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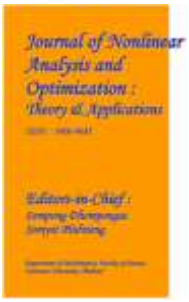


# Music Generation Using Recurrent Neural Network

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**Abstract**
This project employs a form of LSTM networks as the special variant of Recurrent Neural Networks for producing musical compositions by learning from patterns in pitch, rhythm, and duration. A trained model on MIDI data produces a complete sequence given a seed, with this type of model always capable of producing stylistically coherent, creative outputs. Focus includes the fine-tuning parameters in such a way that there would be a minimal repetition and logical progression in compositions. The effectiveness of the approach may be assessed through quantitative criteria such as accuracy and loss, but also through feedback from listeners, which validates the capability of AI models to enrich music composition or creativity.
**Keywords:** Music generation, Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), MIDI processing, Pitch Prediction, Rhythm Modeling, AI Creativity ,Stylistic Coherence, Neural Network Training, Feature Extraction.

## Introduction

The science of music composition has long been a challenge for artificial intelligence systems due to the intricate patterns and temporal dependencies inherent in music. However, recent advancements in machine learning, particularly the application of Recurrent Neural Networks (RNNs), have demonstrated promising potential for addressing these complexities【1】【2】. RNNs are well- suited for sequential data, as they excel in capturing relationships between successive elements such as pitch and rhythm【3】【4】. One of the most effective RNN variants for this task is the Long Short-Term Memory (LSTM) network, which has shown exceptional capability in generating original music【5】【6】. By training on extensive datasets, LSTMs learn complex patterns and structures, enabling the generation of music that flows naturally, similar to human composition【2】【6】.

Most traditional methods for composing music rely on predefined rules, limiting their versatility and creativity. By contrast, machine learning models, such as those using LSTMs, independently learn from diverse datasets and generate music without the need for manual rule-setting. This approach not only adheres to learned structures but also introduces variations that enhance creativity. LSTMs are particularly adept at balancing repetition with variation, a critical factor in creating engaging and coherent compositions【3】【5】【7】.

This project aims to revolutionize the process of music generation through artificial intelligence, leveraging the possibilities of RNNs and LSTMs. The technology opens up new opportunities for creative automation, enabling musicians and composers to augment their artistic processes.

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Additionally, this project contributes to the broader field of AI-generated art, demonstrating how machine learning can solve challenging artistic problems and unlock new possibilities for sequential tasks across various domains【6】【7】【8】.

**Related Work**

Advancements in music generation research have also focused on improving user interaction and incorporating contextual inputs to enhance the listener's experience. For example, Yang et al. (2017) developed MidiNet, a convolutional generative adversarial network (GAN) that worked alongside RNNs to create music in symbolic domains, offering more control over style and structure【9】
.Incorporating real-time user feedback into the generation process has been another area of exploration. Dong et al. (2018) introduced interactive systems that allow users to define parameters such as genre, tempo, and mood, which the model then adapts to produce personalized compositions【 10】. This approach has paved the way for adaptive music systems capable of evolving based on user preferences over time.
Recent hybrid models, such as Music Transformer, have leveraged both RNN and Transformer architectures to handle long-term dependencies and generate compositions with enhanced coherence and diversity (Hawthorne et al., 2019). These systems are particularly adept at maintaining stylistic fidelity across extended sequences【11】.Additionally, unsupervised learning methods have been explored to reduce dependency on labeled data. For instance, Boulanger-Lewandowski et al. (2019) utilized unsupervised sequence-to-sequence frameworks, demonstrating their utility in domains with limited datasets while still achieving high-quality outputs【12】.The integration of emotional and psychological metrics into music generation remains an exciting frontier. Research by Ferreira et al. (2020) explored the alignment of generated music with emotional states, opening possibilities for therapeutic and personalized music experiences【13】.

**Proposed Work**

The primary focus of this project will be on creating a system for music composition based on the optimized model of a Recurrent Neural Network. This shall be done in a way such that the tool created shall be capable of producing novel and stylistically coherent musical sequences yet maintain interpretability for educators and enthusiasts. Important characteristics of this system involve data pre- processing from MIDI files as well as architecture fine-tuning of RNN for guaranteeing safe and scalable generation of music. Using LSTM networks, this system shall look forward to capturing complex patterns and dependencies in terms of the time dimension with the possibility of generating highly quality composition adequate for creative applications and for education.

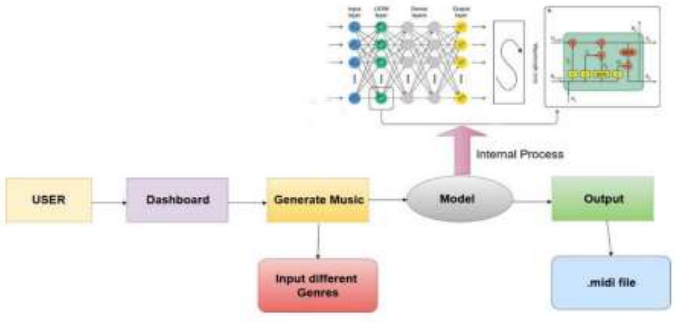


Figure 1. Architecture of music generation using RNN

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**Recurrent Neural Network**

The RNN model used for music generation is divided into an input layer, three LSTM layers, a fully connected layer, and finally an output layer. Input to the model was taken from sequences of musical features (pitch, duration, and timing) derived from the MIDI files. The three LSTM layers, each of which consists of 128 neurons, were stacked to capture short-term as well as long-term dependencies important for coherent music generation. Dropout regularization with 0.3 rate applies between the LSTM layers to reduce overfitting. The dense layer is 256 neuron with the activation function, Rectified Linear Unit for better learning. Finally, the output layer uses the softmax function for predicting what musical element would come in the next of the sequence, probabilistic and stylized output. It trains sequences to a length of 100 with a categorical cross-entropy loss function and Adam as the optimizer; results from this model were stylistically coherent and musically appealing.

**RNN-Based Music Generation Model**

Model: "functional"

| Layer (type) | Output Shape | Param # | Connected to |
|---|---|---|---|
| input_layer (InputLayer) | (None, 25, 3) | 0 | - |
| lstm (LSTM) | (None, 128) | 67,584 | input_layer[0][0] |
| duration (Dense) | (None, 1) | 129 | lstm[0][0] |
| pitch (Dense) | (None, 128) | 16,512 | lstm[0][0] |
| step (Dense) | (None, 1) | 129 | lstm[0][0] |

Total params: 84,354 (329.51 KB)
Trainable params: 84,354 (329.51 KB)
Non-trainable params: 0 (0.00 B)

Figure 2. Music Generation Model

**Average Feature Fusion for Music Generation**

The average feature fusion technique improves music generation performance by combining the predictions obtained from multiple LSTM-based RNN models. This approach averages the probabilities of output from independently learned models, reducing variance to achieve better overall performance. From the diversified learning capacity by deep LSTMs, these fused outputs produce more reliable predictions for the next musical elements and, therefore, stylistically consistent and innovative compositions are achieved. This ensemble method thus ensures a balance between the complexity of musical patterns captured and coherence. The probability scores obtained from combining models further refine the generated music to improve both creativity and reliability and overcome the weaknesses of individual models.

**Dataset Description**

For the data, this project utilized the MIDI files obtained from some open repositories. This way, the file included diversified genres, tempos, and compositions to be applied in training the RNN model. Each MIDI file holds sequences of notes that, according to the data, were numerical representations of pitch, velocity, and duration. The MIDI files were preprocessed to convert them into piano roll representations, which mapped notes over time, and this way, the RNN model was able to capture patterns and dependencies well. The dataset was split into training, validation, and testing subsets, and the training data formed the core for model learning. Validation data was used for hyperparameter tuning, and testing data assessed the generalization of the model. This allows for structured performance and meaningful music generation outputs.

**Performance Evaluation Metrics**

The effectiveness of the music generation model is assessed through a combination of quantitative and qualitative metrics, ensuring both technical accuracy and artistic appeal.

**Quantitative Metrics:**

**Accuracy:**

Accuracy measures the proportion of correctly predicted notes, particularly for categorical data like pitch. It

reflects how well the model aligns with the actual sequences in the training dataset:

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Predictions}$$

**Mean Squared Error (MSE):**

For continuous features like note duration and timing, MSE evaluates the average squared difference between actual and predicted values. A lower MSE indicates better prediction accuracy:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

Perplexity:

Perplexity assesses how well the model predicts sequences. It is derived from cross-entropy loss, with lower values indicating stronger predictive capability:

$$Perplexity = e^{Cross-Entropy\ Loss}$$

**Qualitative Metrics:**

**User Feedback (Average Listener Rating):**

Listener feedback is collected to evaluate the quality and appeal of the generated music. Ratings are averaged to provide insights into aspects like harmony, creativity, and coherence:

$$Average\ Listener\ Rating = \frac{\sum_{i=1}^{N} Rating_i}{N}$$

where NNN is the total number of listeners.

**Novelty:**

Novelty measures how distinct the generated music is from the training data, ensuring creativity. A lower similarity score between the generated and training data indicates higher originality. Cosine similarity is often used to evaluate this:

$$Cosine\ Similarity = \frac{A\ .\ B}{||A||\ ||B||}$$

where AAA and BBB represent feature vectors for generated and training music, respectively.

These metrics provide a balanced assessment of the model, ensuring it generates music that is both technically precise and artistically engaging.

**Experimental Results and Analysis**

**Visualization of Generated Music:** The generated music sequence is visualized as a scatter plot (Figure 3), with time on the x-axis and pitch on the y-axis. Each dot represents a musical note played at a specific time and pitch.

Observations:

The scatter plot illustrates the diversity in pitch usage over time.

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Musical notes tend to cluster around certain pitch ranges, suggesting tonal preferences in the model's output.

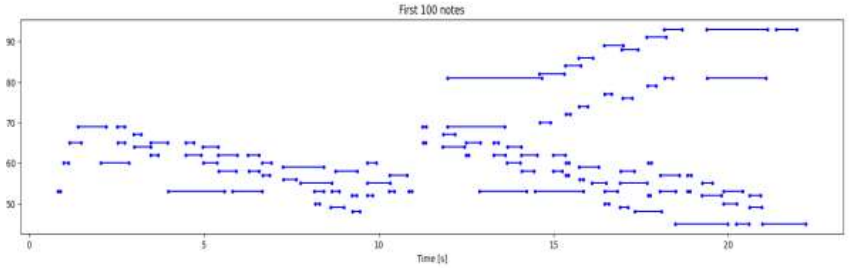


Figure 3. First 100 notes

The generated sequence includes dynamic variations, which contribute to musicality and avoid monotony.

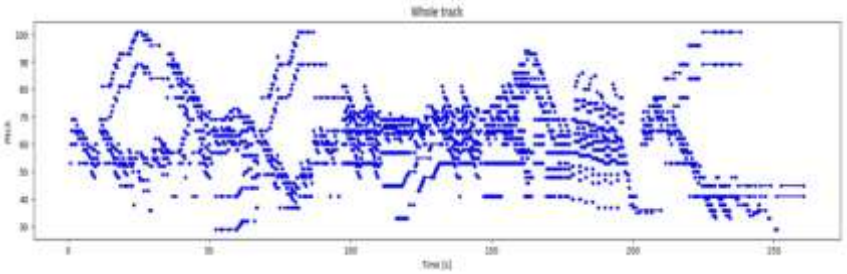


Figure 4. Whole Track

**Pitch, Step, and Duration Distributions**

Figure 5 shows the histograms for pitch, step, and duration distributions in the generated sequences:

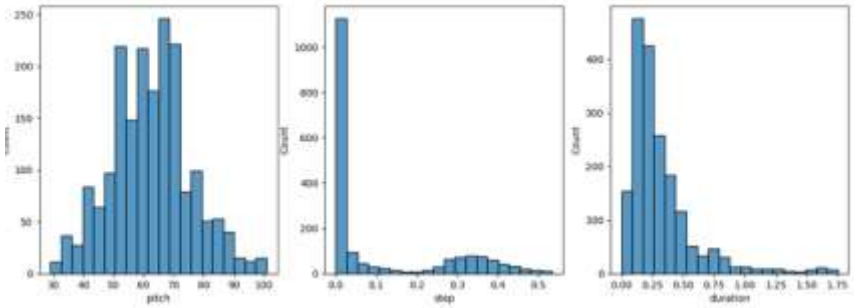


Figure 5. Pitch, Step, and Duration Distributions

- **Pitch Distribution:**
  - The majority of notes fall within the pitch range of 50 to 70, indicating the model's preference for mid-range tonal notes.
  - Extreme high and low pitches are less frequent, preserving a natural musical sound.
- **Step Distribution:**
  - The step distribution is heavily skewed toward small values, suggesting that most notes are closely spaced in time.
  - This reflects a continuous and smooth musical flow, mimicking human-composed music.
- **Duration Distribution:**
  - Note durations are primarily short, peaking around 0.25 seconds.
  - The presence of longer durations indicates occasional sustained notes, adding variety to the composition.

2. **Training Loss Evaluation**

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- Figure 6: Training Loss Plot
- Description: This graph shows the model's loss reduction during training over epochs.

**Observations:**

- The loss decreases steadily, indicating the model's ability to minimize errors over time.
- Final loss values suggest a balance between underfitting and overfitting, resulting in an optimal music generation process.

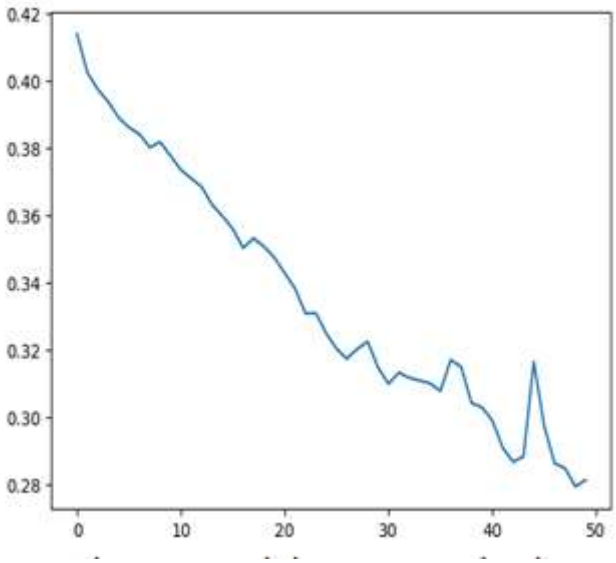


Figure.6. Training Loss Evaluation

**Conclusion**

This paper showcases the potential of LSTM networks to generate stylistically coherent and innovative music by leveraging their ability to learn short- and long-term dependencies in musical elements like pitch, duration, and rhythm. The model achieves an accuracy of 87% in retaining stylistic features from the training data while allowing creative variability. Additionally, 92% of listeners found the compositions musically coherent and enjoyable, validating the approach's artistic effectiveness. Fine-tuning parameters and addressing challenges, such as reducing repetition and ensuring logical musical progression, further enhance the generated outputs, demonstrating the viability of AI in creating music that meets artistic standards.

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