Introduction

This report presents a comprehensive analysis of the machine learning models developed by our team for water quality classification using a neural network. Each team member applied a unique combination of optimization and regularization techniques to explore different performance trade-offs. The goal was to find the most effective model by evaluating key metrics such as F1 score, precision, recall, and validation loss.

Team Members' Model Configurations

Each team member implemented distinct choices for optimization and regularization techniques;

instance	Engineer name	optimizer	Regularizer	Early stopping	Dropout rate	Accuracy	F1Score	Recall	precision
	Willy kalisa	SGD	L2	yes	0.6	0.43	0.3	0.7	N/A
	madol	Adam	L2	yes	N/A	0.72	0.47	0.3	0.7
	Justice	L2	RMSprop	Patience=10, monitor='val_loss'	0.3, 0.2	0.62	0.77	1.0	0.62

Justification for Techniques Used

Each team member selected a unique combination of regularization and optimization techniques to balance generalization, stability, and convergence. Willy Kalisa used L2 regularization with SGD, which prevents overfitting but resulted in slower convergence and lower accuracy (43.45%). Madol Abraham Kuol Madol applied L2 regularization with Adam, achieving a higher F1-score (72.9%**)** due to Adam's adaptive learning rates and stable convergence. Justice Chukwuonye used L1 regularization with RMSprop, which improved feature selection and recall (100%) but led to a higher false positive rate (precision: 62%)**.** Each approach provided insights into model performance trade-offs, with potential improvements including hyperparameter tuning and dropout adjustments to optimize results further.

Performance Analysis

Willy Kalisa's model, using L2 regularization and SGD, achieves 43.45% accuracy with high recall (77.33%) but low precision. The high dropout rate (0.6931) may have impacted performance.
Madol Abraham Kuol Madol's model, with L2 regularization and Adam optimizer, performs better with 72.90% accuracy, 71.00% precision, and 47.90% F1 score, though recall is lower (33.00%).
Justice Chukwuonye's model, using L1 regularization and RMSprop, achieves 62.00% accuracy with an excellent F1 score (77.00%) and perfect recall (100.00%), but lower precision (62.00%).
Overall, each model has trade-offs. Fine-tuning dropout and regularization could further optimize performance.

Recommendations for Improvement

- Hyperparameter Tuning: Adjusting learning rates and dropout rates to find an optimal balance.
- Class Balancing Techniques: Using SMOTE or weighted loss functions to improve recall.
- Threshold Optimization: Experimenting with different classification thresholds to enhance precision-recall balance.
- Alternative Optimizers: Exploring SGD with momentum or RMSprop for potential performance improvements.

Conclusion

This report highlights the strengths and weaknesses of each model, emphasizing how different optimization and regularization techniques impact performance. The insights gained will be valuable for refining future models and improving classification accuracy. Our collaboration as a team ensured diverse approaches, leading to a richer understanding of model performance trade-offs.