Knee Osteoarthritis Severity Prediction from X-Rays Using Ensemble Learning

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Abstract - Knee osteoarthritis (OA) affects millions of individuals globally and is characterized by the degeneration of joint cartilage and underlying bone. This condition leads to pain, limited movement, and reduced mobility. Accurate and timely assessment of OA severity is critical for effective clinical management. In this study, we address the challenge of predicting knee OA severity using X-ray images by leveraging deep learning, particularly convolutional neural networks (CNNs). A novel ensemble model is proposed, combining the strengths of multiple architectures to improve diagnostic accuracy. Specifically, the model integrates feature extraction from EfficientNet and DenseNet, along with other ensemble techniques, achieving an impressive accuracy of **94.76%**.

The high performance of the ensemble model highlights its robustness in classifying OA severity and presents a reliable, precise approach for health assessment. This systematic methodology demonstrates the potential of deep learning to significantly enhance diagnostic accuracy and support informed clinical decision-making in knee osteoarthritis care.

Keywords - *Knee osteoarthritis (OA), severity grading, DenseNet, EfficientNet, Ensemble model*

I. INTRODUCTION

Knee osteoarthritis (OA) is a widespread and disabling joint disorder that primarily impacts older adults. Its prevalence continues to rise globally, fueled by aging populations and increasing rates of obesity. Many individuals remain unaware of their condition in its early stages, often dismissing joint pain as temporary. Unfortunately, by the time severe discomfort emerges, the disease has often progressed significantly. According to estimates, knee OA is expected to affect approximately 130 million people worldwide by the year 2050 [1].

OA is marked by the progressive deterioration of joint cartilage, particularly in the knee—a complex hinge joint made up of bones, ligaments, tendons, cartilage, and connective tissues. The articular cartilage, which ensures smooth joint movement, gradually wears down in OA, leading to stiffness, pain, the formation of bone spurs, and reduced mobility. The condition is more common in individuals over the age of 55, especially those over 65, and is more frequently observed in women than men. In the United States alone, more than 32 million individuals are affected by OA [2].

Given the chronic nature of knee OA and its impact on quality of life, early detection and accurate grading of severity are critical for timely intervention and effective clinical management. One promising approach to achieving this is through the use of deep convolutional neural networks (CNNs) for analyzing knee X-ray images.

CNNs have revolutionized image classification, with transfer learning models playing a vital role in medical imaging tasks. Among these, **EfficientNet** [3] stands out for its innovative compound scaling method, which systematically balances network depth, width, and resolution to maximize accuracy while minimizing computational cost. This architecture offers high performance across a variety of image recognition tasks.

Similarly, **DenseNet** [4] introduces dense connections between layers, enabling improved gradient flow and efficient feature reuse, which in turn reduces the number of parameters and enhances training performance. DenseNet has achieved outstanding results across various image classification benchmarks.

This study harnesses the combined capabilities of EfficientNet, DenseNet, and ensemble modeling techniques to evaluate the severity of knee osteoarthritis using X-ray imagery. By leveraging the complementary strengths of these models, the proposed method aims to improve the precision and reliability of OA diagnosis, contributing to better patient outcomes and more efficient healthcare delivery.

The proposed ensemble model presents several key contributions to the field of knee osteoarthritis (OA) severity classification:

- **Innovative Ensemble Framework**: This work introduces a novel ensemble strategy that integrates the capabilities of multiple transfer learning architectures specifically, EfficientNet and DenseNet to improve the accuracy and robustness of knee OA severity predictions.

- **Probability-Based Decision Mechanism**: The model incorporates a probabilistic decision-making process, where final class predictions are derived by averaging the output probabilities from individual models. The class with the highest combined probability is selected, enhancing the reliability of the final output.

- **High Classification Accuracy**: The ensemble model achieves a commendable accuracy of **94.76%** in classifying OA severity from knee X-ray images, demonstrating its effectiveness for medical image analysis tasks.

The research paper is divided into the following sections: section 2 outlines the literature review performed related to KO classification; section 3 includes the system's architecture along with the design considerations that each component of each architecture; section 4 describes the experimental analysis and findings of the proposed model; section 5 concludes along with the further development for the future.

II. LITERATURE REVIEW

A. Overview of Knee Osteoarthritis

Knee osteoarthritis (OA) is a degenerative joint disease that results from the breakdown of the articular cartilage—a smooth, elastic tissue that protects bones by reducing friction and absorbing shock during movement. As this cartilage erodes, bones begin to rub directly against each other, causing pain, reduced mobility, joint stiffness, and in severe cases, deformities [6].

On radiographic images, the primary indicators of knee OA include **joint space narrowing (JSN)** and the appearance of **osteophytes** or bone spurs [7]. JSN typically results from cartilage loss, which decreases the space between bones and is detectable using X-ray imaging

1) Prevalence and Epidemiology

In 2013, arthritis affected approximately 54.4 million people in the United States. By 2040, this number is projected to rise to 78.4 million. Knee OA alone accounts for millions of clinical visits annually—more than 7 million in the U.S.—and is anticipated to impact at least 130 million people globally by 2050. Treatment for knee OA incurs over $20 billion in healthcare costs each year [8]. Given the limited treatment options for advanced OA, early detection is critical to alleviate symptoms and slow disease progression. While age and sex are notable risk factors, imaging remains a key tool for confirming diagnosis and ruling out other joint disorders [9].

2) Impact on Quality of Life

Knee OA is a chronic condition that affects individuals physically, mentally, and socially. The primary symptoms include joint pain, swelling, and stiffness that worsen with activity. These symptoms significantly hinder daily tasks such as walking, climbing stairs, or dressing. Chronic discomfort can lead to psychological issues, including anxiety, depression, and a loss of independence, thereby greatly diminishing quality of life.

3) Risk Factors

Several risk factors contribute to the development and progression of knee OA. Age remains the most significant, with around one-third of individuals aged 65 and above experiencing OA symptoms, a figure expected to increase with the aging population [10].

- **Gender Differences**: Women, especially post-menopause, are more susceptible to knee OA than men. This may be attributed to hormonal changes and differences in joint anatomy [11, 12].

- **Obesity**: Excess body weight increases mechanical load on the knee, accelerating cartilage wear. Additionally, systemic inflammation associated with obesity may play a role in OA onset [13].

- **Previous Injury**: Post-traumatic OA accounts for about 12% of cases and is often caused by prior joint injuries, such as those sustained during sports or accidents. Individuals with a history of knee trauma face a 3–6 times higher risk of OA [14, 15].

- **Muscle Weakness and Bone Health**: Weakness in periarticular muscles and low bone density can destabilize joints, contributing to OA development.

- **Occupational Risks**: Jobs involving repetitive squatting or kneeling are also associated with a higher prevalence of knee OA.

III. PROPOSED MODEL

In this study, an ensemble model is analyzed for classifying knee X-ray images into three categories: **healthy**, **moderate**, and **severe** knee osteoarthritis (OA). The model employs various transfer learning architectures, including **EfficientNet** and **DenseNet**, to perform ensemble learning and enhance the accuracy of OA severity classification.

A. EfficientNet

EfficientNet, developed by Google for image classification tasks, achieves a balance between accuracy and computational efficiency by uniformly scaling the network's **depth**, **width**, and **input resolution**. Unlike traditional CNN scaling methods that adjust these dimensions arbitrarily, EfficientNet employs a compound scaling method that harmonizes all three, leading to better performance with fewer parameters.

One of the core innovations in EfficientNet is its ability to mitigate the **vanishing gradient** problem, which often arises when increasing network depth. This is addressed through **skip connections** that facilitate the flow of gradients during backpropagation.

EfficientNet’s architecture is composed of **eight blocks** optimized for efficient feature extraction:

- **Block 0** begins with a standard 3×3 convolutional layer, followed by pooling and additional convolutions.

- **Block 1** utilizes a **MBConv1 3×3** module with pointwise convolution and non-linear activation.

- **Block 2** incorporates **MBConv6 3×3**.

- **Block 3** introduces a stride-2 **MBConv6 5×5** module for spatial downsampling.

- **Blocks 4 to 7** continue this pattern, using MBConv6 modules with selective stride-2 operations for further downsampling.

The **MBConv block**, adapted from the **Inverted Residual Block (IRB)**, plays a pivotal role in ensuring computational efficiency while preserving representational power. It uses **depthwise separable convolutions** and **pointwise convolutions** to reduce the number of parameters and computations.

EfficientNet enhances performance through:

- **Depth scaling**, increasing model layers while maintaining trainability via skip connections.
- **Width scaling**, expanding the number of channels for richer feature representations.
- **Resolution scaling**, increasing input image size to capture finer details

Figure 1 illustrates the comprehensive architecture of EfficientNet, highlighting its key components and the flow of feature extraction through the network.

Figure 1 EfficientNet architecture [3]

B. DenseNet

DenseNet, introduced by Huang et al. in 2017, is an innovative convolutional neural network (CNN) architecture that improves information flow and parameter efficiency. Unlike traditional CNNs where each layer receives input only from the immediately preceding layer, DenseNet features **dense connectivity**—each layer in a dense block receives inputs from all previous layers in a feed-forward fashion.

This design allows for better feature reuse and mitigates the vanishing gradient problem, enabling deeper networks with fewer parameters. Within a dense block, every layer is connected to all earlier layers, promoting efficient parameter utilization and improved gradient propagation. Figure 2 provides a comprehensive overview of the DenseNet architecture.

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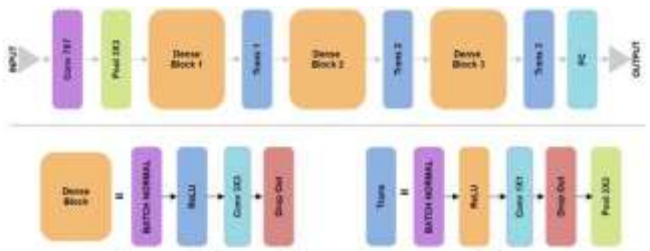

Figure 2 DenseNet architecture [4]

The architecture of DenseNet comprises multiple dense blocks, each consisting of dense layers. Each dense layer consists of a batch normalization layer, a ReLU activation function, and a series of convolutional layers with an equal number of filters. The outputs from all preceding layers in a dense block are concatenated and fed as input into the current layer, reinforcing the dense connectivity pattern. To manage the transition between dense blocks, DenseNet employs transition layers. These layers execute processes to reduce both the number and spatial extents of feature maps. In a typical transition layer, a 2x2 average pooling layer with a stride of 2, a 1x1 convolutional layer, a reduction factor (often set to 0.5) are included alongside a batch normalization layer. The final classification output is produced by applying a global average pooling layer to the feature maps after the last dense block, followed by applying softmax activation with a fully connected layer. The overall architecture of DenseNet includes an input layer, an initial convolutional layer with ReLU activation and batch normalization, dense blocks with dense layers, transition layers, and the final layers for classification output.

C. Ensemble Model Architecture

The ensemble model combines EfficientNet and DenseNet to improve classification accuracy.Each model is fine-tuned on the pre-processed knee X-ray dataset to extract unique features.Extracted features from both models are averaged to promote generalization and balance. This **feature fusion** helps capture comprehensive representations of OA severity.

Batch Normalization is applied to stabilize training and reduce overfitting. The normalized output is passed through three **Dense layers** for deeper learning. **Adamax** optimizer is used to adjust learning rates adaptively across parameters. It leverages the infinity norm, offering stability in high-dimensional spaces. Adamax updates parameters using past gradients, aiding convergence.This combination ensures effective learning and robust performance.

Equations (1) to (3) define the Adamax optimization process.The architecture boosts prediction reliability across OA severity levels.

$$X_m = \gamma_m \cdot X_{m-1} + (1 - \gamma_m) \cdot d_m \tag{1}$$

$$u_m = max(\gamma_2 \cdot u_{m-1}, |d_m|) \tag{2}$$

$$\sigma_m = \sigma_{m-1} - \frac{\mu}{1-\gamma_1^m} \cdot \frac{X_m}{u_m + \epsilon} \tag{3}$$

Where X_m denotes the first moment (mean) of the gradients, representing the average value of the gradients; u_m indicates the weighted gradients; and d_m is the parameter value at time t. σ_m refers to the optimized parameter, μ is the learning rate, and γ_1 and γ_2 are the decay rates for the moment estimates. ϵ is a small constant added to avoid division by zero.

Subsequently, the models are tested independently on a dedicated test dataset, and their respective probability distributions for each class are generated. The learning rate used in this proposed model is 0.001. The ensemble model selects the class with the highest probability distribution as the predicted class through averaging the probability distribution. A combination of these powerful individual models is created to correctly predict the severity of OA. The architecture of the ensemble model is shown in figure 3.

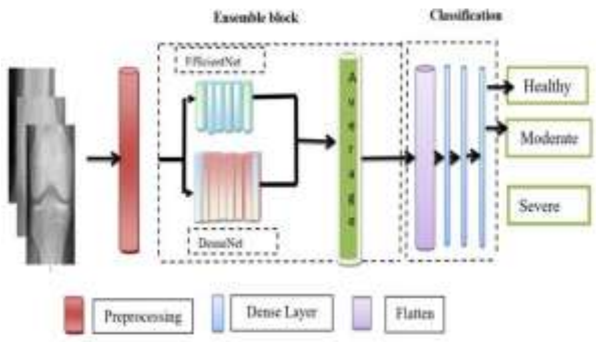

Figure 3: Architecture of the ensemble model

IV. EXPERIMENTAL RESULTS AND DISCUSSION

This section explains about the data acquisition, data pre-processing, model training and validation, visual interpretation and the efficiency of the proposed architecture ensemble

A. Experimental Setup and System Configuration

The proposed model was developed and evaluated using **Anaconda** with **Jupyter Notebook** as the development environment. **OpenCV** was utilized for data augmentation tasks, and the model was implemented in **Python** using the **TensorFlow** deep learning framework.

The experiments were conducted on a system equipped with an **Intel(R) Evo Core(TM) i5-12500H CPU @ 2.30GHz**, integrated **Intel® Iris Xe Graphics**, and **16 GB of RAM**.

B. Dataset

The dataset [5] comprises X-ray scans focusing on the **knee joints** of patients diagnosed with **knee osteoarthritis (OA)**. The severity of OA in each image is assessed using the **Kellgren and Lawrence (K&L) grading method**, a widely accepted standard for evaluating the progression of knee OA. This method assigns a grade from **0 to 4**, where higher grades reflect more severe osteoarthritic changes in the knee joint. Each image in the dataset is labeled with its corresponding K&L grade. For the purpose of model training and evaluation, the dataset is **partitioned into three subsets**:

- **Training set**: 5,778 images
- **Testing set**: 1,656 images
- **Validation set**: 826 images

Table 1: Knee Osteoarthritis Image Count

Grade	Training	Testing	Validation
0	2286	639	328
1	1046	256	153
2	1516	447	212
3	757	223	106
4	173	51	27

C. Data Pre-processing

Data pre-processing plays a crucial role in enhancing the **accuracy, quality, and effectiveness** of data used in machine learning models. In this study, techniques such as **Median Filtering** and **CLAHE (Contrast Limited Adaptive Histogram Equalization)** were employed to refine the input images for improved analysis.

The process began with the application of a **Median Filter**, which helps in reducing noise while preserving important edges in the image. This was followed by **CLAHE**, a technique designed to enhance local contrast without amplifying noise excessively. CLAHE works by dividing the image into small, overlapping sub-regions and performing histogram equalization within each region independently. This localized enhancement ensures that contrast adjustments are

context-specific, making key features more prominent for model interpretation.

These preprocessing steps significantly contribute to the extraction of meaningful patterns and improve the performance of the model. **Figure 4** illustrates a comparison between the original image and the pre-processed version used in the proposed methodology.

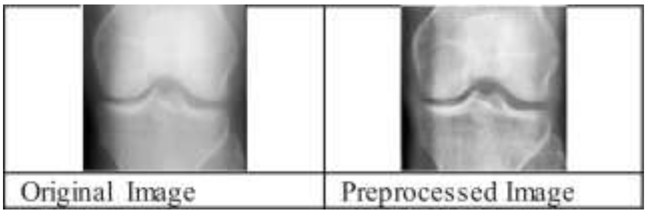

Figure 4 The X-ray image before and after undergoing data pre-processing.

D. Data Augmentation

Data augmentation is a widely adopted technique in image processing used to expand and diversify datasets by applying various transformations such as **rotations**, **flips**, **scaling**, and **brightness or contrast adjustments**. These transformations help in enhancing the model's ability to generalize, **improving robustness**, **reducing overfitting**, and facilitating better **pattern recognition** across diverse input conditions.

In the proposed work, **ImageDataGenerator** is employed to perform augmentation. The applied transformations include:

- **Horizontal flipping**
- **Rotation up to 20 degrees** in both directions
- **Width and height shifting** (range: 0.2)
- **Zooming** (range: 0.2)

These augmentations enrich the training dataset, allowing the model to learn more invariant features. Additionally, the dataset is grouped into

- **Grades 0, 1, and 2** as Healthy
- **Grade 3** as Moderate
- **Grade 4** as *Severe*

Figure 5 displays both the original and the augmented images used in the study.

Figure 5: Original and Augmented Sample Image

E. Model Training and Validation

The training process was conducted using a total of **5,778 images** for training, **1,656 images** for testing, and **826 images** for validation. All images were pre-processed and resized to a standardized input dimension of **224 × 224 pixels** to ensure compatibility with the model architecture.

Training began with an initial **learning rate of 0.001**, which was gradually reduced to **0.0005** over the course of **20 epochs** to enhance convergence and model performance. The **Adam optimizer** was employed for its adaptive learning capability, effectively managing the learning rate adjustments based on gradient information.

The performance of the proposed ensemble model during training and validation was evaluated using **accuracy and loss metrics**, which are illustrated in **Table 2**.

Table 2: Training and Validation Accuracy and Loss of the Proposed Ensemble Model

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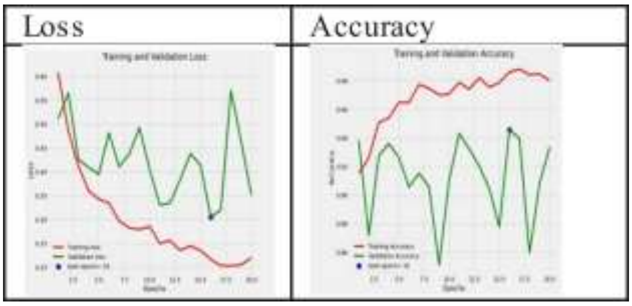

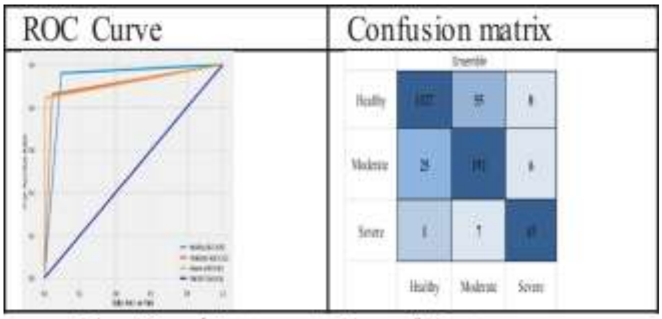

F. Visual Interpretation of Features

F. Model Evaluation: Confusion Matrix and ROC Curve

The performance of the proposed ensemble model was assessed using a **confusion matrix**, which compares the model's predictions against the actual class labels. This matrix provides a comprehensive view of classification accuracy across the three defined classes: **Healthy**, **Moderate**, and **Severe**.

- **True Positives (TP)** and **True Negatives (TN)** indicate correct predictions for positive and negative instances, respectively.
- **False Positives (FP)** represent incorrect positive predictions.
- **False Negatives (FN)** indicate missed positive cases.

Analyzing the confusion matrix enables identification of specific areas where the model performs well and where it may need improvement. It offers insights into **misclassification trends**, supporting further model tuning for enhanced accuracy and reliability.

In addition to the confusion matrix, the **Receiver Operating Characteristic (ROC) curve** was generated to visualize the model's diagnostic ability across different classification thresholds.

Table 3: Confusion Matrix and ROC Curve of the Proposed Ensemble Model

G. Feature Visualization

Figure 6 illustrates the **feature visualizations** produced by the inner layers of the proposed ensemble model. Visualization techniques [18] serve as a powerful tool to gain insights into the **learned representations** within the network, helping to interpret and validate the model's ability to accurately detect various stages of **knee osteoarthritis (OA)**.

The **activation maps** shown correspond to specific layers within the model, including:

- **block1_convolution** layer with dimensions *(1, 224, 224, 64)*
- **block4_pool** layer with dimensions *(1, 14, 14, 512)*

These layers capture features at different abstraction levels—from low-level textures and edges to high-level semantic structures. The resulting feature maps are passed through **fully connected convolutional layers** for classification.

The use of distinct color mappings in the visualizations highlights various **discriminative regions** within the knee X-ray images, demonstrating the model's ability to focus on relevant anatomical features for accurate classification across the defined OA severity stages.

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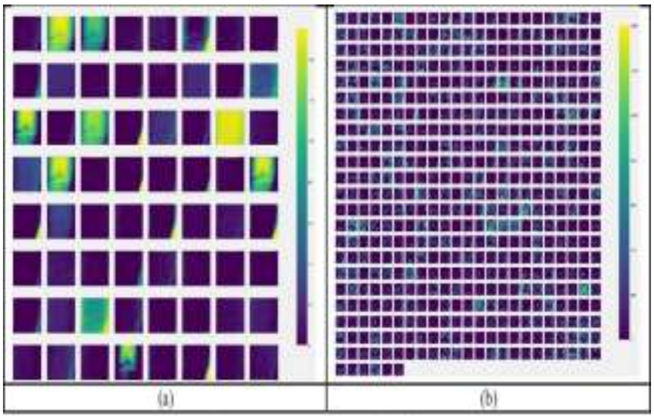

Figure 6. Visual Interpretation of features

H. Evaluation Metrics

To comprehensively assess the performance of the proposed machine learning model, several **standard evaluation metrics** were utilized:

- **Accuracy (ACC):** Measures the overall correctness of the model by calculating the ratio of correctly predicted instances to the total number of predictions.
- **Precision (PR):** Indicates the proportion of true positive predictions out of all predicted positives, reflecting the **reliability** of positive classifications.
- **Recall (RE):** Also known as sensitivity, it evaluates the model's ability to correctly identify all actual positive instances.
- **F1 Score:** Represents the harmonic mean of precision and recall, offering a **balanced metric** that accounts for both false positives and false negatives.

These metrics collectively provide a detailed evaluation of the model's **effectiveness and reliability** in classifying different stages of knee osteoarthritis.

$$\text{Accuracy} = \frac{Tp+Tn}{Tp+Fp+Fn+Tn} \quad (1)$$

$$\text{Recall}\ (RE) = \frac{Tp}{Tp+Fn} \quad (2)$$

$$\text{Precision}\,(PR) = \frac{Tp}{Tp+Fp} \quad (3)$$

$$\text{F1 Score} = \frac{2*PR*RE}{PR+RE} \quad (4)$$

Where, F_n represents False Negatives (FN), T_n represents True Negatives (TN), F_p represents False Positives (FP) and T_p represents True Positives (TP). The support metric quantifies the frequency of each class in the dataset. The value is the number of occurrences that are classified as true for each individual class. Table 4 shows the F1-score, recall, precision and accuracy for the proposed ensemble model.

Table 4 Model Evaluation Metrics of the proposed ensemble model

Model	Class	F-1 score	Recall	Precision	Support	Accuracy
Ensemble	Healthy	0.9704	0.9602	0.9808	1132	94.85
	Moderate	0.8050	0.8610	0.7559	223	
	Severe	0.8600	0.8431	0.8776	51	

V. CONCLUSION AND FUTURE WORK

The proposed study demonstrates the strength of an ensemble approach—combining EfficientNet and DenseNet—in accurately classifying knee X-ray images into three osteoarthritis severity levels: healthy, moderate, and severe. By fusing complementary feature representations from both architectures, the ensemble model achieved an accuracy of **94.96%** on the OAI dataset, underscoring the value of deep transfer learning for medical image analysis. Beyond classification, this work highlights the promise of automating quantitative assessments such as Joint Space Width (JSW). Future efforts should develop specialized networks for precise JSW measurement, further boosting diagnostic consistency and efficiency. Close collaboration with musculoskeletal imaging specialists will be crucial to validate these tools and facilitate their safe integration into clinical workflows.

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