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RESEARCH ARTICLE

# Real-Time Emotion-Based Piano Music Generation Using Generative Adversarial Network (GAN)

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**ABSTRACT** Automatic creation of real-time, emotion-based piano music pieces remains a challenge for deep learning models. While Generative Adversarial Networks (GANs) have shown promise, existing methods can struggle with generating musically coherent pieces and often require complex manual configuration. This paper proposes a novel model called Learning Automata-based Self-Attention Generative Adversarial Network (LA-SAGAN) to address these limitations. The proposed model uses a Generative Adversarial Network (GAN), combined with Self-Attention (SA) mechanism to reach this goal. The benefits of using SA modules in GAN architecture is twofold: First, SA mechanism results in generating music pieces with homogenous structure, which means long-distance dependencies in generated outputs are considered. Second, the SA mechanism utilizes the emotional features of the input to produce output pieces. This results in generating music pieces with desired genre or theme. In order to control the complexity of the proposed model, and optimize its structure, a set of Learning Automata (LA) models have been used to determine the activity state of each SA module. To do this, an iterative algorithm based on cooperation of LAs is introduced which optimizes the model by deactivating unnecessary SA modules. The efficiency of the proposed model in generating piano music has been evaluated. Evaluations demonstrate LA-SAGAN's effectiveness: at least 14.47% improvement in entropy (diversity) and improvements in precision (at least 2.47%) and recall (at least 2.13%). Moreover, human evaluation confirms superior musical coherence and adherence to emotional cues.

**INDEX TERMS** Real-time music generation, generative adversarial network, self-attention mechanism, reinforcement learning, learning automata, emotion-based music.

## I. INTRODUCTION

The rapid development of Artificial Intelligence (AI) techniques has led to its widespread use in solving various problems. With the introduction of deep learning techniques, this progress has been accelerated and its application has been extended to more complex problems [1]. Generating music by computer is one of the issues that AI experts have been trying to achieve over the years [2], [3]. With the introduction of some deep learning models such as Generative Adversarial Networks (GAN) [4] during recent years, significant steps have been taken in this direction; but nevertheless, there is still a significant distance from achieving ideal results [5]. On the other hand, the problem of automatic music generation is a broad issue, and to solve it, several factors must be taken into account, such as the sound characteristics of each instrument or harmony in the produced pieces [6].

To achieve the desired results faster, this broad problem can be broken down into more detailed sub-problems. For example, we can solve the problem of automatic music generation for each instrument (e.g. piano, guitar etc.), separately. Most of the research done for piano music production are based on deep learning strategies, such as GANs [7]. However, current GAN-based methods often face challenges in achieving:

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- Musical Coherence: In the synthesized music, a harmony and connection between different sections is observed, which is necessary to avoid a disordered or incoherent sound.
- Optimal Model Configuration: Configuring the high-level deep learning models, particularly those which use attention mechanisms, is a tough task. This arrangement method can be time-consuming and might need advanced knowledge.

Due to the complexity of the structure, deep learning models such as GAN require precise configuration, which is a time-consuming process. The complexity of this process doubles when the model is combined with other computational techniques such as the attention mechanism. On the other hand, determining the arrangement of components in the deep model often requires examining numerous situations that depend on the problem conditions and each of them can affect the performance of the model. To solve this challenge, the versatility of reinforcement learning models can be used and by automatically configuring the deep model through it, the existing concerns regarding the complexity of the model can be solved. This problem is considered as one of the goals of the current research.

In this paper, a new model called Learning Automata-based Self-Attention Generative Adversarial Network (LA-SAGAN) has been introduced for automatic piano music generation which tries to fill the mentioned research gaps. LA-SAGAN leverages the strengths of both Self-Attention mechanism and Learning Automata to achieve:

- Enhanced Musical Coherence: SAs help with long-range dependencies, which are taken into account by LA-SAGAN, thus enabling it to generate more structured and cohesive pieces. Also, SAs have the ability to use emotional features of the input to create music that sets the mood or the genre that is needed.
- Automated Model Configuration: LA-SAGAN uses LAs which act as a driving force for an iterative optimization progress. With these LAs the underlying SA modules of the model are automatically configured. Therefore, the complexity of the system is significantly reduced and the quality of the piano music output in real time is greatly improved.

By addressing these research questions, LA-SAGAN provides an alternative to the current methods of automatic music generation, which are costly, time-consuming, and ineffective in creating emotionally-driven piano pieces.

The contribution of this paper is twofold:

- First, in this research a new architecture for generating piano music is introduced which is based on combination of GAN and SA mechanism. Adding SA modules to the structure of GAN is useful in considering long-distant dependencies of outputs, along with generating pieces with the same emotional features of themes.
- Secondly, this paper introduces a new iterative mechanism based on cooperation of LA models to optimize the activity state of SA modules in proposed model. This, will result in forming a model with less complexity and higher accuracy.

The above cases have not been addressed in previous researches and can be considered as the novelties of the proposed method. The remainder of the paper is structured as follows: In section II, some of the recent remarkable works about music generation have been studied. In section III, the proposed method has been described in detail, and in section IV, the implementation results are discussed. In section V, the findings of the research are summarized and several suggestions have been provided for future researches.

### A. DEEP LEARNING AND GENERATIVE ADVERSARIAL NETWORKS

Deep learning is a branch of artificial intelligence in which neural network models with multiple hidden layers are used to more efficiently solve complex problems such as pattern recognition, prediction, artificial data construction, etc. [8]. The many advantages of deep learning have caused its techniques to be recognized as one of the most widely used fields of artificial intelligence in recent years. One of the most key concepts of Deep Neural Networks (DNNs) is convolution. Using this operator, two signals can be combined to create a new signal [9]. In fact, the convolution result shows how the first signal has changed under the influence of the second signal. In DNNs, some layers named convolution layers, use convolution operator to extract feature maps from data [10]. Convolution layers are widely used in different architectures of DNNs such as convolutional neural networks (CNNs) and GANs.

GAN is one of the prominent deep learning architectures for generating artificial data such as image, sound, video and so on. The purpose of GAN is to generate artificial data in a way that cannot be distinguished from real data. The GAN model uses two modules in its architecture to fulfill this goal: generator and discriminator. The purpose of the generator component is to create new data based on previously observed samples, and the purpose of the discriminator is to distinguish artificial samples from real samples. Thus, in the GAN architecture, first the generator component creates a number of artificial samples and then the generated samples are classified by the discriminator. Then the generation and discrimination losses are applied to these components and the mentioned process is repeated [11]. The use of two components with seemingly contradictory interests in GAN makes it possible to generate artificial data that, firstly, is difficult to distinguish from real data (based on the purpose of the generator) and secondly, real data is not used in them (based on the purpose of the discriminator).

### B. LEARNING AUTOMATA

Learning automata is one of the efficient reinforcement learning techniques to determine the decision strategy without having prior knowledge of the environment. Learning automata performs the learning process through continuous interaction with the environment and evaluating the quality of its choices. The simplicity of the structure and computational efficiency are considered to be the most important advantages of learning automata. A learning automata can be described through two sets of actions and probabilities. The set of actions includes all possible choices to be applied to the environment by the learning automata. On the other hand, the set of probabilities specifies the probability (or value) of choosing each action of the learning automata. Thus, in a learning automata, the two mentioned sets have the same size and their members correspond to each other [12]. In general, the learning automata has no knowledge of the environment at the moment of starting and all its actions have the same probability. In such a situation, the learning automata chooses one of the actions randomly and waits for the environment's response. The positive response of the environment indicates the selection of an appropriate action, and if it is received, the probability of the selected action increases by using the reward operator. On the other hand, the negative response of the environment specifies the choice of an inappropriate action, which, if received, the learning automata will reduce the probability of the chosen action using penalty operator [13]. This simple process allows the learning automata to achieve an appropriate strategy in choosing actions during interaction with the environment.

### C. MUSICAL INSTRUMENT DIGITAL INTERFACE (MIDI)

MIDI is one of the main communication formats for recording and playing musical data between a computer and an electronic instrument. MIDI can contain up to 16 channels of information from different instruments.

The main use of MIDI format is in music. In specialized music software, the files can be stored and retrieved in a specialized manner, the same software and the common MIDI file format. In fact, a MIDI file contains musical notes, the tension of each note, volume control, breaks, and all specialized music information such as volume, which means high amount and a momentary sound or pan means the left and right direction of the sound is coded. The playback of a MIDI file depends on the preset sounds in the audio source, so the playback of a MIDI file on different digital devices may be played with different qualities and types [14].

MIDI files take up very little space and this is an advantage for storing them. The reason is that these files only contain the information of the notes in the form of short codes and do not contain the sampled information of the instrument or human voice.

## II. LITERATURE REVIEW

During recent years, various approaches for generating music has been proposed. This section, reviews some notable researches in this regard. In [15], a model called Musika has been introduced to generate music based on deep learning models. In this technique, first the music files are described as spectrogram matrices. These features are fed to a GAN in order to reconstruct an artificial spectrogram. Then, the reconstructed spectrogram is converted to audio signal using inverse Short-Time Fourier Transform (iSTFT). Using spectrogram in music generation leads to difficulties for analyzing simultaneous sound of instruments. Research in [16], is an attempt to generate music using deep learning. In this method, Long Short-Term Memory (LSTM) has been used for music generation and dropout coefficients have been considered for optimizing the model. This method also uses an iterative mechanism for tuning hyper-parameters of the model. Despite the simplicity of the structure, this model requires the use of a very large data set to produce acceptable results.

The method presented in [17], is a guitar-focused music generation system based on symbolic music representation. Symbolic representation, can provide additional music information such as rhythm and pitch, in addition to expressive techniques for string instruments such as guitar. This model uses transformer model for music generation which has limitations such as context fragmentation and memory issues which occur while handling long sequences. Researchers in [18], have introduced a library for generating and analyzing symbolic music. This python-based library in addition to containing several generation models, provides several tools for representation and visualization of music files. In [19], a method based on deep learning techniques for producing MIDI files has been proposed. This method has targeted Jazz music genre and uses LSTM for generating music. In this method, first the unique notes are determined and partitioned into sequences. Then, based on the sequences of dataset, the LSTM-based model is trained and the trained model is used for generating Jazz music. Finally, output is converted to MIDI format. High complexity and needing a large training dataset for effective learning are limitations of the LSTM model used in this research.

In [20], a new diffusion model has been introduced to generate multi-track symphonic music. This model is named DiffuseRoll and uses LSTM for generating music. Then, represents generated music in piano-roll format and uses a diffusion model to convert it into MIDI format. DiffuseRoll has a more complex structure than conventional RNN-based models which makes its training time consuming.

AMuseNet [21], is a piano music generation model which tries to compose melodies based on harmony. This system models right and left hand with two separate networks and the pattern of left hand is formed based on right hand. AMuseNet produces outputs in MIDI format. AMuseNet need numerous parameters to be tuned manually according to the specification of training data, which makes this model complicated. Research in [22], has used transformer GAN to generate multi-track music files. The generator part of this network is composed of two parts. The first part which is called single-track generator, is designed to control the relationships in each sequence; while the second part (called multi-track generator), is responsible for controlling the relationship between each track with others. The transformer model in this approach, limits the generator model in handling long sequences.

Research in [23], uses GAN as a base model for generating music and combines it with a deep chord recurrent neural network to form the DCG_GAN model. The generated music files are dual track and generated based on real music which have been fed to generator section of DCG_GAN. However, the problem of sensitivity of GAN to its hyper-parameters has not been addressed in this paper. Research in [24], introduced a deep learning-based model for automatic generation of MIDI files. The researchers have modeled the music generation problem as a sequence-to-sequence task and introduced a learning model based on LSTM-RNN architecture. The resulting model is complicated and need high number of samples for training.

Research in [25], presented a dynamic GAN model for generating videos of sign language from skeletal poses. This model generates artificial samples by random noise vectors and uses VGG-19 to classify them. Then, a new technique is used for improvement of quality in generated samples. Finally, real or fake state of samples is recognized by discriminator. In [26], a deep learning-based framework for sign language was presented which is capable of recognizing, translating and generating sign language videos. This research uses the combination of natural machine translation and GAN for generating sign language videos from sentences.

A problem with music production is to make the quality high enough while the process is fast enough. Lam et al. [27] present MeLoDy, a system that seeks to address the issue of computational complexity by using an existing high-fidelity model (MusicLM) while reducing the number of operations needed for music production. MeLoDy has implemented the diffusion model with MusicLM that has ensured fast sampling times and continuous generation of music.

Along with this, a great deal of attention is needed to enhance the quality of continuous music passages. Muhamed et al. [28] conducted a research that exploited GANs for Transformer-based models. The GANs can in fact train a model to create music that is both realistic and is also continuous over longer periods. First, their method employs a pre-trained language model which gives the model the ability to be more stable. Secondly, they integrate their training with techniques that are able to deal with the memory limitations during the training process.

The characteristic to develop music of the variable duration is also an element of great importance. Sung and Li [29] presented INCO-GAN, a conditional GAN that deploys an inception model architecture. With this method, music length is automatically determined by the model, whereas quality is preserved. Their research reveals that the pieces created by the AI are almost indistinguishable from the music produced by humans.

Thematic development, the other important element in music composition, is another point to consider. Shih et al. [30] introduce Theme Transformer which is a model focused on including a user-defined theme into the generated music. This method involves contrastive learning for the purpose of identifying the thematic patterns and a unique attention mechanism to make sure the generated song agrees with the preset one. This allows for the creation of music that is based on the concept of a thematic structure and includes varying elements.

Table 1, summarizes the reviewed literature.

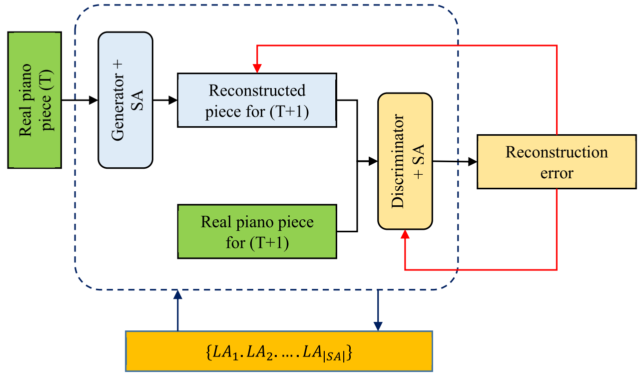


**FIGURE 1.** The architecture of the proposed model for generating piano music.

## III. PROPOSED METHOD

In this research, a new model based on Generative Adversarial Networks (GANs) has been introduced for generating piano music. The proposed GAN model uses the GAN33 basic architecture and combines it with Self Attention (SA) mechanism [31]. GAN33 refers to a specific GAN architecture including total 33 layers (encoder, decoder, skip connections) used as the foundation for our proposed model. Using SA mechanism results in generating notes which its distant sections are compatible with each other. Since the SA mechanism may complicate the GAN model, the proposed method uses a Learning Automata (LA) to determine the active state of each SA module in the deep neural network model. Accordingly, the resulting model is called LA-SAGAN. Based on the general structure of GANs, the proposed model consists of "generator" and "discriminator" parts. The architecture of the proposed model for generating piano music is illustrated in Figure 1.

As shown in figure 1, the generator part of LA-SAGAN is first fed by a real piano piece with limited duration. In proposed method, each real piano song is decomposed into several sections with fixed duration (for example L). Thus, generator attempts to reconstruct the next section of the piano piece (T + 1) using its current section (T). Then, the reconstructed piece and the real one is fed to the discriminator part of LA-SAGAN, which is responsible for evaluating reconstruction error. The error value is used for refining generator and discriminator through backpropagation process. Table 2 lists the definition of the parameters used in this research.

**TABLE 1.** Summary of the reviewed literature.

| Ref. | Year | Research Goal | Method | Advantage | Disadvantage | Music Type |
|---|---|---|---|---|---|---|
| [15] | 2022 | Fast music generation | Spectrogram-based GAN | Efficient spectrogram reconstruction | Difficulty analyzing simultaneous instruments | N/A |
| [16] | 2022 | Music generation with deep learning | LSTM with dropout | Handles sequential data well | Requires large datasets | N/A |
| [17] | 2023 | Guitar music generation | Transformer for symbolic music | Symbolic representation for additional information | Context fragmentation, memory issues with long sequences | Guitar |
| [18] | 2023 | Symbolic music generation and analysis | Symbolic music generation library | Provides tools for music generation and analysis | Not a generative model itself | N/A |
| [19] | 2022 | Jazz music generation | LSTM-based model | Targets specific genre (Jazz) | High complexity, large training dataset requirement | Jazz |
| [20] | 2022 | Multi-track symphonic music generation | Diffusion model (LSTM-based) | Multi-track symphonic music generation | Complex structure, time-consuming training | Symphonic |
| [21] | 2022 | Piano music generation with melody-driven harmony | Dual network GAN | Melody composition based on harmony | High number of parameters for manual tuning | Piano |
| [22] | 2022 | Multi-track music generation | Transformer GAN | Controls relationships within and between sequences | Transformer limitations with long sequences | Multi-track |
| [23] | 2022 | Dual-track music generation | GAN with deep chord network | Dual-track music generation | Sensitive to GAN hyperparameters | Dual-track |
| [24] | 2022 | Automatic MIDI generation | LSTM-RNN | Sequence-to-sequence modeling | Complex architecture, large training data requirement | N/A |
| [27] | 2024 | Efficient music generation | LM-guided diffusion model | High-quality music, reduced computations | Requires high-fidelity model for training | N/A |
| [28] | 2021 | Improved long sequence music generation | Transformer-GANs | Improved quality for long sequences | Requires pre-trained model, memory management techniques | N/A |
| [29] | 2021 | Variable-length music generation | Conditional GAN with inception model | High cosine similarity to human-composed music | Requires pre-defined training data | N/A |
| [30] | 2022 | Theme-conditioned music generation | Theme Transformer | Repetition and variations based on theme | Requires theme extraction techniques | N/A |
| Proposed | | Real-time, emotionally-driven music generation | LA-SAGAN (GAN with SA and LA) | Emotional control, real-time feasibility | Higher training time | Piano |

**TABLE 2.** List of the parameters.

| Parameter | Description |
|---|---|
| L | Length of each piano piece, fed to the generator part of the proposed model |
| T | Index of sections generated by the proposed model |
| $A$ | Selectable actions set in each LA |
| $\alpha_1$ | The action equivalent to activation of SA module using LA |
| $\alpha_2$ | The action equivalent to deactivation of SA module using LA |
| K | The number of selectable actions in each LA |
| $p_j(k)$ | The probability of selecting action j in the k-th cycle for LA |
| a | Reward coefficient in LA |
| b | Penalty coefficient in LA |
| G | The maximum number of iterations for tuning LA-SAGAN |
| S | The threshold of unimproved consecutive iterations during tuning LA-SAGAN |

### A. LA-SAGAN ARCHITECTURE

Decomposing piano pieces into sections and attempting to reconstruct next section of input in each iteration, is effective in generating creative pieces which are compatible with the real piece, in terms of genre and theme. In proposed method, each input sample is described in a matrix structure similar to piano-roll. In this case, the number of rows of this matrix corresponds to the number of notes that can be played on piano (88 notes), and the columns of the matrix specify the order of playing the notes. Each element of this matrix includes 2 numbers: The first number represents the velocity of pressing the key (velocity sensitivity) and described in scale of 1 and 5 (zero means silence); while the second number represents the note duration and described as a real positive number.

Thus, each input piano piece in the proposed method is structures as a matrix with dimensions of $88 \times L \times 2$ where L represents the duration of piece, in terms of number of keys pressed. The proposed 3D structure of matrix, provides a more compatible input for deep learning models, compared to widely used representations such as piano-roll or spectrograms. The structure of the generator part of the proposed LA-SAGAN model is illustrated in Figure 2. Also, the structure of the discriminator part in LA-SAGAN is presented in Figure 3.

As shown in Figures 2 and 3, LA-SAGAN design is based on encoder-decoder architecture of GANs. The encoder/generator part, is responsible for generating artificial

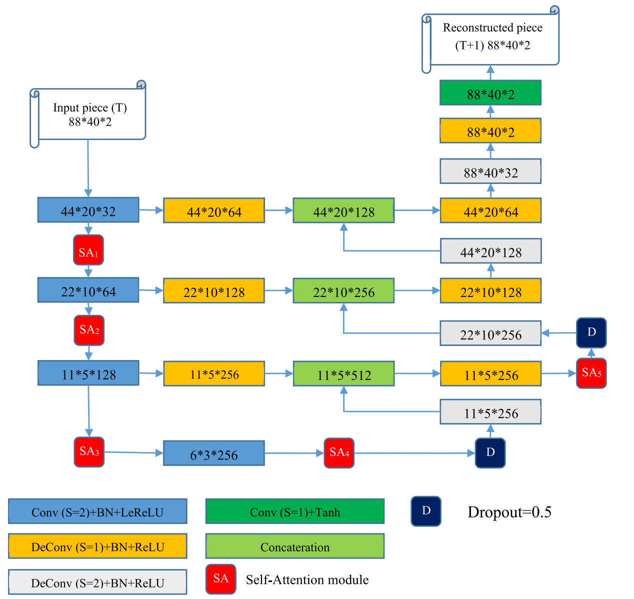


**FIGURE 2.** The structure of the generator part of the proposed LA-SAGAN model.

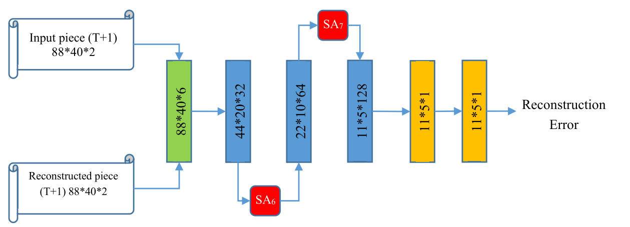


**FIGURE 3.** The structure of the discriminator part of the proposed LA-SAGAN model.

piano notes; while the decoder/discriminator part is used to evaluate the error of reconstruction process.

The generator of LA-SAGAN itself is based on UNet architecture and can be decomposed into encoder and decoder sections. The encoder of generator is composed of four convolution layers with dimensions of 4*4. Also, the decoder of generator includes four deconvolution layers with the same size of encoder part and in the same-level skip connections, in addition to two dropout layers set to 0.5. All convolution layers are followed by Batch Normalization (BN) and activation function layers. The convolution layers of encoder section of generator, use LeakyReLU function; and ReLU functions is considered for deconvolution layers of decoder section. Also, the last convolution layer for reconstructing the output of generator uses tanh activation function.

The reconstructed output of generator, in addition to input notes are fed to the discriminator part of the LA-SAGAN and uses 3 decoders.

The SA mechanism, allows GAN model to utilize attention-driven long-distant dependencies in generating data. This, will result in generating music pieces with homogenous structure. On the other hand, the SA mechanism utilizes the emotional features of the input to produce output

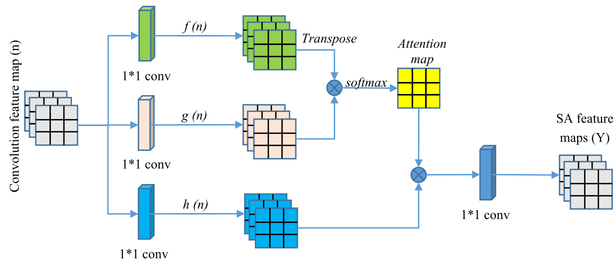


**FIGURE 4.** The structure of SA module in LA-SAGAN.

pieces. This features also, results in generating music pieces with desired genre or theme. These benefits, have led to considering seven SA module in the proposed architecture.

Five SA modules are used in the generator part of LA-SAGAN; while the remaining 2 modules are used in discriminator. The number of SA modules (7) was chosen based on an empirical evaluation of the model's performance with different configurations. We investigated configurations with varying numbers of SA modules and found that 7 SA modules achieved the best balance between accuracy and computational complexity. The architecture of each SA module is illustrated in Figure 4.

Each SA module uses three convolution layers with size of 1*1 to separate input feature maps which are obtained from previous convolution layers. The mechanism of self-attention is applied on the results obtained from three transformation functions: f, g and h. This approach is used to make sure that generated results belonging to distant locations of the output are compatible with each other. In other words, SA mechanism enables GAN networks to consider long-distance dependencies in generating output. To do this, each SA module combines local and global dependencies of features to enhance the details and harmony of the generated outputs. The layers of SA modules are used to provide better information from inputs and their layer structure is complementary to convolutional layers.

### *B. TUNING LA-SAGAN USING REINFORCEMENT LEARNING*

As described earlier, using SA mechanism in the presented SAGAN model may increase the computational complexity. Also, it should be noted that some SA modules of the proposed SAGAN model may have not a positive effect on its efficiency, and could be ignored to reduce the complexity. In fact, the optimal activity state of each SA module in SAGAN could be determined according to the problem. Thus, there is an optimal subset of SA modules that enabling them in SAGAN model will optimize its performance. The proposed model uses reinforced learning capabilities of LAs to determine the optimal activity state of each SA module. In LA-SAGAN, a LA model is assigned to each SA module to determine its activity status.

In LA-SAGAN, reinforcement learning strategy has been used in order to optimally configure the model. This strategy

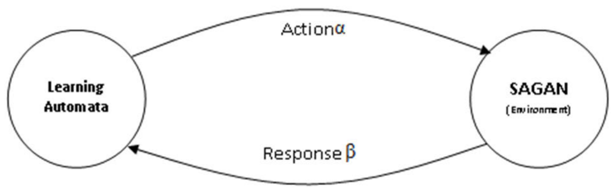


**FIGURE 5.** The structure of LA.

includes a set of LA models, the task of each of which is to determine the optimal activity state for each SA module. A learning automaton uses a simple mechanism to learn. This structure is shown in figure 5.

Each LA, includes a set of selectable actions. In proposed method, the action set of each LA is described as $A = \{\alpha_1, \alpha_2\}$, where $\alpha_1$ is equivalent to activation of SA and $\alpha_2$ represents its deactivation state. Each action in set A corresponds to a selection probability. In the proposed method, selection is done randomly in one third of iterations and in other iterations, based on the probability vector of automata.

Each LA operates by selecting an action from the set A and applying it to the SAGAN structure. By repeating this process by all LA models in each cycle, a candidate configuration for the activity state of SA modules is created. This candidate model is trained using database training instances and its quality is evaluated. In this case, the quality evaluated by the candidate model is considered as the response of the environment. Then, each LA uses the response of the environment to update its probability vector and choose the next action. During this process, each LA learns which configuration mode is optimal for SA modules by adjusting the probability of actions based on reward and penalty parameters.

With these explanations, the proposed reinforcement learning model will include 7 LAs (each one assigned to a SA module), that cooperate together to form the optimal configuration of the SAGAN model. The process of determining the optimal configuration is iterative. During each iteration, each LA first selects one of its actions and applies the selected action to its corresponding SA module in the base model. After applying the selected actions by all LAs, a configured SAGAN will be formed and trained using training instances.

In this way, after receiving the response of the environment, the obtained quality value is compared with the highest value obtained in the previous iterations, and according to the result of this comparison, the process of updating the probability vector of each LA model will be done. In other words, after receiving the response from the environment and comparing it with the highest quality obtained in the previous iterations, the following conditions may occur:

- If the amount of quality in the current iteration is greater than the highest quality in the previous iterations for the currently determined configuration (environment response); Therefore, it can be concluded that the set of LAs have been able to select the activity pattern of the SA modules in a way that improves the performance and can help the system to reach the global optimum. As a result, the set of actions selected by LAs in this cycle will be considered as optimal choices. In this case, each LA increases the probability of its last choice as follows (the current action is i) [32]:

$$p_j(k+1) = \begin{cases} p_j(k) + a[1 - p_j(k)] & j = i, \\ (1-a)\, p_j(k) & \forall j \neq i. \end{cases} \tag{1}$$

- If the quality in the current iteration is lower than the highest quality in the previous iterations; therefore, the response generated in the last cycle will be considered as non-optimal choices. In this case, each LA reduces the probability of choosing the last action as follows [32]:

$$p_j(k+1) = \begin{cases} (1-b)p_j(k) & j = i, \\ \left(\dfrac{b}{K-1}\right) + (1-b)\, p_j(k) & \forall j \neq i. \end{cases} \tag{2}$$

In Equations (1) and (2), $a$ and $b$ are reward and penalty coefficients, respectively. In the proposed method, these two parameters are considered equal to 0.5. Also, $k$ is a discrete time index (the number of times the probabilities are modified) and $K$ represents the number of selectable actions in each LA (K = 2). After applying the above conditions to each of the actions of the LA (individually for each SA module), the probability vector of all the LAs is updated. After updating the LA models, the process of selection, evaluating the environment response and updating the probability vector will be repeated from the first step. This process will continue until one of the termination conditions is met:

- The number of iterations of the algorithm reaches the threshold $G$.
- The quality criterion does not improve after $S$ consecutive iterations.
- The error criterion reaches zero.

In Figure 6, the flowchart of optimizing LA-SAGAN in proposed method is illustrated.

In this research, the activity state of SA modules in LA-SAGAN was determined within G = 20 iterations of LAs. Each LA, had two selectable actions. Also, in each LA the reward and penalty parameters were set to 0.5. It should be noted that during each iteration, the learning model was trained by 25% of samples in training data. The samples were chosen randomly and considered the same during all iterations. After determining the suitable activity state of SA modules based on a quarter of training data, the resulting configuration was applied on LA-SAGAN and it was trained by all training samples.

### C. DATASET AND TRAINING PARAMETERS

The dataset used to train LA-SAGAN and implement the proposed method was obtained through musescore.com. To do this, 1000 music files with different durations (between 50 and 250 seconds) were obtained through this website. All dataset samples are in MIDI format. These samples belong to 10 musical genres of piano, including: 1- classical, 2- Jazz,

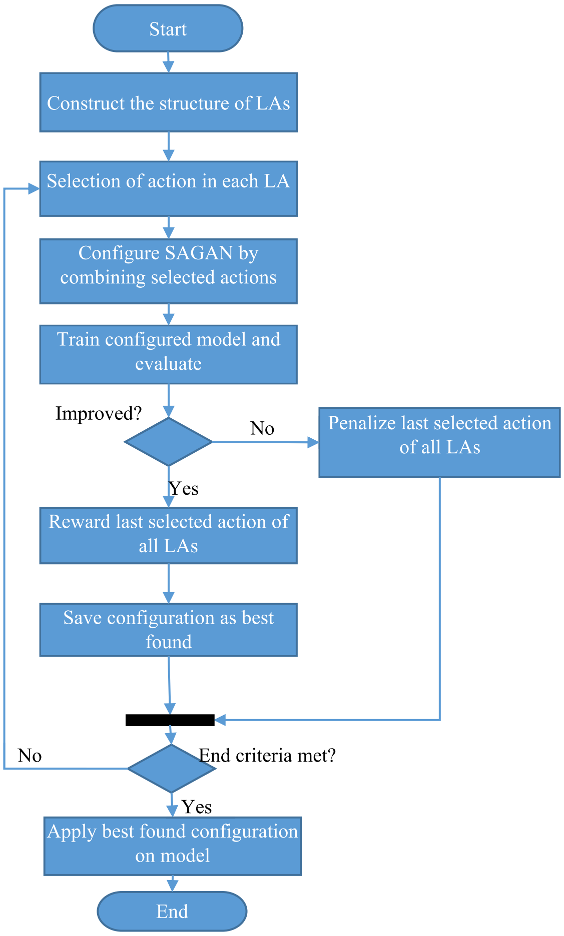


**FIGURE 6.** The flowchart of optimizing LA-SAGAN in proposed method.

3- Blues, 4- Pop, 5- Folk, 6- piano rock, 7- stride, 8- romantic, 9- dance and 10- new age. It should be noted that the collection and analysis method complied with the terms and conditions for the source of the data. A 5-fold cross-validation approach was employed to evaluate the generalizability of the model's performance.

Finally, for the training phase, we used Adam optimizer, batch size of 4, and also combination of WGAN-GP (Wasserstein Generative Adversarial Network with Gradient Penalty) and L1 as loss function. With WGAN-GP loss function, the challenges that traditional WGANs face are resolved that are the reduction of gradient and the mode collapse. It is achieved by introducing a gradient penalty term that regulates the training process in an orderly manner so that the learning process is stable. One the one hand, the L1 loss function is aimed to have the generated piece to be as close to the ground truth (real data) as possible in terms of absolute differences between the values. This module is also responsible for giving the model a higher level of detail in the generated reconstructions. It should be noted that the proposed method is the integration of two loss functions as WGANGP+100L1. Therefore, the L1 loss is multiplied by a factor of 100 and contributes less to the WGAN-GP's training process. Consequently, the WGANGP+100L1 function used in this model allows to produce realistic and detailed outputs while keeping the training process stable.

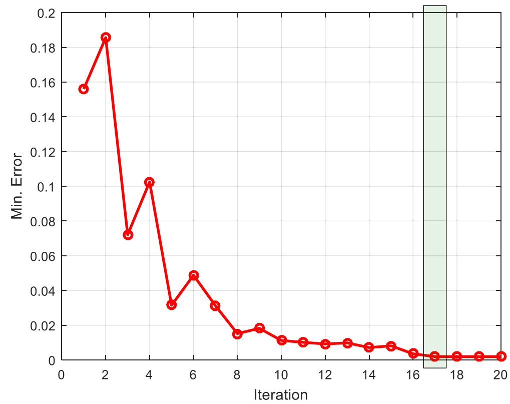


**FIGURE 7.** The average reconstruction error of model during each iteration of optimizing by LAs.

## IV. IMPLEMENTATION AND RESULTS

The proposed method was implemented using MATLAB 2018a software. During the experiments, the efficiency of the proposed method in generating piano music was evaluated by objective evaluation and subjective experiment. The criteria used in objective evaluation include: precision, recall and Entropy. Also, the subjective experiment was performed by scoring outputs of the proposed method using 10 participants.

The dataset used to implement the proposed method was obtained through musescore.com. To do this, 1000 music files with different durations (between 50 and 250 seconds) were obtained through this website. All dataset samples are in MIDI format. These samples belong to 10 music genres with piano pieces. During the experiments, database samples were partitioned into 10 parts and a 10-fold cross validation approach was utilized. Thus, the experiments were repeated 10 times and during each iteration, 90% of database instances (900 MIDI files) were used for training model; while the remaining 10% (100 MIDI files) were used for testing it.

In order to optimize the structure of LA-SAGAN, seven LA models were used to determine the activity state of SA modules in a cooperative manner. In this case, the number of iterations for optimization was set to G = 20 and the threshold of unimproved consecutive iterations was considered as S = 10. Also, the reward and penalty coefficients of each LA was set as $a = b = 0.5$. Figure 7, illustrates the average reconstruction error of model during each iteration of optimization algorithm.

As shown in Figure 7, the proposed optimization algorithm can minimize the reconstruction error of LA-SAGAN using reinforced learning ability of learning automata. According to the results, the minimum reconstruction error is met after 17 iterations. This case is obtained after activating SA modules of $\{SA_2, SA_3, SA_4, SA_6, SA_7\}$, and deactivating other modules.

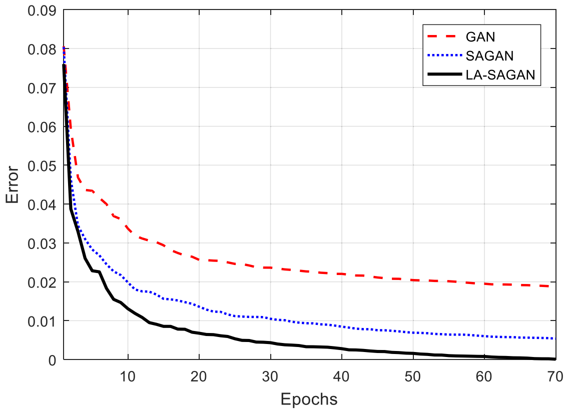


**FIGURE 8.** The convergence effect of the loss function.

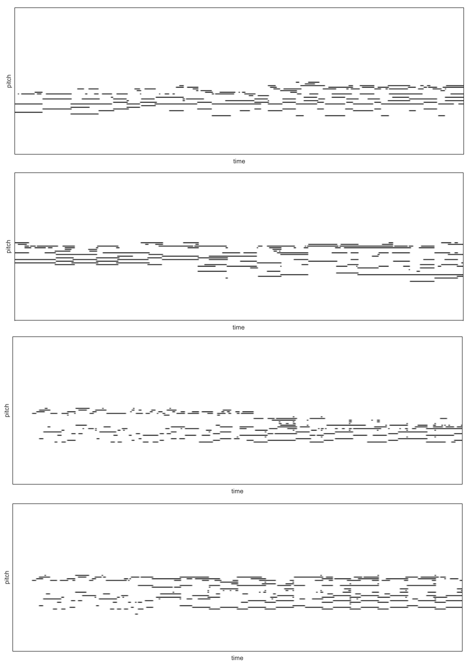

**FIGURE 9.** Several piano pieces generated by LA-SAGAN.

In order to examine the effectiveness of LA-based optimization in improving the performance of LA-SAGAN, the results are compared with the case that all SA modules are activated in the model. This case is called SAGAN (no optimization). Also, if all SA modules be deactivated, the resulting model will be a GAN, which this case has been considered in comparisons too.

In Figure 8, the convergence effect of the loss function in the studied cases is presented.

As shown in figure 8, when a simple GAN model is used for reconstruction, the convergence value is 0.0187. After applying SA modules to this model, a SAGAN is constructed which results in convergence value of 0.0054. These results demonstrate that using self-attention mechanism is effective in achieving better results. On the other hand, after optimizing the structure of SAGAN by proposed algorithm, a LA-SAGAN with convergence value of 0.008754 is obtained which outperforms other cases. These results confirm the effectiveness of proposed LA-based optimization algorithm in achieving a more accurate model for music reconstruction. Several piano pieces generated by LA-SAGAN are presented in figure 9. These outputs are drawn as piano-roll presentations. Figure 10 represents the spectrogram of 4 samples piano pieces generated by LA-SAGAN. Also, sheet of a sample piano piece generated be LA-SAGAN is presented in Figure 11.

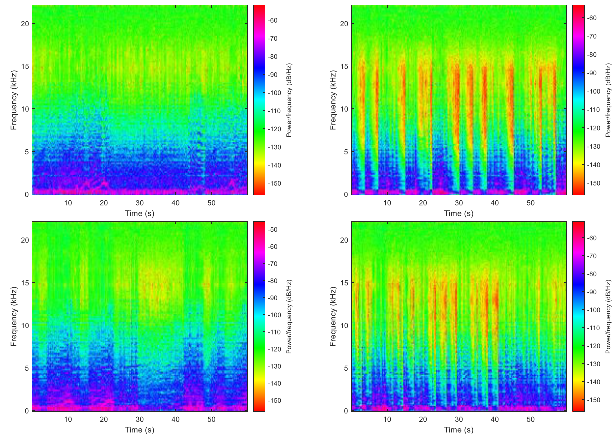

**FIGURE 10.** Spectrogram representation of sample piano pieces generated by LA-SAGAN.

**FIGURE 11.** Two first sheets of a sample piano piece generated by LA-SAGAN.

In Figure 12, the average values of entropy, precision and recall criteria for test phase of the experiments is presented. The information entropy is used for measuring the randomness of data. This criterion is calculated as follows [33]:

$$Entropy = -\sum\nolimits_{x \in X} p\left(x\right) \log_2 \left(\frac{1}{p\left(x\right)}\right) \tag{3}$$

where $p(x)$ is the probability of occurrence of x in data X. Also, precision and recall criteria are formulated as follows:

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

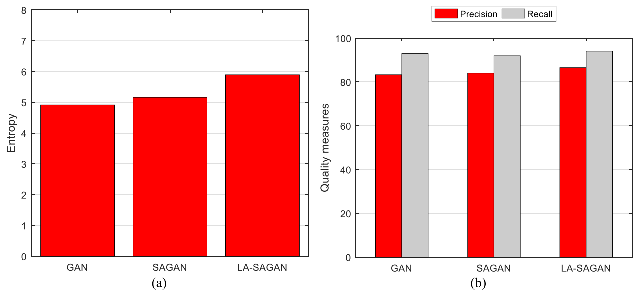


**FIGURE 12. The average values of (a) entropy, and (b) precision and recall criteria.**

where, TP and TN represent the number of true positives and true negatives, respectively. FP and FN also, describe the false positives and false negatives.

As shown in this figure, LA-SAGAN results in higher values of entropy, precision and recall compared to other methods. Higher values of entropy in LA-SAGAN shows that piano pieces generated by proposed method are more diverse; while higher precision and recall values show that outputs of the proposed method are more consistent with real music files. This improvement in proposed method can be attributed to optimizing the structure of the model using reinforcement learning approach.

It can be said that the best and most reliable way for evaluating the generated music is listening to it. For this reason, in order to more accurately evaluate the performance of the proposed method, a group of 10 participants was used and they were asked to rate the music pieces produced by LA-SAGAN and other methods. This scoring is in the scale of 1 to 10 and is determined based on criteria such as quality of the piece and rational connection between different parts. For this purpose, 10 pieces produced by each method were scored by the participants and the average scores were considered. It should be noted that the group of participants, includes 5 regular users and 5 music experts. The samples produced by the proposed method and each of the compared methods were scored by the participants. It should be noted that in order to maintain justice in scoring, the order of all samples was permuted randomly. Also, all samples have been evaluated in the same listening conditions. The results of this experiment are shown in Figure 13.

As the results presented in Figure 13 show, the proposed method has received a higher average score than other methods. This superiority in the proposed method can be seen as the result of two factors: LA-SAGAN decomposes piano pieces into sections and attempts to reconstruct next section of input in each iteration. This mechanism is effective in generating creative pieces which are compatible with the real piece, in terms of genre and theme. Also, using the SA mechanism in the proposed model creates outputs by maintaining the emotional and contextual characteristics of the initial input. This feature is effective in the formation of outputs whose different parts have a better rational connection.

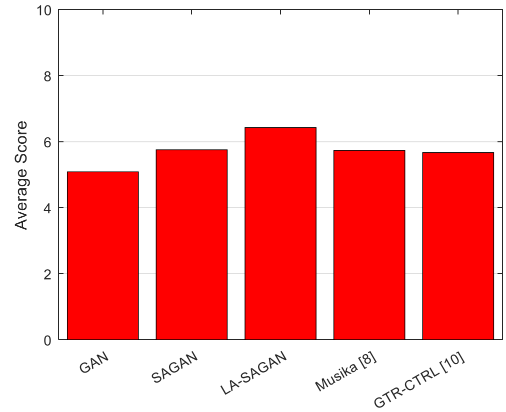


**FIGURE 13. The average scores of participants for various methods.**

**TABLE 3. Summary of the results.**

| | Entropy | Precision | Recall | Score |
|---|---|---|---|---|
| GAN | 4.912 | 0.8328 | 0.9293 | 5.082 |
| SAGAN | 5.148 | 0.8404 | 0.9193 | 5.750 |
| LA-SAGAN | 5.893 | 0.8651 | 0.9406 | 6.426 |
| Musika [8] | - | - | - | 5.733 |
| GTR-CTRL [10] | - | - | - | 5.667 |

Table 3, summarizes the results obtained in the experiments.

According to the evaluation above, the LA-SAGAN is proven to be quite effective in producing high-quality music. Unlike the existing approaches, LA-SAGAN produces at least 14.47% more entropy which means a higher degree of variety and richness of the resultant music. Also, the LA-SAGAN model displays an increased precision of a minimum of 2.47% compared to the recall of a minimum of 2.13%, which indicates a better tradeoff between producing relevant and comprehensive musical sequences.

Besides that human assessment of music supervisors gives LA-SAGAN's outputs the upper hand. The music generated by LA-SAGAN received higher points, which means the music generated had a greater degree of musical coherence and better adherence to the emotional cues needed compared to the music generated by the related methods.

### A. DISCUSSION AND LIMITATIONS OF THE WORK

This research was conducted based on the following hypothesis: LA-SAGAN, a cutting-edge deep learning model combining Self-Attention (SA) and Learning Automata (LAs), is capable of producing elaborate and emotion-based real-time piano music.

Our evaluation strategy used the two types of metrics, objective and subjective, for confirmation of the correctness of the hypothesis. The outcomes supported the hypothesis, presenting LA-SAGAN's ability to produce high-quality piano music. Here's a breakdown of the key findings:

Reconstruction Error: Data of LA-SAGAN's construction error in figure 7 revealed that it produced the least average reconstruction error after the optimization process with LAs. This proves that the presented model is more efficient in generating detailed instances compared to both basic GAN and a model with all SAs active (SAGAN).

Information Entropy: LA-SAGAN generated the outputs with the highest entropy value (Figure 12a) among others, which means that it includes more variety and richness in the generated music. This indeed corroborates with the idea that SA factors are the driving forces behind the diverse and creative outputs.

Precision and Recall: In LA-SAGAN, the precision and recall scores were significantly improved (Figure 12b) as compared to different models. This suggests a better balance between generating relevant musical sequences that are also comprehensive, further supporting the effectiveness of LA-based optimization in refining the model's performance.

Subjective Evaluation: The human listening test results for LA-SAGAN given in Figure 13 indicates that the average score was the highest among all the models. This implies that the music which is actually produced by the proposed model exhibits a higher degree of musical integrity and emotional attachment, as predicted. This can be attributed to two factors:

- The process of deconstructing and reconstructing piano parts could play a crucial role in composing pieces that have a single theme or one that goes well with the input.
- Through SA, the mechanism of preservation of emotional and contextual attributes of the original input is achieved, which leads to more coherent parts of music.

Limitations: Though the results are encouraging, the assessment of the limitations calls for further research as well:

- The size of the dataset (1000 music pieces) is somewhat small for music generation purposes. The number of samples in this dataset could be increased to find out potential generalizability in the data.
- The subjectivity was in the fact that the participants involved were few. An enlarged audience of listeners in the listening part of the test would help to gather more detailed information.
- One of the limitations of the proposed method is a relatively long time to configure the GAN model by the reinforcement learning approach. Because the reinforcement learning strategy, by applying any change to the GAN model configuration, must repeat the training process so that it can evaluate the efficiency of selected action. Although this strategy guarantees the achievement of a more efficient GAN model than static models, it causes the model training time to increase several times. On the other hand, this time occurs only in training phase and does not affect the performance of the model while generating new music.

Generally, the research results are in line with the hypothesis which has been forwarded. LA- SAGAN has shown great potential as a model that generates music in real-time, with a strong emotional touch and a high level of quality. We can obtain even more realistic and personalized outcomes via this way by addressing the limitations in future research.

## V. CONCLUSION

AI-generated music will always be a subject of ongoing research, but deep learning provides an opening for this avenue. The paper introduced LA-SAGAN, a new system that can make efficient use of GANs, SA and LAs for generating piano music. LA-SAGAN uses these two approaches in addressing the issues of distance considerations and emotion-based music generation.

The suggested approach exploits SA processes in GAN architecture to tackle long-range dependences in musical sequences, evoking the coherence and structure in the generated musical outputs. Moreover, LA-based optimization also successfully solves the optimal active state of SA modules, so as for the model to be more efficient and effective.

Evaluation results showed that LA-SAGAN gave better results than other models (basic GAN and a model with all SAs active) in terms of reconstruction error, information entropy, precision, recall, and determining test scores by human subjects. This implies that the LA-SAGAN approach is able to produce the piano pieces of the highest quality, with diverse emotional features, and in real time, being optimized structure.

Although LA-SAGAN represents a significant contribution, but there are some limitations. The training time for the initial period might be also reduced with regard to the usage of real-time applications. Moreover, the appraisal was done with a given data size and a certain number of the human subjects. Based on the research findings and determined limitations, future research directions encompass:

Generalizability: Analyzing LA-SAGAN's level of performance with different types of music and numerous data sets.

Evaluation Methods: To have a more complete evaluation, we employ more humanly advanced techniques like A/B testing for more comprehensive assessment.

Model Enhancements: Looking into ways to cut down training time or develop algorithms for real-time applications.

Multi-Track Generation: Using separate models for each hand to provide in the music generated harmonics a degree of complexity.

Beyond music generating, the general fundamental of LA-SAGAN, such as the fusion of deep learning and reinforcement learning, may find a niche in medical image generation and signal analysis. Nevertheless, it is of paramount importance to carry out more in-depth research in order to understand the mechanism in full.

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