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From Raaga to Notation: Bridging Emotions and Music Through Neural Networks

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Abstract: ***This study pioneers the integration of artificial intelligence with Indian classical music to create a neural network capable of generating raagas and musical notations based on emotional inputs. In the first phase, we trained the neural network on the ten principal thaats of Indian classical music, aiming to synthesize new raagas that maintain the traditional essence. The second phase focused on Bengali songs, using emotion indices derived from song lyrics analyzed by ChatGPT - 4 to generate corresponding Swaralipi. Despite the challenges in accurately capturing the emotional depth of lyrics and translating them into musical notation, our results demonstrate the potential of neural networks in music generation and the preservation of cultural heritage. The research underscores the unexplored richness of Indian classical music and its susceptibility to being overshadowed by contemporary forms. Our findings advocate for the future use of AI in safeguarding and revitalizing the legacy of Indian classical music traditions.***

Keywords: Artificial Intelligence, Indian Classical Music, Neural Networks, Emotion Analysis, Cultural Preservation

1. Introduction

The human brain's deep intertwining with emotions is fundamentally aligned with the concept of harmony. We naturally seek resonance with nature's inherent harmony, as this alignment is essential to our being. Over time, the concept of connecting with this harmony has evolved markedly, giving rise to the development of music. Music, often termed the 'language of emotions) 'Cooke, 1959), is essentially an arrangement of notes that resonate profoundly with us due to the way these combinations echo our internal states.

In their recent research, Juslin and Vastfj¨all¨ (in press) have presented a theoretical framework outlining six mechanisms through which music can induce emotions. These mechanisms describe distinct brain functions that have developed progressively and in an ordered manner during evolution, as they rely on functions with varied evolutionary origins (Juslin & Vastfj¨all¨ D, 2008). The mechanisms delineated in their framework include Brainstem Reflex, Evaluative Conditioning (EC), Emotional Contagion, Visual Imagery, Episodic Memory, and Musical Expectancy. Thus, music can be considered a potent stimulus for inducing or amplifying our emotions.

The dynamical structure of a song, which emerges from the language of music, is an embodiment of human emotions. Ancient song forms often closely intertwined lyrics with melody, suggesting a deep historical connection between music and language. This link also implies that language and music may have co - evolved, sharing a significant relationship. In our modern culture, when composers create songs, they often craft the dynamics of musical notes to reflect the emotions and themes within the lyrics, a process that seems intuitive because our brains are predisposed to under - stand the relationship between emotions (expressed in words) and dynamical musical notes.

This project endeavors to explore and quantify the intrinsic connection between human emotions and musical note combinations. Our study comprises two sections: the first is centered on the relationship between emotions and Indian classical raagas, where we have quantified emotion parameters using the article "Emotional responses to Hindustani raga music: the role of musical structure." The second section focuses on the relationship between emotions and traditional Bengali songs, where emotion parameters were quantified using ChatGPT - 4 based on the lyrics. Here, we have endeavored to study the correlation between emotion parameters and the swaralipi of the songs utilizing a neural network.

2. Section A: Analysis on Thaats with AI

2.1 Motivation

This research delves into the realm of Indian classical music through the innovative lens of artificial intelligence, specifically neural networks. Indian classical music, known for its rich heritage and intricate structure, offers a unique challenge and opportunity for computational creativity. Un - like Western music, which often revolves around chords and harmonies, Indian classical music is fundamentally anchored in Raagas – modes or frameworks for improvisation.

The decision to train our neural network on 'Thaats 'instead of individual Raagas stems from the foundational role of Thaats in the Indian classical system. Thaats provide the basic structure from which numerous Raagas are derived, each Thaat serving as a parent scale for several Raagas. In this project, we focus on the ten principal Thaats – Bhairav, Bhairavi, Bilawal, Kafi, Kalyan, Khamaj, Marwa, Poorvi, Todi, and Asavari – which encompass a comprehensive range of melodic structures in Indian music. We used Poorvi and Todi as our cross validation set and rest of the Thaats as

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training set of the neural network. By training our neural network on these ten thaats, we aim to explore the potential of AI in understanding and generating novel yet traditionally rooted Raagas.

Here are the notes of the Thaats.
1) Bhairav: Sa, Re (Komal), Ga, Ma, Pa, Dha (Komal), Ni, Sa.
2) Bhairavi: Sa, Re (Komal), Ga (Komal), Ma (Komal), Pa, Dha (Komal), Ni (Komal), Sa.
3) Bilawal: Sa, Re, Ga, Ma, Pa, Dha, Ni, Sa.
4) Kafi: Sa, Re, Ga (Komal), Ma, Pa, Dha (Komal), Ni, Sa.
5) Kalyan: Sa, Re, Ga, Ma (Tivra), Pa, Dha, Ni, Sa.
6) Khamaj: Sa, Re, Ga, Ma, Pa, Dha, Ni (Komal), Sa.
7) Marwa: Sa, Re (Komal), Ga, Ma (Tivra), Pa, Dha, Ni, Sa.
8) Poorvi: Sa, Re (Komal), Ga, Ma (Tivra), Pa, Dha (Komal), Ni, Sa.
9) Todi: Sa, Re (Komal), Ga (Komal), Ma (Tivra), Pa, Dha (Komal), Ni (Komal), Sa.
10) Asavari: Sa, Re, Ga (Komal), Ma, Pa, Dha (Komal), Ni (Komal), Sa.

Each of these Thaats forms the basis for various Raagas in Indian classical music. The use of ’komal) ’flat) and ’tivra ’)sharp) notes in certain thaats adds a unique character to each, shaping the mood and feel of the Raagas derived from them.

2.2 Emotional Analysis of Thaats

To evaluate the emotional expressions of the ten principal thaats, we utilized a novel approach by analyzing the correlation between individual swaras (notes) and their associated emotional impacts. These correlation coefficients were figured out by a previous study by A. Mathur, S. H. Vijayaku - mar, B. Chakrabarti and N. C. Singh in 2015, named ”Emotional responses to Hindustani raga music: the role of musical structure” published in Front. Psychol., 30 April 2015, Sec. Emotion Science, Volume 6 - 2015. The correlation coefficients (β) displayed in Table 1 were derived from a comprehensive sentiment analysis, where each swara was rated for six emotional categories: Happy, Romantic, Calm, Longing, Tensed, and Sad. For instance, the happiness score for a thaat was calculated by averaging the happiness coefficients of all the notes comprising the thaat. Following this methodology, we ascertained the predominant emotional character of each thaat, which further allowed us to synthetically generate raagas with targeted emotional expressions.

2.3 Numerical Representation of Thaats

Each thaat within the framework of Indian classical music is constructed from a specific set of swaras (notes), which can be represented numerically to facilitate computational analysis and syn - thesis. In our methodology, we assign a numerical value to each swara corresponding to its position in the chromatic scale, with ’Sa ’as the tonic (1) and proceeding through the octave to the higher ’Sa) ’also designated as 1, completing the cycle). This approach allows us to define each thaat as a sequence of integers. For instance, the Bilawal thaat, which corresponds to the major scale in West - ern music, is represented as [1, 3, 5, 6, 8, 10, 12, 1]. Similarly, Khamaj, Kafi, Asavari, and other thaats are represented by their distinct sequences, capturing their essence in a form that can be readily processed by neural network models. These numerical sequences reflect the ascending (Arohana) and descending (Avarohana) order of notes, which are crucial in defining the mood and characteristics of the respective thaat. Here, we list the numerical representations:

• Bilawal: [1, 3, 5, 6, 8, 10, 12, 1, 12, 10, 8, 6, 5, 3]

Table 1: Correlation Coefficients between Swaras and Emotions

Swaras	Happy	Romantic	Calm	Longing	Tensed	Sad	
Sa	0.17	0.2	0.3	0.11	0.01	-0.12	Note: Correlation
re	- 0.79**	- 0.83**	- 0.88**	0.60*	0.91**	0.74**	
Re	0.66*	0.66*	0.59*	- 0.65*	- 0.67*	- 0.69*	
ga	0.05	0	0.07	0.08	0.04	-0.06	
Ga	0.49	0.52	0.45	-0.47	-0.57	-0.42	
Ma	0	0.15	0.18	0.22	-0.14	0.16	
ma	-0.47	-0.51	- 0.66*	0.2	0.47	0.35	
Pa	0.25	0.08	-0.06	-0.22	0.14	-0.23	
dha	- 0.74**	- 0.67*	-0.41	0.89**	0.61*	0.80**	
Dha	-0.13	-0.1	-0.12	-0.15	0	0.04	
ni	0.05	0.01	0.2	0.16	-0.11	-0.03	
Ni	0.08	0.05	-0.08	-0.39	-0.06	-0.19	

coefficients (β) marked with a single (*) and a double asterisk (**) indicate significant correlations at $p < 0.05$ and $p < 0.001$ respectively.
- Khamaj: [1, 3, 5, 6, 8, 10, 11, 1, 11, 10, 8, 6, 5, 3]
- Kafi: [1, 3, 4, 6, 8, 10, 11, 1, 11, 10, 8, 6, 4, 3]
- Asavari: [1, 3, 4, 6, 8, 9, 11, 1, 11, 9, 8, 6, 4, 3]
- Bhairavi: [1, 2, 4, 6, 8, 9, 11, 1, 11, 9, 8, 6, 4, 2]
- Bhairav: [1, 2, 5, 6, 8, 9, 12, 1, 12, 9, 8, 6, 5, 2]
- Kalyan: [1, 3, 5, 7, 8, 10, 12, 1, 12, 10, 8, 7, 5, 3]
- Marwa: [1, 2, 5, 7, 8, 10, 12, 1, 12, 10, 8, 7, 5, 2]
- Poorvi: [1, 2, 5, 7, 8, 9, 12, 1, 12, 9, 8, 7, 5, 2]
- Todi: [1, 2, 4, 7, 8, 9, 12, 1, 12, 9, 8, 7, 4, 2]

This numerical system serves as the backbone for our neural network’s learning process, pro - viding a structured yet flexible approach to generate new raagas based on the foundational thaats.

2.4 Computation of Emotional Parameters for Thaats

In our study, the emotional parameters of each thaat were quantified by averaging the emotional correlation coefficients of their constituent swaras. Each thaat was analyzed to derive a set of six emotional metrics: Happiness, Romanticism, Calmness, Longing, Tension, and Sadness. The thaats were then sequenced in the following order: Bilawal, Khamaj, Kafi, Asavari, Bhairavi, Bhairav, Kalyan, Marwa, Poorvi, and Todi. The calculated emotional parameters for each thaat, arranged in the specified sequence of emotions, are presented below:

Bilawal: [0.2171, 0.2229, 0.1800, - 0.2214, - 0.1843, - 0.2071]

Khamaj: [0.2129, 0.2171, 0.2200, - 0.1429, - 0.1914, - 0.1843]

Kafi: [0.1500, 0.1429, 0.1657, - 0.0643, - 0.1043, - 0.1329]

Asavari: [0.0629, 0.0614, 0.1243, 0.0843, - 0.0171, - 0.0243]

Bhairavi: [- 0.1443, - 0.1514, - 0.0857, 0.2629, 0.2086, 0.1800]

Bhairav: [- 0.0771, - 0.0714, - 0.0714, 0.1057, 0.1286, 0.1057]

Kalyan: [0.1500, 0.1286, 0.0600, - 0.2243, - 0.0971, - 0.1800]

Marwa: [- 0.0571, - 0.0843, - 0.1500, - 0.0457, 0.1286, 0.0243]

For the purpose of cross - validation, Poorvi and Todi thaats were reserved and analyzed separately. The cross - validation process is crucial for assessing the generalizability of our neural net - work model and its capacity to generate emotionally coherent raagas based on unseen data. The emotional parameters for the cross - validation set are as follows:

Poorvi: [- 0.1443, - 0.1657, - 0.1914, 0.1029, 0.2157, 0.1329]

Todi: [- 0.2071, - 0.2400, - 0.2457, 0.1814, 0.3029, 0.1843]

This methodology ensures that our neural network is trained on a robust dataset, capturing the nuanced emotional landscape of Indian classical music, and evaluated for its ability to extrapolate this knowledge to new, unlearned thaats.

2.5 Neural Network Training and Validation

The neural network employed in our study is a Sequential model, constructed using Keras. It com - prises an input layer with a dimensionality specific to our feature set, followed by one hidden layer with 12 neurons using the ReLU activation function, and an output layer with 14 neurons employ - ing a linear activation function. This architecture was chosen to model the complex relationships between the musical features and the emotional parameters of the thaats.

The model was compiled with the mean squared error loss function and the Adam optimizer. Training was conducted over 1, 000 epochs, with loss values recorded at each epoch to monitor the learning process. Figure 2 illustrates the model’s training loss and cross - validation loss over time. Both metrics exhibit a declining trend, indicating successful learning with a convergence of validation loss, which suggests good generalizability to unseen data.

The loss history and cross - validation loss was stored in separate lists during the training pro - cess. As shown in the graph, both the training loss and the cross - validation loss decrease substantially, with the cross - validation loss closely tracking the training loss. This close correspondence between the two loss curves indicates that the model is not overfitting and is learning generalizable patterns from the data.

2.6 Prediction of Swaralipi from Emotional Input

Given an emotional input vector, our neural network model predicts a corresponding sequence of swaras. For the input [0.22, 0.12, 0.18, −0.1, −0.01, −0.19], the network output, prior to applying the threshold rounding, yielded a sequence of values that map onto the chromatic scale. After round - ing, these predicted values correspond to the numeric sequence [1, 3, 4, 6, 8, 9, 11, 1, 10, 9, 8, 6, 4, 3].

Translating this into the swaralipi notation, we obtain: SA, RE, ga, MA, PA, dha, ni, SA, DHA, dha, PA, MA, ga, RE, SA.

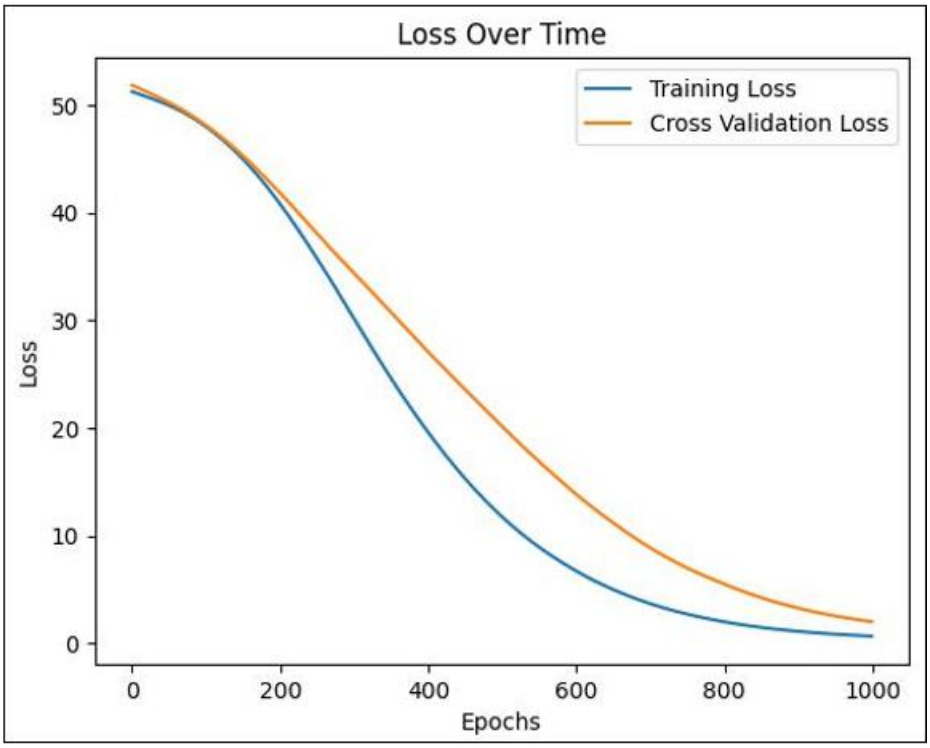

Figure 1: Training and Cross Validation Loss over 1, 000 epochs.

This output sequence demonstrates the model's ability to generate a musically coherent swaralipi from a given set of emotional parameters, validating the effectiveness of our neural network in learning and recreating the structural patterns of Indian classical music based on emotional context.

2.7 Conclusion and Future Directions

The present study marks a significant stride in the domain of computational musicology, demonstrating the viability of neural networks in capturing and expressing the emotional essence of Indian classical music through the generation of swaralipi. The successful prediction of coherent musical note sequences from given emotional inputs suggests that the model has effectively internalized the complex rules and nuances that govern the construction of thaats.

Looking ahead, the implications of this research extend into various exciting prospects. The model can be refined to accommodate live input, allowing for real - time generation of music that responds to dynamic emotional cues. This could revolutionize the way music is composed, taught, and even performed, with potential applications in therapeutic settings, where music is tailored to the emotional needs of individuals. Furthermore, such AI could assist in preserving and disseminating the rich heritage of Indian classical music by providing an accessible platform for learners worldwide.

In future iterations, the integration of more granular emotional data and the expansion of the dataset to include a wider array of raagas could enhance the model's predictive accuracy and creative capabilities. Moreover, the exploration of deep learning techniques like recurrent neural networks (RNNs) and generative adversarial networks (GANs) could yield even more sophisticated models that not only generate notes but also compose full - fledged performances complete with rhythm and expression.

Ultimately, this study paves the way for a new era in the fusion of traditional music and artificial intelligence, where the latter becomes a custodian of cultural expression, preserving and perpetuating the legacy of musical traditions through the digital medium.

3. Section B: Emotion - Driven Music Generation from Bengali Songs

3.1 Motivation

In the second phase of our exploration into the confluence of artificial intelligence and music, we shift our focus to the rich tapestry of Bengali songs, renowned for their emotive depth and lyrical beauty. This segment of our research aims to harness the expressive potential of neural networks to generate musical notations from a given set of emotional inputs, effectively teaching the AI to compose music that resonates with specific emotional tones. By training our model on a curated dataset of Bengali songs, which includes both the emotional undertones and corresponding musical notations, we seek to capture the essence of this genre and enable the creation of new compositions that maintain the cultural and emotional integrity of the traditional forms. The successful implementation of this model could open up avenues for personalized music generation, therapeutic applications, and the digital preservation of cultural music heritage.

3.2 Emotion Analysis and Selection for Bengali Songs

In quantifying the emotional content of Bengali songs, we posited that the emotional sentiment of the lyrics is reflective

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of the song's overall musical emotion. To this end, we employed the advanced linguistic capabilities of ChatGPT - 4 to perform a sentiment analysis on the lyrics of our dataset. Initially, we computed an emotion index for each song, ranging from 0 to 1, covering a broad spectrum of sixteen distinct emotions: Happiness, Sadness, Fear, Anger, Surprise, Disgust, Anticipation, Love, Anxiety, Devotional, Relax, Curiosity, Patriotism, Completeness, Longing, and Focus.

However, upon examination of the emotion indices, we observed significant overlap among the various emotions, which could potentially complicate the learning process for the neural network. To streamline the model's training efficiency and improve its interpretative clarity, we narrowed the focus to six emotions. These were selected based on their distinctness and prevalence in the musical context: the fundamental four of Happiness, Sadness, Fear, and Anger, complemented by Devotional and Patriotism. This reduction aimed to mitigate the confounding effects of emotional overlap and to align the neural network's task with the core emotional themes that are most representative of Bengali music.

3.3 Numerical Representation of Swaralipi for Neural Network Training

In adapting Swaralipi (Indian musical notation) for computational analysis, each note was numerically encoded, spanning three octaves - Mandra, Madhya, and Taar Saptak. This encoding covered the range from Shuddha Ma of the lower octave (Mandra Saptak) to Shuddha Pa of the higher octave (Taar Saptak), using numbers from 1 to 27. The choice of three octaves aligns with the prevalent us - age in Indian classical music, encompassing a wide pitch range essential for capturing the diversity of musical expressions.

Table 2: Numerical Assignment of Notes from Ma of Mandra Saptak to Pa of Taar Saptak including Komal and Tivra Variants

Number	Note	Number	Note
1	Mandra Ma	15	Madhya Pa
2	Mandra Tivra Ma	16	Madhya Komal Dha
3	Mandra Pa	17	Madhya Dha
4	Mandra Komal Dha	18	Madhya Komal Ni
5	Mandra Dha	19	Madhya Ni
6	Mandra Komal Ni	20	Taar Sa
7	Mandra Ni	21	Taar Komal Re
8	Madhya Sa	22	Taar Re
9	Madhya Komal Re	23	Taar Komal Ga
10	Madhya Re	24	Taar Ga
11	Madhya Komal Ga	25	Taar Ma
12	Madhya Ga	26	Taar Tivra Ma
13	Madhya Ma	27	Taar Pa
14	Madhya Tivra Ma		

For the numerical representation of Swaralipi in our dataset, we explored two methods: 1. Direct Numeric Encoding: Assigning a specific number to each note and representing them as an array of these numbers.2. Differential Encoding: Notating the difference between consecutive notes by subtracting their numerical values.

After careful consideration, we opted for the Direct Numeric Encoding approach for two primary reasons. Firstly, this method avoids the introduction of negative elements, which can occur in Differential Encoding. For example, the sequence 'Sa Re Sa 'translates to '8, 10, 8 'in Direct Numeric Encoding, whereas it would be '2, - 2 'in Differential Encoding. Secondly, the first method's output format is more conducive to audio conversion using Python, facilitating the auditory representation of our neural network's output.

To standardize the input for our neural network, each song in our dataset was represented by a fixed length of 20 notes. This uniformity in input size ensures consistent training data for the neural network, enhancing its ability to learn and predict musical sequences effectively.

3.4 Dataset Composition and Training Methodology

Our study utilized a carefully curated dataset of 26 renowned Bengali songs, each characterized by its unique emotional and musical attributes. The songs selected for this study include classics like "Gram Chhara Oi Ranga Matir Poth, " "Momo Chitte Nrite Nritte, " and "Jokhon Porbe Na Mor Payer Chinho, " among others. These songs were chosen for their diverse emotional content and their representation of various facets of Bengali music.

To train our neural network, we divided the dataset into two sets:

- **Training Set**: The first 20 songs were used as the training set. This set forms the primary basis for the neural network to learn the relationship between emotional content and musical notation.
- **Cross - validation Set:** The remaining 6 songs, including "Muktiro Mandiro, " "Karar Oi Louho Kopat, " and "Utho Go Bharotolokkhi, " were reserved as the cross - validation set. This set aids in evaluating the model's performance and generalization capabilities on unseen data.

Each song in the dataset was associated with a set of emotional parameters and corresponding Swaralipi data. The emotional parameters were quantified in a six - dimensional vector, representing six basic emotions: Happiness, Sadness, Fear, Anger, Devotional, and Patriotism. For instance, the emotional data for "Gram Chhara Oi Ranga Matir Poth" is represented as [0.7, 0.6, 0.1, 0, 0.2, 0.5], indicating varying levels of these emotions.

The Swaralipi of each song was numerically encoded, following the scheme discussed earlier, where each note is assigned a specific number. For example, the Swaralipi data for the same song might appear as [5, 8, 8, 8, 8, 8, 8, 10, 12, 15,. . ., 12], representing the sequence of notes in the song. This representation provides a structured format for the neural network to process and learn the musical patterns.

This approach of combining emotional analysis with numerical Swaralipi representation forms the core methodology of our study, aiming to create an AI model that can generate music which resonates with specific emotional tones.

3.5 Neural Network Architecture and Training

For the task of generating Swaralipi from emotional inputs, we designed a neural network model using the Sequential API from Keras. The model is structured as follows:

1) **Input Layer**: The first layer of the model is a dense layer with 12 neurons. It receives input data of dimensions equal to the number of emotional parameters, using the ReLU activation function.
2) **Output Layer:** The output layer comprises 20 neurons, corresponding to the 20 notes in our standardized Swaralipi representation. This layer employs a linear activation function, aligning with the continuous nature of our output data.

The model was compiled using the mean squared error as the loss function and Adam optimizer for efficient training. We trained the model over 600 epochs, with the loss values for each epoch stored for analysis. This training involved:

- Feeding the emotional parameter vectors as input.
- Comparing the model's output to the actual Swaralipi sequences.
- Using a separate set of data for validation, ensuring that the model's performance was robust against unseen data.

The training process was iterative, with the model learning and adjusting its weights epoch by epoch to minimize the loss. The recorded loss history, including both the training loss and validation loss, provides insight into the model's learning curve and its ability to generalize beyond the training data.

3.6 Analysis of Model Performance and Discussion on Output Discrepancies

Upon training our neural network model, we observed the learning progress through a loss curve, as depicted in Figure 2. The graph indicates a steady decrease in both training and cross - validation loss, suggesting that the model is learning from the data and improving its predictions over time.

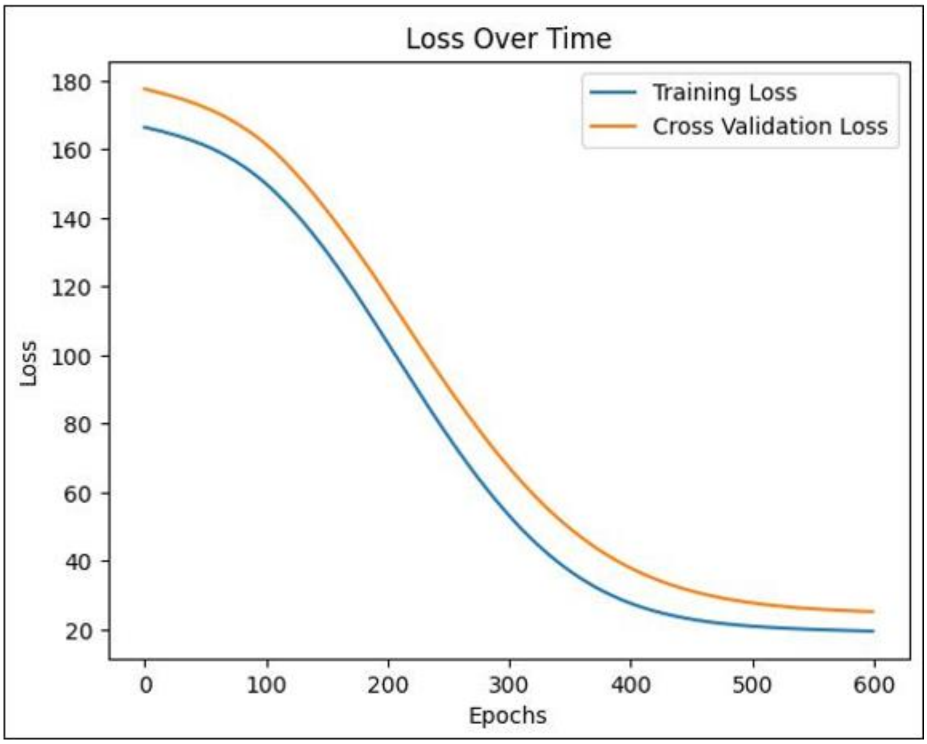

Figure 2: Training and Cross Validation Loss over 600 epochs.

However, when the model was provided with an input vector of emotion indices [0.3, 0.5, 0.9, 0.7, 0.1, 0.1], the predicted Swaralipi sequence did not align with expectations. The output sequence [12, 13, 13,. . ., 14] lacked the desired variability and musical coherence. This outcome prompts a consideration of the potential factors influencing the model's performance:

1) **Accuracy of Emotion Indices:** The emotion indices obtained from ChatGPT - 4 may not have accurately captured the emotional nuances of the lyrics. The subtleties of poetic expression in song lyrics could be lost or oversimplified in the analysis.
2) **Validity of the Postulate:** The underlying assumption that the emotions of the lyrics directly reflect the emotions of the music may not always hold true. The interplay between lyrics and melody can be complex, with the musical composition sometimes conveying different or additional emotional layers.
3) **Other Possible Reasons:** Additional factors that could contribute to the suboptimal pre - dictions include limitations in the dataset size or diversity, insufficient model complexity to capture the richness of the musical structure, or the need for a more nuanced approach to encoding the musical notation for the training process.

Future work could explore these dimensions in greater depth, potentially incorporating alternative emotional analysis tools, expanding the dataset, or experimenting with different neural network architectures. Such improvements might enhance the model's ability to generate Swaralipi that is both emotionally resonant and musically varied.

3.7 Conclusion and Future Outlook on the Preservation of Indian Music

The exploratory nature of our study into AI - driven music generation highlights both the challenges and the profound potential for preserving the rich heritage of Indian music. While our initial results have shown promise, they also underscore the complexity and the nuanced understanding required to faithfully capture the emotional and musical intricacies of Indian songs.

Indian music, with its vast array of raagas, intricate rhythmic patterns, and deep emotional undercurrents, remains largely uncharted in the digital domain. This lack of exploration is not just a matter of academic or technological oversight, but also a reflection of the challenges inherent in encoding and interpreting the music's subtle dynamics. Furthermore, as modernization continues to influence cultural practices, there is a genuine risk of these musical traditions becoming obscured or lost over time.

1) **Digital Preservation:** The use of AI, as demonstrated by our method, offers a digital lifeline to these traditions. By capturing the essence of Indian music in a form that can be learned, replicated, and even evolved by neural networks, we create opportunities for both preservation and global dissemination.
2) **Discovery and Innovation:** The application of neural networks to Indian music opens up new avenues for discovery. By analyzing and generating music computationally, we can uncover patterns and relationships that may not be immediately apparent through traditional analysis.
3) **Cultural Continuity:** Ensuring the continuity of Indian music in the modern age requires innovation that respects tradition. AI can serve as a bridge between the past and the future, enabling new generations to appreciate and engage with their musical heritage.

In conclusion, the future of this method lies not only in refining the AI's capabilities but also in embracing the broader mission of cultural preservation. By continuing to advance our understanding and technological approaches, we can ensure that the treasures of Indian music are not only preserved but also shared and celebrated across the world.

Note: Future iterations of this research should aim to expand the dataset, enhance the accuracy of emotion detection, and explore more complex neural network architectures to capture the full richness of Indian classical music.

4. Project Summary

This research initiative has sought to forge a novel intersection between emotional expression and Indian classical music through the application of neural networks. Our endeavor was structured into two distinct phases, each with its unique focus and methodology.

In the first phase, our objective was to generate new Raagas by leveraging a neural network trained on the ten foundational thaats of Indian classical music. This phase explored the capacity of artificial intelligence to internalize and emulate the structural nuances that define traditional Raagas, thereby paving the way for the creation of original compositions within the classical framework.

The second phase of our project shifted attention to the domain of Bengali songs, employing ChatGPT - 4 to analyze lyrical content and distill the embedded emotions into quantitative indices. These indices, along with the numerically represented Swaralipi, served as the dataset for training our neural network. The challenge was to enable the network to convert emotional data into corresponding Swaralipi sequences.

As the project progressed, we were presented with numerous challenges that necessitated a reevaluation of our approach and the underlying assumptions. The results, while illuminating, underscored the complexities of accurately capturing the essence of musical emotion and its translation into a structured musical format.

In conclusion, the project illuminated the untapped potential of Indian classical music in the context of artificial intelligence and highlighted the importance of such technologies in the preservation and digitalization of cultural heritage. It has set the stage for subsequent inquiries that might refine the accuracy of emotion - to - music translation, expand the diversity of the datasets, and explore more sophisticated neural network models. Our research underlines the promising future of AI in the realm of musicology, where it can act as both a preserver and an innovator of musical traditions.

Acknowledgments

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Special thanks are due to our project supervisor, Br. Atreya, whose guidance and expertise have been pivotal in shaping the direction and success of this project. His unwavering dedication, insightful feedback, and constructive criticism have not only enriched our work but have also fostered a profound learning experience.

We also wish to acknowledge our professors and fellow students at RKMVERI who have contributed their knowledge and assistance. Their collaborative spirit and scholarly camaraderie have greatly enhanced our research experience.

This project is a testament to the collaborative effort and shared vision of all those involved, and we are sincerely grateful for every contribution that made this research possible.

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