
**Abstract**

Researchers in the fields of neural networks, statistics, machine learning, and artificial intelligence have followed three basic approaches to developing new pattern classifiers. Probabilistic or statistical classifiers include Gaussian and Gaussian Mixture classifiers which estimate distributions of input features separately for each class. Neural network classifiers include multi-layer perceptrons with sigmoid nonlinearities and radial basis function networks. These classifiers typically estimate minimum-error Bayesian a posteriori probabilities simultaneously for all classes. Boundary forming classifiers include hard-limiting single-layer perceptrons, hypersphere classifiers, and nearest neighbor classifiers. These classifiers have binary indicator outputs which form decision regions that specify the class of any input pattern. Neural network and boundary-forming classifiers are trained using discriminant approaches which attempt to minimize overall classification error rates. Probabilistic classifiers are trained using maximum likelihood approaches which individually model class distributions without regard to overall classification performance. Analytic results are presented which demonstrate that neural networks can accurately estimate Bayesian a posteriori probabilities and that neural network classifiers can sometimes provide lower error rates than statistical classifiers using the same number of trainable parameters. These results suggest that neural network classifiers may be easier to apply to real-world problems because they are less sensitive to assumed underlying distributional forms than more conventional probabilistic approaches.