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Assignment No. 3

Overview

This report provides a detailed comparison of the performance factors across TensorFlow ANN, Modified_ch11, and Original ch11 based on training and validation metrics, including accuracy, loss trends, prediction results, and macro AUC. The Modified notebook represents our solution and demonstrates significant improvements over the other implementations.

1. Accuracy

TensorFlow ANN:

- **Training Accuracy:** Starts at 11.03% and improves steadily across epochs.
- **Validation Accuracy:** Starts at 12.98%, with consistent growth.
- **Trend:** Both metrics exhibit steady improvement, with validation accuracy closely tracking training accuracy.

Modified_ch11 - My Solution:

- **Training Accuracy:** Rapidly improves, achieving a peak of 95.83%.
- **Validation Accuracy:** Reflects a balanced trend, showing high consistency with training accuracy.
- **Trend:** Demonstrates faster convergence and better alignment between training and validation accuracy, highlighting effective generalization.
- **Key Improvement:** Compared to the other notebooks, the modified solution achieves higher accuracy in fewer epochs, showcasing its efficiency and robustness.

Original ch11:

- **Training Accuracy:** Improves consistently from 9.4% to 94.54%.
- **Validation Accuracy:** Closely mirrors the training accuracy throughout.
- **Trend:** Demonstrates smooth and consistent improvement, indicating well-balanced learning.

2. Loss Trends

TensorFlow ANN:

- **Training Loss:** Decreases steadily.
- **Validation Loss:** Trends downward, aligning closely with training loss.
- **Observation:** Consistent reduction in loss for both training and validation signifies effective optimization.

Modified_ch11 - Our Solution:

- **Training Loss:** Rapidly decreases and stabilizes at lower values.
- **Validation Loss:** Closely aligns with training loss, indicating minimal overfitting.
- **Observation:** The optimized architecture and hyperparameters of the modified solution result in faster and more stable convergence, reducing both training and validation loss more effectively than the other implementations.

Original ch11:

- **Training Loss:** Gradually decreases across epochs.
- **Validation Loss:** Remains close to training loss, suggesting balanced learning.

3. Macro AUC

TensorFlow ANN:

- **Macro AUC:** 0.942 (average across epochs).

Modified_ch11 - Our Solution:

- **Macro AUC:** 0.955 (average across epochs). This demonstrates improved classification performance compared to other approaches.

Original ch11:

- **Macro AUC:** 0.935 (average across epochs).

4. Prediction Results

TensorFlow ANN:

- Predictions align well with true values after sufficient epochs.

Modified_ch11 - My Solution:

- Predictions show high accuracy and consistency, with fewer misclassifications compared to other models.

Original ch11:

- Predictions improve with epochs but exhibit slightly more variability in certain cases compared to the Modified solution.

Conclusion

This report highlights the advantages of the Modified_ch11 solution over the TensorFlow ANN and Original ch11 models. By introducing two hidden layers and optimizing the architecture, the Modified solution achieves faster convergence, higher accuracy, and better generalization. The Macro AUC also confirms its superior classification performance on the MNIST dataset.

The TensorFlow ANN provides a robust baseline with consistent improvements, while the Original ch11 demonstrates strong performance but slower convergence.

In summary, the Modified_ch11 solution meets the assignment objectives by:

1. Enhancing the architecture with two hidden layers.
2. Demonstrating superior performance metrics (accuracy, loss, macro AUC).
3. Providing robust generalization across training and validation data.