Advancement in Graphical User Interface Tailored Quality Classification of Sape Soundboard

Tee Hao Wong,[a,b] Ming Foong Soong,[a] Ahmad Saifizul,[a] and Rahizar Ramli [a,*]

This research introduces an innovative methodology for evaluating and predicting soundboard quality in the intricate craftsmanship of sape instruments. Despite the sape's profound cultural significance, the process of selecting soundboard wood has been inadequately explored, resulting in uncertainties within the crafting community. Addressing this research gap, this study integrates advanced machine learning techniques and devises a specialized Graphical User Interface (GUI) tailored for sape makers. The methodology encompasses a thorough acoustic analysis of three distinct hardwoods—adau, merbau, and tapang—employing machine learning classification through Support Vector Machine with a Gaussian kernel. The study culminates in the development of a user-friendly GUI for soundboard quality assessment. Results underscore the model's proficiency for achieving an optimized accuracy of 87.8% in classifying sape audio samples. The MATLAB App Designer-based GUI streamlines the evaluation process, offering a practical and accessible tool for craftsmen. This integrated approach, harmonizing traditional craftsmanship with cutting-edge technology, holds the potential to revolutionize sape instrument manufacturing, ensuring the preservation and progressive evolution of this rich cultural heritage.

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*Contact information: a: Department of Mechanical Engineering, University of Malaya, 50603, Kuala Lumpur, Malaysia; b: School of Foundation Studies, University of Technology Sarawak, No. 1, Jalan Universiti, 96000, Sibu, Sarawak, Malaysia; *Corresponding author: rahizar@um.edu.my*

INTRODUCTION

The sape, a revered symbol of cultural heritage within Borneo's indigenous communities, holds profound significance owing to its distinctive acoustic properties and exquisite craftsmanship (Lim *et al*. 2020). This single-piece wooden instrument, evocative of a guitar and illustrated in Fig. 1, has undergone an evolutionary journey from its historical roots to emerge as a powerful emblem of cultural identity. Despite its cultural importance and unique sonic attributes, the sape remains relatively understudied, particularly in the context of soundboard wood selection when compared to more mainstream instruments such as guitars or violins.

Recent research emphasizes the critical role of assessing musical instrument quality in the context of music production and performance, influencing the perceptions of musicians and audiences alike (Hu 2022). Various methods and technologies, ranging from smart microphone array sensors (Li *et al*. 2019) to Multi-Criteria Decision-Making models, such as Quality Function Deployment (Chong and Lalla 2020), offer diverse approaches applicable to acoustic, digital, and traditional instruments. Together, these methods contribute to a comprehensive evaluation of musical instrument quality.

Fig. 1. Soundboard sample and the actual sape

While various methodologies and technologies have been employed to assess musical instrument quality across a spectrum of instruments, including acoustic, digital, and traditional ones, a notable gap persists within the traditional crafting process of sape instruments. This gap is characterized by the absence of clear guidelines for selecting soundboard wood, despite the esteemed reputation of certain woods like Adau (Lim *et al*. 2020). This void, coupled with subjective evaluations and uncertainties in wood selection, underscores the necessity for a more systematic and structured approach.

Despite an extensive body of research delving into the categorization of musical compositions, exploration of evaluation criteria using deep learning networks, and the significance of reverberation room methods in measuring sound power (Politis *et al*. 2015; Jin *et al*. 2018; Qiu *et al*. 2021; Jin *et al*. 2021), the traditional crafting process of sape instruments lacks clear guidelines for selecting soundboard wood, posing significant challenges. This research gap, accompanied by subjective evaluations and uncertainties in wood selection, emphasizes the need for a more structured approach.

In response to this challenge, this study endeavors to bridge the existing gap by integrating advanced machine learning techniques and developing a specialized Graphical User Interface (GUI) tailored automation specifically for sape makers. The primary objectives encompass the implementation of machine learning algorithms to facilitate impartial soundboard evaluation and the design of a user-friendly GUI aimed at streamlining the sound quality evaluation process. The study involved the generation of sound data through a flexural vibration test, qualitative assessment by seasoned sape experts, and the creation of an intuitive GUI dedicated to soundboard quality evaluation.

MATERIALS AND METHODS

Wood Sample Preparation

This study focuses on investigating the acoustic properties of three distinct hardwoods—adau (*Elmerrillia mollis*), merbau (*Intsia palembanica*), and tapang (*Koompassia excelsa*). These specific woods were chosen based on recommendations from local sape artisans, ensuring a connection to the traditional craftsmanship of sape instruments. Moreover, the availability of wood samples further facilitated their inclusion in the study. Each of these woods represents a distinct weight category: Adau, with a density of 300 to 705 kg/m³, is classified as a light hardwood; tapang, with a density of 800 to 865 kg/m³, is considered a medium hardwood; and merbau, with a density of 515 to 1040 kg/m³, is categorized as a heavy hardwood. This intentional selection allows for a comprehensive exploration of acoustic properties across a spectrum of wood types commonly used in sape instrument crafting.

To maintain a nuanced understanding of the acoustic nuances inherent to sape instruments, the focus of the research is centered on the soundboard. This emphasis stems from the need to streamline the experimental setup and exert control over variables. Utilizing the complete instrument would introduce complexities due to variations in size, thickness, and other factors. Therefore, rectangular-shaped soundboard samples were chosen as optimal representations of the sape's soundboard. Precision-fabricated through a Computer Numerical Control (CNC) machine, these samples mirror the typical dimensions of sape instruments prevalent in the market. The dimensions of the soundboard samples, set at 1.6 × 16.5 × 70 cm³ (tangential × radial × longitudinal), adhere to established market standards, as depicted in Fig. 1. Ensuring consistency and reliability across the study, a meticulous approach was taken in preparing three samples for each wood type, resulting in a total of nine samples. These samples were stored in a controlled laboratory environment, maintaining a relative humidity of 60 ± 2% and a temperature of 30 ± 1 °C.

Data Collection

In conducting the flexural vibration test to assess soundboard quality, this study adopted a method commonly employed in prior works focused on determining the sound quality of musical instruments (Bremaud 2012; Yang *et al*. 2017). This methodological choice is grounded in its efficacy and relevance to the specific nuances of sape instruments. The flexural vibration test is particularly well-suited for this study as it provides a robust means of capturing the acoustic properties inherent in the selected wood types.

The experimental setup involved a free-free flexural vibration method, utilizing a pendulum mechanism as shown in Fig. 2. Wood samples, representing different weight categories, were suspended on an aluminum profile frame at their nodal positions. A consistent and controlled striking force was applied to the samples using a pendulum weighing 13.9 g with a 15 mm diameter. This setup ensured uniform knocking on the wood samples, positioned strategically 2 cm from the edge.

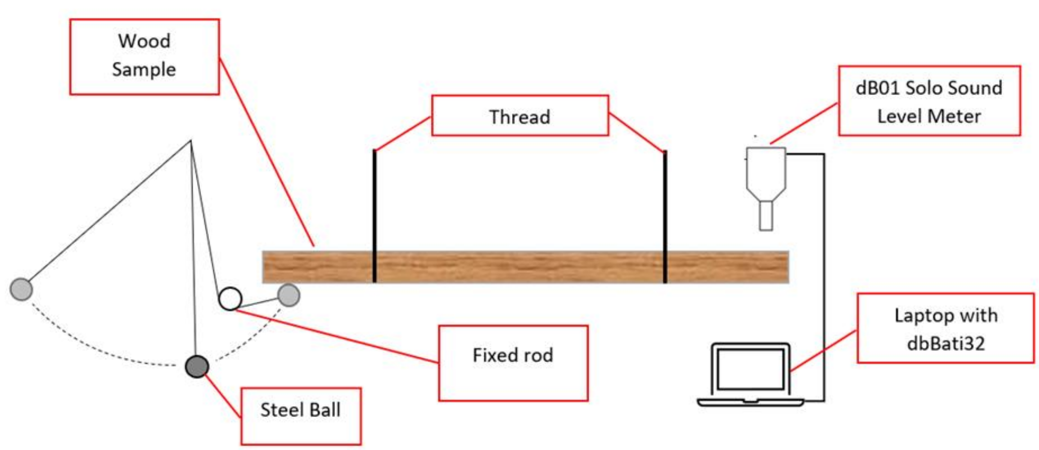

Fig. 2. Schematic diagram of the experimental set-up

To capture and analyze the resulting sounds comprehensively, a 01 dB Solo Sound Level Meter (SLM) was employed, and the acquired data were processed using dbBati32 software, generating WAV format audio files. The meticulous gathering of 360 sound recordings, with 40 repetitions for each wood sample, allowed for a thorough exploration of the acoustic nuances across the weight categories.

Sound Quality Features

The assessment of sound quality relies on a set of acoustic features to comprehensively characterize and evaluate audio signals. These features include dynamic root mean square (rms), dynamic attack time, decay time, spectral flatness, spectral roughness, timbre low energy, and timbre spectral flux (Alías *et al*. 2016). Dynamic rms quantifies the average power of a sound signal across varying amplitudes, capturing energy variations over time. Additionally, dynamic attack time and decay time delineate the onset and duration of sound, reflecting its rapidity in reaching peak amplitude and the duration taken to diminish from its peak level, respectively (Xiang *et al*. 2005). Spectral flatness and spectral roughness provide insights into the uniformity and irregularities in spectral components, differentiating between harmonic and noise-like qualities and assessing perceived roughness in spectral content. Timbre low energy and timbre spectral flux identify the presence of low-frequency components and track changes in spectral content over time, reflecting shifts in timbral color or tonal quality (Alías *et al*. 2016).

The amalgamation of these seven sound quality features into machine learning classification models enables comprehensive analysis and differentiation of audio signals based on their dynamic, temporal, spectral, and timbral characteristics. This integration facilitates the development of robust classification systems capable of precise recognition and categorization of audio signals, enhancing the understanding of their perceptual attributes with greater granularity (Weidman *et al*. 2018).

Sape Experts Evaluation

The assessment methodology employed by five experienced Sarawak sape makers to evaluate the quality of 360 audio samples reflects a comprehensive approach rooted in their extensive expertise in sape craftsmanship. Utilizing a 5-point Likert scale for rating audio quality, albeit ordinal, served as a standardized framework for evaluating perceptions. To ensure consistency in ratings, qualitative descriptions were utilized alongside the Likert scale, despite the absence of “distance” information between categories.

The demographic profile of these five candidates, highlighting their experience and qualifications, is outlined in Table 1. Notably, the analysis revealed that most of the sample populations lacked formal music training, aligning with the traditional mode of transmitting sape craftsmanship within the Borneo tribe. Importantly, this absence of formal training did not hinder the sape makers professionalism, underscoring the significance of their practical knowledge in sape making. Their expertise was chiefly determined by the number of years devoted to crafting sape instruments, consistent with the community’s traditional approach.

Nonetheless, limitations should be considered. The inherent subjectivity in the rating process, combined with the specialized nature of the sape community, could introduce biases in evaluation. Despite these potential biases, as all candidates are recognized as sape experts within their community, their assessments offer valuable insights into the perceived audio quality of the samples. Moreover, the restriction of conducting the listening test once due to workload constraints may limit the classical test theory-based reliability assessment. Nevertheless, exploring inter-rater reliability through non-parametric statistical tests could provide robust insights into the consistency among expert assessments.

Table 1. Demographic Information of Candidates

Candidate	A	B	C	D	E
Age	32	28	42	29	71
Gender	M	M	M	M	M
Ethnicity	Kenyah	Iban	French	Iban	Kenyah
Formal musical training	1 year	None	2 years	None	None
Years of experience	9	8	7	7	30+

Support Vector Machine in Machine Learning

Support Vector Machine (SVM) is a widely embraced classifier rooted in the statistical learning theory developed by Vapnik (1998). Its core principle involves seeking an optimal linear hyperplane to minimize generalization errors when classifying unknown test samples. The objective is to create a linear hyperplane that maximizes the margin, representing the separation between different categories. This margin serves as a decisive boundary, effectively categorizing new test samples based on their position relative to this hyperplane.

In instances where a linear hyperplane falls short in segregating data in a 2-dimensional space, SVM leverages the “kernel trick,” transforming the input space to overcome limitations and enabling effective segregation in higher dimensions. In this research, SVM is proposed as a robust method for classifying sape audio samples based on evaluations from experienced sape makers. In a binary classification scenario, where two distinct quality categories exist (*e.g.*, “Good” and “Poor” audio samples), SVM endeavors to find the hyperplane that maximizes the margin between the nearest data points of each class, often referred to as support vectors. This hyperplane serves as the decision boundary, facilitating the classification of new, unseen data points.

To implement SVM in this study, a framework incorporating a Gaussian kernel function, as expressed in Eq. 1, was adopted:

$$K(x, x') = \exp\left(-\frac{\|x-x'\|^2}{2\sigma^2}\right) \qquad (1)$$

The Gaussian kernel assesses the similarity between data points without explicitly mapping them into higher dimensions. It computes similarity based on the Euclidean distance between points, with σ representing the kernel’s width parameter. A box constraint value of one was selected within the SVM model to regulate its flexibility and prevent overfitting. This parameter, C, balances the trade-off between maximizing the margin and minimizing classification errors. The classification of quality was conducted in MATLAB 2022b, utilizing an AMD Ryzen 7 2700U CPU with 16 GB RAM. The dataset underwent a 70/30 train-test split, following methodology by Vabalas *et al*. (2019) to assess the SVM model’s performance. Additionally, to evaluate the predictive accuracy of the model with limited data, a k-Fold Cross Validation approach with k = 5, advocated by Elmaz *et al*. (2020), was employed.

Graphical User Interface (GUI)

The research methodology in this study combines various computational and machine learning techniques to evaluate and classify soundboard quality in sape instruments. Central to this methodology was the development and implementation of a GUI using MATLAB App Designer (MathWorks, MATLAB version 2023b, Natick, MA, USA). The GUI, crafted within the MATLAB environment, served as the primary tool for feature extraction and classification of soundboard quality. Leveraging MATLAB's extensive signal processing capabilities, the GUI facilitated the extraction of seven fundamental acoustic features crucial for soundboard quality assessment, including dynamic RMS, dynamic attack time, decay time, spectral flatness, spectral roughness, timbre low energy, and timbre spectral flux.

Furthermore, the GUI seamlessly integrated a pre-trained SVM model. This SVM model, trained on a diverse and comprehensive dataset of various soundboard qualities, utilized the extracted acoustic features as inputs for classification. The model underwent optimization to discern and categorize soundboard qualities based on the uploaded sound files. Upon uploading sound files representative of sape soundboard samples, the GUI executed algorithms designed to systematically extract the essential acoustic features, capturing intricate nuances relevant to sape soundboard quality assessment.

The user-friendly interface of the GUI ensured a straightforward process for users to upload sound files. Upon processing the uploaded file, the GUI provided immediate classification results indicating the predicted quality of the soundboard. This seamless interaction facilitated efficient assessment and classification of sape soundboard qualities based on extracted acoustic features, enhancing the research's ability to evaluate soundboard quality accurately and expediently.

RESULTS AND DISCUSSION

The collected dataset of 360 sound samples underwent initial processing steps involving volume normalization and noise reduction. Following this preprocessing, experienced sape makers assessed the sound samples, providing ratings using a 5-point Likert scale. Subsequently, the features inherent in these sound samples were extracted and imported into MATLAB for machine learning purposes. Finally, a GUI was then developed to facilitate streamlined user interaction and seamless application of the machine learning model.

Acoustic Feature Extraction and Experts' Evaluation

In preparation for classification, seven key acoustic features were extracted using the MIRToolbox. A correlation mapping analysis confirmed minimal multicollinearity among these features, ensuring their independence for subsequent analyses. The average values of the features are shown in Table 2. Five sets of quality rating scores were collected and shown in Table 3, revealing a conservative tendency in assigning the lowest score, with no wood samples rated as "very poor" quality. Candidate C consistently provided slightly lower ratings on average, indicating varying interpretations of sound quality.

The correlation analysis between the acoustic features and the evaluations by the raters, presented in Table 4, shows varying degrees of correlation. Most raters exhibited significant correlations with one or more features, suggesting the relevance of these features in their evaluation process. For example, candidate B showed moderate negative correlations with spectral flatness and spectral flux, indicating that as these features increased, the quality rating decreased. Conversely, candidate E demonstrated a weak positive correlation with RMS, highlighting their consideration of this feature in assessing soundboard quality. These findings underscore the subjective nature of the evaluations and the importance of considering multiple expert opinions to capture a comprehensive understanding of sound quality.

Table 2. Average Features Values of the Wood Samples

Sample	RMS	Attack Time	Decay Time	Spectral Flatness	Spectral Roughness	Low Energy	Spectral Flux
A1	0.2544	-0.00961	0.5307	-1.2167	-0.0520	0.3686	-1.0319
A2	0.5179	0.15424	0.6398	-1.0631	-0.8931	0.2286	-1.0276
A3	0.0178	0.48193	0.5367	-1.1454	0.0913	0.6648	-1.0559
T1	-0.3473	0.21259	-0.1605	0.8188	-0.1641	-0.1596	0.2435
T2	-0.7177	-0.04103	-0.2242	1.0194	-1.0275	0.2406	-0.0227
T3	0.7172	-0.23967	0.0166	0.4816	0.3552	-1.0440	1.0547
M1	0.7710	-0.22396	-0.4244	0.0433	0.0911	-0.7639	1.2517
M2	-0.7037	0.12618	-0.4342	0.6314	-0.1348	0.2846	0.2154
M3	-0.5130	-0.48931	-0.4867	0.4501	1.7172	0.1502	0.3732

Table 3. Cross Table of Rating across 9 Wood Samples

Score	**Adau 1**					**Adau 2**					**Adau 3**				
	A	**B**	**C**	**D**	**E**	**A**	**B**	**C**	**D**	**E**	**A**	**B**	**C**	**D**	**E**
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	8	10	0	0	0	15	13	0	0	0	9	19	0
3	0	11	17	18	20	0	20	17	18	9	1	12	20	14	10
4	33	25	14	10	10	2	20	8	8	31	25	21	9	7	30
5	7	4	1	2	10	38	0	0	1	0	14	7	2	0	0
Score	**Tapang 1**					**Tapang 2**					**Tapang 3**				
	A	**B**	**C**	**D**	**E**	**A**	**B**	**C**	**D**	**E**	**A**	**B**	**C**	**D**	**E**
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	2	2	0	0	7	35	8	0	0	19	22	3	0
3	38	30	37	31	0	0	33	5	31	40	25	20	18	21	0
4	2	10	1	7	0	21	0	0	1	0	10	1	0	14	30
5	0	0	0	0	40	19	0	0	0	0	5	0	0	2	10
Score	**Merbau 1**					**Merbau 2**					**Merbau 3**				
	A	**B**	**C**	**D**	**E**	**A**	**B**	**C**	**D**	**E**	**A**	**B**	**C**	**D**	**E**
1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	18	3	24	0	1	14	37	0	0	39	5	20	0
3	0	35	20	28	16	1	39	23	3	9	0	1	30	20	20
4	36	5	1	9	0	35	0	3	0	31	27	0	5	0	20
5	4	0	0	0	0	4	0	0	0	0	13	0	0	0	0

Table 4. Correlation between Features and the Evaluations by the Raters

Rater	RMS	Attack Time	Decay Time	Spectral Flatness	Spectral Roughness	Low Energy	Spectral Flux
A	0.043	0.157**	0.212**	-0.214**	-0.291**	0.140**	-0.346**
B	0.102	0.166**	0.214**	-0.524**	-0.241**	0.248**	-0.472**
C	0.292**	0.025	0.162**	-0.341**	-0.082	-0.058	-0.063
D	0.092	-0.070	0.025	-0.121*	0.253**	-0.028	0.029
E	0.389**	-0.070	-0.025	-0.263**	0.117*	-0.171**	0.236**

*** Correlation is significant at the 0.01 level (2-tailed)*
** Correlation is significant at the 0.05 level (2-tailed)*

To draw meaningful conclusions, statistical tests were conducted on the ordinal data. Non-parametric tests, including Kruskal-Wallis H test, Krippendorff' α, and Kendall's *tau-b*, were used to compare rating scores. The Kruskal-Wallis H test revealed no consistent significant similarities between rating score combinations, suggesting personal preferences contribute to statistically significant variations in sape wood quality ratings. Krippendorff's α and Kendall's *tau-b* also showed disagreements and lack of significant correlations, emphasizing a notable lack of inter-rater reliability.

In summary, all three non-parametric statistical tests consistently revealed statistically significant differences among the sets of rating scores, indicating a lack of inter-rater reliability. Candidate E, Mr. Mathew Ngau, emerges as the preferred source for rating scores due to his extensive experience exceeding 30 years, his prestigious position as a National Living Heritage, and his role as a mentor, adding credibility to his evaluations. Additionally, from the non-parametric tests, Mr. Mathew demonstrated consistency in rating similar wood samples, underscoring his expertise in identifying soundboard quality. His reliability and proficiency further solidify his selection as the primary evaluator in this study.

SVM Machine Learning

The features dataset was combined with Mr. Mathew's rating scores for classification using SVM. Accuracy, along with the confusion matrix, was examined to detect any bias in the model's decisions. A frequency plot of Mr. Mathew's ratings indicated class imbalance, raising concerns about potential biases.

To address this imbalance, the Synthetic Minority Oversampling Technique (SMOTE) was employed to generate synthetic samples for underrepresented classes (Ishaq *et al*. 2021). This expanded the dataset to 604 observations without introducing identical duplicates, mitigating the risk of overfitting associated with random oversampling. The classification results from the SVM model using the normalized dataset are shown in Table 5. The Gaussian Kernel SVM model achieved a validation accuracy of 90.3% and sustained an accuracy of 87.8% on unseen data, demonstrating its strong generalization capability. The dataset was normalized to values between 0 and 1 before applying machine learning, as SVM relies on Euclidean distance.

Assessing misclassifications or errors made by the model, referred to as the 'Total Cost', revealed promising outcomes. The reduction in total cost from the validation phase (41) to the testing phase (22) following the optimization of the Gaussian kernel SVM indicates improved model performance on unseen data. Through careful fine-tuning of key parameters, the model demonstrated enhanced generalization, effectively capturing underlying patterns in sape audio samples.

Table 5. Accuracies of Gaussian Kernel SVM Model

Model Type	Category	Validation		Test	
		Accuracy %	Total Cost	Accuracy %	Total Cost
Gaussian Kernel	SVM	90.30	41	87.80	22

The adjusted box constraint level (445.7) played a crucial role in achieving a balanced trade-off between maximizing the margin and minimizing misclassifications. The optimization of the kernel scale parameter (0.64) also contributed to creating an optimized decision boundary, effectively separating different classes within the sape audio samples.

The optimization process addressed concerns related to overfitting, ensuring the model's complexity was well-suited to the characteristics of the sape audio data.

In summary, the reduction in total cost underscores the effectiveness of the optimized Gaussian kernel SVM in accurately classifying sape audio sample quality, demonstrating improved generalization and robustness on unseen data. Figure 3 displays the confusion matrix of the SVM model, revealing effective predictions for classes 2 and 5 but challenges with classes 3 and 4. The satisfactory accuracy demonstrated by the Gaussian Kernel SVM model reflects its capability to predict the soundboard quality of the sape instrument. This model holds promise as a reliable tool for evaluating and predicting soundboard quality within sape instrument crafting, contributing to the enhancement of traditional instrument craftsmanship.

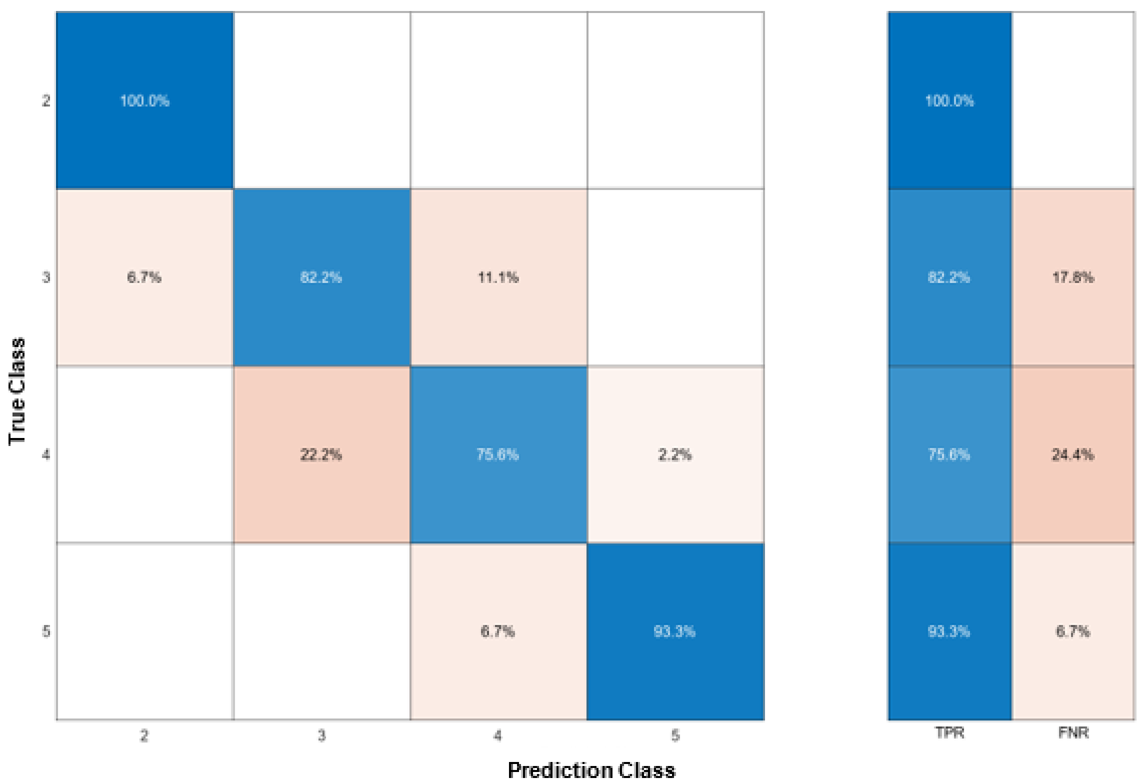

Fig. 3. Normalized confusion matrix of Gaussian Kernel SVM model against dataset

Graphical User Interface

The GUI, developed using MATLAB's App Designer, prominently features the utilization of the trained Gaussian Kernel SVM model as the core classification tool. This model serves as the underlying engine for soundboard quality prediction within the sape instrument manufacturing process. The GUI is designed to offer a seamless experience to potential users, providing an intuitive platform to upload their unique sound files as shown in Fig. 4. Empowered by an 'Upload Sound File' button, users can upload their sound files directly onto the interface. Upon selection, the GUI promptly displays essential details, such as the file location and name, ensuring transparency and easy reference throughout the process.

Integral to the interface is a 'Prediction' button that, when activated, triggers the Gaussian Kernel SVM model to perform real-time quality classification of the uploaded sound file. Subsequently, the predicted result is exhibited in a dedicated box within the interface, providing immediate feedback on the soundboard quality. This functionality empowers users involved in sape instrument manufacturing by enabling swift and informed decision-making based on the model's predictions.

Furthermore, GUI is enriched with quality guidelines, serving as a reference point for users. This guideline encompasses criteria and information utilized by the Gaussian Kernel SVM model during the classification process. Through integrating the trained model and user-friendly functionalities, this GUI streamlines the soundboard quality assessment during the sape manufacturing process, offering an accessible and efficient tool for manufacturers and craftsmen.

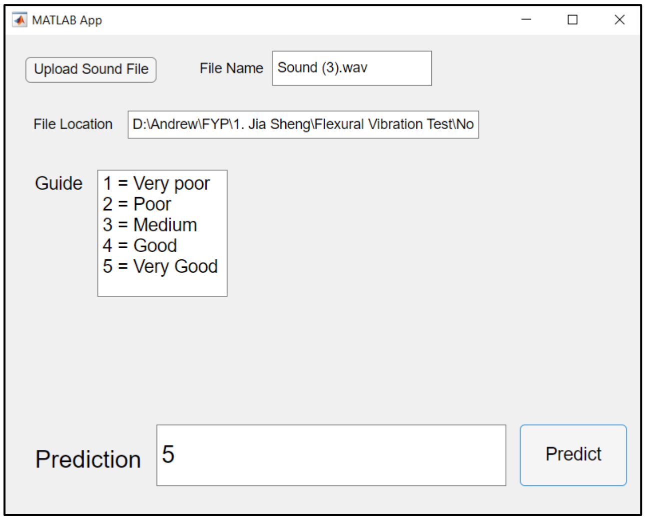

Fig. 4. GUI for soundboard quality classification by MATLAB App Designer

CONCLUSIONS

This study presents an innovative approach to assessing and predicting soundboard quality in sape instrument crafting by combining acoustic analysis and machine learning techniques.

1. The research addresses the understudied aspect of selecting soundboard wood for sape instruments, offering a structured methodology. Utilizing three distinct hardwoods (adau, merbau, and tapang) representing different weight categories, the study employs a flexural vibration test for sound sample collection.
2. The acoustic features extracted are then analyzed using a Gaussian Kernel SVM model. The model, validated with expert ratings, demonstrates a notable accuracy of 87.8%, showcasing its potential as a reliable tool for sape instrument manufacturing.
3. The study not only contributes to the preservation and advancement of the sape instrument's heritage but also bridges traditional craftsmanship with advanced technology through the development of a user-friendly GUI.

Future research could explore additional machine learning techniques and extend the methodology to other traditional instruments, promising continued innovation in instrument craftsmanship and the preservation of diverse musical heritages.

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REFERENCES CITED

Alías, F., Socoró, J., and Sevillano, X. (2016). “A review of physical and perceptual feature extraction techniques for speech, music and environmental sounds,” *Applied Sciences* 6(5), article 143. DOI: 10.3390/app6050143

Chong, P. P., and Lalla, T. (2020). “Applying fuzzy QFD MCDM to evaluate musical instruments,” *The International Conference on Emerging Trends in Engineering and Technology* (IConETech-2020), St. Augustine, Trinidad and Tobago, pp. 780-791. DOI: 10.47412/bgmj4037

Elmaz, F., Yücel, Ö., and Mutlu, A. (2020). “Makine öğrenmesi ile kısa ve elemental analiz kullanarak katı yakıtların üst ısı değerinin tahmin edilmesi [Predicting the upper heating value of solid fuels using short and elemental analysis with machine learning],” *International Journal of Advances in Engineering and Pure Sciences* 32(2), 145-151. DOI: 10.7240/jeps.558378

Hu, M. (2022). “Features of singing in Chinese pop and traditional music: The influence of the music genre on vocal music,” *Musica Hodie* 22, article 73137. DOI: 10.5216/mh.v22.73137

Ishaq, A., Sadiq, S., Umer, M., Ullah, S., Mirjalili, S., Rupapara, V., and Nappi, M. (2021). “Improving the prediction of heart failure patients’ survival using SMOTE and effective data mining techniques,” *IEEE Access* 9, 39707-39716. DOI: 10.1109/access.2021.3064084

Jin, C., Wang, T., Li, X., Tie, C. J. J., Tie, Y., Liu, S., Yan, M., Li, Y., Wang, J., and Huang, S. (2021). “A transformer generative adversarial network for multi-track music generation,” *CAAI Transactions on Intelligence Technology 7*(3), 369-380. DOI: 10.1049/cit2.12065

Jin, C., Zhao, W., and Wang, H. (2018). “Research on objective evaluation of recording audio restoration based on deep learning network," *Advances in Multimedia* 2018, article ID 3748141. DOI: 10.1155/2018/3748141

Li, K., Chen, Y., Jiang, H., and Han, Y. (2019). “Chinese traditional musical instrument evaluation based on a smart microphone array sensor,” *Multidisciplinary Digital Publishing Institute Proceedings* 15(1), article 40. DOI: 10.3390/proceedings2019015040

Lim, C. K. N., Rashidi, N. H., and Yahya, S. A. (2020). *Sarawak Traditional Musical Instrument Sape*, First Ed., Dewan Bahasa dan Pustaka, Kuala Lumpur, Malaysia.

Politis, D., Piskas, G., Tsaligopoulos, M., and Kyriafinis, G. (2015). "variPiano™: Visualizing musical diversity with a differential tuning mobile interface," *International Journal of Interactive Mobile Technologies* 9(3), 58-63. DOI: 10.3991/ijim.v9i3.4472

Qiu, J., Wu, S., Zhao, Y., Huang, H., and Li-Ling, W. (2021). "Sound power characteristics of Chinese traditional wind instrument Qudi," *International Journal of Architecture, Arts and Applications* 7(1), 8-15. DOI: 10.11648/j.ijaaa.20210701.12

Vabalas, A., Gowen, E., Poliakoff, E., and Casson, A. J. (2019). "Machine learning algorithm validation with a limited sample size," *PLOS One* 14(11), article ID e0224365. DOI: 10.1371/journal.pone.0224365

Vapnik, V. (1998). *Statistical Learning Theory*, Wiley, New York, NY, USA.

Weidman, A., Sun, J., Vazire, S., Quoidbach, J., Ungar, L., and Dunn, E. (2018). "(Not) hearing happiness: Predicting fluctuations in happy mood from acoustic cues using machine learning," *PsyArXiv Preprints* 1-55. DOI: 10.31234/osf.io/5w7c8

Xiang, N., Goggans, P., Jasa, T., and Kleiner, M. (2005). "Evaluation of decay times in coupled spaces: Reliability analysis of bayeisan decay time estimation," *The Journal of the Acoustical Society of America* 117(6), 3707-3715. DOI: 10.1121/1.1903845

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