Machine Learning and Neural Network Approaches for the Classification of Compact Stars

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Introduction

Neutron stars are ultra-dense remnants of massive stars formed after supernova explosions, with densities of about 10^{14}–$10^{15}\,\mathrm{g/cm^3}$ and interiors mainly composed of neutrons. Quark stars are hypothetical compact objects that may arise under even more extreme conditions, where matter forms deconfined up, down, and strange quarks. Machine learning and neural networks provide data-driven tools for analyzing compact-star properties, such as mass, radius, compactness, and tidal deformability, and for classifying stellar configurations as neutron-star or quark-star candidates.

Methodology

The dataset includes mass, radius, tidal deformability, Love number k_2, and central pressure as input features, while the supercategory is used as the target variable. It consists of 39,920 samples classified into two categories: neutron stars and quark stars. A Pearson correlation matrix is constructed to quantify the linear relationships among the selected features. The strongest correlation is observed between tidal deformability and the Love number k_2. A confusion matrix is generated to assess the classification accuracy of each machine learning model. Here, we present the confusion matrix for the **XGBoost** classifier, which achieves the best overall performance. The matrix shows perfect classification of both neutron-star and quark-star samples, with no observed misclassified cases.

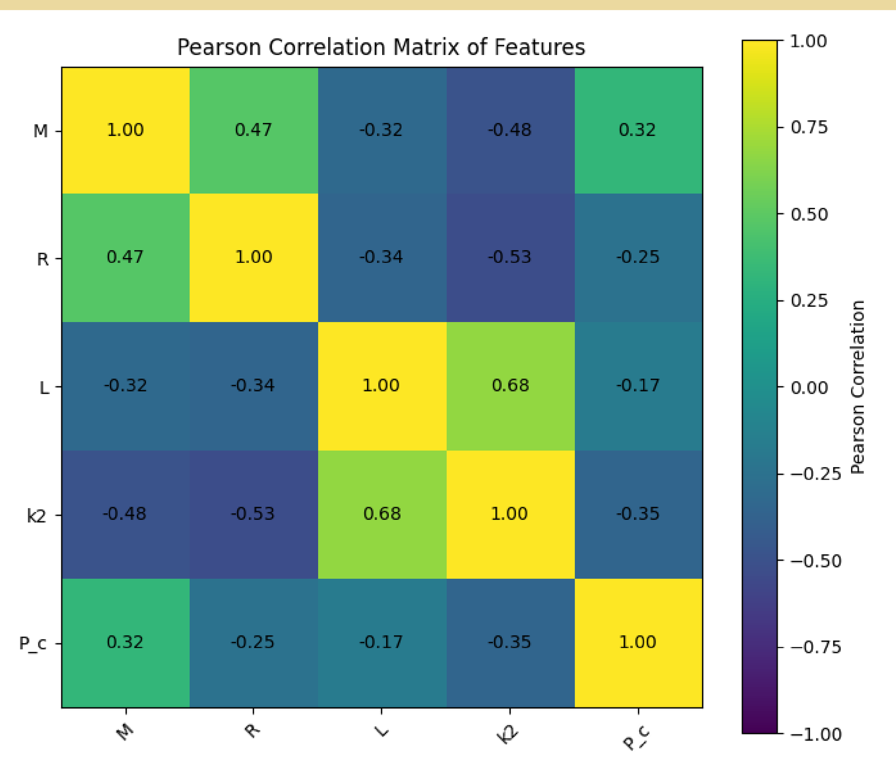

Figure: Pearson correlation matrix showing the linear correlations between the selected features. The color scale represents the strength and direction of the correlations.

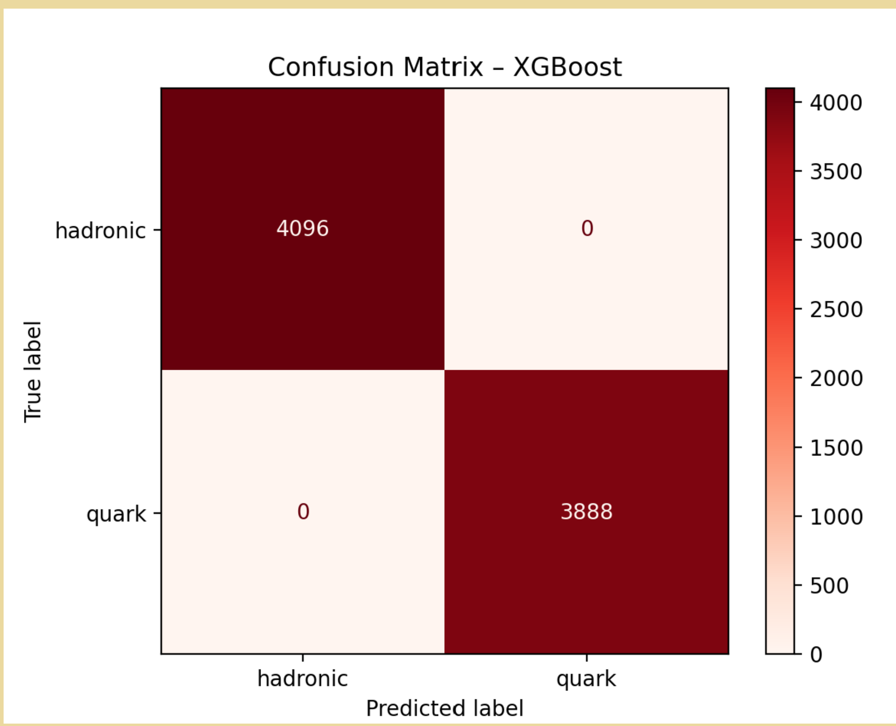

Figure: Confusion matrix of the XGBoost classifier. The model achieves perfect classification, correctly identifying all neutron star (hadronic) and quark star samples with zero misclassifications.

Four classifiers are trained to distinguish neutron stars from quark stars: **Random Forest**, **XGBoost**, **Decision Tree**, and **Logistic Regression**. Hyperparameter tuning is performed using **grid search** with four-fold cross-validation. The models are evaluated with accuracy, recall, precision, F1-score, and AUC (see Table). All models achieve near-perfect results, with **XGBoost** reaching 100% accuracy on the test set, indicating clear class separability. The figure shows the ROC curves for the four machine learning models. All models achieve an AUC of 1.0, indicating perfect classification between neutron stars and quark stars.

Results

Results				
Metrics	**Random Forest**	**XGBoost**	**Decision Tree**	**Logistic Regression**
Accuracy	0.9998	1.0000	0.9993	0.9985
Precision	1.0000	1.0000	0.9987	0.9970
Recall	0.9995	1.0000	0.9998	1.0000
F1-Score	0.9998	1.0000	0.9992	0.9985
AUC-Score	1.0000	1.0000	0.9993	1.0000

Figure: Performance comparison of the four machine learning classifiers.

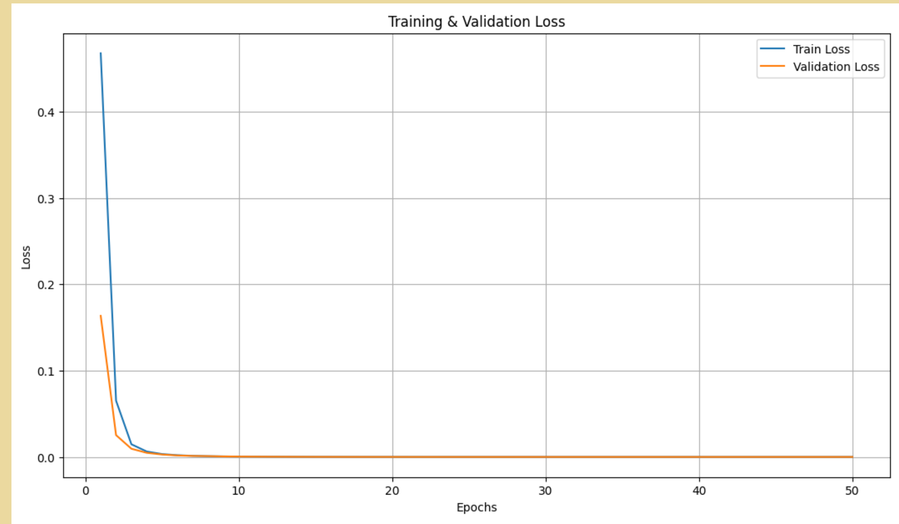

Figure: Training and validation loss curves of the neural network across epochs.

A two-hidden-layer neural network is trained on the same dataset, achieving accuracy, F1-score, and AUC of 1.0. The loss curves converge rapidly to low values, indicating stable training without significant overfitting.
Observational uncertainties are simulated by adding noise to mass, radius, and tidal deformability, generating mild, medium, and maximum error datasets.

Model	Mild Errors	Medium Errors	Max Errors
Random Forest	0.9071	0.8944	0.8838
XGBoost	0.9997	0.9996	0.9993
Decision Tree	0.8739	0.8543	0.8451
Logistic Regression	0.7298	0.7256	0.7176

Figure: AUC scores for different observational error levels.

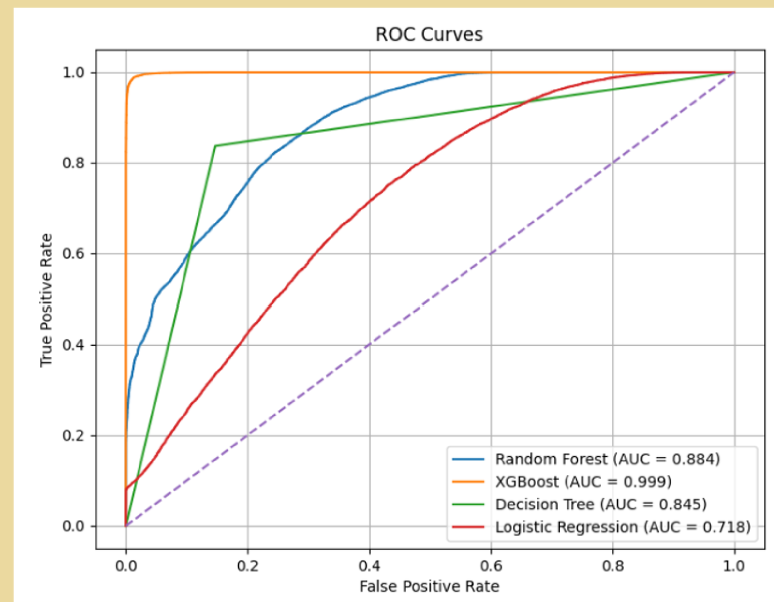

Figure: ROC curves for the maximum observational error scenario.

Two neural networks are compared using either Λ or $\log\Lambda$ as input. Using $\log\Lambda$ improves performance by reducing feature-scale imbalance and preventing Λ from dominating the training process.

Neural Network Results (M, R, Λ)			
Metric	Mild Errors	Medium Errors	Max Errors
Accuracy	0.7456	0.7216	0.7041
F1-Score	0.7462	0.7147	0.7011
AUC-Score	0.8437	0.8171	0.7961

Figure: Neural network performance using M, R, and Λ.

Neural Network Results (M, R, logΛ)			
Metric	Mild Errors	Medium Errors	Max Errors
Accuracy	0.9952	0.9949	0.9939
F1-Score	0.9952	0.9949	0.9939
AUC-Score	0.9998	0.9998	0.9998

Figure: Neural network performance using M, R, and $\log\Lambda$.

Acknowledgements

GCP resources were provided by the National Infrastructures for Research and Technology GRNET and funded by the EU Recovery and Resiliency Facility. (Project: Towards the Quantum Cosmos: Deep Learning and Quantum Computation for Neutron Star Physics - ToQC)

Bibliography

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