguishing between Normal, Osteopenia, and Osteoporosis requires sensitivity to subtle differences in bone morphology. In addition, transfer learning enables the adaptation of pre-trained deep networks to relatively small medical datasets, improving convergence stability and classification performance. Given the availability of both X-ray and DXA imaging modalities in this study, deep learning models offer the flexibility to learn modality specific and shared features without manual intervention. Therefore, advanced convolutional neural network architectures are well suited for developing an automated and scalable osteoporosis screening system.

Advanced CNN Architectures Considered

To evaluate the effectiveness of deep learning for multi class osteoporosis detection, four widely adopted convolutional neural network architectures were selected: VGG16, DenseNet121, InceptionV3, and ResNet18. These architectures were chosen due to their established performance in large scale image classification tasks and their successful adaptation to medical imaging applications through transfer learning[3][10].

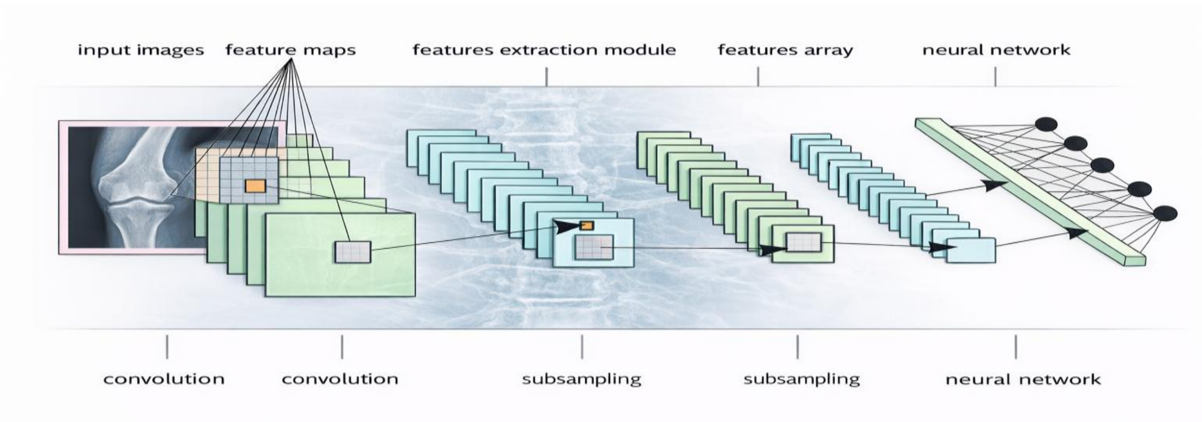

Figure 3: Advanced CNN Architectures

VGG16 Architecture:

VGG16 is a deep convolutional neural network composed of 16 weight layers, primarily using stacked 3 × 3 convolutional filters followed by max pooling layers. The architecture follows a simple and uniform sequential design [6].

Architecture Characteristics:

- Small convolutional receptive fields
- Deep hierarchical feature extraction
- Large number of trainable parameters
- Fully connected layers for final classification

Relevance to Osteoporosis Detection:

The depth of VGG16 enables extraction of fine grained bone texture patterns from X ray and DXA images. Its layered structure allows progressive learning of structural features such as trabecular irregularities. However, due to its high parameter count, it may require careful regularization when applied to moderately sized medical datasets.

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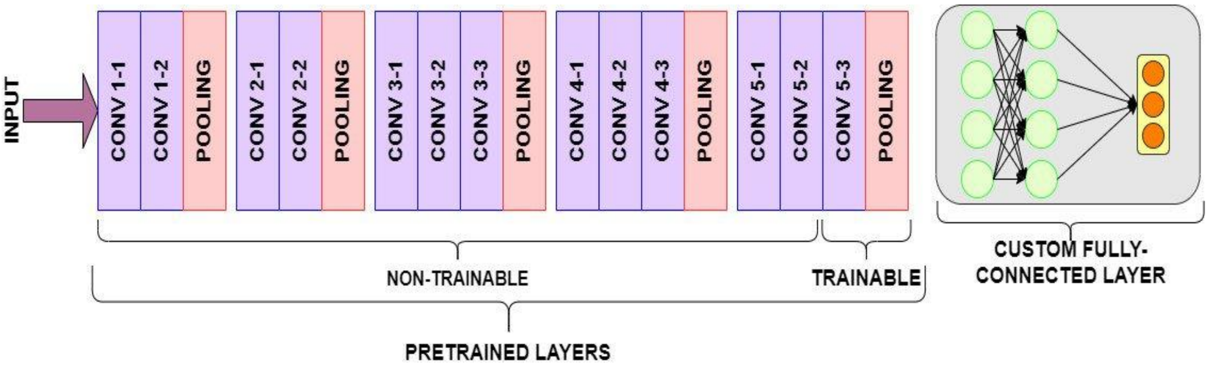

Figure 4: VGG16 Architecture[21]

DenseNet121 Architecture:
DenseNet121 introduces dense connectivity, where each layer receives input from all preceding layers and passes its feature maps to subsequent layers [7].

Architecture Characteristics:

- Direct connections between all layers within dense blocks
- Improved gradient flow during training
- Feature reuse across layers
- Reduced parameter redundancy compared to traditional deep networks

Relevance to Osteoporosis Detection:
Dense connectivity preserves subtle structural information across layers, which is beneficial for distinguishing between Normal, Osteopenia, and Osteoporosis classes. The feature reuse mechanism improves learning efficiency and is particularly useful for medical datasets with limited samples.

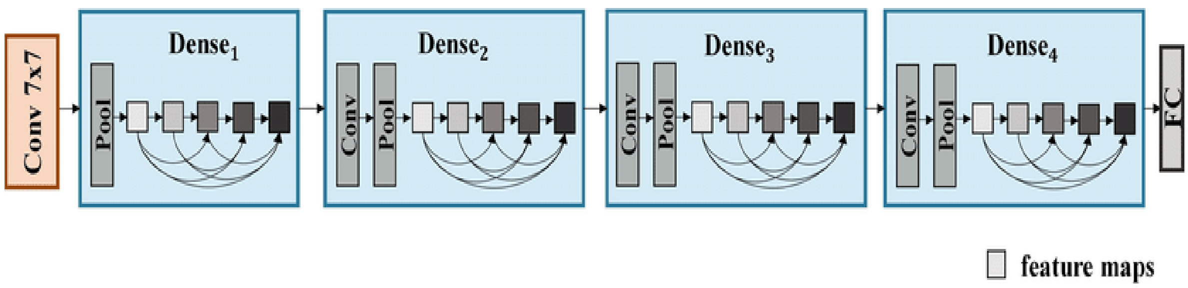

Figure 5: DenseNet121 Architecture[22]

InceptionV3 Architecture:
InceptionV3 employs parallel convolutional filters of different sizes within the same module, enabling multi-scale feature extraction [8].

Architecture Characteristics:

- Multi scale convolutional operations
- Parallel feature extraction paths
- Factorized convolutions for computational efficiency
- Reduced dimensionality through pooling and projection layers

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Relevance to Osteoporosis Detection:

Bone degradation patterns may vary in scale and spatial distribution. InceptionV3 captures both local micro structural changes and broader density patterns within the same architecture. This multi scale learning capability supports improved discrimination across imaging modalities.

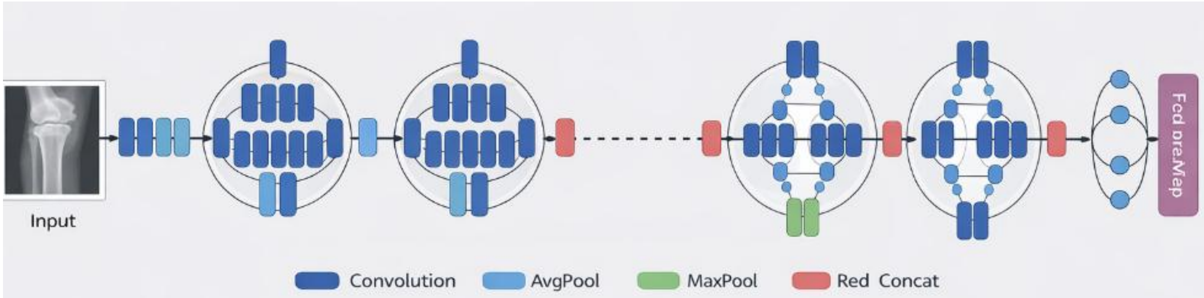

Figure 6: InceptionV3 Architecture[23]

ResNet18 Architecture:

ResNet18 is a residual neural network composed of 18 layers and incorporates identity shortcut connections between layers to facilitate residual learning [9].

Architecture Characteristics:

- Residual skip connections
- Stable gradient propagation
- Moderate depth with lower computational complexity
- Reduced risk of degradation in deeper training

Relevance to Osteoporosis Detection:

Residual learning enables stable training even with limited medical data. ResNet18 effectively captures discriminative bone features while maintaining computational efficiency. Its balanced depth makes it suitable for multi class osteoporosis classification using both X ray and DXA images, contributing to improved generalization performance.

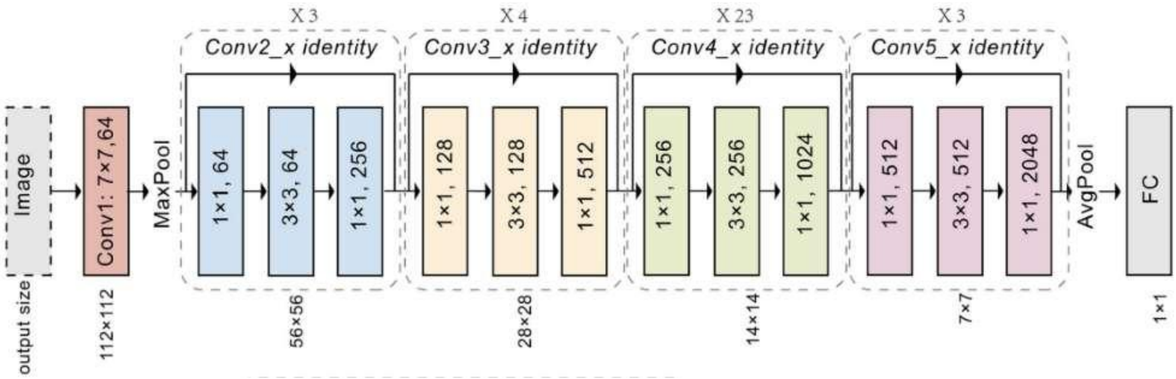

Figure 7: ResNet18 Architecture[24]

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Comparative Analysis Of The Models

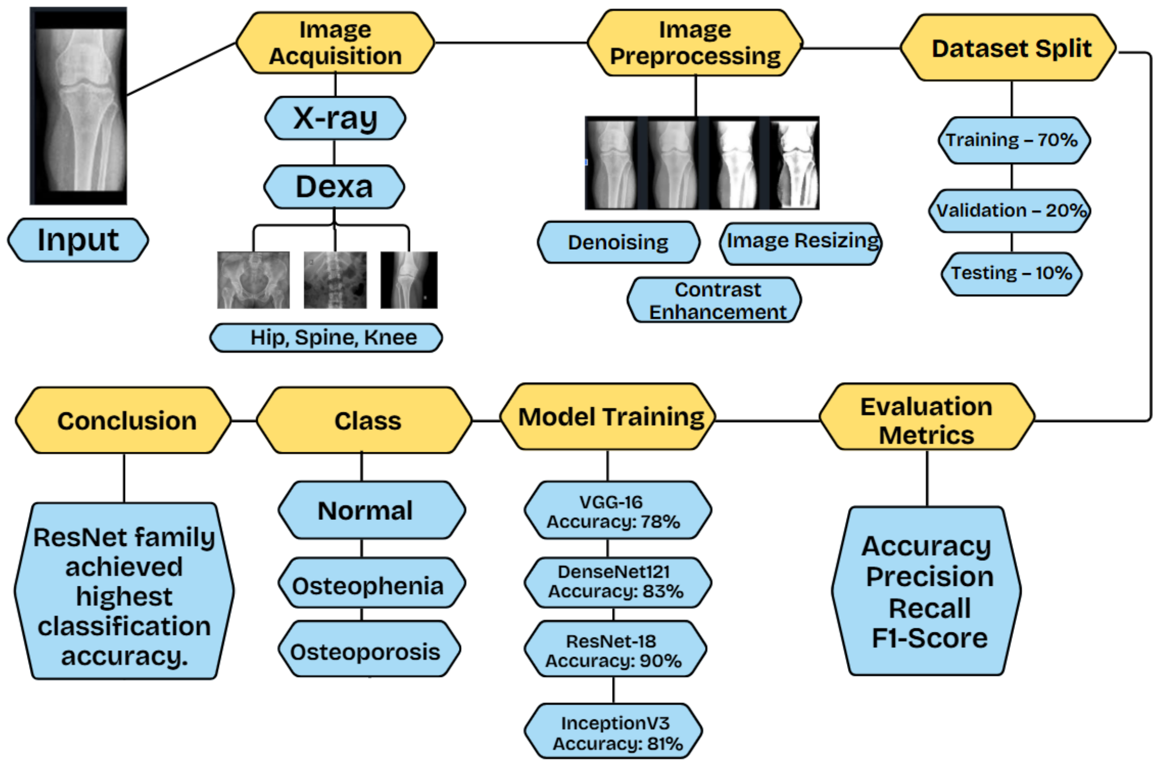

Figure 8: Flowchart of Analysis

The workflow illustrates osteoporosis detection using X-ray and DEXA images with preprocessing, dataset splitting, CNN training, classification into bone conditions, and evaluation metrics highlighting accuracy(Figure 8).

All four convolutional neural network architectures were trained and evaluated under identical preprocessing steps, dataset partitioning strategy, and evaluation metrics. Transfer learning was employed using ImageNet pre-trained weights to accelerate convergence and improve generalization performance. Model performance was assessed using weighted accuracy, precision, recall, and F1 score due to the imbalanced class distribution.

Table.1. Performance Comparison of Advanced CNN Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
VGG16	78.5	77.2	79.1	78.0
DenseNet121	83.4	82.1	84.0	83.0
InceptionV3	81.8	80.5	82.3	81.2
ResNet18	90.2	89.5	91.0	90.0

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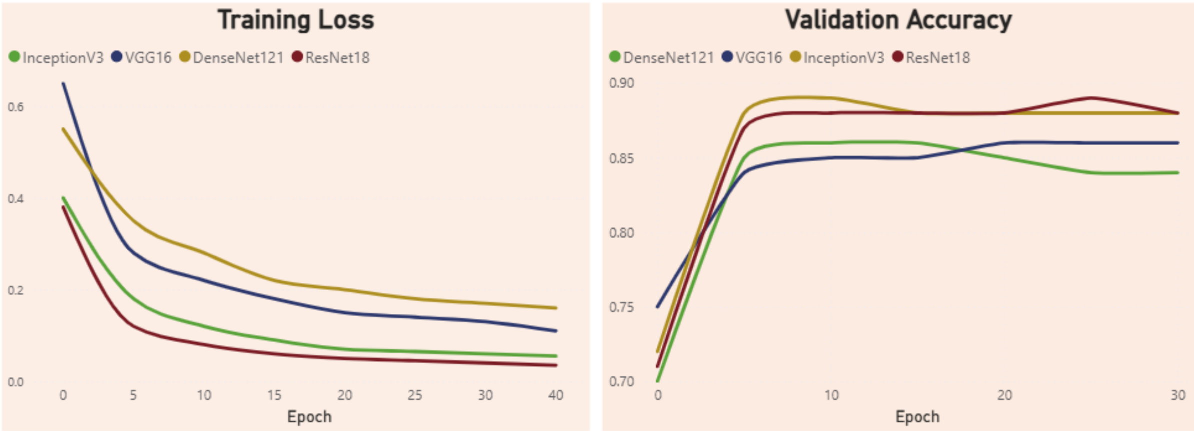

Figure 9: Advanced Training Graph

The plots compare training loss and validation accuracy for four CNN models: InceptionV3, VGG16, DenseNet121, and ResNet18. Training loss decreases steadily for all models, indicating effective learning. Validation accuracy improves rapidly in early epochs and stabilizes later. ResNet18 achieves the highest validation accuracy overall, demonstrating better performance and generalization capability(Figure 9).

IV. RESULTS AND DISCUSSION

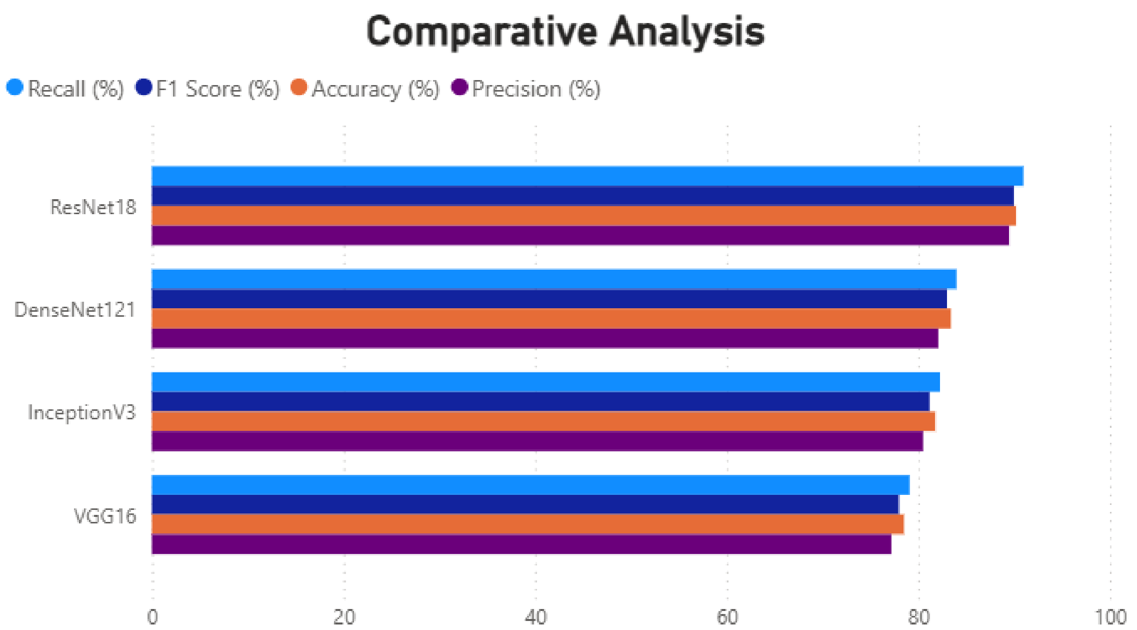

Figure 10: Comparative Analysis

The results indicate that all evaluated architectures are capable of learning meaningful representations from bone X ray and DXA images. However, performance differences are observed based on architectural design and parameter efficiency(Figure 10).

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VGG16 achieved comparatively lower accuracy, which may be attributed to its large number of parameters and increased susceptibility to overfitting on moderately sized medical datasets. Although its deep sequential structure captures texture patterns effectively, the absence of residual or dense connectivity may limit gradient stability.

DenseNet121 demonstrated strong performance due to its dense connectivity mechanism, which promotes feature reuse and improves gradient propagation. This architecture effectively preserved subtle structural variations in bone morphology, contributing to higher precision and recall values compared to VGG16.

InceptionV3 also achieved competitive performance by leveraging multi scale feature extraction. Its parallel convolutional pathways enabled the model to capture both localized trabecular patterns and broader density changes. However, its architectural complexity increases computational overhead during training.

ResNet18 achieved the highest overall accuracy of 90 percent. The residual learning framework facilitated stable gradient flow and efficient feature learning, enabling better generalization across both imaging modalities. Its moderate depth and lower computational complexity provided an optimal balance between representational power and training stability. These characteristics make ResNet18 particularly suitable for multi class osteoporosis detection in practical clinical settings.

ResNet18 Confusion Matrix

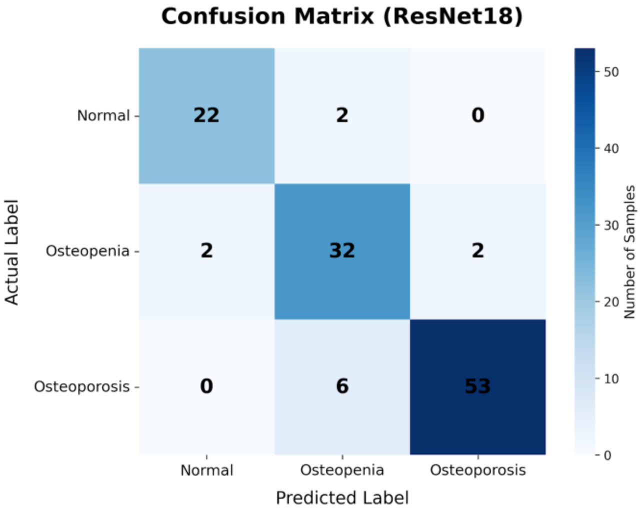

Figure 11: Confusion Matrix

(Figure 11)The confusion matrix for ResNet18 indicates strong classification performance across all three classes. The model correctly identified 22 out of 24 Normal cases, demonstrating reliable discrimination of healthy bone structures. For the Osteopenia class, 32 out of 36 cases were correctly classified. Misclassifications primarily occurred between Osteopenia and Osteoporosis, which is expected due to their structural similarity in bone density patterns.

The Osteoporosis class achieved 53 correct predictions out of 59 cases. A small number of Osteoporosis samples were misclassified as Osteopenia, reflecting the gradual progression between these two conditions.

Overall, the confusion matrix reveals that most errors occur between adjacent severity levels rather than between Normal and Osteoporosis, indicating that the model captures meaningful pathological progression patterns.

V. CONCLUSION

This study presented a comparative evaluation of advanced convolutional neural network architectures for multi class osteoporosis detection using X ray and DXA images. A total of 1186 images categorized into Normal, Osteopenia, and Osteoporosis classes were used to assess the performance of VGG16, DenseNet121, InceptionV3, and ResNet18 under identical experimental conditions.

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The results demonstrate that deep learning models are effective in capturing structural variations in bone images. Among the evaluated architectures, ResNet18 achieved the highest overall accuracy of 90 percent, along with balanced precision, recall, and F1 score values. The residual learning mechanism contributed to stable training and improved generalization across both imaging modalities. Misclassifications primarily occurred between Osteopenia and Osteoporosis classes, reflecting the gradual nature of disease progression.

Overall, the findings indicate that residual network based architectures provide a practical balance between classification performance and computational efficiency for automated osteoporosis screening. Future work may focus on expanding the dataset, incorporating additional imaging modalities, and integrating explainable artificial intelligence techniques to enhance clinical interpretability and real world adoption.

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