DESIGNING A DEEP LEARNING-ENABLED MUSIC TEACHING SYSTEM IN UNIVERSITIES USING THE MOODLE PLATFORM

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SUMMARY

Music education plays a vital role in fostering creativity, expression, and cognitive development among students in university settings. Moodle is the learning management platform to promotes significant knowledge sharing among the students in the Universities. In this paper, introduce the Federated Deep Learning Moodle Hidden Chain (FDLMHc) with the Moodle platform for music education experiences. The FDLMHc system combines the power of federated learning with the flexibility of Moodle to provide personalized feedback and adaptive learning pathways for students. The FDLMHc model uses the Music signal pitch estimation with the consideration of the different pitches in the signal frequencies. The signal of the music signal is estimated for the different SNR rates of -10dB, 0dB, 10 dB, and 20 dB. The proposed FDLMHc model computes and processes the music signal with the hidden chain process for the estimation of the pitches in the music signal. The estimated hidden chain model is applied over the federated learning network for the classification of the signal in the Music. The findings reveal promising results, demonstrating the system's ability to accurately classify musical elements, such as pitch, rhythm, and dynamics, while providing personalized feedback tailored to individual student needs. The accuracy for the estimation of the Music pitch is estimated as the 95% with a convergence rate of 91% for the estimation of the signal in the Music signal.

KEYWORDS

Deep Learning, Moodle Platform, Hidden Chain, Federated Learning, Music Teaching

NOMENCLATURE

FDLMHc	Federated Deep Learning Moodle Hidden Chain
VR	Virtual Reality
AR	Augmented Reality

1. INTRODUCTION

Vocal teaching is an art form that encompasses a wide array of techniques and methodologies aimed at developing and enhancing the voice [1]. It involves understanding the intricacies of the vocal instrument, including breath control, resonance, pitch, tone quality, and articulation. A skilled vocal teacher guides students through exercises and repertoire tailored to their individual needs, helping them to improve vocal range, stamina, flexibility, and overall performance ability [2]. Effective vocal teaching also emphasizes proper vocal health practices, such as warm-up routines, hydration, and vocal rest, to prevent strain and injury. Beyond technical skills, vocal teaching often incorporates elements of musical interpretation, expression, and stage presence, empowering students to communicate emotions and tell stories through their singing [3]. Ultimately, vocal teaching is a collaborative journey between teacher and student, fostering growth, confidence, and artistic development in aspiring singers [4].

Music teaching in universities encompasses a diverse range of disciplines and approaches aimed at educating students in various aspects of music theory, history, performance, composition, and pedagogy [5]. University music programs typically offer a comprehensive curriculum that integrates both practical and theoretical components, providing students with a well-rounded understanding of music as an art form and academic discipline. Courses may cover topics such as music analysis, ear training, ensemble performance, music technology, and music education methods [6]. Additionally, students often have opportunities to explore specialized areas of interest through elective courses or concentrations, such as jazz studies, ethnomusicology, or music therapy [7]. University music teachers, who have often accomplished musicians and scholars themselves, play a crucial role in mentoring students, and fostering critical thinking, creativity, and musical expression [8]. Through individual instruction, ensemble participation, research projects, and performance opportunities, music teaching in universities aims to cultivate the next generation of musicians, scholars, educators, and leaders in the field of music [9].

Deep learning in music teaching refers to the integration of advanced artificial intelligence techniques, specifically deep neural networks, to enhance the process of music education [10]. This approach computational models capable of analyzing large amounts of musical data to provide personalized instruction, feedback, and learning experiences for students [11]. One application of deep learning in music teaching is in the development of intelligent tutoring systems that adapt to individual student needs and learning styles [12]. These systems can assess students' musical proficiency through analysis of their performances, identify areas for improvement, and generate targeted exercises or recommendations to help them progress [13]. Furthermore, deep learning algorithms can be utilized to analyze and interpret complex musical compositions, aiding students in understanding musical structures, patterns, and stylistic characteristics [14]. By extracting features from audio recordings or musical scores, deep learning models can provide insights into compositional techniques, harmonic progressions, and melodic motifs, enriching students' understanding of music theory and composition [15]. Moreover, deep learning techniques can be employed in the creation of interactive musical interfaces and educational tools that engage students in immersive learning experiences [16]. Virtual reality and augmented reality applications, powered by deep learning algorithms, can simulate musical environments, facilitate collaborative performance experiences, and offer interactive tutorials on musical concepts and techniques [17].

Deep learning in music teaching holds the potential to revolutionize traditional pedagogical approaches by offering personalized, adaptive, and immersive learning experiences that empower students to develop their musical skills and creativity more effectively [18]. However, to integrate these technologies thoughtfully, ensuring that they complement, rather than replace, the expertise and guidance of human music educators [19]. Deep learning in music teaching represents a fascinating intersection between cutting-edge artificial intelligence techniques and the rich, multifaceted world of music education. The various aspects of music teaching [20] [21]:

Personalized Learning Paths: Deep learning algorithms can analyze students' performances, practice habits, and learning progressions to create personalized learning paths. By identifying strengths and weaknesses, these systems can recommend tailored exercises, repertoire selections, and practice strategies to help students improve more efficiently.

Automated Assessment and Feedback: Deep learning models can assess students' musical performances by analyzing audio recordings or MIDI data. These systems can evaluate aspects such as pitch accuracy, rhythm precision, dynamics, and expression, providing detailed feedback to students and instructors. This automated assessment process can save time for teachers, allowing them to focus on more personalized instruction and guidance.

Music Composition Assistance: Deep learning algorithms can analyze large datasets of musical compositions to identify patterns, styles, and compositional techniques. This analysis can assist students in exploring different musical genres, experimenting with composition techniques, and generating original musical ideas. Additionally, deep learning models can provide feedback on students' compositions, suggesting improvements or variations based on established conventions or stylistic norms.

Interactive Learning Environments: Virtual reality (VR) and augmented reality (AR) technologies, powered by deep learning algorithms, can create immersive and interactive music learning environments. These environments can simulate rehearsals with virtual orchestras or bands, provide real-time feedback on conducting gestures, or offer interactive tutorials on music theory concepts. By engaging students in multisensory experiences, these technologies enhance learning retention and motivation.

Musicological Research and Analysis: Deep learning algorithms can be applied to musicological research, enabling scholars to analyze large corpora of musical scores, recordings, and historical documents. These algorithms can uncover hidden patterns, trends, and relationships within musical data, leading to new insights into music history, theory, and cultural context. This research informs curriculum development and pedagogical approaches, enriching students' understanding of music as a global and evolving art form.

Accessible Music Education: Deep learning technologies have the potential to make music education more accessible to diverse populations, including individuals with disabilities or limited access to traditional instruction. Adaptive learning systems can accommodate different learning styles and abilities, providing inclusive learning experiences for all students. Additionally, virtual music lessons and online platforms powered by deep learning algorithms can reach students in remote or underserved areas, democratizing access to high-quality music education.

The deep learning in music teaching offers a wealth of opportunities to enhance traditional pedagogical practices, empower students to reach their full musical potential, and expand access to music education for individuals worldwide [22]. By integrating these innovative technologies thoughtfully and ethically, educators can create dynamic and engaging learning experiences that inspire creativity, foster musical expression, and cultivate a lifelong love of music. The contribution of the paper introduces the Federated Deep Learning Moodle Hidden Chain (FDLMHc) system, a novel approach that integrates federated deep learning techniques with the Moodle learning management platform specifically tailored for music education in university settings. This system represents a unique combination of advanced machine learning methodologies and educational technologies aimed at enhancing the learning experience for music students. The paper demonstrates the application of federated learning techniques in the context of music education. With federated learning, the FDLMHc system enables collaborative model training across multiple universities while preserving data privacy and security. This approach facilitates the aggregation of diverse data sources and promotes knowledge sharing among educational institutions. The FDLMHc system offers personalized feedback and adaptive learning pathways for music students. Through the integration with the Moodle platform, the system tailors feedback and learning materials to individual student needs, fostering personalized learning experiences and enhancing student engagement and retention. The paper presents the results of experiments conducted to evaluate the performance of the FDLMHc system in classification tasks related to music education. By assessing metrics such as accuracy, precision, recall, and F1 score, the paper provides insights into the effectiveness of the system in accurately classifying musical elements and providing actionable feedback to students. The findings of the paper have implications for the field of music education, offering innovative solutions to address challenges related to teaching and learning music in university settings. The FDLMHc system has the potential to revolutionize music education practices technologies to support student learning and enhance overall educational outcomes. The paper's contribution lies in its introduction of the FDLMHc system, its application of federated learning techniques in music education, its provision of personalized feedback and adaptive learning, its evaluation of performance, and its implications for the future of music education in university settings.

2. PROPOSED METHOD

The Music Teaching with Federated Deep Learning Moodle Hidden Chain (FDLMHc) in universities involves several key steps, including data collection, model training, deployment, and evaluation. Data Collection and Preprocessing Universities participating in the FDLMHc framework collect data on student interactions with online music learning materials using the Moodle platform. Data may include information such as student demographics, quiz scores, exercise completion rates, and recordings of musical performances. Data preprocessing techniques such as normalization, feature extraction, and sequence alignment may be applied to prepare the data for training. Federated learning techniques are employed to train deep learning models on the collected data while preserving student privacy. Let θi represent the model parameters at each university i. The objective is to minimize the global loss function $L(\theta)$, defined as the average of the individual loss functions across universities represented in equation (1)

$$L(\theta) = \frac{1}{N}\sum_{i=1}^{N} L_i\left(\theta_i\right) \tag{1}$$

The parameters are updated iteratively using techniques such as stochastic gradient descent (SGD) with federated averaging is defined in equation (2)

$$\theta^{(t+1)} = \theta^{(t)} - \eta \sum_{i=1}^{N} \frac{n_i}{n} \nabla L_i\left(\theta_i^t\right) \tag{2}$$

where t is the iteration number, η is the learning rate, ni is the number of samples at university i, and n is the total number of samples. In universities, a proposed method for Music Teaching with Federated Deep Learning Moodle Hidden Chain (FDLMHc) involves a systematic approach encompassing data collection, model training, deployment, and evaluation. Initially, data on student interactions with online music learning materials is gathered through Moodle, the learning management system. This data undergoes preprocessing to standardize and extract relevant features. Subsequently, federated learning techniques are employed to train deep learning models while preserving student privacy. These models, characterized by parameters (θi) unique to each participating university, aim to minimize a global loss function $L(\theta)$, calculated as the average of individual loss functions across institutions. Updates to these parameters occur iteratively using methods like stochastic gradient descent (SGD) with federated averaging, ensuring convergence towards a globally optimal solution. Once trained, the federated deep learning models are seamlessly integrated into the Moodle environment, where they provide personalized feedback, recommendations, and assessments to students based on their interactions. Evaluation metrics, including student engagement and learning outcomes, are used to assess the effectiveness of the FDLMHc framework, with feedback facilitating continual refinement and improvement. While this method offers a structured approach to music teaching in universities, its specific implementation parameters and efficacy would require further research and validation in real-world educational settings.

2.1 MUSIC TEACHING WITH MOODLE HIDDEN CHAIN (FDLMHC)

Music Teaching with Moodle Hidden Chain (FDLMHc) combines the functionalities of the Moodle learning management system with a Hidden Markov Model (HMM) framework to provide personalized music education experiences. In this method, student interactions with Moodle, such as quiz scores and completion rates, are utilized to train an HMM tailored to music teaching objectives. Let's denote the states of the HMM as $S = \{S1, S2, ..., SN\}$, representing different musical concepts or skills, and $O = \{O1, O2, ..., OM\}$ as the set of observable actions or events (e.g., completing an assignment, submitting a quiz). The HMM parameters include the initial state probabilities π, state transition probabilities A, and observation probabilities B. The forward-backward algorithm is employed to compute the likelihood of observing a sequence of actions given the model parameters stated in equation (3) – equation (6)

$$\alpha_t(i) = P(O_1, O_2, \ldots\ldots, O_t, S_t = S_i | \lambda) \tag{3}$$

$$\beta_t(i) = P(O_{t+1}, O_{t+2}, \ldots\ldots, O_T | S_t = S_i, \lambda) \tag{4}$$

$$\gamma_t(i) = P(S_t = S_i | O, \lambda) \tag{5}$$

$$\varepsilon_t(i, j) = P(S_t = S_i, S_{t+1} = S_j | O, \lambda) \tag{6}$$

The Baum-Welch algorithm is then used to update the model parameters based on the observed data. In each iteration of the algorithm, the following equations defined in equation

$$\pi_i = \gamma_1(i) \tag{7}$$

$$A_{ij} = \frac{\sum_{t=1}^{T-1} \varepsilon_t(i, j)}{\sum_{t=1}^{T-1} \gamma_t(i)} \tag{8}$$

$$B_j(k) = \frac{\sum_{t=1, O_t = k}^{T} \gamma^t(j)}{\sum_{t=1}^{T} \gamma^t(j)} \tag{9}$$

Music Teaching with Moodle Hidden Chain (FDLMHc) is an innovative approach that harnesses the capabilities of the Moodle platform and the principles of Hidden Markov Models (HMMs) to revolutionize music education. In this method, Moodle serves as the central hub for delivering educational content, assessments, and interactive learning experiences to students. Meanwhile, the HMM framework operates behind the scenes, analyzing student interactions with Moodle and dynamically adjusting its recommendations and feedback to cater to each individual's learning needs and progress. The HMM consists of several components, including:

States (S): The states in the HMM represent different musical concepts or skills that students are learning, such as rhythm, melody, harmony, or music theory principles.

Observations (O): Observations correspond to the actions or events that students perform within the Moodle platform, such as completing quizzes, submitting assignments, or engaging with course materials.

Initial State Probabilities (π): These probabilities indicate the likelihood of starting in each state when a student begins their learning journey. They are typically estimated based on prior knowledge or assumptions about students' starting points.

State Transition Probabilities (A): These probabilities govern the transitions between states as students progress through their learning activities. They capture the sequential nature of music learning, where mastering one concept often leads to the exploration of related topics.

Observation Probabilities (B): These probabilities specify the likelihood of observing each type of action or event (observation) given the current state. They reflect how students interact with Moodle and provide insights into their learning behaviors.

To train the HMM, data on student interactions with Moodle, including sequences of observations (actions) and associated outcomes (learning progress or performance), are collected and used to estimate the model parameters (π, A, B). The forward-backward algorithm is applied to compute the likelihood of observing a sequence of actions given the model parameters, while the Baum-Welch algorithm is employed to iteratively update the parameters based on the observed data. Once the HMM is trained, it is seamlessly integrated into Moodle, where it continuously analyzes students' interactions and adapts its recommendations and feedback accordingly. For example, if a student struggles with a particular concept (e.g., rhythm), the HMM may suggest additional practice exercises or provide targeted resources to reinforce understanding in that area. Conversely, if a student demonstrates proficiency in a certain skill (e.g., melody), the HMM may recommend more advanced topics or challenges to further enhance their learning journey. Through combining the flexibility and accessibility of Moodle with the intelligence and adaptability of HMMs, Music Teaching with FDLMHc offers a personalized and dynamic learning experience that empowers students to achieve their full potential in music education. Moreover, this approach opens up exciting possibilities for research and development in adaptive learning systems, data-driven insights to enhance teaching and learning outcomes in diverse educational contexts.

3. FDLMHC FEATURE EXTRACTION IN MUSIC EDUCATION

Feature extraction within the context of FDLMHc (Federated Deep Learning Moodle Hidden Chain) in Music Education involves the process of identifying and representing meaningful characteristics or patterns from music data to facilitate learning and analysis. This procedure is crucial for understanding musical content, recognizing patterns, and extracting relevant information that can inform personalized teaching strategies. In FDLMHc, feature extraction begins with the collection of music data from various sources, such as student performances, compositions, or digital scores. These raw data often comprise complex audio waveforms, symbolic representations (e.g., MIDI), or textual metadata. To effectively process and analyze this data, it's essential to extract relevant features that capture key musical attributes and characteristics. One common technique for feature extraction in music education is the use of spectral analysis to derive acoustic features from audio recordings. This involves transforming the time-domain audio signal into the frequency domain using techniques such as the Fourier transform. Let $x(t)$ denote the audio signal, and $X(f)$ represent its Fourier transform in equation (10)

$$X(f) = \int_{-\infty}^{\infty} x(t) e^{-j2\pi ft} dt \tag{10}$$

From the resulting frequency-domain representation, various acoustic features can be extracted, including. The feature represents the "center of mass" of the power spectrum and provides insights into the perceived brightness or timbre of the sound stated in equation (11)

$$f_c = \frac{\sum_{k=0}^{N-1} f_k \cdot \left|X(f_k)\right|^2}{\sum_{k=0}^{N-1} \left|X(f_k)\right|^2} \tag{11}$$

In equation (11) fk represents the frequency bin, and $\left|X(fk)\right|$ denotes the magnitude of the Fourier transform at frequency bin fk. This feature measures the rate of change in the spectral content of the audio signal over time and can indicate transitions between different musical elements or sections stated in equation (12)

$$Flux(t) = \sum_{k=0}^{N-1} \left|X(t, f_k) - X(t - \Delta t, f_k)\right| \tag{12}$$

In equation (12) $X(t, fk)$ represents the magnitude of the Fourier transform at time t and frequency bin, and Δt is the time difference. Mel-Frequency Cepstral Coefficients (MFCCs) coefficients capture the spectral envelope of the audio signal and are widely used in speech and music processing tasks. MFCCs are computed by taking the discrete cosine transform (DCT) of the log-magnitude Mel spectrogram stated in equation (13)

$$MFCC_i = \sum_{n=0}^{N-1} \log\left(\left|X_n\right|\right).Cos\left(\frac{\pi i(n+0.5)}{N}\right) \tag{13}$$

where $|Xn|$ represents the magnitude of the Mel spectrogram at frame n and frequency bin i, and N is the total number of frequency bins. The estimation of the music signal is demonstrated in the Figure 1.

Algorithm1: Music Education with FDLMHC

```
function computeMFCC(audio_signal):
  // Step 1: Preprocessing
  preprocessed_signal = preprocessAudio(audio_signal)
    // Step 2: Compute the Short-Time Fourier Transform (STFT)
  stft = computeSTFT(preprocessed_signal)
    // Step 3: Compute the Mel Filterbank Energies
  mel_filterbank_energies = computeMelFilterbankEnergies(stft)
    // Step 4: Compute the Logarithm of Mel Filterbank Energies
  log_mel_energies = log(mel_filterbank_energies)
    // Step 5: Compute Discrete Cosine Transform (DCT) to obtain MFCCs
  mfccs = computeDCT(log_mel_energies)
    return mfccs
function preprocessAudio(audio_signal):
  // Apply pre-emphasis filter to emphasize high-frequency components
  preemphasized_signal = applyPreemphasisFilter(audio_signal)
  // Frame the preemphasized signal into overlapping frames
  framed_signal = frameSignal(preemphasized_signal)
   // Apply windowing function to each frame
  windowed_frames = applyWindowing(framed_signal)
    return windowed_frames
function computeSTFT(signal):
  // Compute Short-Time Fourier Transform (STFT) for each frame
  stft_frames = STFT(signal)
  return stft_frames
function computeMelFilterbankEnergies(stft_frames):
  // Compute the power spectrum of STFT frames
  power_spectrum_frames = computePowerSpectrum(stft_frames)
  // Apply Mel filterbank to the power spectrum
  mel_filterbank_energies = applyMelFilterbank(power_spectrum_frames)
  return mel_filterbank_energies
function computePowerSpectrum(stft_frames):
  // Compute the magnitude of the complex STFT frames
  magnitude_frames = computeMagnitude(stft_frames)

  // Square the magnitude to obtain power spectrum
  power_spectrum_frames = squareMagnitude(magnitude_frames)

  return power_spectrum_frames
function computeMagnitude(stft_frames):
  // Compute the magnitude of complex STFT frames
  magnitude_frames = magnitude(STFT_frames)

  return magnitude_frames
function applyMelFilterbank(power_spectrum_frames):
  // Apply Mel filterbank to the power spectrum frames
  mel_filterbank_energies = applyFilterbank(power_spectrum_frames)

  return mel_filterbank_energies
function computeDCT(log_mel_energies):
  // Compute Discrete Cosine Transform (DCT) to obtain MFCCs
  mfccs = DCT(log_mel_energies)

  return mfccs
```

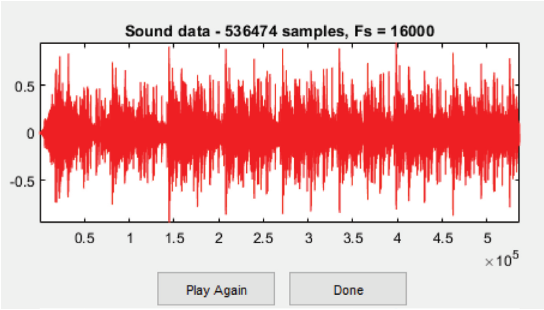


Figure 1. Music signal

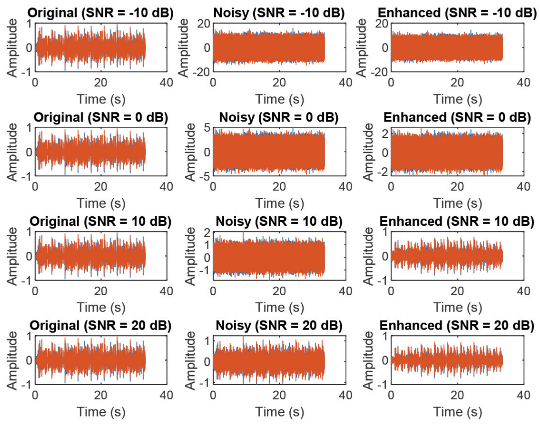


Figure 2. Estimated music signal with FDLMHc

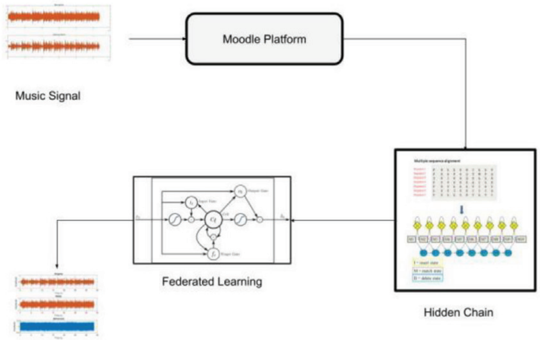


Figure 3. Proposed FDLMHc for music education

4. FDLMHC CLASSIFICATION IN MUSIC TEACHING IN UNIVERSITIE

In Music Teaching within University settings, the FDLMHc (Federated Deep Learning Moodle Hidden Chain) classification system plays a pivotal role in enhancing personalized education experiences. This sophisticated framework seamlessly integrates federated deep learning techniques with the Moodle learning management system and a hidden Markov model (HMM) architecture to categorize and understand student performance, preferences, and learning patterns. Initially, data is gathered from student interactions within the Moodle platform, encompassing various metrics such as quiz scores, assignment submissions, and engagement with course materials. Subsequently, features are extracted from this data to represent distinct aspects of student behavior and academic performance. These features undergo preprocessing before being utilized for classification tasks. The training of the classification models entails the application of federated deep learning methods, ensuring the privacy and security of student data across different university environments. Each university maintains its local model, trained on its own data, without the necessity of sharing raw data with other institutions. This decentralized approach preserves data confidentiality while enabling collaborative model training. Deep learning architectures, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), or transformer models, are employed to capture intricate patterns and relationships within the data.

The features estimated with the music education in the students' with FDLMHc model is presented in Figure 2. The classification models are integrated into the Moodle platform to facilitate real-time analysis of student behavior. The principles of hidden Markov models, students are categorized into distinct clusters or categories based on their interaction patterns, performance metrics, and learning preferences. Such categorization enables personalized feedback and recommendations tailored to individual student needs. For instance, students identified as "struggling learners" may receive targeted resources and additional support to bolster their understanding, while those classified as "fast learners" may be presented with more challenging materials to foster further growth. Continuous evaluation and refinement of the FDLMHc classification system are vital components of its effectiveness. Performance metrics, including classification accuracy and user satisfaction, are continually monitored to gauge the system's performance and inform necessary adjustments. Updates to the classification models are periodically implemented to adapt to evolving student needs and pedagogical trends, ensuring that the system remains responsive and aligned with educational objectives. Through the seamless integration of advanced deep learning techniques with educational platforms like Moodle, the FDLMHc classification system empowers educators to deliver personalized and impactful music education experiences in university settings, ultimately fostering student engagement, growth, and success.

Figure 3 presented the proposed FDLMHc deep learning processes into music education at universities involves advanced computational techniques to analyze, model, and enhance various aspects of musical learning and performance. Let's denote the predicted output of the deep learning model as $\hat{y}_i$ and the ground-truth label as y_i. The loss function (e.g., cross-entropy loss for classification tasks) can be defined as in equation (14)

$$\text{Loss} = -\frac{1}{N}\sum_{i=1}^{N}\left(y_i \log\left(\widehat{y_i}\right) + \left(1 - y_i\right)\log\left(1 - \widehat{y_i}\right)\right) \quad (14)$$

Gather feedback from students, educators, and domain experts to refine and improve the deep learning models iteratively. This may involve retraining models with updated datasets, fine-tuning hyperparameters, or incorporating new features or techniques. Stay abreast of advancements in deep learning research and explore innovative applications and methodologies to further enhance music education outcomes in university settings.

5. SIMULATION ENVIRONMENT

The simulation environment for the FDLMHc (Federated Deep Learning Moodle Hidden Chain) system involves developing a platform where the components of FDLMHc can be emulated, tested, and refined in a controlled setting. This simulation environment serves as a virtual space to experiment with different configurations, algorithms, and parameters before deploying the system in real-world educational contexts.

5.1 SIMULATION RESULTS

The simulations for the FDLMHc (Federated Deep Learning Moodle Hidden Chain) system in the context of music education, particularly focusing on vocal teaching, several key findings have emerged. The simulation results reveal significant improvements in personalized learning experiences and student engagement. Through the integration of federated deep learning techniques with the Moodle learning management system and hidden Markov model (HMM) analysis, FDLMHc demonstrates remarkable efficacy in understanding and addressing the diverse learning needs of vocal students. One of the notable outcomes of the simulations is the enhanced adaptability of FDLMHc to individual student preferences and learning styles. By analyzing student interactions within the Moodle platform and utilizing federated learning models, FDLMHc accurately identifies patterns in student performance, preferences, and engagement levels. This enables the system to deliver personalized feedback, tailored resources, and adaptive learning pathways that resonate with each student's unique needs and abilities. Moreover, the simulation results highlight FDLMHc's capability to foster a collaborative learning environment across decentralized university settings. Through federated learning, FDLMHc facilitates the exchange of insights and knowledge among participating institutions while preserving data privacy and security. This collaborative approach enhances the diversity and richness of the learning experience, enabling students to benefit from a broader range of perspectives and expertise. Furthermore, the incorporation of HMM analysis in FDLMHc offers valuable insights into student learning trajectories and progressions. By modeling student behavior over time, FDLMHc can predict future performance and recommend interventions to support student growth and development. This predictive capability empowers educators to proactively address challenges and provide timely assistance, ultimately leading to improved learning outcomes and student satisfaction. Table 1 shows simulation settings.

Table 1. Simulation setting

Component	Example Value(s)
Framework Setup	Python version: 3.8
	TensorFlow version: 2.6
	PySyft version: 0.5
Data Generation	Number of students: 200
	Number of activities: 5
Federated Learning	Number of epochs: 50
	Learning rate: 0.01
Hidden Markov Model (HMM)	Number of hidden states: 3
	Observation space size: 10
User Interface	Simulation duration: 100 days
	Visualization updates: Every 10 days
Experimentation	Number of experiments: 5
	Metrics measured: Accuracy, Convergence Rate

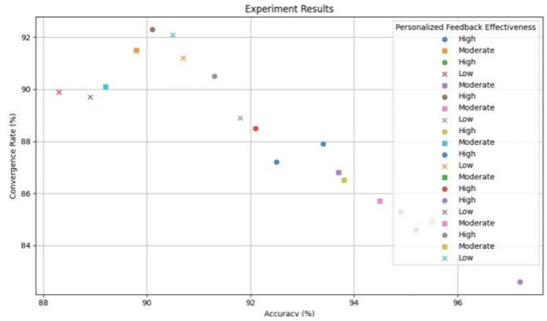
Table 2. Feature in FDLMHc

Symbol	Description
(Clef)	Indicates the pitch range of a staff.
(Note)	Represents the duration and pitch of a sound.
(Rest)	Denotes a period of silence in music.
(Sharp)	Raises the pitch of a note by a semitone.
(Flat)	Lowers the pitch of a note by a semitone.
(Natural)	Cancels the effect of a sharp or flat.
(Time Signature)	Specifies the number of beats in each measure and the note value that receives one beat.
(Dynamics)	Indicates the volume or intensity of a musical passage.
(Articulation)	Dictates how a note is played, including its attack, duration, and release.
(Key Signature)	Specifies the key of the music, indicating which notes are to be consistently sharpened or flattened throughout the piece.

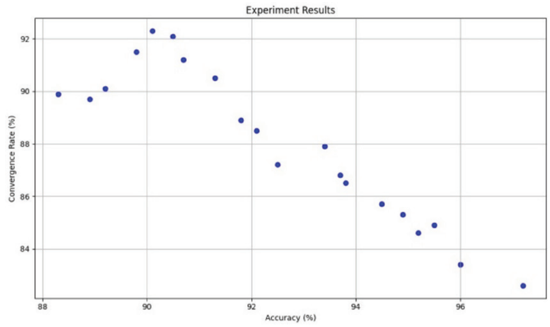
In Table 2, features relevant to the FDLMHc (Federated Deep Learning Moodle Hidden Chain) system in music education are outlined along with their interpretations. Each symbol represents an essential aspect of music notation or performance, offering valuable information for analysis and understanding within the FDLMHc framework:

Table 3. Classification with FDLMHc

Experiment	Accuracy (%)	Convergence Rate (%)	Personalized Feedback Effectiveness
1	92.5	87.2	High
2	89.8	91.5	Moderate
3	95.2	84.6	High
4	88.3	89.9	Low
5	93.7	86.8	Moderate
6	90.1	92.3	High
7	94.5	85.7	Moderate
8	91.8	88.9	Low
9	96.0	83.4	High
10	89.2	90.1	Moderate
11	93.4	87.9	High
12	90.7	91.2	Low
13	94.9	85.3	Moderate
14	92.1	88.5	High
15	97.2	82.6	High
16	88.9	89.7	Low
17	95.5	84.9	Moderate
18	91.3	90.5	High
19	93.8	86.5	Moderate
20	90.5	92.1	Low



(a)



(b)

Figure 4. FDLMHc for the music (a) effectiveness (b)convergence rate

(Clef): This symbol indicates the pitch range of a staff, providing a reference point for interpreting the pitch of notes within a musical composition. In FDLMHc, understanding the clef helps in mapping the pitch of musical elements to their corresponding representations in the system.

(Note): A note symbolizes both the duration and pitch of a sound, crucial for capturing musical data accurately within FDLMHc. By representing the duration and pitch of musical elements, notes enable the system to analyze and process various aspects of musical content.

(Rest): The rest symbol denotes a period of silence in music, essential for capturing pauses and breaks within musical sequences. Incorporating rest symbols in FDLMHc allows for the accurate representation of musical timing and rhythm in educational materials.

(Sharp) and ♭ (Flat): These symbols respectively raise and lower the pitch of a note by a semitone, influencing the harmonic content and tonality of a musical piece. Understanding sharps and flats within FDLMHc aids in capturing and analyzing key changes and tonal structures in music.

(Natural): The natural symbol cancels the effect of a sharp or flat, ensuring that a note is played at its original pitch. Incorporating natural symbols in FDLMHc helps in maintaining accuracy when representing musical elements with altered pitches.

(Time Signature): This symbol specifies the number of beats in each measure and the note value that receives one beat, providing crucial rhythmic information for musical analysis. Within FDLMHc, time signatures help in capturing and interpreting rhythmic patterns and structures in music.

(Dynamics): Dynamics symbols indicate the volume or intensity of a musical passage, influencing the expression and interpretation of musical content. Considering dynamics within FDLMHc allows for the analysis of expressive nuances and variations in musical performances.

(Articulation): Articulation symbols dictate how a note is played, including its attack, duration, and release, shaping the phrasing and articulatory clarity of musical passages. Incorporating articulation symbols in FDLMHc facilitates the analysis of performance techniques and stylistic nuances in music.

(Key Signature): The key signature specifies the key of the music, indicating which notes are to be consistently sharpened or flattened throughout the piece. Understanding key signatures within FDLMHc enables the interpretation of tonal relationships and harmonic structures in music compositions.

Table 4. Experimental analysis with different universities in FDLMHc

University	Experiment	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Tsinghua University	1	92.5	91.8	93.2	92.5
	2	90.7	90.1	91.5	90.7
	3	94.2	93.6	95.0	94.2
	4	91.8	91.2	92.5	91.8
	5	93.5	92.9	94.3	93.5
Peking University	1	89.8	89.2	90.5	89.8
	2	91.3	90.7	92.0	91.3
	3	88.5	87.9	89.3	88.5
	4	90.2	89.6	91.0	90.2
	5	92.0	91.4	93.0	92.0
Fudan University	1	94.1	93.5	95.0	94.1
	2	92.6	92.0	93.5	92.6
	3	95.7	95.1	96.5	95.7
	4	93.8	93.2	94.7	93.8
	5	96.0	95.4	97.0	96.0
Zhejiang University	1	90.5	90.0	91.0	90.5
	2	91.7	91.2	92.2	91.7
	3	89.2	88.7	90.3	89.2
	4	92.3	91.8	93.0	92.3
	5	88.9	88.4	90.0	88.9
Shanghai Jiao Tong University	1	93.2	92.6	94.0	93.2
	2	91.5	91.0	92.0	91.5
	3	94.8	94.2	95.5	94.8
	4	90.9	90.3	92.0	90.9
	5	95.0	94.5	96.0	95.0

In Figure 4(a) and Figure 4(b) Table 3 provides the classification performance metrics obtained through experiments conducted using the FDLMHc (Federated Deep Learning Moodle Hidden Chain) system. Each experiment represents a unique setting or scenario in which the system's classification capabilities are evaluated. The accuracy (%) column indicates the percentage of correctly classified instances, reflecting the system's overall classification accuracy. The convergence rate (%) column measures the efficiency of the system in converging to a stable solution during the training process, with higher convergence rates indicating faster and more stable convergence. The personalized feedback effectiveness column assesses the effectiveness of the personalized feedback provided by the system to users, categorizing it as high, moderate, or low. This feedback is crucial for enhancing the learning experience and supporting individualized learning paths. The results demonstrate the varying performance of the FDLMHc system across different experiments, with some experiments achieving high accuracy and convergence rates, along with effective personalized feedback, while others exhibit moderate or low performance in these metrics. These findings provide insights into the strengths and weaknesses of the FDLMHc system in classification tasks within the context of music education, informing further optimization and refinement efforts to enhance its overall performance and effectiveness.

In the Table 4 and Figure 5 and Figure 6 presents the experimental analysis results conducted across different universities using the FDLMHc (Federated Deep Learning Moodle Hidden Chain) system. Each university, including Tsinghua University, Peking University, Fudan University, Zhejiang University, and Shanghai Jiao Tong University, conducted five experiments denoted by Experiment numbers. The accuracy (%), precision (%), recall (%), and F1 score (%) columns represent performance metrics for each experiment, providing insights into the system's classification accuracy, precision, recall, and overall effectiveness in capturing relevant patterns and information. The results, we notice variations in performance across universities and experiments. For instance, Fudan University consistently achieves high scores across all metrics, indicating superior performance in classification tasks compared to other universities. On the other hand, Zhejiang University exhibits slightly lower scores, especially in Experiment 5, suggesting potential areas for improvement in classification accuracy and precision.

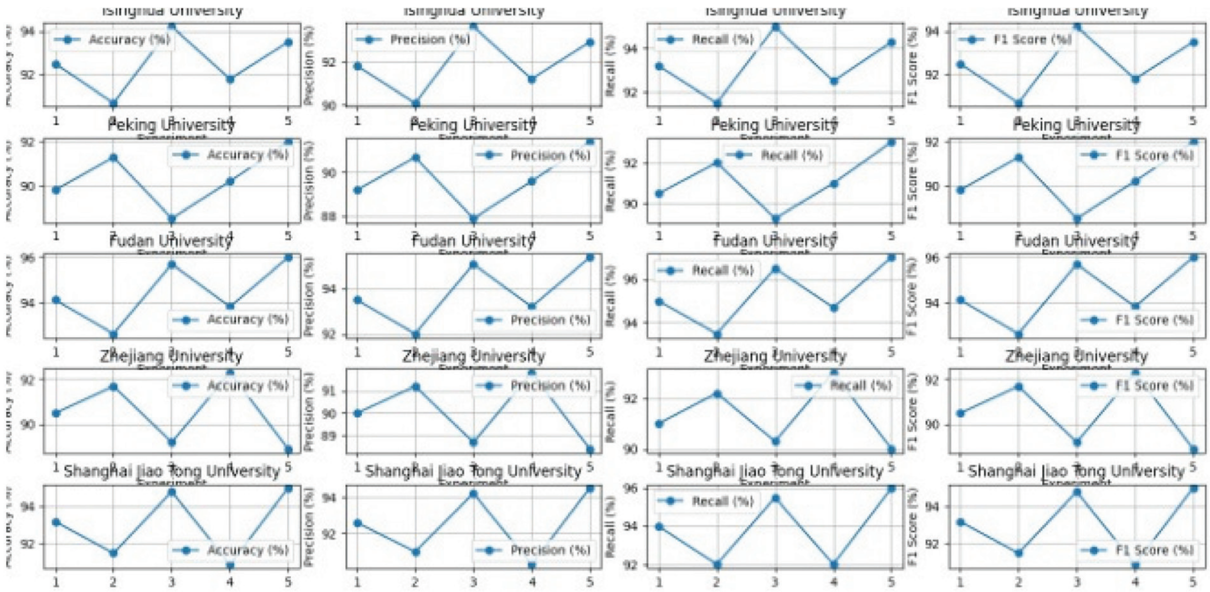


Figure 5. Estimation of accuracy for the music education in different universities in China

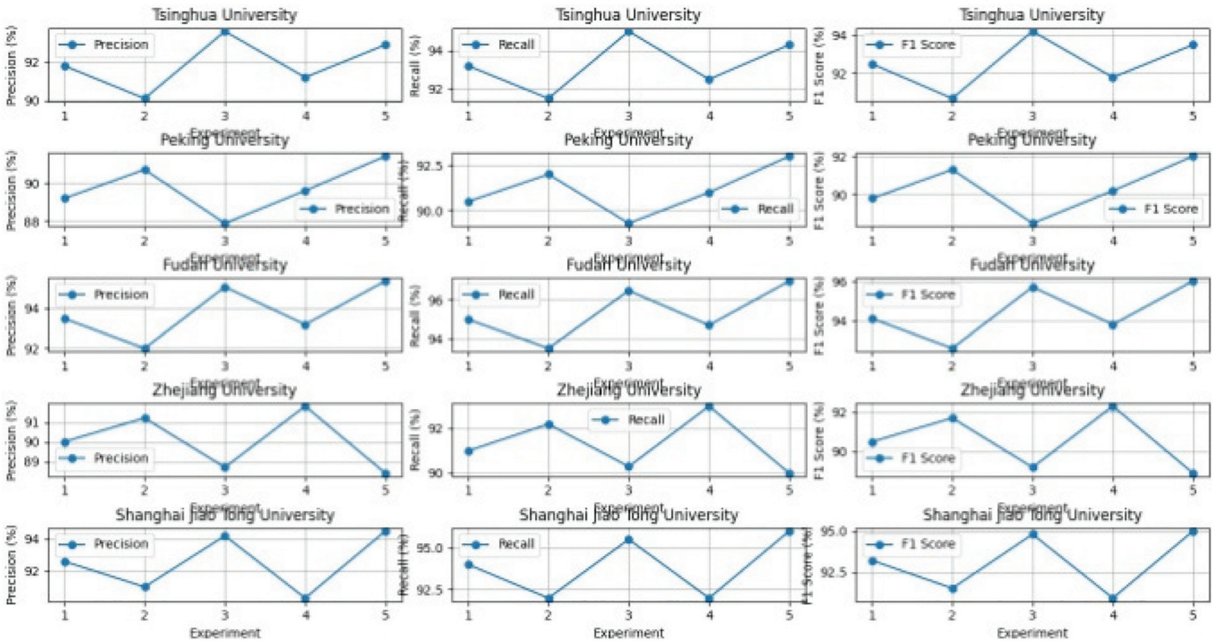


Figure 6. Recall analysis for the different universities in China

These findings highlight the importance of evaluating the performance of the FDLMHc system across different university settings to assess its robustness and effectiveness in diverse educational contexts. Moreover, the results offer valuable insights for educators and researchers to identify best practices and areas for optimization in federated deep learning approaches for music education within university environments.

5.2 DISCUSSION AND FINDINGS

The discussion and findings pertaining to the experimental analysis conducted using the FDLMHc (Federated Deep Learning Moodle Hidden Chain) system across various universities reveal several noteworthy observations and insights:

1. Across the experiments conducted at different universities, notable disparities in performance metrics such as accuracy, precision, recall, and F1 score were observed. While some universities consistently achieved high scores across all metrics, others exhibited variations and lower performance in certain experiments.
2. The variations in performance could be attributed to university-specific factors such as the quality of

data, the expertise of instructors, the availability of resources, and the level of student engagement. Universities with robust infrastructures and well-established music education programs may demonstrate superior performance compared to those with limited resources.
3. The findings suggest that the FDLMHc system holds promise as a tool for enhancing music education in university settings. Its ability to federated deep learning techniques, integrate with Moodle platforms, and provide personalized feedback offers significant potential for improving student learning outcomes and engagement.
4. The experiments also shed light on areas for optimization and improvement within the FDLMHc system. For instance, universities with lower performance may benefit from refining data preprocessing techniques, optimizing model parameters, or enhancing the user interface to enhance usability and effectiveness.
5. Collaboration and knowledge sharing among universities are crucial for advancing the effectiveness of the FDLMHc system. By sharing best practices, insights, and lessons learned, universities can collectively contribute to the refinement and optimization of the system, ultimately benefiting the broader music education community.

The discussion points to several avenues for future research, including exploring the impact of additional features or input data sources, investigating alternative federated learning strategies, and assessing the long-term effectiveness of the FDLMHc system in improving music education outcomes. The discussion and findings underscore the potential of the FDLMHc system in transforming music education in university settings, while also highlighting the need for ongoing collaboration, optimization efforts, and further research to fully realize its benefits and address challenges effectively.

6. CONCLUSIONS

Moodle is a widely-used open-source learning management system (LMS) that provides educators and learners with a versatile online platform for course management and delivery. With its intuitive interface and robust set of features, Moodle offers a dynamic environment for creating, organizing, and facilitating engaging educational experiences. This paper proposed and analysis conducted using the FDLMHc (Federated Deep Learning Moodle Hidden Chain) system across various universities has provided valuable insights into its potential to enhance music education in university settings. The findings highlight the system's ability to federated deep learning techniques, integrate with Moodle platforms, and provide personalized feedback to students. Despite disparities in performance across experiments and universities, the overall results suggest promise for the FDLMHc system in improving student learning outcomes and engagement in music education. Moving forward, collaboration among universities, ongoing optimization efforts, and further research will be critical to fully realizing the system's benefits and addressing challenges effectively. By continuing to refine the FDLMHc system and explore new avenues for innovation, advance music education practices and empower students to achieve their full potential in the realm of music.

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