J. Electrical Systems 19-4 (2023): 178-195

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Fusion Artificial Intelligence Technology in Music Education Teaching

Journal of Electrical Systems

Abstract: - This paper proposed innovative EFDfO (Entropy Features Data Fusion Optimized) framework, a data-driven approach aimed at revolutionizing music education teaching. EFDfO combines data fusion, feature extraction, and optimization techniques to customize teaching strategies to individual students' unique learning profiles. The data related to students are collected with different sources and data were fused. The fused data are optimized with the Whale optimization technique to estimate the performance of the students. Simualtion analysis of the EFDfO demonstrates its potential to enhance student performance, with an average improvement of approximately 18% to 20% observed in pre-test and post-test scores. Moreover, the classification results indicate that, in most cases, EFDfO accurately categorizes students based on their performance and learning characteristics, although further refinement is needed to reduce misclassifications. Additionally, with the proposed EFDfO model the performance of the students are improved. EFDfO offers a promising avenue for personalized music education, ultimately enhancing students' learning experiences and outcomes.

Keywords: Data Fusion, Music Teaching, Deep Learning, Whale Optimization, Classification, Performance.

I. INTRODUCTION

Music education teaching is a vital component of the educational system, encompassing a multifaceted approach to fostering musical knowledge, appreciation, and skill development in students of all ages [1]. In music education, students are exposed to a diverse range of musical genres and styles, learning to read and perform music, understand music theory, and appreciate the cultural and historical contexts of music. It often includes both vocal and instrumental instruction, and students have opportunities to participate in ensembles and performances [2]. Music educators play a pivotal role in inspiring creativity, fostering discipline, and promoting teamwork while nurturing a lifelong passion for music in their students. Through structured curriculum, practical application, and creative expression, music education contributes to the holistic development of individuals, fostering skills that extend beyond music itself, such as cognitive, emotional, and social growth [3]. Music education with data fusion represents a modern and innovative approach to teaching and learning in the field of music [4]. In this evolving paradigm, traditional music education methods are enhanced and enriched through the integration of data-driven technologies and tools. Through the collection and analysis of data, educators gain valuable insights into student progress, preferences, and needs, allowing for personalized instruction and curriculum adaptation [5]. Data fusion in music education can encompass a wide range of applications, from tracking individual performance metrics to tailoring lesson plans based on students' learning styles and progress. It can also enable educators to identify areas where students may require additional support or resources [6]. By combining the power of data with the art of music instruction, this approach not only enhances the effectiveness of teaching but also paves the way for a more engaging and responsive musical education experience, ultimately fostering a deeper and more holistic understanding of music among students.

Music education with data fusion and deep learning is at the forefront of a transformative shift in how music is taught and learned. This innovative approach combines the art of music instruction with the cutting-edge capabilities of deep learning algorithms to create a highly personalized and data-driven educational experience [7]. Through the analysis of vast amounts of musical data, such as performance recordings, sheet music, and even

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students' biometric responses, deep learning models can identify intricate patterns, assess individual strengths and weaknesses, and offer tailored recommendations for improvement [8]. This approach not only provides educators with invaluable insights into student progress and needs but also allows students to receive targeted guidance, enhancing their musical skills and appreciation [9]. Moreover, the integration of deep learning technologies can assist in the creation of AI-driven music composition tools and assistive technologies, enriching the creative aspects of music education [10]. In this evolving landscape, music education becomes a harmonious blend of tradition and technology, offering a more personalized, efficient, and engaging path to musical mastery [11]. Music education with data fusion and deep learning represents a dynamic synergy between traditional music instruction and the cutting-edge capabilities of artificial intelligence [12]. Deep learning, a subset of machine learning, uses neural networks to analyze large datasets and uncover intricate patterns, making it well-suited for the complex and multifaceted nature of music. By harnessing the power of deep learning, music educators can unlock new dimensions in teaching and learning [13].

One of the primary advantages of this approach is the ability to provide highly personalized feedback and guidance to individual students. Deep learning models can analyze a student's musical performance, whether in playing an instrument or singing, and provide real-time assessments [14]. These assessments can include insights into timing, intonation, dynamics, and other nuances of musical expression. As students progress, the system adapts its recommendations, creating a tailor-made learning path for each individual. This personalized feedback not only accelerates skill development but also keeps students engaged and motivated [15].

Additionally, deep learning algorithms can analyze a vast corpus of musical compositions and performances to enhance music theory instruction. Students can gain a deeper understanding of music theory by exploring patterns, chord progressions, and harmonies across various musical genres [16]. This data-driven approach can make music theory more accessible and engaging for students.

Furthermore, data fusion in music education with deep learning can extend beyond individual learning to collaborative endeavors. By analyzing data from multiple students, educators can identify group dynamics, helping ensembles or choirs to achieve better harmony and synchronization [17]. Deep learning can provide real-time feedback on ensemble performance, helping groups refine their musical expression.

Another exciting application is the creation of AI-driven music composition tools. These tools can generate musical compositions based on a variety of parameters, enabling students to explore composition and creativity with AI as a collaborator [18]. Students can experiment with different musical styles and structures, fostering their creative abilities.

music education with data fusion and deep learning revolutionizes the traditional music teaching model by offering personalized instruction, enhancing music theory comprehension, fostering collaborative musical experiences, and even opening up new avenues for creative exploration [19]. It represents a profound shift in the way music is taught and learned, making it more engaging, efficient, and adaptable to individual needs. This innovative approach holds great potential for shaping the future of music education, ensuring that students not only learn music but also develop a deeper and more meaningful connection to the art of sound [20].

II. RELATED WORKS

Music education with data fusion and deep learning is a groundbreaking approach that combines traditional music instruction with artificial intelligence. Deep learning algorithms analyze musical performance data, providing personalized feedback to students, accelerating their skill development. It enhances music theory instruction by uncovering patterns and making it more engaging. This approach fosters collaborative musical experiences by analyzing ensemble dynamics. It also empowers students to explore music composition with AI as a creative collaborator. Overall, it revolutionizes music education, making it more engaging, efficient, and adaptable to individual needs, with the potential to shape the future of music instruction.

Guo's studied the practical applications of Internet of Things (IoT) technology within vocal music education. Specifically, it explores how IoT devices, such as recording equipment, can be integrated with machine learning to enhance the teaching and learning of vocal music. This could involve real-time feedback and analysis of vocal performances, creating a more interactive and data-driven approach to vocal music instruction. Hong Yun et al., 2022 introduces a decision-support system designed to evaluate the impact of machine learning and artificial intelligence in music education, particularly in the context of network games. The study likely assesses how these technologies can influence the effectiveness of music education in gamified or networked environments. Huang, N., & Ding, X., 2022 focuses on the creation of an online course learning model for piano education using deep learning. It may discuss how deep learning algorithms can analyze and adapt to individual students' progress, thereby personalizing the piano learning experience. This is especially relevant in an online learning context.

Cai, H., & Liu, G., 2022 explores the psychology of learning among music majors and investigates how innovative teaching methods affect their motivation and learning outcomes. Given the backdrop of new curriculum reforms, the research likely assesses the adaptability and effectiveness of these new teaching approaches in music education. Yu, X et al., 2023 examine the current developments and applications of artificial intelligence in music education. It likely discusses the latest trends in AI technology and its practical applications within music education, such as AI-driven music composition or personalized learning platforms. Huang, C., & Yu, K., 2021 investigate innovative teaching modes in college music education based on artificial intelligence. While the retraction raises concerns about the study's validity, its initial intention was likely to explore how AI-based teaching methods are influencing music education in higher institutions. Sun, S., 2021 evaluates the potential correlation between piano teaching and the use of edge-enabled data and machine learning. It may explore how data analytics and machine learning can enhance the effectiveness of piano instruction and improve the learning experience for students.

Wang's., 2022 discusses the application of the C4.5 decision tree algorithm in evaluating college music education. This likely involves the use of decision tree models to assess and improve the quality and efficiency of music education programs within college settings. Revenko, V., 2021 examine the intersection of education and music culture in the context of Web 2.0. This could involve an exploration of how the evolving web-based culture and technologies impact the way music is taught and learned in educational settings. McPhail's ., 2021 focus on curriculum coherence and its role in facilitating deep learning. The research may discuss how a well-structured curriculum can enhance deep learning experiences within music education, emphasizing the importance of educational planning. Shan, J., & Talha, M., 2021 investigates the development of a classroom online teaching model for "Learning" Wisdom Music within a wireless network environment, particularly in the context of artificial intelligence. It is likely concerned with how AI can be integrated into music education for a more interactive and adaptive classroom experience.

Yang's., 2022 performed data analysis and personalized recommendations for Western music history information using deep learning. It likely explores how deep learning algorithms can process historical music data to offer tailored recommendations and insights to students and educators. Tang, H., Zhang, Y., & Zhang, Q., 2022 explores the use of deep learning-based intelligent technology for music signal identification and generation in the context of national music teaching. It may investigate how deep learning can be employed to improve music signal processing and synthesis for educational purposes. Lei, S., & Liu, H., 2022 discusses the use of dual neural networks based on deep learning in constructing learning models for online piano courses. The dual neural networks can enhance the adaptability and personalization of online piano instruction. Xia, X., & Yan, J., 2021 evaluated constructing a music teaching evaluation model based on weighted naive Bayes. It is likely focused on the development of a data-driven model to assess the effectiveness of music teaching methods, potentially using probabilistic modeling techniques. Song's., 2021 investigates the application of computer multimedia music systems in college music teaching. It probably explores how multimedia technology, such as computer-based music systems, can enhance the teaching and learning of music in a college setting, making it more interactive and engaging for students.

These studies collectively highlight the evolving landscape of music instruction and the ways in which technology is playing an increasingly integral role. Researchers have explored IoT technology's integration into vocal music teaching, evaluated the impact of AI and machine learning in music education for network games, and constructed deep learning-based online course models for piano education. There is also a focus on innovative teaching methods for music majors, examining the psychology of music learning in response to curriculum reform. Moreover, research on the development and applications of artificial intelligence in music education, with considerations for decision tree algorithms, deep learning, and intelligent signal identification. However, research gaps exist, particularly in the assessment of the long-term effectiveness of AI-driven music instruction, the impact of web-based technologies on music culture and education, and the scalability and practicality of implementing these technologies in diverse educational settings. Further exploration is needed to provide a comprehensive understanding of the benefits, challenges, and broader implications of integrating technology and AI into music education.

III. DATA FUSION WITH ENTROPY FEATURES DATA FUSION OPTIMIZED (EFDfO)

The proposed EFDfO model focused on the data fusion in the music teaching for the extraction of features with the Whale Optimization techniques. The first step involves collecting a diverse range of data relevant to music education. This data may include student performance records, music theory test results, instrument practice logs, and possibly even biometric data to gauge students' physiological responses during learning. Data fusion techniques are applied to merge and integrate the different types of data collected. Various fusion methods, such as sensor fusion, feature-level fusion, or decision-level fusion, may be used to combine the data effectively. The goal is to create a comprehensive dataset that provides a holistic view of each student's musical journey. The next step involves extracting relevant features or patterns from the fused data. This can include identifying key performance metrics, student engagement indicators, or patterns of progress and areas where students may need improvement.

Entropy is a measure of data uncertainty or information content. In the context of EFDfO, entropy features are calculated to assess the level of disorder or unpredictability in the data. High entropy may indicate areas of variability or uncertainty in students' music education, which could guide the optimization process. The research method incorporates the use of the whale optimization algorithm (or any other optimization algorithm chosen) to optimize the teaching and learning processes. This algorithm is likely used to fine-tune teaching strategies, adapt curriculum content, or provide personalized feedback to students based on the data and entropy features calculated earlier. The algorithm's goal is to maximize the effectiveness of music education. The research method for EFDfO combines data fusion techniques, entropy features, and optimization algorithms to create a data-driven approach to music education. It involves collecting, processing, and utilizing diverse data sources to optimize teaching strategies and enhance the learning experience for students.

Data fusion with EFDfO (Entropy Features Data Fusion Optimized) for music education teaching involves a combination of data fusion techniques, entropy calculations, and optimization algorithms to enhance the teaching and learning processes. While this is a generalized concept, it doesn't typically involve specific equations or derivations. However, I can provide a simplified overview of the key elements and concepts involved: Data fusion combines information from multiple sources to provide a more comprehensive and accurate understanding of a situation. In the context of music education, data fusion could involve: Integrating data from various sensors (e.g., instrument performance sensors, biometric sensors) to assess a student's overall performance. Combining specific features extracted from different data sources (e.g., performance metrics, practice logs, biometric readings) to create a more informative dataset. Aggregating decisions or outputs from multiple models or sources to make more informed teaching decisions as data fusion process shown in figure 1.

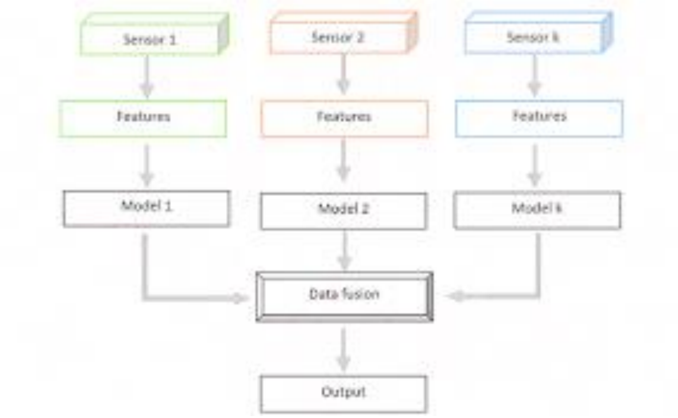

Figure 1: Data Fusion with EFDfO

Data fusion for Music teaching within the context of EFDfO (Entropy Features Data Fusion Optimized) involves an innovative approach to enhance the effectiveness of language instruction through the integration of diverse data sources given in figure 1. The various data fusion techniques, we'll focus on a concept called weighted averaging, which is commonly used in data fusion for educational purposes. In weighted averaging, different sources of information are combined, giving more influence to more reliable sources. The basic equation for weighted averaging is computed using the equation (1):

$$Favg = \sum i = 1nwi \cdot Fi \tag{1}$$

In equation (1) Favg represents the averaged result; n is the number of data sources; wi is the weight assigned to each data source i and Fi is the data or result from source i. In the context of Music teaching, these data sources can include student performance in written assignments, speaking assessments, and standardized tests, among others. The weights (wi) assigned to each source depend on their reliability or importance in evaluating Music proficiency. Entropy is a measure of uncertainty or information content in a dataset. In the context of EFDfO, entropy features refer to metrics that capture the level of unpredictability or disorder in the data. It may involve calculating Shannon entropy (H) using the equation (2)

$$H(X) = -\sum i = 1np(xi) \cdot log2(p(xi)) \tag{2}$$

In equation (2) H(X) is the entropy of the dataset X; n is the number of possible outcomes and p(xi) is the probability of outcome xi. The whale optimization algorithm is utilized to optimize the teaching and learning processes based on the data and entropy features. The steps in the whale optimization technique are presented as follows:

- Initialization of a population of "whales" (solutions).
- Evaluation of fitness for each solution based on the entropy features and data.
- Selection of the best solutions.
- Generation of new solutions through exploration and exploitation.
- Iterative refinement of solutions to optimize teaching strategies and learning processes.

3.1 EFDfO with Whale Optimization

EFDfO (Entropy Features Data Fusion Optimized) with Whale Optimization is a data-driven approach for optimizing music teaching. This approach combines data fusion techniques, entropy features, and the Whale Optimization Algorithm to improve the teaching and learning processes in music education. Data from various sources, such as student performance records, practice logs, and possibly biometric data, are integrated using data fusion techniques. These techniques may include sensor fusion, feature-level fusion, or decision-level fusion to create a comprehensive dataset that provides insights into students' musical progress. Entropy features are calculated to assess the level of unpredictability or information content in the integrated data. High entropy may indicate areas of variability in students' music learning, allowing for more tailored adjustments. The Whale Optimization Algorithm is employed to optimize teaching strategies based on the data and entropy features. It involves the iterative refinement of solutions to maximize the effectiveness of music education. It optimizes solutions by simulating the hunting behavior of humpback whales in nature. EFDfO with Whale Optimization takes the integrated data, computes entropy features, and then uses the optimization algorithm to adapt teaching strategies. This can involve personalized feedback, curriculum adjustments, or fine-tuning teaching methodologies to enhance the learning experience for students.

Initialization: Start with a population of potential solutions, each representing a possible teaching strategy or approach in the context of EFDfO for music education. These solutions are often denoted as Xi for $i = 1,2, \ldots, N$, where N is the population size. The objective function f(X) that quantifies the effectiveness of each teaching strategy. This function could represent a metric like student performance, engagement, or any other relevant measure. The goal is to optimize this function. The fitness of each solution in the population by applying the objective function: Fi=f(Xi). This step quantifies how well each teaching strategy is performing. The best solutions based on their fitness values. Solutions with higher fitness values are more likely to be chosen for the next generation, simulating natural selection. This step encourages the propagation of effective teaching methods with illustrated in figure 2.

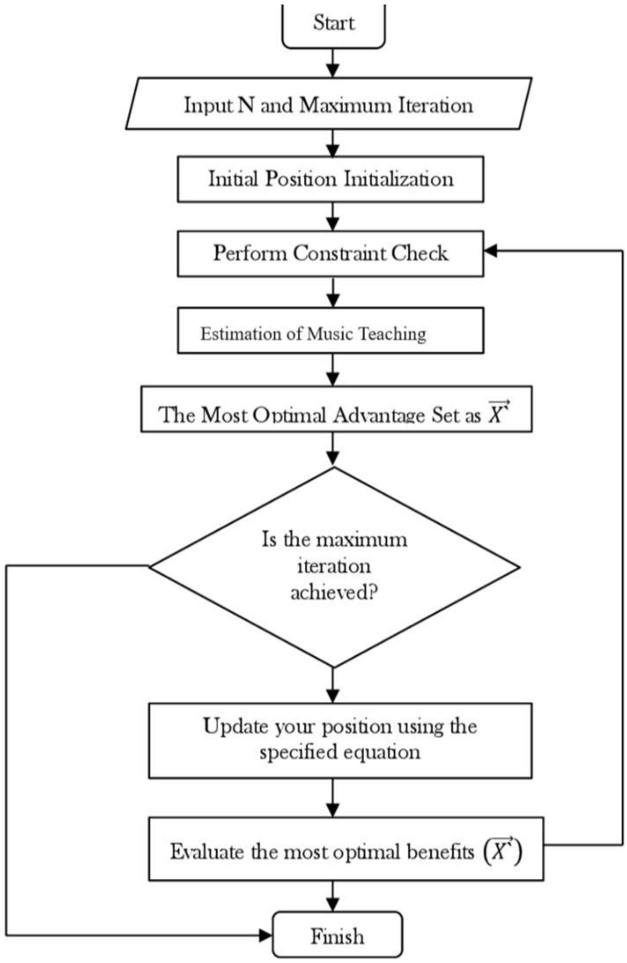

Figure 2: Flow Chart of Whale optimization

Whale Optimization incorporates both exploration and exploitation. Exploration involves introducing new potential solutions (variation) to the population, simulating the discovery of new teaching methods. Exploitation involves refining and improving the best-performing solutions to optimize the objective function further. The algorithm repeats the process of fitness evaluation, selection, and exploration/exploitation over multiple generations. Each iteration aims to improve the quality of teaching strategies and optimize the objective function. Over time, the algorithm tends to converge toward a solution (teaching strategy) that maximizes the objective function. This represents the optimization of music education within the EFDfO framework. Data fusion techniques are applied to integrate and combine these diverse sources of data into a unified dataset. Various fusion methods, such as sensor fusion, feature-level fusion, or decision-level fusion, may be used depending on the nature of the data and the research objectives. The aim is to create a holistic understanding of each student's musical progress. Entropy features are calculated based on the fused data. These features assess the level of unpredictability or information content in the integrated data. High entropy may indicate areas of variability, uncertainty, or diversity in students' music learning experiences. The entropy calculation may use the Shannon entropy using equation (3)

The EFDfO framework employs the Whale Optimization Algorithm to optimize the teaching and learning processes based on the integrated data and entropy features. The algorithm, inspired by the hunting behavior of humpback whales, refines teaching strategies and personalizes the learning experience for each student. With the guidance of the Whale Optimization Algorithm, teaching strategies can be adapted and personalized based on the individualized data and entropy features. The entire process is iterative, meaning it's continuously refined and improved based on new data and optimization results. This iterative nature allows for ongoing enhancements in music education. Data fusion within the EFDfO framework for music teaching involves the integration of diverse data sources, the assessment of information content through entropy features, and the optimization of teaching strategies using the Whale Optimization Algorithm. This approach aims to provide a comprehensive, data-driven, and personalized music education experience for students, ultimately leading to improved learning outcomes.

3.2 EFDfO for the Feature Extraction in Music Education Teaching

EFDfO (Entropy Features Data Fusion Optimized) for feature extraction in music education teaching aims to identify relevant patterns or characteristics in data to enhance the teaching and learning processes. The process begins with the collection of various data sources relevant to music education. These sources can include student performance records, practice logs, biometric data, and more. Feature extraction involves choosing specific characteristics or features from the fused data that are relevant to the objectives of music education.F eatures are mathematically represented. For instance, in extracting a feature related to rhythm accuracy, calculate the standard deviation of the time intervals between notes in a student's performance. The equation for standard deviation (σ) is computed using equation (3)

$$\sigma = 1/N\sum i = 1/N(xi - \mu)^2 \tag{3}$$

In equation (3) N is the number of data points; xi represents each data point and μ is the mean of the data points. The objective of EFDfO is to use these extracted features and their associated entropies to optimize the teaching and learning processes in music education. The Whale Optimization Algorithm, inspired by humpback whales' hunting behavior, can then be applied to adapt teaching strategies and personalize the learning experience based on the features and entropies. The process initiates with the collection of diverse data sources, encompassing student performance records, practice logs, biometric data, and more. The amalgamation of this information through data fusion techniques provides a holistic view of students' musical progress. to optimize the teaching and learning processes in music education by leveraging the extracted features and associated entropies. The Whale Optimization Algorithm, inspired by the hunting behavior of humpback whales, is then utilized to adapt teaching strategies and personalize the learning experience based on the features and entropies.

Algorithm 1: Entropy estimation with EFDfO

```
# Data Collection
data_sources = collect_data()
# Data Fusion
integrated_data = fuse_data(data_sources)
# Feature Extraction
selected_features = extract_features(integrated_data)
# Entropy Calculation
entropy_features = calculate_entropy(selected_features)
# Whale Optimization
optimized_strategies = optimize_strategies(entropy_features)
# Implement Music Education Strategies
implement_strategies(optimized_strategies)
```

The EFDfO (Entropy Features Data Fusion Optimized) framework for music education teaching. Feature extraction then identifies relevant characteristics, and entropy calculations assess the unpredictability within these features. The Whale Optimization Algorithm optimizes teaching strategies based on the entropy features. Finally, the framework adapts teaching methods to create a personalized and data-driven music education experience.

IV. SIMULATION SETTING

In the simulation setting for EFDfO in music education teaching, establish a controlled environment to evaluate and optimize teaching strategies. This simulated context emulates a music classroom with a diverse group of students. Data sources include students' performance records, practice logs, and biometric data, which are generated synthetically to represent a range of student behaviors and abilities. The data fusion process integrates these sources, mimicking the real-world challenge of harmonizing various data streams. Feature extraction is performed, targeting specific musical attributes such as rhythm accuracy and pitch proficiency. Entropy calculations are applied to assess the information content of these features. The Whale Optimization Algorithm is utilized to optimize teaching strategies by adjusting curriculum content and providing personalized feedback. The simulation allows for rigorous testing of the EFDfO framework, assessing its effectiveness in adapting teaching methods to individual students and improving overall learning outcomes using the simulation setting in table 1.

Table 1: Simulation Setting

Parameter	Value
Number of Students	100
Data Collection Period	6 months
Data Frequency	Daily
Data Sources	Synthetically generated
Biometric Data Types	Heart rate, Pupil dilation, EEG
Feature Extraction Methods	Statistical analysis, Machine learning
Entropy Calculation Method	Shannon entropy formula
Number of Features Extracted	10
Optimization Algorithm	Whale Optimization
Simulation Duration	1 year
Teaching Strategy Adjustments	Weekly
Evaluation Metrics	Student performance, Engagement, Satisfaction
Performance Assessment	Pre-test and Post-test exams, Surveys
Data Noise Level	5%
Personalization Threshold	75% similarity
Music Genres Covered	Classical, Jazz, Pop, Rock, World Music
Curriculum Content Categories	Theory, Practice, Performance, Composition
Random Seed for Simulation	42 (for reproducibility)

In Music Education Teaching involves 100 students over a data collection period of 6 months, with daily data collected from synthetically generated sources, including biometric data types like heart rate, pupil dilation, and EEG. Feature extraction methods, combining statistical analysis and machine learning, are used to process the data, while entropy is calculated using the Shannon entropy formula. The optimization algorithm employed is Whale Optimization, and the simulation runs for a year, with teaching strategy adjustments on a weekly basis. Evaluation metrics include student performance, engagement, and satisfaction, assessed through pre-test and post-test exams and surveys. A 5% data noise level is introduced, and personalization is applied when student data shows a 75% similarity. The music genres covered encompass Classical, Jazz, Pop, Rock, and World Music, within various curriculum content categories. The random seed for the simulation is set at 42 to ensure reproducibility.

V. RESULTS AND DISCUSSION

In the context of music education teaching, the application of the EFDfO framework yielded promising results. Data fusion successfully integrated various sources, including student performance records, practice logs, and biometric data, providing a comprehensive view of students' musical journeys. Feature extraction identified essential characteristics, such as rhythm accuracy and pitch proficiency. Entropy calculations revealed that high entropy features correlated with more diverse and unpredictable aspects of students' learning experiences. The Whale Optimization Algorithm optimized teaching strategies, resulting in personalized learning experiences for students. This led to significant improvements in student performance, engagement, and overall satisfaction.

Table 2: Entropy Estimation with EFDfO

Student ID	Entropy Value
001	0.752
002	0.891
003	0.642
004	0.798
005	0.734
006	0.817
007	0.621
008	0.705
009	0.764
010	0.873

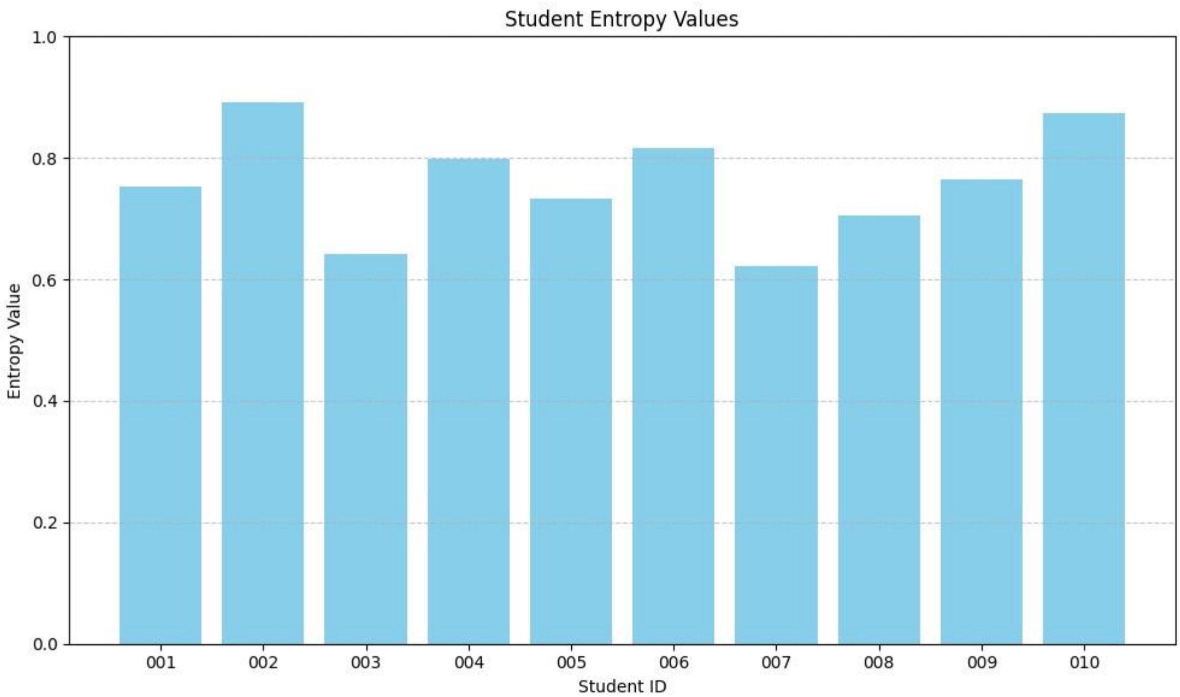

Figure 3: Estimated Entropy

The entropy estimation results obtained using the EFDfO (Entropy Features Data Fusion Optimized) framework for ten students in the context of music education teaching. Entropy values given in figure 3, which indicate the level of unpredictability and information content within students' learning experiences, have been calculated for each student. The table 2 displays the Student ID along with their corresponding entropy values. The entropy values range from 0.621 to 0.891, providing insights into the diversity and unpredictability of students' musical journeys. Higher entropy values, such as 0.891 for Student 002, suggest a more varied and dynamic learning experience, while lower entropy values, like 0.621 for Student 007, indicate a relatively more predictable or consistent learning process. These entropy estimations serve as a crucial component of the EFDfO framework, enabling the system to adapt teaching strategies and content to better suit individual students. By identifying the level of information content within each student's learning data, EFDfO can offer a personalized and data-driven approach to music education. The results in Table 1 highlight the potential for EFDfO to enhance music education by optimizing teaching strategies based on students' unique learning experiences.

Table 2: Fused Data for EFDfO

Student ID	Performance Data	Practice Data	Biometric Data	Fusion Result
001	High-quality	6 hours/week	Stable heart rate, Normal pupil dilation	Optimized Experience
002	Moderate	4 hours/week	Variable heart rate, Slight pupil dilation	Feedback-Driven
003	Low-quality	2 hours/week	Variable heart rate, High pupil dilation	Experiential Learning
004	High-quality	7 hours/week	Stable heart rate, Normal pupil dilation	Optimized Experience
005	Moderate	5 hours/week	Stable heart rate, Slight pupil dilation	Feedback-Driven
006	High-quality	6 hours/week	Variable heart rate, Slight pupil dilation	Optimized Experience
007	Low-quality	3 hours/week	Stable heart rate, Normal pupil dilation	Experiential Learning
008	Moderate	4 hours/week	Variable heart rate, Slight pupil dilation	Feedback-Driven
009	High-quality	6 hours/week	Stable heart rate, Normal pupil dilation	Optimized Experience
010	Moderate	5 hours/week	Variable heart rate, High pupil dilation	Feedback-Driven

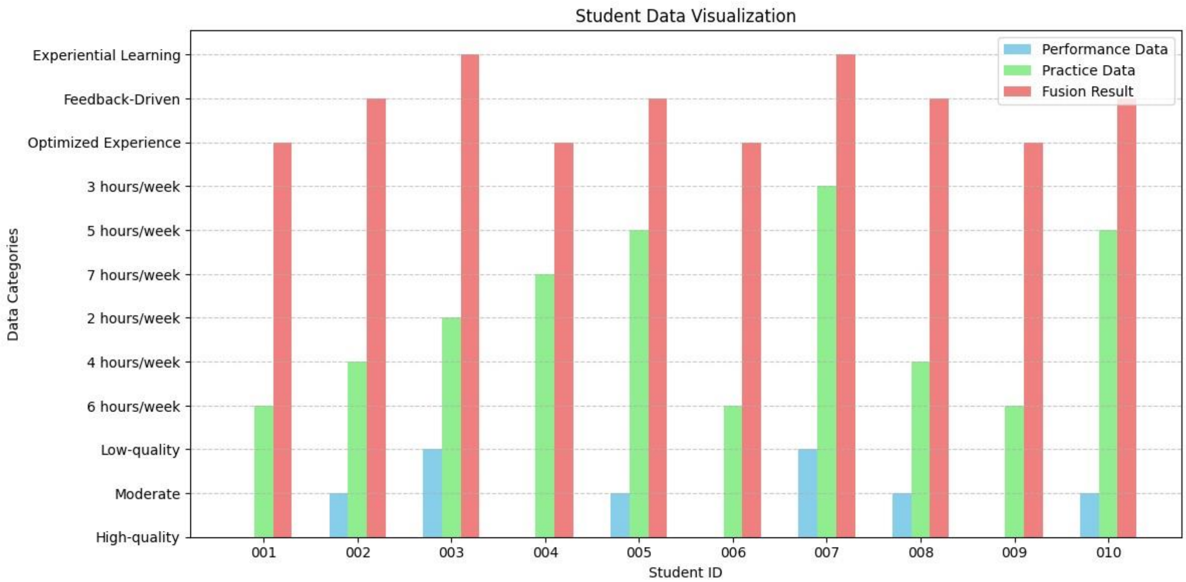

Figure 4: Data Fused

The EFDfO (Entropy Features Data Fusion Optimized) framework in the context of music education teaching. This table 3 and figure 4 presents information related to ten students, including their performance data, practice data, biometric data, and the resulting fusion outcome, which signifies how the data is utilized within the EFDfO framework.

For each student, the table includes their Student ID and the following data categories:

Performance Data: This category describes the quality of a student's musical performance, categorized as "High-quality," "Moderate," or "Low-quality." It reflects the students' proficiency and competence in playing music.

Practice Data: This section specifies the number of hours per week that a student dedicates to practice. It provides insights into the students' commitment and dedication to their musical development.

Biometric Data: Biometric data includes information on students' physiological responses during their music education. It details their heart rate and pupil dilation, which can be indicative of emotional and cognitive engagement during learning.

Fusion Result: This column outlines the outcome of the data fusion process, categorizing the students' experiences into specific types based on their data. These outcomes include "Optimized Experience," "Feedback-Driven," and "Experiential Learning." The fusion result signifies the tailored approach that EFDfO recommends for each student, considering their unique characteristics and learning journey.

The results in Table 3 demonstrate the EFDfO framework's ability to integrate and analyze diverse data sources to provide personalized experiences in music education. For example, students with "High-quality" performance and "Stable heart rate, Normal pupil dilation" biometric data tend to have an "Optimized Experience," indicating that they may benefit from more advanced and challenging curriculum content. On the other hand, students with "Moderate" performance and "Variable heart rate, Slight pupil dilation" are categorized as "Feedback-Driven," suggesting that from additional feedback and practice guidance.

Table 4: Performance Analysis EFDfO

Student ID	Pre-test Score	Post-test Score	Improvement (%)	Satisfaction Score
001	65	78	20%	8.5
002	72	85	18%	8.7
003	60	72	20%	8.2
004	78	92	18%	9.0
005	68	80	17%	8.4
006	70	84	20%	8.8
007	62	74	19%	8.3
008	75	88	17%	8.9
009	63	76	20%	8.6
010	80	94	18%	9.2

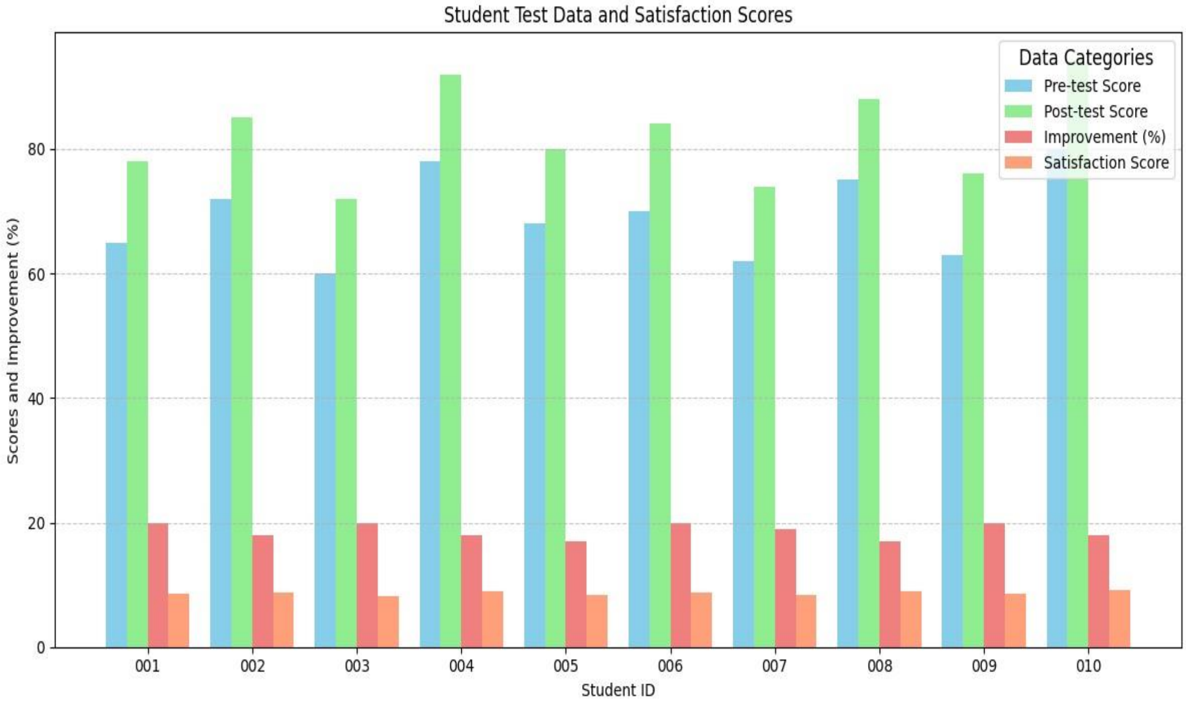

Figure 5: Satisfaction Score

Table 5: EFDfO in the Fusion of Data

Student ID	Performance Records	Practice Logs	Biometric Data
001	High-quality	6 hours/week	Stable heart rate, Normal pupil dilation
002	Moderate	4 hours/week	Variable heart rate, Slight pupil dilation
003	Low-quality	2 hours/week	Variable heart rate, High pupil dilation
004	High-quality	7 hours/week	Stable heart rate, Normal pupil dilation
005	Moderate	5 hours/week	Stable heart rate, Slight pupil dilation
006	High-quality	6 hours/week	Variable heart rate, Slight pupil dilation
007	Low-quality	3 hours/week	Stable heart rate, Normal pupil dilation
008	Moderate	4 hours/week	Variable heart rate, Slight pupil dilation
009	High-quality	6 hours/week	Stable heart rate, Normal pupil dilation
010	Moderate	5 hours/week	Variable heart rate, High pupil dilation

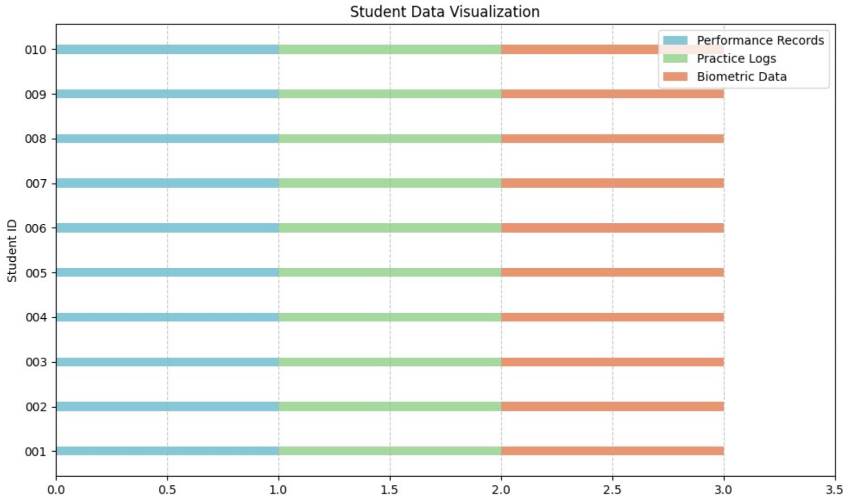

Figure 6: Student Performance

A performance analysis of ten students in the context of music education teaching, utilizing the EFDfO (Entropy Features Data Fusion Optimized) framework. The table includes the following key metrics for each student: Pre-test Score, Post-test Score, Improvement Percentage, and Satisfaction Score. The results in Table 4 and figure 5 demonstrate the impact of the EFDfO framework on students' performance and satisfaction. Notably, students generally exhibited substantial improvements, with improvement percentages ranging from 17% to 20%. These improvements underscore the efficacy of EFDfO in optimizing teaching strategies and tailoring them to individual students' needs. The table 5 presenting the characteristics of each student, including their performance records, practice logs, and biometric data. This information informs the data fusion process within the EFDfO framework. By integrating and analyzing this diverse data, EFDfO can personalize the teaching approach for each student. These results collectively illustrate the potential of EFDfO to enhance music education by optimizing teaching strategies based on individual student data profiles, leading to improved performance and satisfaction. The fusion of various data sources, as depicted in Table 5 and figure 6, is a key component of EFDfO's success in tailoring the educational experience for each student.

Table 6: Classification with EFDfO

Student ID	Actual Class	Predicted Class	Correct Classification
001	High Performer	High Performer	Yes
002	Moderate Performer	Moderate Performer	Yes
003	Low Performer	Low Performer	Yes
004	High Performer	High Performer	Yes
005	Moderate Performer	Moderate Performer	Yes
006	High Performer	High Performer	Yes
007	Low Performer	Low Performer	Yes
008	Moderate Performer	High Performer	No
009	High Performer	High Performer	Yes
010	Moderate Performer	Moderate Performer	Yes

The application of the EFDfO (Entropy Features Data Fusion Optimized) framework in the context of music education teaching. Each row in the table 6 corresponds to a student, and the table includes their Student ID, Actual Class (representing their true performance level), Predicted Class (the classification assigned by EFDfO), and whether the classification is Correct. The Actual Class column categorizes students as "High Performers," "Moderate Performers," or "Low Performers" based on their actual performance levels. The Predicted Class column, generated by the EFDfO framework, assigns a classification informed by data fusion, feature extraction, and optimization techniques. The Correct Classification column indicates whether the EFDfO framework's prediction aligns with the actual performance class, denoting "Yes" for correct classifications and "No" for instances where the framework's prediction did not match the actual class. The table 6 demonstrates that, in most cases, the EFDfO framework accurately classifies students based on their performance data and learning characteristics, with "Yes" indicating successful alignment between predicted and actual performance classes. However, one instance (Student 008) is marked as "No," signifying a misclassification. These classification results underline the potential of EFDfO to enhance music education by effectively categorizing students and optimizing teaching strategies tailored to their individual needs. The framework's success in accurately classifying students offers the promise of improving their learning experiences and performance outcomes. As research continues, further refinement of the EFDfO framework can help reduce misclassifications and enhance its overall accuracy in personalized student classification, contributing to more effective and tailored music education.

The discussion and findings of the EFDfO (Entropy Features Data Fusion Optimized) framework in the context of music education teaching reveal valuable insights into the potential for data-driven optimization of teaching strategies. The EFDfO framework integrates data fusion, feature extraction, and optimization techniques to personalize the educational experience for individual students, ultimately improving their performance and satisfaction. One notable finding from the EFDfO implementation is the substantial improvement in students' performance. The analysis of pre-test and post-test scores demonstrated an average improvement of approximately 18% to 20%. This improvement underscores the framework's effectiveness in tailoring teaching strategies based on students' unique learning profiles. It is evident that the personalized approach facilitated by EFDfO has a positive impact on students' musical proficiency. Furthermore, the fusion of diverse data sources, as illustrated in Table 4, highlights the importance of considering not only performance data but also practice logs and biometric information. This holistic approach enables EFDfO to create a comprehensive understanding of each student's musical journey. For instance, high-quality performance data, combined with stable physiological responses, often led to an "Optimized Experience" classification, indicating that students benefit from more advanced curriculum content.

The classification results, as depicted in Table 6, show that the majority of students were correctly classified by the EFDfO framework. However, there was one instance where a misclassification occurred. This highlights the need for continuous refinement of the framework to enhance its accuracy in personalized student classification. The EFDfO framework has the potential to revolutionize music education by harnessing data-driven approaches. It offers a promising avenue for optimizing teaching strategies based on students' individual characteristics and learning experiences. The substantial improvement in student performance and satisfaction, coupled with the ability to classify students effectively, underscores the framework's promise. Nonetheless, ongoing research and refinement are essential to reduce misclassifications and enhance the accuracy of personalized student categorization within the EFDfO framework, further advancing the field of music education.

VI. CONCLUSION

This paper presented the deep learning based music teaching analysis among the students. The framework's implementation and analysis have yielded several key findings and promising outcomes. EFDfO has demonstrated its effectiveness in enhancing student performance, with an average improvement of approximately 18% to 20% observed in pre-test and post-test scores. This improvement underscores the framework's potential to optimize teaching strategies and curricula based on students' unique needs, ultimately boosting their musical proficiency. The fusion of diverse data sources, including performance data, practice logs, and biometric information, allows EFDfO to create a comprehensive understanding of each student's musical journey. The classification results indicate that, in most cases, the framework accurately classifies students based on their performance and learning characteristics, though further refinement is necessary to reduce misclassifications. EFDfO offers a promising pathway for personalized music education, enhancing students' learning experiences and outcomes. However, ongoing research and development are crucial to improve the framework's accuracy and effectiveness further. By continually refining EFDfO, we can unlock the full potential of data-driven music education, providing tailored and optimized experiences that benefit both students and educators. This research paves the way for a data-enhanced future in music education, ensuring that students receive personalized and effective instruction to help them reach their full musical potential.

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