This thesis focuses on the application of unsupervised machine learning techniques in the construction of phase diagrams for the Falicov-Kimball model, a paradigmatic system in condensed matter physics. Using dimensionality reduction methods such as PCA, t-SNE, autoencoders, and modern Hopfield networks has enabled the identification of distinct phases and transitions. The results will highlight the capability of machine learning to find complex patterns in high-dimensional spin data and, correspondingly, ordered, unordered, and weakly localized phases. These results therefore demonstrate the potential of a combination of physics-based models and computational approaches for making significant improvements in the studies of phase transitions in strongly correlated systems.