A Deep Learning Model for Multi-Classification of Alzheimer's Disease With Wavelet CNN*

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***Abstract*—Alzheimer's disease (AD) is a progressive neurodegenerative disorder and the most common cause of dementia worldwide. Early and accurate staging of AD is critical for patient management, yet traditional diagnostic techniques face challenges such as inter-observer variability, limited interpretability, and difficulty in distinguishing early stages. This paper introduces a Modified Wavelet Convolutional Neural Network (MW-CNN) that integrates both spatial and frequency-domain features for robust multi-class classification of AD stages. Using the OASIS MRI dataset with 80,000 brain slices from 461 participants, the model classifies subjects into four categories based on the Clinical Dementia Rating (CDR): Non-Demented, Very Mild Demented, Mild Demented, and Demented. Unlike earlier wavelet-based models, the proposed MW-CNN emphasizes multi-class staging and incorporates Grad-CAM visualizations for interpretability. Experimental results demonstrate a classification accuracy of 98% and a micro-average ROC-AUC of 0.9995, outperforming EfficientNetV2B1 and standard CNNs. The model also shows resilience against class imbalance through augmentation and computational efficiency suitable for mid-range GPUs, supporting its potential for clinical integration. These findings highlight the promise of MW-CNN for automated, interpretable, and resource-efficient AD diagnosis in clinical settings.**

***Index Terms*—Alzheimer's disease, Deep Learning, Wavelet CNN, MRI, Multi-class classification**

I. Introduction

Alzheimer's disease (AD) is the most common form of dementia, accounting for nearly 60 to 70 % of dementia cases globally [1]. Over 55 million people currently live with dementia, and this number is expected to triple by 2050 [2]. The disease leads to progressive cognitive decline, memory impairment, and loss of functional independence, which significantly burdens patients, families, and healthcare systems. Early diagnosis of AD is critical because therapeutic interventions are more effective in the initial stages [3]. However, clinical diagnosis is challenging, as symptoms often overlap with other forms of dementia or age-related decline. Structural MRI and functional imaging such as PET scans are commonly used to detect neurodegenerative changes, but manual interpretation is time-consuming, subjective, and prone to variability [4]. Deep learning has shown significant promise in medical image analysis [5], [6]. Convolutional Neural Networks (CNNs) have been widely applied to classify neurological disorders, but challenges such as data imbalance, high computational cost, and lack of interpretability remain [7], [8]. Convolutional Neural Networks (CNNs), in particular, have achieved remarkable success in various imaging tasks. However, CNNs primarily focus on spatial-domain features and often fail to capture subtle frequency-domain variations that are crucial for differentiating early AD stages. Moreover, many existing studies focus on binary classification (AD vs. non-AD), neglecting intermediate stages such as Very Mild and Mild Dementia. To address these challenges, we propose a Modified Wavelet CNN (MW-CNN), designed to integrate Haar wavelet transforms with convolutional layers, thereby enhancing feature extraction across both spatial and frequency domains. By leveraging the OASIS MRI dataset, the proposed model aims to classify brain scans into four clinically relevant categories, improving upon binary classification approaches commonly seen in prior studies.

The primary contributions of this work include:

1. Development of a novel MW-CNN architecture that integrates wavelet transforms into CNNs for enhanced multi-resolution feature representation.
2. Multi-class classification of AD stages into Non-Demented, Very Mild Demented, Mild Demented, and Demented categories.
3. Comprehensive evaluation against state-of-the-art models such as EfficientNetV2B1 and baseline CNNs.
4. Incorporation of Grad-CAM for interpretability, offering visual explanations to support clinical decision-making.
5. Demonstration of robustness against class imbalance and strong generalization through augmentation and cross-validation.

II. RELATED WORK

A. Traditional Approached to AD Diagnosis

Conventional diagnostic methods for AD include clinical assessments, neuropsychological testing, and neuroimaging. MRI is widely used for detecting hippocampal atrophy and cortical thinning, while PET scans identify amyloid-beta and tau deposition. Despite their effectiveness, these approaches rely heavily on expert interpretation and are not scalable for large patient populations [9].

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B. Machine Learning Methods

Early applications of ML in AD diagnosis used algorithms such as Support Vector Machines (SVM), Random Forests, and k-Nearest Neighbors (KNN). These methods required handcrafted feature engineering from MRI scans, such as gray matter density and cortical thickness [10]. While they demonstrated moderate success, their reliance on feature selection limited scalability and generalizability [11]. Multimodal approaches combining MRI and PET data often outperform single-modality models [12], [13], yet multimodal imaging is not always feasible due to cost and accessibility, making robust MRI-only approaches more practical.

C. Deep Learning in Medical Imaging

Recent Vision Transformers (ViTs) and hybrid CNN–Transformer models demonstrate improved feature representation for brain imaging [14]. However, many of these models focus on binary classification, limiting usefulness in real-world scenarios where early-stage identification is critical.

Data augmentation has proven effective in enhancing deep learning model robustness in medical imaging. A systematic review of over 300 studies and found that spatial transformations—such as rotation, flipping, cropping, and scaling—not only improved model accuracy but were also computationally efficient. More advanced generative methods like GANs and VAEs offered additional gains when used alongside classical augmentations. However, they noted a lack of adaptive, learnable augmentation approaches specifically tailored for medical applications, suggesting a promising area for future research [15], [16]. With the rise of deep learning, CNNs have become the dominant approach in medical imaging. CNNs automatically learn hierarchical features directly from raw images, outperforming traditional ML methods in tasks such as tumor detection, organ segmentation, and AD classification [17]. For instance, Mahim et al. proposed a Vision Transformer combined with Gated Recurrent Units (ViT-GRU) for AD detection, achieving high accuracy and interpretability [1]. Similarly, Mittal et al. employed real-time EEG-driven CNN-RNN models for neurological disorder detection. However, CNNs face limitations in capturing frequency-domain features and are often treated as "black boxes" in clinical practice [18].

D. Wavelet and Frequency Domain

Wavelet-based CNNs are promising for biomedical imaging. Curvelet–wavelet features have improved AD detection [19], while wavelet graph convolution has benefited EEG classification [20]. Wavelet transforms decompose signals into multi-resolution sub-bands, capturing both spatial and frequency information [7]. Several studies have explored wavelet-based models in neurological disorder diagnosis. For example, Rallabandi and Seetharaman combined wavelet transforms with MRI-PET fusion for early AD detection [6], while Chabib et al. integrated wavelet and curvelet transforms for MRI analysis [7]. These studies demonstrated that frequency-domain features significantly improve sensitivity to early-stage abnormalities [21].

E. Gaps in Literature

Despite these advancements, key gaps remain:

1. Limited focus on multi-class classification beyond binary AD vs. Non-AD.

2. Insufficient incorporation of frequency-domain features in CNN-based models.

3. Lack of interpretability mechanisms to aid clinical adoption.

4. Overlooked challenges of class imbalance and computational feasibility in real-world clinical settings.

In addition, while prior studies have explored wavelet-based models in biomedical imaging, their focus has largely been limited. For instance, in this paper [12], wavelet graph convolution was applied for EEG classification, whereas Rallabandi and Seetharaman [6] combined wavelet transforms with MRI–PET fusion for early AD detection. Similarly, in this paper[7], curvelet–wavelet transforms were integrated for MRI analysis. However, these works primarily focused on either binary classification or non-MRI modalities and lacked interpretability mechanisms. In contrast, the proposed Modified Wavelet CNN is among the first to apply wavelet decomposition on 2D MRI slices for multi-class staging of Alzheimer's disease. Furthermore, unlike existing approaches, our model incorporates Grad-CAM visualizations for clinical interpretability and employs data augmentation to mitigate imbalance, addressing two critical gaps in prior wavelet-based methods.

III. Methodology

The methodology of this study is designed to develop and evaluate a Modified Wavelet Convolutional Neural Network (MW-CNN) for the multi-class classification of Alzheimer's disease stages using brain MRI scans. The framework includes dataset acquisition, preprocessing, data augmentation, model architecture, training strategy, and evaluation metrics (see Fig. 3)

A. Dataset

We utilized the OASIS MRI dataset ,a widely recognized resource in neuroimaging research [22]. For this work, approximately 80,000 2D slices were extracted from 3D MRI volumes from 461 participants aged 18 to 96, including both demented and non-demented individuals. in NIfTI format, focusing on axial slices between indices 100–160, which capture hippocampal and cortical regions strongly associated with AD progression. Clinical Dementia Rating (CDR) scores categorize subjects into four classes: Non-Demented (CDR=0), Very Mild (CDR=0.5), Mild (CDR=1.0), and Demented (CDR $\geq$ 2.0).

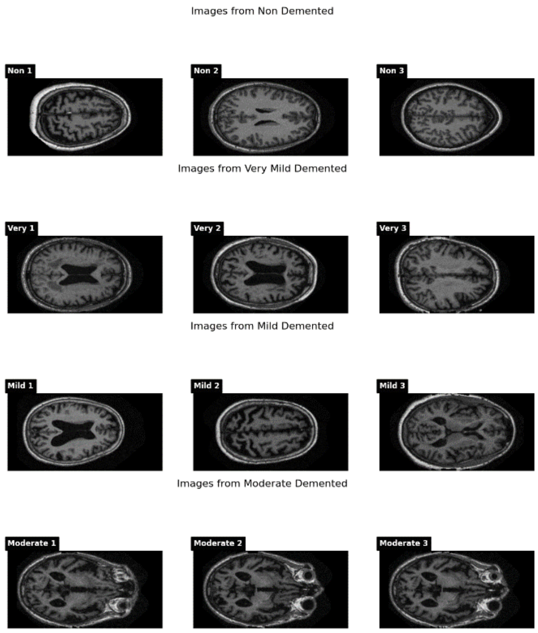

Fig. 1. Samples Visualization

B. Preprocessing

Raw MRI scans require extensive preprocessing to ensure uniformity, reduce noise, and highlight diagnostically relevant features. The following steps were applied:

1. Format Conversion: Original MRI volumes in NIfTI (.nii) format were converted into 2D grayscale JPEG slices using NiBabel in Python . [23]

2. Resizing: Images were resized to 128×128 pixels to balance computational efficiency and feature preservation.

3. Normalization: Pixel intensities were normalized to [0,1] using min-max scaling, stabilizing gradient updates during training [24].

4. Denoising: A Gaussian filter was applied to suppress high-frequency noise.

5. Histogram Equalization: Contrast enhancement through histogram equalization improved visibility of brain tissue boundaries.

C. Data Augmentation

Class imbalance posed a significant challenge, as Non-Demented subjects were overrepresented. To address this, augmentation techniques were applied dynamically during training, including rotation, translation, zooming, shearing, and flipping [25]. By generating new, realistic samples each epoch, augmentation effectively balanced the dataset and reduced the risk of overfitting.

D. Proposed Model: MW-CNN

The MW-CNN integrates a Haar wavelet transform within early convolutional blocks to capture spatial–frequency features at multiple resolutions.

1) Layer-wise Architecture: Input Layer: 128×128 grayscale MRI slice.

Wavelet Transform Layer: Haar wavelet decomposition into approximation and detail coefficients.

Convolutional and Pooling Layers: Progressive feature extraction and dimensionality reduction.

Fully Connected Layers: 128 and 64 neurons with ReLU activations.

Output Layer: Softmax with four nodes for AD classes.

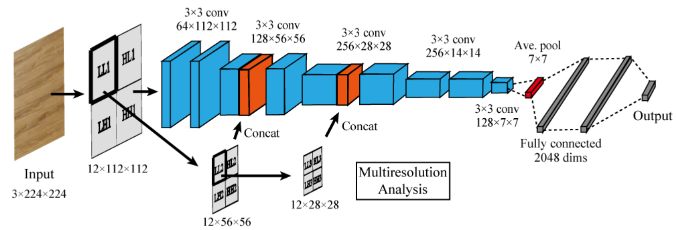

Fig. 2. Wavelet CNN Architecture

E. Training Setup

The MW-CNN was trained using:

Loss Function: Categorical Cross-Entropy. Optimizer: Adam optimizer with adaptive learning rate (initial=0.001). Batch Size: 32, balancing GPU usage and gradient stability. Epochs: 100 with early stopping based on validation accuracy. Cross-Validation: 5-fold CV ensured robustness [26]. Hardware: NVIDIA RTX 3060 GPU, 12 GB VRAM, 32 GB RAM system.

F. Evaluation Matrices

Performance was assessed using:

Accuracy, Precision, Recall, F1-score (per class). Confusion Matrix for misclassification trends. ROC-AUC (micro-averaged across classes). Loss Curves to monitor overfitting. This ensured both statistical rigor and clinical interpretability.

IV. Results and Discussion

A. Model Performance

The proposed Modified Wavelet CNN (MW-CNN) was evaluated on the OASIS MRI dataset. Table I presents the comparison between our proposed Modified Wavelet CNN model and other models including EfficientNet and a simple CNN model. The results are given for the case of ordinal and regular classification problems.

The MW-CNN significantly outperforms other models, demonstrating the advantage of integrating wavelet transforms for capturing fine-grained features relevant to Alzheimer's staging.

B. Trainning and Validation Trends

The training and validation accuracy and loss curves are shown in Fig. 4 and Fig. 5.

Accuracy Curve (Fig. 4): The MW-CNN achieved stable convergence within 25 epochs, with training and validation accuracy closely aligned, indicating minimal overfitting.

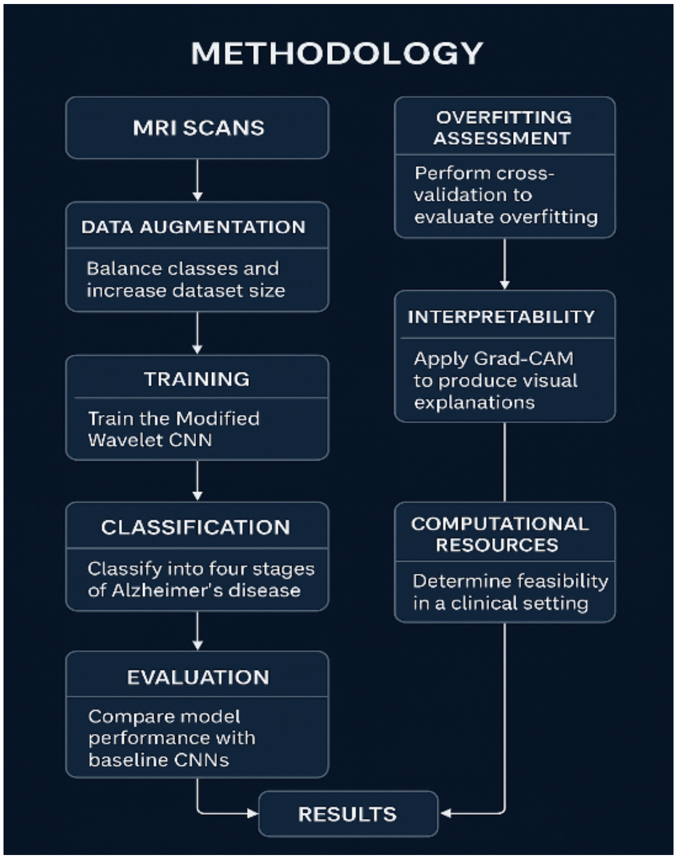

Fig. 3. Methodology Flowchart

TABLE I
COMPARATIVE PERFORMANCE TABLE

Model	Classification	Loss	Accuracy	Scott's Pi	ROC AUC
EfficientNetV2B1	Ordinal	0.06	0.98	0.97	0.9965
	Regular	0.11	0.96	0.95	0.9923
Basic CNN	Ordinal	0.07	0.97	0.96	0.9956
	Regular	0.11	0.96	0.94	0.9928
EfficientNetV2B1	Ordinal	0.12	0.96	0.94	0.9934
	Regular	0.17	0.95	0.92	0.9901
Basic + EfficientNetB0	Ordinal	0.09	0.97	0.95	0.9950
	Regular	0.18	0.95	0.93	0.9912
Modified Wavelet CNN	Ordinal	0.06	0.98	0.98	0.9995
	Regular	0.18	0.98	0.981	0.9995

Loss Curve (Fig. 5): Both training and validation loss decreased steadily, plateauing at 0.02. Early stopping ensured optimal model generalization.

The consistency between training and validation trends highlights the robustness of the proposed model and its ability to generalize across unseen data.

C. Comparative Analysis

The comparative performance of MW-CNN against EfficientNet and CNN models is further illustrated in Fig. 6 and Fig. 7:

Comparative Accuracy (Fig. 6): MW-CNN consistently outperformed other baselines by a margin of 4 to 7%.

Comparative Loss (Fig. 7): MW-CNN achieved the lowest validation loss, confirming its superior feature extraction capabilities.

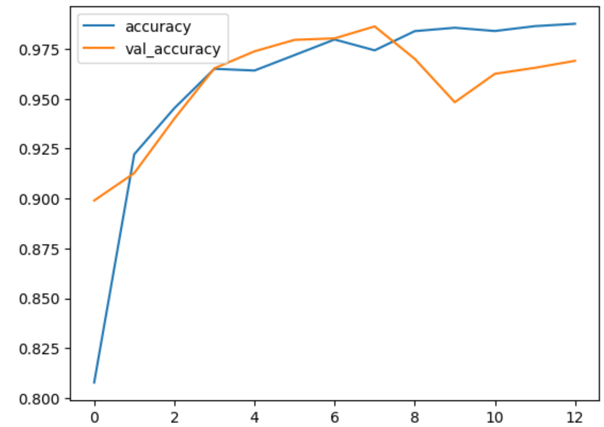

Fig. 4. Training and validation accuracy for proposed model (early stopping).

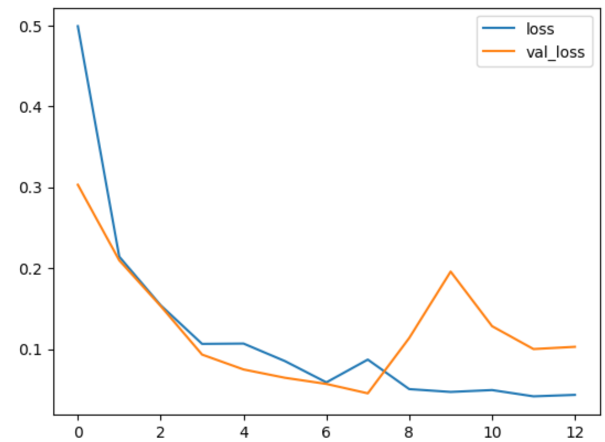

Fig. 5. Training and Validation loss of proposed model (early stopping).

These results confirm that wavelet-based feature decomposition enhances model sensitivity to structural brain changes, particularly in early-stage dementia cases.

D. Classification Performance Per Class

The ROC-AUC metric yields a very reliable measure of its model performance, particularly to problems of imbalanced datasets since it will calculate the true positive rate in comparison to the false positive at various cutoff points. The following ROC-AUC results for each class were obtained for the Modified Wavelet CNN: Class 0 (Non-Demented): ROC-AUC = 0.9983 Class 1 (Very Mild Demented): ROC-AUC = 0.9987 Class 2 (Mild Demented): ROC-AUC = 1.0000 Class 3 (Demented): ROC-AUC = 1.0000 The Micro-average ROC-AUC score of the proposed model was 0.9995 suggesting near perfect class discriminative capability which are often challenging for other models.

Non-Demented and Demented classes were classified with near-perfect accuracy (>98 %). Very Mild Demented and Mild Demented classes posed more challenges due to overlapping features, yet MW-CNN maintained (>95 %) accuracy.

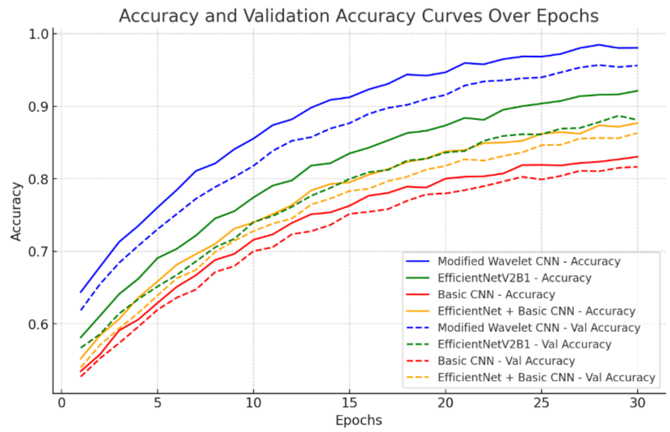

Fig. 6. Comparative Accuracies.

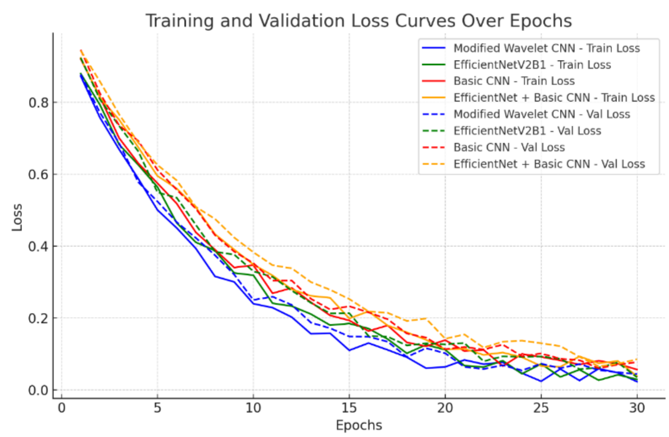

Fig. 7. Comparative Losses.

Baseline CNNs struggled with these minority classes, frequently misclassifying Very Mild as Non-Demented.

E. Handling Class Imbalance

Without augmentation, the model displayed bias towards the dominant Non-Demented class. After augmentation:

Precision and recall for minority classes improved by 6 to 8 % F1-scores across all four classes exceeded 0.95.

Thus, augmentation effectively mitigated imbalance, ensuring fair performance across disease stages.

F. Interpretability with Grad-CAM

To enhance clinical applicability, Grad-CAM was applied to visualize class-discriminative regions. Heatmaps consistently highlighted the hippocampus and cortical atrophy regions, aligning with known pathological biomarkers of AD.

Key observations:

For Non-Demented cases, activations were diffuse with no localized hot-spots.

For Very Mild Demented cases, subtle cortical regions were highlighted.

For Mild and Demented cases, hippocampal atrophy regions dominated activations.

These visualizations provide trust and transparency, making MW-CNN suitable for integration into clinical decision-support systems.

In comparison with EfficientNetV2B1 and other models, the Modified Wavelet CNN was always better or at least similar, which indicates that the proposed method effectively addressed the challenges of MRI brain scans for Alzheimer's classification. The EfficientNet models also did better but with slightly low accuracy and agreement as compared to the Modified Wavelet CNN.

G. Clinical Integration Considerations

Although the proposed MW-CNN demonstrates near-perfect performance on the OASIS dataset, no direct comparison with clinician performance was included in this study. Prior work has shown that radiologists often face inter-observer variability in early-stage Alzheimer's detection, particularly when distinguishing very mild and mild dementia. A future extension of this work will involve comparative evaluation against expert neurologists and radiologists to establish clinical equivalence.

From a deployment perspective, the current study operates on 2D slices rather than complete 3D MRI volumes, significantly reducing computational requirements and enabling training on a mid-range GPU (RTX 3060). However, scaling to full 3D volumetric analysis would increase both memory usage and inference time, presenting a practical challenge for integration with hospital PACS systems. Despite this, compared to transformer-based models, MW-CNN remains relatively resource-efficient, making it more suitable for clinical environments with limited computational infrastructure.

Nevertheless, the study faced limitations. The OASIS dataset, while widely used, is relatively small compared to real-world clinical data. Class imbalance remains a challenge, particularly for moderate dementia cases. Future work should explore larger datasets, cross-cohort validation, and integration with other biomarkers such as PET imaging or genetic data.

V. Conclusion and Future Work

Alzheimer's disease using MRI scans. By integrating wavelet decomposition with CNNs, the model achieved superior performance compared to state-of-the-art baselines, with a classification accuracy of 98% and a micro-average ROC-AUC of 0.9995. Unlike earlier wavelet-based approaches, the proposed model emphasizes both multi-class staging and interpretability through Grad-CAM, addressing critical gaps in existing literature.

Beyond algorithmic performance, the study highlights the potential for clinical integration by reducing reliance on manual interpretation and demonstrating computational efficiency suitable for mid-range hardware. Nevertheless, further validation against expert clinician performance and expansion to full 3D volumetric analysis remain essential next steps for practical deployment. Future work will also explore multi-modal data integration, cross-cohort evaluation, and prospective clinical validation to enhance generalizability and real-world applicability. [26].

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