Table 6 shows the comparison of our CAD system with previous work done on the basis of type of classes considered, classifiers, databases, type of MRI images, performance measures used to detect MS lesion and brain tumor. Following abbreviations are used in this table: DSC- Dice Similarity Index, TPF- True Positive Factor, FPF- False Positive Factor, FD- False Detection, PPV - Positive Predictive Value and EDSS- Expanded Disability Status Scale.

Table 6. Comparison of Our CAD system with previous work done

Author	Classes	MRI images	Method	Measures	Result	Database
A. A. Ballin et al. [1]	lesion & non lesion (MS)	PD, T1, T2, FLAIR	Decision Forest	Accuracy	0.98 ± 0.01	Scientific Institute Ospedale San Raffaele
				Sensitivity	0.57 ± 0.14	
				Specificity	0.99 ± 0.01	
				DSC	0.55 ± 0.09	
				FPF	0.39	
C. P. Loizou et al. [4]	EDSS ≤ 2 and EDSS > 2 (MS)	T2	SVM	correct rate	0.86	Ayios Therissos Medical Diagnostic Center
				Sensitivity	0.79	
				Specificity	0.90	
C.Elliot et al.[5]	lesion and non- lesion (MS)	T1, T2, FLAIR, T1	Bayesian classifier	Sensitivity at FD rate=0.1	0.83 ± 0.08	NA
				Sensitivity at FD rate=0.2	0.89 ± 0.05	
P. K. Roy et al.[6]	lesion and non- lesion (MS)	T1, T2, FLAIR	SVM (linear kernel	mean F1 score	0.5	MS Lesion Segmentation Challenge 2008 dataset
				No. of win, drawn and loss (W;D;L)	20;0;4	
Zahra K. et al. [8]	Lesion and non- lesion (MS)	PD, T1, T2, FLAIR	Conditional Random Fields (CRF)	Sensitivity	0.98	multicenter clinical data set
				Average FP No.	2.43	
M. Nazari et al. [10]	Normal, Tumor and MS class	T2	Support Vector Machine (SVM)	Accuracy for Normal	95%	Harvard Medical School website
				Accuracy for Tumor	84%	
				Accuracy for MS	100%	
Sahar Jafarpour et al. [11]	Normal, Tumor and MS class	T2	MNN and K-Nearest Neighbor	Accuracy for MS	92.86%	Laboratory of Neuro Imaging (LONI)and Harvard Medical School
				Accuracy for Normal and tumor	100%	
M. Maleki et al. [12]	Normal and MS MRI	FLAIR	multilayer neural network (MNN)	Accuracy	92.6%	-
				Sensitivity	92.13%	
				Specificity	84.12%	
Petronella Anbeek [14]	MS lesion and non-lesion	T1 and FLAIR	K-Nearest Neighbor		All Average	MS Lesion Segmentation Challenge 2008
				Sensitivity	50.92%	
				Specificity	97.39%	
				PPV	67.26%	
Our CAD system	MS and Normal	T2	K-NN	Accuracy (K = 9)	98.25%	MS Lesion Segmentation Challenge 2008 dataset [15] + Harvard Medical School data + data from hospitals in India
			SVM	Accuracy (Linear Kernel)	100%	
			Ada-Boost	Accuracy (T=27)	100%	
	MS and Tumor		K-NN	Accuracy (K = 5)	100%	
			SVM	Accuracy (Polynomial order =5)	100%	
			Ada-Boost	Accuracy (T=48)	100%	
	Benign and Malignant		K-NN	Accuracy (K = 1)	100%	
			SVM	Accuracy (Linear Kernel)	100%	
			Ada-Boost	Accuracy (T=33)	100%	

Table 7 presents the performance of each classifier for all 3 models for set of test images collected from the different hospitals in India (True Labels are in "Blue" Color and misclassification labels are in "Red" color):

Table 7. Test Image results

Model			Images									
			1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
MS and Normal	True Labels >>		**MS**	**MS**	**MS**	**MS**	**MS**	**N**	**N**	**N**	**N**	**N**
	K-NN	k=1	MS	MS	MS	MS	MS	N	N	N	N	N
	SVM	Poly-5	MS	MS	MS	MS	MS	N	N	N	**MS**	**MS**
	Ada-Boost	T= 8	MS	MS	MS	MS	MS	N	N	N	N	N
MS and Tumor	True Labels >>		MS	MS	MS	MS	MS	T	T	T	T	T
	K-NN	k=1	MS	MS	MS	MS	MS	T	T	T	T	**MS**
	SVM	Poly-5	MS	MS	MS	MS	MS	T	T	T	T	T
	Ada-Boost	T= 66	MS	MS	MS	MS	MS	T	T	T	T	**MS**
Benign and Malignant	True Labels >>		B	B	B	B	B	M	M	M	M	M
	K-NN	k=1	**M**	**M**	B	B	B	**B**	M	M	M	M
	SVM	Linear	B	B	B	B	B	**B**	M	M	**B**	M
	Ada-Boost	T= 46	B	**M**	B	B	**M**	**B**	M	M	**B**	M

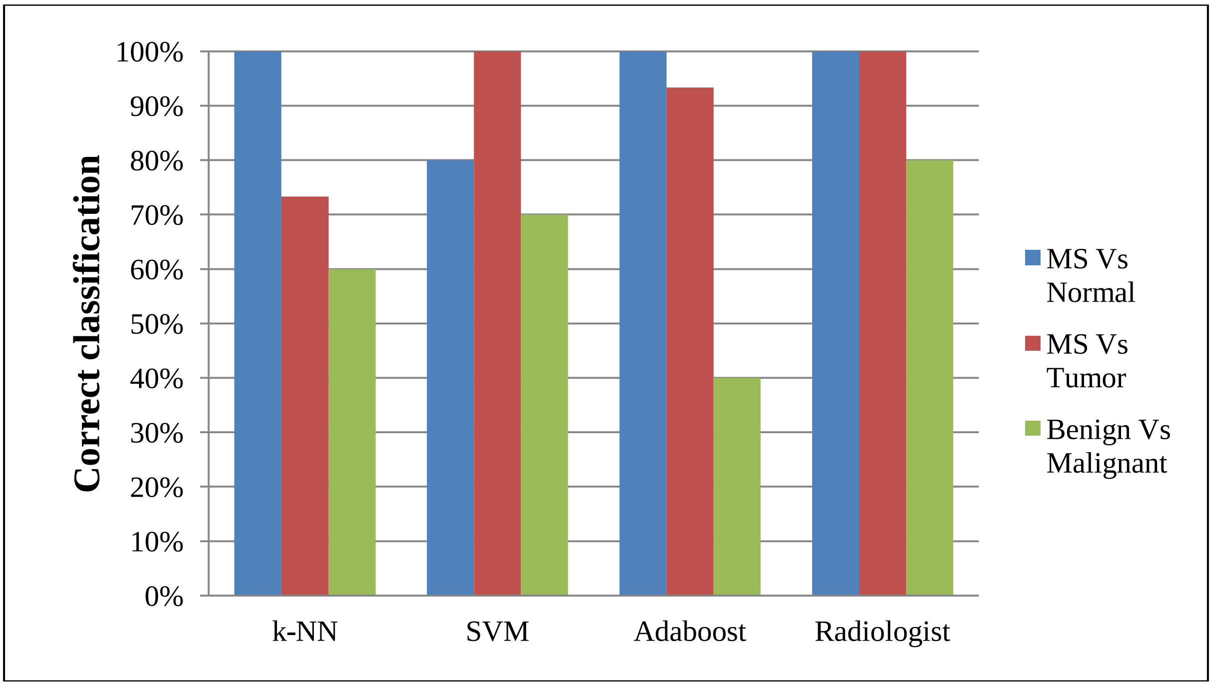

Figure 1. Comparison of Test results and radiologist feedback

6. Discussions

As can be seen Table 3 SVM gives better performance than K-NN and Ada-boost for classification of MS and Normal images. Table 4 shows that all 3 classifiers gives 100% accuracy with K-fold = 9. However SVM classifier with polynomial of order = 5 and RBF at sigma = 1 gives better performance than K-NN and Ada-boost for classification of MS and tumor images. Also, from Table 5, SVM classifier with linear kernel gives better performance than K-NN and Ada-boost for classification of Benign and Malignant Tumor images. Table 6 shows that the CAD system implemented in this work outperforms the previous systems implemented. As can be seen in Table 7, K-NN classifier with K=1 and Ada-boost with 8 number of iterations gives best performance than SVM for ‘MS and Normal’ model in terms of comparing the assigned label to the test image by the specified classifier with respect to the truth label. SVM gives better performance than K-NN and Ada-boost classifiers for model ii and iii. The above test scans are also shown to radiologist and the comparison is presented in Figure 1; which shows the performance of CAD system using SVM is better for all 3 models under consideration as compared to K-NN and Ada-boost.

7. Conclusion

The CAD system for efficient classification of the human brain MR images into MS and Normal, MS and Tumor or Benign and Malignant has been implemented with the three learning algorithms with minimum number of features.

For all 3 models the classification accuracy is 100% as compared to previous work in this field. For test images the developed CAD system has done equally well as that of the radiologist. SVM proved to be best among three classifiers used in this automated diagnosis system.

This work presents significant contribution in the field of automatic classification of brain MRI using different models proposed. Such system can be proved to be helpful to radiologist and particularly to trainee or new reader to identify MS or tumor lesions with improved accuracy.

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