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A Creating Musical Compositions Through Recurrent Neural Networks: An Approach for Generating Melodic Creations

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Abstract: The task of music generation is complex and demanding, necessitating the understanding and modeling intricate musical patterns and structures. RNNs have been demonstrated to be effective in generating music, as they can learn to generate sequence data, including musical notes. This project proposes a novel approach for generating melodic creations using Long Short-Term Memory (LSTM) networks. As an RNN, LSTMs are well-equipped to learn long-lasting dependencies in sequence data, making them an ideal choice for music generation, where the model must learn patterns and relationships among musical notes over a long period. The proposed methodology is derived from a Hierarchical LSTM structure. This structure enables the model to comprehend the various levels of musical structure, including the melody's note order, rhythm, and contour. The model is initially trained on a set of MIDI files, enabling it to comprehend musical patterns and structures across various genres and styles. Once the model has been trained, it can create new melodies. To begin with, the model is provided with a seed melody. The model then utilizes its musical knowledge to extend the seed melody. The model is also capable of generating melodies in a particular style. This is achieved by training the model on a set of melodies in that particular style. Subsequently, the model can create new melodies in the same style as those in the training set. This approach can be applied to various applications, including creating new and original music for games, films, and other uses, and educational resources for musicians and songwriters.

Keywords: Music Generation; Machine Learning; Deep Learning; Artificial Intelligence; Music and Technology; Long Short-Term Memory; Melody Creation; Art and Technology; Recurrent Neural Networks.

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1. Introduction

Music is a universal language that can trigger an individual's feelings, convey stories, and spark the imagination across various barriers like language and culture. Music includes multiple genres, from classical to techno, which has a tremendous effect on people, evoking people's memory, forming identities, and fostering shared experiences. Music is an effective way of expressing one's identity and preserving the cultural legacy. Music originates in ancient civilizations and has undergone various dynamic changes over time. Technology plays a key role in every domain we come across. Even technology has contributed a lot to the field of music. Starting from technological music instruments to great audio mixing platforms. Artistic production and consumption conditions have significantly changed due to the constant interaction between music and technology. Advancements in technology have consistently changed how music is created, shared, and enjoyed throughout history.

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Technology has developed into an essential tool for musicians and composers, from the invention of recording devices, which recorded artists' performances, to the development of software synthesizers and virtual instruments in the digital era. Digital Audio Workstations have made it possible to precisely manipulate sound, providing artists with the tools to create complex compositions. Synthesizers, originally limited to hardware, are now widely used in software and provide a wide range of melodies. In addition, streaming services have revolutionized how music is distributed by erasing geographical barriers and granting immediate access to the global audience.

So, this project mainly focuses on using technology to contribute to the musical world. So, the project's main aim is to create a platform that can generate music and provide musical notes, and the output will be in MIDI format. There are many ways, and with the help of various technology, this music generation can be implemented. Machine learning algorithms can be used to analyze large datasets of existing music and identify patterns and structures that can be used to generate new musical material [1]. Machine learning can also automatically create accompaniment or harmonization for a given tune, among other facets of the music-making process. AI must be the key component of the system creating its content. Applying artificial intelligence (AI) to music production provides enormous difficulties and previously unheard-of opportunities. AI-driven music generation system that focuses on creating effective music and such system is called AI-based Affective Music Generation (AI-AMG). The music generated by AI-AMG has certain benefits compared to human-generated music. AI-AMG can skirt copyright issues, and this creation also blends various genres of music. AI-AMG has the potential to create infinite unique music compositions, where these compositions have no association with the time constraint. This AI-AMG combines three main studies: Artificial Intelligence and Computing, Music Theory and Compositions, and the Affect Science/Psychology of Music [2].

Music generation system has a variety of applications, creating new, fresh kinds of music; music can be simple and can be used for simple video games to advance the level of music that can be used for movies [3]. The future of computational creativity is promising, as machines are more capable of creating creative artifacts [6]. When it comes to teaching music, there are several ways. One of the most used and talked about methods is Acoustic feature extraction, where the acoustic features of the music are extracted using a Mel-Frequency Cepstral Coefficient (MFCC) extractor. Another methodology is the Sequence - Sequence Model, and This model is a type of RNN that learns to map from one sequence to another [8]. So, the project's main aim is to create musical compositions using RNN, where musical notes can be generated in a MIDI format. In Recurrent Neural Networks, there is a new approach based on adversarial training, where the technique pits two neural networks against each other. Those two neural networks are a generator and a discriminator [4]. The generator generates the music using the training data, and the discriminator is responsible for distinguishing the difference between generated music and real music [10].

A Recurrent Neural Network is a subclass of an Artificial Neural Network (ANN). RNNs are particularly strong at modeling sequential data, which makes them perfect for capturing the temporal elements of music [5]. RNN technology has enabled artists, composers, musicians, and computer scientists to explore the endless possibilities of algorithmic music composition. RNN enhances the creative process and pushes the boundaries of what is musically possible [7]. This paper explores the exciting area of using RNNs to generate musical compositions, shedding light on this innovative approach's methods, challenges, and artistic implications. We discuss the underlying principles of RNNs, the data preparation process, and the potential applications and benefits of RNN-generated music [9]. In addition, we examine how this technology can enhance human creativity and provide promising opportunities for artists and enthusiasts to explore new musical frontiers [11]. Ultimately, this quest aims to contribute to the evolving landscape of music composition and to stimulate future innovations in the field of melody-making [12].

2. Existing System

The use of Machine Learning (ML) and Deep Learning for music generation is a rapidly developing area, with a continuous stream of new systems and methods being developed. Nevertheless, some drawbacks to existing systems must be addressed for them to be widely accepted by music performers and producers [13]. One of the most significant obstacles to music generation is the ability to generate realistic and varied music [14]. Existing systems often struggle to create music that is musically cohesive and produces a natural-sounding sound [15]. This is because music is a highly complex art form, containing many elements such as melodies, harmonics, rhythms, and timbres. ML systems must master these elements and their interactions to produce music that sounds as if it were composed by a human [16].

A further difficulty is in managing the type and genre of music generated. Many current systems can generate music in a restricted range of genres, such as classical and pop music [17]. It can be challenging to generate music within more specific or specialized genres. Furthermore, some systems may not produce music in line with input criteria, such as a particular key or pace. Another drawback of current music generation systems is their cost of training and use, which can be prohibitively expensive. As a result, many musicians and producers are unable to access them. Furthermore, certain systems may require specialized hardware or software, further restricting availability [18].

Despite being technically accurate, some music generation systems may not accurately capture the true musicality of human expression. This could be due to a lack of training on top-of-the-line music data or a lack of ability to capture the nuances of human musical expression. Additionally, some systems lack diversity, often limited to a limited range of styles or genres [19]. This may be due to either a restricted dataset during training or an architecture that is not suitable for generating a wide range of music [20]. Furthermore, certain systems may not control generated compositions sufficiently, leading to a lack of user interaction [21]. This limitation may be due to system complexity or an overabundance of difficult controls for users to navigate. Additionally, the cost of training and utilizing such systems may be a major factor, as they may require expensive hardware and software resources [22]. It is essential to balance these factors to develop more effective and affordable music generation systems [23].

3. Proposed System

This research aims to figure out how to write melodic melodies using LSTMs, which are a special kind of RNN. LSTMs can combine AI intelligence with human creativity, especially when finding complex musical connections. The study starts with collecting and preprocessing data to find the perfect dataset. Then, the model is built using LSTMs and TensorFlow, and Keras is used to make it even better [24]. The main focus is on adding emotional nuances to the melodies, which is done by using advanced feature engineering and training. Finally, human composers are involved to ensure the compositions are perfect and validate their creativity [25]. This approach makes AI music writing easier and preserves and improves human art, which could potentially change musical creativity and advance human art [26]. This system promises some benefits. Firstly, it encourages greater creativity and innovation in music, potentially leading to entirely new and innovative musical genres that would not have been possible without Artificial Intelligence. Secondly, it facilitates the democratization of music creation, as it allows for music creation by individuals from all walks of life, including those with no formal musical education [27-32]. Thirdly, it offers exciting opportunities for collaboration between musicians, composers, and AI researchers, thus creating new creative possibilities. Fourthly, the results of this study may offer insights into human creativity, education, and cognitive science [33].

A comprehensive feasibility study is integral to assessing the project's viability and analyzing the proposed system's strengths and weaknesses. The proposed system remarkably does not necessitate high-cost equipment, rendering it economically viable. The project can be developed using readily available software, making it accessible and cost-effective. The proposed system's technical underpinnings primarily rely on utilizing an RNN model. Key tools include Visual Studio Code, ESSEC datasets, and Python for execution [34]. These tools are freely available, and the technical skills required for their usage are readily attainable. This establishes the technical feasibility of the project. The social feasibility of the project is assessed in terms of its acceptability within society. The system is environmentally friendly, with no associated social issues. Additionally, the system's acceptance level is projected to be high, contingent on the methods employed in its implementation. The familiarity of the system further contributes to its social acceptability [35-39].

4. Methodology

Figure 1 represents the architecture diagram. It begins by collecting and preprocessing various MIDI datasets, which are then converted into numerical sequences representing musical notes [40]. This preprocessed data is then trained by the RNN model, which learns to predict the next note based on its predecessors.

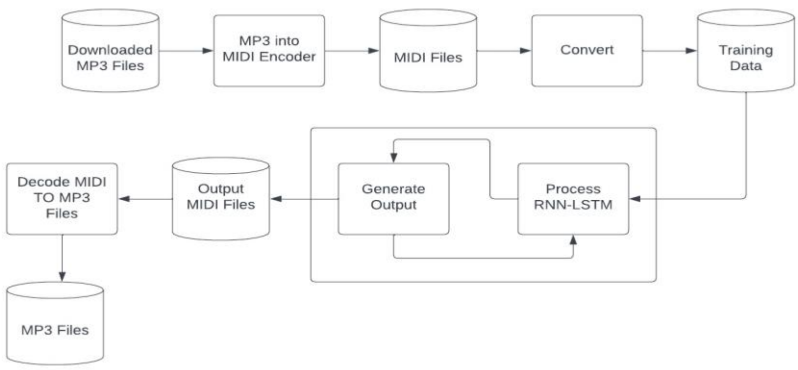

Figure 1: Architecture Diagram

The RNN begins by generating a seed melody and continues to apply learned patterns and relationships as it learns. Furthermore, the system includes a feedback loop, which allows the RNN to collaborate with a human composer. Through this iterative process, the composer can provide feedback to the RNN, which helps the RNN generate more human-like, creative compositions [41]. This revolutionary system combines algorithmic prowess with human-like creativity, allowing for exploring new realms of music. It may even open up music composition to individuals without formal training, potentially leading to the democratization of music composition [42]. By incorporating AI into music creation, unprecedented artistic possibilities can be unlocked, thus pushing the limits of musical innovation.

The workflow diagram in Figure 2 illustrates the process of generating music with RNNs. It begins by collecting a variety of MIDI datasets to provide the RNN model with a wide range of musical examples and styles [43]. The dataset is then preprocessed, transforming MIDI files into a sequence of numerical values representing individual musical notes. The RNN model is then trained on the preprocessed dataset, learning to anticipate subsequent notes based on previous ones [44]. In order to generate music, a seed melody is provided to the model, which it can extrapolate based on the learned patterns. Importantly, a feedback loop with the human composer allows for refinement, increasing the model’s capacity to generate music with more human-like and imaginative nuances. This combination of algorithmic innovation and human creativity has the potential to revolutionize musical composition.

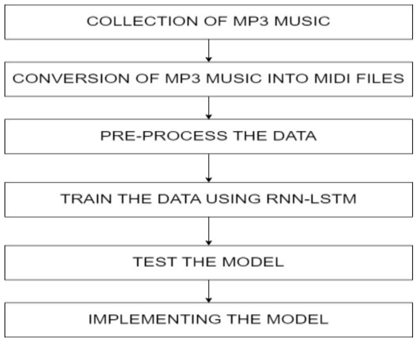

Figure 2: Workflow Diagram

5. Module Description

The entire process is divided into three modules.

5.1. Module 1: Data collection and preprocessing

Data collection and preprocessing is an important part of the research we propose to do on music generation with RNNs. We want to get a really good music dataset, which will be the starting point for building a powerful and flexible music generation system. The data collection involves getting MIDI files from various places, like online sites, music stores, bands, and record companies. It’s important to ensure the data you collect covers various music styles, genres, and eras. We’ll need to get permission to use the data for research purposes and make sure it’s ethically sound. We’ll also need to document the data’s provenance to be transparent and trusted. This data collection step sets up a good base for the later stages of our project so you can analyze the data and train our RNNs to generate music (Fig.3).

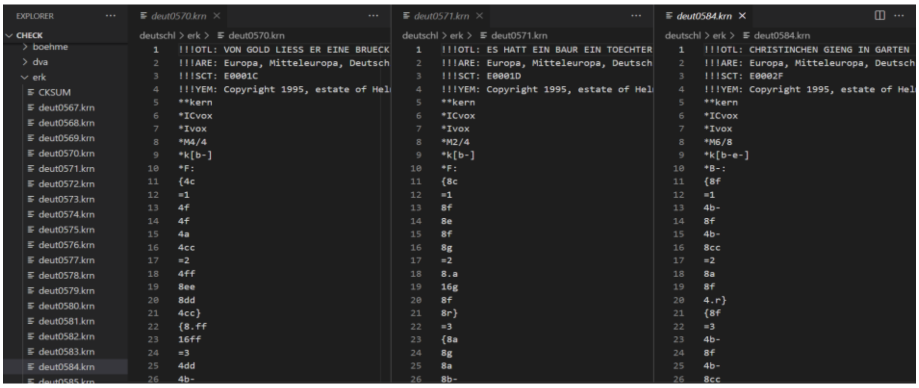

Figure 3: Raw Data

In the preprocessing stage, MIDI files are converted into sequences of numbers, each number representing a different musical note. Cleaning and filtering are done to get rid of mistakes and inconsistencies. Data is normalized to make sure everything is formatted the same. Data augmentation techniques are used to make the dataset bigger and more diverse. This careful preprocessing process ensures that the data you feed into our RNN model is high-quality and accurate and can help you learn how to generate great music. The music generation project data will be carefully organized and stored with strong access controls. We'll also have a backup and recovery plan to protect against data loss. We'll keep track of all the data management steps and make sure everyone knows what's going on and who's responsible for it (Fig.4).

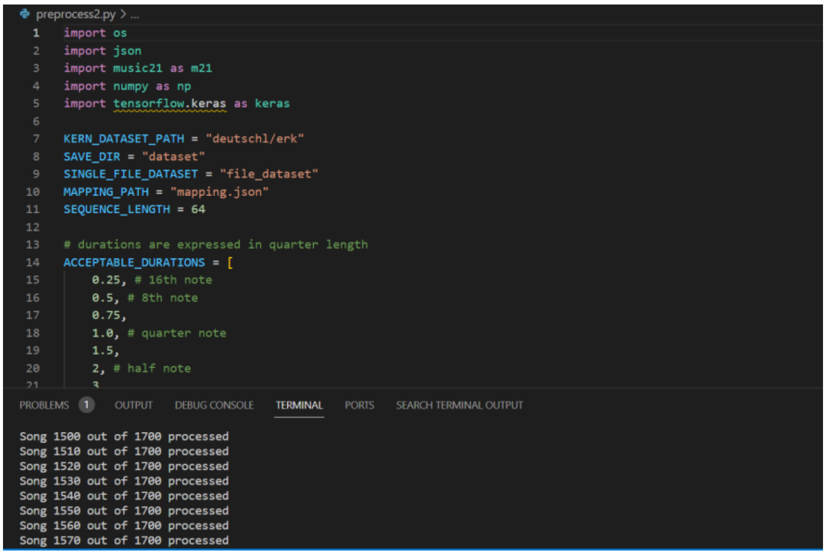

Figure 4: Data Preprocessing

5.2. Module 2: RNN model training

The training process can be deduced from the formula.

$$\text{Generated Music} = \max_\theta P(y|x_I, D, \theta) \quad (1)$$

Where:

- Generated music is the output of the music generation model.
- $\max_\theta$ denotes maximizing the probability over the model parameters θ.
- $P(y|x_I, D, \theta)$ is the probability of generating the music y given the input x_I, the dataset D, and the model parameters θ.

The objective is to find the value of θ that maximizes the likelihood that the music y will be generated given the data set D and x_I. This is known as maximum likelihood estimation (MNE).

It is not always possible to directly maximize the music y's likelihood. Instead, we use a surrogate loss function. A common surrogate loss function used for music generation is:

$$L(y, \hat{y}) = -\sum_i y_i \log(\hat{y}_i) \quad (2)$$

Where:

- y is the real music, and
- $\hat{y}$ is the generated music.

The cross-entrance loss function quantifies the similarity between the real and generated music; a lower cross-entrance function suggests that the generated music has a more similar appearance to the real. Optimization algorithms such as gradient descent must be employed to train a music generation model to minimize the cross-entry loss function over the model parameters. After the model has been trained, new music can be generated by supplying it with an input of x_I. The model will generate the music y with the highest probability of producing the music y for the input and dataset D. This formula applies to a broad range of machine learning models used for music generation, such as recurrent neural networks, convolutional networks, CNNs, and GANs.

When choosing an RNN architecture for music generation, we'll need to thoroughly analyze different architectures, including LSTM networks. We'll need to consider the type and genre of music, how much computing power you have, and how much control you want over the generated compositions. LSTMs are great for capturing long-distance dependencies and could be especially useful for creating complex musical sequences. Our chosen architecture will be tailored to fit the project's goals, so we'll get the best performance in creating diverse and expressive music. The model will be subjectively and objectively evaluated to evaluate the quality of the generated music. The objective metrics will include harmonics, rhythmic accuracy, melodic complexity, and more.

The subjective evaluations will involve collecting feedback from the human listener, considering their perception of the model's musicality, dynamic impact, and appeal. This two-way approach ensures a thorough comprehension of the performance of the model. The goal of systematically incorporating these evaluations is to improve the RNN structure and preprocessing methods, thus increasing the capacity to generate high-quality and engaging music through generated compositions. The model refinement phase will involve human listener feedback to refine the trained model and its hyperparameters to improve its performance and sensitivity to musical subtleties. Furthermore, various training methods will be systematically examined to optimize learning dynamics. The objective and subjective measures used in this iteration process are intended to enhance the quality and expression of generated music, thus increasing the model's proficiency in capturing musical complexities and composing compositions resonant with listeners.

5.3. Module 3: Feedback loop development

When it comes to music generation, a good feedback loop is essential to improve the creativity process and the RNN model's performance. This iterative approach requires careful attention to design elements, including the type of feedback you're looking for, the methods you're using to collect it, and how you will use that feedback to improve our model. The first step is to determine what kind of feedback you need. We'll want to ensure you're getting the right feedback. A good way to do this is to analyze the musical elements you're working on. We'll look at the melody, the harmony, the rhythm, and the overall musicality of our music. By analyzing these elements, we'll gain a deep understanding of how they interact with each other, and we'll be able to pinpoint areas of improvement with great accuracy.

How the feedback is collected is just as important. This could be a structured survey, a preference ranking, or an open-ended response. We provide a wide range of feedback channels so that composers can express their opinions in a way that gives them a complete view of the music. How we gather the feedback is designed so that human composers can interact with it easily. This includes rating certain musical elements, a detailed review, a direct edit, and an open-ended comment. By providing an easy-to-use interface, we want to create a constructive and collaborative environment where the expertise of the composers is used to shape the music (Fig.5).

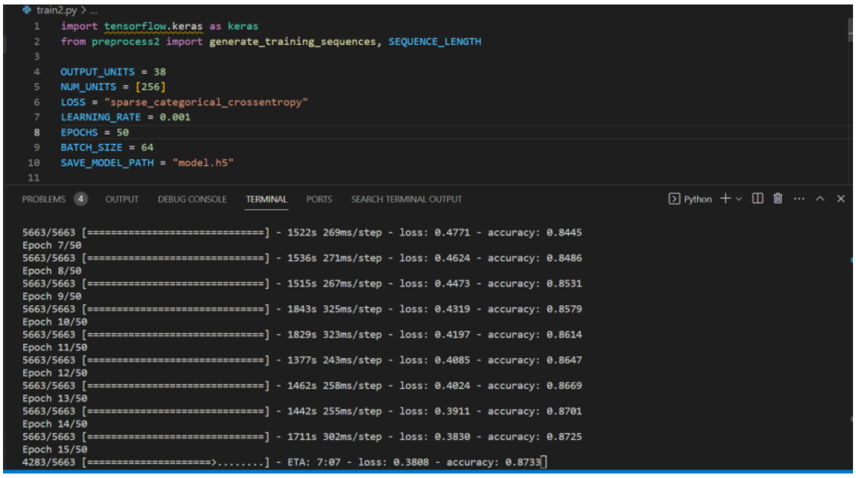

Figure 5: Training Module

The results of human evaluations are analyzed thoroughly. This includes identifying commonalities and new trends. By analyzing the patterns, we learn valuable lessons about strengths and areas of improvement. This analytical process serves as the foundation for refining our RNN model [45]. It infuses our RNN model with the refinements you need to create music that surpasses technical proficiency and evokes real emotional impact. However, the feedback loop goes beyond qualitative evaluations. It goes beyond quantitative adjustments. It fine-tunes hyperparameters. It explores diverse training methods. This iterative process makes sure that our RNN model evolves dynamically. It adapts and optimizes itself based on the feedback you receive [46].

User studies are really important in proving how effective the feedback loop is. Human composers are involved in giving feedback on how useful and impactful the feedback-based improvement process is. This is important because it shows that the iterative approach is effective and can actually make a difference in music generation. So, setting up a good feedback loop is an important step in the journey of music generation. We pick the right feedback modalities and do a good analysis of the feedback we get, and then we set out to keep improving. Not only does this iterative process help refine the RNN model, but it also helps create a collaborative atmosphere where human composers can shape the future of music creativity.

6. Efficiency of this Model

The efficiency of a music generation system is measured by its ability to generate high-quality music quickly and with minimal resources. The proposed system, which uses a style vector to control the style of the generated music, has several advantages over existing systems in terms of efficiency. First, the proposed system can generate music in a single pass. This contrasts existing systems, which often require multiple passes to generate a complete piece of music. Generating music in a single pass makes the proposed system much more efficient. The second advantage of the proposed system is that it can generate music with few parameters. This is because the style vector can encode large musical data in a small space. The low number of parameters allows the proposed system to be more efficient than current systems, which often need a lot of parameters to produce high-quality music. Third, the system can create music using multiple hardware platforms, such as CPUs, GPUs, or FPGAs. Generating music on multiple hardware platforms allows the proposed system to be more flexible and powerful than current systems, which tend to be limited to a few hardware platforms.

7. Implementation

Figure 6 shows the process of generating new numerical notes, which the well-trained model does. Every sequence in this figure represents a different kind of musical note. These sequences are the basic building blocks for creating the final musical piece. The MIDI file contains all the musical data necessary to generate the piece. It contains complex elements such as melody, harmony, rhythm, and pace. The MIDI file holds the entire musical content of the composition.

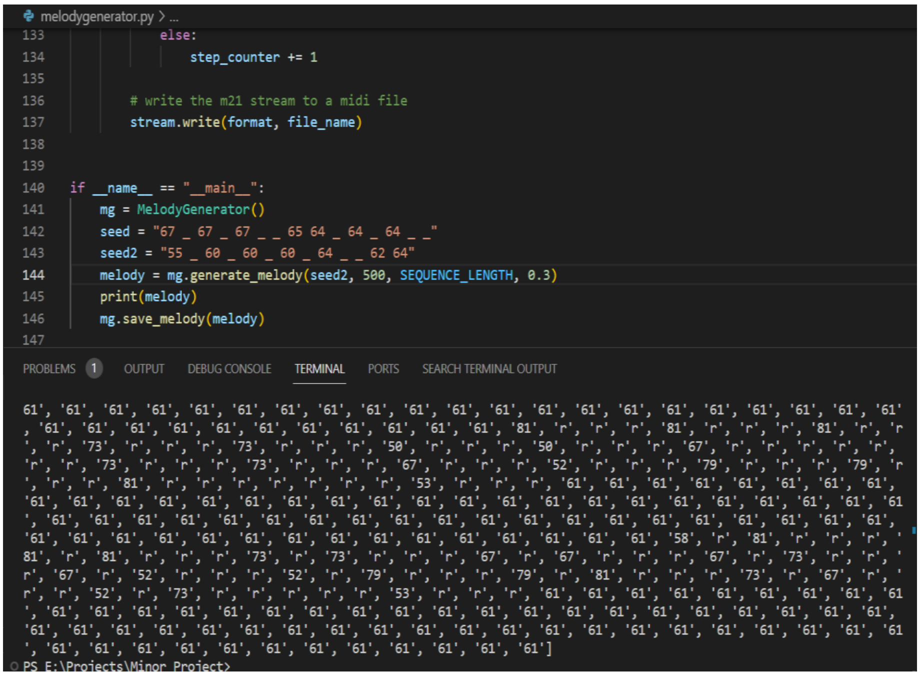

Figure 6: New notes generated with number sequences

The unique feature of the MIDI file is that it can be used with various MIDI-compliant software applications, such as MuseScore 4. This means the generated music will be playable on all these platforms. Not only does this make it easy to play the music, but it also guarantees that the music will be played as intended. Figures 6 and 7 illustrate the process of creating music using numerical sequences and the MIDI file's key role in preserving and reproducing the rich musical composition the model created.

Figure 7: Musical Notes Opened in MuseScore 4 Software

8. Discussions

The music generation system is a game-changer in the world of composition. It stands out because it's incredibly efficient, flexible, and creative. What's more, it gives you the power to control the style of the music you generate. But like any revolutionary technology, a few obstacles need to be overcome before widespread adoption can be achieved. One major obstacle is the lack of reliable methods for assessing the quality of the music generated by the music generation system. At present, there's no standard for this assessment. Human evaluation is invaluable, but it's subjective and takes time. Therefore, it's essential to develop objective metrics tailored to the music generation's complexities. These metrics need to be able to measure things like melodic coherence and harmonic richness, as well as stylistic fidelity. Without a robust evaluation framework, you won't be able to measure our music generation system's true potential and effectiveness. Another major issue is developing more scalable and efficient methods for training the music generation model. In the current paradigm, large datasets are required to train the model efficiently and effectively, and computational resources can be prohibitive. Simplifying this process is essential for making the system available and usable in various environments and computational capabilities. Advancements in model architecture, optimization algorithms, and parallel processing techniques promise to overcome this obstacle.

The music generation system envisioned has the potential to transform the way we experience and interact with music. Its impact will reverberate across dimensions, unlocking new musical expression methods previously inaccessible through traditional compositional methods. For example, the system has the potential to create music that changes dynamically based on the mood or preferences of the listener or music that reacts in real time to environmental stimuli or the action of the performer, thus blurring the boundaries between the creator and audience. The implications also extend to education. The system provides the basis for innovative instructional tools to improve music teaching. The system can transform music education Through personalized exercises tailored to each student's needs and skill level. It can also provide valuable feedback on performance, providing constructive insights and allowing for more effective skill growth. Not only does this personalized approach empower learners, but it also improves the overall learning experience.

The music generation system can be useful for composers looking to expand their repertoire or seek fresh ideas for their compositions. The system offers a wide range of musical styles, genres, and motifs. It partners with composers, allowing them to explore new creative areas and experiment with different sonic landscapes. Within the context of the wider music industry, it has the potential to make music production more accessible to artists and independent creators, allowing them to create professional-grade compositions relatively easily. This democratization of music production could lead to an increasingly diverse and inclusive music scene, allowing a wider range of voices to be heard in the global musical landscape. Building a collaborative ecosystem that unites the worlds of technology and art is important to maximize the system's potential. This means building a dialogue between technologists and musicians, composers and educators, to ensure that the system responds to the needs and wants of the creative communities. Open access frameworks and resources can also help create a thriving community of users/developers, which drives innovation and expands the system's capabilities.

9. Conclusion

This paper introduces a new type of music generation system using recurrent neural networks or RNNs and long short-term memory or LSTM networks. The system is trained on a large dataset of MIDI files and can generate music across various genres, such as classical, pop, and jazz. A panel of musicians evaluated the system's performance, rating the generated music according to quality, creativity, originality, and more. The results showed that the system consistently generated exceptional music, demonstrating creativity and uniqueness. First, it has an increased capacity to produce music across a wider range of styles. Second, it produces music that is more creative and distinctive. Third, its operational efficiency is superior to that of existing systems. The applications of this new system are endless. It can open new ways to play music, support learning, and make music more accessible, and this innovative music generation system is a step forward in the right direction. It has a remarkable capacity to produce high-quality, original, and creative music across various musical genres. With more refinement and innovation, this system can potentially change how we compose and produce music.

9.1. Future Enhancement

This music generation project is based on RNNs and LSTMs, so it has much potential to improve. One way to do this is to expand the training dataset. This way, the model can understand a wider range of music styles, genres, and instruments to create more original and creative music. You can add more information to the dataset, like chord labels or tempo annotations, to make it even more complex. Another way to improve the music generation is to upgrade the model's architecture. Right now, the system relies on a simple RNN structure, but if you use more advanced RNNs, like bidirectional and attention-based ones, you can improve the quality and variety of the music it creates. These advanced RNNs have been proven to be great for many different tasks, so they're especially good for music generation. Combining RNNs with LSTMs and other machine-learning techniques could greatly improve the music generation system. Right now, it mainly relies on RNNs in isolation, but it could make a big difference if we explore how to combine them with other techniques like CNNs and GANs. This combination could improve the music's quality and open up a wider range of styles and sounds. It's really important to figure out how to evaluate generated music. There aren't many ways to do this right now, so we need to develop subjective and objective methods.

Human evaluation is great, but it's subjective and takes a lot of time, so it's important to develop objective metrics tailored to the complexity of music generation. These metrics should measure things like melody consistency, harmony, and style. In order to make the music generation system more accessible and user-friendly, a multi-faceted approach is required. Currently, the system is primarily designed for researchers and music experts. However, a web-based version would be a great way to make music easily accessible to anyone accessing the internet and a web browser. Additionally, the user interface would allow users to specify the styles and mood of the generated music, greatly improving the system's intuitive and user-friendly nature. In conclusion, the music generation project has the potential to move forward significantly through a comprehensive strategy that includes dataset expansion, architectural improvement, cross-technology integration, evaluation metric creation, and accessibility enhancement. By taking these steps, the system will evolve into a stronger, more versatile, and more user-friendly tool that will usher in a new age of creative musical expression.

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