High dimensional spaces pose a serious challenge to the learning process. It is a combination of limited number of samples and high dimensions that positions many problems under the âcurse of dimensionalityâ , which restricts severely the practical application of density estimation. Many techniques have been proposed in the past to discover embedded, locally-linear manifolds of lower dimensionality, including the mixture of Principal Component Analyzers, the mixture of Probabilistic Principal Component Analyzers and the mixture of Factor Analyzers. In this paper, we present a mixture model for reducing dimensionality based on a linear transformation which is not restricted to be orthogonal. Two methods are proposed for the learning of all the transformations and mixture parameters: the first method is based on an iterative maximum-likelihood approach and the second is based on random transformations and fixed (non iterative) probability functions. For experimental validation, we have used the proposed model for maximum-likelihood classification of five âhardâ data sets including data sets from the UCI repository and the authorsâ own. Moreover, we compared the classification performance of the proposed method with that of other popular classifiers including the mixture of Probabilistic Principal Component Analyzers and the Gaussian mixture model. In all cases but one, the accuracy achieved by the proposed method proved the highest, with increases with respect to the runner-up ranging from 0.2% to 5.2%.