Assignment 1 - Deep Learning Fundamentals

Hazim Shaikh
University of Adelaide
a1894307@adelaide.edu.au

Abstract

This paper examines the performance of two neural network models—the Single-Layer Perceptron (SLP) and Multi-Layer Perceptron (MLP)—in predicting diabetes onset using the Pima Indians Diabetes dataset. Diabetes is a global health concern, and early diagnosis is crucial for preventing serious complications. We compare how well these models distinguish between diabetic and non-diabetic cases, particularly focusing on their ability to handle non-linear relationships in the data.

The SLP serves as a basic model, while the MLP, with a hidden layer of 100 neurons, is designed to capture more complex patterns. Interestingly, the SLP achieved higher overall accuracy, especially in classifying non-diabetic patients. However, the MLP showed better recall for diabetic cases, which could make it more suitable for medical applications where correctly identifying positive cases is critical.

1. Introduction

Diabetes is a widespread chronic condition, and early detection is key to preventing severe complications. Neural networks, including the Single-Layer Perceptron (SLP) and Multi-Layer Perceptron (MLP), have been applied to predict diabetes based on features such as glucose levels, insulin, and BMI. The Pima Indians Diabetes dataset (1) is often used in this context due to its diverse feature set, making it ideal for testing different machine learning models.

This study compares the performance of two types of neural networks: the SLP, a simple linear classifier, and the MLP, which has hidden layers that help it detect more complex patterns (2). By evaluating their performance using accuracy, precision, recall, and F1-score, we aim to determine which model is more effective for this dataset.

2. Methodology

2.1. Single-Layer Perceptron (SLP)

The Single-Layer Perceptron (SLP) is a straightforward neural network that uses a linear decision boundary for classification. It calculates a weighted sum of input features and applies an activation function to predict the class. Although simple, the SLP is effective for linearly separable data and serves as a good baseline for this study.

2.2. Multi-Layer Perceptron (MLP)

The Multi-Layer Perceptron (MLP) builds upon the SLP by adding one or more hidden layers between the input and output layers. These hidden layers enable the MLP to model non-linear relationships. In this experiment, the MLP has one hidden layer with 100 neurons and uses the backpropagation algorithm to optimize the weights. The added complexity of the MLP is expected to improve its ability to identify more intricate patterns in the data.

2.3. Data Preprocessing

The Pima Indians Diabetes dataset contains 768 samples and 9 features. Several features, such as glucose and BMI, had zero values that were treated as missing. We filled in these missing values using the median for each feature. To ensure consistency, the features were normalized using `StandardScaler`, which standardized them to have a mean of 0 and a standard deviation of 1. The data was then divided into 80% training and 20% testing sets for evaluation.

3. Experimental Results

3.1. Model Accuracy

The accuracy of both models was calculated to compare their performance. Table 1 shows that the SLP slightly outperformed the MLP in terms of accuracy.

3.2. Confusion Matrices

Confusion matrices provide a detailed view of how well each model classified diabetic and non-diabetic cases. Fig-

Model	Accuracy (%)
Single-Layer Perceptron (SLP)	75.32
Multi-Layer Perceptron (MLP)	71.43

Table 1. Accuracy comparison between SLP and MLP models.

ures 1 and 2 display the confusion matrices for the SLP and MLP, respectively.

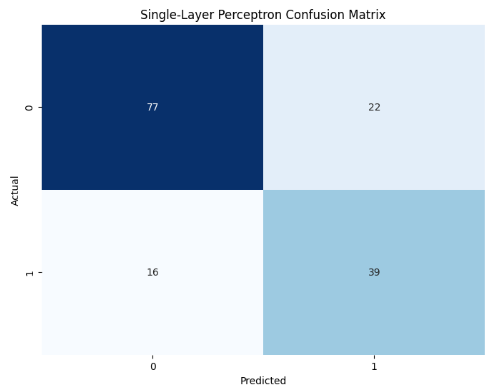

Figure 1. Confusion Matrix for Single-Layer Perceptron (SLP).

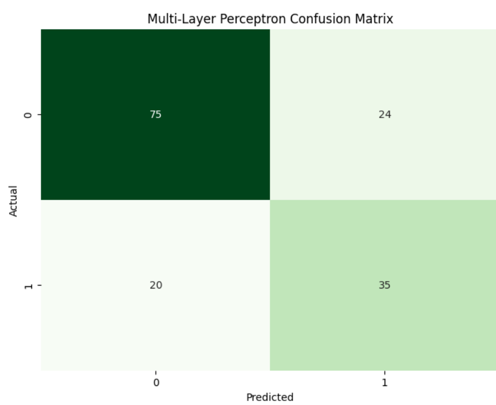

Figure 2. Confusion Matrix for Multi-Layer Perceptron (MLP).

3.3. Classification Metrics

To further evaluate the models, we calculated the precision, recall, and F1-scores for both classes (0 = No Diabetes, 1 = Diabetes). These metrics offer deeper insights into the models' classification capabilities. Table 2 summarizes these results.

3.4. Outcome Distribution Bar Plot

We also visualized the distribution of diabetic and non-diabetic outcomes using a bar plot, shown in Figure 3.

Model	Precision	Recall	F1-Score
SLP (Class 0)	0.83	0.78	0.80
SLP (Class 1)	0.64	0.71	0.67
MLP (Class 0)	0.79	0.76	0.77
MLP (Class 1)	0.59	0.64	0.61

Table 2. Precision, Recall, and F1-Score for SLP and MLP models by class.

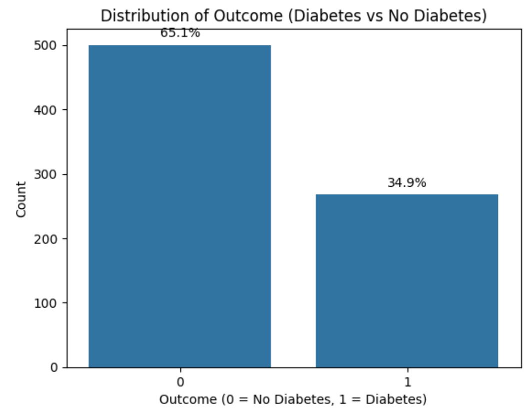

Figure 3. Bar Plot for Outcome Distribution (0 = No Diabetes, 1 = Diabetes).

3.5. Heatmap for Correlation Matrix

To better understand the relationships between the features, we generated a heatmap of the correlation matrix, shown in Figure 4.

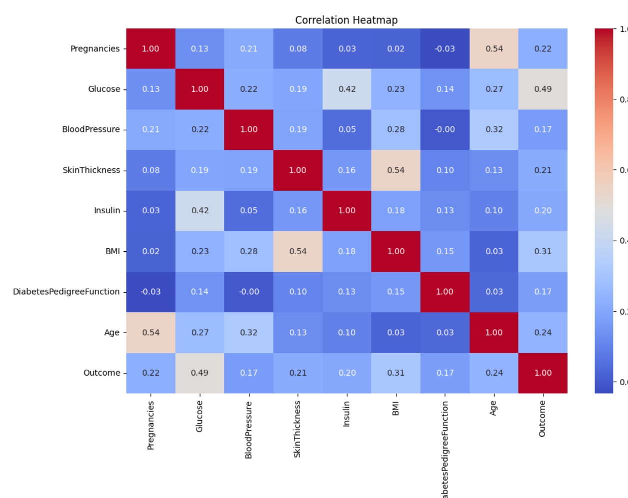

Figure 4. Heatmap of Feature Correlations.

4. Discussion

The SLP achieved higher accuracy and performed better in classifying non-diabetic cases compared to the MLP. However, the MLP demonstrated better recall for diabetic cases, meaning it was more successful in identifying true diabetic patients. One of the key limitations of the MLP in this experiment was the relatively small dataset, which restricted its ability to fully utilize its hidden layer. Future experiments could benefit from tuning hyperparameters such as learning rate and neuron count to improve MLP performance.

5. Code

The code for this experiment is available on GitHub for review and reproduction. You can access it via the following link:

`https://github.com/Hazimshaikh/Deep-Learning-`

6. Conclusion

This study compared the effectiveness of Single-Layer Perceptron (SLP) and Multi-Layer Perceptron (MLP) models in predicting diabetes using the Pima Indians Diabetes dataset. The SLP outperformed the MLP in terms of accuracy, while the MLP showed higher recall for diabetic cases. These results highlight the need for careful model selection and tuning, especially in healthcare applications where both precision and recall are important. Future work could involve exploring deeper neural networks or other algorithms like decision trees and support vector machines.

References

[1] Lakhwani, K., Yadav, R., and Saxena, A. (2020). *Prediction of Diabetes Using Artificial Neural Network and Pima Indian Diabetes Dataset*. International Journal of Advanced Research in Computer Science, 11(1), 34-39.

[2] Ramkumar, M., Sivasankari, S., Surendiran, J., Yuvaraj, N., and Ravi, C.N. (2022). *Classification of Diabetes using Multilayer Perceptron*. 2022 IEEE International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE). DOI: 10.1109/ICDCECE53908.2022.9793085.