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Music Teaching Mode of Colleges and Universities Based On Hierarchically Gated Recurrent Neural Network (HGRNN) and Lyrebird Optimization Algorithm (LOA)



Abstract: - Colleges and universities play a crucial role in nurturing talent and providing highly skilled individuals for various sectors of society. Through modifications over time, the model of music education at colleges and universities has advanced. However, there are still numerous issues that demand careful consideration. This manuscript proposes a hierarchically gated recurrent neural network (HGRNN) optimized with the lyrebird Optimization Algorithm (LOA) for predicting music teaching mode of colleges and universities (MTM-HGRNN-LOA). Initially, the data is collected via real time basis. Afterward, the data is fed to an unscented trainable kalman filter (UTKF) based pre-processing process. In the pre-processing segment, it enhances training rate and eliminates the of batch size dependency. The pre-processing output is given to modified spline-kernelled chirp let transform (MSKCT). The input signal undergoes feature extraction to derive the primary features, which are subsequently combined to yield more comprehensive features in an efficient manner. After that, the extracted features are given to a hierarchically gated recurrent neural network and lyrebird optimization algorithm for effectively classifying the music teaching mode for best, good, normal, satisfactory and poor. The weight parameters of hierarchically gated recurrent neural network are optimized using the lyrebird optimization algorithm. The proposed method is implemented in python and evaluated their performance with existing methods. The performance metrics, like precision, F1-score, accuracy, specificity, sensitivity, and ROC is analysed to the proposed method's performance. The proposed MTM-HGRNN-LOA methods of accuracy are provide 97% best, 98% good, 95% normal, 98% satisfactory and 97% poor music teaching mode. The existing methods MTM-CNN, MTM-BPNN and MTM-GNN, the specificity becomes 90%, 70%, 79% best, 77%, 75%, 65% good, 66%, 85%, 84% normal, 59%, 58%, 70% satisfactory, 61%, 79%, 81% poor music teaching mode. The results show that the proposed MTM-HGRNN-LOA method outperforms other existing techniques, such as online vocal music teaching quality using Back Propagation neural network and convolutional neural network based College-Level Music Teaching Quality Evaluation.

Keywords: Music Teaching Mode, Colleges, Universities, Unscented Trainable Kalman Filter, Modified Spline-Kernelled Chirplet Transform.

I. INTRODUCTION

In recent times, due to the fast expansion of knowledge, the existing awareness structure is no longer sufficient to meet the demands of the evolving era [1]. The focus of music education has shifted from skill development to nurturing students' attitudes, emotions, and values [2]. The evaluation of music teaching has transitioned from being solely summative to incorporating formative assessment. It has also moved from evaluating specific aspects to a more holistic and comprehensive approach. Active participation in the evaluation process has replaced passive waiting for the evaluation, as well [3]. In terms of evaluation theory, there is now an emphasis on assessing comprehensive qualities such as problem-solving abilities, innovation, practical skills, psychological well-being, and a scientific mind set. Additionally, fostering a positive learning environment is considered crucial [4]. Evaluation now focuses on students' development and progress rather than just selection and screening. The aim is to create an education system that is suitable for children, rather than selecting children who are suitable for education. Evaluation should be viewed in terms of its motivational and integrative functions [5]. Evaluating a teacher's performance enables them to understand their own development trajectory through self-evaluation and external evaluation. This allows them to harness the power of evaluation to enhance their teaching abilities and improve their classroom practices [6]. With on-going reforms, the introduction of advanced foreign teaching methods, and the deepening of the education system, art education, particularly music education, has gained increasing recognition as a vital component of quality education [7].

Currently, despite the quick progress of music teaching in universities, there are still unresolved issues [8]. The effective application of music teaching is strongly impacted by the improper alignment of the aim of music education in colleges [9]. Furthermore, there are a number of factors that inhibit the rapid growth of music education, including insufficient content, inadequate instructional facilities, and unclear instructional objectives [10]. There's a significant gap in the professional skill development and overall ability structure of music majors at teacher's universities when it comes to meeting the current demands of basic music teaching, especially with the introduction of competency-based teaching [11].

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Under the direction of synergy, the synergetic theory of competency-based education and music education seeks to fully use the unique artistic role that music instruction plays. This maximizes the competency-based education system's total performance by enabling collaboration, cooperation, integration, and mutual enhancement with each of its subsystems [12]. Enhancing music competency education in universities has several benefits, including enhancing college students' aesthetic experiences, stimulating their various perceptual and cognitive abilities, and fostering their expressiveness, imagination, and creativity, ultimately enhancing and refining their overall comprehensive qualities [13].

An essential component of instructional management is the evaluation of classroom quality [14]. The assessment index system serves as a means of demonstrating how instructional assessment is evaluated in institutions [15]. This system aids school leaders and managers in understanding the extent to which instructional objectives are achieved, enabling them to accurately and comprehensively assess the state of teaching in order to enhance the level of instructional. Since the inception of university-based instructional assessment, many institutions have implemented their own assessments based on their specific circumstances. Consequently, assessment of instruction in universities has garnered significant attention from both scholars and the wider society [16]. Teaching, being a nonlinear classification problem, presents considerable challenges for comprehensive assessment [17]. The distinctive qualities of neural networks adaptive learning, nonlinear processing and high fault tolerance have led to their widespread use in a wide range of assessment problems. Additionally, Neural Network provides clear benefits in tackling the problem of assessment at the instructional level [18]. This study builds on this basis by examining the basic theories and practices of traditional instructional assessment, along with its features and contemporary issues. It proposes a prediction model based on HGRNN (Hierarchically Gated Recurrent Neural Network) and integrates Neural Network technology into the evaluation of music instructional levels, building upon conventional assessment methodologies [19]. This approach proves effective in predicting issues that lack identifiable rules. Simultaneously, a set of assessment index systems for the quality of music education in colleges is being created [12].

The main contributions of this manuscript are summarized below:

- A hierarchically gated recurrent neural network (HGRNN) optimized with the LOA is proposed for music teaching in colleges and universities for identifying the music teaching modes as “best”, “good”, “normal”, “satisfactory”, and “poor” teaching mode (MTM-HGRNN-LOA).
- The data's are initially collected from real time basis dataset. Afterward, the data's are fed to pre-processing.
- In pre-processing segment, it enhances training rate and eliminates the of batch size dependency
- The output of pre-processing is directed towards the feature extraction segment. The extracted features such as operability, targeted, wholeness, superiority, and openness.
- Following the pre-processing and feature extraction processes, the resulting output is inputted into the classification method.
- The proposed technique is executed and the efficiency of proposed MTM-HGRNN-LOA teaching classification is evaluated by several performances analysing metrics like accuracy, specificity, f-score, sensitivity, precision, and recall.
- The proposed HGRNN-LOA approach is simulated by MATLAB utilizing the dataset of atmosphere turbulence. From the result, it concludes that the proposed approach is better compared with existing approaches like CNN, BPNN and GNN respectively.

Remaining manuscript is organized as: part 2 depicts survey of literature, part 3 describes proposed approach; the outcomes are proved in part 4, and finally, the conclusion is presented in part 5.

II. METHODOLOGY

Among the frequent research work on music teaching mode prediction based on deep learning; In this section, some of the most recent investigations were evaluated.

Shi [20] has developed a cutting-edge neural network (NN) technology using a conventional approach to evaluate music teaching. They propose a unique method called MTQEN. This method uses a 1D-CNN that has been tuned in three important areas: increasing the receptive field, decreasing training parameters, and improving operational efficiency. To increase the effectiveness of feature extraction and expand the local receptive field, the dilated convolution layer is used in place of the conventional convolution layer.

Guo and Tang [21] created a unique education index system to address the shortcomings of the traditional techniques for assessing the quality of online vocal instruction. Additionally, they introduced an enhanced Back Propagation neural network-based adaptive variant Genetic Algorithm model for vocal instruction quality assessment. This model, in conjunction with the newly established index system, was employed to assess the quality of vocal music teaching.

Liu and Wu [22] have developed a system to assess the quality of music art education, which has been a large-scale project for teaching management in Chinese universities and colleges for the past ten years. Assessing the teaching skills of professors of music and art in a fair and impartial way is one of the main management difficulties of these institutions. To address this, the system utilizes a browser and server architecture, separating the front end and back end, and delivers examination services through cloud computing.

Chu [23] has created an interactive music design based on AI technology and presents a novel approach to music learning. This design not only enhances students' inquiry skills but also empowers teachers to guide the learning process. This paper offers a mathematical model for an AI music teaching evaluation system based on DL theory, along with a thorough explanation of the way DL theory is used to assess music education. After the network has been trained, the model can evaluate the effectiveness of AI-powered music teaching.

Shi and Ning [24] have presented a novel approach to college music teaching research using technology utilizing artificial intelligence. In order to create a two-level teaching evaluation index system, this method integrates a fuzzy evaluation algorithm. Fuzzy mathematical theory is used to compute the weights of each index. The collected teaching evaluation data is first identified using the SVM method from the data mining area using supervised learning in order to improve data processing efficiency.

Luo [25] have developed on 5G technology's incorporation into music education. The research focused on examining the principles of applying 5G in the teaching of music and exploring the effect of digital technology on the advancement of music education. Additionally, the study emphasized the importance of aligning innovation and reform in online music education with the advancements in communication technology, notably by fusing artificial intelligence with a 5G network environment.

Li and Wang [26] have conducted research on the efficacy of AI-driven music instruction. The purpose of the study is to replace piano instruction at seven different music schools with AI-powered chatbots, then evaluate the effect on student performance.

Mao [27] has introduced an algorithm for optimizing information systems in order to intelligently analyze Higher education institutions' teaching of music. This algorithm selects the most suitable technique for processing music information and establishes a system of music instruction in higher education based on this foundation.

A. Problem Statement and Motivation

The traditional classroom teaching paradigm is no longer adequate to fulfill the different demands of students in the context of Internet+ education. Modern network-based vocal music instruction has broken the monopoly of conventional teaching techniques and changed the focus of music education from focusing primarily on higher education to being more widely available and popular. With Internet+ education, the barriers to learning vocal music have been significantly lowered. As long as individuals have access to a computer or smartphone with an internet connection, they can freely search for and access the vocal music courses they desire, enabling them to pursue independent learning. This has particularly benefited vocal student's in general educational institutions that may not have access to specialized vocal teachers or comprehensive teaching resources. They can now leverage the internet to find online vocal teaching resources and study at their own pace. However, the integration of education and the internet also brings forth new challenges. The media and information era has introduced issues such as the credibility and quality of online vocal music resources. It is crucial for vocal teachers to navigate this landscape and guide students towards reliable and reputable sources for their learning. Furthermore, vocal teachers must adapt their teaching methods to effectively utilize the advantages of both the internet and traditional teaching. They need to strike a balance between online and offline interactions, leveraging the internet to supplement classroom instruction and provide additional learning resources. By embracing technology and incorporating online tools, vocal teachers can enhance their teaching effectiveness and engage students in a more interactive and dynamic learning experience. The researchers were inspired to work on this project by the weaknesses in the existing methods.

III. PROPOSED METHODOLOGY

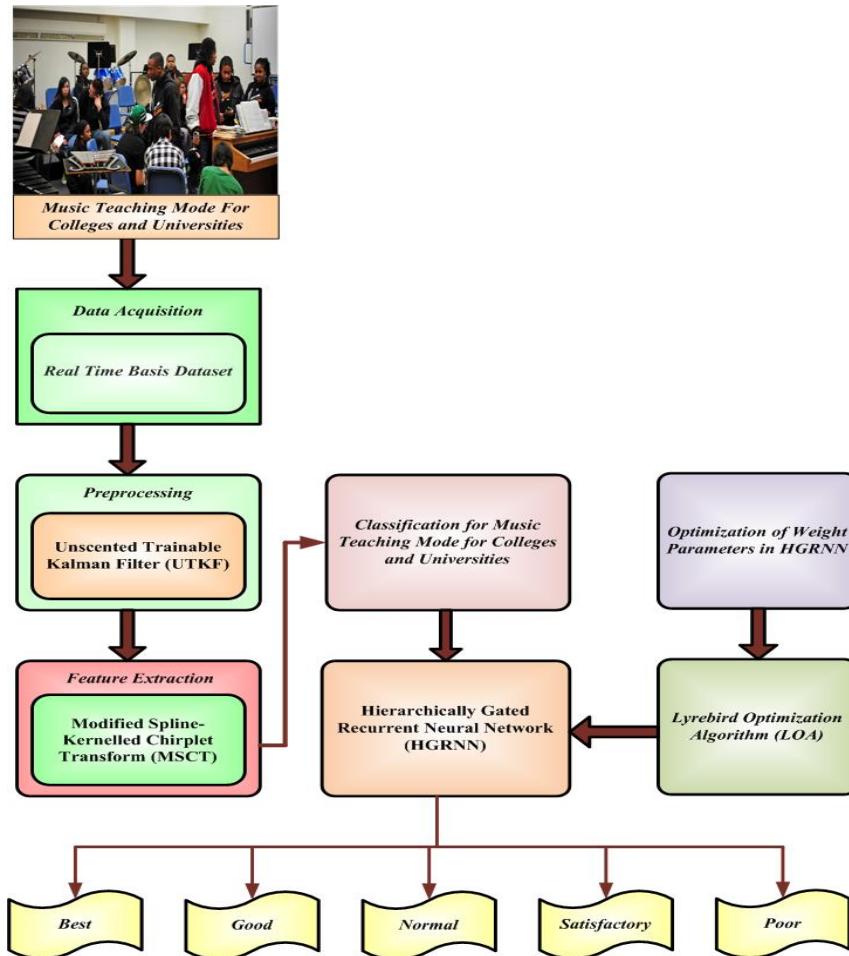


Figure 1: Block diagram of proposed MTM-HGRNN-LOA approach

In this research work, MTM-HGRNN-LOA is proposed for detecting Mode of teaching for music through colleges and universities by extracting features from the music teaching mode in colleges. The system used a real time basis data set for classify the music teaching mode as best, good, normal, satisfactory and poor music teaching mode. The block diagram of proposed MTM-HGRNN-LOA approach is represented in Figure 1. The detailed description of proposed MTM-HGRNN-LOA method regarding music teaching mode prediction is described as follows

A. Data Acquisition

In order to generate the necessary dataset, this study collects data on the caliber of music instruction in higher education institutions. The training set is comprised of 20,381 samples, while the test set consists of 12,049 samples. The inputs/logits are converted into probabilities that represent the expected class or target using the softmax activation function. The model is designed to classify an input instance into one of five music teaching (MT) categories, namely ‘MT1 (best)’, ‘MT2 (good)’, ‘MT3 (normal),’ ‘MT4 (satisfactory),’ and ‘MT5 (poor)’.

B. Pre-processing using unscented trainable kalman filter (UTKF)

To improve the data's cleanliness, we utilized the UTKF [28]. To address the nonlinearity and minimize estimation errors, we employed the unscented transition method, which effectively transports variables without altering the original data distribution, thereby eliminating model non linearization. When the prediction procedure is finished, sigma points are applied.

$$Z^{(1)}(S+1) = \hat{z}(S+1) \tag{1}$$

$$Z^{(1)}(S+1) = \hat{z}(S+1) + \left[\sqrt{(K+\lambda)\hat{\Sigma}_z(S+1)} \right]_K \tag{2}$$

$$Z^{(K)}(S+1) = \hat{z}(S+1) - \left[\sqrt{(K+\lambda)\hat{\Sigma}_z(S+1)} \right]_K \tag{3}$$

Where $Z^{(K)}(S+1)$ represent the Kth sigma point of prediction $z(S+1)$; $\hat{\Sigma}_z(S+1)$ indicates the state prediction covariance matrix; K are from 2 to $m+1$ and $m+2$, to $2m+1$ respectively; $(\cdot)_K$ indicates the matrix's k column and $\sqrt{\cdot}$ indicates the cholesky factorization process, respectively. One way to characterize the measuring procedure after the creation of olf sigma points is

$$\gamma^{(K)}(S+1) = H(Z^{(K)}(S+1)), K = 1, \dots, 2m+1 \tag{4}$$

$$\hat{x}(S+1) = \sum_{K=1}^{2m+1} \theta^{(K)} \gamma^{(K)}(S+1) \tag{5}$$

$$\hat{\Sigma}_x(S+1) = \sum_{K=1}^{2m+1} \theta^{(K)} (\gamma^{(K)}(S+1) - \hat{x}(S+1)) (\gamma^{(K)}(S+1) - \hat{x}(S+1))^s + O(S+1) \tag{6}$$

The measurement's sigma point is represented by $\gamma^{(K)}(S+1)$, the measurement matrix based prediction is indicated by $\hat{\Sigma}_x(S+1)$, The measurement variance matrix is indicated by $\hat{x}(S+1)$, and the measuring process's noise matrix is represented by $O(S+1)$. These equations are utilized iteratively for each data point in the UTKF algorithm to enhance the training rate and remove reliance on batch size filter, ultimately calculating the last value. The particular values of γ , \hat{x} , and θ can be resolved based on the prediction of the music teaching mode in colleges and universities.

C. Feature Extraction using modified spline-kernelled Chirplet transform (MSCT)

This section focuses on the utilization of the MSCT for feature extraction. The MSCT is introduced in this paper [29] as a solution for signals with interested frequencies concentrated in a narrow band. The main idea of the MSCT is to use the CZT operator instead of the FFT operator in the ‘spline-kernelled chirplet transform’. The higher time-frequency distribution concentration and frequency resolution of the MSCT are achieved by utilizing the outstanding frequency band subdivision capacity of the CZT. The principle and implementation procedure of the MSCT are explained in detail in the section that follows.

The SCT's discrete form

$$SCT(n, \omega, g) = \sum_{m=-\infty}^{+\infty} Z(m) \phi_g^R(m) \phi_{n,g}^S(m) C_\sigma^*(m-n) \exp(-i\omega m) \tag{7}$$

The STFT's discrete form is

$$STFT = \sum_{m=-\infty}^{+\infty} Z(m) h_\sigma^*(m-n) \exp(-i\omega m) \tag{8}$$

The CZT's discrete form is

$$CZT = \sum_{m=0}^{M-1} Z(m) B^{-m} V^{mK} \tag{9}$$

By comparing equation (7) and (8), it can be observed that the SCT primarily consists of 3 operators, namely the frequency-shift operator, STFT operator and frequency-rotate operator. The discrete form expression of the MSCT can be represented as follows if the CZT operator is used in place of the STFT operator in the SCT:

$$CZSCT(n, \omega, g) = \sum_{m=0}^{M-1} Z(m) \phi_g^R(m) \phi_{n,g}^S(m) C_\sigma^*(m-n) B^{-m} V^{mK} \tag{10}$$

Where $Z(m)$ represent the signal sequence, $\phi_g^R(m)$ represent the frequency rotate operator, $\phi_{n,g}^S(m)$ indicates the frequency shift operator, $C_\sigma(m)$ indicates an σ time-width Gaussian window function.

From pre-processing output it has significant characteristics of music teaching mode such as operability, targeted, wholeness, superiority, and openness are extracted with the help of modified spline-kernelled chirplet transform.

1. Operability: In music teaching mode, operability can refer to the ease of use and functionality of the teaching method or platform. It focuses on how effectively and efficiently students can interact with the system or materials provided for learning music. The music teaching model relies heavily on maneuverability, particularly in the field of music where interactivity is crucial. Without a sense of intuition, there will inevitably be disconnect between theory and practice. The operability of primary features in music teaching mode can be expressed as

$$Z(\sigma, j) = Z(j) * g_\sigma^*(m-n), j=1,2,\dots, m \tag{11}$$

When signal $Z(m)$ is intercepted by Function of the Gaussian window $g_\sigma(m)$ with a time-width of σ .

2. Targeted: In music teaching, being targeted implies that the teaching method or materials are designed to meet specific learning goals or objectives. It suggests that the content and approach are tailored towards achieving specific outcomes, such as developing certain musical skills or understanding specific concepts. The targeted of primary features in music teaching mode can be expressed as

$$IF = \sum_{i=1}^n C_i B_{i,m}(m) \tag{12}$$

Where C_i indicates the control mode and n represent the count of the B-splines. $B_{i,m}(m)$ denotes the i th m -order b-spline for a knot sequence.

3. Wholeness: Wholeness in music teaching mode suggests that the curriculum or teaching approach encompasses a comprehensive range of musical elements. It implies that the teaching method covers various aspects of music, including music theory, technique, interpretation, performance, and appreciation, providing a well-rounded musical education. The wholeness of primary features in music teaching mode can be expressed as

$$M_{i,l}(t) = \sum_{j=0}^{m-1} C_{i,l}(Z) * t^j \tag{13}$$

Where $C_{i,l}(Z)$ represent the spline transform kernel's coefficients.

4. Superiority: In the context of music teaching, superiority can refer to the effectiveness and quality of the teaching method or materials compared to alternative approaches. It implies that the chosen teaching method offers advantages or benefits that make it stand out in terms of facilitating student learning and musical development. The superiority of primary features in music teaching mode can be expressed as

$$Z_R(m) = Z(m) * \phi_C^R(m) \tag{14}$$

Where $Z_R(m)$ represent the rotated signal, $Z(m)$ is the frequency rotation operator, $\phi_C^R(m)$ represent the frequency rotation operator.

5. Openness: Openness in music teaching mode can refer to the flexibility and adaptability of the teaching approach. It suggests that the method allows for personalized learning experiences, encourages creativity, and provides opportunities for students to explore different musical genres, styles, or instruments. The openness of primary features in music teaching mode can be expressed as

$$FR_{STFT} = \frac{F_S}{M} \tag{15}$$

Where F_S represent the frequency of sampling, M is the window's length.

These features are subsequently obtained and utilized in the classification process. The classification process is done by hierarchically gated recurrent neural network. The detail about the classification process is given in the below section.

D. Classification Using Hierarchically Gated Recurrent Neural Network (HGRNN)

In this section, music teaching mode prediction in colleges and universities using Hierarchically Gated Recurrent Neural Network (HGRNN) is discussed [30]. The HGRU and GLU token and channel mixing modules are found in each of the stacked layers that make up the Hierarchically Gated Recurrent Neural Network (HGRNN). A gated linear recurrent linear unit is as follows:

HGRU exploration: A basic gated linear recurrent layer is described as follows:

$$F_T = \text{Sigmoid}(Z_T M_F + A_F) \in D^{1 \times F} \tag{16}$$

$$J_T = \text{Sigmoid}(Z_T M_J + A_J) \in D^{1 \times F} \tag{17}$$

Here F_T and J_T represent forget and input gates respectively.

Complex-valued recurrence: To obtain element-wise linear recurrence for linear RNNs with fixed decay rates, eigen decompositions are frequently performed on the recurrent weight matrix. Nevertheless, if we only permit real-valued eigenvalues, it imposes a constraint on the recurrent weight matrix, requiring it to be symmetric and thereby restricting the model's power for expression.

We parameterize the real and imaginary sections of the input G_T separately in the manner described below:

$$\text{Re}(G_T) = \text{SiLU}(Z_T M_{GR} + A_{CR}) \in D^{1 \times F} \tag{18}$$

$$\text{Im}(G_T) = \text{SiLU}(Z_T M_{Gj} + A_{Cj}) \in D^{1 \times F} \tag{19}$$

The forget gate values have a lower bound, which is determined solely by the magnitude argument λ_T . Specifically, this lower bound is used to parameterize the forget gate values independently for all hidden states, considering that there are E layers. Assuming the layer index is P , the calculations for the lower bounds can be expressed as follows:

$$Q = (\text{Soft max}(\Gamma, \text{dim}=0)) \in D^{E \times F} \tag{20}$$

$$\gamma^P = [\text{Cumsum}(Q, \text{dim}=0)]_P \in D^{1 \times F} \tag{21}$$

Finally, The parameterization of λ_T in the P-th layer is as follows:

$$\mu_T = \text{Sigmoid}(Z_T M_\mu + A_\mu) \in D^{1 \times F} \tag{22}$$

The saturated areas of the sigmoid activation function will be shifted away from μ_T in order to obtain the same value for forget rate, $\bar{\gamma}$ closed to one.

$$\mu_T = \frac{\bar{\gamma} - \gamma^P}{1 - \gamma^P} < \bar{\gamma} \tag{23}$$

By the problem of gradient vanishing is alleviated, thus simplifying the process of gradient-based optimization.

To minimize the count of parameters, it is a common practice to employ leaky units, which are closely associated with the discretization of systems with continuous time and exponential moving averages. Empirical evidence has demonstrated their effectiveness. This approach enables a distinct interpretation of encoding relative position information.

$$E_T = \lambda_T \odot \exp(j\theta) \odot E_{T-1} + (1 - \lambda_T) \odot G_T \in \mathbb{C}^{1 \times F} \tag{24}$$

Here \odot denotes the element wise product.

The incorporation of gates into the output of the recurrent layer has proven to be successful in state space models. Prior to executing the output projection, the output gate functions in the following manner and yields HGRU.

$$k_T = \text{Sigmoid}(M_k Z_T + A_k) \in D^{1 \times 2r} \tag{25}$$

The artificial intelligence base optimisation was then used in the HGRNN classifier due to its ease and relevance. In this work, lyrebird Optimization Algorithm (LOA) exploited for optimizing the optimum parameters of LOA classifier. Additionally, the optimization of the HGRNN optimum parameter (γ) can be achieved through the use of LOA, which is utilized to tune the weight and HGRNN's bias parameter.

E. Lyrebird Optimization Algorithm (LOA)

In these part, the proposed hierarchically gated recurrent neural network optimizes its weight parameters through the devised lyrebird optimization algorithm. With the release of the LOA, a unique bio-inspired metaheuristic algorithm that imitates lyrebird behavior in its natural habitat is presented. The core concept behind LOA is derived from the survival strategy employed by lyrebirds when confronted with potential threats [31]. The LOA theory is expounded upon and scientifically formulated in two distinct stages: (i) exploration, which emulates the lyrebird's escape strategy through simulation, and (ii) exploitation, which replicates the lyrebird's hiding strategy through simulation. Figure 2 displays the flowchart of the LOA algorithm. The proposed LOA approach—discussed below—was designed using mathematical modeling of this lyrebird technique in times of danger.

Step 1: Initialization

At the initialization phase, the Lyrebird population is represented by the following equation:

$$Z = \begin{bmatrix} Z_{1,1} & Z_{1,2} & \dots & Z_{1,H} \\ Z_{2,1} & Z_{2,2} & \dots & Z_{2,H} \\ \dots & \dots & \dots & \dots \\ Z_{n,1} & Z_{n,2} & \dots & Z_{n,H} \end{bmatrix} \tag{26}$$

Here Z denotes the LOA population matrix, n indicates the count of lyrebirds, H indicates the count of decision variables, correspondingly.

Step 2: Random Generation

The LOA approach is used to produce the input weight parameters at random after the initialization phase.

Step 3: Fitness Function

The initialized evaluations are used to generate a random solution. Fitness function is assessed with parameter optimization value for optimizing weight parameter (γ) of the classifier. Equation (27), which provides this,

$$fitness\ function = optimizing(\gamma) \tag{27}$$

Step 4: Escaping Strategy (Exploration Phase)

During this stage of LOA, the population member's location is modified within the search space by taking inspiration from the lyrebird's escape from a dangerous location to a safe area. In the design of LOA, the safe areas for every Participant are determined by considering the positions of additional individuals in the population with superior objective function values. The set of safe regions for every Participant of the LOA can be found using equation (28).

$$DB_j = \{Z_p, \quad E_p < E_j \text{ and } P \in \{1, 2, \dots, M\}\}, \quad \text{Where } j=1, 2, \dots, M, \tag{28}$$

Here, Z_p indicates the P th row of the Z matrix, which has a higher value of the objective function than the j th LOA Participant, and DB_j indicates the set of safe regions for the j th lyrebird.

In the design of the LOA, it is postulated that the lyrebird will haphazardly seek refuge in one of the designated safe areas. Utilizing the lyrebird displacement modelling during this stage, a fresh position is computed for every LOA member using Equation (29). Subsequently, if the objective function value shows improvement, the previous position of the corresponding member is substituted with this new position as per Equation (30).

$$z_{j,i}^{k1} = z_{j,i} + l_{j,i} \cdot (SSB_{j,i} - J_{j,i} \cdot z_{j,i}) \tag{29}$$

$$Z_j = \begin{cases} Z_j^{k1}, & E_j^{k1} \leq E_j \\ Z_j, & Else \end{cases} \tag{30}$$

Here, SSB_j indicates the j th Lyrebird's selected safe area, $SSB_{j,i}$ indicates its i th dimension, z_j^{k1} indicates the novel position determined for the j th Lyrebird using the proposed LOA's escape strategy, $z_{j,i}^{k1}$ indicates its

ith dimension, E_j^{k1} indicates its value of the objective function, $l_{j,i}$ are random values inside the range [0, 1], and $J_{j,i}$ are counts that are chosen at random to be either 1 or 2.

Step 5: Hiding Strategy (Exploitation Phase)

During this stage of LOA, the population member's location is adjusted within the search space by following the lyrebird's strategy of concealing itself in a secure area nearby. In the design of LOA, a novel position is determined for each member by considering the lyrebird's movement towards a more suitable hiding spot. This calculation is performed using Equation (31). If the new position enhances the objective function's value as per Equation (32), it replaces the previous position of the respective member.

$$z_{j,i}^{k2} = z_{j,i} + (1 - 2l_{j,i}) \cdot \frac{vc_i - qc_i}{T} \tag{31}$$

$$Z_j = \begin{cases} Z_j^{k2}, & E_j^{k2} \leq E_j \\ Z_j, & \text{Else} \end{cases} \tag{32}$$

Here, z_j^{k2} indicates the jth Lyrebird's new position as determined by the proposed LOA's hiding strategy, $z_{j,i}^{k2}$ indicates its ith dimension, E_j^{k2} indicates the value of its objective function, $l_{j,i}$ are arbitrary values from the range [0, 1], and T indicates the iteration counter.

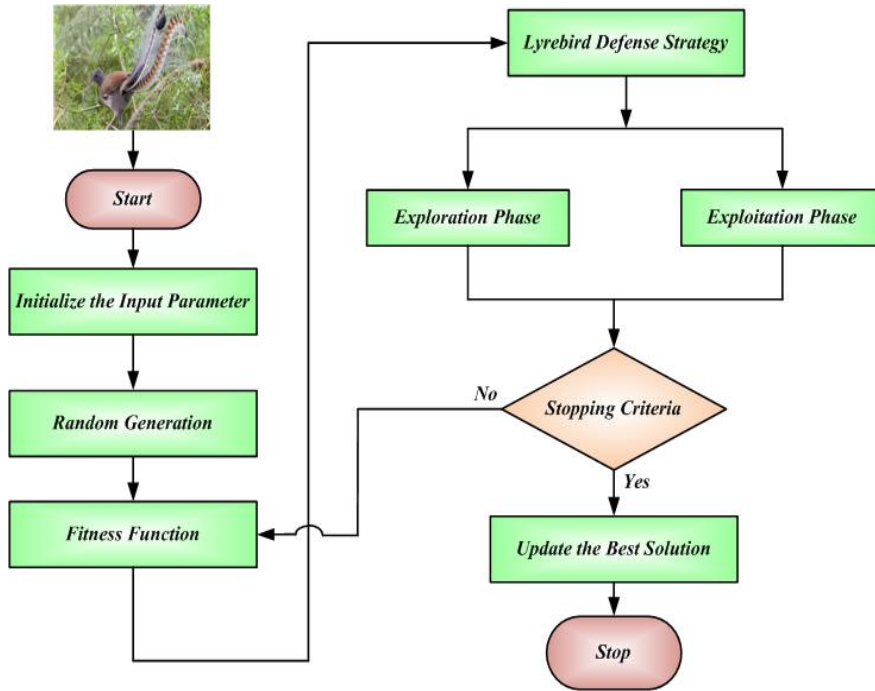


Figure 2: Flowchart of LOA

Step 6: Termination Criteria

Verify the termination criteria; if it is met, the best possible solution has been found; if not, repeat the procedure. In order to accurately detect music coaching mode in colleges and universities, HGRNN is effectively optimized with LOA for music teaching mode prediction.

IV. RESULT AND DISCUSSION

This section discusses the proposed method's experimental result. Python is used to simulate the proposed strategy under a number of performance criteria, including sensitivity, specificity, F1-score, accuracy, and precision. The outcomes of the proposed MTM-HGRNN-LOA method are analysed with the existing methods, like convolutional neural network based College-Level Music Teaching Quality Evaluation, online vocal music teaching quality using Back Propagation neural network, Music Art Teaching Quality Based on Grey Neural Network.

A. Performance Measures

These are an important step in selecting the best classifier. In order to assess performance, metrics like, Specificity, F1-score, accuracy, precision, Sensitivity and Error rate are looked at. It is decided to use the confusion matrix to scale the performance measures.

Accuracy

It is the ratio of count of exact prediction with overall count of forecasts generated for a dataset. It is measured through equation (33),

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{33}$$

True negative is represented by TN s, false negative by FN , true positive by TP , in this instance.

Precision (P)

Precision is a metric which quantifies the count of correct positive prediction made. This is scaled by equation (34),

$$Precision = \frac{TP}{(TP + FP)} \tag{34}$$

F-Score

Equation (35), which represents the F-score composite measure, rewards techniques with higher sensitivity and presents obstacles for approaches with more specificity.

$$F - score = \frac{TP}{TN + \frac{1}{2}[FN + FP]} \tag{35}$$

Specificity

The percentage of true negatives that the method correctly identifies is called specificity. It is determined by equation (36),

$$Specificity = \frac{TN}{TN + FP} \tag{36}$$

Error Rate

This is determined by equation (37),

$$ErrorRate = 100 - Accuracy \tag{37}$$

B. Performance Analysis

Figure 3 to 9 shows the simulation outcomes of HGRNN- LOA. Then the outcomes are analysed with existing CNN, BPNN, and GNN methods.

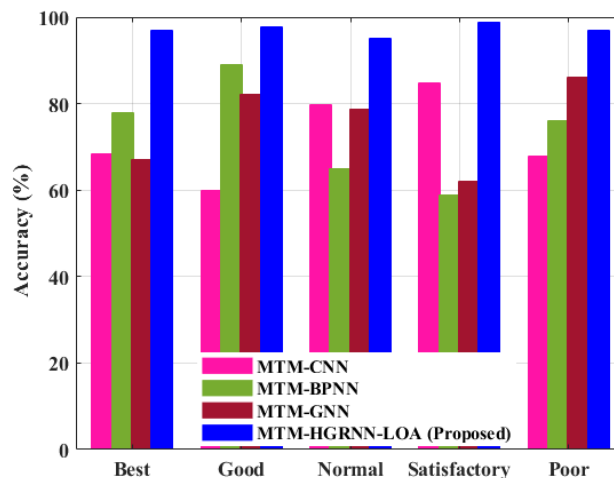


Figure 3: Performance Analyses of Accuracy

Figure 3 demonstrates the performance Analyses of accuracy. The performance accuracy of different models or approaches used to analyse Music Teaching Mode of Colleges and Universities. This could involve

comparing statistical models, machine learning algorithms, or any other methods used for this. The proposed MTM-HGRNN-LOA methods of accuracy are 97% best, 98% good, 95% normal, 98% satisfactory and 97% poor music teaching mode. The existing methods MTM-CNN, MTM-BPNN and MTM-GNN, the accuracy become 70%, 77%, 68% best, 60%, 90%, 83% good, 80%, 65%, 78% normal, 84%, 59%, 62% satisfactory and 70%, 75%, 86% poor music teaching mode. The proposed MTM-HGRNN-LOA method shows higher accuracy compare with existing methods.

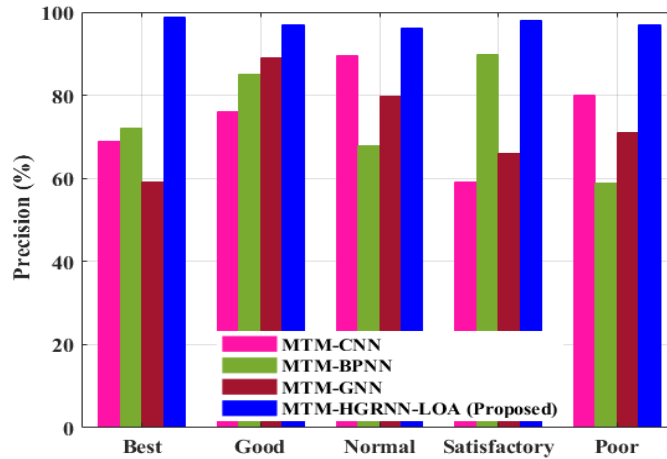


Figure 4: Performance Analyses of precision

Performance Analyses of precision is displayed in figure 4. Precision is a metric used to evaluate the accuracy of a predictive model or algorithm. The figure provides the model's effectiveness in identifying and predicting music teaching mode accurately. The precision of proposed MTM-HGRNN-LOA methods becomes 98% best, 96% good, 96% normal, 98.5 satisfactory, 97% and poor music teaching mode. The existing methods MTM-CNN, MTM-BPNN, MTM-GNN the precision attain 70%, 74%, 59% best, and 75%, 85%, 90% good, 90%, 70%, 80% normal, 59%, 90%, 65% satisfactory, 80%, 59%, 70% poor music teaching mode. The proposed MTM-HGRNN-LOA method shows higher precision value compare with existing methods.

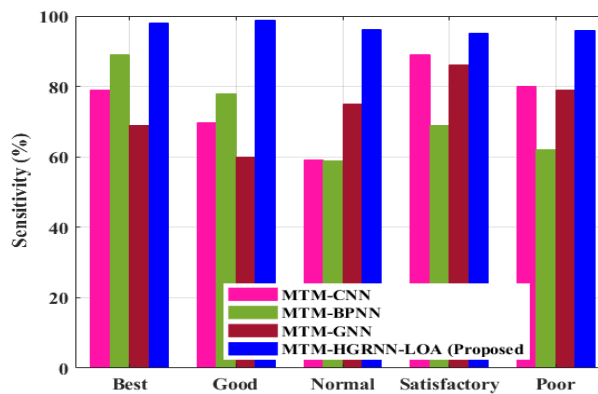


Figure 5: Performance Analyses of Sensitivity

Performance Analyses of sensitivity is illustrated in figure 5. Here, one can gain insights into the trade-off between sensitivity and performance in the music teaching mode of colleges and universities prediction model. This information can be useful for optimizing the model and finding the right balance between accurately predicting music teaching modes and minimizing false predictions. The proposed MTM-HGRNN-LOA methods the sensitivity provides 97% best, 99% good, 96% normal, 95% satisfactory, 96% poor music teaching mode. The existing methods MTM-CNN, MTM-BPNN, and MTM-GNN, the sensitivity becomes 79%, 89%, 68% best, 70%, 78%, 60% good, 59%, 58.5%, 76% normal, 90%, 70%, 87% satisfactory, 80%, 62%, 79% poor teaching mode. The proposed MTM-HGRNN-LOA method shows higher sensitivity compare with existing methods.

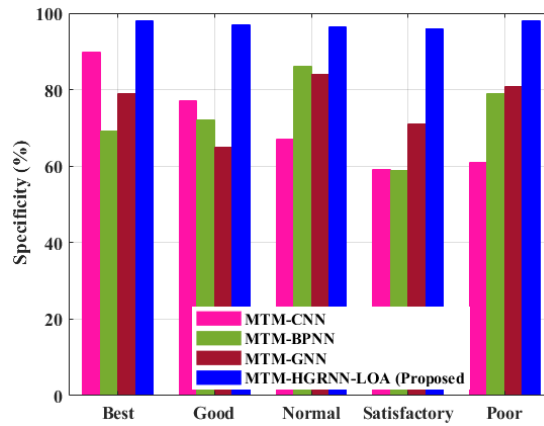


Figure 6: Performance analysis of Specificity

Performance analysis of Specificity is illustrated in figure 6. The graph shows the specificity of the model changes as the threshold for classification is varied. At lower thresholds, more instances are classified as positive, leading to a decrease in specificity. This means that the model may incorrectly identify some negative instances as positive. As the threshold increases, the model becomes more conservative in classifying instances as positive, resulting in higher specificity. This means that the model is better at correctly identifying negative instances. In specificity the proposed MTM-HGRNN-LOA methods provide 98% best, 97% good, 97% normal, 96% satisfactory, and 98% poor music teaching mode. The existing methods MTM-CNN, MTM-BPNN, and MTM-GNN the specificity becomes 90%, 70%, 79% best, 77%, 75%, 65% good, 66%, 85%, 84% normal, 59%, 58%, 70% satisfactory, 61%, 79%, 81% poor music teaching mode. The proposed MTM-HGRNN-LOA method shows higher specificity compare with existing methods.

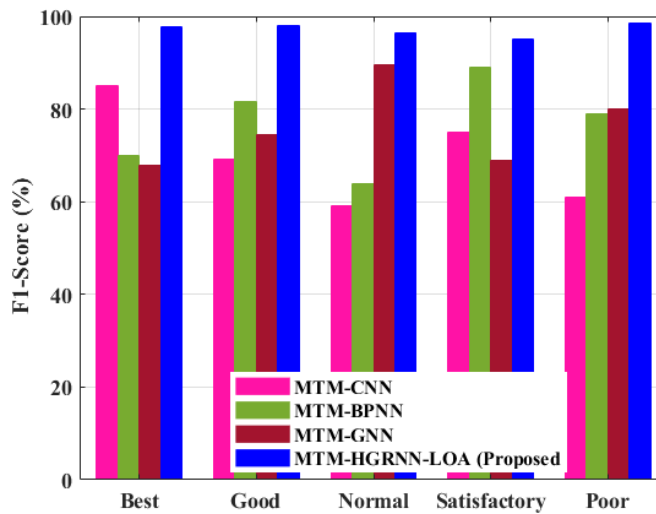


Figure 7: Performance Analyses of F1-Score

Performance Analyses of f1-score is depicted in figure 7. Compare the performance of different approaches for classifying music teaching mode based on their F1-score values. Higher F-score values indicate better predictive performance, while lower values suggest room for improvement. The proposed MTM-HGRNN-LOA method provides 96% best, 97% good, 96% normal, 95% satisfactory and 99% poor music teaching mode. The existing methods MTM-CNN, MTM-BPNN, and MTM-GNN the f1-score become 85%, 70%, 68% best, 70%, 82%, 75% best, 70%, 81%, 76% good, 59%, 63%, 90% normal, 75%, 90%, 65% satisfactory, and 61%, 79%, 80% poor music teaching mode. The proposed MTM-HGRNN-LOA method shows higher F1-score value compare with existing methods.

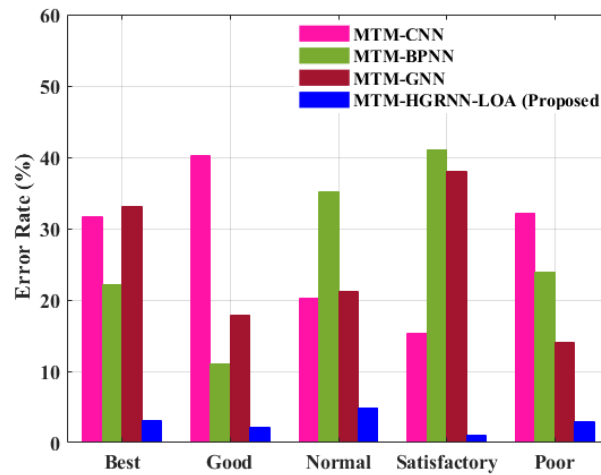


Figure 8: Performance Analyses of Error rate

Performance analyses of Error Rate is displays in figure 8. The proposed MTM-HGRNN-LOA error rate are 3% best, 2% good, 5% normal, 1% satisfactory and 2% poor music teaching mode. The existing methods MTM-CNN, MTM-BPNN and MTM-GNN, the error rate become 32%, 23%, 34% best, 41%, 11%, 17% good, 20%, 35%, 21% normal, 16%, 41%, 38% satisfactory and 33%, 24%, 15% poor music teaching mode. The proposed MTM-HGRNN-LOA method shows lower error rate compare with existing methods

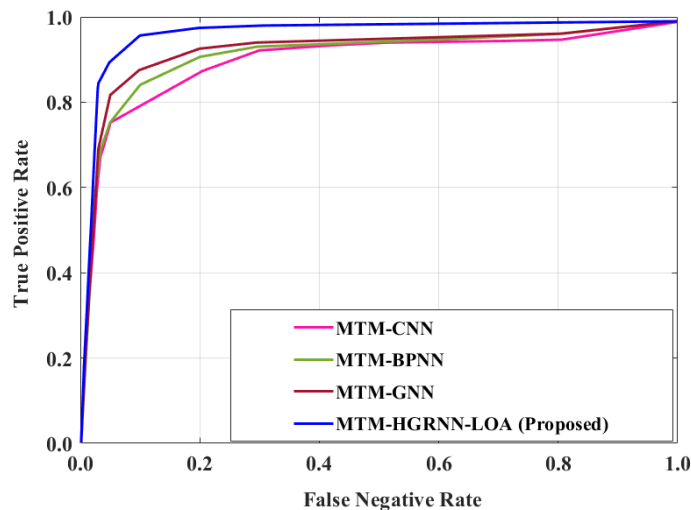


Figure 9: Performance Analysis of ROC

Performance analysis of ROC is illustrated in figure 9. Each point on the curve represents a different threshold value, and the curve is created by connecting these points. The closer the curve is to the graph's top-left corner, the better the prediction system performs. The area under the curve (AUC) of a perfect classifier would be 1.0 and would have a curve that goes straight up the left side and then straight across the top. A higher ROC indicates better performance in distinguishing between positive and negative instances. The proposed MTM-HGRNN-LOA methods the ROC provides high music teaching mode compare with existing methods. The existing methods like MTM-CNN, MTM-BPNN, and MTM-GNN the ROC become low compare with proposed MTM-HGRNN-LOA.

V. CONCLUSION

Currently, the majority of colleges still use the manual evaluation method and have not developed a comprehensive system for evaluating the quality of instruction in music. The creation of a neural network for the purpose of evaluating the quality of music instruction takes into account the recently developed artificial neural network. Hierarchically gated recurrent neural network is optimized by lyrebird optimization algorithm for detecting music teaching mode of universities and colleges by extracting features from the music teaching mode MTM-HGRNN-LOA is successfully executed. The proposed technique is executed in Python. The data set for best, good, normal, satisfactory and poor music teaching mode is used. A novel hybrid computational

model that is able to both simulate and extract explanations from real-world data is the key contribution. At first, the data's are collected via real time data dataset. Later the data's are fed to pre-processing. The input music teaching mode is pre-processed with unscented trainable kalman filter (UTKF) technique. Primary feature, teaching mode can be retrieved in colleges and university using the modified spline-kernelled chirplet transform (MSKCT) for extracting the optimized features. After that, the extracted features are given to hierarchically gated recurrent neural network and LOA for effectively classify the music teaching mode as best, good, normal, satisfactory and poor. Training this MTM-HGRNN-LOA model, according to the model, enhances classification performance, identifies the music instruction mode, outperforms other powerful techniques, and ensures sufficient evidence to support the prediction. In accuracy the proposed MTM-HGRNN-LOA methods provide 97% best, 98% good, 95% normal, 98% satisfactory and 97% poor music teaching mode. The existing methods MTM-CNN, MTM-BPNN and MTM-GNN, the specificity becomes 90%, 70%, 79% best, 77%, 75%, 65% good, 66%, 85%, 84% normal, 59%, 58%, 70% satisfactory, 61%, 79%, 81% poor music teaching mode. Based on the findings, it can be concluded that the proposed MTM-HGRNN-LOA approach performs better than the existing methods, such as MTM-CNN, MTM-BPNN, and MTM-GNN, respectively.

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