Performance Evaluation of Retrained CNN Models for Grape Leaf Disease Identification

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***Abstract*— In smart agricultural systems, the identification of diseases from leaf images plays a crucial role in achieving prompt diagnosis and enhancing crop production. Convolutional Neural Network (CNN) models based on deep learning have demonstrated substantial improvements in the accuracy of disease detection. This study focuses on the detection of grape leaf diseases using a retraining approach applied to standard CNN models. The evaluation encompasses popular CNN architectures such as VGG, ResNet, Xception, Inception, DenseNet, and MobileNet for classifying grape diseases. The research involves experimentation on two established datasets and the compilation of a new dataset, named Dataset 3, to expose the model to diverse training scenarios. The findings underscore the pivotal role of data quality in model performance. Significantly, the models exhibit excellence on Dataset 3, showcasing potential for early detection of grape diseases. This research contributes to the advancement of agricultural technology, influencing precision agriculture and promoting sustainability.**

Keywords: CNN Models, Grape Leaf Disease, Deep Learning, Dataset Quality, Agricultural Technology.

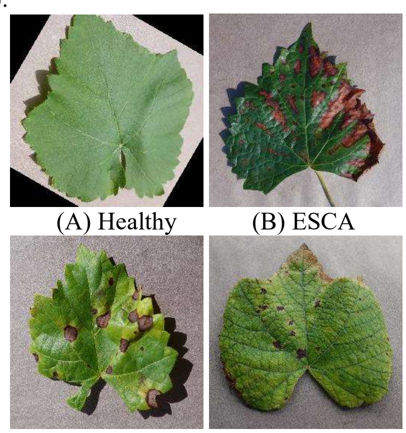
I. INTRODUCTION

Grapevine cultivation is a significant agricultural practice worldwide, contributing to the production of grapes for various purposes, including winemaking, fresh fruit consumption, and raisin production. However, grapevine health is vulnerable to various diseases that can significantly impact yield and quality. Early detection and accurate diagnosis of these diseases are crucial for effective disease management and ensuring a sustainable grape industry [1].

Traditional crop disease detection relies on manual inspection, burdened by time constraints, subjectivity, and early-stage invisibility. Computer vision and deep learning, especially convolutional neural networks (CNNs), revolutionize this with their pattern recognition prowess [2]. CNNs learn from labeled datasets, excelling in discerning intricate visual cues like color, texture, and shape changes on grape leaves. They process high-res leaf images, extract features, and iteratively fine-tune, becoming adept at accurate disease identification. Thus, automated CNN-based systems offer efficient, early, and precise grapevine disease detection, transcending human limitations in agricultural disease management.

Automated CNN-powered disease detection redefines agriculture, promising swift, unbiased diagnosis, early detection, and resource efficiency. Evolving technology transforms disease management for resilient and sustainable crops like grapevines, enhancing yields and minimizing pesticides [3]. CNN-based grape leaf disease research aids timely intervention, accurate detection, and efficient vineyard screening. Data-driven insights improve disease databases, and GIS-integrated models optimize precision agriculture, reducing environmental impact.

Black Rot devastates grapes, causing dark lesions on leaves and fruit, harming quality and spreading. Grapevine Esca Disease, from Phaeomoniella chlamydospora, causes "tiger stripe" leaf discoloration, hurting vine and grape production. Management involves pruning, resistant varieties, and prevention. Leaf Blight, from Phomopsis viticola, leads to brown lesions, affecting leaves and fruit. Control includes fungicides and airflow maintenance. The article's classification work on leaf images displays the four classes (Figure 1).



(A) Healthy (B) ESCA
(C) Black Rot (D) Leaf Blight

Figure 1: Grape Diseased and Healthy Leaf Images

Automated grape leaf disease detection powered by CNN-based models represents a transformative advancement in the field of viticulture. The contributions of this work extend beyond disease identification, encompassing early detection, accuracy, scalability, data-driven insights, and broader agricultural and environmental benefits. As technology continues to evolve, the synergy between agriculture and artificial intelligence holds the promise of a more resilient and sustainable grape industry.

II. RELATED WORK

The recent surge in deep learning, especially Convolutional Neural Networks (CNNs), for plant disease detection has sparked notable research. Abade et al. [4] investigated CNN algorithms, emphasizing trends like PlantVillage and TensorFlow. Dhaka et al. [5] delved into CNN-based techniques, highlighting framework choice, model architecture, and pre-processing's role. Their study underscored dataset quality's impact. Nagaraju et al. [6] reviewed 80+ Deep Learning (DL) disease studies, emphasizing pre-processing's significance. Kamilaris et al. [7] showcased DL's superiority in addressing agricultural challenges, surpassing traditional methods. Fernandez-Quintanilla et al. [8] explored crop weed monitoring, stressing weed control and data collection through diverse monitoring methods, cloud platforms, and accessible information. These studies collectively reveal the transformative potential of deep learning in agriculture.

Lu et al. [9] evaluated CNN performance in plant disease classification, exploring architectures, strengths, and improvements. Golhani et al. [10] highlighted hyperspectral data's potential for plant disease diagnosis, emphasizing comprehensive data collection. Mosleh et al. [11] developed an effective CNN model for potato disease detection, showcasing high accuracy. Huang et al. [12] introduced DenseNet, enhancing CNN architectures for information flow. Li et al. [13] extended this with fire-FRD-CNN and mobile-FRD-CNN, optimizing feature map generation. Lee et al. [14] simplified disease classification with GoogleNet-BN for Plant Village dataset. Mao et al. [15] optimized models with depth-wise separable convolution and filter pruning. Singh et al. [16] proposed joint pruning and fine-tuning for model efficiency. Li et al. [17] emphasized compact, accurate models through CNNPruner, aligning with efficiency demands.

Hosny et al. [18] propose a lightweight deep CNN model that fuses deep features with traditional LBP features for plant leaf image analysis across three datasets (Apple Leaf, Tomato Leaf, and Grape Leaf). Arun et al. [19] present the CCDL architecture, employing Complete Concatenated Blocks for multi-crop disease detection. The model's design, with point convolution layers and complete concatenation paths, enhances feature map utilization, achieving high accuracy on the Plant Village dataset. Sharma et al. [20] introduce the DLMC-Net, a lightweight CNN for real-time plant leaf disease detection across diverse crops. Collective blocks, a passage layer, and point-wise/separable convolution reduce parameters, exhibiting superior performance on citrus, cucumber, grapes, and tomato datasets. Shoaib et al. [21] explore ML and DL techniques for plant disease identification, emphasizing advancements, challenges, and limitations from 2015 to 2022.

Collectively, these studies underscore the dynamic landscape of plant disease detection, driven by the evolution of deep learning models and their application-specific adaptations. The pursuit of accurate, efficient, and scalable disease detection systems remains a driving force in the realm of agricultural technology, with implications for precision agriculture, crop management, and sustainable food production.

This study's limitations encompass its focus on specific neural network architectures and datasets, potentially hindering generalization. The proposed techniques, although effective, may require further optimization. The scope extends to enhancing model efficiency, but does not extensively explore alternative approaches or real-world deployment challenges.

III. Proposed Work

CNNs have revolutionized the field of computer vision by enabling machines to recognize and understand visual data. These networks are designed to mimic the human visual system, making them highly effective at tasks such as image classification, object detection, and more. In this article, we will delve into the details of some influential CNN architectures: VGGNet-16, VGGNet-19, ResNet-50, ResNet-101, Xception, Inception, MobileNet-V1, MobileNet-V2, DenseNet-121, and DenseNet-201.

1. VGGNet-16 and VGGNet-19

VGGNet [22] from Oxford University in 2014, is praised for simplicity and depth. VGG-16 and VGG-19 vary in layer count. Using 3x3 filters and max-pooling, they excel in image features capture, ideal for image classification. Yet, depth increases computational complexity and training time.

2. ResNet-50 and ResNet-101

ResNet [23] a pioneering architecture, introduced residual blocks with skip connections, mitigating the vanishing gradient issue. Residual blocks aid learning residual functions, enhancing deep network optimization. ResNet-50 and ResNet-101, with 50 and 101 layers, leveraged skip connections for improved training and facilitated deeper network designs.

3. Xception

Xception [24] short for Extreme Inception, is an extension of the Inception architecture that emphasizes depthwise separable convolutions. These convolutions split the standard convolution into depthwise and pointwise convolutions, reducing computational complexity while maintaining performance. This design results in a more efficient and effective network, particularly suited for mobile and embedded devices.

4. Inception

The Inception architecture [25] introduced by Google in 2014, aimed to address the trade-off between computational efficiency and model accuracy. Inception networks employ a combination of parallel convolutional layers with different kernel sizes to capture features at various scales. This design allows the network to efficiently process both fine-grained and coarse-grained features within the same layer.

5. MobileNet-V1 and MobileNet-V2

MobileNet [26] is designed for resource-constrained environments such as mobile devices and IoT devices. MobileNet-V1 introduced depthwise separable convolutions to reduce model size and computational cost while maintaining reasonable accuracy. This architecture achieved a good balance between efficiency and performance. MobileNet-V2 builds upon the success of its predecessor by introducing inverted residual blocks and linear bottlenecks. These improvements further enhance the efficiency and effectiveness of the network, making it even more suitable for deployment on low-power devices.

6. DenseNet-121 and DenseNet-201

DenseNet [27] maximizes feature reuse by connecting each layer to all previous layers, boosting information flow. DenseNet-121 and DenseNet-201, with 121 and 201 layers respectively, achieve impressive efficiency and effectiveness in computer vision tasks. Retraining CNN models like VGGNet, ResNet, Xception, Inception, MobileNet, and DenseNet are potent options for grape leaf disease recognition. VGGNet suits moderate datasets due to its uniform structure. ResNet, with skip connections, excels in complex feature learning. Xception's efficiency is ideal for resource-constrained setups. Inception's diverse-scale convolutions capture varied features, while MobileNet's lightweight design suits mobile deployment. Retraining choice hinges on factors like data size and resources, impacting the system's efficacy and real-world feasibility. DenseNet's dense connectivity promotes feature reuse, which can be beneficial for capturing intricate patterns in grape leaves. Retraining DenseNet-121 or DenseNet-201 can yield accurate disease classification, especially if the dataset contains fine-grained details that need to be captured. Comparative of Models used in this work have details as shown in table 1.

TABLE 1: COMPARISON OF MODEL DETAILS

Model	Layers Count	Important Layer	Input Image Size	Number of Learnable Parameters
VGGNet-16	16	Fully Connected	Variable	138 million
VGGNet-19	19	Fully Connected	Variable	143.6 million
ResNet-50	50	Residual Block, Final Layer	224x224	25.6 million
ResNet-101	101	Residual Block, Final Layer	224x224	44.6 million
Xception	71	Depthwise Separable	299x199	22.9 million
Inception-V3	48	Mixed-3 Layer	299x199	16 Million
MobileNet-V1	28	Depthwise Separable	224x224	4.2 million
MobileNet-V2	53	Bottleneck Layer	224x224	3.4 million
DenseNet-121	121	Transition Layer	224x224	8 million
DenseNet-201	201	Transition Layer	224x224	20 million

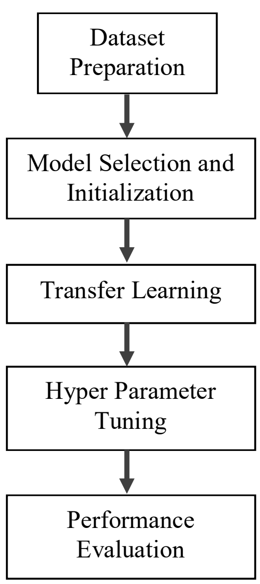


Figure 2: Proposed Processing Flow for Experimental Evaluation

The proposed work is carried out in the steps shown in Figure 2. The details are:

1. **Data Preparation:** A labeled dataset of grape leaf images is collected, including both healthy and diseased leaves. The images are pre-processed by resizing, normalizing, and augmenting them to increase the diversity of training samples.
2. **Model Selection and Initialization:** Choose the CNN architecture that best fits your dataset and computing resources. The selected pre-trained model's weights with weights learned from a large general dataset are initialized (e.g., ImageNet) to leverage learned features.
3. **Transfer Learning:** The selected model is retrained on grape leaf dataset. The initial layers (pre-trained weights) are frozen and fine-tune the remaining layers using your dataset. This approach leverages the pre-trained features while adapting the model to the specific disease identification task.
4. **Hyperparameter Tuning:** The hyperparameters such as learning rate, batch size, and number of hidden neurons in second last dense layer are adjusted to ensure efficient training convergence and avoid overfitting.
5. **Evaluation and Fine-Tuning:** The dataset is split into training, validation, and test sets. Monitor the model's performance on the validation set and fine-tune hyperparameters if needed. The test set is used to evaluate the final model's accuracy, precision, recall, and F1-score.

IV. RESULTS AND ANALYSIS

a. Dataset Preparation

The grape leaf datasets are collected from standard public repositories. Two different datasets are used to analyze the performance of models and 3rd combined dataset is prepared for classification task. The images from common diseases in different datasets are combined in single directory. The details of Dataset are shown in Table 2.

TABLE 2: DATASET INFORMATION

Dataset	Diseases	Classes	Images
Dataset 1	Black Rot	4	1888
	ESCA		1920
	Leaf Blight		1722
	Healthy		1692
Dataset 2	Black Rot	4	1180
	ESCA		1383
	Leaf Blight		423
	Healthy		1076
Dataset 3 (Combined 1 and 2)	Black Rot	4	3060
	ESCA		3303
	Leaf Blight		2145
	Healthy		2768

The performance of the models are evaluated by training on Dataset 1, 2 and Combined dataset 3.

b. Performance Parameters

The Grape Leaf Disease Detection task involves classifying images of grape leaves into four distinct disease classes. The goal is to accurately identify the presence of diseases on the leaves based on the visual patterns and features present in the images. This classification task is crucial for early disease detection and effective disease management in vineyards. The performance of the models are evaluated using parameters accuracy, specificity, sensitivity and F1 Score the formulae for these parameters are shown in Table 3.

TABLE 3: PERFORMANCE PARAMETERS

Accuracy	TP+TN / (TP+TN+FP+FN)
Specificity	TN/(TN+FP)
Sensitivity (Recall)	TP/(TP+FN)
Precision	TP/(TP+FP)
F1 Score	2*(Recall*Precision) / (Recall + Precision)

c. Performance Analysis

In evaluating diverse CNN models for this task, performance is assessed using key metrics: accuracy, sensitivity, specificity, and F1-score. These gauges reveal overall classification accuracy, positive instance recognition (sensitivity), negative instance recognition (specificity), and the precision-recall balance (F1-score). The dataset is split in 80%-20% parts. 80% part is used for training the models. Comparative analysis in Figure 3 highlights model performance for dataset 1. Results exhibit strong disease classification (accuracy: 0.86 - 0.965). Inception-V2, MobileNet-V2 shine with high accuracy, sensitivity, and F1-score. Dataset 2's limited training data impacts CNNs, underscoring data's role. Strategies like augmentation, transfer learning bolster results. Dataset 3, a comprehensive merge, boosts model performance, emphasizing quality data's importance. Enhanced metrics in Dataset 3 spotlight models' potential in precise disease detection, aiding viticulturists for early identification and optimized vineyard health.

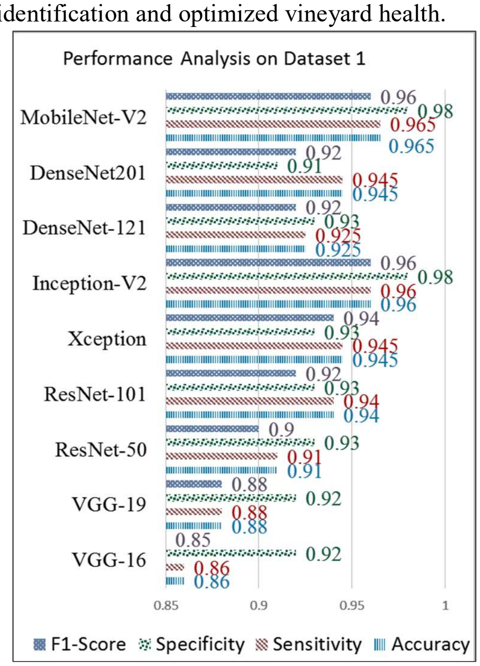


Figure 3: Performance Analysis on Dataset 1

TABLE 4: HYPER PARAMETER ANALYSIS

Model	Number of Epoch	Number of Hidden Neurons	Batch Size
VGG-16	1600	256	32
VGG-19	1366	256	32
ResNet-50	1230	256	32
ResNet-101	1100	256	32
Xception	850	256	32
Inception-V2	600	256	32
DenseNet-121	860	128	32
DenseNet201	740	128	32
MobileNet-V2	400	256	64

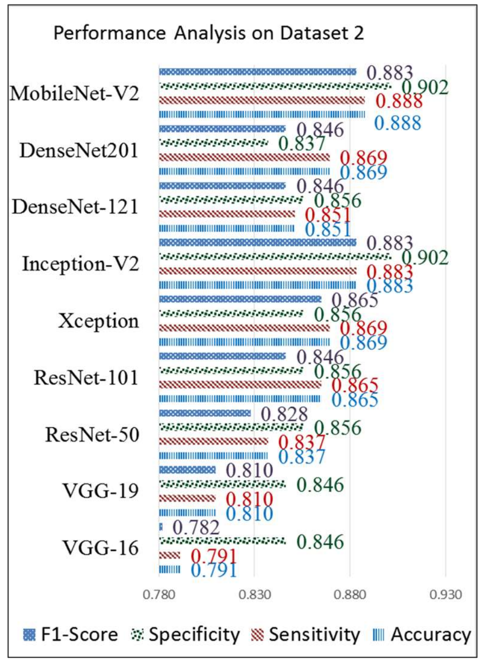


Figure 4: Performance Analysis on Dataset 2

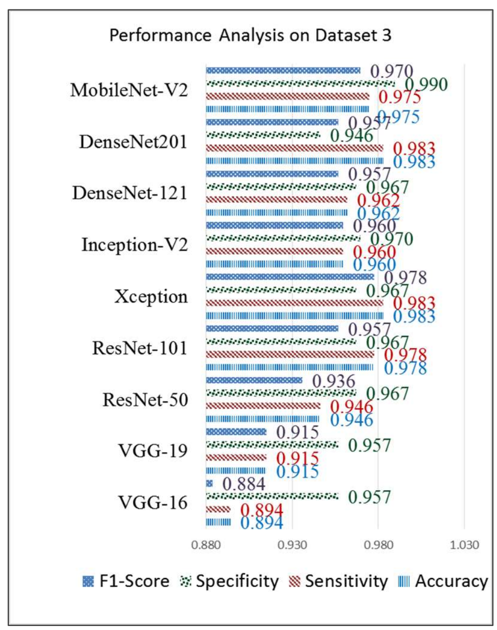
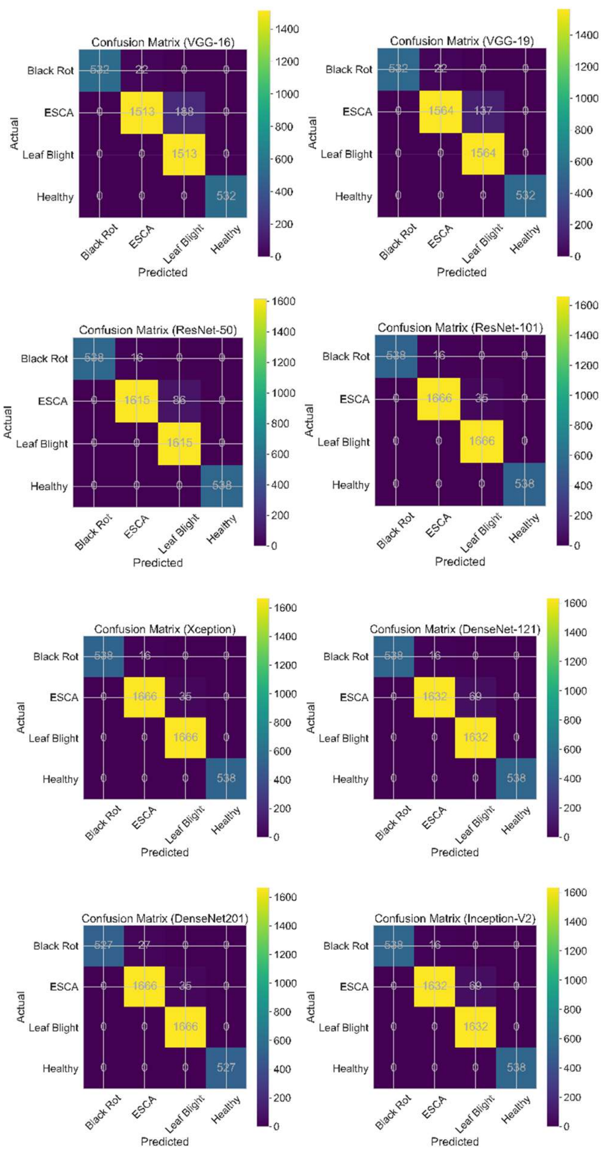


Figure 5: Performance Analysis on Combined Dataset 3

The important criteria for selecting specific hyper parameters starts with the consideration of fundamental hardware configuration of the experimentation machine and most importantly RAM and processing capabilities. Also, to avoid the overfitting and under fitting problems of the CNN model, hyperparameter analysis is conducted to optimize the model's performance. Specific values for batch size and hidden neurons in the last Dense Layer are set. Table 4 displays the average epochs needed for model convergence. Experiments utilized an Intel Core i5 11th gen processor, 32 GB RAM, and GTX 1650 GPU. The top-performing MobileNet-V2 model is trained for 400 epochs with a batch size of 64 and 256 hidden neurons.

Figure 6 shows the confusion matrix results for all models when trained for best performance. The performance is evaluated using 20% split part as test set. The confusion matrix thus compares the predicted and actual labels based on which model's performance can be validated.



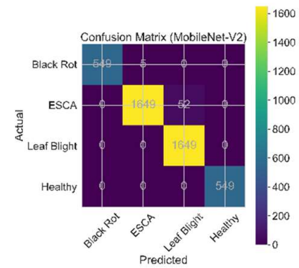


Figure 6: Confusion Matrix for All the models Considered in Comparative Analysis

The outcomes of our experimental study serve as a compelling testament to the efficacy of a diverse array of deep learning models in the realm of grape leaf disease classification. Particularly noteworthy are the exceptional achievements of ResNet-101, Xception, and MobileNet-V2, which exhibited commendable levels of accuracy, sensitivity, and specificity. This robust performance underscores their capacity to reliably and precisely categorize distinct disease classes, thereby accentuating their suitability for integration into real-world automated disease detection systems.

Moreover, our meticulous examination of sensitivity and specificity has unveiled a deeper layer of insight into the models' proficiency. By achieving balanced identification of both positive and negative instances, these models manifest their ability to make astute disease predictions while minimizing false positives and negatives. The divergent performances across various diseases emphasize the significance of adopting tailored strategies when addressing specific grape leaf ailments.

The implications of these findings reverberate through the realm of viticulture, promising to revolutionize disease identification practices. The knowledge garnered from this study holds the potential to usher in a new era of reliable and efficient solutions for grape leaf disease recognition. By enhancing the precision of disease assessment, these advancements have the power to augment crop management practices and mitigate the detrimental impact of yield losses. Our work, thus, paves the way for innovative applications of deep learning in the agricultural domain, with far-reaching ramifications for sustainable and effective viticulture practices.

V. Conclusion

This paper presents a thorough investigation into diverse deep learning models for the classification of grape leaf diseases, offering valuable insights and promising implications for viticulture. The experimental results reveal an impressive performance landscape, with ResNet-101, Xception, and MobileNet-V2 standing out as notable contenders. These models demonstrate a remarkable combination of accuracy, sensitivity, and specificity, showcasing their effectiveness in precisely detecting and categorizing various disease classes. This robust performance not only emphasizes their potential for practical integration into automated disease detection systems but also underscores the transformative impact of cutting-edge technology on agriculture.

The nuanced sensitivity and specificity analysis showcases the holistic effectiveness of the models, minimizing false alarms. This reliability in real-world scenarios streamlines disease management, facilitating well-informed agricultural decisions. Variable model performance underscores the need for tailored disease approaches, acknowledging the uniqueness of each disease. Adaptive algorithms that accommodate these intricacies are crucial. Our study guides the refinement of disease detection models, promising a revolution in viticulture. Advanced deep learning contributes to accurate diagnostics, optimizing crop management, yield, and resource utilization, ensuring agricultural sustainability. Our work not only advances knowledge in grape leaf disease detection but also highlights the potential of AI in agriculture, bridging computer science and farming for future global food security.

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