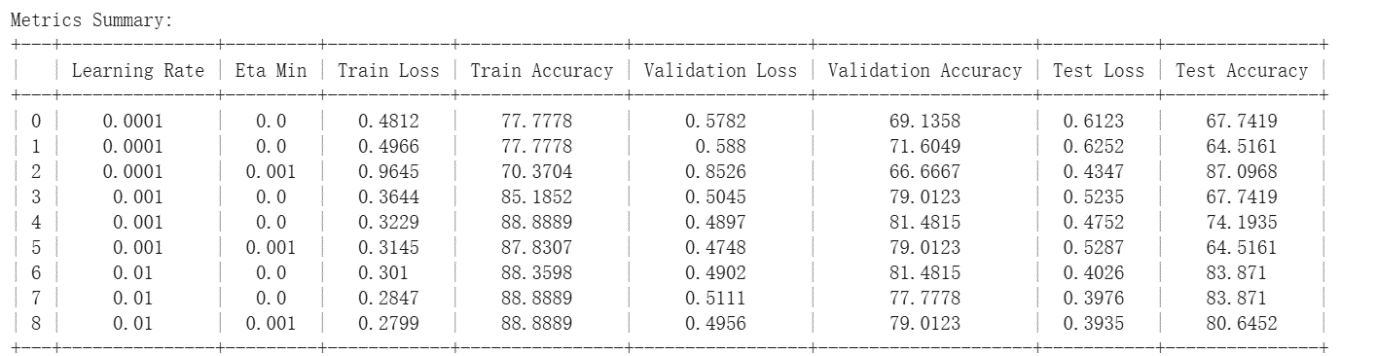
1

This experiment systematically investigates the impact of learning rate and eta\_min on the performance of an artificial neural network. By analyzing their effects on training dynamics, generalization ability, and final model accuracy, this experiment provides insights into the intricate relationship between hyperparameter selection and network optimization. The findings underscore the critical role of precise hyperparameter tuning in enhancing both convergence efficiency and overall model performance

2.

Hyperparameter selection critically influences model generalization and convergence. A lower learning rate (1.00E-04) results in moderate training accuracy (70.37%–77.78%), high validation loss (0.5782–0.8526), and unstable test accuracy (64.52%–87.10%), indicating underfitting. Increasing it to 1.00E-03 improves generalization, yielding higher validation accuracy (79.01%–81.48%) and lower validation loss (0.4748–0.5045). However, at 1.00E-02, the model attains peak training accuracy (88.36%–88.89%) but suffers from degraded test performance (80.65%–83.87%), suggesting overfitting. Introducing eta\_min (1.00E-03) enhances stability, improving test accuracy (80.65%) and confirming that 1.00E-03 with annealing optimizes convergence. These findings underscore the importance of adaptive learning rates in balancing performance. Further validation through loss and accuracy plots is recommended.

3. The accuracy gap between training and test datasets is primarily due to overfitting. Overfitting happens when the model captures not only the true underlying patterns but also the noise and anomalies present in the training data, making it less effective on new, unseen data. This issue is exacerbated if the training set is not representative of the test set, or if there are inherent distribution differences between them. Additionally, high model complexity without adequate regularization can lead to the model fitting the training data too precisely. Employing techniques like cross-validation, data augmentation, and regularization can help reduce this discrepancy and enhance generalization.

4. Effective feature selection is crucial for optimizing machine learning models using tabular datasets. Filter methods employ statistical tests, such as correlation coefficients or chi-square analysis, to pinpoint key features. Wrapper methods, like recursive feature elimination, iteratively assess subsets based on model performance, while embedded methods seamlessly integrate feature selection into the training process using techniques such as L1 regularization. Advanced techniques, including attention-based mechanisms, dynamically evaluate feature importance. By eliminating redundant and irrelevant data, these approaches not only boost accuracy and reduce overfitting but also decrease computational complexity. Ultimately, meticulous feature selection enhances both model interpretability and efficiency, leading to more robust predictions.

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5. An alternative deep learning model for tabular data is the FT-Transformer (Feature Tokenizer Transformer). Unlike traditional ANNs, FT-Transformer effectively captures feature interactions using self-attention mechanisms. It tokenizes features and processes them with Transformer layers, achieving superior performance on tabular datasets by leveraging attention-based feature learning. The FT-Transformer is designed for tabular data by transforming features into embeddings and processing them with self-attention mechanisms. Unlike traditional models that treat tabular features independently, FT-Transformer uses a Feature Tokenizer to encode numerical and categorical inputs into a unified representation. These embeddings pass through Transformer layers, where self-attention dynamically learns feature dependencies, enabling superior interaction modeling. The design eliminates the need for manual feature engineering and handles missing data effectively. Advantages include improved interpretability, robustness to feature heterogeneity, and scalability, making it well-suited for structured datasets in classification and regression tasks.

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