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Research Article

Enhancing Osteoporosis and Osteopenia Diagnosis from Knee X-Rays with Attention-based Deep Learning

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ABSTRACT

Osteoporosis and osteopenia are prevalent bone disorders that have a profound effect on mobility and overall well-being, especially in older adults. Timely detection is vital to avoid severe complications, but existing diagnostic techniques, like bone densitometry, can be costly and difficult to access. This research proposes a deep learning-based approach for detecting osteopenia and osteoporosis in the knee by analysing X-ray images. The suggested model employs the effective channel attention (ECA) mechanism to improve feature extraction, ultimately leading to increased classification accuracy. The dataset employed in this research consists of labelled knee X-Ray images, divided into three groups: normal, osteopenia, and osteoporosis. To guarantee optimal performance, the model underwent rigorous training and validation using a comprehensive pipeline that incorporated data augmentation and adaptive learning techniques. The evaluation results clearly indicate that the proposed model outperforms existing methods in terms of accuracy and reliability. The findings from the experiments suggest that the ECA-based model greatly enhances the accuracy of diagnosing bone density problems, providing a more affordable and easily accessible option for early detection.

Keywords: Osteoporosis, Osteopenia, Knee X-ray, Deep Learning, Efficient Channel Attention.

INTRODUCTION

Osteoporosis and Osteopenia are common bone conditions that significantly affect the elderly population, leading to reduced mobility, increased risk of fractures, and a decline in overall quality of life. These conditions develop as a result of decreased bone mineral density (BMD), leading to bones becoming porous, fragile, and more prone to fractures, even with minor impacts. Osteoporosis is commonly known as a 'silent disease' because it typically develops without noticeable symptoms until a fracture happens, usually impacting the hip, spine, or wrist. The World Health Organization (WHO) acknowledges Osteoporosis as a significant global health concern, particularly impacting postmenopausal women and older individuals. Globally, around 200 million individuals are affected by osteoporosis, and its prevalence is projected to increase as the population continues to age. Osteopenia, a precursor to osteoporosis, also poses significant health risks and serves as an early indicator of potential bone degeneration. Timely diagnosis and intervention are essential to reduce the risks linked to decreased bone density, such as fractures, chronic pain, long-term disability, and heightened mortality. Classic diagnostic techniques, such as dual-energy X-ray absorptiometry (DEXA), tend to be expensive, limited in accessibility, and dependent on specialized equipment, making regular screening difficult, especially in resource-limited environments.

In medical practice, knee X-ray imaging is widely utilized as one of the most commonly performed radiological examinations due to its affordability, availability, and non-invasive nature. These images provide critical insights into bone structure and density, making them a valuable tool for diagnosing degenerative bone diseases such as osteoporosis and osteopenia. However, accurately identifying these conditions from knee X-rays remains challenging due to subtle changes in bone density that are difficult to discern through visual inspection alone. Traditional image interpretation by radiologists can be subjective and vary based on expertise, leading to inconsistent diagnostic outcomes. Moreover, manual analysis is time-consuming and prone to errors, highlighting the need for automated, efficient, and accurate diagnostic systems. Furthermore, the shortage of qualified radiologists, particularly in resource-constrained settings, further exacerbates the challenge of timely diagnosis and intervention. Therefore, there is a pressing need for innovative methods that can provide consistent, accurate, and rapid analysis of knee X-rays.

Advancements in artificial intelligence, especially deep learning (DL), have transformed medical image analysis by facilitating automated extraction of features from complex datasets. Convolutional Neural Networks (CNNs) have demonstrated outstanding efficacy in analysing medical images, including X-rays, by learning hierarchical features directly from raw data. However, conventional CNN architectures may struggle to capture fine-grained variations in bone density, particularly when dealing with complex anatomical structures in knee X-rays. To overcome this challenge, we present an innovative deep learning model that integrates the Efficient Channel Attention (ECA) mechanism, which adaptively recalibrates channel-wise feature responses to enhance diagnostic precision. The proposed model's compact design makes it efficient, allowing for faster computation.

Suitable for immediate clinical use. This model provides a comprehensive overview of the findings hence developing a method for early detection of osteoporosis and osteopenia enhancing diagnostic precision and consistency. The salient contributions of this study are outlined as follows:

- An innovative deep learning model integrating the Efficient Channel Attention (ECA) mechanism to effectively classify knee X-ray images.
- A dynamic channel-wise attention module that enhances the extraction of fine-grained features while maintaining model efficiency.
- A portable and real-time diagnostic system that is well-suited for clinical use, especially in areas with limited resources.

The organization of the paper is as follows:

The related works section presents a brief review of related work. The materials and methods section details the methodology introduced in this study. The experimental result section discusses the evaluation and performance analysis of the proposed approach. Finally, the conclusion section concludes the paper with key findings and future directions.

RELATED WORKS

Researchers have performed various studies for the diagnosis of knee osteoporosis and osteopenia, employing a range of conventional and learning-based approaches.

The initial research, carried out by Sarhan et al. [17], introduced an innovative deep learning approach for detecting knee osteoporosis from x-ray images. The researchers utilized transfer learning with various convolutional neural network (CNN) architectures, including AlexNet, VGG-16, ResNet-50, VGG-19, InceptionNet, XceptionNet, and a custom-designed CNN. Their methodology involved integrating transfer learning from these architectures and implementing dataset augmentation. Among the models, VGG-19 achieved the greatest level of accuracy, with 92.0% for multiclass and 97.5% for binary classifications, emphasizing the efficacy of deep learning in early osteoporosis detection.

Ramesh and Santhi [16] investigated the application of Support Vector Machines (SVM) for differentiating between osteoporosis and osteopenia utilizing clinical data. They evaluated polynomial, linear, radial basis function (RBF), and Gaussian kernels to identify the most suitable method for achieving accurate classification. The study demonstrated that the choice of kernel significantly influences the performance of SVM in detecting bone diseases.

In a separate study, Wani and Arora [23] proposed a deep ensemble learning model aimed at diagnosing knee osteoporosis using X-ray images. The study evaluated four CNN models—AlexNet, ResNet, VGGNet, and DenseNet—and integrated them with deep neural networks (DNNs) to incorporate clinical data. ResNet and AlexNet achieved

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the highest accuracy in categorizing knee X-rays, and the ensemble models combining CNNs with DNNs further improved diagnostic precision.

Naguib et al. [13] introduced a deep learning approach with a novel superfluity mechanism for detecting knee osteoporosis and osteopenia using X-ray images. The superfluity mechanism involves concatenating multiple layers to allow feature flow through two branches instead of one. The study demonstrated that the Superfluity Deep Learning (DL) model outperformed AlexNet and ResNet50, achieving the highest accuracy of 85.42% and 79.39% for two datasets.

Additionally, the study by Dzierżak and Omiotek [4] employed deep convolutional neural networks (DCNNs) for diagnosing osteoporosis using spinal CT images. Among the architectures tested, VGG16 demonstrated the highest accuracy, underscoring its potential in analyzing bone density from spinal imaging.

Feng et al. [5] focused on hip X-ray image analysis using deep learning to predict osteoporosis. Their model demonstrated that deep learning techniques could effectively assist in identifying osteoporosis from hip imaging.

Furthermore, the study by Hua Xie et al. [24] introduced a few-shot learning (FSL) framework to diagnose osteopenia and osteoporosis using knee X-rays. This framework effectively addressed the issue of limited labeled data, showing potential for accurate classification with minimal training examples.

Furthermore, Sukegawa et al. [18] developed an ensemble deep learning model designed to detect osteoporosis using dental panoramic radiographs. The study demonstrated that integrating multiple neural network architectures enhances the diagnostic accuracy of osteoporosis screening.

Despite notable progress, achieving consistent outcomes across various datasets and clinical environments remains a challenge. Future research should focus on integrating multimodal data sources and enhancing model generalizability.

METHODS

This section presents a detailed explanation of the methodology adopted in the proposed study. The conceptual framework is depicted in **Figure 1**, with each stage comprehensively described in the following subsections.

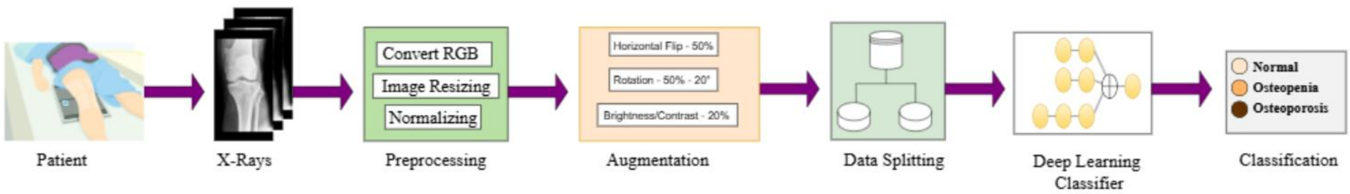

Figure 1. Schematic Flow of the Proposed Work

Dataset Details

The input data leveraged in the research is publicly available and serves as a valuable resource for diagnosing knee osteoporosis and osteopenia using X-ray images. The dataset is categorized into three classes based on the severity of the condition: Normal, Osteopenia, and Osteoporosis. Specifically, the dataset contains 780 Normal, 374 Osteopenia, and 793 Osteoporosis X-rays.

Data augmentation methods were employed to increase the model's ability to generalize and maintain high accuracy on unseen inputs. After augmentation, the final dataset comprises a total of 7,788 images, including 3,120 Normal X-rays, 1,496 Osteopenia X-rays, and 3,172 Osteoporosis X-rays. This diverse and comprehensive dataset aids in effectively training deep learning models for accurate classification of bone density conditions. The dataset can be accessed from [6].

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Pre-processing

During data acquisition, knee X-ray images often exhibit variations in contrast and brightness, which may hinder accurate feature extraction and classification. To ensure consistency and improve model performance, pre-processing steps are applied to enhance image quality. All X-ray images are initially modified to a standardized resolution of 224 × 224 pixels, ensuring uniform input size for the deep learning model while preserving essential structural details for accurate classification.

To further improve the quality of the input data, pixel intensity normalization is performed. Normalization helps adjust the pixel values to a standardized range, thereby mitigating the effects of varying brightness and contrast across the dataset. The min-max normalization technique is used, where each pixel intensity value is scaled to lie within the range [0, 1]. This process ensures that the input images are well-suited for training the neural network, as it stabilizes gradient updates and accelerates model convergence. The normalization equation is given by:

$$X_{norm} = \frac{X - \min(X)}{\max(X) - \min(X)} \cdot \left(new_{max}(X) - new_{min}(X)\right) + new_{min}(X)$$

Here, X and X_{norm} represent the input and normalized X-ray image, respectively. The minimum and maximum image pixel intensity values, denoted $min(X)$ and $max(X)$, are standardized to *0* and *1,* respectively. The $new_{min}(X)$ and $new_{max}(X)$ after normalization are also *0* and *1*, respectively. This normalization technique effectively scales the pixel intensity values to a uniform range, reducing the impact of variations caused by imaging conditions and enhancing the model's robustness.

Data augmentation methods are applied to increase the dataset's diversity artificially. These augmentations include random rotations, horizontal flips, and brightness adjustments. By incorporating augmented data during training, the model gains robustness to variations commonly encountered in real-world clinical settings, thereby enhancing its generalization ability.

Proposed Architecture

Deep learning methods, particularly Convolutional Neural Networks (CNNs), have revolutionized clinical image analysis by facilitating the automated identification of complex features within visual data. CNNs have been extensively utilized in various medical applications, including image classification, disease diagnosis, and anomaly detection. In the context of osteoporosis and osteopenia diagnosis from knee X-rays, traditional CNN models can struggle to capture fine-grained details related to bone density variations, especially when dealing with complex anatomical structures. Moreover, standard CNN architectures may result in high computational costs, making them impractical for real-time clinical use. To overcome these limitations, we propose an innovative deep learning architecture that effectively balances accuracy and computational efficiency. The proposed model leverages the Efficient Channel Attention (ECA) mechanism to dynamically enhance critical feature representation while maintaining a lightweight structure.

Our proposed work builds upon the efficiency and effectiveness of attention-based convolutional architectures. The Efficient Channel Attention (ECA) mechanism is utilized to dynamically adjust channel-wise feature responses, highlighting the most relevant features while minimizing redundant information. ECA is a lightweight and efficient attention module for feed-forward CNNs, shown in **Figure 2**. The proposed model comprises multiple convolutional blocks, each integrating convolutional layers, batch normalization, and ReLU activation functions. These blocks play a crucial role in extracting hierarchical features from knee X-ray scans, improving the framework's capacity to identify essential patterns. After each convolutional block, the ECA module refines the extracted features by prioritizing the most relevant channels, thereby optimizing feature maps without imposing significant computational costs.

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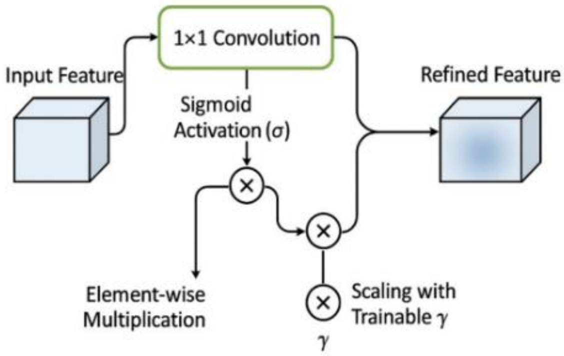

Figure 2. **Custom Framework of ECA**

Once feature extraction is complete, the model applies global average pooling (GAP) to reduce spatial dimensions while retaining vital information. This step is followed by fully connected dense layers responsible for classification. The GAP layer effectively compresses feature data, preserving key insights while minimizing dimensional complexity. To prevent overfitting and enhance generalization, the final layers incorporate dropout regularization. To achieve optimal performance, the proposed model is trained using the Adam optimization algorithm, with categorical cross-entropy selected as the loss function to handle multi-class classification. The output layer incorporates a softmax activation function to estimate the probability of the input X-ray image belonging to one of the three categories: Normal, Osteopenia, or Osteoporosis. The lightweight and efficient nature of the proposed architecture makes it suitable for real time integration in hospital settings, providing an automated and accurate tool for bone density diagnosis. Table 1 presents a comprehensive breakdown of the layers and parameters used in our model.

Table 1. **Detailed Configuration of the Model**

Layer Type	Output Shape	Kernel Number	Kernel Size	Padding	Activation	Connected to
conv2d-1	(222, 222, 32)	32	3×3	valid	ReLU	input
conv2d-2	(222, 222, 32)	32	3×3	same	ReLU	conv2d-1
conv2d-3	(222, 222, 32)	32	3×3	same	ReLU	conv2d-1
Add-1	(222, 222, 32)					conv2d-2 & conv2d-3
MaxPooling-1	(111, 111, 32)					Add-1
conv2d-4	(109, 109, 32)	32	3×3	valid	ReLU	MaxPooling-1
conv2d-5	(222, 222, 32)	32	3×3	valid	ReLU	input
conv2d-6	(109, 109, 32)	32	3×3	same	ReLU	conv2d-4
conv2d-7	(109, 109, 32)	32	3×3	same	ReLU	conv2d-4
conv2d-8	(222, 222, 32)	32	3×3	same	ReLU	conv2d-5
conv2d-9	(222, 222, 32)	32	3×3	same	ReLU	conv2d-5
Add-2	(109, 109, 32)					conv2d-6 & conv2d-7

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Add-3	(222, 222, 32)		conv2d-8 & conv2d-9
ECA-1	(222, 222, 32)		Add-1
ECA-2	(109, 109, 32)		Add-2
ECA-3	(222, 222, 32)		Add-3
Global MaxPooling-1	(32)		ECA-1
Global MaxPooling-2	(32)		ECA-2
Global MaxPooling-3	(32)		ECA-3
Flatten-1	(32)		Global MaxPooling-1
Flatten-2	(32)		Global MaxPooling-2
Flatten-3	(32)		Global MaxPooling-3
Concatenate	(96)		Flatten-1, Flatten-2, Flatten-3
Dense-1	(512)	ReLU	Concatenate
Dense-2	(256)	ReLU	Dense-1
Dense-3	(3)	Softmax	Dense-2

Network Training

The proposed model is developed using the augmented knee X-ray dataset, which contains images classified into three groups: Normal, Osteopenia, and Osteoporosis. To perform a thorough evaluation of the model performance, the data set was divided into training and validation subsets using an 80:20 ratio. During the training process, the model architecture and hyperparameters are fine-tuned using an iterative trial-and-error approach to optimize accuracy and minimize loss.

The network employs the Adam optimizer, known for its adaptive learning rate and rapid convergence, with the initial learning rate configured to 0.0001. Categorical cross-entropy is employed as the loss function to measure the difference between the predicted probabilities and the actual class labels, making it an appropriate choice for multi-class classification problems. A batch size of 16 is chosen to maintain an optimal balance between memory usage and training stability. The model is trained for 100 epochs to achieve optimal performance.

Early stopping is implemented to reduce the risk of overfitting and improve the model's ability to generalize by tracking validation accuracy, utilizing a patience of 30 and a minimum delta of 0.001. Early stopping is configured to restore the best weights once the monitored metric stops improving. Additionally, a model check-pointing mechanism is employed to save the best model weights during training, based on the highest validation accuracy. The check-pointed model is stored in the specified directory with the epoch number appended to the filename. The training process is set to be verbose, providing real-time updates on the training progress.

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The model is trained and validated using the Keras framework with a TensorFlow backend, taking advantage of Python 3.8 for its comprehensive deep learning library support. The model's effectiveness in diagnosing knee osteoporosis and osteopenia is analysed using performance metrics, including accuracy, precision, recall, and F1-score.

EXPERIMENTAL RESULTS

Evaluation Metric

To assess the effectiveness of the proposed model and benchmark its performance against current state-of-the-art approaches, four essential evaluation metrics were employed: precision, recall, accuracy, and F1-score.

Precision measures the reliability of positive predictions by determining the proportion of true positive cases among all instances labelled as positive by the model, including any false positives. It is mathematically defined as:

$$\text{Precision} = \frac{TP}{TP+FP} \quad \{\text{TP= True Positive; FP= False Positive}\}$$

Recall measures the percentage of correctly identified positive instances (true positives) out of all actual positive instances, including false negatives. It can be expressed using the following formula:

$$\text{Recall} = \frac{TruePositive(TP)}{TruePositive(TP)+FalseNegative(FN)}$$

Accuracy quantifies the proportion of correctly classified instances out of the total instances, calculated as follows:

$$Accuracy = \frac{TruePositive + TrueNegative}{TruePositive + TrueNegative + FalsePositive + FalseNegative}$$

The F1-score, representing the harmonic mean of precision and recall, is computed as follows:

$$F1 - score = \left(2 * (\Pr e\, cision * Recall)\right)/(\Pr e\, cision + Recall)$$

Within this framework, *TP, TN, FP,* and *FN* correspond to the correctly identified positives, correctly identified negatives, incorrectly identified positives, and incorrectly identified negatives, respectively.

Furthermore, the Area Under the Curve (AUC) is computed based on the Receiver Operating Characteristic (ROC) curve, offering an in-depth evaluation of the model's classification accuracy and discriminative capability. An elevated AUC score indicates strong discriminative capability of the model, underscoring its robustness and reliability.

Results

The proposed model's effectiveness on unseen data is assessed by evaluating its performance on the test dataset. The accuracy of the model is observed to be 82.22%, with a total of 277 errors out of 1558 test samples. **Figure 3** illustrates the confusion matrix of the proposed method, where rows indicate the actual class labels, and columns represent the predicted labels generated by the model. The diagonal values are significantly higher than the off-diagonal values, indicating that the majority of the predictions are correct. This outcome indicates that the proposed model demonstrates high effectiveness in differentiating between normal, osteopenia, and osteoporosis X-ray images.

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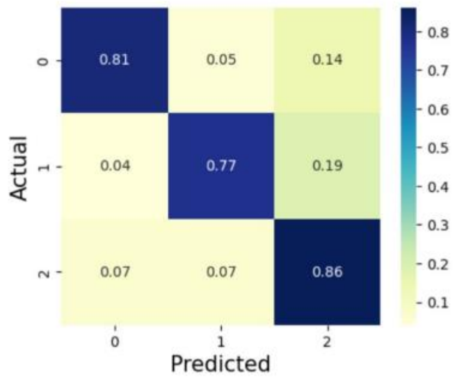

Figure 3. Confusion Matrix of the Model

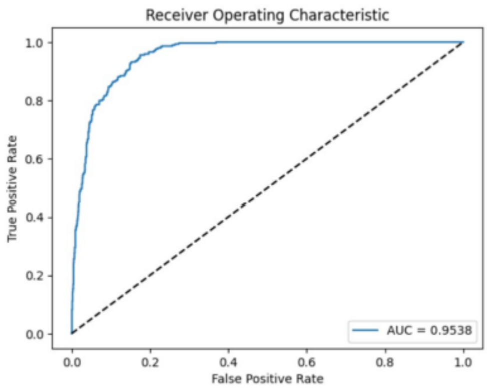

Figure 4. ROC Curve of the Model

As shown in **Figure 4**, the ROC curve visualizes the variation in true positive and false positive rates under different classification thresholds. The AUC value derived from this curve quantifies the model's discriminative power, with higher scores indicating more accurate class separation. The proposed model achieves an AUC of 0.9538, demonstrating its strong ability to accurately differentiate between normal, osteopenia, and osteoporosis cases.

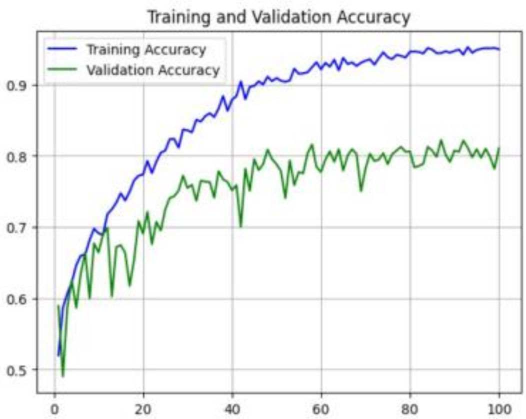

Figure 5. Training and Validation Accuracy Curve of the Model

Figure 5 displays the training and validation accuracy curves, illustrating the model's learning progression over multiple epochs. The upward trend in both training and validation accuracy indicates effective learning, while the minimal gap between the two suggests a strong generalizability, with no significant overfitting.

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Table 2. Performance Evaluation of the Proposed Method.

Class	Precision	Recall	F1-score	Support
Normal	90	81	85	635
Osteopenia	75	77	76	294
Osteoporosis	79	86	82	629
Macro Average	81	81	81	1558
Weighted Average	83	82	82	1558

Accuracy: 82.22%

Table 2 provides a detailed performance analysis of the proposed approach, reporting key metrics such as precision, recall, F1 score, macro average and weighted average (expressed as percentages). Together, these evaluation metrics provide detailed insight into the model's performance in accurately classifying knee X-ray images into normal, osteopenia, and osteoporosis categories.

CONCLUSION

This research presents an innovative deep learning model incorporating the Efficient Channel Attention (ECA) mechanism to automatically identify osteoporosis and osteopenia from knee X-ray scans. The model is trained on an augmented version of the original X-ray dataset, which substantially improves its ability to generalize. The lightweight architecture of the proposed model, comprising approximately 248,486 parameters, makes it highly suitable for deployment in real-time clinical settings. Incorporating the ECA mechanism enables the model to effectively highlight essential features while preserving computational efficiency.

The proposed model attained an accuracy of 82.22% on the test set, along with an AUC of 0.9538, demonstrating its strong performance for distinguishing between normal, osteopenia, and osteoporosis categories in knee X-rays. The results demonstrate that the model successfully captures subtle variations in bone density, making it a reliable tool for early diagnosis. In future work, the focus will be on incorporating additional datasets to further improve model generalization and exploring more advanced attention mechanisms to enhance diagnostic precision.

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