

Predicting Concert Hall Reverberation Time and Clarity from Geometric Features Using Machine Learning

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Abstract—Concert Hall acoustics are traditionally evaluated through direct measurements or acoustic simulations, both of which require significant resources and expertise. This study bridges a critical gap in architectural acoustics by systematically evaluating 28 Machine Learning (ML) algorithms for predicting frequency-dependent Reverberation Time (RT) and clarity (C80) from geometric features. Unlike prior work, our analysis identifies transition frequencies (250–1000 Hz for RT, 250–500 Hz for C80) where geometric influence shifts, offering actionable insights for preliminary acoustic design and renovation planning. We analyzed data from 58 concert halls, utilizing 10 geometric features and acoustic measurements across six octave bands (125–4000 Hz). 28 different ML algorithms were trained and validated using 5-fold cross-validation, with performance evaluated using the coefficient of determination (R^2) and Root Mean Square Error (RMSE). The results demonstrate that geometric attributes explain up to 47% of RT variations at lower frequencies (125–500 Hz) and up to 47% of C80 variations at mid-frequencies (250–1000 Hz). Support Vector Machines (SVMs) and Gaussian process regression (GPR) models showed the best performance for RT and C80 estimation, respectively. These findings provide insights into the frequency-dependent influence of architectural geometry on concert hall acoustics and establish a foundation for ML-assisted acoustic design and renovation planning.

Keywords—Clarity (C80), concert hall acoustics, machine learning, Reverberation Time (RT), room acoustic parameters; architectural acoustics.

I. INTRODUCTION

Concert hall acoustics significantly influence the quality of musical performances and audience experience. Traditional methods for evaluating acoustic properties rely on direct measurements using standardized equipment or computer-based acoustic simulations. However, both approaches present practical challenges: measurements require specialized equipment and may be impractical for preliminary design studies, while simulations demand detailed knowledge of surface materials and absorption coefficients that are often unavailable [1].

The renovation and adaptive reuse of existing concert halls have become increasingly important for economic and sustainability reasons. Many historic venues require acoustic improvements while preserving their architectural heritage [2]. In such cases, understanding the relationship between geometric features and acoustic parameters becomes crucial for making informed design decisions without extensive preliminary measurements.

Reverberation Time (RT) represents the time required for sound to decay by 60 dB after the source stops, fundamentally affecting the perceived acoustic quality of a space [3]. Optimal RT values depend on the intended use and volume

of the space; excessive RT can lead to poor speech intelligibility and musical clarity, while insufficient RT may result in a perceived lack of warmth and envelopment [4].

Clarity (C80) quantifies the ability of listeners to distinguish individual sounds in a musical performance by comparing early arriving sound energy (within 80 ms) to late-arriving energy. Higher C80 values indicate better clarity, with the parameter being particularly important for musical performances where note separation is critical [5].

II. LITERATURE REVIEW

ML applications in acoustics have grown significantly, though their use in concert hall design remains limited. Previous studies have explored neural networks for sound propagation prediction [6], RT estimation using geometric features [7], and various acoustic parameter predictions [8–12]. Recent work by Ref. [13] demonstrated Random Forest Regression (RFR) for mid-frequency RT estimation, while neural network approaches have shown promise for multiple acoustic parameters [14, 15].

However, existing research typically focuses on individual acoustic parameters or limited frequency ranges. Comprehensive studies comparing multiple ML algorithms across the full frequency spectrum for concert hall applications remain scarce. Furthermore, most studies lack a detailed analysis of which geometric features are most influential at different frequencies, limiting their practical application in architectural design. This study addresses these gaps by:

- Systematically comparing 28 ML algorithms for RT and C80 estimation,
- Identifying frequency-dependent geometric influences (e.g., volume dominates RT at low frequencies),
- Providing practical guidelines for designers to prioritize geometric modifications based on target acoustic parameters.

III. MATERIALS AND METHODS

A. Dataset Description

The dataset was extracted from Beranek's comprehensive survey of concert halls [4], which provides measured acoustic data and geometric specifications for 100 renowned venues worldwide. From this collection, 58 halls with complete geometric and acoustic data were selected for analysis. Ten geometric parameters were considered:

- Volume (v): Total interior volume [m^3]
- Area of Floor Space (AFS): Seating area [m^2]
- Acoustical Audience Area (AAA): AFS plus 0.5m strips around seating blocks [m^2]

- Stage Area (SA): Performance area [m²]
- Acoustical Absorption Area (ST): Sum of AAA, SA, and choir areas [m²]
- Number of seats (*n*): Total seating capacity
- Average height (*h*): Mean ceiling height [m]
- Average width (*w*): Mean Hall width [m]
- Average length (*l*): Mean Hall length [m]
- Distance (*d*): Maximum distance from stage to audience [m]

RT and C80 measurements were available across six octave bands (125, 250, 500, 1000, 2000, and 4000 Hz). Additionally, C80(3) values (average of 500, 1000, and 2000 Hz bands) were included in the analysis.

B. Data Processing

All geometric attributes were standardized using z-score normalization to account for different measurement units and scales:

$$z_{ij} = \frac{x_{ij} - \mu_i}{\sigma_i}, i=1, \dots, 10 \text{ and } j=1, \dots, 100 \quad (1)$$

where *i* represents the attribute index (1–10), *j* represents the hall index (1–58), and μ_i and σ_i are the mean and standard deviation for attribute *i*.

Pearson correlation coefficients were calculated between RT and C80 across all frequency bands to understand their fundamental relationship. Correlation analysis revealed significant redundancy among geometric features, where the results are tabulated in Table 1. To mitigate multicollinearity effects, forward selection was employed to identify the most predictive subset of features for each acoustic parameter:

- RT models: volume (*v*), stage area (*SA*), number of seats (*n*), height (*h*), width (*w*), and acoustical absorption area (*ST*)
- C80 models: stage area (*SA*), height (*h*), width (*w*), and acoustical absorption area (*ST*)

Table 1. Correlation coefficients: Pearson correlations

	<i>v</i>	<i>AFS</i>	<i>AAA</i>	<i>SA</i>	<i>ST</i>	<i>n</i>	<i>h</i>	<i>w</i>	<i>l</i>	<i>d</i>
<i>v</i>	1	0.386	0.788	0.504	0.778	0.729	0.131	0.705	0.588	0.570
<i>AFS</i>	0.386	1	0.274	0.354	0.272	0.263	0.274	0.077	0.158	0.304
<i>AAA</i>	0.788	0.274	1	0.324	0.995	0.933	0.128	0.618	0.722	0.732
<i>SA</i>	0.504	0.354	0.324	1	0.315	0.271	0.221	0.312	0.206	0.275
<i>ST</i>	0.778	0.272	0.995	0.315	1	0.931	0.150	0.595	0.712	0.728
<i>n</i>	0.729	0.263	0.933	0.271	0.931	1	0.158	0.546	0.639	0.729
<i>h</i>	0.131	0.274	0.128	0.221	0.150	0.158	1	−0.225	−0.109	0.249
<i>w</i>	0.705	0.077	0.618	0.312	0.595	0.546	−0.225	1	0.591	0.335
<i>l</i>	0.588	0.158	0.722	0.206	0.712	0.639	−0.109	0.591	1	0.669
<i>d</i>	0.570	0.304	0.732	0.275	0.728	0.729	0.249	0.335	0.669	1

*Bold numbers denote statistically significant correlations at 0.05. The number of observations (Concert Halls) is 58.

Table 2. The results of factor analysis of RT and C80 in six-octave bands

Frequency	RT		C80	
	Factor 1 (Scores)	Factor 2 (Scores)	Factor 1 (Scores)	Factor 2 (Scores)
125	0.942	NA	0.924	NA
250	0.892	0.411	0.788	0.513
500	0.760	0.618	0.542	0.758
1,000	0.547	0.815	NA	0.897
2,000	NA	0.93	NA	0.875
4,000	NA	0.94	NA	0.916

*NA stands for factor scores less than 0.40. **The scores in bold indicate the transition frequencies.

Principal component analysis with varimax rotation was performed to identify frequency groupings and transition regions where acoustic behavior shifts between low, mid, and high-frequency characteristics. The transition frequencies for RT and C80 are RT₂₅₀, RT₅₀₀, and RT_{1,000}, and C80₂₅₀, C80₅₀₀, respectively. They have an impact on both factors, but a transition is observed such that RT₂₅₀ has a stronger impact in Factor 1 and RT_{1,000} has a stronger impact in Factor 2. The impact of RT₅₀₀ is compatible with both factors. Similarly, C80₂₅₀ has a stronger impact on Factor 1, and C80₅₀₀ has a stronger impact on Factor 2. The findings are tabulated in Table 2.

C. Machine Learning Implementation

We evaluated 28 regression algorithms spanning linear models (e.g., stepwise regression), kernel methods (SVMs),

Gaussian processes, and neural networks to ensure a comprehensive comparison. Hyperparameters were optimized via MATLAB's default routines, and 5-fold cross-validation was used to prevent overfitting. The selection of 28 algorithms was motivated by the need for a systematic comparison across diverse model families (linear, kernel-based, tree-based, neural networks, and Gaussian processes). While this approach introduces complexity, it ensures robustness in identifying optimal methods for different frequency bands. We mitigated overfitting risks via 5-fold cross-validation and hyperparameter optimization, prioritizing interpretability where models exhibited comparable performance (e.g., SVMs for RT at low frequencies). Performance was assessed using R^2 and RMSE, with the best models selected for each frequency band.

- Linear Models: Linear Regression (LR), Interactions linear Regression (ILR), Robust Linear Regression (RLR), Stepwise Linear Regression (SLR)
- Tree-Based Models: Fine Tree (FT), Medium Tree (MT), Coarse Tree (CT), Boosted Trees (BoT), Bagged Trees (BaT)
- Support Vector Machines: Linear SVM (LSVM), Quadratic SVM (QSVM), cubic SVM (CSVM), Fine Gaussian SVM (FGSVM), Medium Gaussian SVM (MGSVM), Coarse Gaussian SVM (CGSVM), Efficient Linear Least Squares SVM (ELLSSVM), Efficient Linear SVM (ELSSVM)

- Gaussian Process Regression: Squared Exponential GPR (SEGPR), Matérn 5/2 GPR (MGPR), Exponential GPR (EGPR), Rational Quadratic GPR (RQGPR)
- Neural Networks: Narrow Neural Network (NNN), Medium Neural Network (MNN), Wide Neural Network (WNN), Bilayered Neural Network (BNN), Trilayered Neural Network (TNN)
- Kernel Methods: SVM Kernel (SVMK), Least Squares Regression Kernel (LSRK)

All models were trained using 5-fold cross-validation to ensure robust performance estimates. Hyperparameters were automatically optimized using MATLAB's default optimization routines for each algorithm. Model performance was evaluated using the coefficient of determination (R^2) and Root Mean Square Error (RMSE).

D. Model Testing

Independent testing was conducted on concert halls not included in the training set:

RT Testing: Three halls with complete RT measurements:

- Academy of Music, Philadelphia (1857, 2,827 seats)
 - Verizon Hall, Kimmel Centre, Philadelphia (2001, 2,519 seats)
 - Benedict Music Tent, Aspen, Colorado (2000, 2,050 seats)
- C80 Testing: One hall with complete C80 measurements:
- War Memorial Opera House, San Francisco (1932, 3,252 seats)

IV. RESULT AND DISCUSSION

A. Correlation Analysis

RT and C80 exhibited strong negative correlations across all frequency bands, with correlation strength increasing with frequency. The strongest correlations occurred at mid-frequencies (1000–2000 Hz: $r = -0.746$ to -0.740), while the weakest correlation was observed at 125 Hz ($r = -0.465$). The results are tabulated in Table 3.

Table 3. Correlations between RT and C80 (*All correlations significant at $p < 0.05$)

	Octave bands (Hz)					
	125	250	500	1,000	2,000	4,000
	C80					
RT	-0.465	-0.569	-0.71	-0.746	-0.74	-0.706

B. Factor Analysis

Factor analysis revealed distinct frequency groupings for both acoustic parameters.

RT Factor Structure:

- Factor 1 (Low-frequency): Dominated by 125 Hz, with transition frequencies at 250–500 Hz
- Factor 2 (High-frequency): Dominated by 2000–4000 Hz, with transition at 1000 Hz
- Transition frequencies: 250, 500, and 1000 Hz showed mixed loadings

C80 Factor Structure:

- Factor 1 (Low-frequency): Dominated by 125 Hz, with transition at 250 Hz
- Factor 2 (High-frequency): Dominated by 1000–4000 Hz, with transition at 500 Hz
- Transition frequencies: 250 and 500 Hz showed mixed loadings

These findings suggest that acoustic behavior transitions occur at different frequencies for RT and C80, with RT showing more gradual transitions across the frequency spectrum.

C. Machine Learning Performance

Different algorithms performed optimally at different frequencies for RT estimation.

- 125 Hz: Quadratic SVM (QSVM)–RMSE: 0.095, R^2 : 0.40
- 250 Hz: Stepwise Linear Regression (SLR)–RMSE: 0.103, R^2 : 0.40
- 500 Hz: Cubic SVM (CSVM)–RMSE: 0.093, R^2 : 0.47
- 1000 Hz: Squared Exponential GPR (SEGPR)–RMSE: 0.122, R^2 : 0.25
- 2000 Hz: SEGPR–RMSE: 0.119, R^2 : 0.22
- 4000 Hz: Fine Tree (FT)–RMSE: 0.110, R^2 : 0.30
- Model explanatory power was highest at low to mid frequencies (125–500 Hz), where R^2 values ranged from 0.40–0.47. Performance declined at higher frequencies, with R^2 values dropping to 0.22–0.30 at 1000–4000 Hz.

Gaussian process regression models dominated across frequencies in C80 estimation.

- 125 Hz: SEGPR–RMSE: 0.315, R^2 : 0.18
- 250 Hz: Matérn 5/2 GPR (MGPR) - RMSE: 0.279, R^2 : 0.35
- 500 Hz: SEGPR–RMSE: 0.348, R^2 : 0.39
- 1000 Hz: SEGPR–RMSE: 0.114, R^2 : 0.47
- 2000 Hz: SEGPR–RMSE: 0.425, R^2 : 0.20
- 4000 Hz: MGPR–RMSE: 0.378, R^2 : 0.16

D. Geometric Influence on Acoustic Parameters

The identification of six key geometric attributes for RT (volume, stage area, number of seats, height, width, and acoustical absorption area) versus four for C80 (stage area, height, width, and acoustical absorption area) reveals important insights into the physical mechanisms governing these acoustic parameters.

Volume and number of seats emerged as critical for RT estimation at low frequencies (125–500 Hz), while stage area and height influenced both RT and C80 above 250 Hz. This aligns with acoustic theory: low-frequency sound decay is governed by room dimensions (volume), whereas mid/high-frequency clarity depends on early reflections (stage geometry). Compared to traditional simulations, our ML approach requires only geometric inputs, enabling faster *early-stage assessments*.

E. Frequency-Dependent Acoustic Behavior

The observed frequency dependence in model performance aligns with established acoustic theory. Lower frequencies are more influenced by overall room dimensions due to their longer wavelengths, explaining the superior RT prediction at 125–500 Hz. Mid-frequency performance optimization for C80 (250–1000 Hz) corresponds to the frequency range most critical for musical clarity and human auditory perception.

The identification of transition frequencies (250–1000 Hz for RT, 250–500 Hz for C80) suggests that acoustic design strategies should account for these frequency-dependent effects. For example, modifications to room volume - a dominant feature at low frequencies - may disproportionately impact RT below 500 Hz, while stage geometry adjustments could optimize C80 in the 250–1000 Hz range. These

thresholds enable designers to target specific frequency ranges—e.g., adjusting volume for RT below 500 Hz or stage geometry for C80 at 250–1000 Hz—while avoiding over-optimization for less influential bands.

F. Machine Learning Algorithm Selection

The diversity in optimal algorithms across frequencies indicates that no single ML approach is universally superior for acoustic parameter estimation. Support vector machines performed well for RT at lower frequencies, likely due to their ability to handle non-linear relationships in the geometric-acoustic mapping. Gaussian process regression dominated C80 estimation, suggesting that the uncertainty quantification capabilities of GPR may be particularly valuable for clarity prediction.

The superior performance of non-linear algorithms (SVM, GPR, neural networks) compared to linear regression indicates significant non-linear relationships between geometric attributes and acoustic parameters, supporting the use of advanced ML techniques for this application.

G. The Practical Implications for Acoustic Design

The findings have several implications for concert hall design and renovation. In the design phase, preliminary acoustic assessments can be conducted using geometric parameters alone, providing valuable guidance before detailed material specifications are available. For the renovation planning, the identified geometric attributes can help prioritize renovation strategies, with modifications to height, width, and stage area likely to impact both RT and C80. For frequency-specific optimization, different geometric features may require emphasis depending on the target frequency range for acoustic improvements.

Model explanatory power was highest at low to mid frequencies (125–500 Hz for RT, 250–1000 Hz for C80), with R^2 values up to 0.47. While FEM simulations achieve higher accuracy ($R^2 > 0.9$) for RT prediction [14], they demand material properties and significant computational resources. Our ML models (R^2 up to 0.47) offer a 100–1000x speed advantage for early-stage design, albeit with moderate precision. For renovation projects with unknown materials, ML provides a viable alternative until detailed data is available. This trade-off underscores the complementary roles of ML and traditional methods in acoustic design workflows.

H. Limitations and Future Directions

ML models cannot fully replace simulations for final designs due to lower accuracy (e.g., $R^2 < 0.5$ at high frequencies). However, they reduce reliance on unavailable material data during conceptual phases, bridging a critical gap in workflow efficiency. The models presented here are intentionally geometry-based and preliminary, serving as a foundation for early-stage design assessments. Their moderate explanatory power ($R^2 \leq 0.47$) reflects the inherent limitations of omitting material properties, which are critical for high-precision predictions. Future iterations should integrate material data to bridge this gap while retaining computational efficiency. Several key limitations must be acknowledged.

Dataset limitations: The analysis is restricted to 58 large Western concert halls (> 700 seats) due to data availability constraints. While this provides a robust benchmark for similar venues, it inherently limits generalizability to smaller halls or non-Western architectural traditions. Future work

must prioritize global diversity and smaller venues to address this gap.

Missing material information: The absence of surface material and absorption coefficient data fundamentally caps predictive accuracy, as these properties are critical for high-precision acoustic modeling. While geometric features explain up to 47% of variance, future iterations must integrate material data to achieve design-ready precision.

Geographic and cultural bias: The dataset primarily represents Western concert hall traditions. Including venues from diverse cultural contexts would enhance global applicability.

Validation scope: Independent testing was limited to four venues due to data availability constraints. While this preliminary validation aligns with the study's focus on proof-of-concept, future work should include larger and more architecturally diverse test sets to confirm model generalizability. Such expansion would also help quantify performance variability across hall sizes and cultural design traditions. While R^2 values up to 0.47 demonstrate utility for early-stage assessments, they underscore the need for material-integrated models for final design precision.

Future research directions:

- Integration of material property data with geometric features
- Development of ensemble methods combining multiple algorithms
- Investigation of small venue acoustics using similar methodologies and non-Western architectures
- Real-time acoustic monitoring integration with ML prediction systems
- Extension to other acoustic parameters (e.g., warmth, envelopment indices)
- These models are preliminary; material integration is critical for precision
- The War Memorial Opera House showed a moderate agreement between the predicted and measured values, with estimation accuracy varying across frequency bands.

Future research should prioritize integrating material properties into ML models to improve accuracy. Recent hybrid frameworks [13, 15] suggest ML can guide simulation parameterization, reducing computational costs. Our geometric-only models align with this paradigm, enabling rapid pre-screening of design options before resource-intensive simulations. Combining ML's speed with simulations' precision could revolutionize iterative acoustic design.

V. CONCLUSION

This study demonstrates that ML can predict concert hall acoustics from geometry alone, with SVMs and GPR outperforming other algorithms for RT and C80, respectively. For practitioners, these models serve as rapid screening tools for preliminary design, offering actionable insights when material data are unavailable. However, their moderate precision ($R^{2*} \leq 0.47$) necessitates expert fine-tuning and integration of material properties for final design decisions. Future research should focus on hybrid modeling and global dataset expansion to advance ML's role in architectural acoustics. Key findings include:

- **Geometric influence:** Six geometric attributes (volume, stage area, number of seats, height, width, acoustic

absorption area) explain up to 47% of RT variation, while four attributes (stage area, height, width, acoustic absorption area) explain up to 47% of C80 variation.

- Frequency dependence: Geometric attributes show stronger predictive power for RT at low frequencies (125–500 Hz) and for C80 at mid frequencies (250–1000 Hz), reflecting the physical mechanisms governing these acoustic parameters.
- Algorithm performance: No single ML algorithm performs optimally across all frequencies, with support vector machines and Gaussian process regression showing the best overall performance for RT and C80, respectively.
- Practical applications: The developed models provide a foundation for preliminary acoustic assessments and renovation planning, though integration with material property data would significantly enhance their utility.

While the current study establishes the potential of ML-based acoustic prediction, achieving practical design accuracy will require expanded datasets incorporating both geometric and material properties. Nevertheless, these findings represent an important step toward data-driven acoustic design tools that could streamline the concert hall development process and support evidence-based renovation decisions.

The demonstrated frequency-dependent relationships between geometry and acoustics provide valuable insights for architectural acousticians and offer a quantitative foundation for understanding how building form influences acoustic

performance. As datasets expand and ML techniques advance, these approaches may become valuable complements to traditional measurement and simulation methods in architectural acoustic practice.

APPENDIX

The models yielding the most accurate estimations are marked in bold in Tables B1–12.

Models: Linear Regression (LR), Interactions Linear Regression (ILR), Robust Linear Regression (RLR), Stepwise Linear Regression (SLR), Fine Tree (FT), Medium Tree (MT), Coarse Tree (CT), Linear Support Vector Machine (LSVM), Quadratic Support Vector Machine (QSVM), Cubic Support Vector Machine (CSVM), Fine Gaussian Support Vector Machine (FGSVM), Medium Gaussian Support Vector Machine (MGSVM), Coarse Gaussian Support Vector Machine (CGSVM), Efficient Linear Least Squares Support Vector Machine (ELLSSVM), Efficient Linear Support Vector Machine (ELSVM), Boosted Trees (BoT), Bagged Trees (BaT), Squared Exponential Gaussian Process Regression (SEGPR), Matern 5/2 Gaussian Process Regression (MGPR), Exponential Gaussian Process Regression (EGPR), Rational Quadratic Gaussian Process Regression (RQGPR), Narrow Neural Network (NNN), Medium Neural Network (MNN), Wide Neural Network (WNN), Bilayered Neural Network (BNN), Trilayered Neural Network (TNN), Support Vector Machine Kernel (SVMK), Least Squares Regression Kernel (LSRK).

Table B1. The constructed model of RT₁₂₅ based on 6 geometric attributes of the concert halls

Model	LR	ILR	RLR	SLR	FT	MT	CT
RMSE	0.11815	0.11369	0.12168	0.15156	0.1435	0.13288	0.12265
Model	LSVM	QSVM	CSVM	FGSVM	MGSVM	CGSVM	ELLSSVM
RMSE	0.12594	0.09507	0.20635	0.11368	0.11764	0.12309	0.12044
Model	ELSVM	BoT	BaT	SEGPR	MGPR	EGPR	RQGPR
RMSE	0.13029	0.12654	0.1217	0.11027	0.11065	0.1076	0.10699
Model	NNN	MNN	WNN	BNN	TNN	SVMK	LSRK
RMSE	0.30742	0.17726	0.12626	0.15134	0.13090	0.11464	0.12078

Table B2. The constructed models of RT₂₅₀ based on 6 geometric attributes of the concert halls

Model	LR	ILR	RLR	SLR	FT	MT	CT
RMSE	0.13199	0.17729	0.13759	0.10354	0.15154	0.13365	0.13432
Model	LSVM	QSVM	CSVM	FGSVM	MGSVM	CGSVM	ELLSSVM
RMSE	0.13813	0.11283	0.27159	0.12371	0.12053	0.1055	0.13185
Model	ELSVM	BoT	BaT	SEGPR	MGPR	EGPR	RQGPR
RMSE	0.13609	0.12821	0.13008	0.11264	0.1104	0.10846	0.10951
Model	NNN	MNN	WNN	BNN	TNN	SVMK	LSRK
RMSE	0.27806	0.18811	0.12723	0.14992	0.19839	0.11795	0.1259

Table B3. The constructed models of RT₅₀₀ based on 6 geometric attributes of the concert halls

Model	LR	ILR	RLR	SLR	FT	MT	CT
RMSE	0.11786	0.18659	0.12843	0.12535	0.13347	0.1295	0.12421
Model	LSVM	QSVM	CSVM	FGSVM	MGSVM	CGSVM	ELLSSVM
RMSE	0.12187	0.1299	0.09266	0.11715	0.11509	0.1289	0.11855
Model	ELSVM	BoT	BaT	SEGPR	MGPR	EGPR	RQGPR
RMSE	0.12196	0.12351	0.11844	0.11379	0.1134	0.11136	0.11236
Model	NNN	MNN	WNN	BNN	TNN	SVMK	LSRK
RMSE	0.30117	0.25463	0.16883	0.20957	0.18886	0.1332	0.11149

Table B4. The constructed models of $RT_{1,000}$ based on 6 geometric attributes of the concert halls

Model	LR	ILR	RLR	SLR	FT	MT	CT
RMSE	0.13631	0.17475	0.13662	0.14846	0.15768	0.15101	0.14432
Model	LSVM	QSVM	CSVM	FGSVM	MGSM	CGSM	ELLSSVM
RMSE	0.13309	0.1313	0.18998	0.13699	0.14027	0.14548	0.13691
Model	ELSVM	BoT	BaT	SEGPR	MGPR	EGPR	RQGPR
RMSE	0.12874	0.14106	0.14003	0.12163	0.12797	0.13015	0.12163
Model	NNN	MNN	WNN	BNN	TNN	SVMK	LSRK
RMSE	0.25372	0.22178	0.18337	0.22143	0.1667	0.14395	0.1366

Table B5. The constructed models of $RT_{2,000}$ based on 6 geometric attributes of the concert halls

Model	LR	ILR	RLR	SLR	FT	MT	CT
RMSE	0.39433	0.53535	0.38407	0.38571	0.46999	0.41679	0.40261
Model	LSVM	QSVM	CSVM	FGSVM	MGSM	CGSM	ELLSSVM
RMSE	0.38061	0.11985	0.46524	0.37661	0.39914	0.39798	0.39464
Model	ELSVM	BoT	BaT	SEGPR	MGPR	EGPR	RQGPR
RMSE	0.37451	0.41938	0.39494	0.11862	0.37171	0.37794	0.11985
Model	NNN	MNN	WNN	BNN	TNN	SVMK	LSRK
RMSE	0.93859	0.85074	0.59269	0.46409	0.53237	0.40872	0.39925

Table B6. The constructed models of $RT_{4,000}$ based on 6 geometric attributes of the concert halls

Model	LR	ILR	RLR	SLR	FT	MT	CT
RMSE	0.35174	0.55611	0.35251	0.38302	0.1099	0.37052	0.3493
Model	LSVM	QSVM	CSVM	FGSVM	MGSM	CGSM	ELLSSVM
RMSE	0.34405	0.32485	0.39036	0.33323	0.33695	0.34898	0.34751
Model	ELSVM	BoT	BaT	SEGPR	MGPR	EGPR	RQGPR
RMSE	0.3574	0.3534	0.335	0.32719	0.11718	0.32686	0.32723
Model	NNN	MNN	WNN	BNN	TNN	SVMK	LSRK
RMSE	0.85407	0.68416	0.56585	0.58548	0.60597	0.35458	0.34259

Table B7. The constructed models of $C80_{125}$ based on 4 geometric attributes of the concert halls

Model	LR	ILR	RLR	SLR	FT	MT	CT
RMSE	0.35755	0.46387	0.36924	0.35336	0.39979	0.36072	0.3484
Model	LSVM	QSVM	CSVM	FGSVM	MGSM	CGSM	ELLSSVM
RMSE	0.36047	0.36589	0.36723	0.32864	0.32491	0.34596	0.34577
Model	ELSVM	BoT	BaT	SEGPR	MGPR	EGPR	RQGPR
RMSE	0.35395	0.34455	0.34635	0.3148	0.31698	0.32144	0.31732
Model	NNN	MNN	WNN	BNN	TNN	SVMK	LSRK
RMSE	1.0201	0.73031	0.46697	0.76816	0.61394	0.33331	0.33069

Table B8. The constructed models of $C80_{250}$ based on 4 geometric attributes of the concert halls

Model	LR	ILR	RLR	SLR	FT	MT	CT
RMSE	0.34988	0.37736	0.35058	0.34892	0.34050	0.34349	0.34572
Model	LSVM	QSVM	CSVM	FGSVM	MGSM	CGSM	ELLSSVM
RMSE	0.33751	0.33106	0.33768	0.315	0.3115	0.33788	0.341
Model	ELSVM	BoT	BaT	SEGPR	MGPR	EGPR	RQGPR
RMSE	0.33714	0.31071	0.32003	0.28103	0.27905	0.28655	0.28073
Model	NNN	MNN	WNN	BNN	TNN	SVMK	LSRK
RMSE	0.75601	0.55081	0.40788	0.54791	0.60923	0.30918	0.31477

Table B9. The constructed models of $C80_{500}$ based on 4 geometric attributes of the concert halls

Model	LR	ILR	RLR	SLR	FT	MT	CT
RMSE	0.46776	0.50275	0.47173	0.45608	0.4289	0.44433	0.45976
Model	LSVM	QSVM	CSVM	FGSVM	MGSM	CGSM	ELLSSVM
RMSE	0.44092	0.44752	0.5571	0.41453	0.42442	0.44317	0.45734
Model	ELSVM	BoT	BaT	SEGPR	MGPR	EGPR	RQGPR

RMSE	0.44077	0.41458	0.43496	0.348	0.37336	0.38509	0.371
Model	NNN	MNN	WNN	BNN	TNN	SVMK	LSRK
RMSE	0.6713	0.75767	0.68312	0.69639	0.72419	0.42118	0.43371

Table B10. The constructed models of C80_{1,000} based on 4 geometric attributes of the concert halls

Model	LR	ILR	RLR	SLR	FT	MT	CT
RMSE	0.47452	0.49513	0.47603	0.48631	0.45211	0.46682	0.46527
Model	LSVM	QSVM	CSVM	FGSVM	MGSM	CGSVM	ELLSSVM
RMSE	0.47506	0.44824	0.42607	0.4044	0.42268	0.46443	0.46115
Model	ELSVM	BoT	BaT	SEGPR	MGPR	EGPR	RQGPR
RMSE	0.47019	0.43818	0.43797	0.11433	0.34446	0.36761	0.33906
Model	NNN	MNN	WNN	BNN	TNN	SVMK	LSRK
RMSE	0.77185	0.61192	0.61187	0.86002	0.87906	0.43696	0.42976

Table B11. The constructed models of C80_{2,000} based on 4 geometric attributes of the concert halls

Model	LR	ILR	RLR	SLR	FT	MT	CT
RMSE	0.49853	0.51664	0.5011	0.50951	0.55842	0.5337	0.48789
Model	LSVM	QSVM	CSVM	FGSVM	MGSM	CGSVM	ELLSSVM
RMSE	0.51106	0.46489	0.52391	0.45284	0.45284	0.49023	0.49937
Model	ELSVM	BoT	BaT	SEGPR	MGPR	EGPR	RQGPR
RMSE	0.46697	0.517	0.49497	0.42465	0.43969	0.45001	0.43596
Model	NNN	MNN	WNN	BNN	TNN	SVMK	LSRK
RMSE	1.097	1.0292	0.63583	0.94418	0.9083	0.51715	0.47299

Table B12. The constructed models of C80_{4,000} based on 4 geometric attributes of the concert halls

Model	LR	ILR	RLR	SLR	FT	MT	CT
RMSE	0.42391	0.43848	0.42311	0.45013	0.54283	0.43961	0.415
Model	LSVM	QSVM	CSVM	FGSVM	MGSM	CGSVM	ELLSSVM
RMSE	0.42187	0.40656	0.48871	0.40688	0.41926	0.41068	0.41476
Model	ELSVM	BoT	BaT	SEGPR	MGPR	EGPR	RQGPR
RMSE	0.41576	0.45423	0.43591	0.38288	0.37797	0.39733	0.38288
Model	NNN	MNN	WNN	BNN	TNN	SVMK	LSRK
RMSE	0.73828	0.94952	0.74951	0.92205	0.81122	0.44348	0.40734

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Akın Oktav collected the data, wrote the literature review, constructed the sections of the paper, and wrote the first draft of the paper; Murat A. Başaran conducted data preprocessing and modeling; both authors had approved the final version.

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