Proceedings of 10th IOE Graduate Conference
Peer Reviewed
ISSN: 2350-8914 (Online), 2350-8906 (Print)
Year: 2021 Month: October Volume: 10

Performance Analysis and Classification of Rice Plant Disease using Multi-class Support Vector Machine and Transfer Learning Models

Prajwol Amatya [a], Hari KC [b]

[a, b] *Department of Electronics and Computer Engineering, Pashchimanchal Campus, IOE, Tribhuvan University, Nepal*
Corresponding Email: [a] prajwolamatya11@gmail.com, [b] harikc@wrc.edu.np

Abstract
Cereal crops, such as rice, share a major portion of the gross income of most countries whose economy is based on agriculture. Timely detection of rice plant diseases, if any, is critical to avoid losses and ensure a healthy harvest. Due to the lack of information and the absence of skilled specialist support, it is difficult and time consuming for farmers to diagnose diseases accurately. This research is aimed at effectively classifying five main rice plant diseases using image processing and machine learning approaches. Initially, the diseased region in the image of the infected rice plant leaf is segmented to remove the healthy leaf portion and the background. Then, different features are extracted from it. Using these features, a multiclass SVM model was developed that gave an accuracy of 89.5%. Also, two models using transfer learning approach were developed with MobileNetV2 and ResNet50 to classify rice diseases from the segmented images, which gave an accuracy of 94.8% and 74.4% respectively.

Keywords
SVM, CNN, Transfer Learning, ResNet, MobileNet

1. Introduction

Rice is an important cereal crop worldwide. Every year, because of various pest infestations and diseases, farmers around the world are forced to fall prey to depressing losses in the annual crop yield and the consequent economic losses. Like all other crops, bacteria, fungi, and viruses are the primary causes of diseases leading to major plant damages and consequently agriculture and economic losses. Timely identification of diseases is a critical factor to minimize plant damages and make harvest as healthy and fruitful as possible. A specific class of rice plant diseases creates certain patterns on the leaves of the plant. Experts can identify specific classes of diseases from the patterns seen on the infected plant's leaf. Machine learning techniques can be employed to train a system about the association of these patterns to specific classes of rice plant diseases.

Image processing operations can be applied to infected leaf images and specific features can be extracted from them for machine learning modeling and training. In this research, the diseased regions were first identified through image segmentation. Then, standard feature extraction methods were used to extract various features from segmented images. Multiclass Support Vector Machine (SVM) classifier was used to classify different diseases from the image features. Also, the segmented image dataset was used to develop models based on transfer learning approach. Finally, a comparative performance analysis of the three machine learning models; Multiclass SVM and Transfer learning models (MobileNetV2 and ResNet50) was done.

2. Related Works

In an attempt to overcome the problem of identifying numerous diseases in rice or paddy crop farming, various image processing techniques and machine learning algorithms have been used. The research work done in [1] has carried out the classification problem using the Support Vector Machine (SVM). To separate the diseased region of the images of the infected plant leaves, fuzzy C-means segmentation was employed. 11 distinct characteristics were retrieved from the segmented leaf dataset, and a one-vs-rest approach multiclass SVM was used. When evaluating different kernel functions, the linear kernel came out on top with an 86.10% score.

Several studies suggested using several types of images to diagnose plant diseases, such as RGB imaging, L*a*b (L-luminous, a*b-chromous), multispectral imaging, and so on. Khan et al. [2] has discussed the classification of different plant diseases using image processing and Multiclass Support Vector Machine (SVM), in which the RGB leaf images are converted into L*a*b color space to perform the image segmentation process. K-means algorithm was used for the image segmentation process by extracting the chroma (a*b) component of the image.The proposed model produced an accuracy of 92.85%.

Similar approach was implemented by [3] where only "a" component i.e., color component was provided to k-means algorithm for image segmentation. The thresholding in this method is performed using Otsu's method, which divides the greyscale histogram into only two classes. When the background is noisy, this strategy is ineffective. With 500 iterations, the accuracy of different kernel functions (Linear, Radial Based Function, and Polynomial) was compared. Each kernel function had an accuracy of 96.77%, 95.16%, and 96.77%, respectively.

Similarly, Hasan et al. [4] proposed integrating support vector machine with deep convolution neural network to identify and classify rice plant diseases. The Inception v3 model was utilized to extract the essential features from the images, which were then used to train the support vector machine having training phase accuracy of 97.5%.

Identification of rice plant diseases was compared using four machine learning algorithms: Decision tree, k-nearest neighbor, Logistic Regression, and Naive Bayes [5]. Three diseases were identified: brown spot, bacterial blight and leaf smut. The image filter (Color Layout Filter) in WEKA was used to choose five properties. With 97.91% accuracy, decision tree outperformed the other three methods.

Swetha R et al. [6] compared the performance of Support Vector Machine and K-nearest neighbor for rice disease classification. Color and spot geometry were the features employed for classification in this method, with SVM outperforming KNN. Rath and Meher [7] employed the Gabor filtering approach to extract texture and shape features from the hue component, as well as color features. The study stressed the importance of image processing techniques that use a low-complexity radial basis function neural network (RBFNN) classifier to accurately identify plant diseases.

Rice leaf disease was recognized and classified using an optimized deep neural network using the Jaya algorithm [8]. The image segmentation was performed by using the K-means clustering algorithm, which was then fed into the deep neural network.

[9] conducted a comparison between deep learning and traditional machine learning techniques for plant leaf diseases. Support vector machine (SVM), k-nearest neighbor (k-NN), fully connected neural network (FCNN), and convolution neural network (CNN) were compared. The results revealed that SVM and FCNN scored 91.7% and 91.4%, respectively. With a score of 99.3%, CNN came out on top, whereas k-NN had a far lower score.

In [10], a Deep Convolution Neural Network-based transfer learning model was constructed. AlexNet was used to extract features, while SVM was used to classify three types of rice illnesses. The proposed model correctly classified the rice disease with 91.3% accuracy.

3. Methodology

Figure 1 depicts the proposed methodology.

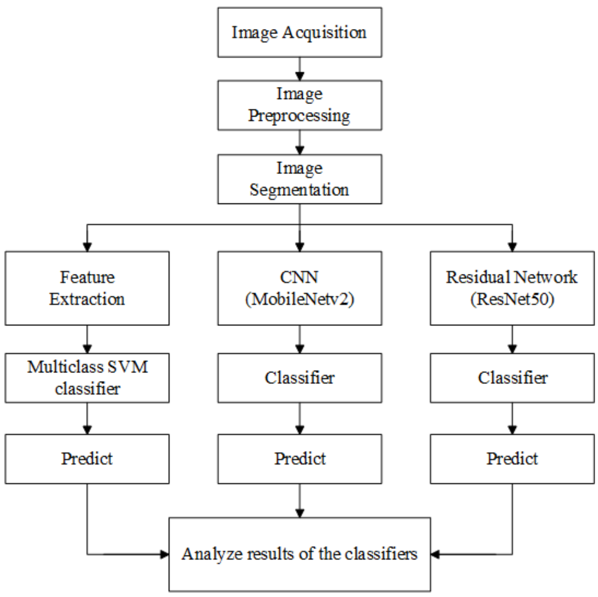

Figure 1: Research methodology

3.1 Image Acquisition

The rice leaf images were collected from online resources named IRRI (International Rice Research Institute) [11], BRRI (Bangladesh Rice Research Institute) [12], Plantix [13]. Five different rice diseases are collected – Brown spot, leaf blast, hispa, leaf blight, and sheath blight, which consists of 2550 total leaf images. Each disease category consists of 510 leaf images.

3.2 Image Preprocessing

For real-world data that is frequently noisy and uneven, image preprocessing is critical. The images are all scaled to the same 256 x 256 pixel size. The leaf image includes three parts: the disease part, the healthy leaf, and the background. The background is removed as it is not the region of interest. The RGB image is transformed to HSV color space. Then, threshold value is applied on the saturation component to make binary image. Finally, the background is eliminated from the original image by fusing it with the binary image. Figure 2 depicts the stages involved in preprocessing.

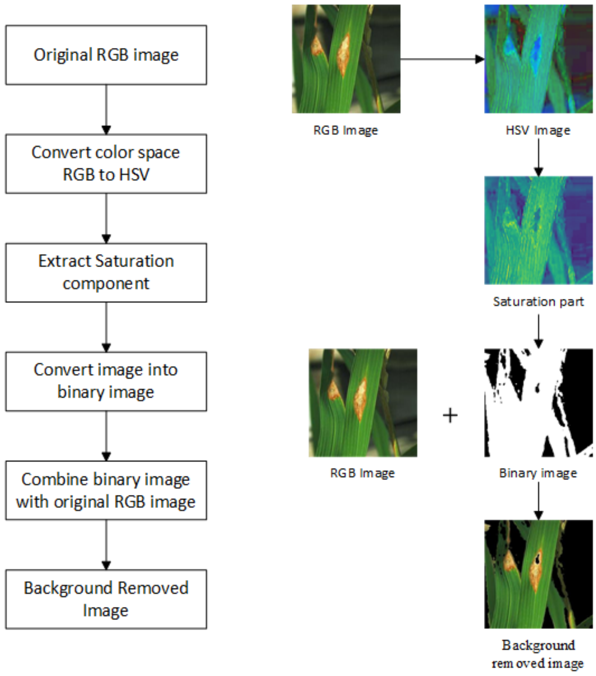

Figure 2: Image Preprocessing

3.3 Image Segmentation

The process of segmenting an image into its constituent regions or objects is known as image segmentation. The color and texture of the diseased areas of the leaf differ from the healthy areas and background. The disease-affected part is segregated from the healthy portions during this step. The background-removed image is transformed to HSV color space, and a threshold value is applied on the hue component. As a result, the image only shows the disease part. Figure 3 depicts the steps involved in image segmentation.

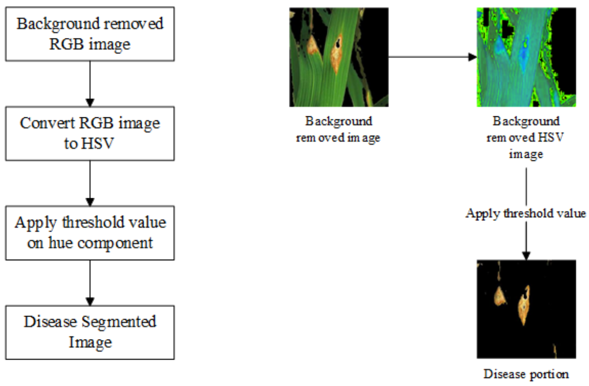

Figure 3: Image Segmentation

3.4 Feature Extraction

Thirteen distinct features are extracted from the disease segmented image. The mean, standard deviation, entropy, root mean square, variance, smoothness, kurtosis, skewness, and inverse difference are all determined based on intensity. Likewise, Gray Level Co-occurrence Matrix (GLCM) is used to extract texture-based features - Contrast, correlation, energy, and homogeneity. The classifier takes the selected features as input and uses them to classify diseases into distinct categories.

3.5 Multiclass Support Vector Machine (SVM)

A popular supervised machine learning model, Support Vector Machine (SVM) employs classification algorithms for two group classification problems. It finds a hyperplane in an N-dimensional space that clearly categorizes data points which contribute to data classification. Different classes can be assigned to data points lying on either side of the hyperplane. Multiclass classification problem is solved by decomposing it into numerous binary problems.

For multiclass problems, the SVM employs two alternative approaches. The first method, called one-vs-all, separates a multi-class dataset into many binary classification problems, each binary classification job trained with a binary classifier, and the most confident model is used to make predictions. The one-vs-one strategy, in which the multiclass problem is split down into several binary classification cases, is the second approach. The one-vs-one strategy was used to solve the multiclass classification problem which divides the dataset into one dataset for each class versus every other class.

3.6 Transfer Learning

Transfer learning is a machine learning technique that involves repurposing a model created for one task for another. In the transfer learning approach, a pre-trained model is chosen from a existing models for similar problems. These models can then be utilized to develop a model for the second task of interest. Finally, the model may need to be adjusted or enhanced depending on the input-output data pair available for task intended. It is accomplished by freezing the intermediary layers of the models, i.e., they are not trained for the new classification task. The pre-trained models are used as the feature extractor, with the output layer being changed with a new softmax layer that is relevant to the new challenge. Two transfer learning models, MobileNetV2 and ResNet50, are implemented to solve the classification problem.

MobileNetv2 is a popular neural network architecture designed primarily for mobile and resource-constrained situations. Both in terms of accuracy and model complexity, this neural network architecture has proven itself better for the imagenet database [14]. This design is made up of two types of blocks: a residual block with a stride of 1 and a downsizing block with a stride of 2. Both types of blocks have three layers. The first layer is a ReLU6 1x1 convolution, the second layer is a depthwise convolution, and the third layer is another 1x1 convolution with no non-linearity. MobileNetV2's overall design includes a fully convolutional layer with 32 filters, followed by 19 bottleneck layers.

ResNet-50 is a deep residual network consisting of 50 layers. It's a type of convolutional neural network, which is the most widely used for image categorization. ResNet's standout feature is the skip connection. Deep networks frequently face with vanishing gradients, which means that the gradient becomes smaller as the model backpropagates and learning can be difficult. The skip connection aid the network to learn the identity function allowing it to bypass the other weight layers and route the input through the block. This allows to build a deeper network by stacking extra layers and countering the disappearing gradient by enabling the network to skip through layers that it believes are less significant in training. It has been observed that training this type of network is easier than training simple deep convolutional neural networks, and the issue of accuracy degradation has been handled [15].

4. Result and Analysis

For the multiclass classification problem one-vs-one approach was implemented with linear kernel. K-fold cross validation was applied on the dataset which shuffles the dataset and splits it into k groups from which one fold is used as test dataset and the remaining (k-1) folds for training. The model will be trained for all k groups. The k-fold cross validation was applied for k=10 and k=5 for different values of regularization parameter 'C'. The regularization parameter specifies the Multiclass SVM how much to keep each training example from being misclassified. The train and test accuracy of the Multiclass SVM for different values of C for two different values of k are shown in the table 1 and table 2.

When a data point is correctly identified and is further from the decision boundary than the margin in a Support Vector Machine, the loss is zero. The loss is just the size of the slack variable when the point is within the margin or falsely categorized, and the loss rises linearly for misclassified points. Figure 4 shows the loss values of Multiclass SVM for different values of C. It can be seen that the loss value increases when the value of the regularization parameter (C) is increased, that is, if higher value of C is chosen, the model is likely to overfit. When the value of C was 1000, the loss value increased to 0.282. When the value of C is between 1 and 10, it can noticed that the loss value is the minimum. The loss values for C in the range of 0-10 are shown in Figure 5.

It can seen that the loss is decreasing till the value of C reached 5. Further increasing the value of C, it can be seen that there is slight increase in loss and the loss value reaches to 0.262 when the value of C=10. In the range of 3-5 there is rapid decrease of loss, the minimum loss value achieved at C=5 was 0.226. So, the slack variable will be optimal when the value of C is near 5 where the loss is minimal. When the value of C=5 was used, the accuracy was 89.5%.

Table 1: Train Test Accuracy of Multiclass SVM for different value of C at k = 10

C	Average Accuracy at k=10 (%)	Average Training Accuracy (%)	Training Accuracy (%)					Test Accuracy (%)				
			Blast	Blight	Brown Spot	Hispa	Sheath Blight	Blast	Blight	Brown Spot	Hispa	Sheath Blight
0.1	88.07	88.11	67.60	91.06	84.98	97.08	99.80	68.24	91.18	84.31	96.86	99.80
1	89.09	89.57	73.96	92.09	84.07	97.99	99.71	72.75	92.75	82.54	97.65	99.80
5	88.74	89.70	76.53	92.89	81.63	98.01	99.43	75.09	92.15	79.60	97.84	99.02
10	88.54	89.29	77.47	92.74	79.04	98.12	99.06	76.27	92.75	77.05	97.84	99.82
100	88.03	88.53	79.87	92.85	72.81	98.12	98.99	77.25	92.49	73.13	98.24	98.62
1000	88.35	88.35	76.90	92.59	75.59	97.09	99.30	76.08	92.16	76.07	98.24	99.21

Table 2: Train Test Accuracy of Multiclass SVM for different value of C at k = 5

C	Average Accuracy at k=10 (%)	Average Training Accuracy (%)	Training Accuracy (%)					Test Accuracy (%)				
			Blast	Blight	Brown Spot	Hispa	Sheath Blight	Blast	Blight	Brown Spot	Hispa	Sheath Blight
0.1	87.45	87.74	66.42	91.02	84.75	97.02	99.80	65.69	90.98	84.70	96.08	99.08
1	88.78	89.42	73.48	92.34	83.97	97.99	99.36	72.16	92.16	82.54	97.84	99.21
5	88.98	89.32	76.37	92.99	79.55	98.13	99.55	76.66	91.56	79.41	97.84	99.41
10	88.58	88.77	77.15	91.9	77.45	98.08	99.26	77.25	91.96	76.47	97.84	99.41
100	88.86	89.56	78.03	92.01	80.24	98.23	99.26	77.65	91.57	77.84	98.84	99.41
1000	87.84	88.74	79.34	92.20	75.14	97.75	97.75	78.63	91.37	72.74	97.65	99.82

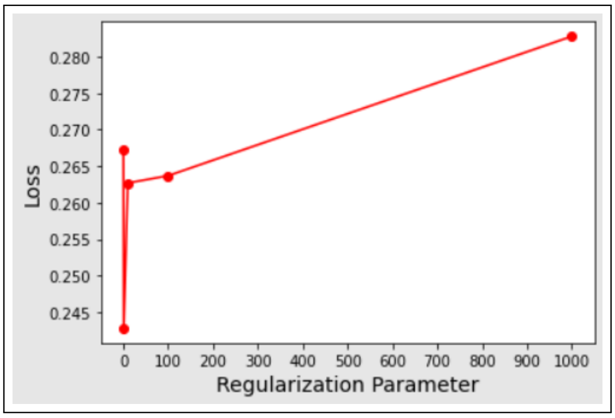

Figure 4: Loss at different values of C

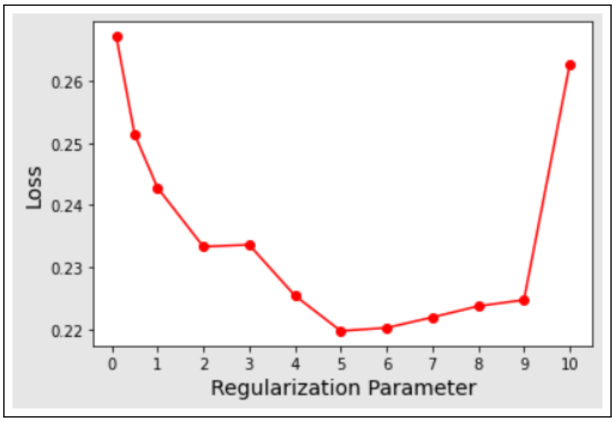

Figure 5: Loss at different values of C in range 0-10

The transfer learning models (MobileNetV2 and ResNet50) takes the image input dimension of 224x224, so the dimension of disease segmented images is reduced as required. The dataset was split into train and test set in a 70-30 manner. The segmented images are fed into the model, and the final classification layer for our chosen disease class labels is built to obtain the correct classification. Both models were trained with 200 epochs, and training and validation accuracy, as well as training and validation loss, were determined for each epochs. Figures 6 through 9 depict the accuracy and loss curves for training and validation of both models.

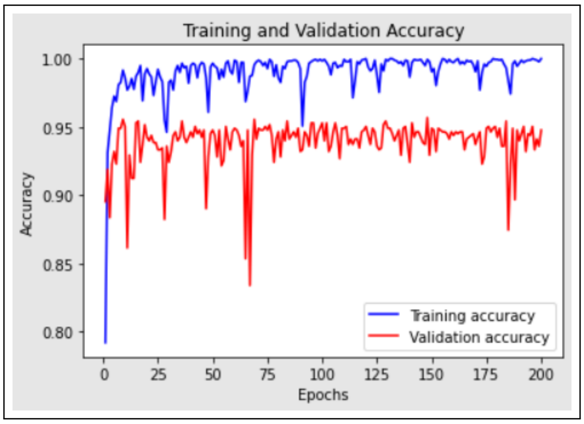

Figure 6: Training and Validation Accuracy of MobileNetV2

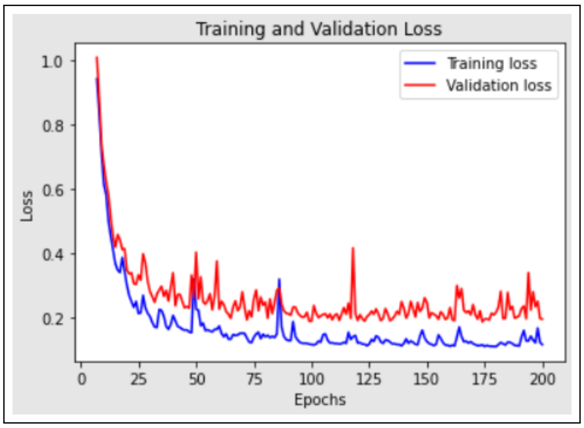

Figure 7: Training and Validation Loss of MobileNetV2

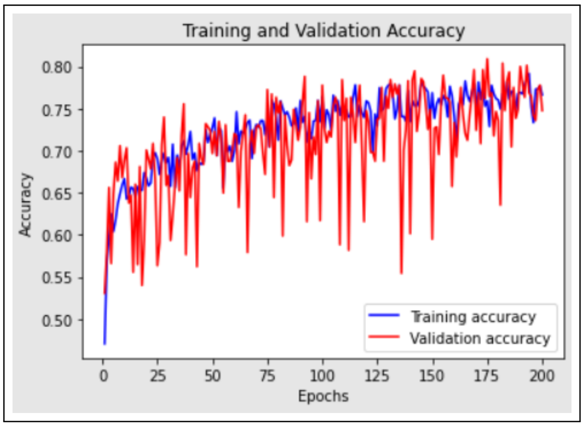

Figure 8: Training and Validation Accuracy of ResNet50

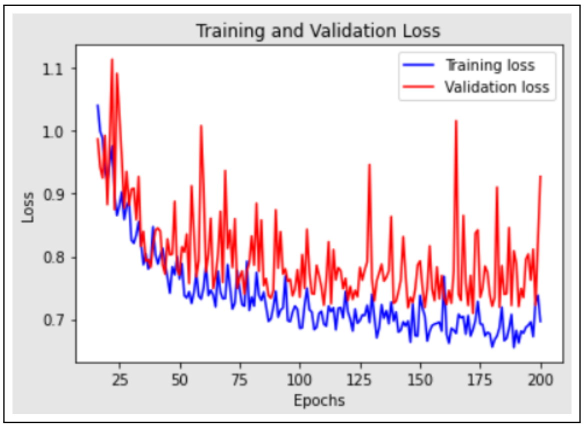

Figure 9: Training and Validation Loss of ResNet50

For the classification of rice plant diseases, three separate models (Multiclass SVM, MobileNetV2 and ResNet50) were trained. New test dataset were loaded to the developed model to compute their performance metrics. For each models, accuracy, precision, recall and f1-score are computed. Table 3 depicts the comparison between the developed models. ResNet50 has a much lower accuracy score compared to the other models, that is, 74.4%. Both Multiclass Support Vector Machine (one-vs-one, one-vs-rest) produced similar results with an accuracy of 89.5% and 89.4% respectively. The highest accuracy of 94.8% was achieved from MobileNetV2 model.

Table 3: Comparison of Tested models

	Accuracy	Precision	Recall	F1 Score
SVM(one-vs-one)	0.895	0.899	0.895	0.893
SVM(one-vs-all)	0.894	0.898	0.894	0.893
MobileNetV2	0.948	0.949	0.948	0.947
ResNet50	0.744	0.739	0.744	0.732

5. Conclusion and Future Work

For the classification of rice plant diseases, three different models were applied in this study. The disease area was segmented from the leaf image using image processing techniques. The Multiclass Support Vector Machine was trained by extracting key features from segmented images, resulting in an accuracy of 89.5%. The study showed that the leaf blast and brown spot had comparatively lower train test accuracy compared to leaf blight, hispa and sheath blight. Both the disease type have similar color pattern of the disease region which caused misclassification between the two disease classes resulting lower train test accuracy.

The disease classification task was also carried out using two transfer learning models, MobileNetV2 and ResNet50. The ResNet50 has low accuracy metrics, it is because of the availability of fewer image dataset to train the model. Increasing the amount of image dataset can improve the ResNet50 performance. The model created with MobileNetV2 outperformed the other two, with an accuracy of 94.8%.

The presented models have a good level of accuracy and, given the right dataset, can be used to diagnose various other rice plant diseases. Furthermore, expanding the dataset of rice leaf images can improve the model's accuracy score.

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