Given all the models evaluated, ranging from decision trees to neural networks, for predicting loan default and loss amount, performance was assessed using classification accuracy, AUC, and RMSE. Random Forest proved to be the most accurate model overall, with the best test accuracy and AUC for classification, as well as a solid RMSE of 2,463 for regression. It showed strong generalization and consistency, making it the most reliable choice for real-world deployment.

Gradient Boosting performed nearly as well, with an AUC of 0.93 and an RMSE of 2,294, which solidifies its status as a competitive alternative. The REG_ALL logistic regression model yielded good classification results, but ensemble methods slightly outperformed it in terms of accuracy. TensorFlow underperformed, with an AUC of 0.63, a classification accuracy of 79%, and an RMSE of 7,476. The model's inconsistent results across multiple runs mean it struggles with stability and generalization.

Key risk indicators, such as TRUNC_M_DEROG, O_IMP_DELINQ, and TRUNC_M_NINQ, showed a strong correlation with higher default risk, which aligns with typical credit scoring expectations. A more extended credit history (e.g., higher TRUNC_M_YOJ) was negatively associated with default, indicating stability. Coefficients like TRUNC_IMP_MORTDUE = -2.4×10^{-6} had near-zero values, indicating a negligible impact and warranting removal. Overlapping predictors, such as the IMP_, TRUNC_, and O_ variables, can lead to multicollinearity.

Overall, Random Forest stood out as the strongest and most dependable model, which struck an outstanding balance between high performance and interpretability through its feature importance scores. If transparency is a bigger priority, especially in settings with strict regulations, Logistic Regression is still a solid and trustworthy choice. If performance is the priority, Random Forest is the preferred model; if interpretability is paramount, Logistic Regression is a sound choice.