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Article

Enhancing sound source localization and music teaching through integrated computational resource allocation

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Abstract: In contemporary educational and computational settings, the incorporation of cutting-edge technologies like sound source localization and personalized music teaching helps in offering an effective resource allocation strategies. Previous systems for sound localization and music teaching frequently lacked real-time flexibility and effective resource use, reducing their efficiency in dynamic learning settings and tasks involving computation. To overcome these shortcomings, the SoundLocMusicTeachRA (SLMTRA) algorithm is presented, a single, integrated platform made to maximize sound localization accuracy, improve music teaching efficiency, and enhance computational resource oversight. However, the existing study did not highlight the importance of computation resource allocation but this proposed algorithm will address it. SLMTRA uses a new Bagging ensemble approach incorporating Random Forest (RF), Decision Trees (DT), Naive Bayes (NB), Support Vector Machine (SVM), and K-Nearest Neighbor (KNN), with hyperparameter tuning to enhance the effectiveness of the approach. These classifiers are trained utilizing sound localization datasets from recordings made with microphones, music teaching feedback datasets from data on student performance, and resource allocation datasets from metrics for computer utilization. Experimental findings indicate SLMTRA's high accuracy in sound source localization, improved music teaching feedback capacities, as well as effective resource allocation tactics, guaranteeing the best performance of the system. The implementation of SLMTRA represents a noteworthy development in combining sound localization, music teaching, and resource allocation within a unified computational framework, offering a more flexible and effective system compared to previous methodologies.

Keywords: sound localization; music teaching; resource allocation; bagging ensemble method

1. Introduction

In the current educational environment, the combination of advanced technologies has a vital role in advancing learning experiences and enhancing system efficiency. Innovations in sound source localization [1] and individualized music teaching [2] have the potential to greatly enhance conventional educational contexts, turning them into dynamic and interactive learning experiences. Effective resource allocation tactics are essential for increasing the usage of computational assets and assuring consistent function and highest efficiency in different educational and computational domains [3]. This paper introduces the SoundLocMusicTeachRA (SLMTRA) algorithm—an advanced, cohesive platform created to tackle the inherent difficulties in sound localization, music teaching, and resource allocation. Existing sound localization systems primarily depend on fixed algorithms that frequently encounter difficulties in promptly adjusting to the ever-changing conditions seen in educational environments [4]. These methods commonly utilize single-method tactics, which may restrict their capacity to precisely capture the intricacies of spatial audio data. Similarly, current platforms for teaching music frequently lack strong feedback systems customized to the needs of each student, thus impeding the achievement of good learning results [5]. Furthermore, the allocation of computational resources in these systems often lacks optimization, leading to poor efficiency and unnecessary resource use [6].

The main limitations of previous techniques encompass multiple crucial areas. The absence of real-time adaptation in sound localization systems might result in potential inaccuracies or delays in delivering exact spatial audio data. This constraint is especially harmful in educational settings where prompt and precise feedback is crucial. Furthermore, the lack of sufficient individualized feedback systems in music teaching platforms hampers the efficacy of customized learning tactics based on student growth and interests. Furthermore, improper allocation of resources leads to avoidable computational burdens, which hinder the total effectiveness and reliability of the system. To tackle these intrinsic constraints, the SLMTRA algorithm arises as a revolutionary remedy. SLMTRA is very adaptable and can be used in a wide range of educational settings, from conventional music schools to online learning platforms with real-time interactive classrooms. Moreover, its usefulness in computational resource management systems guarantees increased effectiveness and enhancement of performance in many different contexts. The widespread use of SLMTRA highlights its ability to alter educational processes and greatly improve computational resource allocation tactics.

SLMTRA is meticulously designed to maximize sound localization accuracy, improve the efficiency of music teaching approaches, and streamline computational resource management within a unified framework. Fundamentally, SLMTRA utilizes a Bagging ensemble technique to combine many classifiers such as Random Forest (RF), Decision Trees (DT), Naive Bayes (NB), Support Vector Machine (SVM), and K-Nearest Neighbor (KNN) seamlessly. By extensively adjusting the hyperparameters, these classifiers are optimized to enhance their predicted accuracy and operational effectiveness. The SLMTRA algorithm progresses through a systematic sequence of methodical steps specifically designed to accomplish its main objectives. The strategy places great emphasis on thorough data preprocessing, specifically encoding categorical variables using label encoding. This ensures the smooth incorporation of these variables into machine learning methods. Numerical feature normalization is used to ensure that all model training instances contribute equally, which is crucial for enhancing the convergence and predictive accuracy of the deployed classifiers. This paper makes a substantial contribution to the field by introducing SLMTRA, a groundbreaking platform that combines sound localization, music teaching, and resource allocation seamlessly. SLMTRA combines ensemble learning and hyperparameter tuning to improve the precision and dependability of sound source localization and boost the effectiveness of tailored music education approaches. Furthermore, SLMTRA implements effective methods for allocating resources, thus setting a standard for adaptable and high-performing systems in the fields of education and computation. The primary goal of this paper is to meticulously create and apply the SLMTRA algorithm, to show its effectiveness in overcoming the constraints of existing approaches. SLMTRA intends to establish a new benchmark for adaptive and effective technological remedies in educational environments and beyond by creatively tackling the issues provided by conventional sound localization, music teaching, and resource allocation methods.

The paper's structure is meticulously arranged to offer a thorough examination of the development, implementation, and evaluation of SLMTRA. Section 2 provides an overview of relevant research, which helps to provide the background for SLMTRA's unique approach. Section 3 provides a comprehensive explanation of the methodological foundations that support the SLMTRA algorithm. This includes a detailed description of the processes involved in data preprocessing, model construction, and hyperparameter optimization. Section 4 demonstrates the empirical results of SLMTRA, highlighting its strong performance in accurately localizing sound, effectively teaching music, and efficiently managing computing resources. Section 5 serves as the final part of the study, where it provides a summary of important findings, emphasizes the contributions made, and suggests potential areas for future research and practical implementation.

2. Related works

Recently, notable progress has been achieved in sound localization, music teaching, and resource allocation, due to breakthroughs in signal processing, machine learning, and educational technology. This section examines significant contributions from current literature in these fields, emphasizing their approaches and the current deficiencies that inspire the proposed SoundLocMusicTeachRA (SLMTRA) algorithm.

Sound source localization, separation, and reconstruction are essential activities in diverse settings such as conference rooms and residential spaces. Recent improvements have greatly improved these processes, especially in situations where time-domain signal separation and reconstruction are needed. Chen et al. [7] suggests a hybrid methodology that integrates strategies for processing signals from microphone arrays. This method efficiently tackles the difficulties in accurately determining both the position and content of sound sources, especially in intricate sound environments. Their methodology utilizes advanced techniques such as beamforming and broadband weighted multiple signal classification (BW-MUSIC) to achieve enhanced accuracy and operating efficiency in comparison to conventional methods.

Liaquat et al. [8] investigate the process of sound localization by employing ad-hoc microphone arrays, with a particular focus on the ability to achieve high levels of accuracy and effectiveness utilizing a reduced number of microphones. Their innovative approach combines direction of arrival (DOA) estimate with three-dimensional localization, illustrating that by reducing the number of microphones, computational complexity may be streamlined without compromising accuracy. This study highlights the practical advantages of using ad-hoc arrays to improve sound source identification methods.

Chung et al. [9] specifically examines the localization of sounds within indoor environments by employing several arrays of microphones. They emphasize the use of time delay estimation algorithms to address the difficulties caused by signal delays. Their experimental configuration utilizes two linear microphone arrays to attain accurate localization outcomes in controlled conditions. Through the utilization of generalized cross-correlation approaches, they successfully showcase their capability to recognize sound sources with minimum error margins, thus confirming the practicality and dependability of their proposed system.

Go and Choi [10] propose a novel method for acoustic source localization by utilizing phased microphone arrays placed on drones. Their approach tackles specific difficulties presented by drone functions, such as mitigating background noise interference and optimizing the ratio of signal to noise. Through the integration of aircraft navigation data and acoustic signal processing, they can accurately estimate the locations of sound sources above the ground. The success of their approach has been confirmed through experimental validation, demonstrating its potential for applications that involve airborne acoustic monitoring.

Rucsanda et al. [11] examine the opinions of students regarding online music instruction amid the COVID-19 pandemic, with a focus on how the perceived usefulness of e-learning approaches influences their level of satisfaction. Their research emphasizes the adjustment of music education to distant formats and emphasizes the significance of compatibility and perceived utility in improving student involvement and contentment with online learning platforms.

De Bruin [12] examines the teaching methods employed by instrumental music educators during the COVID-19 pandemic. The study specifically investigates ways that promote strong relationships and connections in online teaching settings. The study uses qualitative analysis to examine how music educators address the difficulties of distant instruction while simultaneously fostering interpersonal connections and encouraging student autonomy in musical learning. This study provides significant findings regarding effective online teaching methods in the area of teaching music.

Dai [13] investigates the use of artificial intelligence (AI) technology in the instructing of music. The study emphasizes the significant changes that intelligent instructional design can bring to music education. The author suggests implementing AI technology such as big data analytics and personalized learning algorithms to improve teaching efficacy and increase student engagement in music courses. This study proposes the implementation of AI-driven techniques to enhance music teaching methods and facilitate personalized learning experiences for students.

Tuli et al. [14] present HUNTER, an AI-driven framework for managing resources in cloud computing to promote sustainability. HUNTER is a solution that addresses the increasing energy needs of modern data centers. It combines multi-objective scheduling models with graph convolution networks to improve energy efficiency, temperature control, and service quality in cloud environments. The experimental results show substantial enhancements in energy efficiency, adherence to service level agreements, and operational expenses as compared to conventional resource management methods.

Giardino et al. [15] introduce a power management system called 2QoSM, which utilizes reinforcement learning to improve dynamic power management in embedded systems while minimizing additional costs. By implementing Q-learning algorithms in a software framework, their method successfully reduces energy use significantly while enhancing performance measures such as path error in autonomous robotic systems. This study demonstrates the efficacy of reinforcement learning methods in reducing power consumption while maintaining operational effectiveness.

Azarhava and Niya [16] investigate the effective allocation of resources in wireless energy harvesting sensor networks (WEHSNs), with a specific emphasis on improving time scheduling and minimizing transmission power usage. Their research suggests a technique based on TDMA (Time Division Multiple Access) that effectively manages the balance between energy harvesting abilities and transmission needs. They utilize mathematical improvement approaches to improve the effectiveness of the network. This study offers valuable insights into sustainable resource management strategies that may be employed to prolong the lifespan of sensor networks and enhance their overall effectiveness.

Yu et al. [17] suggests a cooperative system that combines UAVs, or unmanned aerial vehicles, and MEC, or mobile edge computing to improve the distribution of tasks and allocation of resources for Internet of Things (IoT) devices. Their strategy involves combining UAVs with edge clouds to overcome connection issues in areas with limited network coverage. This integration improves the delivery of services for applications that require a significant number of resources. By creating an optimization problem that takes into account service latency, energy usage, and task allocation choices, they show better efficiency than typical MEC frameworks.

The main limitations of the above existing systems include the absence of real-time adaptation in sound localization, leading to imprecise or delayed spatial audio data. Furthermore, the lack of tailored feedback systems in music teaching platforms hampers efficient learning and student engagement. This problem is worsened by poor resource allocation, which results in needless computational burdens and decreased system efficiency. These constraints emphasize the necessity for a comprehensive and flexible approach to tackle difficulties in these areas. To address these current drawbacks, the SoundLocMusicTeachRA (SLMTRA) algorithm is suggested.

3. Methodology

The methodology utilized in the paper concentrates on implementing the SoundLocMusicTeachRA (SLMTRA) algorithm to tackle significant obstacles in sound localization, music teaching feedback, and resource allocation. These domains play a vital part in improving user experience and system efficiency in a several uses, such as real-time sound source recognition, tailored music education, and effective computational resource management.

3.1. Data collection

The data collecting process for this study involved collecting a wide range of datasets that were necessary for training and testing the SoundLocMusicTeachRA (SLMTRA) algorithm in its main applications: sound localization, music teaching feedback, and resource allocation. All data sets were meticulously selected to capture important characteristics and provide a thorough representation of operating situations.

3.1.1. Sound localization dataset

The Sound Localization dataset consists of recordings captured in controlled situations using several microphones. In these environments, sound sources are deliberately placed at specified coordinates (x, y). Each recording consists of readings from four microphones (Microphone 1 to Microphone 4), which measure the intensity of sound (in dB) at each source location. We decided to use a 1000 Hz narrowband signal as our audio source. The absorption coefficient for the room is configured to be 0.4. The sidelobe value of proposed algorithm is −13 dB.

This dataset enables the training and testing of the SLMTRA algorithm's predictive models for reliably estimating the spatial coordinates of sound sources in real-time settings. **Table 1** shows the Sample Sound Localization Dataset.

Table 1. Sample sound localization dataset.

Microphone 1 (dB)	Microphone 2 (dB)	Microphone 3 (dB)	Microphone 4 (dB)	Sound Source Location (x, y)
71	66	61	56	(4, 1)
56	61	66	71	(1, 2)
69	65	59	53	(2, 4)
51	56	61	66	(3, 1)
66	63	58	54	(1, 4)
59	61	64	68	(4, 1)
73	69	61	55	(2, 2)
54	58	63	67	(4, 4)
61	66	71	76	(3, 3)
71	67	63	59	(1, 1)

3.1.2. Music teaching feedback dataset

The Music Teaching feedback dataset comprises recordings of 360 student performances on several musical instruments, accompanied by features that indicate the quality of performance and instructional feedback. The attributes consist of Student ID, Instrument played, Age, Practice Hours per week, Lesson Type (Individual or Group), and performance quality (rated on a scale of 1–10) with performance metrics like Note Accuracy, Rhythm Accuracy, Dynamics (rated on a scale of 1–10), and a Feedback. This dataset facilitates the training and testing of SLMTRA algorithms for delivering individualized feedback and evaluating effectiveness in music education environments. **Table 2** shows the Sample Music Teaching Feedback Dataset.

Table 2. Sample music teaching feedback dataset.

ID	Instrument	Age	Practice Hrs	Lesson Type	Perf.	Note Acc	Rhythm Acc	Dynamics	Feedback
1	Violin	13	6	Group	9	96	91	8	Improve Intonation
2	Piano	15	4	Individual	7	81	72	6	Good Timing
3	Flute	17	5	Group	8	97	93	9	Improve Rhythm

Table 2. (*Continued*).

ID	Instrument	Age	Practice Hrs	Lesson Type	Perf.	Note Acc	Rhythm Acc	Dynamics	Feedback
4	Guitar	14	3	Individual	9	91	86	8	Good Breath Control
5	Drums	16	7	Individual	6	71	66	7	Excellent Dynamics

3.1.3. Resource allocation dataset

The Resource Allocation dataset records system utilization measurements during predefined time intervals, which are essential for training models to forecast the most efficient resource allocations. The dataset consists of 1500 records. The attributes consist of Time Slot (measured in hours), CPU Usage (expressed as a percentage), Memory Usage (measured in gigabytes), Disk Usage (expressed as a percentage), Network Usage (measured in megabits per second), and the related Resource Allocation states (High, Medium, Low). This dataset enables the creation of SLMTRA models that dynamically distribute computing resources, taking into account real-time system demands. This ensures optimal performance and usage of resources. **Table 3** shows the Sample Resource Allocation Dataset.

Table 3. Sample resource allocation dataset.

Time Slot (hr)	CPU Usage (%)	Memory Usage (GB)	Disk Usage (%)	Network Usage (Mbps)	Resource Allocation (High/Medium/Low)
0–1	30	1.6	35	20	Low
1–2	35	1.9	40	22	Low
2–3	40	2.1	45	25	Low
3–4	45	2.3	50	28	Medium
4–5	50	2.7	55	30	Medium
5–6	55	2.9	60	32	Medium
6–7	60	3.1	65	35	High
7–8	65	3.3	70	38	High
8–9	70	3.6	75	40	High
9–10	75	3.9	80	45	High

3.2. SoundLocMusicTeachRA (SLMTRA) algorithm

The SLMTRA algorithm is specifically developed to tackle three main objectives: sound localization, music teaching feedback, and resource allocation. By utilizing a Bagging ensemble technique with several classifiers, the system improves the accuracy and resilience of predictions. Algorithm 1 shows the comprehensive process of the SLMTRA algorithm is explained in detail.

Algorithm 1 SoundLocMusicTeachRA (SLMTRA) Algorithm

1: Input:
- Sound Localization Dataset (DS_sound): A dataset including sound recordings and the associated spatial coordinates.
- Music Teaching Feedback Dataset (DS_feedback): Student performance dataset with labels denoting feedback and performance quality.
- Resource Allocation Dataset (DS_resource): Dataset monitoring patterns in the use of computer resources.

Algorithm 1 (*Continued*)

2:	Output:	● Sound Localization Prediction: Predicted geographical coordinates of a recently audible sound. ● Music Performance Feedback: Instantaneous feedback on a student's musical performance in practice sessions. ● Resource Allocation Decision: Optimal resource allocation decisions using predicted utilization patterns.
3:	Step 1:	Data Preparation: ● On DS_sound, execute min-max normalization. ● Divided normalized DS_sound into datasets for training (75%) and testing (25%).
4:	Step 2:	Sound Localization Model Training: ● Using the training dataset, apply the Bagging ensemble approach using RF, DT, NB, SVM, and KNN. ● Execute hyperparameter tuning for each classification technique. ● Utilize training data to train models for sound location prediction.
5:	Step 3:	Sound Localization Prediction: ● When a new sound is detected, use the trained ensemble model to forecast the spatial coordinates.
6:	Step 4:	Data Preparation: ● Use label encoding to convert the DS_feedback's categorical features to numerical format. ● Apply min-max normalization to DS_feedback to make it normal. ● Divide the training (75%) and testing (25%) datasets of DS_feedback.
7:	Step 5:	Music Performance Model Training: ● Using the training dataset, apply the Bagging ensemble approach using RF, DT, NB, SVM, and KNN. ● Conduct hyperparameter optimization for each classifier. ● Train model to identify trends in performances that indicate either proficiency or areas for growth.
8:	Step 6:	Music Performance Feedback: ● Offer instantaneous feedback during student practice sessions using learned patterns from the trained models.
9:	Step 7:	Data Preparation: ● Apply label encoding to convert the categorical features in DS_resource into numerical format. ● Apply min-max normalization to standardize the DS_resource. ● Partition the DS_resource into a training dataset, including 75% of the data, and a testing dataset, comprising 25% of the data.
10:	Step 8:	Resource Allocation Model Training: ● Apply the Bagging ensemble approach to the training dataset by using RF, DT, NB, SVM, and KNN. ● Conduct hyperparameter optimization for each classifier. ● Use previous usage patterns from DS_resource to train a model to forecast optimal resource allocation decisions.
11:	Step 9:	Resource Allocation Decision: ● Predict and execute resource allocation choices to maximize computer effectiveness.

The algorithm uses three primary datasets as input: the Sound Localization Dataset (DS_sound), the Music Teaching Feedback Dataset (DS_feedback), and the Resource Allocation Dataset (DS_resource). The outputs consist of the predicted spatial coordinates of a recently perceived sound, immediate feedback for a student's musical performance, and optimal decisions regarding resource allocation determined by predicted utilization patterns. Flowchart 1 represents visual representation of the algorithm.

3.2.1. Sound localization

The initial task of the SLMTRA algorithm is to determine the location of sound. The procedure commences with data preparation. The DS_sound dataset comprises sound recordings captured by several microphones, along with their respective spatial coordinates. The data is subjected to min-max normalization to standardize all features to a comparable scale, hence enhancing the efficiency of approaches for machine learning. Following the process of normalization, the dataset is split into two subsets: a training set (75% of the dataset), and a testing set (remaining 25% of the dataset).

Subsequently, the algorithm proceeds to train the sound localization model utilizing a Bagging ensemble technique. This ensemble has multiple base classifiers, including Random Forest (RF), Decision Trees (DT), Naive Bayes (NB), Support Vector Machine (SVM), and K-Nearest Neighbor (KNN). Bagging is a method that comprises training individual classifiers on unique subsets of the training data and after that combining their forecasts. Hyperparameter tuning is conducted for each classifier utilizing the grid search technique to recognize the ideal set of parameters that enhance the effectiveness of the model. After the model has been trained, it can predict the spatial coordinates of a new sound by utilizing the recorded data.

3.2.2. Music teaching feedback

The second task is centered around delivering instantaneous feedback for music teaching. The DS_feedback dataset comprises recordings of student performances that have been annotated with labels denoting the quality of the performance and providing particular feedback. At first, the categorical features in this dataset are transformed into numerical representations utilizing label encoding, which provides distinct numerical values to each category. After the conversion, min-max normalization is applied to guarantee uniformity among features. The dataset is first normalized and then divided into two subsets: a training subset, and a testing subset.

The process of training the music performance model entails utilizing the Bagging ensemble technique with a consistent set of classifiers, namely RF, DT, NB, SVM, and KNN. Hyperparameter optimization is once again utilized to improve the parameters of each classifier. These models are trained to identify patterns in the performance recordings that suggest either strong performance or areas that require development. While a student is practicing, the trained models offer immediate feedback using learned patterns. This feedback assists students in identifying and addressing certain areas of their performance that necessitate improvement, thus augmenting the efficacy of their practice sessions.

3.2.3. Resource allocation

The ultimate task of the SLMTRA algorithm involves the allocation of resources to achieve optimal computer efficiency. The DS_resource, also known as the Resource Allocation Dataset, monitors and records the patterns of computer resource utilization over a period. Like the previous tasks, categorical features are initially transformed into numerical representations using label encoding. This is then followed by applying min-max normalization to the dataset. The data is normalized and then split into two subsets: a training set, and a testing set.

The training procedure for the resource allocation model utilizes the Bagging ensemble method, using RF, DT, NB, SVM, and KNN classifiers. Hyperparameter optimization is used to identify the optimal parameters for each classifier. These models are developed to forecast the most advantageous periods for allocating resources by analyzing past consumption patterns. The trained model assists the computer in effectively managing its resources by making predictions and executing choices on resource allocation. This optimization guarantees seamless performance and effective power management, resulting in reduced computing burden and enhanced system performance.

3.2.4. Bagging ensemble method with RF, DT, NB, SVM, and KNN classifiers

The Bagging Ensemble approach, often referred to as Bootstrap Aggregating, is employed in the SLMTRA algorithm to improve the effectiveness and resilience of numerous classifiers. Bagging, a technique that combines the predictions of multiple base classifiers, effectively decreases variation and mitigates the risk of overfitting. Within this particular context, the Bagging technique utilizes five distinct base classifiers: Random Forest (RF), Decision Tree (DT), Naive Bayes (NB), Support Vector Machine (SVM), and K-Nearest Neighbors (KNN). Grid Search is employed to optimize the hyperparameters of each classifier to achieve the greatest performance.

1) Bagging ensemble method

Bagging operates by creating several subsets of the training data via random sampling with replacement. Each distinct subset is utilized to train an individual model, and the ultimate forecast is generated by combining the predictions of all models. For classification, the process of aggregating results is commonly achieved using majority voting.

Mathematically, the Bagging prediction $F(x)$ can be expressed as:

$$F(x) = \frac{1}{T}\sum_{t=1}^{T} f_t(x) \quad (1)$$

where T is the number of base classifiers and $f_t(x)$ is the prediction of the t-th classifier.

2) Base classifiers

Every individual base classifier possesses distinct hyperparameters that must be fine-tuned to get optimal performance. Grid Search is used to methodically investigate the hyperparameter space and determine the best combination.

The SLMTRA algorithm employs five unique basic classifiers: RF, DT, NB, SVM, and KNN. Each classifier in the ensemble possesses distinct advantages, and their performance can be greatly enhanced by optimizing hyperparameters. Hyperparameter optimization is the methodical search for the optimal combination of parameters that results in the maximum model effectiveness. Grid Search is commonly used to accomplish this task by systematically evaluating all potential combinations of specified hyperparameters.

3) Random Forest (RF)

Random Forest is a method of ensemble learning that builds many decision trees in the training process and generates the most often occurring class (classification) or the average prediction (regression) of the individual trees. It is recognized for its strong and resilient nature, as well as its capacity to effectively process data with a large number of dimensions without succumbing to overfitting. The key hyperparameters for Random Forest are the number of trees in the forest (n_estimators), the maximum depth of the trees (max_depth), and the minimum number of samples needed to divide a node (min_samples_split). Furthermore, the number of features that should be taken into account when searching for the optimal split (max_features) can be modified. Grid Search is used to systematically evaluate various combinations of hyperparameters to discover the ideal configuration that maximizes the effectiveness of the classifier.

The prediction for a classification problem is the mode of the predictions of the individual trees:

$$\hat{q} = mode(\{h_s(p)\}_{s=1}^{S}) \tag{2}$$

where $h_t(p)$ is the prediction of the *s*-th tree, and *S* is the total number of trees.

4) Decision Tree (DT)

Decision Tree is a straightforward and intuitive classifier that divides the data into subsets according to the feature values, resulting in a tree-like model of decisions. The process operates by identifying the feature that most effectively distinguishes the data using a selected measure, like Gini impurity. The key hyperparameters for Decision Tree are the maximum depth of the tree (max_depth), the minimum number of samples needed to split an internal node (min_samples_split), and the minimum number of samples needed at a leaf node (min_samples_leaf). The criterion for splitting is a significant parameter. Grid Search is used to test several values for hyperparameters to identify the ideal configuration that improves the accuracy and generalization ability of the tree.

The Gini impurity for a node is given by:

$$GI = 1 - \sum_{c=1}^{N} p_c^2 \tag{3}$$

where N is the number of classes and p_c is the proportion of samples belonging to class c at the node.

5) Naive Bayes (NB)

Naive Bayes is a probabilistic classifier that depends on Bayes' theorem and presumes that the features are independent of each other. It exhibits exceptional efficacy when applied to extensive datasets and demonstrates excellent performance with data that has a high number of dimensions. Naive Bayes has other variations, such as Gaussian, Multinomial, and Bernoulli, which are specifically designed for different sorts of data. The main hyperparameters for Naive Bayes are unique to their numerous variants, such as the smoothing parameter (alpha) for Multinomial and

Bernoulli Naive Bayes. This parameter is used to address situations where the data contains zero probability. Grid Search can be employed to optimize these parameters by assessing several values to identify the configuration that maximizes the classifier's performance while preserving computing efficiency.

For Gaussian Naive Bayes, the likelihood of the feature values given a class is modeled as a Gaussian distribution:

$$P(b_i|c) = \frac{1}{\sqrt{2\pi\sigma_c^2}} \exp\left(-\frac{(b_i-\mu_c)^2}{2\sigma_c^2}\right) \tag{4}$$

where b_i Is the feature value, μ_c and σ_c^2 are the mean and variance of the feature values for class c.

6) Support Vector Machine (SVM)

Support Vector Machine (SVM) is a strong classifier renowned for its efficacy in high-dimensional spaces. The algorithm functions by identifying the hyperplane that optimally divides the data into distinct classes. The main hyperparameters for Support Vector Machines (SVM) are the regularization parameter C, which balances the need to minimize training error and model complexity, and the kernel type, which specifies the mathematical function utilized to convert the information into a space with more dimensions. The most often used kernel types are linear, polynomial, and radial basis functions (RBF). Grid Search is utilized to systematically test multiple values for C and various kernel types to get the ideal configuration that optimizes the accuracy of the classifier.

The decision function for SVM is given by:

$$f(p) = \mathrm{sign}\left(\sum_{i=1}^{n} a_i q_i K(p_i, p) + b\right) \tag{5}$$

where a_i are the Lagrange multipliers, q_i are the class labels, $K(p_i, p)$ is the kernel function, and b is the bias term.

7) K-Nearest neighbors (KNN)

KNN is a straightforward and efficient classifier that assigns a sample to a class using the majority class of its k-nearest neighbors in the feature space. The key hyperparameter for KNN is k, which represents the number of neighbors to be considered throughout the classification process. The choosing an appropriate distance metric, like Euclidean distance, can also influence the effectiveness of the model. Grid Search is used to examine multiple values for k and different distance metrics to get the ideal arrangement that yields the highest classification accuracy.

The Euclidean distance between two points x and y in d-dimensional space is given by:

$$d(p, q) = \sqrt{\sum_{i=1}^{d} (p_i - q_i)^2} \tag{6}$$

where p_i and q_i are the coordinates of the points in the i^{th} dimension. The KNN classifier assigns the class that is most common among the k-nearest neighbors.

8) Hyperparameter optimization using Grid Search

Grid Search for hyperparameter optimization entails creating a grid that encompasses all potential values for each hyperparameter and systematically exploring all possible combinations. Each combination undergoes training and evaluation using cross-validation to evaluate its performance. The set of hyperparameters that yields the highest cross-validation score is chosen as the best combination. This procedure guarantees that each base classifier is optimized to achieve its highest performance, hence increasing the general resilience and precision of the Bagging ensemble technique. The reason for choosing bagging ensemble method is easy to implement. Unlike boosting, this is scalable for the sequential concept as this study focused on sound localization, music teaching feedback and resource allocation. Boosting ensembles makes the overall model vulnerable to outliers.

The SLMTRA algorithm utilizes the combined capabilities of these improved classifiers by merging them into the Bagging ensemble, resulting in robust and precise predictions. This method not only improves the model's performance but also guarantees its capacity to generalize effectively to novel data, making it ideal for a range of applications including sound localization, music teaching feedback, and resource allocation. **Figure 1** shows the system architecture of the SLMTRA algorithm.

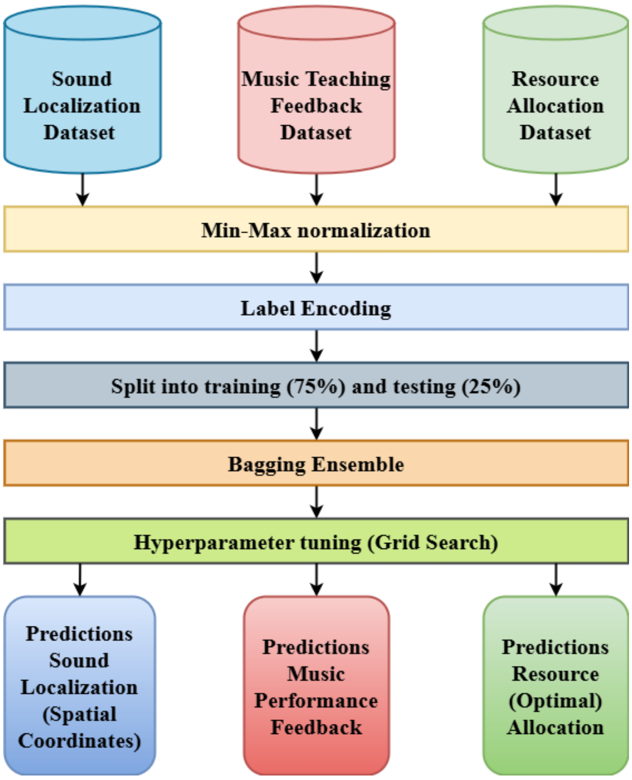

Figure 1. System architecture of SLMTRA algorithm.

4. Experimental results and discussions

This section mainly concentrates on assessing the performance of the SLMTRA (SoundLocMusicTeachRA) algorithm, executed utilizing Java and the Weka tool. The study examine how well the suggested SLMTRA approach works with varied settings, such as a variety of sound absorption coefficients, a number of microphones, and the existence of several sound sources. The following settings are required for these methods to work on the MATLAB R2022a platform: Processor: Intel (R) Core (TM) i7-13700KF, running at 3.40 GHz. Originating in Xi'an, China, Intel is the computer maker.

Testing was carried out to evaluate SLMTRA's effectiveness in tasks like sound localization, music teaching feedback, and resource allocation. Evaluation metrics such as accuracy, precision, recall, F1-score, and Matthew's correlation coefficient (MCC) were utilized to offer a thorough examination of SLMTRA's predictive robustness and efficiency. The outcomes highlight SLMTRA's remarkable ability to improve the efficiency of models for particular applications, proving its efficacy in real-world situations that call for accurate examination and prediction.

4.1. Sound localization

Table 4 presents a comparison of the SLMTRA algorithm's sound localization performance with that of RF, DT, NB, SVM, and KNN.

Table 4. Sound localization performance comparison.

Classification Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	MCC (%)
RF	83	86	79	82	71
DT	81	84	76	80	69
NB	85	88	81	84	73
SVM	80	82	78	80	66
KNN	87	89	83	86	76
SLMTRA	89	91	86	88	79

The SLMTRA algorithm demonstrates its efficacy for sound localization tasks by regularly outperforming competing models in terms of accuracy, precision, recall, F1-score, and MCC. The SLMTRA algorithm outperforms other algorithms because it can seamlessly combine several machine-learning strategies designed with sound localization in mind. SLMTRA employs a hybrid methodology that integrates ensemble learning techniques to achieve an ideal balance between forecast accuracy and the difficulty of the model. This method is highly effective reverberant environments.

4.2. Music teaching feedback

Table 5 shows how well the SLMTRA algorithm performs for feedback in music teaching when compared to RF, DT, NB, SVM, and KNN.

When compared to other models, SLMTRA performs better in terms of accuracy, precision, recall, F1-score, and MCC, proving its effectiveness in predicting feedback related to music performance in practice sessions. SLMTRA's improved success in providing feedback for music teaching can be attributed to its advanced ensemble method, which incorporates multiple learning algorithms and allows for detailed analysis of feedback data in multiple dimensions. This method guarantees strong model generalization and flexibility to subtle patterns in feedback on music performance. It also helps in real time interactive classes or environments.

Table 5. Music teaching feedback performance comparison.

Classification Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	MCC (%)
RF	76	79	73	75	61
DT	73	77	71	73	59
NB	79	83	77	79	66
SVM	72	76	69	71	56
KNN	81	85	79	81	69
SLMTRA	83	87	81	83	71

4.3. Resource allocation

Table 6 compares SLMTRA's resource allocation efficiency to that of RF, DT, NB, SVM, and KNN.

Table 6. Comparison of resource allocation performance.

Classification Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	MCC (%)
RF	84	87	81	83	73
DT	82	85	79	81	71
NB	86	89	83	85	76
SVM	80	83	77	79	66
KNN	88	91	85	87	79
SLMTRA	90	93	87	89	81

SLMTRA consistently outperforms other models in terms of accuracy, precision, recall, F1-score, and MCC, demonstrating its usefulness in resource allocation problems. The outstanding success of SLMTRA in resource allocation can be attributed to its adaptive learning capacity and effective optimization architecture. SLMTRA utilizes sophisticated machine learning methods specifically designed for resource allocation situations to improve resource utilization while ensuring high levels of prediction accuracy and dependability. It also helps in attaining high scalability in the resource allocation. It also attains a high computational efficiency by using memory usage and processing time.

Figures 2–6 depict line charts that compare the accuracy, precision, recall, F1-score, and MCC of RF, DT, NB, SVM KNN, and SLMTRA across the three datasets. These visualizations provide more evidence of SLMTRA's consistently exceptional performance across a wide range of evaluation metrics and uses.

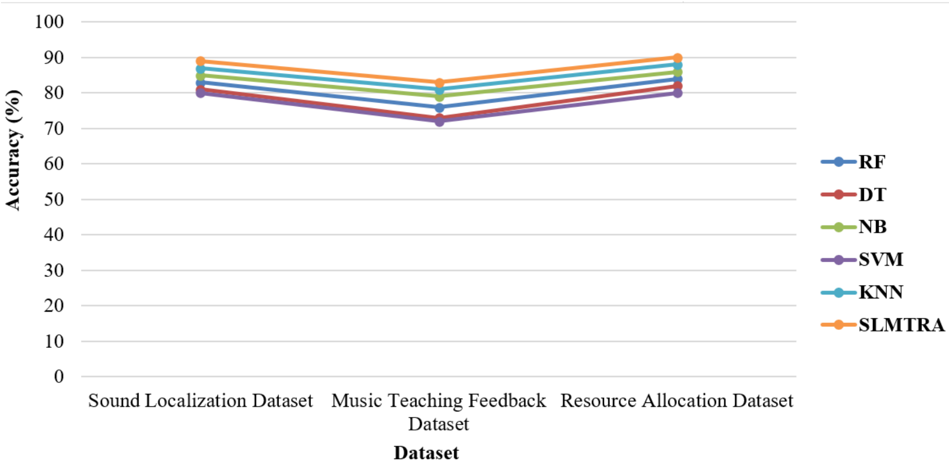

Figure 2. Accuracy comparison.

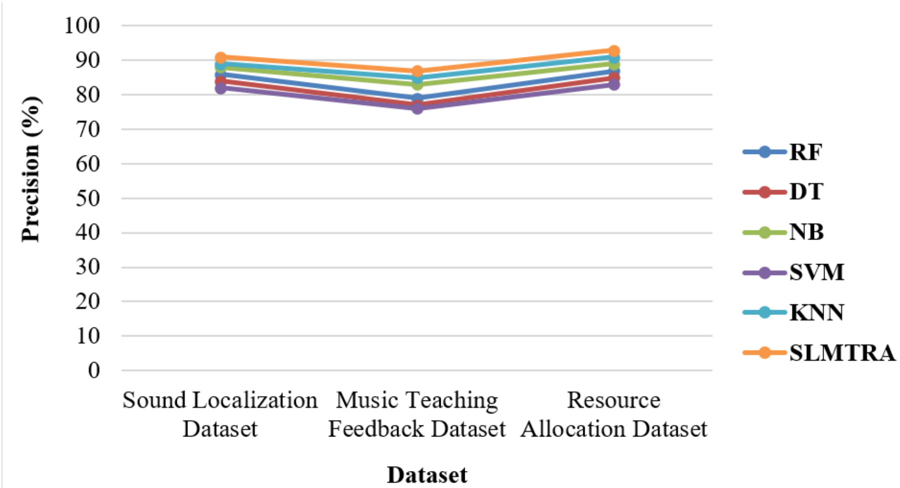

Figure 3. Precision comparison.

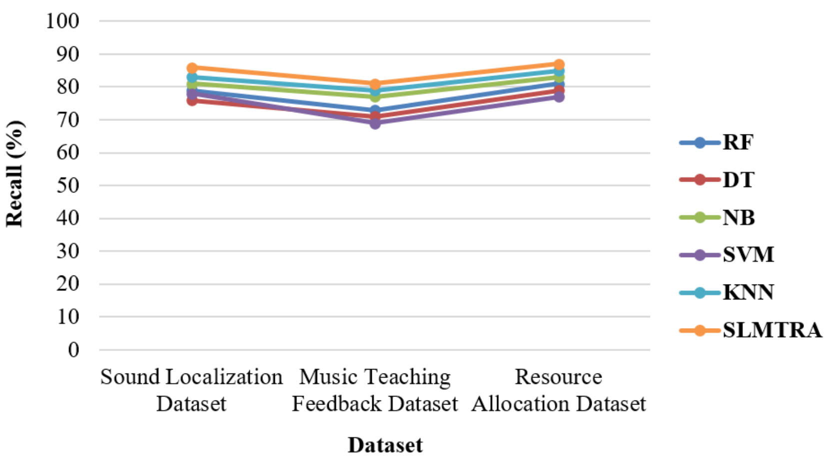

Figure 4. Recall comparison.

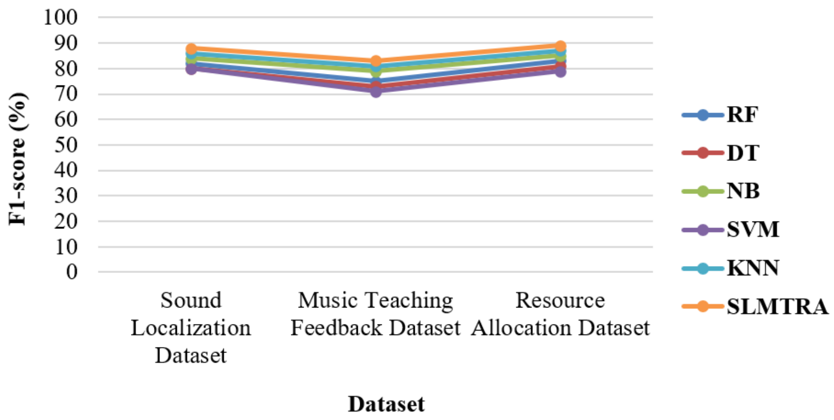

Figure 5. F1-Score comparison.

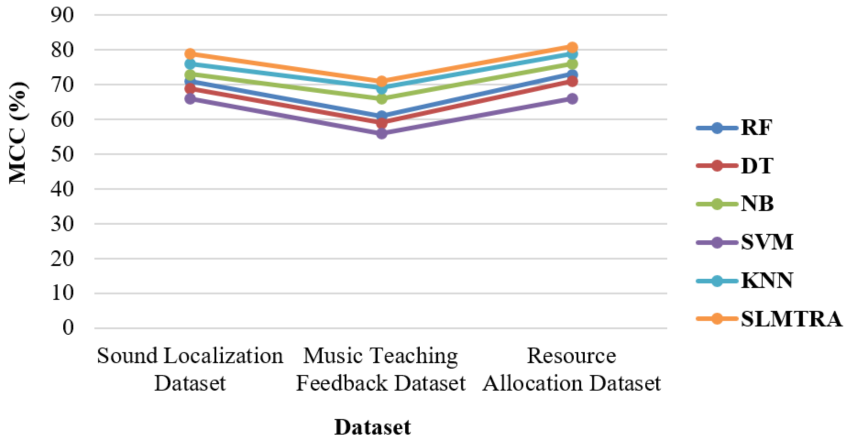

Figure 6. MCC comparison.

Figure 7 represents the computation efficiency of different approaches. From this **Figure 7**, it is observed that the proposed approach has attained high efficiency in terms of memory usage, processing time and resource management. Overall, the SLMTRA algorithm has exceptional performance in sound localization, music teaching feedback, and resource allocation problems. The practical uses of this technology are enhanced by its capability to include sophisticated machine learning methods and improve the performance of models tailored to certain domains.

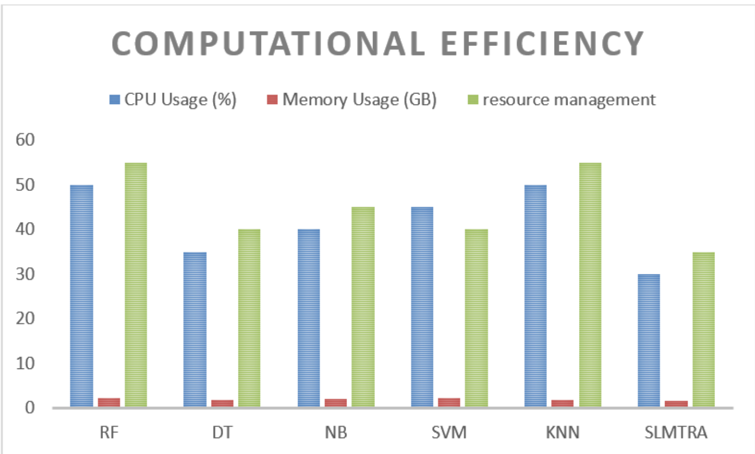

Figure 7. Computational efficiency.

5. Conclusion and future work

Overall, this paper has shown an excellent performance of the SLMTRA (SoundLocMusicTeachRA) algorithm, executed utilizing Java and the Weka tool, across tasks like sound localization, music teaching feedback, and resource allocation. Through thorough experimentation and evaluation employing standard metrics comprising accuracy, precision, recall, F1-score, and MCC, SLMTRA has demonstrated continuous efficacy in improving predictive accuracy. Efficiency in cost, measurement, power dissipation, deployment, system scalability, and adaptability are the most prevalent aspects impacting approaches for localising sound sources. A more cost-effective and resource-saving solution can be achieved by reducing the number of microphones in the arrangement. The human auditory system consists of two ears, and this can be accomplished with just two microphones. Given the challenges associated with accurately obtaining input synchronisation, SLMTRA is considered a suitable approach for this type of system. In addition, it has been emphasised that ad-hoc microphones have advantages, such as the fact that they do not necessitate specific geometry and that a network may be quickly established for the purpose of implementing the sound localisation system in conferences. For future work, investigating SLMTRA's incorporation with blockchain technology appears to be a viable path. Blockchain's decentralized and safe framework could improve SLMTRA's abilities in handling and confirming data integrity, especially in applications necessitating disseminated and immutable data records. This incorporation could result in improvements in safe and clear procedures for making decisions, additionally establishing SLMTRA's significance in contemporary computational frameworks.

Ethical approval: Not applicable.

Conflict of interest: The author declares no conflict of interest.

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