In this thesis, we examine two kinds of models of the primary visual cortex: a deep neural network for system identification and a spiking model of a cat's primary visual cortex. Further progress in modelling visual systems can help us comprehend the brain's inner workings in greater detail; moreover, it can help to develop better visual prosthesis or further improve models that handle visual inputs, such as those used for object classification. We employ the state-of-the-art deep neural network to predict the responses of the spiking model when presented with natural stimuli. We demonstrate that by tuning the hyperparameters, the deep neural network explains approximately 85% of the explainable variance observed in the responses of the spiking model. That is significantly more accurate than predictions of real neural responses, suggesting that real neurons possess certain characteristics not captured in the spiking model. However, we also argue that the network would not be capable of perfect predictions even when a large amount of data is provided. We show that the network encounters notable difficulties in modelling neurons with high noise and precisely predicting high firing rates. Furthermore, we analyse the network's representations by phase, orientation and size tuning. We illustrate that the modelled receptive fields of most layer IV neurons exhibit orientation and phase selectivity. Layer II/III neurons demonstrate orientation selectivity and more varying levels of phase invariance. This observation suggests the predominance of simple cells in layers IV and the presence of complex cells within layers II/III. A small number of neurons exhibit observable surround suppression. However, the neural network has difficulty accurately capturing the precise characteristics of size tuning.