J. Electrical Systems 20-3s (2024): 2665-2676

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# Music Tone Synthesis based Anti-Interference Dynamic Integral Neural Network optimized with Artificial Hummingbird Optimization Algorithm

***Abstract: -*** Music Tone Synthesis is an applied science or method that implies to identify and study of specific orchestral tone currently part of a music. It is especially effective in the area of oral music training system classes, somewhere be able to support in the practice and growth of musicians. Music Tone Synthesis provides singer and writer to produce large number of noises as well as imitate several tools and impact it cannot be flexible otherwise realistic for create over standard classical instrument. In this manuscript, Music Tone Synthesis based Anti-Interference Dynamic Integral Neural Network enhanced with artificial hummingbird Optimization algorithm (MTS-AIDINN-AHOA) is proposed. The input data are obtained from the audio signal. Then the data are pre-processing using Stein Particle Filtering (SPF) to remove the noise. The pre-processed data is given into the Two-sided Offset Quaternion Linear Canonical transform (TSOQLCT) for extracting the musical features such as melody, harmony, tempo, and dynamics. After this the extracted feature is provided to the Anti-Interference Dynamic Integral Neural Network (AIDINN) is used for the music tone synthesis and it is classified as pitch, chronaxie, volume, tone color. In general, the Anti-Interference Dynamic Integral Neural Network (AIDINN) does no express adapting optimization strategies to determine ideal parameters to assure precise prediction. Thus, it is proposed to utilize the Artificial Hummingbird Optimization Algorithm enhancement AIDINN for Music Tone Synthesis. The proposed MTS-AIDINN-AHOA method is implemented on MATLAB. Then performance of proposed technique is evaluated to other existing techniques. The proposed technique attains 26.36%, 20.69% and 35.29% higher accuracy, 19.23%, 23.56%, and 33.96% higher precision, 26.28%, 31.26%, and 19.66%higher recall, 28.96%, 33.21% and 23.89%higher specificity comparing with the existing methods such as a research on Musical Tone Recognition Method Based on Improved RNN for Vocal Music Teaching Network Courses (MTS-RNN), Music Timbre Extracted from Audio Signal Features (MTS-BPNN)and Feature Extraction and Categorization of Music Content Based on Deep Learning(MTS-SMNN) respectively.

***Keywords:*** Anti-Interference Dynamic Integral Neural Network, Artificial Hummingbird Algorithm, Audio signal, Stein Particle Filtering, Two-sided Offset Quaternion Linear Canonical transform, music tone synthesis.

## I. INTRODUCTION

The development of web-based instruction over the internet is attributed to advancements in computer technology, leading to a wide range of vocal music career options. Numerous establishments have launched online vocal education programs that assist students in refining their vocal technique and enhancing their ability to perform pattern songs, create it simple to scientifically achieve the aim of learning of important music, help learner best to understand music and arise a crucial position in the learner's quality education. It is also tough for teachers to examine and realize all students completely, that does not secure that learners accept target training in learning vocal music. The basic concept behind musical sound appreciation is to take an instrument's vocal qualities and use that information to classify musical sounds. The ability to do so is dependent on how well the musical characteristics are presented and how unfairly the recognizer performs [1, 2]. Deep learning approaches have brought to a considerable advancement in the development of audio realization technology [3–5]. In a vocal music training course, Operating systems replace the teacher in the duty of differentiating between musical notes, saving a significant amount of time, money, and energy. Computer algorithms can also recognize songs and even automate the process of creating musical notation [6-8]. To provide a varied musical effect, intensity and tone might be used to significant notes on a wonderful instrument. The variety of musical characteristics is increasing with the growth of music information retrieval technology. Current music recognition technology primarily consists of a basic fusion of all musical features, which falls short of the high technical requirements for music appreciation [9- 11]. The next research area for the existing music appreciation model is feature selection, screening, and combination [12]. Two essential pieces of technological equipment for the cepstral area assessment are the Mel frequency cepstral factor and the straight predictive cepstral factor. Simultaneously, the music education curriculum is heavily influenced by noise and leads to the existing audio classifiers implementation that fall short of potential needs [13- 15]. Most of the common methods of research depend on traditional signal processing techniques and a less study on music appreciation utilizing deep neural networks and much growth potential in the appreciation precision along productivity [16].

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The Mel frequency cestrum factor is primarily selected manually, which limits the growth of the fundamental feature appreciation on the music recognition techniques module. Additionally, the traditional sound deletion algorithm mode is unsatisfactory in terms of productivity and appreciation precision as well as the ability to detect unusual noise [17].

However, there are still a number of issues with the way that musicians are taught and students' vocal music in schools that must be disregarded. Because various students have varied fundamental musical qualities, it is challenging to meet the learning objective when instructors are the only ones to deliver consistent training. Relying on teachers to provide consistent instruction is a challenging way to achieve the teaching objective. It is difficult for teachers to examine and realize every students completely, that does not secure that learners accept target training in learning vocal music. These motivate us to carry out this research work. The proposed MTS-AIDINN-AHOA method provides a deep learning based music tone synthesis with high accuracy to accomplish the aforementioned goals.

The major contributions of this proposed method are abbreviated below:

- The Music Tone Synthesis based Anti-Interference Dynamic Integral Neural Network optimized using artificial hummingbird Optimization algorithm (MTS-AIDINN-AHOA is proposed.
- Develop a Stein Particle Filtering for noise removal from the input audio signal and TSOQLCT is used for extracting the features such as melody, harmony, tempo, and dynamics.
- Music tone synthesis has done by using Anti-Interference Dynamic Integral Neural Network and is optimized with Artificial Hummingbird Optimization Algorithm for music tone synthesis.
- The performance metrics like accuracy, precision, recall, specificity, RoC are examined.
- The proposed technique is compared to existing MTS-RNN, MTS-BPNN and MTS-SMNN methods.

The remaining manuscript organized as: part 2 presents literature survey, part3 describes proposed methodology, part4 proves outcomes, part 5 concludes manuscript.

## II. METHODOLOGY

Numerous research studies were presented in the literature related to deep learning depend music tone synthesis, a few recent works are reviewed here,

Long et al. [18] have presented a study on improved RNN-based method for musical tone recognition for vocal music teaching network courses. The presented paper improve in information science be required the growth of online virtual training was directed to modification of oral music paths. The detriment bend rate for the convolutional recurrent network technique was considerably below another three patterns. The music tone recognition pattern improves study. It provides greater accuracy and less recall.

Zhao et al. [19] have presented tone recognition database of electronic pipe organ based on artificial intellect. In this pap consider the structure of a databank of automated pipe instrument tone appreciation on the basis of neural networks. The tone synthesis component understands the automated pipe instrument tone synthesis based on the presented tone framework. The audio time area data is structured and countered and fast Fourier transform is executed on any framework for acquire the prevalence area details of any framework. It provides high sensitivity and less precision.

Mo et al. [20] have presented music timbre extracted from audio signal features. The goal of the presented research was to examine an algorithm which improves the efficiency and accuracy of music timbre feature extraction. The research presented an audio feature depend on harmonic constituents to characterize the harmonic structural data in the audio signal spectrum for the purpose of audio signal feature extraction. The suggested research presents an algorithm that examines the recognition accuracy by extracting timbre features from sound data of both Western and native musical instruments. It provides low accuracy and low RoC.

Zhang and Li [21] have presented automatic synthesis technology of music teaching melodies based on recurrent neural network. The presented paper attempts to increase a spontaneous synthesis technology of tune training melodies in reference to periodic neural network. The scheme was suggested to remove the audio features from music tune. Then sequence model was accepted to combining common music tunes. After this, recurrent neural network was fixed to combine music tune with singing tune, for instance to discover the proper singing section for the music tune in teaching scheme. It provides low precision and low recall.

Liu [22] have presented research on music teaching along creation based on deep learning. The presented paper uses two convolution-based deep learning models consisted planned and created and a multidimensional sense was applied a benchmark technique for execution assessment and long short-term memory network was utilized for the category work. It discusses the value and application schemes of deep learning in junior high school music training and hopes to give few cite for all educational associate. It provides greater accuracy and lesser precision.

Li and Zhou [23] have suggested the application of multiple source data fusion analysis in the instruction of collegiate vocal music. The efficiency of the two-level combination pattern was verified in the suggested study through the use of two evaluation indices: the correlation factor and the method total part error. Next, the presented study was demonstrated by contrasting the results of the better method's calculations with those of the old technique that the better method's probability collection is more evident and consistent with the anticipated outcomes, demonstrating the optimization impact of the better method. It provides low specificity and low sensitivity.

Shi and Co [24] have presented feature extraction and classification of music content depend on deep learning. The presented paper researches the advantage of comprehensive instruction in identifying and classifying the satisfied with music sampling, the use of an algorithm to recognize and order musical genres based on a deep philosophical network, and the ability to remove and classify conventional musical instruments, through real-world research to trial its show after training. It provides high specificity and high recall.

Chung et al. [25] have presented Decoding Imagined Musical Pitch from Human Scalp Electroencephalograms. The presented paper examines the possibility of decryption pitch imagery data instantly from human electroencephalography. Twenty parties performed an irregular imagery assignment through seven musical pitches. The method of training has been acknowledged for its capacity to reduce cognitive abnormalities when compared with standard training methods. It offers high recall and precision.

## III. PROPOSED METHODOLOGY

The MTS-AIDINN-AHOA is proposed in this section. The proposed MTS-AIDINN-AHOA music tone synthesis system is shown in Figure 1. It includes five stages including data acquisition, preprocessing, feature extraction, music tone synthesis categorization and optimization. Thus the detailed description about MTS-AIDINN-AHOA is given below in Figure 1,

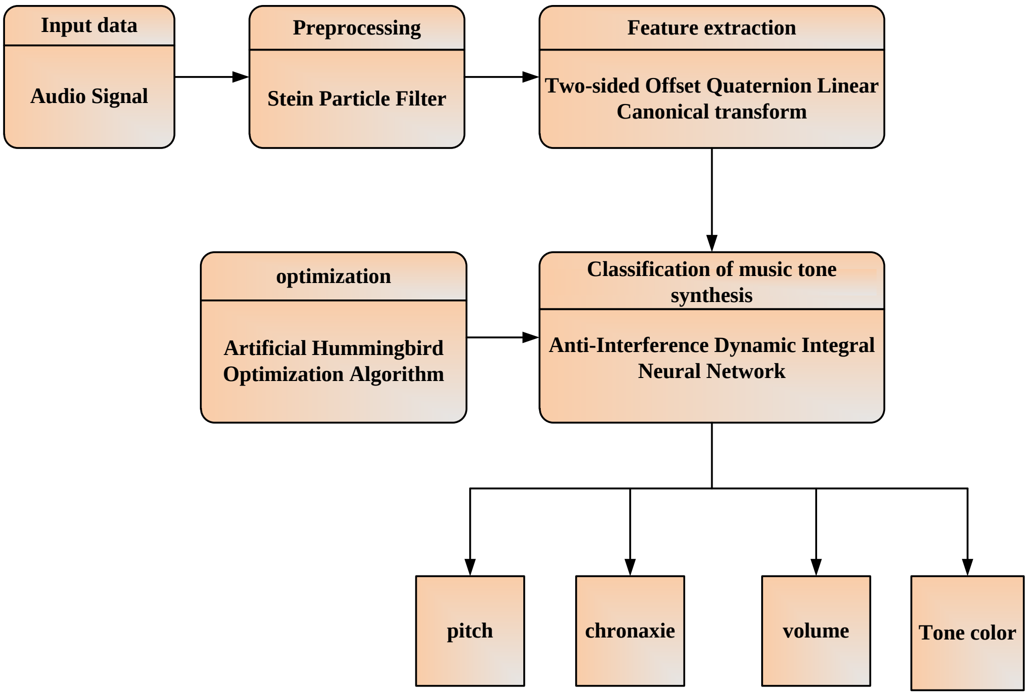


**Figure 1:** Block diagram for proposed MTS-AIDINN-AHOA model for music tone synthesis

### *A. Data Acquisition*

The input data is audio signal. The audio files of student presentations from an online vocal instruction course were used as the source of data for the experiment. A total number of audio files are 3568. The training set samples are derived from 70% of the sample data, whereas the test set samples are derived from 30% of the sample data.

### *B. Pre-processing using Stein Particle Filtering*

In this step, data pre-processing using Stein Particle Filtering [26] is discussed. The stein particle filtering is rather easy to execute and tune, its major handicap is specifically entirely computer intense, with the virtual difficulty growing rapidly with the declare dimension. Individual remedy to this problem such as marginalize out the states surface straight in the dynamics. The stein particle filtering removes the noise in the data. To calculating the standard predictive distribution is given in equation (1)

$$s(Y_u \mid X_{1:u-1}, v_{1:u}) \approx \frac{1}{M}\sum_{i=1}^{M} s(Y_u \mid Y_{u-1}^{i}, v_u) \tag{1}$$

where, s represents speed of sound, $Y_u$ represents the carrier frequencies and modulating, distribution of the time, $\frac{1}{M}$ signifies density, $\sum_{i=1}^{M}$ is equal and remove the noise to input data and $\approx$ negative log-target density at a particle position. The predictive distribution is given in equation (2)

$$\log s(Y_u \mid X_{1:u}) = \log\eta + \log s(X_u \mid Y_u) + \log s(Y_u : X_{1:u-1,} v_{1:u}) \tag{2}$$

where, $Y_u$ and $X_u$ represents the carrier frequencies and modulating , log $\eta$ denotes approximate expected curvature, logs to express the music sound, $v_{1:u}$ represents the major scale and $X_{1:u}$ can be natural minor scale and $X_{1:u-1,}$ signifies non-natural minor scale. To propagate the particle is given in equation (3)

$$s(Y_u \mid X_{1:u}, v_{1:u}) \alpha s(X_u \mid Y_u) s(Y_u \mid X_{i:u-1}, V_{1:u}) \tag{3}$$

where, s represents speed of sound, $Y_u$ denotes modulating and carrier frequencies $\alpha$ can be the rhythm frequencies, Also, scales the gradient update in given equation (4)

$$P_j = Y_{j+1} - Y_j \tag{4}$$

where, $P_j$ represents the gradient, $Y_{j+1}$ improves noise in the input data and $Y_j$ frequency of the input data. To variation of the frequency is given in equation (5)

$$Y^i = Y^i + \in Q\phi * (Y^i) \tag{5}$$

where, $Y^i$ represents initialized frequency of the data, $Q\phi$ it axis variable to a frequency of zero is multiplied for the data frequency. Finally, the data removes the noise by using Stein Particle Filter. Then the pre-processed data is fed to feature extraction stage.

*C. Feature extraction using Two-Sided Offset Quaternion Linear Canonical Transform*

The TSOQLCT [27] is proposed for feature extraction. TSOQLCT method is used to extract the musical features such as melody, harmony, tempo, and dynamics. It can represent a large type of linear and non linear transformations. It enables that change for signals one and the other time and frequency domain, take it proper for a scope of applications. Quaternion valued frequency domain signal is given in equation (6),

$$E_P\{e\}(v) = \frac{1}{\sqrt{(2r)^2}} \int f^{-cs_1 v_i} e(s) f^{-ds_2 v_2} \tag{6}$$

where $E_P$ represent the extract from the dynamics, $\{e\}$ is the elements for an the input data $(v)$ is the variations of, $\frac{1}{\sqrt{(2r)^2}}$ represents the rhythmic value, $f^{-cs_1 v_i}$ is the sound organized first time, $f^{-ds_2 v_2}$ is the sound organized in second time. Time frequency analysis of music tone is given in equation (7).

$$\Delta n_h^2 = (\oint n_h^2 |e(n)|^2 dn \tag{7}$$

where $\Delta n_h^2$ represents the number of the time frequency, $\oint n_h^2$ is the total calculation of the time frequency, $e(n)$ denotes total count of dynamic value, $dn$ signifies dynamic value. Then the variation of Enhancing musical features is calculated is given in equation (8).

$$\Delta v_h^2 = (\oint_{S^2} v_h^2 |E_P\{e\}(v)|^2 sn) \tag{8}$$

where $\Delta v_h^2$ the variation of enhancing the musical features, $\oint v_h^2$ is the total calculation of variation musical features, $E_P$ are the, $\{e\}$ is the changes of data, $sn$ is the synthesis detection. The musical features are as follows; melody, harmony, tempo, and dynamics.

**Melody:** It is also voice, tune, is a linear sequence of musical tones for the auditor observes as an individual object.

**Harmony:** It refers to simultaneously played or sung that are corresponding to one another. For example, a group of singers can sing in harmony in the event certain portions sing the tune and other areas sing the harmony that corresponds with it. It is given in equation (9),

$$\text{Harmonic mean} = n/[(1/e.)+(1/f)+(1/g)+(1/h)+\ldots] \tag{9}$$

**Tempo:** The tempo of an individual segment of music is its speed. The most widely used quantity of measurement is beats per minute, which refers to the total number of beats that occur in a minute. The most widely used tempos include grave, lento, largo, andante, allegro and presto.

**Dynamics:** It means quietly or loudly a musical composition can be played. Dynamics are a significant way of conveying the tone of a part and with the use of dynamics is a distinct element of your execution. It is given in equation (10),

$$v2 = u2 + 2as \tag{10}$$

Finally, TSOQLCT is extracted the features such as melody, harmony, tempo, and dynamics. After completing the feature extraction, the extracted features are fed to AIDINN.

*D. Music Tone Synthesis using Anti-Interference Dynamic Integral Neural Network*

In this section, the classification using AIDINN is discussed for classifying pitch, chronaxie, volume, tone color [28].The relevant method of design is given, and AIDINN is offered for an approach to the TVLNME. Furthermore, two standard methods, or rather, integrated continuous neural network. That have been suggested that the algorithm AIDINN correctly manages the time-varying applications and successfully resisting many periodic noises. It is increased the robustness to reduce periodic sounds and a faster rate of convergence. The variation of time given in equation (11),

$$D(t)Y(t) = C(t) \tag{11}$$

where, $C(t)$ represents the coefficient of time variable, $D(t)$ signifies variation of time and $Y(t)$ denotes coefficient of matrix. Time varying interference is given in equation (12),

$$\varepsilon(t) := D(t)Y(t) - C(t) \tag{12}$$

where, $\varepsilon(t)$ represents the interference of time variation, $D(t)$ signifies variation of time, $Y(t)$ denotes coefficient of matrix and $C(t)$ represents the coefficient of time variable. The total calculation of frequency time is given in equation (13),

$$\int_0^t \varepsilon(v) fv = \Re - kV(\varepsilon(t)) - i(t)\nabla G(t) \tag{13}$$

where, $\nabla G(t)$ represent in the periodic noise, k is the positive scalar parameter, $i(t)$ denotes the initialization of time, $\int_0^t \varepsilon(v) fv$ is the total calculation variation of frequency time. It is calculated for a period of the time is given in equation (14),

$$\nabla \eta(t) = \frac{\lambda}{V} \cdot \left( e - \frac{2}{V} \right) \tag{14}$$

where, $\lambda$ denotes the slope, $V$ represents the weight parameter, $e - \frac{2}{v}$ means remainder of t divided by v and $\nabla \eta(t)$ can be efficiency of the time. To constant of the time frequency is given in equation (15),

$$F(t) = -\alpha s(F(t)) \tag{15}$$

where, $F(t)$ represents the time coverage to zero, $\alpha$ is the constant value of the time. Finally, the AIDINN for the music tone synthesis classifier considers the tone color, pitch, chronaxie, volume. The artificial intelligence-based optimization technique is measured by the AIDINN classifier due to its convenience and pertinence. In this work, AHOA is used to enhance the AIDINN optimal parameter $\alpha$ *and* $V$. Here, AHOA is used for tuning the AIDINN weight and bias parameter.

*E. Optimization using Artificial Hummingbird Algorithm (AHOA)*

The weight parameter $\alpha$ *and* $V$ of AIDINN is optimized using the AHOA [29] is discussed. Despite falling under the meta-heuristic category, AHOA differs significantly from the current algorithms. AHOA differs greatly from them in that it has a different biological background. Three hummingbird foraging techniques and three hummingbird flight talents observed in the wild served as inspiration for AHOA. Hummingbirds are unique because of their remarkable foraging memory. Hummingbirds have brains with far larger hippocampus than any other bird studied to date. These hippocampi are important for learning and memory. Hummingbirds have a prodigious memory, which is demonstrated by the fact that they are small but incredibly intelligent birds with a brain that is greater than their body size.

*1) Stepwise Procedure OF AHOA*

Here, step by step process is defined to get ideal value of AIDINN based on AHOA. Initially, AHOA makes the equally distributing populace to optimize the parameter of AIDINN. The best solution is promoted using AHOA algorithm and related flowchart is illustrated in Figure 2.

***Step 1:*** Initialization

The population of $m$ humming birds placed on $m$ food sources, randomly initialized as given in equation (16),

$$W = \begin{bmatrix} w_{1,1} & w_{1,2} & \cdots & w_{1,d} \\ w_{2,1} & w_{2,2} & \cdots & w_{2,d} \\ \vdots & \vdots & \vdots & \vdots \\ w_{s,1} & w_{s,2} & \cdots & w_{s,d} \end{bmatrix} \tag{16}$$

here, $Low\&Up$ represents upper and lower boundaries for $d$ -dimensional problem, $e$ represents the random vector and $y_j$ signifies the $j^{th}$ food source position.

***Step 2:*** Random generation

The input parameters produced randomly after initialization. Ideal fitness values were selected depend on obvious hyper parameter condition.

***Step 3:*** Fitness Function Estimation

A random solution is created using initialized evaluations. Using parameter optimization value, fitness function is evaluated for optimizing weight parameter $\alpha$ *and* $V$ of the music tone synthesis. This is given in the below equation (17),

$$Fitness\ function = optimizing(\alpha\ \&\ V) \tag{17}$$

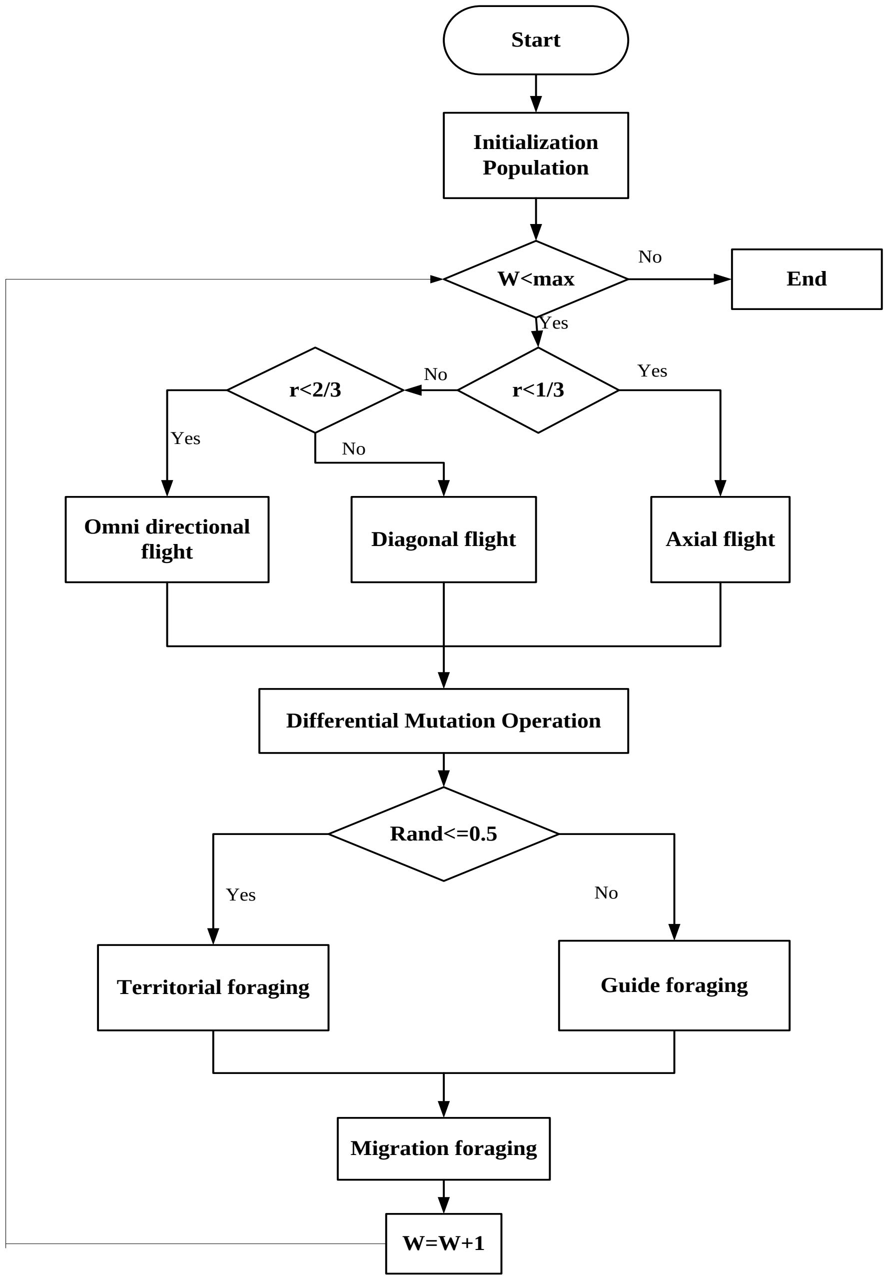


**Figure 2:** AHOA for optimizing AIDINN parameter

***Step 4:*** Guided foraging

A hummingbird's guided foraging behaviour is to identify the food sources with the maximum visitation level and select one from which it receives the greatest nectar refill rate as the target food source. The availability of one or more directions in d-dimensional space is controlled by this vector. The stimulation of guided foraging behavior along candidate food source is expressed in equation (18),

$$A_j(w+1) = y_{j,tar}(w) + q.S.(y_j(w) - y_{j,tar}(w)) \tag{18}$$

where, $y_j(w)$ represents the location of $j^{th}$ food source at time $w$, $y_{j,tar}(w)$ represents the target food source position that $j^{th}$ hummingbird intends to approach, $A_j$ represents the integer and $q$ represents the guided factor. It is given in equation (19)

$$y_j(w+1) = \begin{cases} y_j(w) & r(y_j(w)) \le r(A_j(w+1)) \\ A_j(w+1) & r(y_j(w)) > r(A_j(w+1)) \end{cases} \tag{19}$$

where, $r(.)$ represents the function fitness value

***Step 5:*** Exploration phase

Hummingbirds are inclined to seek out new food sources rather than returning to previously visited ones after visiting their target food source and consuming nectar from the flowers. Since a novel food supply is identified as a potential solution is preferable to the present one, a hummingbird might therefore easily relocate to its nearby region in its territory. A mathematical formula is derived that replicates the hummingbirds' local search for food in their territorial foraging method is given in equations (20)& (21),

$$A_j(w+1) = y_j(w) + h.F.y_j(w) \tag{20}$$

$$h \sim M(0,1) \tag{21}$$

where, $h$ represents territorial factor subjected to normal distribution $M(0,1)$using $mean = 0$ .This allows all hummingbird, using its unique flight abilities, to locate a novel food source in its area with easy based on its own position. The visit table needs to be modified following the implementation of the territorial foraging strategy.

***Step 6:*** Exploitation phase for optimizing $\alpha \& V$

The hummingbird locates the food source with lowest rate of nectar refilling and migrates to a novel food source that is produced randomly throughout search space, if the number of iterations surpasses the predefined value of the migration coefficient. The hummingbird's migration foraging from the source that refills nectar the least to a novel source created at random is given in equation (22),

$$y_{wor}(w+1) = Low + v.(Up - Low) \tag{22}$$

where, $y_{wor}$ denotes food source with worst nectar-refilling rate in population.

***Step 7:*** Termination Condition

With the aid of AHOA, the weight parameter value $\alpha$ $\&V$ from the Anti-Interference Dynamic Integral Neural Network are optimized using AHOA, will repeat iteratively step 3 until halting criteria $W = W + 1$is satisfied. Then, the MTS-AIDINN-AHOA method effectively accesses the music tone synthesis through high accuracy and low computational time.

## IV. RESULT WITH DISCUSSION

In this part, the experimental outcomes of the indicated procedures are discussed. The proposed MTS-AIDINN-AHOA method is applied by using MATLAB. The obtained outcome of the proposed is analyzed with existing methods such as MTS-RNN [18],MTS-BPNN [19] and MTS-SMNN[20] respectively.

### *A. Performance measures*

Performance metric like accuracy, specificity, precision, recall and RoC mean Intersection over Union, error rate, computational time are examined for performance measures. The performance matrix is deemed to measure the performance measures. The following matrixes are required to calculate the performance metrics.

- True Negative (TN): Presents count of values which are appropriately predicted as negative.
- True Positive (TP): Presents count of positive values which are appropriately recognized as positive.
- False Positive (FP): Presents count of positive values which are inappropriately recognized as positive.
- False Negative (FN): Presents count of values which are inappropriately recognized as negative.

*1) Accuracy*

The ratio of precise synthesis with total count of predictions made for a dataset. It is measured through the equation (23),

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{23}$$

*2) Precision*

Precision is a metric which quantifies the count of correct positive prediction made. It is scaled using equation (24),

$$precision = \frac{TP}{(TP + FP)} \tag{24}$$

*3) Recall*

It measures the predictions made by accurate number of positive forecasts to total positive predictions. It is calculated using equation (25),

$$\mathrm{Re}call = \frac{TP}{TP + TN} \tag{25}$$

*4) Specificity*

The percentage of true negatives that the method correctly identifies is called specificity. It is determined by equation (26),

$$Specificity = \frac{TN}{TN + FP} \tag{26}$$

*5) RoC*

An integrated measurement of a measurably effect or phenomena is the RoC. It is scaled by equation (27),

$$RoC = 0.5 \times \frac{TN}{FP + TN} + \frac{TP}{FN + TP} \tag{27}$$

*B. Performance Analysis*

Figure 3 to 7 determines stimulation results of proposed MTS-AIDINN-AHOA method. Then, the proposed MTS-AIDINN-AHOA method is likened to existing methods such as MTS-RNN, MTS-BPNN, and MTS-SMNN respectively.

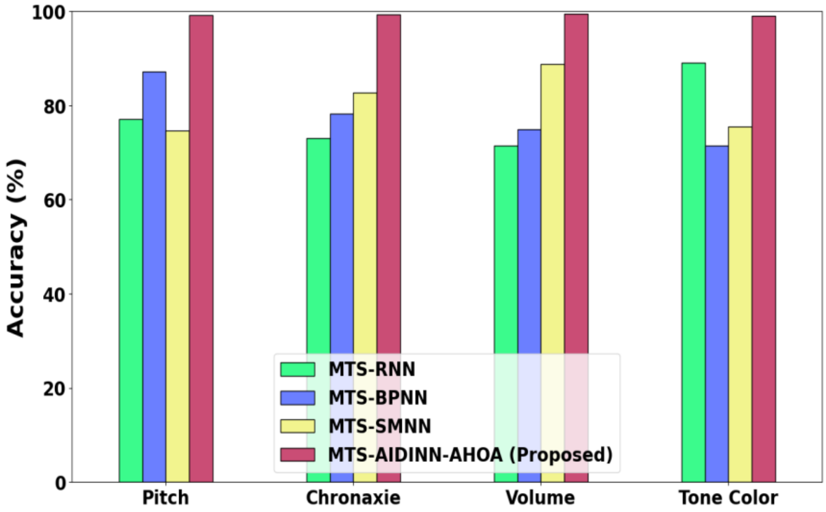


**Figure 3**: Accuracy analysis

Figure 3 shows accuracy analysis. Here, MTS-AIDINN-AHOA attains 22.45%, 15.45% and 17.34% higher accuracy for pitch; 18.65%, 16.78%, and 21.33% higher accuracy for chronaxie; 17.12%, 14.50% and 13.6% higher accuracy for volume; 14.45%, 24.12% and 25.16% higher accuracy for tone color; comparing to the existing MTS-RNN, MTS-BPNN, and MTS-SMNN methods.

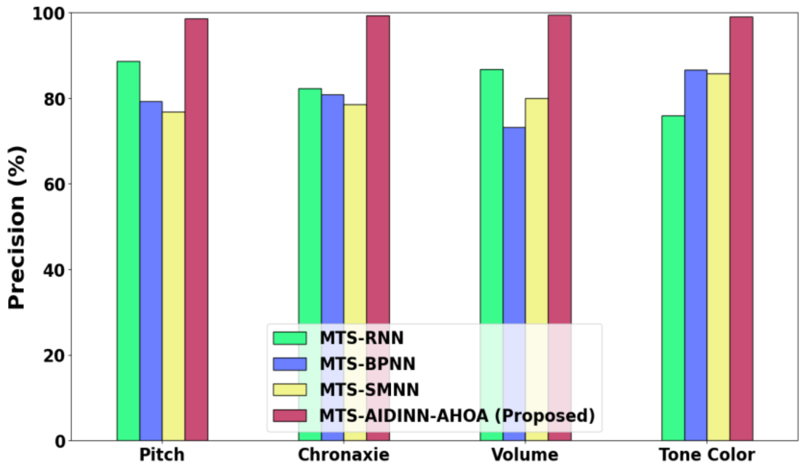


**Figure 4:** Precision analysis

Figure 4 shows precision analysis. Here, MTS-AIDINN-AHOA attains 19.23%, 23.56%, and 13.66% higher Precision for pitch; 26.34%, 20.45% and 23.59%higher Precision for chronaxie; 15.40%, 29.20% and 13.27% higher Precision for volume; 10.55%, 25.47% and 20.39% higher Precision for tone color; comparing to the existing MTS-RNN, MTS-BPNN, and MTS-SMNN methods.

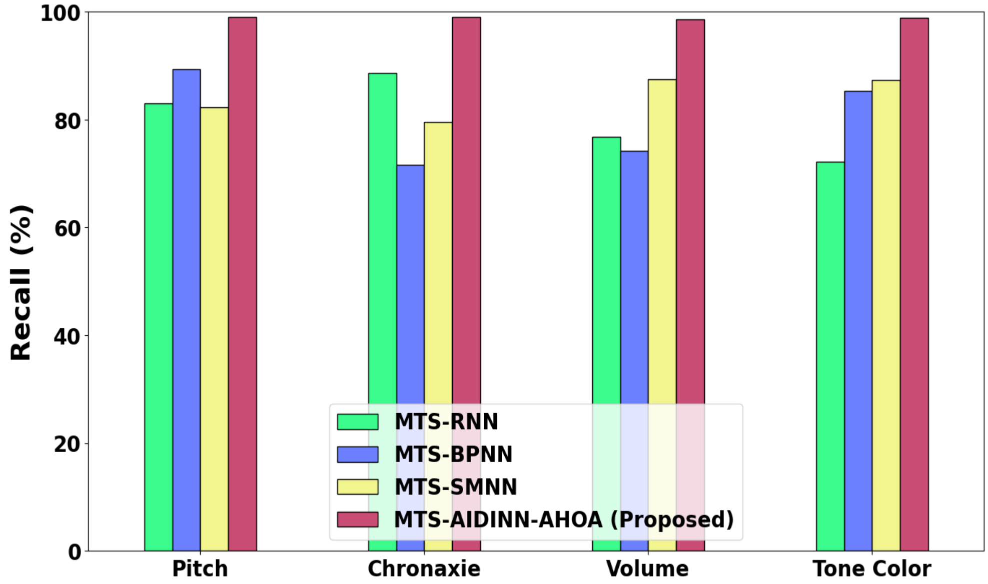


**Figure 5:** Recall analysis

Figure 5 shows Recall analysis. Here, MTS-AIDINN-AHOA attains 30.33%, 23.45 %, and 32.85% higher Recall for pitch; 26.18%, 21.6% and 19.46% higher Recall for chronaxie; 90.40%, 79.10% and 66.17% higher Recall for volume; 22.40%, 17.47% and 23.40% higher Recall for tone color; 20.59%, 15.25% and 24.45% comparing to the existing MTS-RNN, MTS-BPNN and MTS-SMNN methods.

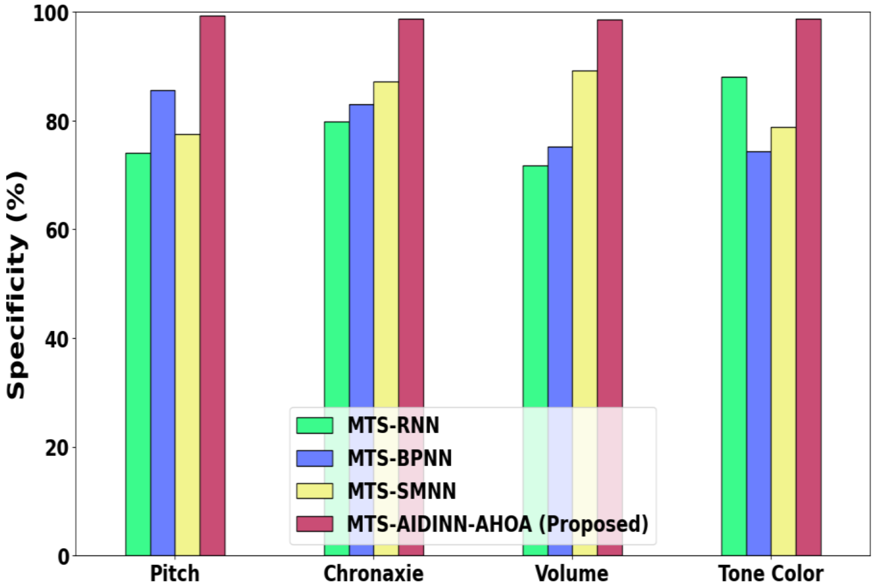


**Figure 6:** Specificity analysis

Figure 6 shows Specificity analysis. Here, MTS-AIDINN-AHOA attains 18.96%, 22.21% and 23.89% higher Recall for pitch; 12.80%, 29.60% and 24.80% higher Recall for chronaxie; 18.30%, 29.20% and 26.57% higher Recall for volume; 15.34%, 27.70% and 13.43% higher Recall for tone color; 28.25%, 27.5% and 16.35% comparing to the existing MTS-RNN, MTS-BPNN and MTS-SMNN methods.

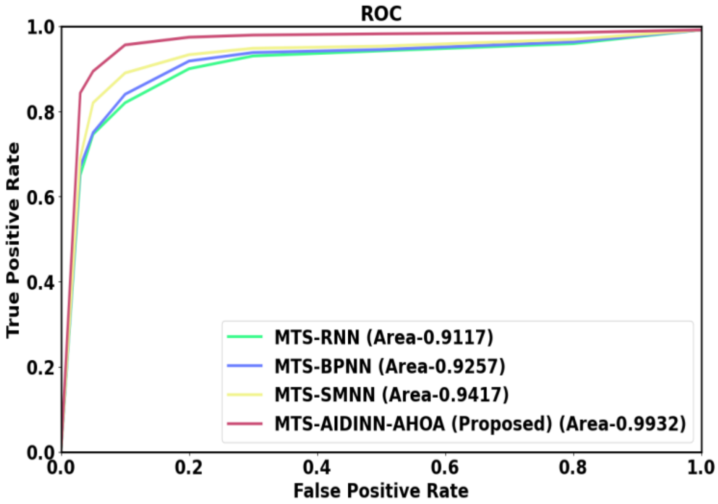


**Figure 7:** RoC Analysis

Figure 7 shows RoC analysis. Here, MTS-AIDINN-AHOA method attains 24.25%, 18.69% and 25.35% higher RoC comparing to the existing methods such as MTS-RNN, MTS-BPNN, and MTS-SMNN respectively.

*C. Discussion*

In this work, MTS-AIDINN-AHOA model for the music tone synthesis is discussed. The empirical evaluation of proposed MTS-AIDINN-AHOA method is highlighted through a range of evaluation metrics, including accuracy, specificity, Recall, Precision, and RoC. Presenting a comparison of the accuracy achieved the proposed technique to that of MTS-RNN, MTS-BPNN, and MTS-SMNN. The fundamentals of vocal music are imparted with the use of video and image materials in standard vocal teaching courses, which place a greater emphasis on the instructor's combined teaching experience and methods than on the conceptual and spontaneous nature of vocal instruction. If AIDINN and vocal instruction are combined, learners can learn vocal technique in a more clear and understandable method and can gain an improved comprehension of the vocal method. Combining AIDINN with vocal educational institutions allows learners to learn vocal method is a way that is easier to understand and improves their understanding of the vocal approach. It concludes that the proposed MTS-RNN, MTS-BPNN, and MTS-SMNN method is better than existing models for music tone synthesis.

## V. CONCLUSION

In this manuscript, Music Tone Synthesis based Anti-Interference Dynamic Integral Neural Network optimized Artificial Hummingbird Optimization Algorithm (MTS-AIDINN-AHOA) is successfully implemented. The performance of the proposed MTS-AIDINN-AHOA method approach contains 32.46%, 20.34%, and 28.27% greater F1-score, 17.20%, 20.36%, and 15.30% lower Error rate, 25.35%, 18.27%, and 29.64% lower Computation time and 30.20%, 16.70% and 32.35% greater RoC when analyzed to the existing methods such as MTS-RNN, MTS-BPNN, and MTS-SMNN respectively. The implementation of music tone acknowledgment pattern in the classroom for vocal music instruction in the future will enable human-computer interaction, facilitate automatic music grade production by the data processor, and enable real-time complement and achievement calculations.

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