**Capstone project report**

**AUTOMATIC MUSIC GENERATION**

A Project Report

submitted in partial fulfillment of the requirements

of

**AIML Fundamentals with Cloud Computing and Gen AI**

by

Name :B.somasundaram

Naan Mudhalvan ID :au810021127705

Under the Guidance of

**Name of Guide (P.Raja, Master Trainer )**

**ACKNOWLEDGEMENT**

We would like to take this opportunity to express our deep sense of gratitude to all individuals who helped us directly or indirectly during this thesis work.

Firstly, we would like to thank my supervisor**,P Raja,** for being a great mentor and the best adviser I could ever have. His advice, encouragement and the critics are a source of innovative ideas, inspiration and causes behind the successful completion of this project. The confidence shown in me by him was the biggest source of inspiration for me. It has been a privilege working with him for the last one year. He always helped me during my project and many other aspects related to the program. His talks and lessons not only help in project work and other activities of the program but also make me a good and responsible professional.

#### **ABSTRACT of the Project**

Automatic music generation has become an exciting field within artificial intelligence, blending deep learning with creative expression. This project explores end-to-end automatic music generation using deep learning models, specifically focusing on the WaveNet architecture and Long Short-Term Memory (LSTM) networks. WaveNet, developed by DeepMind, is known for its ability to produce high-quality audio by capturing temporal dependencies in waveforms , while LSTM networks excel in learning sequential data. The primary goal of this project is to implement WaveNet from scratch using Keras and compare its performance against LSTM for generating coherent, melodically pleasing music. A large dataset is utilized to ensure robust generalization of both models, allowing for an in-depth analysis of their capabilities and limitations. This research aims to provide insights into the potential of WaveNet for creative applications and evaluate its effectiveness compared to traditional recurrent neural networks for automatic music generation.

**TABLE OF CONTENTS**

**INDEX**

|  |  |  |
| --- | --- | --- |
| **Sr. No.** | **Table of Contents** | **Page No.** |
|  |  |  |
|  |  |  |
|  |  |  |
|  |  |  |
|  |  |  |
|  |  |  |
|  |  |  |
|  |  |  |
|  |  |  |
|  |  |  |
|  |  |  |
|  |  |  |

**CHAPTER 1**

**Introduction**

* 1. **Problem Statement:**

The project tackles the challenge of **automatic music generation**, focusing on comparing two advanced deep learning architectures: WaveNet and Long Short-Term Memory (LSTM). Music, with its intricate patterns, melodies, harmonies, and rhythms, is difficult for AI to generate coherently and meaningfully. Developing a system that can produce music autonomously requires deep models capable of capturing long-term dependencies, emotional nuances, and compositional structure. This problem is significant as it addresses the demand for scalable, creative, and adaptive music generation, potentially benefiting multiple industries and advancing the field of AI for creative purposes.

* 1. **Motivation:**

This project was chosen due to the growing interest in AI-driven creativity, especially in music and art, and the need for intelligent systems that can produce original, high-quality content. Music generation through AI could revolutionize how music is created, used, and accessed, making it a valuable tool in entertainment, gaming, advertising, and therapeutic applications. Furthermore, this project contributes to a broader understanding of sequence modeling and generative AI, potentially impacting fields beyond music, such as language and speech processing, by refining models that handle long-term dependencies.

**Potential Applications and Impact**:

* **Creative Support**: AI-generated music can assist composers, musicians, and hobbyists in creating original compositions, exploring new styles, or simply providing accompaniment.
* **Dynamic Soundscapes**: In interactive media, AI can create adaptive soundscapes that respond to user interactions, enhancing user experience in gaming and VR.
* **Personalized Content**: Music generation enables the creation of unique, personalized playlists or soundtracks that adapt to individual preferences.
* **Therapeutic Uses**: Generated music can be used in therapeutic settings to create calming, uplifting, or focused soundscapes for mental health and well-being.
  1. **Objective:**

The primary objectives of this project are:

* To develop an end-to-end automatic music generation model using both WaveNet and LSTM architectures.
* To implement the WaveNet model from scratch in Keras, gaining a deep understanding of its functionality and intricacies.
* To compare the performance of WaveNet and LSTM in generating coherent and musically relevant compositions.
* To analyze each model’s strengths, weaknesses, and suitability for music generation tasks.
  1. **Scope of the Project:**

**Scope**:

* This project involves implementing and training deep learning models (WaveNet and LSTM) for the purpose of generating music automatically.
* It includes the collection of a substantial dataset of music samples to ensure model generalization.
* The project encompasses a comparative analysis of the WaveNet and LSTM architectures, highlighting differences in their ability to capture musical structures and dependencies.

**Limitations**:

* Computational requirements are high, given the complexity of WaveNet and the need for large datasets, which may impact training speed and resource usage.
* The generated music will be evaluated subjectively based on coherence and aesthetic appeal, as music quality is challenging to measure quantitatively.
* Model performance and quality of the generated music may vary based on dataset size and diversity, as well as tuning of hyperparameters.

**CHAPTER 2**

**Literature Survey**

* 1. **Review relevant literature or previous work in this domain.**

The domain of automatic music generation has been extensively explored, with early approaches rooted in rule-based systems and probabilistic models. However, the advent of deep learning has led to significant advancements. Early works, such as the **Markov chain model** and **Hidden Markov Models (HMM)**, captured basic musical patterns but were limited in modeling long-term dependencies. Recently, neural networks, particularly **Recurrent Neural Networks (RNNs)** and **Convolutional Neural Networks (CNNs)**, have been adopted to improve sequence modeling for generating more coherent and stylistically consistent music.

**Key recent developments include:**

* **WaveNet (Van Den Oord et al., 2016)**: Developed by DeepMind, WaveNet revolutionized the field by using a deep convolutional architecture with dilated convolutions, enabling it to capture long-range dependencies without the vanishing gradient problem. Originally designed for audio synthesis, WaveNet demonstrated potential in music generation as it can produce high-quality sound samples with realistic temporal structure
* **Long Short-Term Memory (LSTM) Networks (Hochreiter & Schmidhuber, 1997)**: LSTMs are popular in sequence modeling due to their gated architecture, which helps retain long-term dependencies in sequences. In music generation, LSTM-based models have been effective at learning musical structure, rhythm, and harmony, making them suitable for tasks requiring melody and chord generation.
* **Generative Adversarial Networks (GANs)**: GANs, notably **MidiNet** and **MuseGAN**, have shown promise in music generation by leveraging a generator-discriminator architecture. These models are effective for generating discrete sequences like MIDI but face challenges in producing high-quality, complex musical textures.
* **Transformers (e.g., Music Transformer by Huang et al., 2018)**: Transformers, known for their self-attention mechanism, have gained popularity in sequence tasks, including music generation. The Music Transformer model introduced relative position encoding, allowing it to capture musical phrasing and long-term patterns better than RNN-based models.
  1. **Mention any existing models, techniques, or methodologies related to the problem.**

Several techniques and architectures have been explored in music generation:

* **RNNs and LSTMs**: RNNs and LSTMs are widely used in music generation due to their ability to handle sequential data. Many music generation systems rely on LSTM variants to produce melodies, harmonies, and rhythms. **Examples**: Google’s Magenta project used LSTM for melody generation; Bach-bot utilized LSTM to generate music in the style of Bach.
* **WaveNet**: A CNN-based model designed to generate raw audio waveforms, WaveNet uses **dilated causal convolutions** to model temporal dependencies. This architecture is particularly relevant for applications requiring high-fidelity audio synthesis, including music generation.
* **GANs for MIDI Generation**: GAN-based models, such as **MuseGAN**, are effective in generating polyphonic music by creating MIDI sequences rather than raw audio. While they produce musically structured outputs, they often face limitations in audio quality and consistency.
* **Transformers for Music**: The self-attention mechanism in Transformers has made them adept at learning complex musical structures. **Music Transformer** adapts this approach for symbolic music generation, excelling in capturing musical phrases over extended sequences.
  1. **Highlight the gaps or limitations in existing solutions and how your project will address them.**

While these models and techniques have advanced automatic music generation, several gaps and limitations remain:

* **Complexity in Capturing Temporal Structure**: RNNs, even with LSTM enhancements, struggle with long-term dependencies in music, especially in capturing complex temporal and harmonic structures over long sequences. While Transformers address some of these issues, they are computationally intensive and memory-demanding.
* **Audio Quality and Continuity**: Models generating MIDI sequences, like GANs and some Transformer-based models, are effective for discrete notes but lack the smooth audio quality and tonal richness of real music. Additionally, converting MIDI to audio requires further processing, which may impact quality and continuity.
* **Resource-Intensive Models**: Architectures like WaveNet, while powerful, are computationally expensive due to their deep convolutional structure, which may limit their accessibility for smaller projects or real-time applications. Training such models on large datasets requires significant processing power and memory.
* **Limited Generalization Across Genres and Styles**: Existing models often require style-specific training, making it difficult for them to generalize across different genres or adapt to complex stylistic nuances without extensive retraining or fine-tuning.

**How This Project Addresses These Gaps**:

* **WaveNet vs. LSTM Comparison**: By comparing WaveNet and LSTM, this project seeks to analyze which architecture more effectively captures the long-term dependencies in music. WaveNet’s ability to generate raw audio could address MIDI limitations, offering higher-quality audio and continuous sound.
* **Implementation from Scratch**: Implementing WaveNet from scratch in Keras allows for custom modifications and experimentation, which could optimize performance while minimizing computational costs.
* **Dataset and Generalization**: This project plans to use a large and diverse dataset, allowing both models to better generalize across musical styles and patterns, addressing limitations in style-specific training.

**CHAPTER 3**

**Proposed Methodology**

**3.1 System Design**

In the context of the Automatic Music Generation project, the system design involves building a robust workflow for training and evaluating deep learning models (WaveNet and LSTM) for generating coherent, high-quality music. Key components include data collection, preprocessing, model training, and performance evaluation.

**3.1.1 Data Collection and Registration**

The **Data Collection and Registration** phase involves gathering a large and diverse dataset of music samples, preferably across different genres and tempos. This data is then preprocessed to segment it into smaller, manageable sequences that the models can work with effectively. For audio-based training (WaveNet), data is transformed into waveforms, while for symbolic music training (LSTM), data is stored in MIDI format. This phase "registers" the data within the system, making it accessible for model training.

**3.1.2 Feature Extraction and Recognition**

In the **Feature Extraction and Recognition** phase, the system analyzes and extracts relevant musical features such as rhythm, pitch, tempo, and harmony. These features enable the models to "recognize" the musical structure and dependencies within the data, aiding in generating coherent and stylistically consistent music. WaveNet processes raw waveforms, learning temporal dependencies through its convolutional layers, while LSTM models use note-based sequences, capturing long-term patterns and musical motifs.

* 1. **Modules Use**

In the context of the **Automatic Music Generation** project, the primary modules focus on data processing, model training, and evaluation rather than face detection. Here’s a breakdown of the modules involved in creating and comparing music generation models using WaveNet and Long Short-Term Memory (LSTM) architectures:

**3.2.1 Music Data Preprocessing and Feature Extraction**

This module is essential for transforming raw music data into a format suitable for training both the WaveNet and LSTM models. Steps include:

* **Data Collection**: Gathering a diverse dataset of music across various genres to ensure the models learn a broad range of musical styles and patterns.
* **Data Cleaning and Preparation**: Cleaning the dataset to remove noise, inconsistencies, or irrelevant samples. This ensures high-quality data for training.
* **Segmentation**: Dividing music data into manageable sequences. WaveNet processes raw audio segments (waveforms), while LSTM models work better with symbolic representations like MIDI, which contain note and timing information.
* **Feature Extraction**: Extracting musical elements such as rhythm, pitch, tempo, and harmony. For MIDI data, features like note sequences and timing are derived. For WaveNet, the raw audio waveforms are kept for temporal learning.
* **Data Augmentation**: Applying augmentation techniques like pitch shifting, time stretching, and adding slight noise to increase data diversity and improve model generalization.

**3.2.2 WaveNet Model Training**

This module focuses on implementing and training the WaveNet model using Keras. Key components include:

* **Dilated Causal Convolutions**: Essential for enabling the model to learn long-range dependencies in raw audio data by widening the receptive field with each layer.
* **Residual and Skip Connections**: These help maintain information flow across layers, improving the model’s ability to synthesize coherent audio over long sequences
* **Training Process**: The model is trained on the audio data using backpropagation, and the generated audio samples are compared against real samples to measure quality.

**3.2.3 LSTM Model Training**

This module trains an LSTM - based model on symbolic music data (e.g., MIDI) to generate sequential note patterns:

* **Sequence Modeling with LSTM Layers**: The LSTM model captures the order and timing of musical notes, learning the dependencies and structure of melodies and chords.
* **Embedding Layer**: Used for MIDI data, it converts notes into dense vector representations, improving the model’s understanding of musical relationships.
* **Training and Evaluation**: The LSTM model is trained to predict the next note or chord in a sequence. The output is evaluated to assess how well it mimics realistic music patterns.

**3.2.4 Performance Comparison Module**

Once both models are trained, this module handles performance evaluation, comparing WaveNet and LSTM in terms of music quality, coherence, and computational efficiency.

* **Qualitative Evaluation**: The generated music is reviewed for subjective quality, coherence, and appeal.
* **Quantitative Metrics**: Metrics such as loss values and continuity scores help determine each model's effectiveness in capturing musical patterns.
  1. **Data Flow Diagram**

A Data Flow Diagram (DFD) is a graphical representation of the "flow" of data through an information system, modeling its process aspects. A DFD is often used as a preliminary step to create an overview of the system, which can later be elaborated. DFDs can also be used for the visualization of data processing (structured design).

A Data Flow Diagram (DFD) visualizes the flow of data within the Automatic Music Generation system. It illustrates how data moves from input to processing and ultimately to the output, which is the generated music.

**3.3.1 DFD Level 0 - System Overview**

At the Level 0 DFD, we show the high-level process of the entire Automatic Music Generation System, from data input to music generation.

* **Input:** Raw music data (e.g., audio files or MIDI sequences).
* **Preprocessing Module:** Segments and extracts features from raw music data.
* **WaveNet and LSTM Training Modules:** Train models on processed music data.
* **Music Generation Output**: The models generate new music sequences based on learned patterns.

**3.3.2 DFD Level 1 - Data Collection and Preprocessing Module**

This module handles the initial preparation of the music data. It includes:

* **Data Collection**: Acquiring a diverse set of music samples.
* **Data Cleaning**: Removing noise and irrelevant parts of the data.
* **Segmentation**: Dividing the music data into smaller sequences for model training.
* **Feature Extraction**: Extracting key musical features (pitch, tempo, rhythm) for the LSTM model, and preparing waveform data for the WaveNet model.

Data from this module flows into the WaveNet Training Module or LSTM Training Module based on the architecture used.

**3.3.3 DFD Level 1 - WaveNet and LSTM Training Modules**

These modules train the WaveNet and LSTM models on the preprocessed data. Each model learns to generate music by identifying and replicating patterns in the data.

* **WaveNet Training Module:** Processes waveform audio data, using dilated causal convolutions to capture temporal dependencies for coherent music synthesis.
* **LSTM Training Module:** Processes MIDI sequences, using LSTM layers to capture note sequences and timing relationships.

Once trained, the models are ready to generate music.

**3.3.4 DFD Level 1 - Music Generation and Evaluation Module**

This module handles the actual music generation and evaluation:

* **Music Generation:** The trained WaveNet and LSTM models generate new music based on the patterns they learned during training.
* **Evaluation:** The generated music is evaluated both qualitatively (subjective listening) and quantitatively (e.g., loss metrics) to compare the performance of the two models.

The output of this module is a comparison of the generated music and a final selection of the best-performing model for practical use.

* 1. **Advantages**

Implementing an Automatic Music Generation system using deep learning models like WaveNet and Long Short-Term Memory (LSTM) offers numerous advantages:

**High-Quality Music Generation**

The WaveNet architecture, in particular, can produce high-fidelity audio, enabling it to generate realistic and nuanced musical compositions. LSTM models can capture the temporal patterns of musical sequences, resulting in compositions that are musically coherent.

**Versatility Across Genres and Styles**

With a diverse training dataset, both models can learn to generate music in various styles, genres, and tempos. This versatility is beneficial for applications ranging from film scoring to personalized playlists.

**Automation and Efficiency**

Automatic music generation streamlines the creative process, allowing composers or content creators to generate music quickly without manual composition. This is particularly useful for generating background music, soundscapes, or variations of themes in less time.

**Enhanced Creativity and Inspiration**

The system can serve as a tool for musicians and producers, offering new compositions or patterns that inspire creativity. By suggesting unique melodies or harmonies, it provides a base from which artists can create and customize further.

**Scalability with Larger Datasets**

Both WaveNet and LSTM models scale well with larger datasets, improving their ability to generate more complex and sophisticated music as additional data is incorporated.

**Comparative Performance Insights**

By evaluating the performance of WaveNet versus LSTM for music generation, this project can provide valuable insights into the strengths and weaknesses of each model, guiding future developments in AI-generated music.

**Potential for Real-Time Applications**

With optimized training and efficient models, the system could potentially be adapted for real-time music generation in interactive applications, such as video games, virtual concerts, or VR environments.

**Cost-Effective Solution for Music Creation**

For businesses that need background music or customized soundtracks, an automatic music generator can provide an economical solution compared to hiring composers, especially for non-unique or repetitive soundtracks.

* 1. **Requirement Specification**

The requirements for building and running the Automatic Music Generation system are divided into hardware and software components to ensure smooth implementation and optimal model performance.

**3.5.1 Hardware Requirements**

**High-Performance GPU**

* Recommended: NVIDIA GPUs like RTX 3080, 3090, or A100 for faster training. Deep learning models like WaveNet and LSTM require high computational power, especially with large datasets.
* Minimum: GTX 1060 or equivalent (may increase training time).

**CPU**

* Recommended: Intel i7 or higher, AMD Ryzen 7 or higher.
* Minimum: Intel i5 or equivalent.

**RAM**

* Recommended: 16 GB or higher for efficient data handling and faster processing during training.
* Minimum: 8 GB (may cause slower performance with larger datasets).

**Storage**

* Recommended: SSD with 500 GB or more for faster data access and storage of large music datasets.
* Minimum: HDD with 250 GB (may increase loading times).

**Other Peripherals**

Good-quality audio output (e.g., speakers or headphones) for evaluating generated music sampl

**3.5.2 Software Requirements**

**Operating System**

* Recommended: Linux (Ubuntu 20.04 or higher) for optimal performance with deep learning libraries.
* Alternative: Windows 10/11 or macOS (limited GPU support).

**Programming Languag**e

* Python (version 3.7 or higher) for developing and implementing the models.

**Deep Learning Libraries**

* Keras: for implementing both WaveNet and LSTM architectures, as it provides high-level APIs for model building.
* TensorFlow: backend framework for Keras, especially for GPU acceleration and efficient model training.
* Librosa: for music and audio data processing, such as feature extraction and waveform manipulation.
* Music21: for handling and analyzing symbolic music data (e.g., MIDI files) in LSTM models.

**Data Handling and Processing**

* NumPy: for numerical operations, including matrix manipulations and array processing.
* Pandas: for data handling, organization, and preprocessing.

**Visualization and Evaluation**

* Matplotlib and Seaborn: for plotting and visualizing loss trends, model performance, and generated music characteristics.
* Jupyter Notebook: for an interactive development environment, useful for testing, debugging, and displaying visualizations.

**Additional Software**

* MIDI File Editors (e.g., MuseScore) for manually inspecting and evaluating MIDI files generated by the LSTM model.
* Audio Playback Software: Tools to play back generated audio, especially for evaluating WaveNet-generated waveforms.

These specifications provide the foundation for setting up an effective development environment for the Automatic Music Generation system.

**CHAPTER 4**

**Implementation and Result**

**4.1 WaveNet Results**

* Implementation: Built with dilated causal convolutions in Keras, trained on audio data.
* Output: Produced realistic, continuous music with rich audio quality.
* Limitations: High computational demand and longer training time.

**4.2 LSTM Results**

* Implementation: Multi-layer LSTM network trained on symbolic music (MIDI).
* Output: Generated coherent melodies with structured patterns, ideal for MIDI applications.
* Limitations: Sometimes repetitive; less detailed than WaveNet in audio realism.

**4.3 Comparative Evaluation**

* WaveNet: Best for high-fidelity audio generation.
* LSTM: Better for note-based MIDI sequences with lower resource requirements.

**CHAPTER 5**

**Discussion and Conclusion**

* 1. **Key Findings:**

**WaveNet Model Performance**

WaveNet generated high-quality, lifelike audio that captured complex sound characteristics, making it suitable for applications needing realistic music synthesis.

However, it required substantial computational resources and longer training times, limiting scalability for smaller setups.

**LSTM Model Performance**

LSTM effectively generated structured, coherent symbolic music (MIDI), especially suitable for applications focusing on melodies and rhythm sequences.

It was computationally efficient compared to WaveNet but sometimes produced repetitive patterns and lacked the detailed audio richness of WaveNet.

**Comparative Insights**

WaveNet is ideal for generating raw audio with intricate details, whereas LSTM is advantageous for generating structured, note-based compositions (MIDI).

Both models have unique strengths: WaveNet excels in audio fidelity, and LSTM is optimal for sequence coherence with a lighter computational load.

**Potential for Hybrid Approach**

The combination of WaveNet’s audio realism with LSTM’s structural coherence could be explored in future work to optimize both sound quality and musical structure.

* 1. **Git Hub Link of the Project:**

Share the GitHub link

* 1. **Video Recording of Project**

Demonstration: Record the demonstration of the Project and share the relevant link.

* 1. **Limitations**
* · **High Computational Demand**

The WaveNet model requires significant computational resources due to its complex architecture and high-dimensional audio data processing. This limits accessibility and scalability, especially for users with limited hardware resources.

* **Training Time**

Both WaveNet and LSTM models need extensive training on large datasets to produce high-quality music. WaveNet, in particular, has lengthy training times, which can delay experimentation and model tuning.

* **Repetitive Patterns in LSTM**

The LSTM model occasionally generates repetitive sequences or limited musical diversity, as it sometimes struggles to break from learned patterns, leading to less creative outputs over extended sequences.

* **Limited Music Structure in WaveNet**

While WaveNet generates realistic audio, it may lack structural coherence in longer compositions, as it does not inherently understand musical form (e.g., verse, chorus, melody progression).

* **Dataset Dependency**

The models’ performance heavily depends on the quality and diversity of the training dataset. A narrow dataset can limit the style and variety of generated music, leading to overfitting and less generalizable results.

* **Lack of Real-Time Application Feasibility**

Due to the resource-intensive nature of these models, real-time music generation is challenging without significant optimizations, which limits applications in live, interactive environments.

* 1. **Future Work:**

To enhance the effectiveness and applicability of the Automatic Music Generation models, several improvements and research directions could be pursued:

**Optimize Computational Efficiency**

Explore model compression techniques like quantization and pruning to reduce the computational demand of WaveNet and LSTM. This could make the models more accessible and enable real-time music generation on devices with limited resources.

**Implement a Hybrid Model Approach**

Combine WaveNet’s audio quality with LSTM’s structural advantages to produce both realistic and musically cohesive compositions. A hybrid approach could capture the best of both architectures, balancing audio fidelity with melodic coherence.

**Incorporate Attention Mechanisms**

Attention layers could help the models focus on key musical patterns, allowing them to generate more diverse and creative sequences, especially in LSTM. This approach may reduce repetitive outputs and improve the quality of longer compositions.

**Expand and Diversify Training Data**

Gathering a larger, more diverse music dataset across genres and styles would help the models generalize better, reducing overfitting and increasing versatility. Experimenting with data augmentation techniques, such as pitch shifting and time stretching, could also enhance dataset diversity.

**Explore Transformer-Based Architecture**

Transformers have shown promising results in sequential data processing and could be tested for music generation to potentially outperform LSTM and WaveNet. This architecture may provide advantages in handling long-range dependencies and generating structurally cohesive music.

**Develop Real-Time Adaptations**

Investigate model optimization and parallelization techniques to enable real-time or near-real-time music generation, expanding applications to live performances, interactive media, and adaptive soundscapes.

**Enhance Musical Structure with Reinforcement Learning**

Reinforcement learning could be applied to help models understand and follow musical forms like verse-chorus structures, introducing a reward-based approach to learning song structure and enhancing composition cohesion.

* 1. **Conclusion:**

The Automatic Music Generation project has successfully explored the use of deep learning models, particularly WaveNet and LSTM, for generating music, demonstrating the potential of AI to create coherent and engaging musical compositions. By implementing these models from scratch using Keras, the project highlights the strengths of each approach: WaveNet’s ability to produce realistic, high-quality audio and LSTM’s strength in generating structured, sequence-based music.

This project contributes valuable insights into the applications of AI in creative domains, showcasing how advanced neural architectures can support music generation. It also reveals key challenges, such as high computational demands, limitations in structural coherence, and the need for diverse datasets, providing a foundation for future research and development.

Overall, this work advances the field of automatic music generation by comparing two prominent architectures, identifying improvement areas, and suggesting future directions. It represents a meaningful step toward making AI-driven music creation more accessible, versatile, and musically sophisticated.

**REFERENCES**

* Van den Oord, A., Dieleman, S., Zen, H., Simonyan, K., Vinyals, O., Graves, A., Kalchbrenner, N., Senior, A., & Kavukcuoglu, K. (2016). WaveNet: A Generative Model for Raw Audio. arXiv preprint arXiv:1609.03499.
* Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. Neural Computation, 9(8), 1735-1780.
* Dong, H. W., Hsiao, W. Y., Yang, L. C., & Yang, Y. H. (2018). MuseGAN: Multi-track Sequential Generative Adversarial Networks for Symbolic Music Generation and Accompaniment. Proceedings of the AAAI Conference on Artificial Intelligence, 34(1), 34-41.