Automatic Modulation Classification Using Cumulants and Ensemble Classifiers

M. Venkata Subbarao and P. Samundiswary

1 Introduction

Security is the key issue in many communication applications especially for military applications. In contrast to this, the authorities of boarder security may wish to monitor unlicensed transmitters for jamming their signals [1]. The necessary action of doing so is to identify or recognize the modulation class of that intercepted signal. Such type of actions also arises in several other applications such as interference management, signal authorization, verification, and selection of appropriate demodulation techniques in electronic combat, threat analysis, and so on. Modulation recognition is also useful to recognize the suspicious transmitter in the near geographical site and to generate jamming signals to stop communication between the suspicious users. In recent civilian applications, a greater number of modulation formats can be employed by a transmitter to manage the data rate, to reduce the individual bandwidths of every user, and to assure the integrity of the message [2]. However, the group of modulation formats is known both to transmitter and receiver. The choice of the modulation format is adaptive and may not be known at the receiving end. Therefore, an AMC mechanism is required for the receiving end to recognize modulation format of the received signal and to select the proper demodulation approach in order to recover the original message. Moreover, in civilian applications, several techniques developed to reduce overhead of reference signals required for channel estimation have motivated the research in blind and semi-blind MIMO techniques [3].

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Blind techniques are also expected to play a role in software defined radio and cognitive radio. Configuration information required by a software defined radio system is transmitted as overhead to the data. Intelligent receivers capable of extracting this information blindly may improve transmission efficiency through reductions in overhead, i.e., automatic modulation classification eliminates the need for supplementary information on the modulation type [4].

AMC techniques are mainly classified into decision theoretic (DT) or maximum likelihood and feature-based (FB) or pattern recognition approaches. Some of the AMC approaches are tabulated in Table 1. From the literature, it is observed that many authors considered a basic modulation classes as a dataset. So that the accuracy achieved is about 90%. This paper performs AMC of higher order modulation classes.

Table 1 AMC techniques

Ref. No.	Approach type	Features used	Modulation type	Accuracy (%)
[5]	DT	Ratio of variance of envelope to square of mean	AM, FM, SSB, DSB	80–95
[6]	DT	Likelihood ratio of Phase	BPSK, QPSK	100
[7]	DT	Instantaneous amplitude and phase	AM, DSB, SSB, VSB, LSB, USB, FM	91–100
[8]	FB	Instantaneous amplitude, phase, freq, spectrum symmetry	ASK2, ASK4, PSK2, PSK4, FSK2, FSK4	97
[9]	DT	I-Q data	16QAM, 32QAM, 64 QAM	100
[10]	FB	Combination of spectral and higher order cumulant	QAM16, QAM64, ASK2, ASK4, PSK2, PSK4, FSK2, FSK4	98
[11]	FB	Power and cyclic spectral features	QPSK, PSK8, QAM8, 16QAM CW, FSK2, FSK4, FSK8, ASK4, BPSK	94.9
[12]	DT	Moments	PSK4, PSK8, QAM16 ASK4, ASK8, FSK4, BPSK,	89.76
[13]	FB	Moments of wavelet	ASK4, ASK8, PSK8, QAM16,32, 64, FSK4, BPSK, PSK4	98
[14]	FB	Energy of signal, zero crossing rate, variance	ASK4, ASK8, PSK8, QAM16, 32, 64 FSK4, BPSK, PSK4	91
[15]	FB	Two stage classification	BPSK, QPSK, QAM16 & 64	70–100
[16]	DT	Cumulants	16 QAM, 64 QAM, BPSK, QPSK & 8 PSK	50–90

Organization paper is as follows: Sect. 1 describes about the scenario of existing wireless communication systems and their current challenges. Also, an elaborate study on existing different AMC techniques is presented. Section 2 deals with the extraction of different higher order statistical features and framework of PR approach. Section 3 presents the development of PRC for AMC algorithms using ensemble classifiers. Section 4 deals with the performance analysis of proposed ensemble-based PRCs under non-ideal channel conditions. Section 5 depicts the important surmises of the research work.

2 Framework

The functional block diagram representation of proposed PR classification model is shown in Fig. 1. In order to classify the modulation classes, a set of features are extracted from each class. The set of features are considered in the proposed approach are cumulants, and they are extracted from the moments.

The received signal $y(n)$ by a communication receiver is

$$y(n) = \mathrm{M}e^{i(2\pi nTf_o+\theta_n)} \sum_{l=-\infty}^{\infty} x(l)h((n-l+\epsilon)T) \tag{1}$$

where T is duration of the symbol, M is the magnitude, θ_n is phase shifts and ε is time shifts caused by the channel. $h(n)$ is channel impulse response, and $x(l)$ is input binary data.

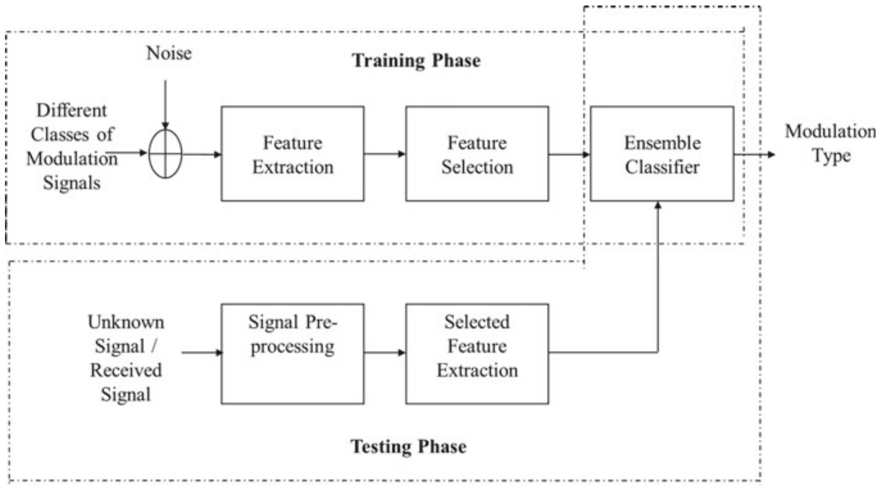

Fig. 1 Proposed classification model

The moments of signal $y(n)$ are

$$M_{ab} = E\left[y(n)^{a-b} y^*(n)^b\right] \tag{2}$$

Here, a and b are integers. $y(n)$ and $y^*(n)$ are received signal and *its* conjugate.

Multi-Order moments (for $a=$ 2, 4, 6 and 8) are derived from Eq. 2. To train the classifier a set of 11 cumulants of order 2, 4, 6 and 8 are derived from the moments [17].

3 Ensemble Classifiers

The performance of PR classifiers such as DT, KNNs, and SVMs is varied across different data sets because of their strategy in classification. Prediction of best model for all data sets is not at all possible for all the time. Keeping this in mind, the proposed classifiers are built with a combination of various classes of classifiers to achieve better accuracy than individuals. It works on a principle of majority vote, i.e., initially individual classifiers identified the class of unknown signal and finally ensemble classifiers identify the majority vote, and gives the class label for unknown signal. An ensemble classifier contains a set of independently trained classifiers whose predictions are pooled when recognizing new object. The block diagram representation of an proposed classifier is shown in Fig. 2 [17].

In this paper, a varity of classifiers are used for AMC. These are boosted trees, bagged tress, subspace KNN, RUSBoosted trees, and discriminant KNN. Boosted trees and bagged are constructed from decision trees, and these are slower in speed.

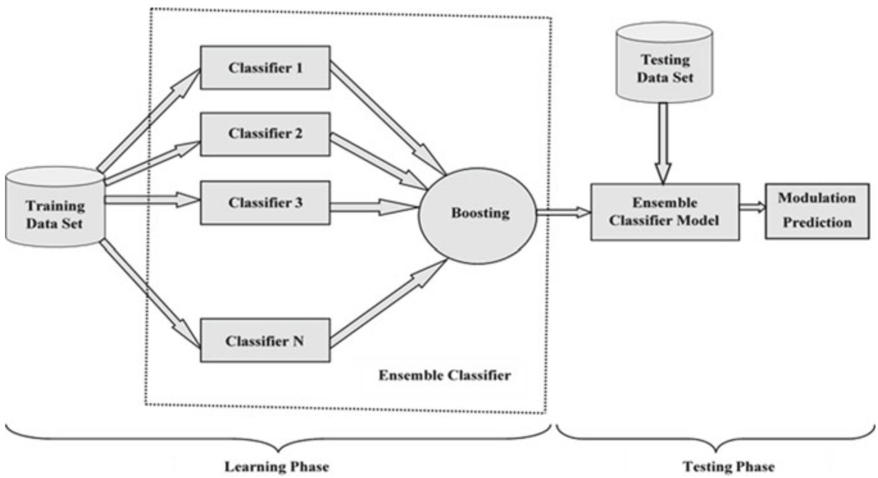

Fig. 2 Ensemble classification model

Whereas, discriminant KNN and subspace KNN both used nearest neighbors and discriminant analysis. Based on random undersampling, weak learners are boosted in RUSBoosted trees.

4 Simulation Results

In this section, the performance analysis of proposed ensemble-based PRCs is carried out under SNR of 0 dB to 20 dB with modulation classes of M-ary QAM ($M = 4$, 16 and 64) and M-ary PSK ($M = 2$, 4 and 8). The simulation parameters are tabulated is shown in Table 2.

The performance of five ensemble classifiers is tested with different SNR conditions. Table 2 represents the confusion matrix for different ensemble classifiers using multi-order cumulants at different SNRs. Diagonal elements in the confusion matrix denote the true classification rates, and off diagonal elements represent misclassification rates. From Table 3, it is proved that the proposed ensemble classifiers are able to distinguish the different modulating classes at low SNR than that of existing classifiers.

The performance accuracy of boosted tree classifier for different modulation classes with different SNR values is shown in Fig. 3. The average modulation classification accuracy of boosted tree from 0 dB to 20 dB is 81.7%, 95%, 98.3%, 98.9%, and 100%, respectively.

The classification performance of proposed bagged tree classifier with 90% training is shown in Fig. 4. At 0 dB, the average classification accuracy of bagged tree classifier is 81.7%. The classification performance of proposed subspace discriminant classifier with 90% training is shown in Fig. 5. At 0 dB, the average classification accuracy of subspace discriminant classifier is 77.8%.

The classification performance of proposed subspace KNN classifier with 90% training is shown in Fig. 6. At 0 dB, the accuracy of subspace KNN is 72.2% because the classifier is unable to distinguish higher order modulation classes at lower SNR values.

Table 2 Simulation parameters

Parameters	Description
Modulation types	MQAM ($M = 4$, 16 and 64), MPSK ($M = 2$, 4, 8)
Channels	Fading and Gaussian
SNR	0–20 dB
Data set	6000 * 11 (11 features, 1000 of each class)
Data set for training	50-90%
Data set for testing	10-50%

Table 3 Confusion matrix of proposed ensemble classifiers with 90% training

Classifier	True class	SNR																													
		0						5						10						15						20					
Boosted trees	BPSK	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0
	QPSK	0	97	0	0	0	3	0	97	0	0	3	0	0	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0	0	0
	8PSK	0	0	84	0	3	13	0	0	97	0	3	0	0	0	100	0	0	0	0	0	97	0	3	0	0	0	100	0	0	0
	4QAM	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0
	16QAM	0	0	33	0	30	37	0	0	0	0	87	13	0	0	3	0	90	7	0	0	0	0	100	0	0	0	0	0	100	0
	64QAM	0	3	10	0	7	80	0	0	0	0	10	90	0	0	0	0	0	100	0	0	0	0	3	97	0	0	0	0	0	100
Bagged trees	BPSK	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0
	QPSK	0	97	0	0	3	0	0	97	0	0	0	3	0	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0	0	0
	8PSK	0	0	83	0	7	10	0	0	97	0	3	0	0	0	100	0	0	0	0	0	97	0	3	0	0	0	100	0	0	0
	4QAM	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0
	16QAM	0	0	30	0	50	20	0	0	0	0	90	10	0	0	3	0	90	7	0	0	0	0	100	0	0	0	0	0	100	0
	64QAM	0	3	10	0	27	60	0	0	0	0	10	90	0	0	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0	100
Subspace discriminant	BPSK	97	3	0	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0
	QPSK	0	93	0	0	0	7	0	93	0	0	0	7	0	100	0	0	0	0	0	97	0	0	0	3	0	100	0	0	0	0
	8PSK	0	0	80	0	17	3	0	0	97	0	3	0	0	0	100	0	0	0	0	0	97	0	3	0	0	0	100	0	0	0
	4QAM	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0
	16QAM	0	0	47	0	30	23	0	0	0	0	90	10	0	0	3	0	84	13	0	0	0	0	90	10	0	0	0	0	100	0
	64QAM	0	6	7	0	20	67	0	0	0	0	17	83	0	0	0	0	10	90	0	0	0	0	0	100	0	0	0	0	0	100
Subspace KNN	BPSK	97	3	0	0	0	0	97	3	0	0	0	0	97	0	0	0	0	3	97	3	0	0	0	0	100	0	0	0	0	0
	QPSK	13	77	4	0	3	3	0	90	0	0	0	10	0	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0	0	0
	8PSK	0	3	63	4	23	7	0	0	90	0	10	0	0	0	97	0	3	0	0	0	97	0	3	0	0	0	100	0	0	0
	4QAM	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0
	16QAM	3	0	27	0	40	30	0	0	4	0	73	23	0	0	0	0	93	7	0	0	3	0	90	7	0	0	0	0	100	0
	64QAM	0	13	0	0	27	57	3	0	4	0	23	70	0	0	0	0	10	87	0	0	0	0	7	93	0	0	0	0	0	100

(continued)

Table 3 (continued)

Classifier	True class													SNR																	
		0						5						10						15						20					
RUSBoosted trees	BPSK	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0
	QPSK	0	93	0	0	0	7	0	97	0	0	0	3	0	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0	0	0
	8PSK	0	0	73	0	14	13	0	0	97	0	3	0	0	0	100	0	0	0	0	0	97	0	3	0	0	0	100	0	0	0
	4QAM	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0	0	0	0	100	0	0
	16QAM	0	0	23	0	40	37	0	0	0	0	87	13	0	0	3	0	90	7	0	0	0	0	97	3	0	0	0	0	100	0
	64QAM	0	7	10	0	3	80	0	0	0	0	10	90	0	0	0	0	0	100	0	0	0	0	3	97	0	0	0	0	0	100

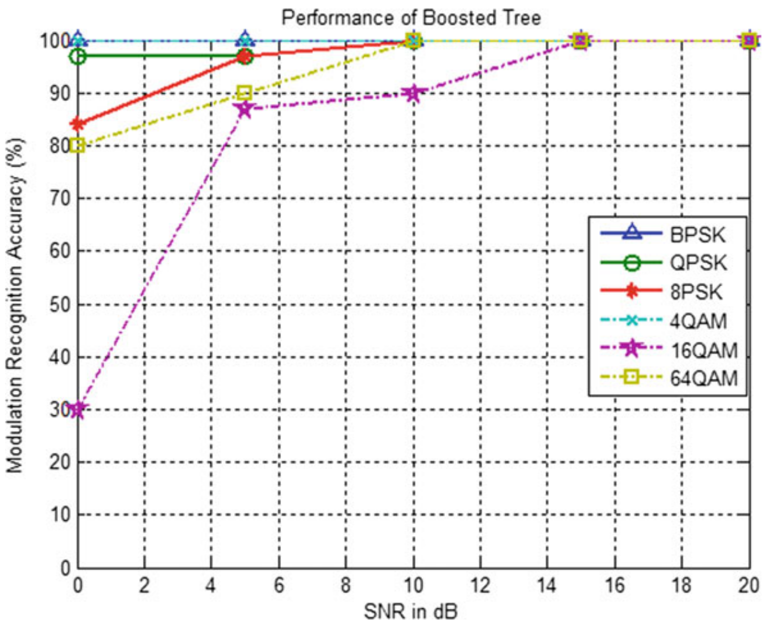

Fig. 3 Performance of boosted tree classifier

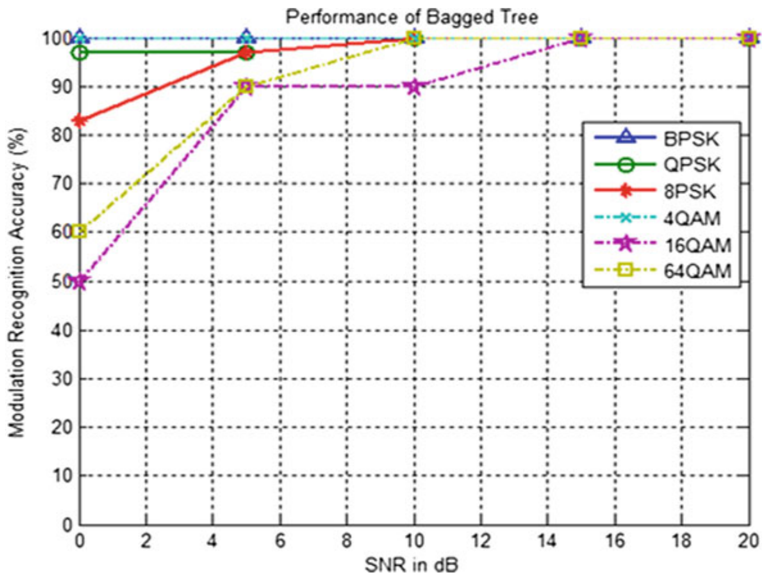

Fig. 4 Performance of bagged tree classifier

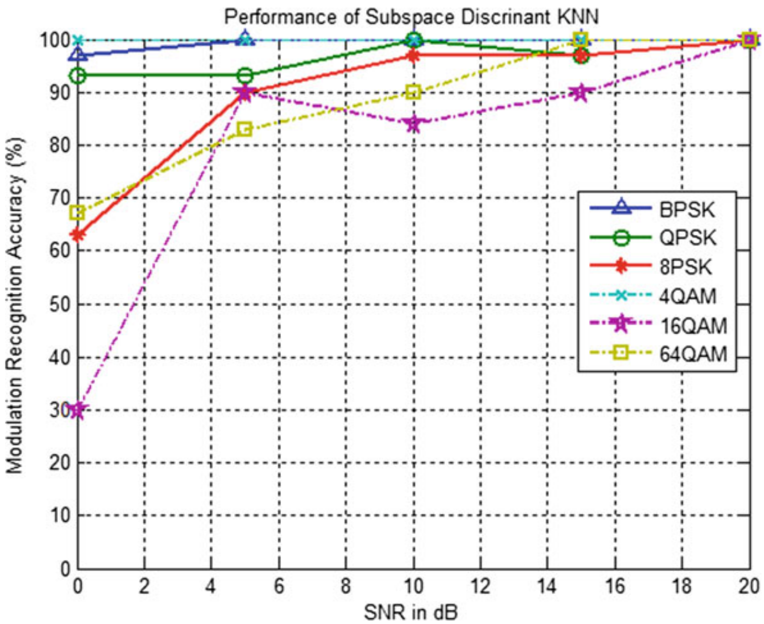

Fig. 5 Performance of subspace discriminant KNN classifier

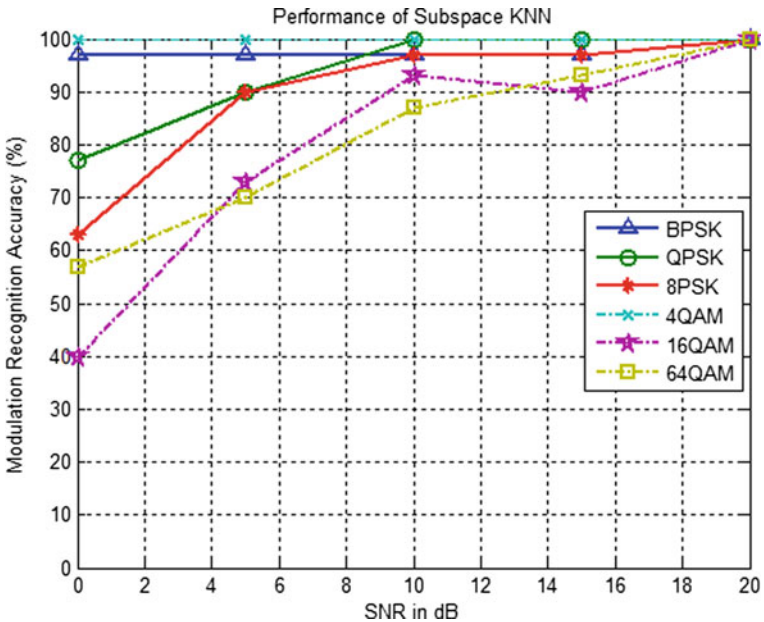

Fig. 6 Performance of subspace KNN classifier

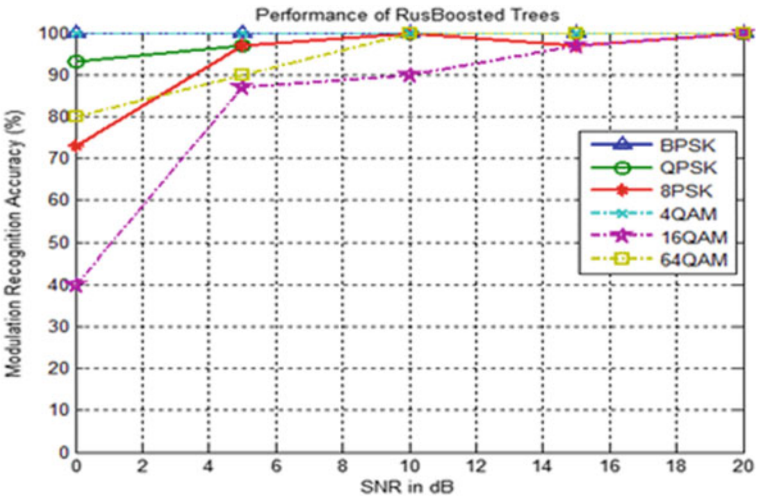

Fig. 7 Performance of RUSBoosted tree classifier

The classification performance of proposed RUSBoosted tree classifier with 90% training is shown in Fig. 7. At 0 dB, the average classification accuracy of RUSBoosted tree is 81.1%. From simulations, bagged, boosted, and RUSBoosted tree classifiers have higher classification accuracy than others.

At different training rates, the performance of ensemble classifiers is tabulated in Table 4. It is showed that the accuracy of classifiers is higher even at high testing rates. Among all the classifiers, bagged tree classifier has the highest accuracy.

5 Simulation Results

In this paper, a varity of ensemble classifiers is developed for AMC. Thereafter, performance of proposed ensemble classifiers is analyzed under non-ideal channel conditions with various values of SNR along with different cases of training. Further, performance of proposed ensemble classifiers is compared with the existing approaches to prove the efficiency of the proposed classifiers in modulation recognition. From the simulation results, it is proved that even with more classes the proposed ensemble classifiers achieve more classification accuracy even at lower SNRs.

Table 4 Performance at different training rates

Training %	Classifier	Classification accuracy (%)				
		0 dB	5 dB	10 dB	15 dB	20 dB
80	Boosted Trees	81.2	94.6	99.2	99.5	100
	Bagged Trees	81.2	95.2	99.3	99.3	100
	Subspace Discriminant KNNs	77.5	93.4	96.8	97.5	100
	Subspace KNNs	71.6	86.2	96.0	96.9	100
	RUSBoosted trees	80.8	94.7	98.8	98.7	100
70	Boosted trees	80.4	94.1	98.8	99.2	100
	Bagged trees	80.3	94.8	99.1	99.3	100
	Subspace discriminant KNNs	76.2	93.1	96.2	97.4	100
	Subspace KNNs	71.1	85.4	95.8	96.4	100
	RUSBoosted trees	79.9	94.2	98.3	98.2	100
60	Boosted trees	80.1	93.8	98.3	99.1	100
	Bagged trees	80.1	94.1	98.7	99.5	100
	Subspace discriminant KNNs	75.7	92.5	95.6	97.7	100
	Subspace KNNs	70.9	85.4	95.2	96.5	100
	RUSBoosted trees	79.8	93.9	97.9	98.6	100
50	Boosted trees	79.8	93.3	98.1	98.9	100
	Bagged trees	79.8	93.7	98.2	99.3	100
	Subspace discriminant KNNs	75.4	92.1	95.6	97.2	100
	Subspace KNNs	70.1	85.3	95.1	96.2	100
	RUSBoosted trees	79.2	93.7	96.8	98.6	100

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