e-ISSN: 0976-516
p-ISSN: 2231-385

- Roughness(Rg) computes the spectrum's peaks and takes the average of all dissonance between all possible pairs of peaks.
- Irregularity(Ir) gives degree of variation of the successive peaks of the spectrum.
- The flatness(Fl) indicates whether the distribution is smooth or spiky. It calculates ratio between the geometric mean and the arithmetic mean given by Eq.6.

$$Fl = \frac{\sqrt[N]{\prod_{n=0}^{N-1} y(n)}}{\left(\frac{\sum_{n=0}^{N-1} y(n)}{N}\right)} \tag{6}$$

- Mel-frequency cepstral coefficients (MFCC) represent the spectral shape of a sound with a small number of cooeficients. The cepstrum is the Fourier Transform of the spectrum's logarithm. The Mel-cepstrum is the cepstrum computed using Mel-bands rather than the Fourier spectrum shown in Figure 2.First 13 features of MFCC have been considered for experiment.

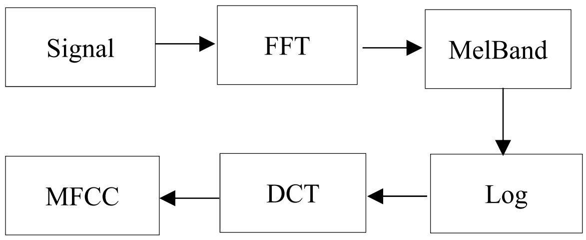

Fig. 2. MFCC formulation

Statistical information is also extracted like min, max, mean, standard deviation, dynamic range, entropy, crest factor included in feature set.

3.3. *Feature Selection*

One of the most important steps before classification is feature selection. Filter methods [Bommert *et al.* (2020)] are useful for reducing the number of features in a small dataset .The filter approach was used to select features. Two methods are used to filter out the least significant features and select the most prominent ones: multivariate analysis of variance (MANOVA) and chi-squared test [McHugh (2013)] features. The top five distinguishing features have been identified.

- ***One-way Multivariate analysis of variance (MANOVA)***

It is used to measure difference between one continuous dependent variable and one independent grouping variable. The F value and p scores are computed. The F value measure defines whether or not the means of different samples differ significantly.

Sum of squares between group ($SS_{betwween}$) is calculated as

$$SS_{betwween} = \sum_{i=1}^{k} n_k(\bar{X}_\imath - \bar{X}_G)^2 \tag{7}$$

where X_i is sample means and X_G is grand mean

Mean Squares between group ($MS_{betwween}$) is calculated by

$$MS_{betwween} = SS_{betwween} / k - 1 \tag{8}$$

where k-1 is degree of freedom

Sum of squares within group (SS_{within}) is calculated by Eq.(9)

$$SS_{within} = \sum(X_{ij} - \bar{X}_j)^2 \tag{9}$$

Mean Squares within group (MS_{within}) is calculated by

$$MS_{withinn} = SS_{within} / N - k \tag{10}$$

where N-k is degree of freedom N =sum of the sample sizes k= number of samples

$$\text{F } \boldsymbol{value} = \boldsymbol{MS_{between}} / \boldsymbol{MS_{within}} \tag{11}$$

Features whose F value is high and p-value less than 0.05 are given importance .

- ***Chi-squared test***

The chi-squared test calculates scores for each feature which gives how much difference exists between your observed output and the actual output given in below Equation 12 . A **low value** for chi-square means there is a high correlation between feature and output.

$$x_d^2 = \sum (Obs_i - Exp_i)^2 / Exp_i \tag{12}$$

where d is degree of freedom, Obs is observed output and Exp is expected output.

3.4. *SVM Classification*

The goal of SVM is to separate data points by hyper plane and using kernel trick extends nonlinear boundaries of hyper plane. Accordingly SVM, find support vectors i.e. points that are close to both the classes. In the next step, find the nearness of support vectors with dividing plane. The margin is the distance between the points and the dividing line. The purpose of an SVM algorithm is to maximize margin[Liu *et al.* (2010)]. Maximum margin means hyper plane is optimal. Selection of proper kernel enhances the performance of SVM.

Kernel transforms input data into high dimensional feature space. In the new feature space data is easily separable. There are different types of kernel functions are available. In this paper, experimentation has been carried out using *linear, radial basis function (RBF) and quadratic(Quad) kernels.*

Linear kernel : It is the most basic type of kernel, usually one dimensional in nature.

$$F(x_i, x_j) = \sum x_i \,.\, x_j \tag{13}$$

Where x_i , x_j are data points and . is dot product

Gaussian Radial Basis Function (RBF) :

$$F(x_i, x_j) = exp(-gamma\left\|(x_i - x_j)\right\|^2) \tag{14}$$

The value of gamma varies from **0 to 1**.

Quadratic Function :

$$F(x_i, x_j) = (x_i \,.\, x_j + 1)^2 \tag{15}$$

Multi class classification is accomplished by one versus one approach in SVM.

4. Experiments and Results

4.1. *Experimental setup*

Database composed of monophonic recordings of Indian string instruments. The majority of the recordings are from commercial CDs. Each sample is 5 seconds long. Pre - processing stage removes the silence at the beginning and end of the audio. Audio features are extracted based on their temporal, spectral, and statistical properties. Max-Min normalisation is used to normalise features. In the case of negative values, the absolute of the minimum negative value is added to each value of that feature, and then Min-Max normalisation is applied.

MANOVA and the Chi-Square test are used to identify significant features, which are then classified using SVM. The method of 5 fold cross validation is used. The model is trained with 70% of the samples and tested with 30% of the samples.

- **Experiment 1 : Feature Selection using One-way MANOVA method**

To identify the top five prominent features, the one-way -MANOVA [Steyn and Ellis (2009)] method is used. Features with a high F value and a low p value are chosen. Table 1 and Table 2 show the statistics for the top five selected features: The highest F value was obtained for the mean feature. In the first five, only 4^{th} and 8^{th} coefficient of MFCC got selected.

Top 5 Features	***Type***	***F***	***P value***
Mean	Statistical	981.0082	1.9E-149
Flatness(Fl)	Spectral	279.0453	5.95E-90
MFCC-4th Coefficient(M4)	MFCC	271.8336	8.16E-89
MFCC-8th Coefficient(M8)	MFCC	182.3868	3.25E-72
Standard Deviation(Std)	Statistical	176.3588	6.93E-71

Table 1. One-way MANOVA-Top 5 Features with MFCC

Top 5 Features	***Type***	***F***	***P value***
Mean	Statistical	981.0082	1.9E-149
Flatness	Spectral	279.0453	5.95E-90
Standard Deviation	Statistical	176.3588	6.93E-71
Spectral Spread(Ss)	Spectral	166.1547	1.48E-68
Spectral Rolloff(Sr)	Spectral	162.5816	1.02E-67

Table 2. One-way MANOVA-Top 5 Features without MFCC

After forming a vector of the top five features and training an SVM classifier model, new samples are classified. Figure 3 represents the average accuracy obtained using selected features.

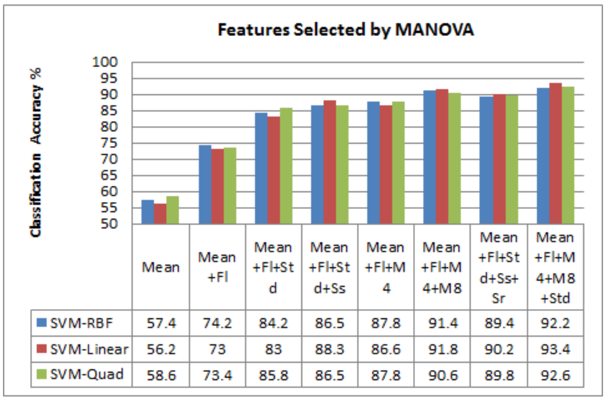

Fig. 3. SVM Average Accuracy(%) for MANOVA-Selected Features

- **Experiment 2: Feature Selection using Chi-square test**

Tables 3 and Table 4 show the top five features based on the Chi-square test. Among the first five features, the 4th coefficients of MFCC (out of 13 coefficients) are chosen using Chi-square.

Top 5 Features	***Abbreviation***	***Type***
Mean	Mean	Statistical
Flatness	Fl	Spectral
Zero crossing rate	Zc	Time
MFCC-4th Coefficient	M4	MFCC
Spectral Rolloff	Sr	Spectral

Table 3. Chi-square-Top 5 Features with MFCC

Feature	*Abbreviation*	*Type*
Mean	Mean	Statistical
Flatness	Fl	Spectral
Zero crossing rate	Zc	Time
Spectral Rolloff	Sr	Spectral
Standard Deviation	Std	Statistical

Table 4. Chi-square-Top 5 Features without MFCC

The average accuracy obtained by SVM classifiers using different kernels for Chi-square selected features is shown in Figure 4.

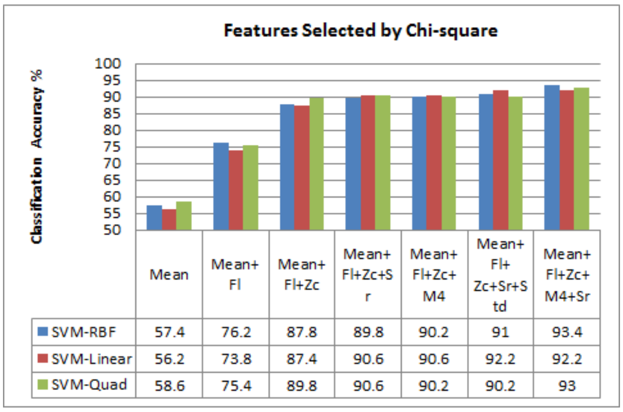

Fig. 4. SVM average accuracy(%) for Chi-square selected features

- **Experiment 3: Feature Selection using Category**

In this experiment, we have explored features by their type. A set of features is grouped by type (as shown in table 5) and then given to SVM classifier.

Type	**No. of features**	**Feature Name**
Temporal Feature	1	Zero Crossing Rate
Statistical Features	7	Mean, Min, Max, Standard Deviation, Dynamic range, Crest Factor, Entropy
Spectral Features	9	Spectral Rolloff-85% and 95% , Spectra Spread, Spectral Centroid, Flatness, Brightness, Roughness, Irregularity, Kurtosis
Mel-frequency cepstral coefficient (MFCC)	13	1 to 13 coefficients

Table 5. Category wise features

Category wise classification accuracy (%) is shown in Figure 5.

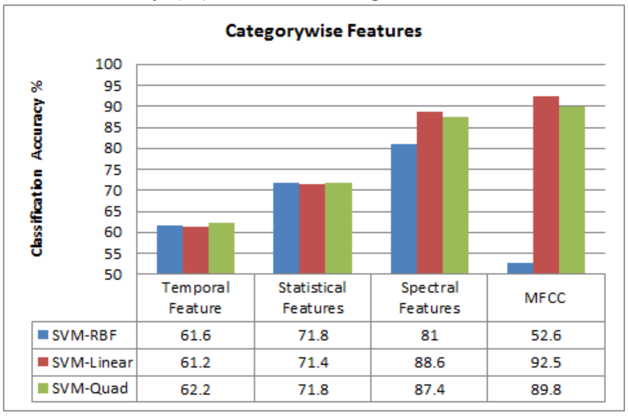

Fig. 5. SVM average accuracy(%) for category wise selected features

MFCC has given highest accuracy 92.5% using SVM linear kernel

5. Conclusion

In this paper, three experiments were conducted to assess the impact of feature selection using filter approach using statistical methods such as MANOVA and Chi-square test and SVM kernels to classify Indian string instruments. Total 30 audio features including temporal, spectral, statistical and MFCC were extracted and used for experiments. Before classification, 25 of the 30 features are filtered, and only the top 5 are chosen Both methods have a diverse set of selected features. In MANOVA, features selected are Mean, Flatness,MFFCC 4th and 8th coefficient and standard deviation whereas in Chi-square, Mean, Flatness, Zero crossing rate, MFCC 4th coefficient and spectral rolloff with 85 frequency are selected as a prominent features. Similarly, without the MFCC 13 coefficients, 17 features are considered, and significant features are identified, notably, in MANOVA, mean, flatness, standard deviation, spectral spread, and spectral rolloff, and in Chi-square, mean, flatness, zero crossing rate, spectral rolloff, and standard deviation. SVM classifier was used to validate the impact of feature selection.

In experiment 1, the top five features with MFCC and SVM classifier using Linear kernel gave the highest accuracy of 93.4 % and without MFCC 90.2 %. In experiment 2, the top 5 features with MFCC and SVM classifier with radial basis kernel achieve 93.4 % highest accuracy, while the top 5 features without MFCC and SVM with linear kernel achieve 92.2 % highest accuracy. In experiment 3, a set of features is classified according to their type. The 13 MFCC coefficients achieve the highest accuracy of 92.5 %.

Although the results show that the filter approaches Chi-square and MANOVA have nearly the same accuracy for combining all top 5 features, the features ranked by chi-square are more significant than MANOVA. After examining the confusion matrix, it was discovered that Guitar and Santoor instruments are rarely misclassified with the remaining instruments, with the exception of Sitar, Sarod, and Veena, which have a high misclassification rate with each other.

References

[1] Ashwini and K. A. Vijaya(2020). Feature Selection For Indian Instrument Recognition Using SVM Classifier. International Conference on Intelligent Engineering and Management (ICIEM), pp. 277-280. DOI: 10.1109/ICIEM48762.2020.9160223.
[2] Bosch Juan J., Jordi Janer, Ferdinand Fuhrmann and Perfecto Herrera(2012). A Comparision of Sound Segregation Techniques for Predominant Instrument Recognition in Musical Audio Signals. International Society for Music Information RetrievalConference
[3] Bommert Andrea, Xudong Sun, Bernd Bischl, Jörg Rahnenführer, Michel Lang(2020). Benchmark for filter methods for feature selection in high-dimensional classification data. Computational Statistics & Data Analysis,Volume 143. DOI: 10.1016/j.csda.2019.106839.
[4] Chandan S. V, M. R. Naik, Ashwini and A. V. Krishna(2019). Indian Instrument Identification from Polyphonic Audio using KNN Classifier. International Conference on Wireless Communications Signal Processing and Networking (WiSPNET), pp. 135-139. DOI: 10.1109/WiSPNET45539.2019. 9032860.
[5] Chen Shi-Huang , Chen Shih-Hao(2009). Content-based Music Genre Classification Using TimbralFeature Vectors and Support Vector Machine. ICIS,ACM
[6] Elaiyarajaa V., P. Meenakshi Sundaramb(2012). Audio Classification Using Support Vector Machines and Independent Component Analysis.Journal of Computer Applications (JCA),ISSN: 0974-1925, Volume V, Issue 1.
[7] Ghosal Arijit, Suchibrota Dutta and Debanjan Banerjee(2020). Classification of Speech and Song Using Co-occurrence-Based Approach. Computational Intelligence in Pattern Recognition,Advances in Intelligent Systems and Computing,Springer Nature,pp-138-146. DOI- 10.1007/978-981-13-9042-5_11
[8] Joder Cyril, Slim Essid, and Gaël Richard(2009). Temporal Integration for Audio Classification With Application to Musical Instrument Classification. IEEE Transactions on Audio, Speech and Language Processing, vol. 17, NO. 1.
[9] Joshi Swarupa, Chitre Abhijit(2015). Identification of Indian Musical Instruments by Feature Analysis with Different Classifiers. International Conference on Computer and Communication Technology,ACM, pp 110–114. DOI-10.1145/2818567.2818588
[10] Kakarwal Sangeeta, Chaudhary Seema R(2020). Analysis of Musical String Instruments using k-NN.IEEE International Conference on Smart Innovations in Design, Environment, Management, Planning and Computing
[11] Kothe R.S, D.G.Bhalke,P.P.Gutal.Musical(2016). Instrument Recognition using K-Nearest Neighbour and Support Vector Machine.IEEE International Conference on Advances in Electronics, Communication and Computer Technology (ICAECCT).
[12] Kumar A., S. S. Solanki and M. Chandra(2020). Study of Indian instruments for designing a speech/music classifier, 5th International Conference on Computing, Communication and Security (ICCCS),pp. 1-7, DOI: 10.1109/ICCCS49678.2020.9276825.
[13] Liu J. and L. Xie (2010). SVM-Based Automatic Classification of Musical Instruments. International Conference on Intelligent Computation Technology and Automation, pp. 669-673, DOI: 10.1109/ICICTA.2010.64.
[14] McHugh Mary L(2013). The Chi-square test of independence.,DOI:10.11613/BM.2013.018.
[15] Ozerov A., E. Vincent, and F. Bimbot(2013). A General Flexible Framework for the Handling of Prior Information in Audio Source Separation. IEEE Transactions on Audio, Speech and Language Processing, vol. 20, no. 4, pp. 1118 – 1133.
[16] Peetersa Geoffroy, Bruno L. Giordano, Patrick Susini and Nicolas Misdariis, Stephen McAdams(2011). The Timbre Toolbox: Extracting audio descriptors from musical Signals.J. Acoustical Society of America.
[17] Racharla Karthikeya, Vineet Kumar, Chaudhari Bhushan Jayant, Ankit Khairkar and Paturu Harish(2020), Predominant. Musical Instrument Classification based on Spectral Features. IEEE International Conference on Signal Processing and Integrated Networks (SPIN)

[18] Sangeetha Rajesh and. Nalini N. J(2020). Singer Identification Using MFCC and CRP Features with Support Vector Machines. Computational Intelligence in Pattern Recognition,Advances in Intelligent Systems and Computing,Springer Nature,pp. 306-317. DOI- 10.1007/978-981-13-9042-5_25
[19] Shetty Surendra and Hegde Sarika(2020). Automatic Classification of Carnatic Music Instruments Using MFCC and LPC. Data Management, Analytics and Innovation, Advances in Intelligent Systems and Computing,Springer Nature Singapore, pp. 458-469 . DOI- 10.1007/978-981-32-9949-8_32
[20] Steyn H. S. Jr. & S. M. Ellis[2009]. Estimating an Effect Size in One-Way Multivariate Analysis of Variance (MANOVA). Multivariate Behavioral Research, 44:1, 106-129, DOI:10.1080/00273170802620238
[21] Vinutha T. P., Suryanarayana Sankagiri and Preeti Rao(2016). Reliable Tempo Detection for Structural Segmentation in Sarod Concerts,Twenty Second National Conference on Communication (NCC) ,IEEE..DOI- 10.1109/NCC.2016.7561163

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