Time series is a fundamental existing form for a large amount of data in the real world. To build reliable intelligent systems for enhancing the experience of such interactions, it is critical to design sophisticated machine learning algorithms for extracting robust time series features. Motivated by the successful application of deep learning in computer vision, more and more machine learning researchers put their attentions on the topic of applying deep learning techniques to time series data. However, directly employing current deep models to most time series domain could be problematic. A major reason is that the temporal pattern types that current deep models are aiming at are very limited, which cannot meet the requirement of modeling different underlying patterns of data coming from various sources. In this study we address this problem by designing different network structures explicitly based on specific domain knowledge such that we can extract features via most salient temporal patterns. More specifically, we mainly focus on two types of temporal patterns: order patterns and frequency patterns. For order patterns, which are usually related to brain and human activities, we design a hashing-based neural network layer to globally encode the ordinal pattern information into the resultant features. It is further generalized into a specially designed Recurrent Neural Networks (RNN) cell which can learn order patterns in an online fashion. On the other hand, we believe audio-related data such as music and speech can benefit from modeling frequency patterns. Thus, we do so from two aspects by developing two types of RNN cells. The first type tries to directly learn the long-term dependencies on frequency domain rather than time domain. The second one aims to dynamically filter out the 'noise' frequencies based on temporal contexts.