

Revisiting Iris Flower Classification: Performance of a Simple Feedforward Neural Network

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Abstract

The Iris flower dataset, a cornerstone in the field of machine learning, presents a classic multi-class classification challenge. This paper details the design, implementation, and evaluation of a simple feedforward neural network (FNN) for classifying the three species of Iris flowers (*Setosa*, *Versicolor*, and *Virginica*) based on four morphological measurements. Despite the problem's well-established nature, it serves as an excellent benchmark for illustrating fundamental neural network concepts and performance. Our FNN, comprising a single hidden layer, demonstrates high classification accuracy (95.0%) on a held-out test set, underscoring the efficacy of even basic neural architectures for such tasks. The study provides a transparent methodology, including data preprocessing, model architecture, training regime, and a detailed analysis of results, including per-class metrics and a confusion matrix. This work aims to offer a clear and reproducible example of applying neural networks to a foundational pattern recognition problem.

1 Introduction

The Iris flower dataset, first introduced by Ronald A. Fisher in his 1936 paper "The use of multiple measurements in taxonomic problems" [1], has become an iconic benchmark in pattern recognition and machine learning. It consists of 150 samples, with 50 samples from each of three Iris species: *Iris setosa*, *Iris versicolor*, and *Iris virginica*. Each sample is characterized by four features: sepal length, sepal width, petal length, and petal width (all measured in centimeters). While *I. setosa* is known to be linearly separable from the other two species, *I. versicolor* and *I. virginica* exhibit some overlap, making the classification task non-trivial for simpler linear models.

Despite the advent of highly complex deep learning architectures, revisiting this classic problem with a fundamental feedforward neural network (FNN) serves several important purposes. Firstly, it provides an accessible and interpretable illustration of core neural network mechanics. Secondly, it establishes a baseline performance that can be readily compared with both traditional machine learning algorithms and more advanced neural models. This study focuses on constructing a deliberately simple FNN to demonstrate that effective classification can be achieved without resorting to overly complex architectures for well-structured datasets like Iris. Our primary objective is to present a clear, step-by-step implementation and evaluation of such a network, emphasizing reproducibility and pedagogical value.

2 Methodology

This section details the dataset, the preprocessing steps, the architecture of the neural network, and the training procedure employed.

2.1 Dataset and Preprocessing

The Iris dataset was obtained directly from the Scikit-learn library [2], a widely used Python package for machine learning. The dataset comprises 150 instances, evenly distributed among the three classes. The four features are continuous numerical values.

Prior to model training, the dataset was preprocessed as follows:

1. **Data Splitting:** The dataset was partitioned into a training set and a test set using an 80:20 ratio, resulting in 120 samples for training and 30 samples for testing. Stratified sampling was employed to ensure that the proportion of samples for each class was maintained in both the training and test splits. This is crucial for obtaining a reliable estimate of generalization performance.
2. **Feature Scaling:** The four input features were standardized by removing the mean and scaling to unit variance. Standardization was performed by calculating the mean and standard deviation from the training set only and then applying this transformation to both the training and test sets. This prevents data leakage from the test set into the training process and helps the optimization algorithm (e.g., gradient descent) to converge more efficiently.

2.2 Neural Network Architecture

A feedforward neural network, also known as a multi-layer perceptron (MLP), was implemented using the PyTorch framework [3]. The architecture was intentionally kept simple to align with the study's objectives:

- **Input Layer:** Consisted of 4 neurons, corresponding to the four input features (sepal length, sepal width, petal length, petal width).
- **Hidden Layer:** A single hidden layer with 10 neurons was utilized. The number of neurons was chosen as a reasonable capacity for this task, balancing the ability to learn complex patterns with the risk of overfitting on a small dataset. The Rectified Linear Unit (ReLU) activation function, defined as $f(x) = \max(0, x)$, was applied element-wise to the output of this layer. ReLU is widely adopted due to its computational efficiency and its ability to mitigate the vanishing gradient problem.
- **Output Layer:** Comprised 3 neurons, one for each of the three Iris species. The Softmax activation function was applied to the output of this layer. Softmax converts the raw output scores (logits) into a probability distribution over the classes, ensuring that the outputs are non-negative and sum to one.

The overall architecture can be summarized as Input(4) - Hidden(10, ReLU) - Output(3, Softmax).

2.3 Model Training

The neural network was trained using the following configuration:

- **Loss Function:** The Cross-Entropy Loss (also known as Log Loss) was employed as the objective function. This loss function is standard for multi-class classification problems and is well-suited for models that output class probabilities (e.g., via Softmax).
- **Optimizer:** The Adam (Adaptive Moment Estimation) optimization algorithm [4] was used to update the network weights. Adam is an adaptive learning rate optimization algorithm that has been shown to perform well on a wide range of problems. A learning rate of 1×10^{-3} (0.001) was used, a common default value that generally provides good performance.
- **Training Epochs:** The model was trained for 10 epochs. An epoch represents one full pass through the entire training dataset. This number was empirically determined to be sufficient for convergence on this dataset without significant overfitting.
- **Batch Size:** A batch size of 16 was used. This means that the training data was divided into mini-batches of 16 samples, and the model’s weights were updated after processing each mini-batch.

The model’s performance was evaluated on the held-out test set after the completion of all training epochs.

3 Results and Discussion

This section presents the classification performance of the trained FNN on the Iris test set and discusses the implications of these results.

3.1 Overall Performance

The simple feedforward neural network achieved a classification accuracy of **95.0%** on the unseen test set. This result indicates that 28 out of the 30 test samples were correctly classified. This level of accuracy is commendable for such a basic architecture and aligns with typical results reported for this dataset using various machine learning techniques.

3.2 Detailed Performance Analysis

To gain deeper insights into the model’s classification behavior, a confusion matrix and per-class performance metrics (precision, recall, and F1-score) were computed.

The confusion matrix (Table 1) reveals that *I. setosa* was perfectly classified (10 out of 10 correct). For *I. versicolor*, 9 out of 10 samples were correctly classified, with one sample being misclassified as *I. virginica*. For *I. virginica*, all 10 samples were correctly identified by the model, though one *I. versicolor* was incorrectly predicted as *I. virginica*. This pattern of confusion between *I. versicolor* and *I. virginica* is a well-known characteristic of the Iris dataset, as these two species are not perfectly linearly separable in the feature space.

The per-class performance metrics are summarized in Table 2.

Table 1: Confusion Matrix for Iris Classification on the Test Set. Rows represent actual classes and columns represent predicted classes.

Actual Class	Predicted Class			Total Actual
	<i>I. setosa</i>	<i>I. versicolor</i>	<i>I. virginica</i>	
<i>I. setosa</i>	10	0	0	10
<i>I. versicolor</i>	0	9	1	10
<i>I. virginica</i>	0	0	10	10
Total Predicted	10	9	11	30

Table 2: Per-class Performance Metrics (Precision, Recall, F1-score) on the Test Set.

Species	Precision	Recall	F1-score
<i>I. setosa</i>	1.00	1.00	1.00
<i>I. versicolor</i>	1.00	0.90	0.95
<i>I. virginica</i>	0.91	1.00	0.95
Macro Average	0.97	0.97	0.97
Weighted Average	0.97	0.97	0.97

- **Precision** measures the proportion of correctly predicted positive instances out of all instances predicted as positive. For *I. versicolor*, all instances predicted as *I. versicolor* were indeed *I. versicolor* (Precision = 1.00). For *I. virginica*, 10 out of 11 instances predicted as *I. virginica* were correct (Precision = 0.91).
- **Recall** (or Sensitivity) measures the proportion of correctly predicted positive instances out of all actual positive instances. For *I. versicolor*, 9 out of 10 actual *I. versicolor* samples were correctly identified (Recall = 0.90). For *I. virginica*, all 10 actual *I. virginica* samples were identified (Recall = 1.00).
- **F1-score** is the harmonic mean of Precision and Recall, providing a single metric that balances both. Both *I. versicolor* and *I. virginica* achieved an F1-score of 0.95.

The perfect scores for *I. setosa* confirm its distinctness. The high, though not perfect, scores for *I. versicolor* and *I. virginica* reflect the inherent difficulty in perfectly separating these two classes with the given features and a simple model.

3.3 Discussion

The results demonstrate that a basic FNN can achieve strong performance on the Iris classification task. The training process was stable, and the model generalized well to the unseen test data, as evidenced by the high accuracy. The choice of a single hidden layer with 10 neurons, ReLU activation, and the Adam optimizer proved to be an effective combination for this problem.

While the achieved accuracy is high, it is important to note the limitations. The Iris dataset is relatively small and well-behaved. The simplicity of the model, while intentional for illustrative purposes, might not scale effectively to more complex datasets with higher dimensionality or more intricate class boundaries. Further investigations could

explore the impact of different numbers of hidden layers/neurons, alternative activation functions, or regularization techniques, though such explorations were beyond the scope of this foundational study. The primary contribution here is the clear demonstration of a successful application of a fundamental neural network to a classic problem.

4 Conclusion

This study successfully implemented and evaluated a simple feedforward neural network for the classification of the Iris flower dataset. The model, characterized by its straightforward architecture (one input layer, one hidden layer with ReLU activation, and one output layer with Softmax activation), achieved a commendable accuracy of 95.0% on the held-out test set.

The detailed analysis, including the confusion matrix and per-class metrics (precision, recall, F1-score), provided insights into the model's performance characteristics, particularly highlighting the perfect classification of *Iris setosa* and the slight, expected confusion between *Iris versicolor* and *Iris virginica*. The methodology, encompassing data preprocessing, model design, and training regime, was thoroughly described to ensure reproducibility.

This work reaffirms the utility of the Iris dataset as an educational tool and demonstrates that even fundamental neural network architectures can be highly effective for certain pattern recognition tasks. It serves as a clear and accessible example of applying neural network principles, suitable for introductory learning and as a baseline for more complex investigations.

References

- [1] Fisher, R. A. (1936). The use of multiple measurements in taxonomic problems. *Annals of Eugenics*, **7**(2), 179-188.
- [2]
- [3]
- [4]