# Identifying Quark and Hadronic Compact Stars with Supervised Learning

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Compact stars are important astrophysical objects for studying the behavior of matter under extremely high-density conditions. However, their internal composition remains uncertain. One of the main challenges in this field is distinguishing hadronic neutron stars from quark stars, since both types of compact stars may produce similar mass–radius relations and can therefore be difficult to separate using standard observational quantities alone. In this study, machine learning methods and neural networks are used to classify compact stars according to their physical properties. The classification is based on features such as mass, radius, tidal deformability, Love number, and central pressure, which provide valuable information about the structure and tidal response of compact stars. The dataset used in the analysis consists of 39,920 stellar configurations generated from 3,992 equations of state. More specifically, it includes 2,048 hadronic models and 1,944 quark-matter models. The quark-star models are described using the MIT bag model and the Color–Flavor-Locked approach. This large and diverse dataset enables the algorithms to identify patterns that may help separate hadronic compact stars from quark compact stars. Several supervised learning algorithms are tested, including Random Forest, XGBoost, Decision Tree, and Logistic Regression, and their performance is compared with that of a feedforward neural network. Under ideal noise-free conditions, all methods show strong classification performance, while XGBoost, Logistic Regression, and the neural network achieve particularly high results in terms of accuracy, F1-score, and AUC. Feature-importance and ablation studies indicate that the Love number plays a key role in the classification process, highlighting the diagnostic importance of tidal-response observables. To examine the robustness of the models under more realistic conditions, uncertainties are introduced in mass and radius, while tidal deformability is reconstructed through a compactness–deformability relation that includes intrinsic scatter. Although these observational uncertainties reduce the performance of some classifiers, XGBoost and the neural network maintain strong predictive capability. Overall, the results suggest that machine learning can provide an effective framework for distinguishing between hadronic and quark compact stars.

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