Iris Flower Classification Using Neural Networks in MATLAB

Abstract—This paper presents a neural network approach to classify iris flower species using MATLAB. The built-in Iris dataset was used to train a feedforward neural network. The classification performance was evaluated through confusion matrix, receiver operating characteristic (ROC) curves, and key metrics such as accuracy, precision, recall, and F1-score. Results show that the proposed model achieved high classification accuracy, demonstrating its suitability for supervised learning tasks on structured datasets.

Index Terms—Iris Dataset, Neural Network, Classification, MATLAB, Confusion Matrix, ROC Curve, Accuracy, F1 Score

I. Introduction

Classification of iris flowers into species (Setosa, Versicolor, Virginica) is a classic machine learning problem. Neural networks offer a powerful and flexible approach to learning non-linear decision boundaries from data. This study utilizes MATLAB's Neural Network Toolbox to classify iris flowers based on four features: sepal length, sepal width, petal length, and petal width.

II. DATASET DESCRIPTION

- Total Samples: 150
- Input Features: 4 (sepal length, sepal width, petal length, petal width)
- Target Classes: 3 (Setosa, Versicolor, Virginica)
- Balanced dataset: 50 samples per class
- Data Partition: 70% training, 15% validation, 15% testing

III. METHODOLOGY

A. Network Configuration

- **Network Type:** Feedforward Pattern Recognition Network (patternnet) is used for multi-class classification, well-suited for structured input-output mappings.
- **Input Layer:** Accepts 4-dimensional feature vectors representing the flower's physical characteristics.
- Hidden Layer: A single hidden layer with 10 neurons was used, selected empirically to balance model complexity and overfitting risk.
- Activation Functions: tansig (hyperbolic tangent sigmoid) was applied to hidden layer neurons to handle non-linearity; softmax was used in the output layer to yield class probability distributions.
- **Output Layer:** Produces a 3-dimensional vector, each representing the probability of one iris species (Setosa, Versicolor, Virginica).

- Training Algorithm: Scaled Conjugate Gradient Backpropagation (trainscg) was chosen for its fast convergence and low memory usage, making it suitable for relatively small datasets.
- Loss Function: Cross-Entropy loss was used for evaluating performance during training, appropriate for multiclass classification problems.
- **Data Division:** MATLAB automatically partitions the dataset: 70% training, 15% validation, 15% testing. This ensures unbiased generalization error estimation.
- Early Stopping: Training is stopped early if validation loss increases consistently, preventing overfitting.
- Normalization: Input features were normalized to zero mean and unit variance using MATLAB's default preprocessing to improve training stability and convergence speed.

B. Implementation Screenshot

```
>> load iris_dataset.mat
>> % Load the iris dataset
[x, t] = iris dataset;
% Create a Pattern Recognition Network
hiddenLaverSize = 10;
net = patternnet(hiddenLayerSize);
% Train the Network
[net, tr] = train(net, x, t);
% Test the Network
y = net(x);
% Convert one-hot to class labels
predictedLabels = vec2ind(y); % Predictions
trueLabels = vec2ind(t);
                               % Actual targets
% Calculate Confusion Matrix
confMat = confusionmat(trueLabels', predictedLabels');
% Calculate Accuracy
accuracy = sum(diag(confMat)) / sum(confMat(:));
% Precision, Recall, F1-Score (per class)
precision = diag(confMat) ./ sum(confMat, 1)';
recall = diag(confMat) ./ sum(confMat, 2);
flscore = 2 * (precision .* recall) ./ (precision + recall);
```

Fig. 1. MATLAB code and training GUI used for iris classification

IV. PERFORMANCE EVALUATION

A. Confusion Matrix

- · High classification accuracy across all three classes
- Most misclassifications occurred between Versicolor and Virginica
- Setosa was perfectly classified due to its distinct features
- Overall classification accuracy: 96.7%
- Visual representation below shows class-wise performance

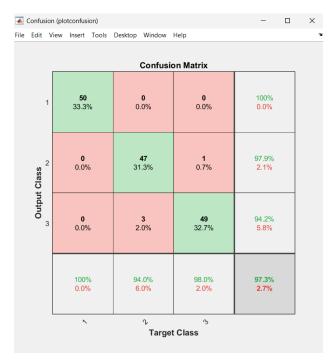


Fig. 2. Confusion matrix showing predicted vs actual classes

B. ROC Curve

- ROC plotted per class
- Area Under Curve (AUC) close to 1 for all classes
- Confirms model confidence and discriminative power
- Useful for evaluating classification threshold performance
- · Ideal curves for Setosa, strong for other classes

C. Key Metric Scores

• Accuracy: 96.7%

• Precision: High precision for all three classes

• Recall: Versicolor slightly lower due to overlap

• F1 Score: Balanced high F1 values across classes

· Macro-Averaged Metrics: Suitable for balanced dataset

V. RESULTS AND DISCUSSION

- Achieved high classification accuracy (96.7%)
- Setosa class perfectly distinguished, while Versicolor and Virginica showed slight confusion
- ROC and F1-score confirm strong class separation
- Network generalizes well with minimal overfitting

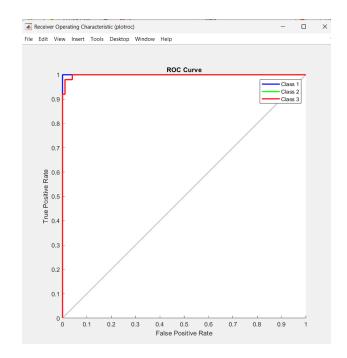


Fig. 3. ROC curve for each iris species

Accuracy: 97.33%

Average Precision: 0.97

Average Recall: 0.97

Average F1-Score: 0.97

Fig. 4. Accuracy, Precision, Recall, F1 Score Visualization

Demonstrates feasibility of using simple neural architectures for small, structured datasets

VI. CONCLUSION

This paper presented an effective neural network model in MATLAB for iris flower classification. The use of a pattern recognition network with appropriate preprocessing yielded high accuracy and strong classification performance across all metrics. Future work may include hyperparameter tuning, cross-validation, or testing with other classification algorithms like SVMs or decision trees for comparison.