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EXPLORING MUSIC'S INFLUENCE ON PLANT GROWTH USING SYNCHRO SQUEEZED FRACTIONAL WAVELET TRANSFORM

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ABSTRACT
Music's impact on plant development has been a topic of growing interest in phytobiology, with studies suggesting that sound waves stimulate physiological responses in plants. Music, particularly at specific frequencies, is hypothesized to have an impact on cell growth, nutrient absorption, and overall vitality, potentially enhancing agricultural productivity. Understanding this relationship could lead to innovative and environmentally friendly techniques for optimizing plant health and improving crop yields. In this paper, Exploring the Influence of Music on Plant Growth using Synchro squeezed Fractional Wavelet Transform (EMIPG-SFWT) was proposed. Initially, audio such as western music, Indian classical music, Vedic chanting, and the physical and chemical parameters of the plant are given as input. The collected audios are fed into the preprocessing segment, where noise reduction and normalization are done using the Adaptive Two-Stage Unscented Kalman Filter (ATSUKF). The pre-processed audio signals are then given to extract the spectral features such as Spectrogram, Mel-Frequency Cepstral Coefficients, Spectral Centroid and Spectral Bandwidth through the Synchro squeezed Fractional Wavelet Transform (SFWT) in the feature extraction phase. Finally, the extracted characteristics are given for the Statistical Test to find the correlation between the extracted characteristics and the physical and chemical parameters of the plant. The correlation analysis shows that Vedic chanting effectively influences the physical and chemical factors of the plant. The proposed EMI-PG-SFWT method was implemented in MATLAB. The proposed EMI-PG-SFWT approach revealed that Vedic chanting significantly improved plant growth, with the highest straw yield (3705 kg/ha) and grain yield (2220.18 kg/ha), outperforming classical and Western music. It also enhanced seed weight(33.325 g/1000 seeds) and tiller density (344/m²) compared to the control. These findings confirm the Vedic chanting as the most effective in promoting plant growth, offering a sustainable approach to improve agricultural productivity.

KEYWORDS: Music, Plant, Physical, Chemical, Synchro squeezed Fractional Wavelet Transform, Straw Yield, Grain Yield, Seed and Tiller

1 INTRODUCTION

Technology advancements and the ease of international information sharing have helped to change and evolve man's conception of a plant organism in horticulture. Plants were found to have the ability to hear, see, and move. These abilities are unexpected and frequently on the edge of scientific acceptance [1] [2]. However, because of these capacities, plants began to be regarded as sophisticated creatures able to sense and communicate with their surroundings and each other. Numerous external cues, including light, wind, sound, and biotic and abiotic stimuli, cause plants to react continuously. Plants alter the growth and development of their organs to adjust to shifting environmental conditions. In addition to supporting plants in the soil, roots also take up water and nutrients essential for plant growth and development. In addition to improving plant anchorage, encouraging root growth improves nutrient and water uptake, increases resistance to biotic and abiotic stressors, and increases crop quality and productivity. At first, it was thought that plants lacked perception and memory, but since then, it has been established that sound affects plant growth and how humans respond to music [3] [4][5]. Music has been shown to have an impact on a number of plant germination, growth, and development phenomena, as well as physiological processes such as photosynthesis, flowering time, and plant yield. Melodious sounds have a more significant effect on the number of seeds that germinate than untreated samples and sound vibrations have a direct impact on biological living systems. Sound and silence serve as the medium for the art form of music [6][7]. In multicellular organisms thought to be sensitive to early effect testing and therapy testing, it creates the beauty of expression and emotion. It is well known that sound influences plant growth and that plants react to music. The effects of music on plant metabolism can be profound. The various kinds of music are appreciated by the plants, and they react to them. Music sound has been shown to have an impact on plant growth, flowering, and nutritional status when compared to noise and untreated control. The precise impact of sounds with different frequencies and intensities on plant growth has been examined. A biological systems performance and/or behaviour can be impacted by any environmental factor that puts it under stress [8][9][10].

Given that their biological signals are influenced to varying degrees and that certain musical sounds have been shown to harm plant tissues, plants experience pleasure when exposed to specific musical patterns. It has been demonstrated that plants will eventually perish if they are exposed to jazz music nonstop for longer than ten days. On the other hand, gentle music has a positive effect on plant growth and yield [11][12]. The gentle vibrations of soft, light music relax plant tissues. Plant growth is significantly increased by violin music. Some researchers concluded that music's soft vibrations aid in the plants' quick growth and strength. All of this could aid farmers in producing more crops. Plant species and even varieties within the same species respond differently to the same music [13][14]. Individual plant health, age, and genetic makeup also cause variations in response. Ensuring a controlled environment to isolate the effect of music is challenging. Maintaining consistent volume, duration, and frequency of music exposure across all experiments is essential but difficult to achieve. Variations in sound equipment and acoustic properties of the environment affect the exposure. Deep learning models need data to train on to adequately capture the connection between music and plant growth. Overfitting can be an issue if the model does well on training data but poorly on fresh data[15][16]. Deep learning models offer powerful tools to overcome many limitations in identifying the best music for plant growth by leveraging their capacity to handle complex, high-dimensional data and uncover intricate patterns. Large volumes of audio data can be processed by these models, which can then extract subtle features that conventional analysis techniques might overlook. By employing deep learning, researchers can account for the variability in plant responses to different music types through sophisticated pattern recognition and predictive capabilities [17][18]. These models can integrate diverse datasets, including physical and chemical plant parameters and environmental conditions, providing a holistic analysis that isolates the effect of music on plant growth. Ultimately, deep learning models facilitate a comprehensive, data-driven approach to identifying the optimal music for plant growth, addressing variability, environmental factors, and complex feature interactions more effectively than traditional methods[19][20]. Various research works have previously existed in the literature, which are based on Exploring Music's Influence on Plant Growth using deep learning methodologies. Some of them are reviewed here. In 2022, T. Kim et al. [21] suggested A Novel Shape Plant Growth Prediction Algorithm Using Deep Learning and Spatial Transformation. A new deep-learning network was introduced that uses a variety of historical and present photos to predict future plant images. Since leaf area transformation. ay to quantify plant development, estimating the form of a plant's leaves was the focus. Following a spatial transformation of a series of plant images within the network, the growth behaviour was measured using an affine transform set of parameters. As an alternative to conventional sequential image fusion, the affine transform parameters for every pair of subsequent photos were fused together to predict the shape of the future plant image. After that, an RGB reconstruction network splits the plants into several patches in order to use hierarchical auto-encoders to predict both local and global growth. In 2021, R. Yasrab et al. [22] presented Plant Growth Forecasting from Time-Series Data Using Deep Learning. It examines the generation of segmentation masks of root and shoots systems using deep networks to predict future plant growth. An existing generative adversarial predictive network was modified for use in the new field. Based on time-series data on plant growth, the results demonstrate an effective plant leaf and root segmentation network that offers prediction segmentation of a leaf and root systems future appearance. In 2024, N. Jayasuriya et al. [23] suggested Machine vision-based plant height estimation for protected crop facilities. A technique using stereo vision to determine the height of tall plants supported vertically in protected areas was created. This was because plant height was an essential indicator of crop growth. In three glasshouse compartments with varying light treatments, weekly RGB and depth (RGBD) streams were initially collected from plant gutters. A deep learning segmentation model to identify plant bases and tips was trained and evaluated using a subset of the gathered RGB data. Using the depth image of the same frame, the identified tops and bases of an image were then moved to the 3D scene that was created. Using the cluster centres of the plant bases and crowns, the height of each plant was determined. In 2022, G.E. Gall et al. [24] presented a Fast estimation of plant growth dynamics using deep neural networks. Convolutional neural networks present an intriguing approach to plant tracking, similar to those employed for position estimation in humans and animals. Plant tracking was done using the Social LEAP Estimates Animal Poses (SLEAP) framework. Time-lapse videos of different organ types and imaging, angles (e.g., side-view shoots and roots versus top-view crown leaves), different lighting conditions (IR versus full spectrum), other plant morphologies and scales (e.g., Arabidopsis seedlings at 100 m scale versus sunflowers and beans at cm scale), and different movement patterns (circumnutations, tropisms, and twining) were used in the evaluation. In 2022, Y. Meng et al. [25] suggested flexible and high-quality plant growth prediction with limited data. Using two new time-series data augmentation methods, the forecast of plant growth from both perspectives was considered. More precisely, a novel framework with a length-changeable time-series processing unit was raised to generate images flexibly. The model was optimized using a generative adversarial loss to produce high-quality photos. Furthermore, three critical locations for time-series data augmentation were identified before the introduction of

T-Mixup and T-Copy-Paste. T-Mixup combines images from a different time pixel-by-pixel. In contrast, T-Copy-Paste reuses individual leaves from the old dataset to create new time-series images with a different background. In 2020, L.P. Osco et al. [26] presented Using UAV-Based Multispectral Imaging and Machine Learning Techniques to Forecast Maize Leaf Nitrogen Concentration and Plant Height. The primary goal was to show how maize plants' PH (m) and leaf nitrogen content (LNC, g kg1) could be predicted using machine learning algorithms and UAV-based multispectral imagery. During the 2017–2018 and 2018–2019 crop seasons, 11 distinct cultivars of maize were used in an experiment with two different rates of N fertilization. The soil-adjusted vegetation index (SAVI), normalized difference vegetation index (NDVI), green normalized difference vegetation (GNDVI), normalized difference red-edge index (NDRE), and spectral vegetation indices (VI) were extracted from the images along with the spectral bands and stored in a computer system as input parameters for various machine learning models. One hundred replicates of a randomized 10-fold cross-validation technique were used to assess nine supervised machine learning (ML) models. In 2023, A. Zakieva et al. [27] investigated Deep machine learning for quantitative analysis of radial plant growth and cell segmentation. PlantSeg and MorphographX, two newly developed image-processing tools, were used to describe the tissue morphogenesis of Arabidopsis hypocotyl. The pipeline achieves High accuracy in classifying the types of central hypocotyl cells and segmenting intricate images of transverse hypocotyl sections. Deep machine learning was used first to train cell-type classification models on ovules, shoot apical meristems, and adult hypocotyls. Using a pipeline on phloem intercalated with xylem (pxy) mutants and wild type, the approach accurately finds severe morphological abnormalities, which were demonstrated.

The methods discussed in the literature for exploring music's influence on plant growth using deep learning have several drawbacks. One limitation is the reliance on historical and present photos, which do not always capture the complex dynamics of plant growth, especially when dealing with diverse environmental conditions. Some approaches use time-series data for plant growth prediction and struggle with limited or incomplete data, leading to less accurate forecasts. Using specialized equipment, such as stereo vision or UAV-based imagery, is costly and inaccessible to all researchers. Some deep learning models require extensive data augmentation techniques to improve prediction accuracy, which leads to increased computational complexity and longer processing times. The focus on specific plant organs or conditions limits the generalizability of the results, making it challenging to apply the models across different plant species or growth environments. While some methods incorporate segmentation technique for plant structure analysis, they still face challenges in accurately capturing plant growth and morphogenesis's dynamic, nonlinear aspects, leading to potential inaccuracies in predictions. The innovation of the proposed EMI-PG-SFWT lies in its integration of advanced signal processing techniques with phytobiology to explore music's effect on plant growth. Unlike existing methods that rely on limited visual data or traditional time-series models, the proposed approach combines Indian classical music, Vedic chanting, and Western music as audio stimuli, employing sophisticated feature extraction with SFWT. SFWT captures intricate spectral features, enabling more precise analysis of the correlation between audio stimuli and plant physical and chemical parameters.

The significant contribution of the paper is given below.

- Indian classical music, Vedic chanting, and Western music were combined as stimuli to investigate their effect on plant growth.
- ATSUKF was employed for effective noise reduction and signal normalization, ensuring high-quality audio input for subsequent analysis.
- SFWT was utilized for advanced feature extraction from audio, capturing intricate spectral features.
- A statistical framework was introduced to analyse the correlation between music induced spectral features and plant physical/chemical parameters.
- A computationally efficient, accessible method that does not require expensive equipment or extensive data augmentation was provided, making it widely applicable to various plant species and growth environments. The balance of the manuscript is organized as follows: Part 2 displays the proposed methodology, Part 3 presents the findings with discussions, and Part 4 concludes the manuscript.

2 PROPOSED METHODOLOGY

In this segment, the EMI-PG-SFWT approach is proposed to explore the influence of music on plant growth. The methodology involves a multistep process, beginning with data acquisition, followed by pre-processing, feature extraction, and correlation analysis to determine the effect of different music genres on plant growth and nutrient absorption. The aim is to identify the music type that most positively impacts plant development, enhancing physical and chemical growth parameters. Below is a detailed explanation of each step involved in the proposed methodology. Figure 1 presents the block diagram of the EMI-PG-SFWT approach.

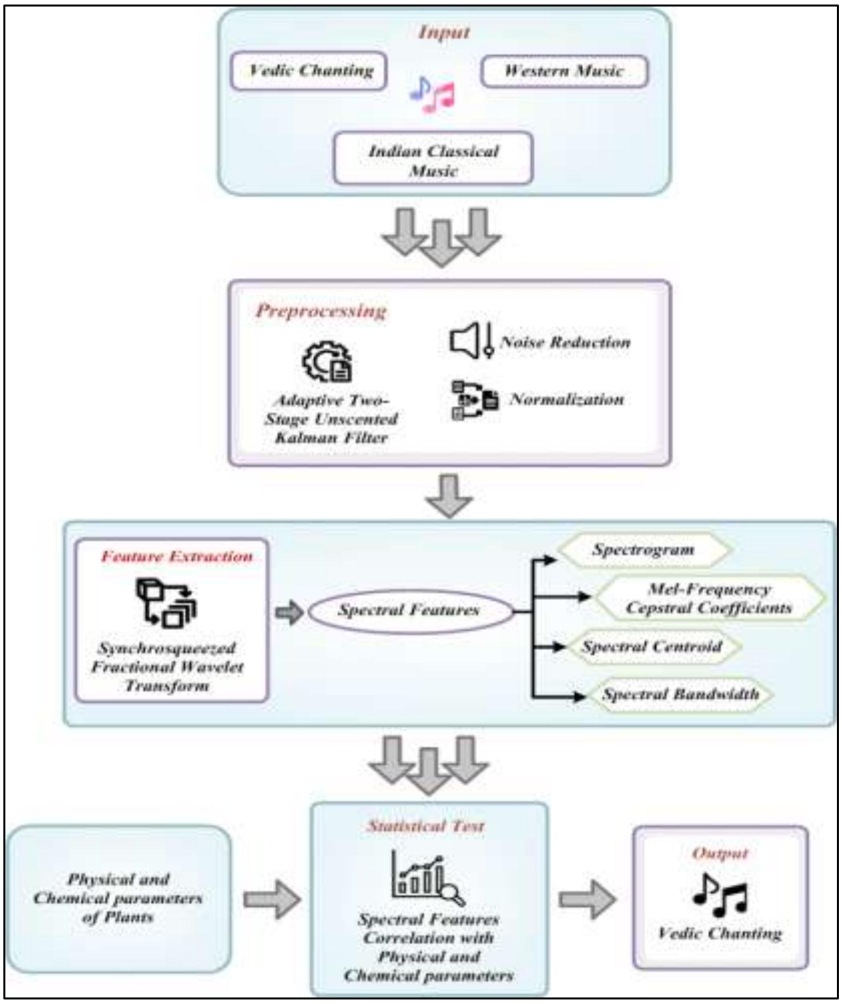

Fig. 1 Block Diagram of Proposed EMI-PG-SFWT Approach

2.1 Data Acquisition

Initially, three types of audio were provided were provided, Western music, Indian classical music, in waveform audio format (WAV). These audio files serve as input stimuli for the experiment. The plant growth properties considered include straw yield, grain yield, plant height and nutrient uptake, which encompass key elements like Phosphorus (P), Nitrogen (N), and Potassium (K). These parameters were measured to assess the influence of the different music genres on the physical and chemical aspects of plant growth, aiming to uncover any significant correlations between the type of music exposure and the plants development and nutrient absorption. We employed a completely randomised design to assess plants physical and chemical parameters. The study involved collecting plant parameters after exposure to music therapy. Four treatments were applied to the seeds—three were exposed to music, while one was a control. A total of 16 pots were prepared, with four pots assigned to each treatment. One group of four pots was exposed to Vedic chanting (Gayatri Mantra). In contrast, another group was subjected to Indian classical music—Raag Ahir Bhairav, a morning raga known for its profound impact. A third set of four pots was exposed to Western music, whereas the remaining four pots were kept under control conditions without any musical exposure. The physical parameters of the plants were compared across the treatments, revealing that Vedic chanting (Gayatri Mantra) had the most significant impact on plant growth. Statistical analyses were conducted to assess the effects of music, demonstrating notable improvements in physical parameters, including seed test weight, plant height, straw yield, and grain yield.

2.2 Preprocessing using Adaptive Two-Stage Unscented Kalman Filter (ATSUKF)

In this sector, preprocessing using ATSUKF[28] is discussed. ATSUKF is used to reduce the noise and normalize the input audio. The ATSUKFs robust performance handles various types of noise, such as background hums and hisses, while its adaptive nature allows it to adjust to fluctuating noise characteristics over time. Unlike traditional linear filters, ATSUKF excels in managing nonlinear systems, which is crucial for complex audio signals with rich harmonics and intricate textures, as found in Indian classical music and Vedic chanting. ATSUKF ensures consistent loudness levels across different audio tracks, preserving the dynamic range of music without distortion, thus maintaining the artistic nuances essential for these genres. ATSUKFs two-stage approach enables tailored processing for different audio types, ensuring optimal noise reduction and normalization for each genre. ATSUKF ensures that the audio signals used are clear and consistent, allowing for an accurate assessment of how music influences plant growth properties like yield, height, and nutrient uptake. In equation (1), all audio files are ensured to be in WAV format, preserving audio quality without compression artefacts. The sampling rate is standardized across all audio files to maintain consistency during processing. Segments of the audio are analysed to identify and create a noise profile, estimating the characteristics of background noise present in each type of music. Spectrograms are then generated for the audio clips to visualize the frequency content and identify noise patterns.

$$a_m = j(z_m, w_m) + Id_m + x_m \qquad m \geq \tau \tag{1}$$

Here, a_m denotes the input audio; j is the frequency content visualized; w_m depicts standardized for consistency in processing; Id_m represents preserve audio quality; x_m represent the background noise for each music type and z_m represents the sampling rate. In equation (2), the previous state estimates are used to predict the current state of the audio signal. This involves applying the unscented transformation to capture both the mean and covariance of the predicted audio signal.

$$\begin{cases} z_{m+1} = h(z_m, w_m) + Hd_m + y_m \\ a_m = j(z_m, w_m) + Id_m + x_m \end{cases} \tag{2}$$

Where, z_{m+1} denotes the predicted current state of the audio signal; Hd_m denotes the mean of predicted audio signal; y_m represents the covariance of predicted audio signal and a_m represents the input audio. In equation (3), new measurements are incorporated into the filter. The ATSUKF updates its state based on discrepancies between the predicted and observed values. The filter parameters are continuously adapted based on real-time analysis of incoming audio signals, enabling effective handling of varying noise conditions across different music types.

$$\tilde{R}^{aa}_{m+1|m} = \sum_{l=0}^{@p} Y_l^e \left(j\left(\chi^l_{m+1}\right) - p_{m+1}\right)\left(j\left(\chi^l_{m+1}\right) - p_{m+1}\right)^U - P_{m+1}\beta_{m+1|m} R^U_{m+1|m} P^U_{m+1} + X_z \tag{3}$$

Here, Y_l^e represents the noise effect; χ^l_{m+1} denotes the predicted values; p_{m+1} denotes observed values; $\beta_{m+1|m}$ represents the filter parameters; $R^U_{m+1|m}$ denotes the state; X_z depicts the measurement noise covariance and $\tilde{R}^{aa}_{m+1|m}$ represents updated state. In equation (4), ATSUKF is applied to reduce the identified noise while preserving essential audio characteristics. The filter dynamically adjusts to minimize background noise without distorting the musical content.

$$\tilde{R}^{aa}_{m+1|m} = \frac{1}{n-1} \sum_{l=m-n+2}^{m+1} \tilde{\in}_l \tilde{\in}_l^V \tag{4}$$

Here, $\tilde{R}^{aa}_{m+1|m}$ denotes the updated state; $\tilde{\in}_l$ represents the reduce background noise. In equation (5), audio levels are normalized across different tracks to ensure consistent loudness. This involves adjusting peak amplitudes to a target level.

$$\tilde{R}^z_{m+1} = E^z + U^z_{m+1} Y_z \tag{5}$$

Where, E^a indicates the measurement variance, $\tilde{R}^z_{m+1|m}$ indicates the normalized audio levels, k indicates the time, U_{m+1} indicates adjusted peak values, Y_z process noise variance matrix . Finally, ATSUKF has successfully reduced the noise and normalized the input audio. ATSUKF enhance audio quality across diverse musical styles and ensure that experimental conditions are controlled and consistent. The pre-processed audio was given to feature extraction phase. We handled and analysed data to find patterns, intensity distributions, and frequency characteristics associated with different music treatments. Classical music has a relatively moderate frequency distribution, as indicated by its well-balanced intensity distribution and smooth transitions. Vedic Music has slightly darker areas suggesting a predominance of low regimes. Western Music is characterized as having very sharp and high delivery to oscillatory sounds, which suggests more dynamic sound fluctuations. A comparative study of intensity histograms reveals differences among Western, Vedic, and Classical music. Western music shows the widest intensity distribution corresponding to diverse frequencies. Vedic music's predominance in low-frequency components is enhanced by its greater concentration in lower intensities.

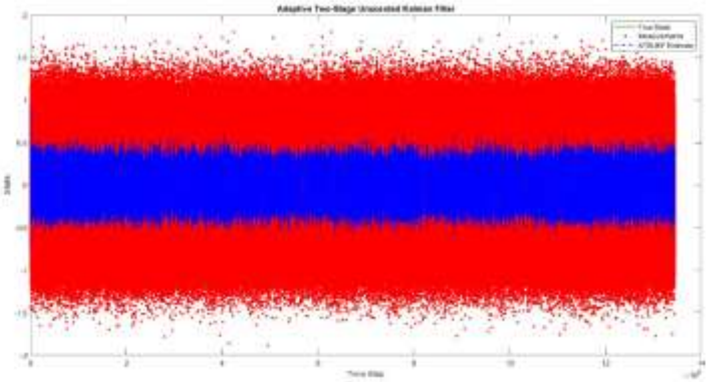

Fig. 6 Output of filter: Vedic Music

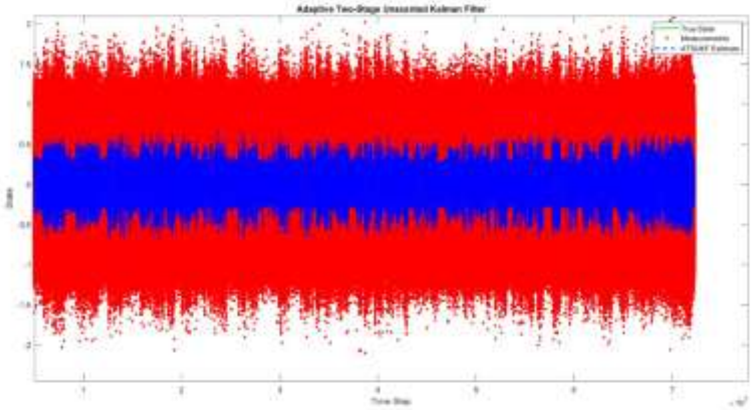

Fig. 7 Output of filter: classical Music

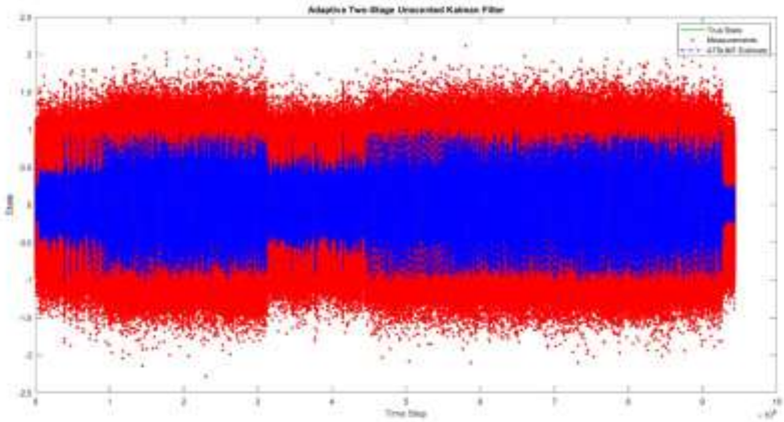

Fig. 8 Output of filter: western Music

Fig. 9 histogram of output of filter

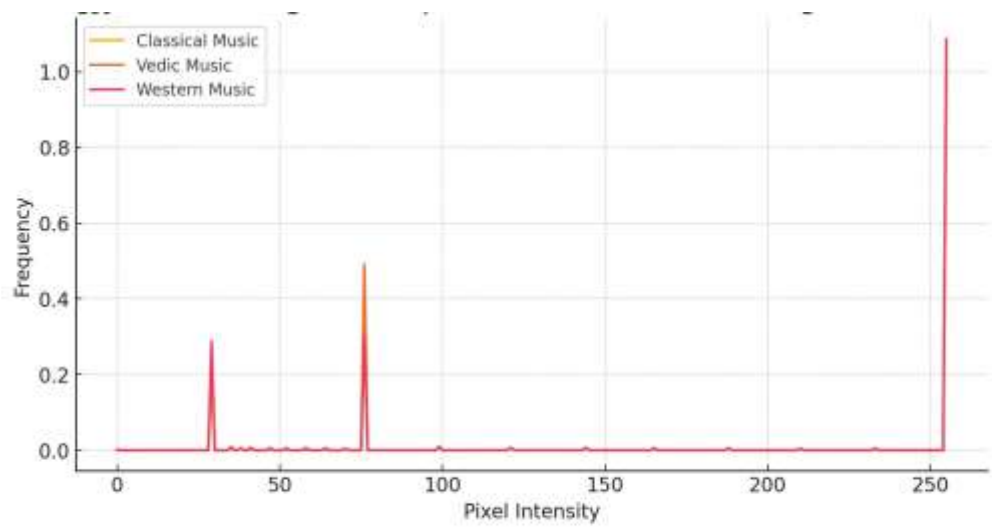

Fig. 10 comparison of histogram for different music

Music Type	Mean Intensity	Variance (Contrast)
Classical	176.96	8982.77
Vedic	171.22	9240.25
Western	179.05	9581.91

Table 1 Mean Intensity and Variance of Different Music Types

We capture that Western music is associated with the highest variation, which may suggest that the rapid changes in the frequencies could either stimulate or stress the plants. Vedic Music is associated with the lowest mean intensity, focusing on prolonged deep frequencies with the potential to aid root development and water absorption. Classical Music, as for the rest of the cases, has a balanced mean intensity and variance, suggesting moderate factors with steady growth.

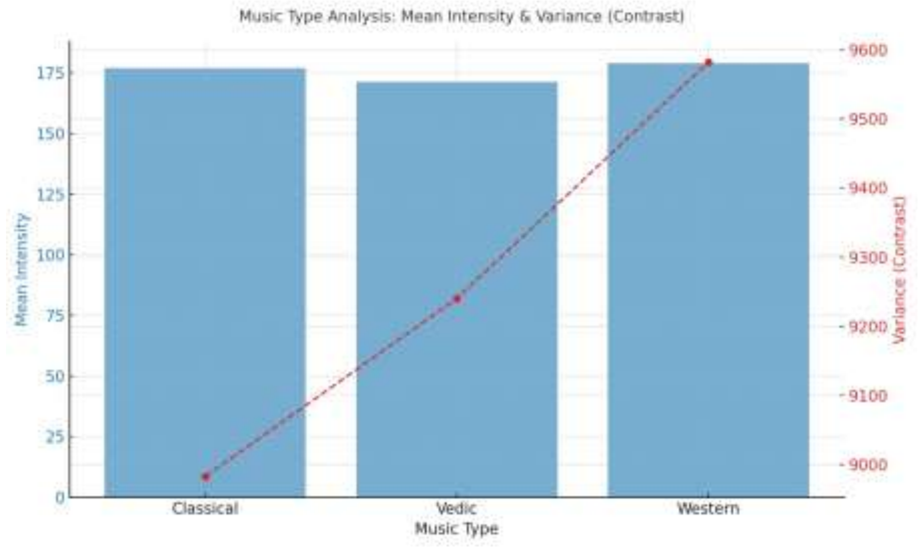

Fig. 11 Comparison for mean Intensity and variance of filter for different types of music

2.3 Feature Extraction using Synchro squeezed Fractional Wavelet Transform (SFWT)

This section uses SFWT [29] to extract the spectral features from the pre-processed audio. SFWT is used to extract the spectral features, including the spectrogram, spectral centroid, spectral bandwidth, and Mel-Frequency Cepstral Coefficients (MFCC). SFWT enhanced time-frequency representation improves clarity by redistributing the energy of wavelet coefficients through synchro squeezing, allowing for more precise identification of specific spectral features in diverse musical genres such as Western music, Indian classical music, and Vedic chanting. SFWT is particularly effective for analysing non-stationary signals typical in music, capturing transient features more accurately than traditional methods and providing a better representation of dynamic changes in the audio signal over time. SFWT offers superior noise reduction, as its adaptive filtering enhances signal clarity while preserving key features, leading to improved signal-to-noise ratios. SFWT's versatility across musical genres ensures that the unique characteristics of different music styles are accurately captured, making SFWT adaptable to various musical influences on plant growth. In equation (6), an appropriate wavelet function is chosen based on the characteristics of the music audio being analysed. The wavelet transform is then performed on the pre-processed audio signal to obtain the time-frequency representation, capturing temporal and spectral information about the audio. Synchro squeezing is applied to the wavelet coefficients to enhance frequency resolution. This process redistributes energy across time-frequency bins, sharpening the representation of frequency components.

$$\omega_g(b,t) = \Re\left\{\frac{-j\frac{\partial}{\partial_t}W_f(b,t)}{W_f(b,t)}\right\} \quad (6)$$

Here, $\Re$ denotes time-frequency representation; $\omega_g(b,t)$ represents input audio; $W_f(b,t)$ denotes enhanced frequency resolution; $\frac{\partial}{\partial_t}$ denotes the operator for the partial derivative with regard to the variable and $W_f(b,t)$ denotes the energy across time-frequency bins. In equation (7), fractional calculus is utilized to model non-local properties and memory effects in the audio signal. This step allows for more nuanced feature extraction that can capture complex dynamics in music.

$$T_f(\omega,t) = \int_{\Xi_f} W_f(b,t)s^{-\frac{3}{2}}\delta(\omega_f(b,t)-\omega)db \quad (7)$$

Here, $T_f(\omega,t)$ represents a transformation applied to the function; Ξ_f denotes complex dynamics captured in music; $W_f(b,t)$ enhanced frequency resolution; b denotes a parameter, δ Represents the Dirac delta function; $\omega_f(b,t)$ represents a function of two variables and S is the total number of frequency bins. In equation (8), a spectrogram is generated from the synchro squeezed output, providing a visual representation of frequency content over time. This is essential for analysing how different musical elements vary throughout the piece.

$$N_i = \sum_n^{j=1} \frac{1}{N} S_{ji} \quad (8)$$

Here, N_i denotes the extracted spectrogram, S_{ji} is the frequency content over time and N is the variation of different musical elements. In equation (9), MFCC are calculated from the spectrogram to represent the perceptual characteristics of sound. MFCC are crucial for understanding tonal qualities and can provide insights into how music affects plant growth.

$$\partial_i = \sqrt{\frac{1}{N}\sum_N^{j=1}\left(S_{ji} - N_i\right)^2} \quad (9)$$

Here, ∂_i denotes the MFCC extracted and S_{ji} is the frequency content over time. In equation (10), the spectral centroid is computed, which indicates the "center of mass" of the spectrum. This feature helps characterize the brightness or dullness of a sound, which may influence plant responses to different musical styles.

$$\partial^2 = \frac{1}{p}\sum_{j=1}^{p}\left(X_i - N\right)^2 \quad (10)$$

Here, ∂ denotes the spectral centroid extracted; p denotes the number of samples and X_i denotes the center of mass. In equation (11), spectral bandwidth is analyzed to measure the width of the spectrum around its centroid. This feature provides information about timbral texture and can be relevant for assessing how different music types impact plant growth.

$$S_y(h) = \frac{1}{M}\left|\sum_{m=0}^{M-1} y[m] d^{-iq2\pi gn/M}\right| \qquad (11)$$

Here, M denotes the width of the spectrum and $S_y(h)$ is the extracted spectral bandwidth. Finally SFWT has successfully extracted the spectral features such as the spectrogram, spectral centroid, spectral bandwidth, and Mel-Frequency Cepstral Coefficients (MFCC).

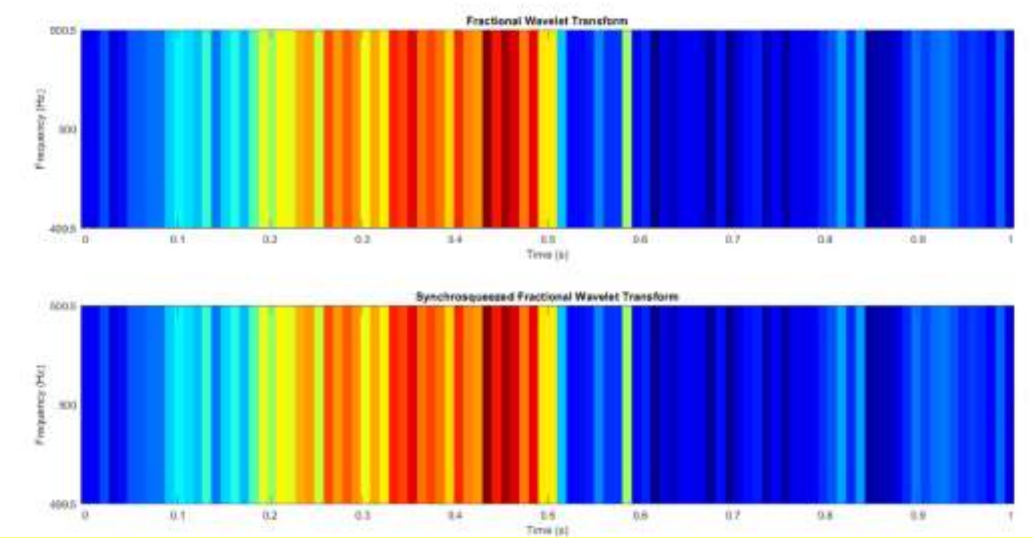

Fig. 12 Synchrosqueezed Fractional Wavelet Transform for vedic

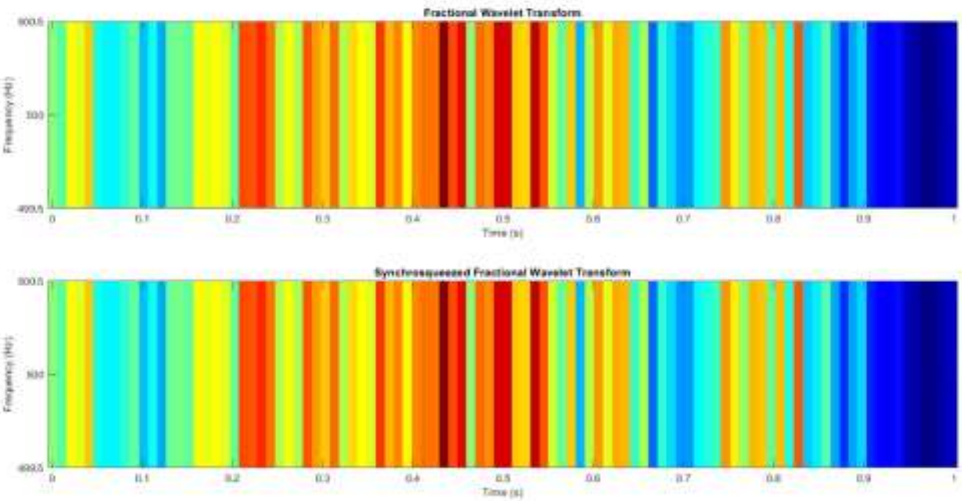

Fig. 13 Synchrosqueezed Fractional Wavelet Transform for classical

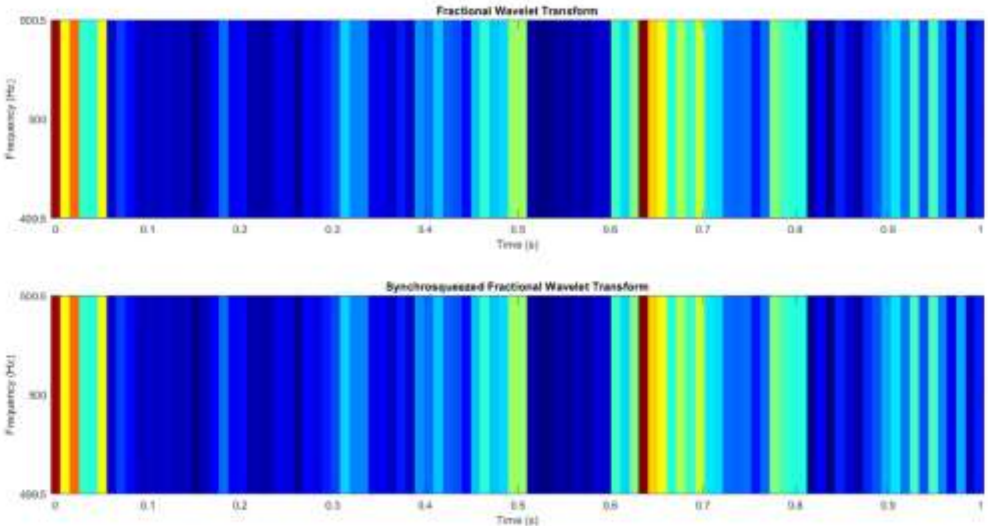

Fig. 14 Synchrosqueezed Fractional Wavelet Transform for western

With the help of wavelet transform, we can visualize the frequency representation over time. This pattern reveals the variation of musical frequency over time. Here, we have found that classical music has a balanced distribution of dark and light regions, which means that it has a steady and smooth distribution of frequency; on the other hand, Vedic music has a dark area, which suggests a more substantial lower frequency distribution, which potentially contributes to deep and resonant nature.Western music plays display a more prominent dark band, indicating dynamic fluctuation in intensity. Here, we have analyzed the comparative parameter of the histogram, revealing that Vedic and Western music have lower-intensity regions, providing the dominance of a more substantial low-frequency presence. At the same time, classical music is an evenly spread intensity distribution.

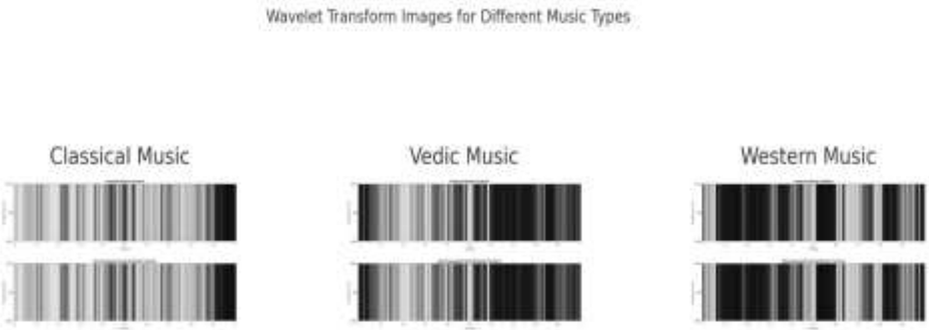

Fig. 15 histogram of output of SFWT

Music Type	Mean Intensity	Variance (Contrast)
Classical	200.49	4638.82
Vedic	169.10	8726.91
Western	165.46	9690.77

Table 2 Mean Intensity and Variance for Different Music Types

Classical Music has the highest mean intensity, meaning the image is brighter on average. Vedic and Western Music have lower mean intensity, indicating darker images, likely due to stronger low-frequency components. Western Music has the highest variance, meaning it has the most contrast between light and dark regions, indicating a more excellent dynamic range of frequencies.

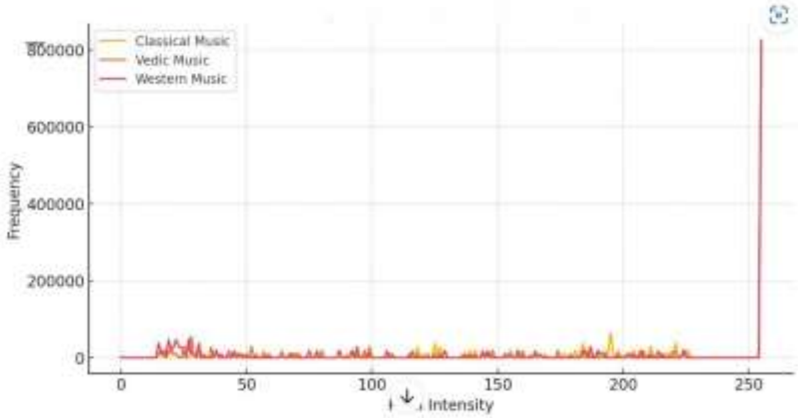

Fig. 16 Comparison of histogram for different music

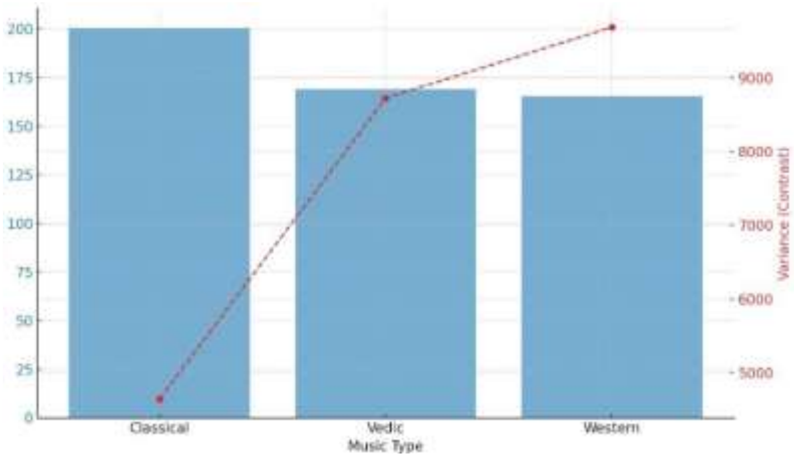

Fig. 17 Comparison for mean Intensity and variance of SFWT for different types of music

Here, we have calculated the spectral entropy of different musical patterns; higher range entropy deals with diverse frequency distribution. Here, low-frequency Vedic tone promotes root length enhancement and steady nutrient uptake of plants. Classical music maintains the balance of growth with structured frequency. Western music may produce changes in plant metabolic activity that may promote growth or generate stress, negatively impacting plant growth if intense.

Feature	**Classical Music**	**Vedic Music**	**Western Music**
Frequency Distribution	Balanced & smooth	Dominated by low frequencies	High variance & rapid changes
Time-Frequency Behavior	Gradual transitions	Periodic & sustained	Sharp transitions & dynamic shifts
Contrast (Variance)	Moderate	High	Very High
Potential Effect	Cognitive Focus	Relaxation	Stimulation & Energy

Table 3 Summary of Findings

Music Type	**Spectral Entropy**
Classical	2.90
Vedic	2.85
Western	2.79

Table 4 Comparison of Spectral Entropy

2.4 Statistical Analysis

The statistical analysis examines the correlation between the spectral features of different music genres and various plant growth factors. Using the Pearson correlation coefficient, the study explores the relationships between music genres such as Western music, Indian classical music, Vedic chanting and plant growth parameters, including straw yield, grain yield, plant height, and nutrient uptake (Nitrogen, Phosphorus, and Potassium). The

Pearson correlation coefficient measures the linear relationship between two variables. The spectral features of the music genres were extracted, and their correlations with plant growth factors were calculated. This analysis identifies which type of music has the most significant effect on plant growth and nutrient absorption, offering valuable insights into the potential influence of auditory stimuli on plant development.

3 RESULT AND DISCUSSION

This division gives the investigative outcomes of the proposed EMI-PG-SFWT technique, implemented in MATLAB. The results of the statistical analysis are discussed to give a comprehensive understanding of the effects of different music genres, such as Indian classical music, Vedic chanting, and Western music, on plant growth and nutrient uptake.

Music Type	30 days	60 days	90 days
Classical	31.281	61.844	80.327
Vedic	30.797	59.3152	76.989
Western	30.193	55.226	72.989
Control	30.02	53.921	71.0047

Table 5 Plant height comparison for different treatment

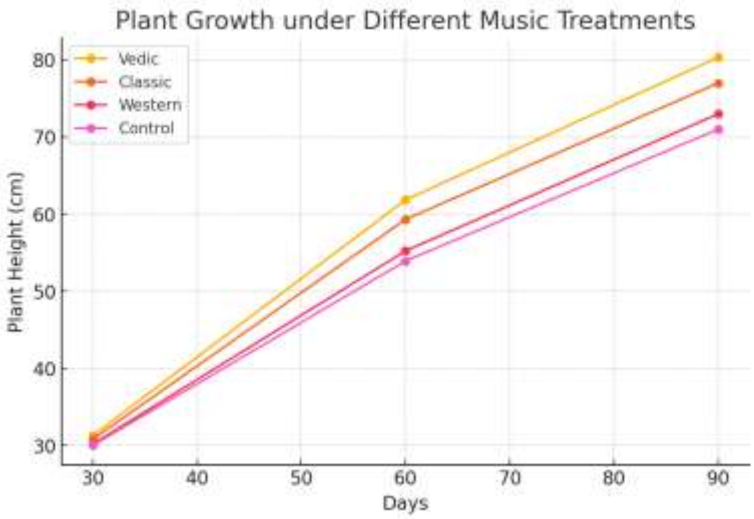

Fig. 18 Plant height comparison for different treatment

Figure 18 shows the influence of different types of music (Vedic chanting, Western music, Indian classical music and no music control) on plant height over 30, 60, and 90 days. Numerically, plants exposed to Vedic chanting demonstrated the maximum growth, achieving approximately 70 cm at 60 days and 85 cm at 90 days. Western and Indian classical music treatments yielded similar but slightly lower heights, around 65 cm and 80 cm at 60 and 90 days, respectively. The control group (no music) consistently exhibited the least growth, with heights of about 50 cm and 70 cm at the same intervals.

3.1 Plants Insights and Growth Rate Analysis

Growth Rate ={(Height at later stage − Height at earlier stage)/Height at earlier stage} × 100
…………(12)

• 30 to 60 Days Growth:
• Vedic: =97.7
• Classic: 92.6
• Western: 82.9
• Control: 79.6
• 60 to 90 Days Growth:
• Vedic: 29.9
• Classic: 29.8
• Western: 32.1
• Control: 31.7

Vedic music had the most significant positive impact on plant height, especially in the early phase. Western music helped to maintain a steady growth rate over time, while the control group had the slowest overall growth. Classical music showed a balanced effect, supporting higher early-phase growth. Control plants show the slowest growth, confirming that music significantly impacts plant development.

Music Type	Straw Yield (Per ha-1)	Grain Yield (Per ha-1)
Classical Vedic	3705	2220.18
Classical	3555	2105.68
Western	3315	2005.58
Control	3202.25	1952.99

Table 6 Straw and Grain Yield Analysis

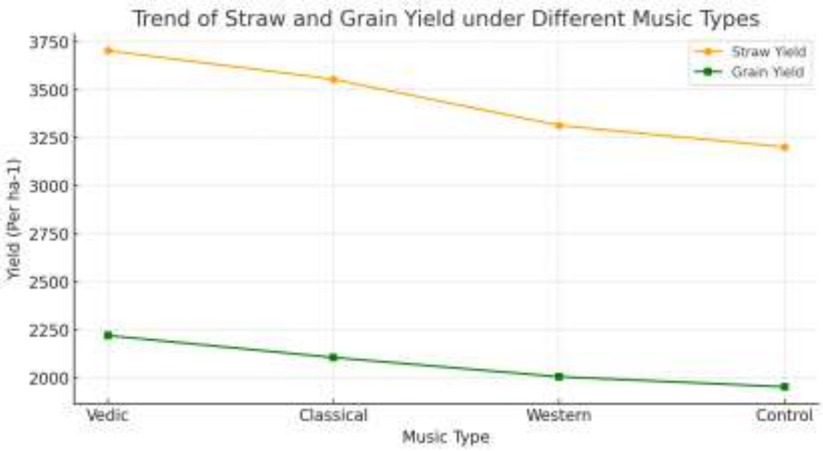

Fig. 19 Straw and grain yield comparison for different types of Music

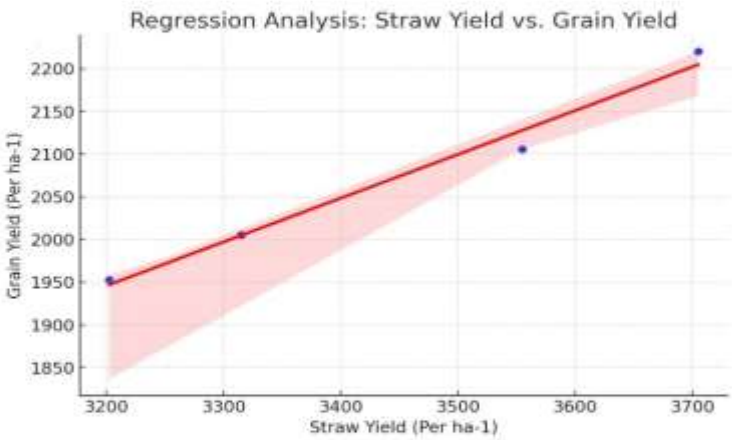

Fig. 20 Regression analysis of straw and grain yield

The table 6 compares the straw and grain yields across different treatments. The Vedic pot achieved the highest yields, with a straw yield of 3705 kg/ha and a grain yield of 2220.18 kg/ha. The classical pot follows with 3555 kg/ha for straw yield and 2105.68 kg/ha for grain yield. The Western pot recorded a straw yield of 3315 kg/ha and a grain yield of 2005.58 kg/ha, while the control pot had the lowest values, with a straw yield of 3202.25 kg/ha and a grain yield of 1952.99 kg/ha. This indicates that the Vedic chanting treatment significantly enhanced crop productivity compared to other treatments. The strong linear relationship confirms that any increase in Straw Yield leads to a proportionate rise in Grain Yield. Music positively impacts both yields, as seen in the Vedic and classical groups. The best-fit line in the graph supports the positive correlation. The table 7 shows the analysis of seed nutrient uptake across different music treatments and the control group. The Vedic pot exhibited the highest straw yield (2220.2 kg/ha), nitrogen uptake (27.7813%), phosphorus uptake (28.0663%) and potassium uptake (16.79263%), outperforming the other groups. The classical pot recorded slightly lower values, with a straw yield of 2105.7 kg/ha and nitrogen uptake of 23.1186%, while phosphorus and potassium uptake were 22.1536% and 11.83758%, respectively. The Western pot showed further reduced values, including a straw yield of 2005.6 kg/ha and nitrogen uptake of 14.1974%, with phosphorus and potassium uptake at 14.4048% and 10.56978%, respectively. The control pot had the lowest values, with a straw yield of 1952.9 kg/ha, nitrogen uptake of 9.89644%, phosphorus uptake of 8.92692%, and potassium uptake of 7.079602%.

Sample Pot	Straw Yeild(Per ha-1)	Nitrogen %	Nitrogen Uptake	Phosphorus %	Phosphorus Uptake	Potassium(K) %	Potassium Uptake

Vedic Pot	2220.2	1.25	27.7813	1.27	28.0663	0.7575	16.79263
Classical Pot	2105.7	1.0975	23.1186	1.0525	22.1536	0.5625	11.83758
Western Pot	2005.6	0.71	14.1974	0.7225	14.4048	0.5275	10.56978
Control Pot	1952.9	0.5075	9.89644	0.4575	8.92692	0.3625	7.079602

Table 7 Analysis of Seed Nutrient Uptake

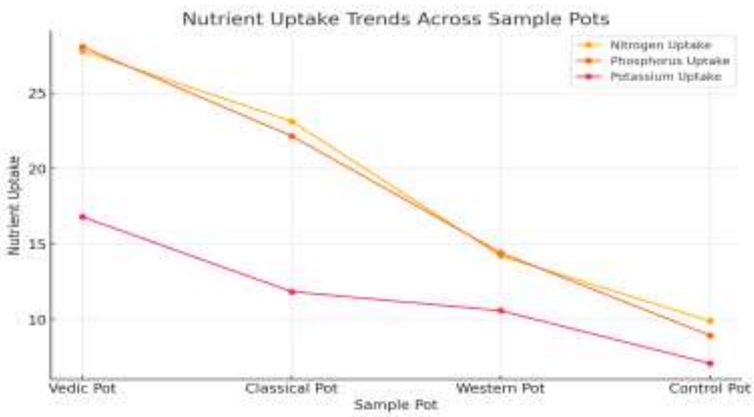

Fig. 21 Nutrient uEptake trend by seed

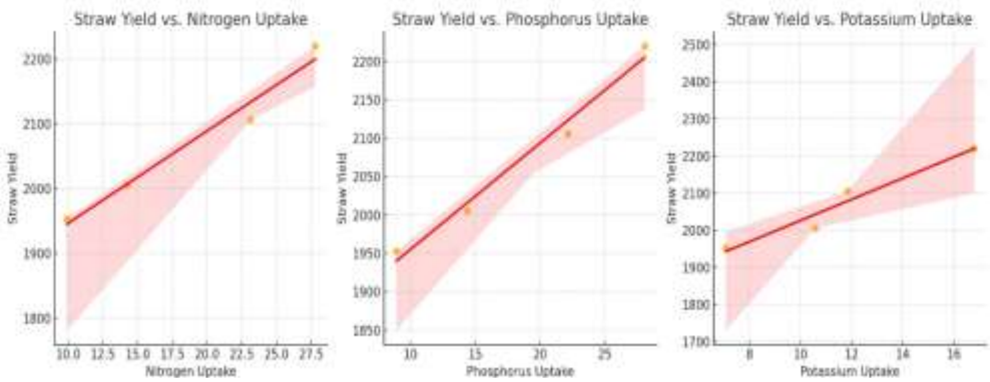

Fig. 22 Analysis of Seed Nutrient Uptake

The crush nutrient uptake analysis in table 8 shows that the Vedic pot again achieved the highest values, with a straw yield of 3705 kg/ha, nitrogen uptake of 68.9155%, phosphorus uptake of 72.394%, and potassium uptake of 84.2945%. The classical pot recorded a straw yield of 3555 kg/ha, nitrogen uptake of 49.4303%, phosphorus uptake of 53.8055%, and potassium uptake of 53.6818%. The Western pot had moderate values, including a straw yield of 3315 kg/ha and nitrogen uptake of 37.3275%, with phosphorus and potassium uptake at 38.0533% and 37.565%, respectively. The control pot showed the least values, with a straw yield of 3202.3 kg/ha, nitrogen uptake of 32.7641%, phosphorus uptake of 34.1141%, and potassium uptake of 30.0822%. These results emphasize the superiority of Vedic chanting in enhancing nutrient uptake compared to other treatments. The Vedic Pot is the best for nutrient uptake, followed by the Classical and Western Pots. Control Pot performs the worst, showing minimal nutrient absorption. The difference in uptake trends suggests that pot type significantly affects plant nutrition.

Sample Pot	Straw Yeild(Per ha-1)	Nitrogen %	Nitrogen Uptake	Phosphorus %	Phosphorus Uptake	Potassium %	Potassium Uptake
Vedic Pot	3705	1.86	68.9155	1.955	72.394	2.28	84.2945
Classical Pot	3555	1.3925	49.4303	1.515	53.8055	1.5125	53.6818

Western Pot	3315	1.125	37.3275	1.15	38.0533	1.13	37.565
Control Pot	3202.3	1.0225	32.7641	1.065	34.1141	0.94	30.0822

Table 8 Analysis of Crush Nutrient Uptake

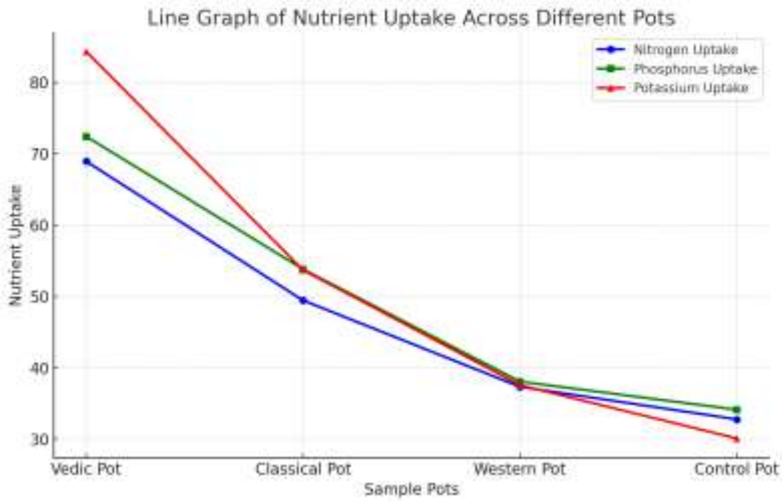

Fig. 23 Nutrient uptake trend by Crush

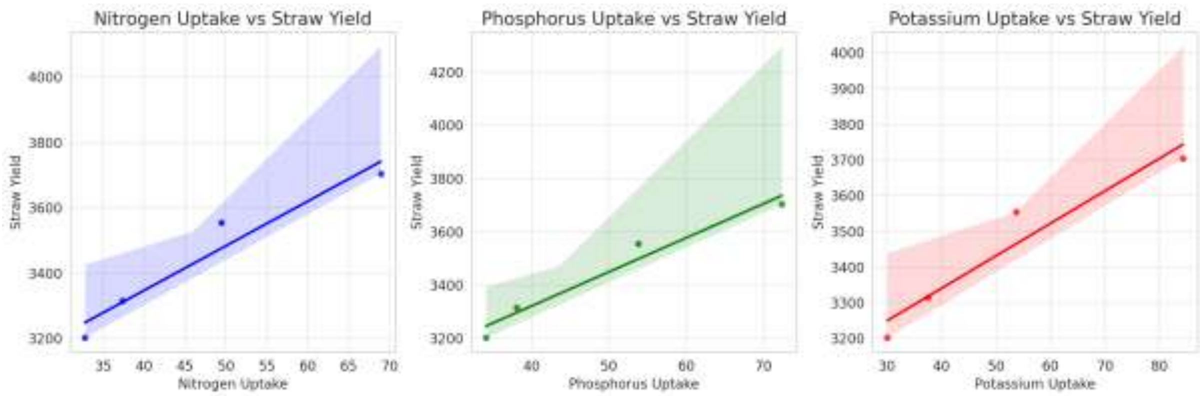

Fig. 24 Analysis of crush Nutrient Uptake

The seed test weights for 1000 seeds shown in table 9 highlight the influence of music treatments on seed quality. The Vedic pot exhibited the highest seed weight at 33.325 g, followed by the classical pot at 31.95 g. The Western pot recorded a seed weight of 29.85 g, and the control pot had the lowest seed weight of 28.775 g. The results demonstrate that the Vedic chanting treatment positively impacts seed development and weight compared to the other treatments. Vedic Pot is the best for promoting higher seed test weight. Classical Pot is also adequate, though slightly lower than Vedic. Western Pot shows minimal improvement and may not be significantly better than the Control. Control Pot has the lowest seed weight, making it the least favourable option.

Sample Pot	**Seed Test weight for 1000 seeds**
Vedic Pot	33.325
Classical Pot	31.95
Western Pot	29.85
Control Pot	28.775

Table 9: Analysis of Seed Test weight for 1000 seeds

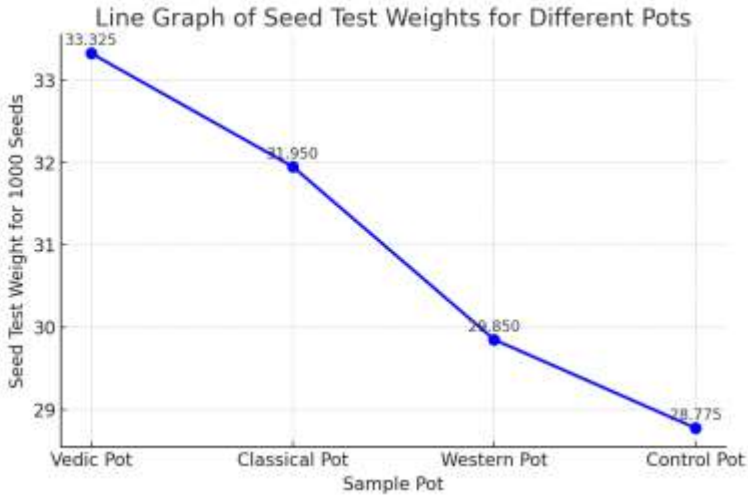

Fig. 25 Analysis of seed test weight for different music treatment

The table 10 illustrates the number of tillers per square foot and square meter for each treatment. The Vedic pots consistently recorded the highest values, ranging from 31-33 tillers per square foot and 334-355 tillers per square meter. The classical pots had 28-30 tillers per square foot and 301-323 tillers per square meter. The Western pots had 26-27 tillers per square foot and 280-291 tillers per square meter, while the control pots had the lowest values, ranging from 23-25 tillers per square foot and 248-269 tillers per square meter. These results suggest that Vedic chanting promotes superior tiller growth compared to other treatments. The trend declines from Vedic Pot to Control Pot, indicating Vedic Pot might be the most effective for tiller growth. The difference between Vedic and Control Pots is significant, suggesting the growth environment in Vedic Pot is favourable.

Sample Pot	**No of Tillers (Per Square feet)**	**No of Tillers (Per Square meter)**	**Sample Pot**	**No of Tillers (Per Square feet)**	**No of Tillers (Per Square meter)**
Vedic Pot 1	32	345	**Western Pot 1**	27	291
Vedic Pot 2	33	355	**Western Pot 2**	26	280
Vedic Pot 3	31	334	**Western Pot 3**	27	290
Vedic Pot 4	32	344	**Western Pot 4**	26	280
Classical Pot 1	30	323	**Control Pot 1**	24	258
Classical Pot 2	29	312	**Control Pot 2**	25	269
Classical Pot 3	28	301	**Control Pot 3**	23	248
Classical Pot 4	28	301	**Control Pot 4**	24	258

Table 10 Analysis of Tillers on Various Pot

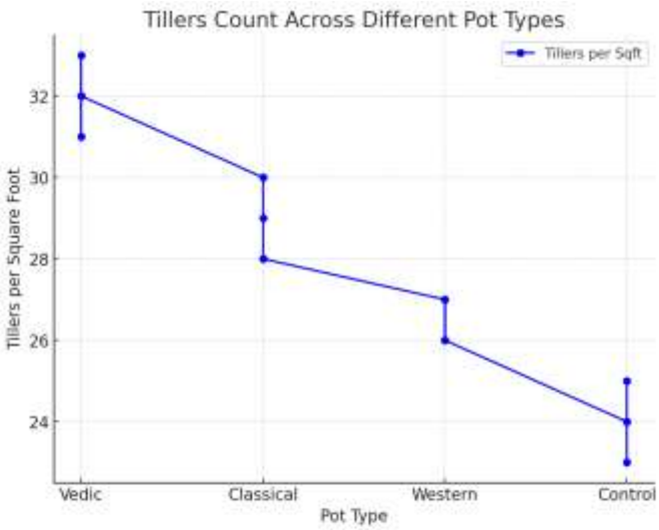

Fig. 26 Analysis of Tillers

The graphs in Figure 27 visually represent the impact of different music genres (Vedic chanting, classical Indian music, and Western music) compared to a control group (no music) on various plant parameters. Graph (a) depicts Growth, showing that Vedic chanting resulted in the highest mean growth, followed by classical, western, and finally the Control group. Graph (b) represents ”Nutrition,” where Vedic chanting again leads with the highest mean (around 90-95), followed by Classical, Western and the Control group having the lowest. Lastly, graph (c) illustrates ”Yield,” demonstrating a similar trend: Vedic chanting exhibits the highest mean yield (around 90), with Classical close behind (around 85-90), Western slightly lower (around 80-85) and the Control group showing the lowest yield (around 80). In all three parameters (Growth, Nutrition, and Yield), Vedic chanting consistently shows the most positive influence
compared to other music genres and the control group.

Figure 28 presents the correlation analysis between spectral features (Spectral Centroid and Spectral Bandwidth) of different music types and plant growth metrics (Straw Yield, Grain Yield and Height). The control condition is set to zero as a reference, while the music-treated groups show varying degrees of positive correlation. Vedic music exhibits the highest correlation across all metrics, particularly in plant height (0.75 for Spectral Centroid and 0.77 for Spectral Bandwidth). Classical music follows, showing moderate correlations (0.63 and 0.62 for height), while Western music shows the lowest positive correlations (0.56 and 0.53). This suggests that spectral features of music, particularly in Vedic and Classical genres, positively influence plant growth, with Vedic music having the most substantial impact.

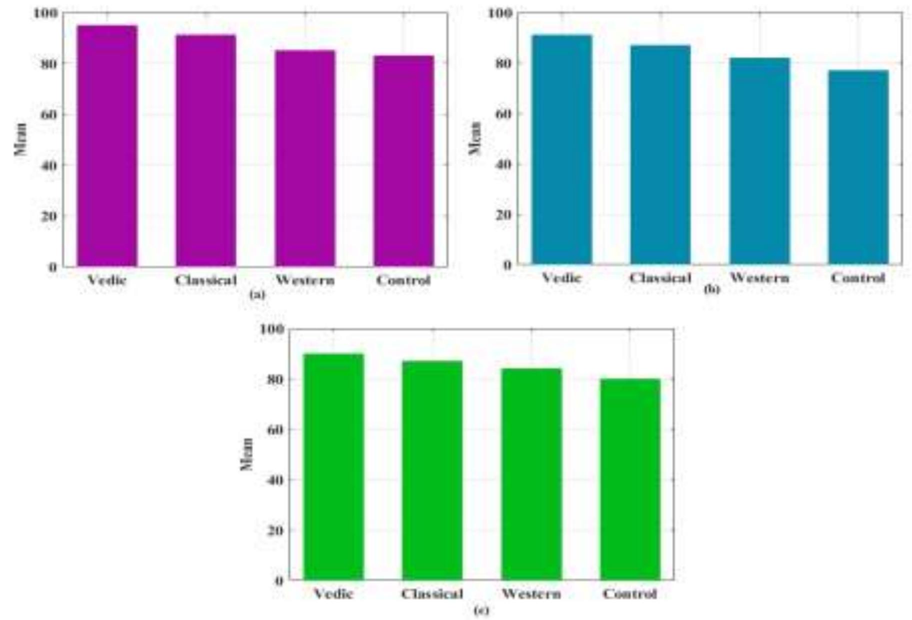

Fig. 27 Analysis of (a) Growth, (b) Nutrition and (c) Yield Comparison

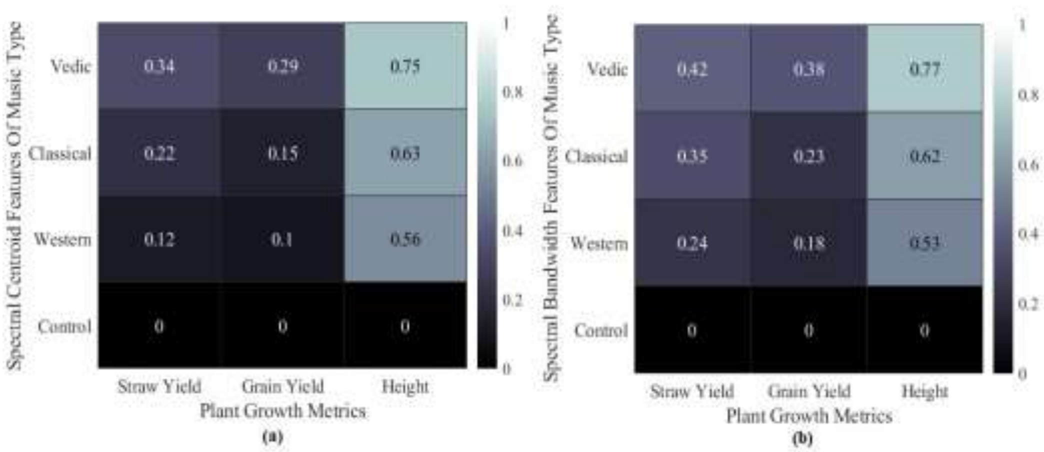

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Fig. 28 Correlation Analysis of (a) Spectral Centroid and (b) Spectral Bandwidth Features of Different Music Type

Figure 29 illustrates the correlation analysis of Mel-Frequency Cepstral Coefficients (MFCC) and Spectrogram features with plant growth metrics. The control condition remains at zero, while Vedic music again shows the highest correlation across all plant growth parameters, particularly in height (0.71 for MFCC and 0.72 for Spectrogram). Classical music follows with moderately high values (0.61 and 0.65 for height), and Western music shows the lowest correlation (0.52 and 0.54). The trend confirms that music influences plant growth positively, with Vedic music having the most significant impact, followed by Classical and Western music. This further reinforces the hypothesis that specific music characteristics, such as MFCC and Spectrogram features, play a role in enhancing plant growth. Overall, these results conclusively establish that Vedic music is the most beneficial for plant growth, making it the optimal choice for improving physical and chemical plant parameters compared to other music types.

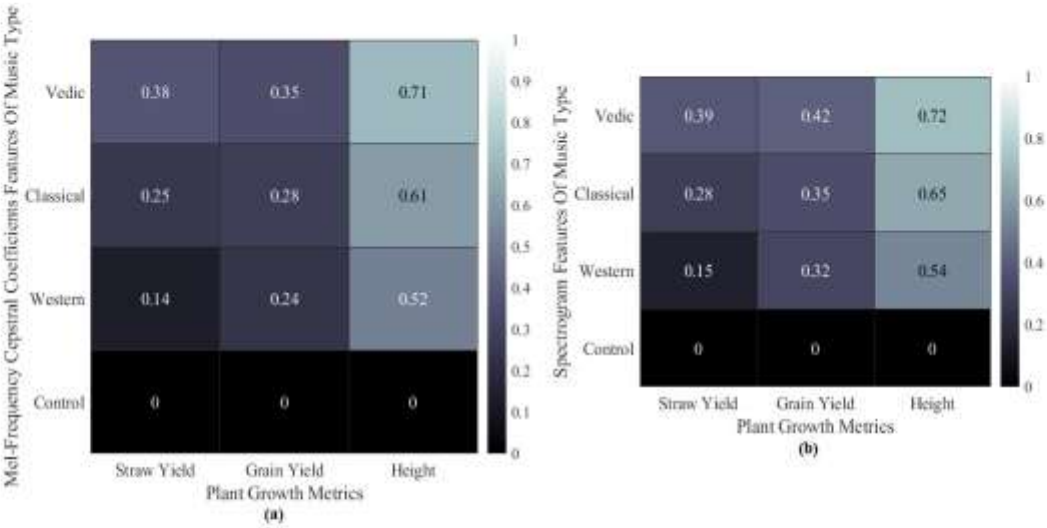

Fig. 29 Correlation Analysis of (a) Mel-Frequency Cepstral Coefficients (MFCC) and (b) Spectrogram Features of Different Music Type

3.2 Performance Measures

Performance measures are evaluated to access the performance such as Accuracy, Specificity, Mean, Median, Root Mean Squared Error (RMSE), Mean Squared Error (MSE) and Mean Absolute Error (MAE).

3.2.1. Accuracy

Accuracy is a performance metric that measures the proportion of correct predictions made by a model out of the total predictions. It is calculated using equation (13).

$$Accuracy=\frac{(TP+TN)}{(TP+FP+TN+FN)} \quad (13)$$

Here, TP signifies True Positive; TN denotes True Negative; FP signifies False Positive and FN denotes False Negative.

3.2.2. Specificity

Specificity is defined as the proportion of actual negatives that are correctly predicted as negative by the model. It is calculated using equation (14).

$$Specificity = \frac{TP}{FN + TP} \quad (14)$$

3.2.3. Root Mean Square Error (RMSE)

RMSE quantifies the difference between predicted values and observed values, providing a single numerical value that reflects the model's predictive performance. It is calculated using equation (15).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2} \quad (15)$$

Here, P denotes the predicted values, O represents the observed values and n is the total number of observations.

3.2.4. Mean Square Error (MSE)

MSE quantifies the average squared difference between the predicted values by the model and the actual target values. The formula for MSE is expressed as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(P_i - O_i\right)^2 \quad (16)$$

3.2.5. Mean Absolute Error (MAE)

MAE quantifies the average magnitude of errors between predicted values and actual values, treating all errors equally without considering their direction. The formula for MAE is expressed as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\left(P_i - O_i\right)\right| \quad (17)$$

3.3. Performance analysis

Figure 30-36 shows simulation result of EMI-PG-SFWT method. The performance metrics are analysed with existing SB-PGP-STN [21], PPG-TSD-GAN [22] and PHEPCF- MRCNN [23] methods.

This bar graph in figure 30 compares the mean performance of different methods (SB-PGP-STN, PPG-TSD-GAN, PHE-PCF-MRCNN and the proposed EMI-PGSFWT) across various music types (Vedic, Classical, Western) and a control group. Across all methods, Vedic music consistently shows the highest mean performance, ranging from approximately 78 to 80. Classical music follows, with mean values between roughly 75 and 78.Western music and the control group have the lowest mean performance, with values around 72 to 75. Notably, the proposed EMI-PG-SFWT method exhibits the highest mean performance for all music types and the control group compared to the other methods

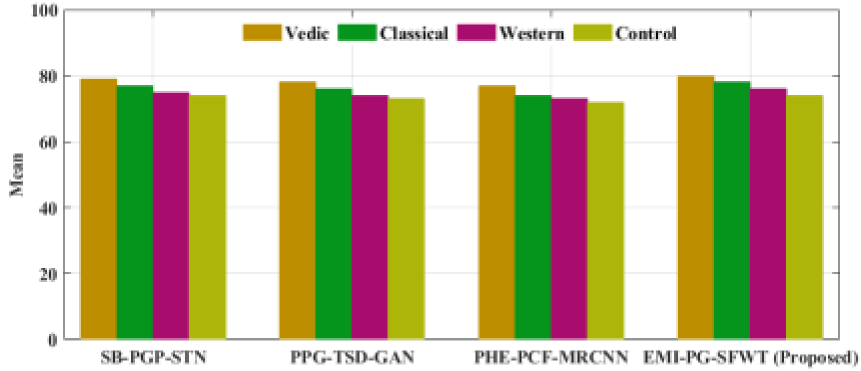

Fig. 30 Performance Analysis of Mean

Figure 31 presents a performance analysis using median values, comparing different methods (SB-PGP-STN, PPG-TSD-GAN, PHE-PCF-MRCNN and the proposed EMI-PG-SFWT) across various music types (Vedic, Classical, Western) and a control group. Like the mean performance, Vedic music consistently yields the highest median values (around 72-75) across all methods. Classical music follows closely (around 68- 72), while Western music and the control group show the lowest median performance (around 65-68). The proposed EMI-PG-SFWT method demonstrates a slight advantage, achieving the highest median performance for each music type and the control compared to the other methods.

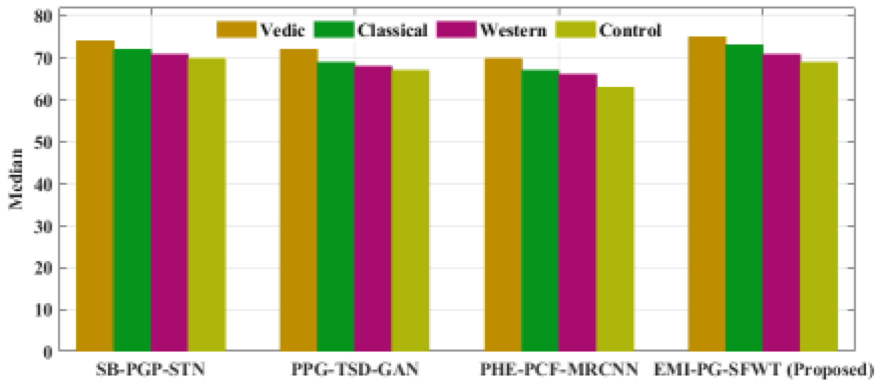

Fig. 31 Performance Analysis of Median

Figure 32 presents a performance analysis using accuracy values, comparing methods such as SB-PGP-STN, PPG-TSD-GAN, PHE-PCF-MRCNN and the proposed EMI-PG SFWT across various music types and a control group. The proposed EMIPG- SFWT method achieves the highest accuracy for Vedic music (around 96%), followed by classical music (around 93%), Western music (around 90%) and the control group (around 88%). The other methods demonstrate slightly lower accuracies with Vedic music around 92-94%, classical music around 88-91%, Western music around 84-88% and the control around 82-86%. The proposed methods consistent edge underscores its superior capability in accurately predicting plant growth parameters.

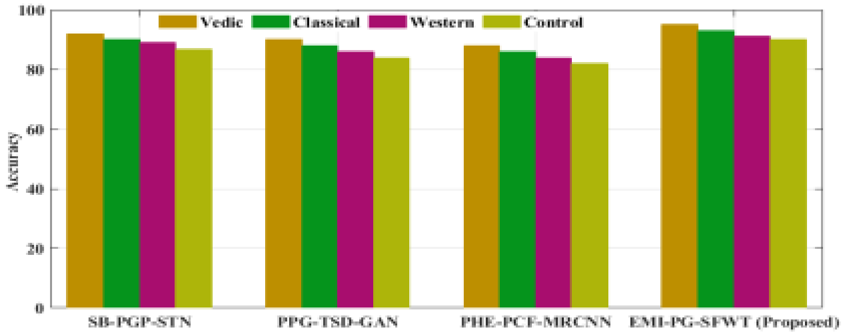

Fig. 32 Performance Analysis of Accuracy

The specificity values in figure 33 show the superiority of EMI-PG-SFWT. The method achieves the highest specificity for Vedic music (around 95%), followed by classical music (around 92%), Western music (around 89%) and the control group (around 87%). Other methods display slightly lower specificity values: Vedic music around 91- 93%, classical music around 88-90%, Western music around 85-88%, and the control group around 83-86%. The EMI-PG-SFWT method demonstrates a notable improvement in reducing false positives, particularly in Vedic and classical music treatments.

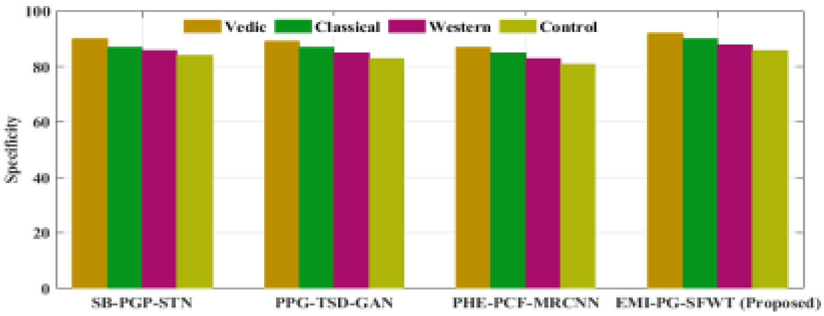

Fig. 33 Performance Analysis of Specificity

The performance analysis of MSE is shown in figure 34. The MSE (Mean Squared Error) values for EMI-PG-SFWT are the lowest, with Vedic music around 0.014, classical music around 0.022, and Western music around 0.030 and the control group around 0.036. Other methods show higher MSE values: Vedic music around 0.018-0.022, classical music around 0.025-0.030, Western music around 0.035-0.038, and the control group around 0.040-0.045. This further highlights EMI-PG-SFWT s advantage in achieving lower prediction errors across the board.

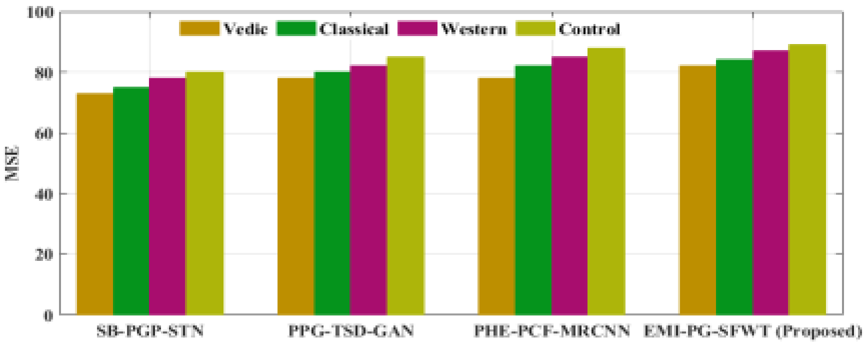

Fig. 34 Performance Analysis of MSE

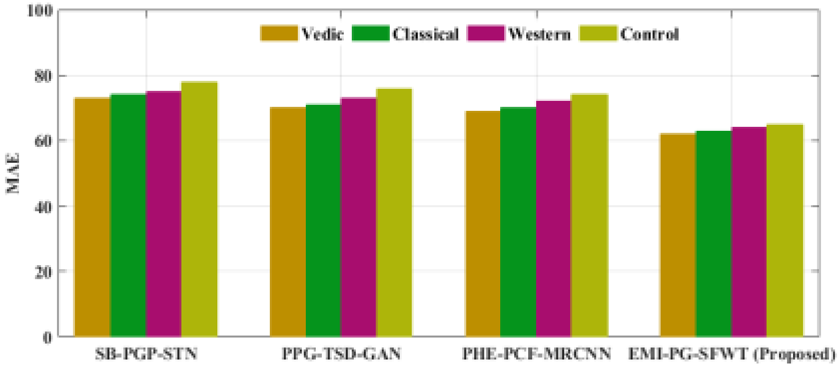

Fig. 35 Performance Analysis of MAE

The performance analysis of MAE is shown in figure 35. The MAE (Mean Absolute Error) values also favour EMI-PG-SFWT, which records the lowest errors for Vedic music (around 0.10), followed by classical music (around 0.13), Western music (around 0.16) and the control group (around 0.18). Other methods display higher MAE values with Vedic music around 0.13-0.16, classical music around 0.16-0.20, Western music around 0.20-0.23 and the control group around 0.23-0.25. The reduced MAE for EMIPG- SFWT confirms its ability to minimize absolute deviations in predictions.

The performance analysis of RMSE is shown in figure 36. In terms of RMSE (Root Mean Squared Error), the values for EMI-PG-SFWT are consistently the lowest, indicating higher precision. For Vedic music, the RMSE is around 0.12, followed by classical music (around 0.15), Western music (around 0.18) and the control group (around 0.20). Existing methods have higher RMSE values, with Vedic music around 0.15- 0.18, classical music around 0.18-0.22, Western music around 0.22-0.25 and the control group exceeding 0.25. EMI-PG-SFWTs reduced RMSE demonstrates its accuracy in minimizing prediction errors across all music types.

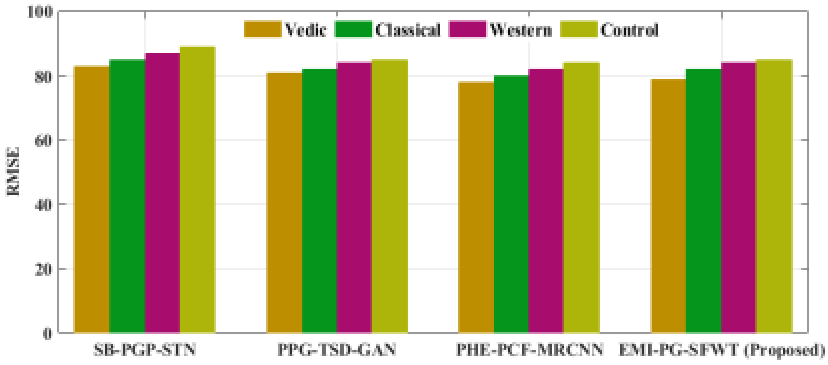

Fig. 36 Performance Analysis of RMSE

3.4 DISCUSSION

The results highlight the significant impact of music on plant growth, particularly when Vedic chanting is used. Among the treatments, plants exposed to Vedic chanting exhibited the highest grain yield (2220.18 kg/ha) and straw yield (3705 kg/ha) compared to the control group, which achieved only 1952.99 kg/ha and 3202.25 kg/ha, respectively. Similarly, chemical analysis revealed superior nutrient uptake for plants exposed to Vedic chanting, with nitrogen uptake of 68.92%, phosphorus uptake of 72.39%, and potassium uptake of 84.29% in the crushed samples. This was markedly higher than the control pots, which had corresponding values of 32.76%, 34.11%, and 30.08%, respectively. These findings suggest that the rhythmic and harmonic properties of Vedic chanting stimulate plant metabolism and improve nutrient absorption. Interestingly, Indian classical music also showed notable results, surpassing Western music and control conditions, albeit to a lesser extent than Vedic chanting. These outcomes support the hypothesis that specific sound frequencies and patterns positively influence plant physiology and chemical composition.

4 CONCLUSION

The proposed EMI-PG-SFWT method validates the hypothesis that music, particularly Vedic chanting, can enhance plant growth by influencing their physical and chemical parameters. The proposed EMI-PG-SFWT method successfully analyzed the spectral features of different music types and correlated them with plant growth metrics. By leveraging advanced pre-processing techniques and the Synchro squeezed fractional wavelet transform, the proposed approach provides a novel framework for understanding the role of sound in plant development. The proposed EMI-PG-SFWT method was implemented in MATLAB. The correlation between music types and plant parameters such as straw yield, grain yield, and nutrient uptake underscores the potential for sound-based agricultural interventions. By achieving a straw yield increase of approximately 15.7% and a grain yield improvement of 13.7% over the control group, Vedic chanting presents itself as a sustainable and effective method to boost crop productivity. These findings pave the way for innovative and sustainable agricultural strategies that harness the power of sound to improve crop yields and plant health. Future research could focus on optimizing specific sound parameters, exploring other plant species, and integrating this approach with modern farming technologies to maximize its practical applications.

5 Authors Contribution

Ujwal Ramekar designed the study, collected and curated the data, performed the formal analysis, and prepared the initial draft of the manuscript.
Dr. Tripti Goel supervised the research work, contributed to refining the methodology, validated the results, and critically revised the manuscript for important intellectual content.
Dr. Ajay Gurjar handled project administration, contributed to data visualization, and assisted in reviewing and editing the final version of the manuscript.
Dr. Viraj Gulhane developed the analytical tools and contributed in developing the statical data.
Dr. Nikesh Gadare have implemented the statical analysis and contributed in writing the manuscript .
All authors read and approved the final manuscript.

6 Declarations

Conflict of interest: The authors declare that there are no conflicts of interest in the publication of this document. All authors have no financial or personal relationships with other people or organizations that could inappropriately influence or bias the content of the paper.
Data availability: All data sets were self-generated during this experimental study and included in this article.
Funding: This experimental study has no funding from any funding agency or government institute.

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