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

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Compact stars provide a unique probe of matter under extreme density conditions, yet their internal composition remains uncertain. In particular, hadronic neutron stars and quark stars may exhibit overlapping mass–radius relations, making their distinction challenging through conventional observables alone. In this work, we apply machine learning and neural-network methods to classify these two compact-star families using stellar mass, radius, tidal deformability, Love number, and central pressure. A dataset of 39,920 stellar configurations was generated from 3,992 equations of state, including 2,048 hadronic models and 1,944 quark-matter models based on the MIT bag and Color–Flavor-Locked frameworks. Several supervised classifiers, namely Random Forest, XGBoost, Decision Tree, and Support Vector Machine, were evaluated together with a feedforward neural network. In the noise-free case, the models achieved near-perfect classification performance, with XGBoost, SVM, and the neural network reaching accuracy, F1-score, and AUC values close to unity. Feature-selection and ablation analyses showed that the Love number is particularly important, highlighting the role of tidal-response quantities in distinguishing between the two classes. To assess robustness under realistic observational conditions, synthetic datasets were generated by adding Gaussian uncertainties to mass and radius, while tidal deformability was reconstructed through a compactness–deformability relation with intrinsic scatter. Although observational uncertainties reduced the performance of some models, XGBoost and the neural network remained highly robust. Overall, this study demonstrates that machine learning can effectively support the classification of compact stars and emphasizes the importance of precise tidal-response measurements for constraining the dense-matter equation of state.

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