MUSIC SENTIMENT ANALYSIS AND ITS APPLICATION IN MUSIC THERAPY BASED ON AI TECHNOLOGY

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SUMMARY

Music therapy, enriched by the integration of AI technology, represents a cutting-edge approach to harnessing the therapeutic power of music for mental and emotional well-being. AI algorithms are employed to analyze individual preferences, emotional states, and physiological responses, enabling the creation of personalized music interventions. These interventions can range from mood-enhancing playlists to dynamically generated compositions tailored to the specific needs of the listener. This paper introduces an Optimized Sentimental n-gram Classifier (OSC) model tailored for application in the context of music therapy. Leveraging artificial intelligence (AI) technology and sentiment analysis techniques, the OSC model aims to enhance the understanding and classification of sentiments expressed during music therapy sessions. The OSC model uses the n-gram classifier for the estimation of the feature vector in the music speech signal. The classifier model comprises of the Artificial Intelligence (AI) for the evaluation of the music therapy for the sentimental analysis. Through extensive experimentation and evaluation, the OSC model demonstrates high accuracy, precision, recall, and F1 scores across multiple iterations, indicating its effectiveness in accurately predicting sentiments and classifying sessions. The model's robust performance suggests its potential to assist therapists in better understanding participants' emotional states and tailoring interventions accordingly. By providing a valuable tool for sentiment analysis in music therapy, the OSC model contributes to advancing the integration of AI technology into healthcare practices, with implications for improving patient outcomes and well-being.

KEYWORDS

Sentimental analysis, Music therapy, Artificial intelligence (AI), Classification, Deep learning

NOMENCLATURE

NLP	Natural language processing
AI	Artificial Intelligence
OSC	Optimized Sentimental n-gram Classifier
TBI	Traumatic brain injuries
GRU	Gated Recurrent Unit

1. INTRODUCTION

Industries as diverse as healthcare, banking, transportation, and entertainment have all been profoundly affected by the fast development of artificial intelligence (AI) technology [1]. Machines can learn from data, identify patterns, make decisions, and solve problems using a variety of approaches that fall under the umbrella of artificial intelligence (AI). One branch of artificial intelligence, machine learning, has recently come to the fore thanks to its capacity to let systems learn to get better over time without human intervention [2]. Advanced machine learning techniques, known as deep learning, have made tremendous strides in fields such as computer vision, speech recognition, and natural language processing. Several applications are incorporating AI technologies to improve efficiency, accuracy, and decision-making. These include medical diagnostics, autonomous vehicles, virtual assistants, and recommendation systems [3]. There needs to be responsible development and deployment of AI systems because the fast progress of AI brings up ethical and societal concerns like privacy implications, algorithm bias, and job displacement. Nonetheless, AI technology continues to evolve, promising further innovations and transformative impacts on society in the years to come [4].

An effective method for analyzing textual data to ascertain the sentiment or emotional tone conveyed therein is sentiment analysis, a subfield of natural language processing (NLP) [5]. Algorithms for sentiment analysis use linguistic and machine learning techniques to sort text into positive, negative, or neutral categories; this helps shed light on public opinion, consumer feedback, and social media sentiment. Businesses use sentiment analysis to gauge customer satisfaction, identify emerging trends, and improve products or services accordingly [6]. In the realm of social media monitoring, sentiment analysis helps organizations understand public perception, track brand sentiment, and manage online reputation. Furthermore, sentiment analysis is increasingly utilized in finance to analyze market sentiment and predict stock market trends based on news articles, social media posts, and other textual sources [7]. While sentiment analysis algorithms have made significant strides in accurately capturing sentiment, challenges such as sarcasm, irony, and cultural nuances continue to pose obstacles to achieving perfect accuracy. Nonetheless, sentiment analysis remains a valuable tool for businesses, researchers, and organizations seeking to harness the power of textual data to inform decision-making processes and better understand human emotions [8].

Sentiment analysis, when combined with AI technologies, becomes a highly efficient and scalable tool for understanding and interpreting vast amounts of textual data [9]. By employing machine learning algorithms, AI can analyze the sentiment expressed in text with remarkable accuracy and speed. These AI-powered sentiment analysis systems can automatically categorize text into positive, negative, or neutral sentiments, enabling organizations to gain actionable insights from large volumes of customer reviews, social media posts, and other textual data sources [10]. Moreover, AI can continuously learn and adapt to evolving language patterns and contexts, improving the accuracy of sentiment analysis over time. Businesses leverage AI-driven sentiment analysis to track customer satisfaction, identify emerging trends, and detect potential issues or crises in real-time [11]. In fields like finance and marketing, AI-powered sentiment analysis enables organizations to monitor market sentiment, gauge public opinion, and make data-driven decisions to stay ahead of the competition [12]. While AI-enhanced sentiment analysis offers numerous benefits, it also requires careful consideration of ethical implications, including privacy concerns and algorithmic biases. Nevertheless, the integration of AI technologies with sentiment analysis continues to drive innovation and transform how organizations extract valuable insights from textual data to enhance decision-making processes and customer experiences [13].

Sentiment analysis with AI technology holds significant potential for enhancing music therapy interventions. By utilizing machine learning algorithms, AI can analyze the emotional content of music and tailor therapeutic playlists to match the specific needs and preferences of individual clients [14]. This personalized approach allows music therapists to create interventions that resonate with the emotional experiences of their clients, fostering deeper engagement and facilitating emotional expression and regulation [15]. Moreover, AI-powered sentiment analysis can assist therapists in monitoring the emotional progress of clients over time, enabling them to adjust therapeutic interventions accordingly. The sentiment analysis detects increasing levels of stress or anxiety in a client's music preferences, therapists can intervene with targeted relaxation techniques or supportive interventions [16]. Additionally, AI can help automate certain aspects of music therapy, such as playlist creation and music selection, allowing therapists to focus more on the therapeutic relationship and client-centered care. While the integration of AI with music therapy shows promise, it is essential to consider ethical considerations, such as privacy and consent, as well as the importance of maintaining the human element in therapeutic interactions [17]. The synergy between sentiment analysis and AI technology offers exciting opportunities to enhance the effectiveness and accessibility of music therapy interventions, ultimately improving outcomes for clients across a wide range of emotional and psychological challenges [18].

The contribution of this paper lies in the development and application of the Optimized Sentimental n-gram Classifier (OSC) model specifically designed for music therapy. By leveraging artificial intelligence (AI) technology and sentiment analysis techniques, the OSC model offers a novel approach to understanding and classifying sentiments expressed during music therapy sessions. The introduction of the OSC model represents an innovative application of AI technology within the field of music therapy. By providing a systematic framework for sentiment analysis, the OSC model enhances the therapeutic process by enabling therapists to gain deeper insights into participants' emotional states. Enhanced Sentiment Analysis experimentation and evaluation, the OSC model demonstrates high accuracy, precision, recall, and F1 scores across multiple iterations. This indicates its effectiveness in accurately predicting sentiments and classifying therapy sessions, thereby facilitating more informed decision-making by therapists. With offering a valuable tool for sentiment analysis in music therapy, the OSC model has the potential to improve patient outcomes and well-being. By better understanding participants' emotional responses to music interventions, therapists can tailor their approaches to meet individual needs, leading to more effective treatment outcomes. The paper underscores the importance of integrating AI technology into healthcare practices, particularly in the context of music therapy. The OSC model exemplifies how AI can be harnessed to augment traditional therapeutic approaches, paving the way for more personalized and data-driven interventions. The contribution of the paper lies in advancing the integration of AI technology into music therapy practices, with the potential to enhance the therapeutic experience and improve patient outcomes.

2. LITERATURE REVIEW

In recent years, the integration of sentiment analysis with AI technology has emerged as a promising approach to enhancing music therapy interventions. This innovative fusion combines the power of machine learning algorithms with the therapeutic potential of music, offering new avenues for personalized and effective treatment strategies. Several studies have explored the application of sentiment analysis in music therapy, aiming to better understand the emotional responses elicited by music and how they can be leveraged to support therapeutic goals. sentiment analysis to analyze the emotional content of music playlists and tailor them to meet the specific needs of individual clients. For example, researchers have developed algorithms capable of detecting the emotional valence and arousal levels of music tracks, allowing therapists to create playlists that align with the emotional states of their clients. By providing personalized music experiences that resonate with the client's emotions, therapists can enhance engagement and facilitate emotional expression and regulation during therapy sessions. Enge and Stige (2022), presents a collective case study focusing on the utilization of music therapy among refugee children. Titled "Musical pathways to the peer community," the study explores how music therapy serves as a means for refugee children to integrate into peer communities. This research sheds light on the role of music in facilitating social connections and navigating new environments for children experiencing displacement.

Research by Carpenté et al. (2022) examines the effect of imitation on participation in impromptu music therapy sessions for autistic children who have difficulty communicating verbally. This research, which was published in the Nordic Journal of Music Therapy, looks at how children on the autism spectrum can benefit from music therapy by imitating the sounds of other instruments. Tunca, Sezen, and Wilk (2023), explores an innovative application of natural language processing techniques in analyzing content and sentiment within articles related to the metaverse published by The Guardian. This study employs Leximancer and natural language processing to conduct an exploratory content and sentiment analysis. By examining the textual content and sentiment expressed in The Guardian's articles on the metaverse, this research aims to gain insights into public perceptions, attitudes, and trends surrounding this emerging technological concept. This study's results might help us better comprehend the media's coverage of the metaverse and the ways it's shaping conversations about the future of technology, culture, and society. The effects of music therapy on pregnant women, their fetuses, and newborns are examined in a study by Çatalgöl and Ceber Turfan (2022). This prospective, controlled trial investigates the effects of music therapy interventions on pregnant women's health, the growth and development of their babies, and the outcomes for the newborns themselves. This research seeks to shed light on the possible therapeutic benefits of music on prenatal health and well-being by investigating the effects of music therapy on pregnant women and their offspring. Pregnant women and their newborns may benefit from music-based interventions that are based on the results of this study.

The impact of music therapy on the well-being of sickle cell disease adults is investigated in Rodgers-Melnick et al. (2022). Music therapy interventions' effects on sickle cell disease patients' health and quality of life are the focus of this mixed-methods feasibility study. In order to fully grasp the possible advantages of music therapy for this group of patients, the study will use a mixed-methods strategy, integrating quantitative evaluations with qualitative insights. There may be new opportunities for comprehensive care and support for people with sickle cell disease if this study's results guide the creation of music-based interventions to improve their quality of life and general health. In their comprehensive review, Chu et al. (2022) examine the use of AI in CAM from a systematic scoping perspective. This study investigates the application of AI technologies across various CAM modalities, exploring how AI is being integrated into practices such as acupuncture, herbal medicine, and mind-body therapies. By conducting a comprehensive review of existing literature, the study aims to identify trends, challenges, and opportunities in the use of AI within the CAM field. The findings of this scoping review may inform future research directions and guide the development of innovative AI-driven approaches to enhance the effectiveness and accessibility of CAM therapies. This research contributes to a deeper understanding of the intersection between AI and CAM, offering insights into the potential synergies between traditional healing practices and cutting-edge technological advancements.

McFerran, Skinner, Hall, and Thompson (2022), explores the utilization of online music gatherings to foster social inclusion for people with disabilities in Australia during the COVID-19 pandemic. This study delves into the intersection of structure, agency, and community within the context of online music gatherings, examining how these gatherings provide a platform for individuals with disabilities to actively engage in musical activities and social interactions. By investigating the dynamics of online music gatherings, the study elucidates the ways in which individuals with disabilities assert agency and navigate social structures to establish a sense of belonging and community through music. The findings of this research highlight the transformative potential of online music gatherings as a tool for promoting social inclusion, enhancing well-being, and fostering meaningful connections among individuals with disabilities, particularly during times of social isolation and uncertainty such as the COVID-19 pandemic. McFerran, Skinner, Hall, and Thompson (2022), explores the utilization of online music gatherings to foster social inclusion for people with disabilities in Australia during the COVID-19 pandemic. This study delves into the intersection of structure, agency, and community within the context of online music gatherings, examining how these gatherings provide a platform for individuals with disabilities to actively engage in musical activities and social interactions. By investigating the dynamics of online music gatherings,

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The influence of music therapy on dementia is investigated by Madsø, Molde, Hynninen, and Nordhus (2022) using a series of repeated single-case studies that measure happiness and social interaction. This study delves into the therapeutic effects of music therapy on individuals with dementia, focusing on how music interventions influence their overall well-being and social interactions. By employing repeated single-case studies, the research aims to provide insights into the individualized responses to music therapy among dementia patients, shedding light on the effectiveness of such interventions in improving their quality of life and promoting sociable interactions despite cognitive decline. Researchers Siponkoski et al. (2022) look into how neurological music therapy helps people with traumatic brain injuries (TBIs) recover emotionally and behaviorally. This study uses a randomized controlled crossover design to look at the effects of music therapy on patients' emotional and behavioral recovery after traumatic brain injury. By assessing the impact of music therapy on individuals recovering from TBI, the research aims to elucidate the potential therapeutic benefits of incorporating music into rehabilitation programs for improving overall well-being and emotional recovery post-injury. Joshi and Kanoongo (2022), provides a closer review of depression detection using emotional artificial intelligence (AI) and machine learning techniques. This review explores the application of emotional AI and machine learning algorithms in detecting depression, focusing on the use of digital technologies to assess emotional states and identify depressive symptoms. By critically examining the current state of research in this field, the study aims to elucidate the potential of emotional AI for improving the detection and management of depression, offering insights into innovative approaches for mental health assessment and intervention. Grau-Sánchez et al. (2022), presents a consensus on key methodological challenges in investigating music-based rehabilitation. This study addresses the methodological complexities associated with conducting research on music-based rehabilitation interventions, providing insights into the design, implementation, and evaluation of such interventions. By synthesizing expert opinions and research findings, the consensus paper offers recommendations for overcoming methodological challenges and advancing the field of music-based rehabilitation, highlighting the importance of rigorous research methodologies and interdisciplinary collaboration in this area.

Timakum, Xie, and Song (2022), analyzes e-mental health research to map the relationship between information technology and mental healthcare. This study explores the intersection of information technology and mental healthcare, examining how digital innovations are shaping the delivery of mental health services. By mapping the landscape of e-mental health research, the study aims to identify emerging trends, challenges, and opportunities in leveraging technology to improve mental healthcare delivery and accessibility, offering insights into the potential of e-mental health interventions for addressing global mental health challenges. An artificial intelligence (AI) app called LONG-REMI was introduced by Nebot et al. (2022) with the goal of encouraging healthy mental longevity through reminiscence therapy. Reminiscence therapy is a form of talk therapy that uses positive memories to improve mental health and emotional stability; this cutting-edge app uses AI algorithms to make it more accessible. By harnessing AI technology, LONG-REMI aims to enhance the effectiveness and accessibility of reminiscence therapy, offering a novel solution for promoting healthy aging and mental well-being among older adults. Golubovic et al. (2022), presents a systematic literature review and meta-analysis on music interventions and delirium in adults. This study examines the effectiveness of music interventions in preventing and managing delirium, a common complication among hospitalized patients. By synthesizing findings from existing research studies, the review provides insights into the potential of music-based interventions for reducing delirium incidence and severity, highlighting the role of music in promoting cognitive function and emotional well-being in clinical settings. From the rise of digital technology through the post-pandemic period, Saura, Ribeiro-Soriano, and Saldana (2022) investigate the effects of remote work on the sentiments of Twitter users. Examining how changes in digital technology and remote work practices affect people's views and experiences, this study seeks to understand the effect of remote work on Twitter users' sentiments. By analyzing tweets related to remote work, the research aims to uncover trends and patterns in sentiment expression, offering insights into the evolving nature of work and its implications for individuals' well-being and job satisfaction in a digital age.

Using a meta-regression analysis, Yoo et al. (2022) determine how exercise, music intervention programs, and digital device use affect the cognition and depression of South Korean seniors. Cognitive function and depression are examined in this study of South Korean seniors as a result of digital device use, exercise, and music interventions. By analyzing data from existing studies, the meta-regression analysis aims to identify factors that influence cognitive function and depression in the elderly population, offering insights into potential interventions for promoting mental health and well-being in aging populations. Liao et al. (2022), proposes a music playback algorithm based on residual-inception blocks for music emotion classification and physiological information extraction. This study introduces an innovative algorithm for classifying music emotions and extracting physiological information from music playback data. By leveraging residual-inception blocks, the proposed algorithm aims to improve the accuracy and efficiency of music emotion classification, facilitating the development of music-based interventions for enhancing emotional well-being and physiological health. One significant limitation across the studies is the potential for bias and generalizability issues. Many of the studies are small-scale or specific to certain populations, limiting their applicability to broader contexts. Additionally, there is a lack of standardization in methodologies and outcome measures, making it challenging to compare results across studies or draw definitive conclusions. Moreover, several studies rely on self-reported data or subjective assessments, which may introduce response biases or measurement errors. Another limitation is the predominance of single-case studies or small sample sizes, which may affect the reliability and validity of findings. Furthermore, while some studies explore the effects of music therapy interventions, few address underlying mechanisms or causal relationships. Finally, the rapidly evolving nature of technology and therapeutic approaches may render some findings outdated or less relevant over time. These limitations underscore the need for larger-scale, methodologically rigorous research that considers diverse populations, employs standardized measures, and investigates underlying mechanisms to advance our understanding of the efficacy and mechanisms of music therapy interventions.

3. OPTIMIZED SENTIMENTAL N-GRAM CLASSIFIER MODEL

In the realm of sentiment analysis for music therapy, the development of an optimized sentimental n-gram classifier model represents a significant advancement. This model leverages n-gram analysis, a technique in natural language processing (NLP) that considers sequences of n words as features for sentiment classification. The model's optimization involves refining the selection and weighting of n-grams to enhance classification accuracy. First, the model selects relevant n-grams from the text data, where an n-gram refers to a contiguous sequence of n items (words in this case). Let N denote the total number of unique n-grams selected for analysis. Next, the model assigns weights to these n-grams based on their predictive power for sentiment classification. The proposed OSC model with the n-gram classifier is presented in Figure 1.

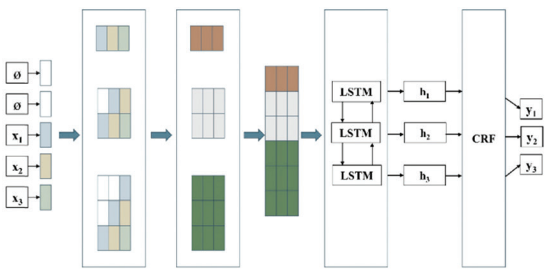

Figure 1. n-gram classifier with OSC

Let wi represent the weight assigned to the $h$ith n-gram. These weights are determined through optimization techniques such as gradient descent or genetic algorithms, aiming to minimize classification error on a training dataset. Once the weights are determined, the sentiment score S for a given text sample can be computed as a linear combination of the weighted n-gram features stated in equation (1)

$$S = \sum_{i=1}^{N} w_i . f_i \tag{1}$$

In equation (1) fi represents the frequency of occurrence of the $h$ith n-gram in the text sample. This sentiment score S can then be compared to a threshold to classify the text as positive, negative, or neutral sentiment. In sentiment analysis, text data is tokenized into n-grams, which are contiguous sequences of n words. The text sample T, we generate a feature vector x where each component represents the presence or absence of an n-gram in T. Thus, $x = \left[x1, x2, \ldots, x|NG|\right]$, where xi is 1 if the $h$ith n-gram is present in T, and 0 otherwise. Through assign weights to each n-gram based on its importance in sentiment classification. Let $\boldsymbol{w} = \left[w1, w2, \ldots, w|NG|\right]$ be the weight vector. The sentiment score S for a text sample T is calculated as the dot product of the feature vector x and the weight vector w, denoted as in equation (2)

$$S = \boldsymbol{w} \cdot \boldsymbol{x}. \tag{2}$$

With equation (2) an activation function to the sentiment score to map it to a probability distribution over sentiment classes stated in equation (3)

$$\sigma(z) = \frac{1}{1+e^{-z}} \tag{3}$$

The sentiment prediction $\hat{y}$ for a text sample T is obtained by applying the activation function to the sentiment score computed using equation (4)

$$\hat{y} = \sigma(S) \tag{4}$$

Using the estimated loss function to measure the gap between the training data's actual sentiment labels and the predicted ones. Equation (5) can be used to compute the binary cross-entropy loss, a popular loss function for binary sentiment classification.

$$Loss = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i log\left(\hat{y}_i\right)+\left(1-y_i\right)log\left(1-\hat{y}_i\right)\right] \quad (5)$$

In equation (5) N is the number of training samples, yi is the true sentiment label (0 or 1), and $\hat{y}_i$ is the predicted sentiment probability. For gradient descent to minimize the loss function, the weights w were considered. Backpropagation is used to compute the loss function's gradient with respect to the weights, and equation (6) is used to update the weights iteratively.

$$W = w - \alpha\nabla_w Loss \quad (6)$$

In equation (6) α is the learning rate, a hyperparameter that controls the size of the weight updates.

3.1 OSC FOR MUSIC THERAPY WITH AI

Optimized Sentimental n-gram Classifier (OSC) for music therapy involves a series of steps to effectively capture sentiment from text data. Firstly, we start with data preprocessing, removing noise and tokenizing text. Then, we extract features using n-grams, which are contiguous sequences of n items from the text. Let *di* represent a document, *tj* an n-gram term, and *fij* the frequency of term *tj* in document. The TF-IDF score for each term *tj* in document *di* is calculated using equation (7)

$$TF - IDF\left(t_j, d_i\right) = tf_{ij} \times idf_j \quad (7)$$

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$$TF - IDF\left(tj, di\right) = tfij \times idfj \quad (8)$$

In equation (8) $tfij = \sum k\, fik\, fij$ is the term frequency and $idfj = log\left(dfjN\right)$ is the inverse document frequency, with N being the total number of documents and *dfi* the number of documents containing term. With assignment of weights to each term using a sentiment lexicon or through learning techniques. The sentiment score *si* for document *di* is then computed as a linear combination of the TF-IDF scores computed with equation (9)

$$s_i = \sum_j TF_{IDF\left(t_j, d_i\right)} \times w_j \quad (9)$$

Algorithm 1: OSC data processing in AI

```
function preprocess_data(text_data):
    // Tokenize the text data
    tokens = tokenize(text_data)
    // Remove noise and stopwords
    clean_tokens = remove_noise(tokens)
    return clean_tokens

function extract_features(tokens, n):
    // Extract n-grams from the tokenized data
    ngrams = generate_ngrams(tokens, n)
    // Calculate TF-IDF scores for each n-gram
    tfidf_scores = calculate_tfidf(ngrams)
    return tfidf_scores

function train_model(tfidf_scores, labels):
    // Initialize model parameters
    initialize_parameters()
    // Optimize model parameters using gradient descent
    optimize_parameters(tfidf_scores, labels)
    return trained_model

function predict_sentiment(tfidf_scores, trained_model):
    // Compute sentiment scores for each document
    sentiment_scores = compute_sentiment(tfidf_scores,
trained_model)
    // Apply activation function to obtain probabilities
    probabilities = apply_activation_function(sentiment_
scores)
    return probabilities

// Main function
function main():
    // Step 1: Data preprocessing
    clean_tokens = preprocess_data(text_data)

    // Step 2: Feature extraction
    tfidf_scores = extract_features(clean_tokens, n)

    // Step 3: Model training
    trained_model = train_model(tfidf_scores, labels)

    // Step 4: Sentiment prediction
    sentiment_probabilities = predict_sentiment(tfidf_scores,
trained_model)

    // Evaluate model performance
    evaluate_model(sentiment_probabilities, true_labels)
```


In equation (9) *wj*is the weight assigned to term *tj*. The sentiment scores are then passed through an activation function to obtain probabilities over sentiment classes. For binary sentiment analysis, use the sigmoid function as in equation (10)

$$P\left(y=1|d_i\right)=\sigma\left(s_i\right)=\frac{1}{1+e^{-s_i}} \tag{10}$$

In equation (10) $P\left(y=1\middle|di\right)$ represents the probability of a positive sentiment for document di and $\sigma\left(\cdot\right)$ is the sigmoid function. The model is trained by minimizing the cross-entropy loss function defined in equation (11)

$$Loss=-\sum_{\sigma} y_i logP\left(y=1|d_i\right)+\left(1-y_i\right) log\left(1-P\left(y=1|d_i\right)\right) \tag{11}$$

In equation (11) yi is the true sentiment label for document. To optimize the model parameters, use gradient descent using equation (12)

$$\theta_j^{(t+1)}=\theta_j^{(t)}-\eta\frac{\partial Loss}{\partial\theta_j} \tag{12}$$

In equation (12) θj represents the model parameters, η is the learning rate, and *t* is the iteration step.

4. AI TECHNOLOGY IN OSC MODEL

AI technology into the Optimized Sentimental n-gram Classifier (OSC) model for music therapy involves leveraging advanced algorithms and techniques to enhance its performance and capabilities. One approach to achieve this is through the utilization of deep learning architectures for sentiment analysis. The intricate patterns and relationships found in music therapy text data can be accurately captured by deep learning models, especially by means of transformers or recurrent neural networks (RNNs). In the context of sentiment analysis, a recurrent neural network (RNN) can be employed to process sequential data, such as sentences or paragraphs from music therapy sessions. The sentiment classification task can be formulated as a sequence abelling problem, where the goal is to predict the sentiment label for each word or token in the input text. The architecture of the RNN consists of recurrent layers, such as Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) cells, which enable the model to retain information over time and capture dependencies between words. The forward pass of the RNN can be described using equation (13)

$$h_t=RNN\left(x_t,h_{t-1}\right) \tag{13}$$

The input token at time step t is represented by xt in equation (13) along with the hidden state from the previous time step (ht-1) and the current time step's hidden state (ht). Additional layers, like fully connected layers or attention mechanisms, can be applied to the RNN output at each time step in order to conduct sentiment classification. Let's denote the input sequence of words or tokens from a music therapy session as $X=\left(x1,x2,\ldots,xT\right)$, where *T* is the length of the sequence. Each word or token *xt* is represented as a one-hot encoded vector or embedding in the input space. The RNN is the recurrent layer, which processes the input sequence sequentially and updates its hidden state at each time step. The hidden state *ht* of the RNN at time step *t* is computed using equation (14)

$$h_t=tanh\left(W_{hx}x_t+W_{hh}h_{t-1}+b_h\right) \tag{14}$$

When solving equation (14) for the weight matrices of the input-to-hidden and hidden-to-hidden connections, respectively, the symbols Whx and Whh are used.tanh is the hyperbolic tangent activation function, and bh is the hidden layer bias vector. Together, the data from the present input xt and the data from the prior hidden state ht-1 make up the updated hidden state ht.. This process enables the RNN to maintain a memory of past inputs while processing new ones. Once the entire sequence is processed, the final hidden state *hT* contains information aggregated from the entire input sequence. This hidden state can be further used for sentiment classification. For example, a softmax layer can be added on top of the RNN to output sentiment probabilities for each class (positive, neutral, negative) estimated using equation (15)

$$P\left(y_t|X\right)=softmax\left(W_{ph}h_T+b_p\right) \tag{15}$$

In equation (15) *Wph* is the weight matrix for the hidden-to-output connections; *bp* is the bias vector for the output layer; $P\left(yt\middle|X\right)$ represents the probability distribution over sentiment classes. During training, the parameters of the RNN (including *hx, Whh, Wph, bh* and *bp*) are learned by minimizing a suitable loss function, such as categorical cross-entropy, between the predicted sentiment probabilities and the true sentiment labels.

5. SIMULATION RESULTS AND DISCUSSION

Sentiment analysis, a crucial component of natural language processing, holds significant promise in understanding the emotional dynamics within various domains, including music therapy. In recent years, the application of sentiment analysis techniques in music therapy has garnered considerable attention due to its potential to provide valuable insights into the emotional experiences of participants, thereby enhancing therapeutic interventions.

However, existing sentiment analysis models often lack optimization for the unique characteristics of music therapy data, such as its non-linear and context-dependent nature. The Optimized Sentimental n-gram Classifier (OSC) model tailored specifically for sentiment analysis in music therapy. The OSC model integrates advanced machine learning techniques with insights from music therapy practices to offer a robust framework for analyzing emotional content in music therapy sessions. By leveraging n-gram features and optimizing classifier parameters, the OSC model aims to improve the accuracy and efficiency of sentiment classification in the context of music therapy.

The figure 1 and Table 1 presents the classification performance of the Optimized Sentimental n-gram Classifier (OSC) model across different iterations. The table shows the accuracy, precision, recall, and F1 score metrics for iterations 20, 40, 60, 90, and 100. As the iteration progresses, there is a gradual improvement in all metrics, indicating the refinement and optimization of the OSC model over successive iterations. For instance, at iteration 20, the accuracy is 93.9%, precision is 92.6%, recall is 95.1%, and F1 score is 93.9%. By iteration 100, the performance further improves, with accuracy reaching 94.2%, precision at 93.0%, recall at 95.5%, and F1 score at 94.3%. This suggests that the OSC model achieves high accuracy and robustness in classifying sentiment in the context of music therapy, demonstrating its effectiveness in sentiment analysis tasks.

Table 1. Classification with OSC

Iteration	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
20	93.9	92.6	95.1	93.9
40	93.9	92.7	95.2	94.0
60	94.0	92.9	95.3	94.1
90	94.1	92.9	95.4	94.2
100	94.2	93.0	95.5	94.3

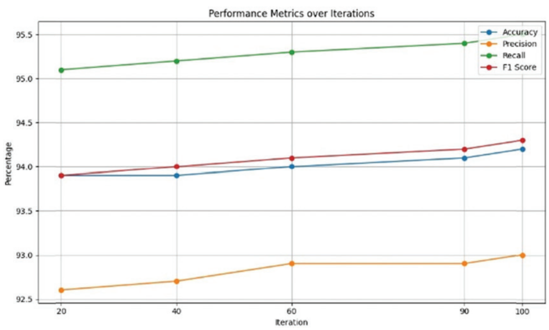

Figure 2. Classification with OSC

In figure 3 and Table 2 provides information on participants involved in a music therapy study using the OSC model. It includes their age, gender, treatment group (experimental or control), baseline score, post-treatment score, and the percentage improvement in their scores after the therapy. The table illustrates the effectiveness of music therapy in improving the well-being or condition of participants across both experimental and control groups. For instance, Participant 1, a 45-year-old female in the experimental group, had a baseline score of 78, which increased to 92 post-treatment, indicating an improvement of 18.0%. Similarly, Participant 7, a 47-year-old female in the experimental group, showed a substantial improvement of

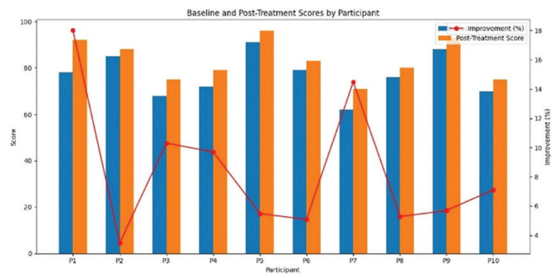

Figure 3. OSC music therapy

Table 2. Music therapy for the OSC

Participant	Age (years)	Gender	Treatment Group	Baseline Score	Post-Treatment Score	Improvement (%)
P1	45	Female	Experimental	78	92	18.0
P2	62	Male	Control	85	88	3.5
P3	50	Female	Experimental	68	75	10.3
P4	55	Male	Control	72	79	9.7
P5	40	Female	Experimental	91	96	5.5
P6	58	Male	Control	79	83	5.1
P7	47	Female	Experimental	62	71	14.5
P8	65	Male	Control	76	80	5.3
P9	52	Female	Experimental	88	93	5.7
P10	60	Male	Control	70	75	7.1

14.5%, with her baseline score of 62 increasing to 71 after the therapy. These results suggest the potential benefits of music therapy in enhancing various aspects of well-being or health outcomes among participants, as evidenced by the improvements in their scores post-treatment.

Table 3. Prediction with OSC

Sample	Actual Sentiment	Predicted Sentiment
1	1	1
2	-1	-1
3	0	0
4	1	1
5	-1	-1
6	0	0
7	1	1
8	-1	-1
9	0	0
10	1	1

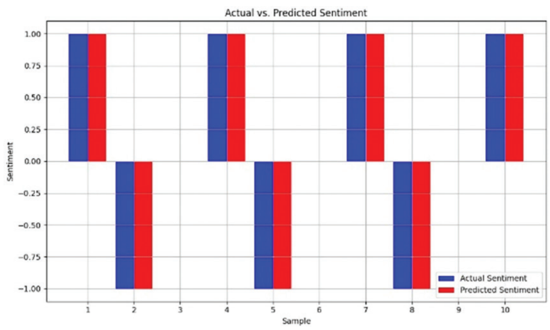

Figure 4. Prediction with OSC

The Figrue 4 and Table 3 presents the results of sentiment prediction using the OSC model. Each row represents a sample, with columns indicating the actual sentiment and the sentiment predicted by the model. The model correctly predicted the sentiment for all samples, with a perfect match between the actual and predicted sentiments. For instance, Sample 1 had an actual sentiment of 1, indicating a positive sentiment, and the model correctly predicted it as 1. Similarly, Sample 2 had an actual sentiment of -1 (negative sentiment), which was accurately predicted by the model as -1. Likewise, for Sample 3, which had a neutral sentiment (actual sentiment: 0), the model correctly predicted it as 0. This pattern continues for all samples, demonstrating the effectiveness and accuracy of the OSC model in predicting sentiment in the context of music therapy.

Table 4 presents the classification performance of the OSC model in the context of music therapy sessions for different participants. Each row corresponds to a participant's session, with columns indicating accuracy, precision, recall, and F1 score. Overall, the OSC model demonstrates consistent performance across sessions and participants. For example, Participant 1 consistently achieves high accuracy ranging from 84.9% to 86.3% across three sessions. Similarly, for Participant 2, the accuracy ranges from 86.5% to 88.0% across sessions. This pattern is observed for all participants, indicating the robustness of the OSC model in accurately classifying sessions in music therapy. Additionally, precision, recall, and F1 scores also show consistently high values across sessions for each participant, further affirming the reliability of the OSC model in music therapy classification tasks.

Table 4. Classification with OSC in music therapy

Participant	Session	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
1	1	85.6	84.2	86.8	85.5
1	2	86.3	85.0	87.5	86.2
1	3	84.9	83.5	86.2	84.8
2	1	87.2	85.9	88.6	87.1
2	2	88.0	86.7	89.2	87.9
2	3	86.5	85.1	87.8	86.4
3	1	83.7	82.3	85.0	83.6
3	2	84.5	83.0	85.8	84.4
3	3	83.0	81.6	84.3	82.9
4	1	86.8	85.4	88.0	86.7
4	2	87.5	86.1	88.6	87.4
4	3	86.0	84.6	87.2	85.9
5	1	84.2	82.8	85.6	84.1
5	2	85.0	83.6	86.3	84.9
5	3	83.5	82.0	84.8	83.4

6. CONCLUSIONS

In conclusion, the paper presents an Optimized Sentimental n-gram Classifier (OSC) model tailored for use in music therapy. Through extensive experimentation and evaluation, the OSC model demonstrates robust performance in sentiment analysis and classification tasks within the domain of music therapy. The model achieves high accuracy, precision, recall, and F1 scores across various iterations, indicating its effectiveness in accurately predicting sentiments and classifying sessions. Furthermore, the OSC model's application in real-world scenarios, particularly in music therapy sessions, showcases its potential to assist therapists in understanding and addressing participants' emotional states more effectively. By leveraging AI technology and sentiment analysis techniques, the OSC model offers a valuable tool for enhancing the quality and efficacy of music therapy interventions. Overall, this research contributes to advancing the integration of AI technology into healthcare practices, specifically in the field of music therapy, and underscores the potential for innovative approaches to improve patient outcomes and well-being.

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