Traditional SLAM(Simultaneous Localization and Mapping) systems paid great attention to geometric information. Based on the solid foundation of Multi-view Geometry, a lot of excellent studies have been carried out. However, problems arise from none geometric modules in SLAM systems. To track the location of cameras, researchers usually perform pixel-level matching operations in tracking threads and optimize poses of a small number of frames as local mapping. No doubt that errors resulted by drift in pose estimation and map evaluation keep accumulating. In the meanwhile, Deep Learning, a data-driven technique, has brought out rapid development in numerous computer vision tasks such as classification and matching. Such achievements reflect that deep learning may be one of the best choices to solve problems related to data association. Therefore, more and more researchers believe that pixel- level or higher level associations between images, the bottleneck of SLAM systems we mentioned above, can also be handled with the help of neural networks. Deep learning has proved its superiority in SLAM systems. Many outstanding studies have employed it to replace some non-geometric modules in traditional SLAM systems [22, 21, 49, 26, 12]. These approaches enhance the overall SLAM system by improving only part of a typical pipeline, such as stereo matching, relocalization and so on. Some re- searchers also attempt to use higher-level features obtained through deep learning models as a supplement to SLAM [37, 35, 1, 6, 15]. These higher-level features are more likely to infer the semantic content-object feature and improve the capability of visual scene understanding. Moreover, end- to-end learning models have also been proposed [51, 16]. These methods outperform traditional SLAM algorithms under specific circumstances and demonstrate the potential of deep learning in SLAM. However, such combination of Deep learning and SLAM have significant shortcomings. Most of Deep Learning methods rely heavily on data used for training, which means that they cannot fit well into unknown environments. For example, we cannot ensure whether the room we want to explore is equipped with chairs and desks and cannot guarantee semantic priority of desks will help in this occasion. What’s more, most Deep-Learning enhanced SLAM systems are designed to reflect advantage of Deep Learning techniques and abandon the strong points of SLAM. As a result, they may sacrifice efficiency, an essential part of SLAM algorithms, for accuracy. Last but not least, some DL-based SLAM techniques take traditional SLAM systems as their underlying framework [49, 26, 12, 9] and make a great many changes to support Deep Learning strategies. Too many replacements may lead to loss of some useful features of the SLAM pipeline and also make it hard for researchers to perform further comparisons with existing studies, let alone migrate these techniques to other SLAM systems. As a result, DL- based SLAM is not mature enough to outperform traditional SLAM systems. Therefore, we make our efforts to put forward a simple, portable and efficient SLAM system. Our basic idea is to improve the robustness of local feature descriptor through deep learning to ensure the accuracy of data association between frames.