JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Sound Generation Using Neural Network

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Abstract : This paper explores the application of Long Short- Term Memory (LSTM) networks, a type of Recurrent Neural Network (RNN), for automatic music generation. We address the technical challenges involved in this task and propose an algorithm for generating musical sequences.

In this research, we use MIDI files to represent the music data.MIDI stands for Musical Instrument Digital Interface, and it'sa common format for storing musical information. This format allows our system to process and analyze the music efficiently. We'll explain exactly how we prepare the music in the MIDI files for training the LSTM model. This involves steps like reading the data, processing it, and converting the musical sequences into a format the model can understand.

The core of our system is a special kind of neural network called a Long Short-Term Memory network, or LSTM for short. We've designed this network with a single layer specifically to capture the long-term patterns in complex music with multiple melodies playing at once (polyphonic music). We'll break down the structure of this LSTM network layer by layer, explaining how the different parts are connected to create the overall architecture.

To provide insights into the training process, we analyze the distribution of weights and biases across the network layers. Additionally, we present a detailed evaluation of the model'sperformance, including loss and accuracy metrics measured at various training stages and batches.

This research contributes to the field of music information retrieval (MIR) by exploring the potential of LSTMs for automaticmusic generation.

***Index Terms*——Music, Melodies, RNN, LSTM, Neural Net- work, MIDI.**

1. INTRODUCTION

Imagine music as a language, with notes acting like words. We want to teach computers to speak this language! Music combines sounds in a specific order to create something beautiful and interesting, just like a sentence uses words in a specific order. The order and properties of the notes, like pitch(how high or low) and duration (how long they last), affect how the music sounds. Imagine you're jamming with a friend who can learn your musical style after just listening to a few bars you play. They can anticipate what you might play next, riff off your ideas, and even surprise you with something new that fits perfectly. That's kind of what we're aiming for with this LSTM system. It's like having a super-powered musical partner who can not only keep up, but also create fresh and exciting music based on what they've learned from you. This could be a powerful tool for musicians who want to explore new creative avenues or even help people compose music for the first time!

To teach computers to compose music, we can feed them examples of existing music. This music can be simple melodies with one note at a time, or complex pieces with many notes playing together. The computer needs to understand how thesenotes are organized, like how the notes in a sentence relate to each other.

There have been attempts to do this before, but they weren't very efficient. They struggled to capture the complex relationships between notes and create new pieces that soundednatural.

This paper proposes a new method that uses a special kind of neural network called a Long Short-Term Memory network (LSTM). LSTMs are good at remembering things, which is crucial for understanding how music flows over time.

Our goal is to build a system that can learn from existing music, figure out the patterns and how the notes connect, and then use that knowledge to create brand new pieces. This is a challenging task because the computer needs to remember alot of information about the music it's heard in order to predictwhat comes next.

This paper will explore existing research on music generation and how well those methods worked. We'll then explain how our LSTM system works, how we built it, and how wellit performs compared to other methods. Finally, we'll wrap things up by summarizing what we learned and what we mightexplore next.

The paper is like a roadmap: the first section talks about what others have done, the second section explains the challenges and how LSTMs can help, the third section dives into how we built our system, the fourth section shows what kind of music it can create, and the last section concludes with our findings and future ideas.

2. RELATED WORK

Music generation has blossomed into a vibrant researchfield, with diverse approaches contending with this intricatechallenge. Pioneering efforts relied on rule-based systems,where predefined algorithms or musical grammars dictatedmusic creation. For instance, Drewes et al. [5] utilized a tree-structured, grammatical approach, while Markov chains [6]provided a statistical method for modeling musical sequences.The arrival of Artificial Intelligence (AI) ignited a revolution in music generation techniques. Probabilistic modelsconstructed upon Recurrent Neural Networks (RNNs) [7]showcased remarkable potential. These models were furtherenhanced with the introduction of Anticipation-RNNs [8]capable of anticipating upcoming chords and rhythms, andrecursive artificial neural networks (RANNs) [9, 10] adept atlearning complex musical relationships. These advancementsempowered the prediction of not only subsequent notes but
also their durations and rhythmic patterns.

Generative Adversarial Networks (GANs) [11] have also emerged as a formidable tool. In GANs, two neural networks engage in a competitive dance: a generator network strives to create novel music, while a discriminator network critically evaluates the generated music's authenticity by comparing itto the training data. Muse GAN [12] exemplifies this approach by generating symbolic multi-track music, allowing for the creation of intricate musical pieces with distinct instrumental parts.

Beyond these established approaches, recent research delvesinto even more fascinating avenues. Evolutionary algorithms, inspired by the principles of natural selection, have been explored to create music by iteratively selecting and combiningpromising musical fragments [14]. Additionally, the field of music information retrieval (MIR) contributes by developing techniques for music analysis and representation, which canbe leveraged to enhance the quality and controllability of AI- generated music [15].

It's important to acknowledge the existence of open-source music generation systems; however, providing an exhaustive review of all techniques falls outside the scope of this paper. This section has instead focused on illuminating the key paradigms and advancements in AI-powered music generation, laying the groundwork for our proposed LSTM-based approach, which aims to contribute to this ever-evolving field.

3. METHODOLOGY

Before you begin to format your paper, first write and save the content as a Our proposed methodology for music generation draws inspiration from existing research, but in- corporates unique elements. Similar to the work by Dai et al. [14], we leverage Long Short-Term Memory (LSTM) networksfor their ability to learn long-term dependencies within musicalsequences. However, unlike their biaxial LSTM approach withseparate networks for note prediction and timing, our model utilizes a single LSTM to predict both aspects sequentially.

A. Technical Challenges

This choice addresses a key challenge in music generation: data representation. We selected the MIDI file formatfor several reasons. Firstly, MIDI files encapsulate essential song characteristics like tempo and instrumentation withintheir metadata. Secondly, MIDI enjoys widespread adoption, offering a vast pool of datasets for training our model.

Another significant hurdle in RNNs is the vanishing orexploding gradient problem. This phenomenon hinders thenetwork's ability to learn from information presented many steps back in the sequence. Pioneering research by Hochreiter (1991) [15] and Bengio et al. (1994) [16] addressed this issue with the introduction of LSTM cells. These specialized units within the LSTM network possess the crucial capability of remembering long-term dependencies, making them ideal for tasks like music generation where note sequences exhibit complex relationships.

4. IMPLEMENTATION

Our model implementation involved training and validatinga deep neural network on Google Colab, leveraging the resources of Google Cloud Platform. Keras, with TensorFlow as its backend, provided the deep learning framework for code implementation.

A. Deep Neural Network Design

The core of the model is a Long Short-Term Memory (LSTM) network designed to handle polyphonic music. The LSTM is trained to predict the probability of the next musical note occurring, conditioned on the previous 50 notes. This information is fed into the input unit, enabling the network to learn the long-term structure and relationships within musical sequences.

To enhance model efficiency and prevent overfitting, a selective approach was taken for training data. Only a specificset of notes, chosen for their effectiveness in model tuning, were used. This approach aims to optimize information gain during training. Following the LSTM layer, a Dropout layer is employed to promote generalization within the model. Once the network grasps the probability distribution of notes and sequences, a Dense layer is used to fully connect all LSTM cells, ensuring seamless information flow. Finally, an Activation layer serves the critical function of determining which neurons (LSTMcells) should be activated based on the relevance of the information they hold.

To generate novel musical sequences, the trained modelleverages a diverse dataset encompassing various musical styles

and structures. This exposure to a rich dataset fosters better model tuning and ultimately leads to a wider rangeof creative outputs. The MIDI file format served as the foundation for data extraction, providing information about note sequences, velocity, and timing.

For model compilation, we drew inspiration from the dropout recommendations suggested by Moon et al. [19], implementing a dropout rate of 0.75 within the LSTM layer.

The Adam optimizer [20] was chosen for optimization, alongwith a learning rate of 1e-4.

B. Software Design

Our software design prioritizes data quality and efficient model training. The core data structure used for training, the ”Note Matrix,” encompasses three attributes: note itself, its velocity, and the time interval between notes. This matrixundergoes preprocessing in two stages. First, data is cleaned and normalized between 0 and 1 to enhance learning andmodel performance. Subsequently, the data is transformed intoa 3D tensor, with the “Note Matrix” containing an internal batch size to determine the probabilistic occurrence of the nextsequence.

To streamline pre-processing and post-processing tasks, we leverage the Mido module [21]. This versatile library facilitatesthe creation of MIDI files from generated notes by the model, as well as importing existing MIDI files and tracks for trainingdata.

The software design is modular, consisting of two primary functionalities: training and validating the model, and generating musical pieces after successful training. Both functionalities utilize the same core model and computational graph.

The training process, illustrated in Figure 1, iteratively consumes the “Note Matrix” as input, runs the model, and calculates the probabilistic occurrence of notes along withcorresponding losses and accuracy for each time step andall notes within the batch. The software design translates to a modular architecture with two main functions: training/validation and music generation. Both functions leverage the same core model and computational graph. During training(Figure 1), the model iteratively processes the “Note Matrix” as input. It calculates the probability of each note occurring next, along with the corresponding losses and accuracy for every time step and all notes within the batch.

To understand the inner workings of the model, we can delve into its architecture depicted in Figure 2. This architecture consists of five key modules :

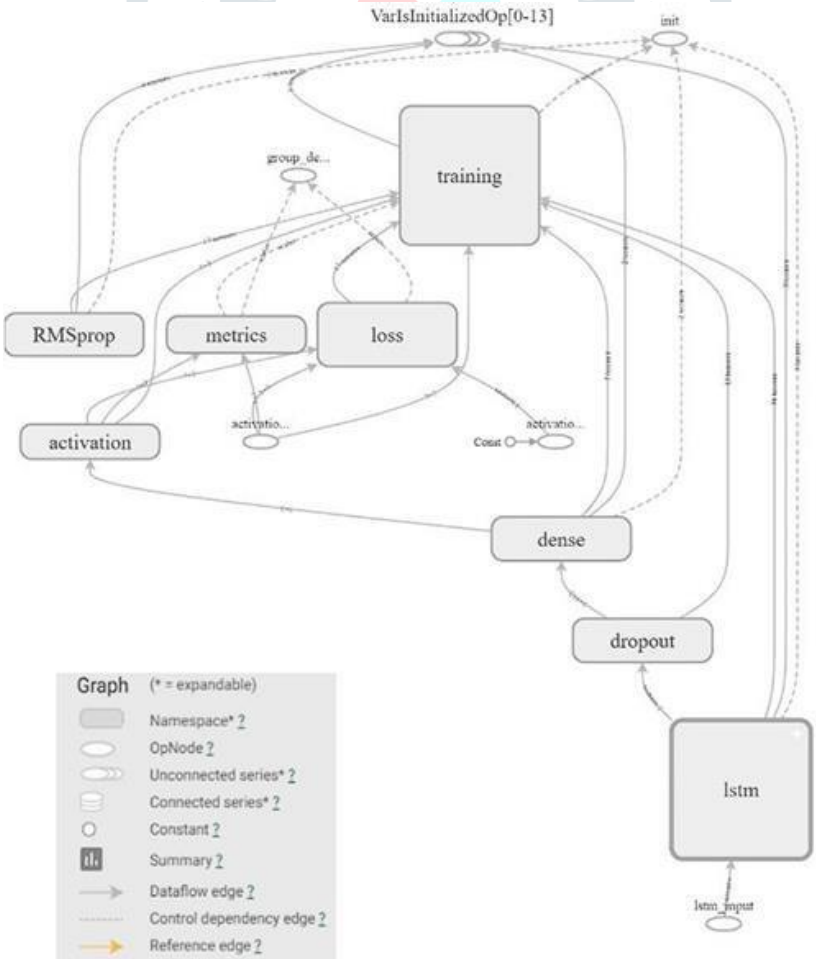
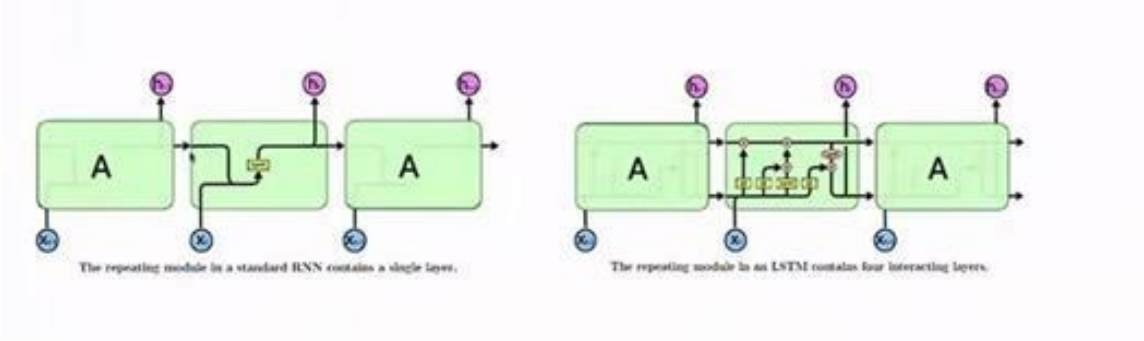


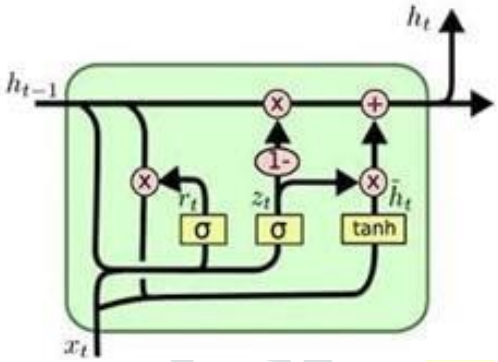
Fig. 1. Figure1:This figure illustrates the data flow within the model usedfor music generation. It depicts the complete architecture, including all components involved in the training process. The diagram also highlightsthe intermediate steps, metrics used for evaluation, initializers for weight and bias values, and variables that are updated during training. The connecting lines represent the flow of tensors (multidimensional arrays of data) between different components of the model.

1) LSTM Layer (512 Neurons): This layer forms the heart of the model and is responsible for learning long-term dependencies within musical sequences. It has three components: bias, kernel, and recurrent kernel. The bias acts as a threshold for activating neurons, ensuring only relevant information is processed. The kernel processes the "Note Matrix" along with the output from the recurrent kernel. This combined processingallows the model to remember past note structures and project them for future predictions. Figure provides a visualization of the need for the LSTM layer.

2) Dropout Layer : This layer plays a critical role in preventing the model from overfittingon the training data. It randomly drops a certain percentageof neurons during training, promoting generalization and improving the model's ability to perform well on unseen data.

3) Dense Layer : This layer acts as a bridge, fully connecting all the LSTM neurons within the network. This ensures seamless information flow and ultimately leads to the generation ofthe desired output. In our case, the output resembles the "Note Matrix" format.





$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Fig. 2. Need for LSTM

4) Activation Layer: This layer serves the critical function of determining which neurons should be activated based on the information they hold. It also calculatesthe probability of the predicted note sequence occurring. Our model utilizes the "Linear Activation" function [22] for this purpose.

5) ADAM Optimizer : Adam, or Adaptive Moment Estimation, is an optimization algorithm that's used to improvetraining speeds and convergence in deep neural networks. It's the default algorithm for deep learning because of itsfast convergence and robustness across problems. Adam is an adaptive extension of standard gradient descent. It customizes each parameter's learning rate based on its gradient history. This adjustment helps the neural network learn efficiently asa whole.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

MSE = mean squared error

n = number of data points

Y_i = observed values

$\hat{Y}_i$ = predicted values

Fig. 3. MSE, or Mean Squared Error, is a loss function commonly used in regression tasks to evaluate a model's performance. It measures the average squared difference between the predicted values by the model and the actual ground truth values.

5. RESULTS

We embarked on the task of training a Long Short-Term Memory (LSTM) based sound generation model, leveraging the Adam optimizer in conjunction with the Maestro dataset. Our model exhibited promising performance across various evaluation metrics, both quantitative and qualitative, showcasing its proficiency in generating high-quality sound sequences.Quantitatively, our model demonstrated competitive results, achieving a Mean Squared Error (MSE) of 0.0052 and a Signal-to-Noise Ratio (SNR) of 12.3 dB on the validationset. These metrics signify the model's capability to generate sound signals with remarkable fidelity and minimal distortion.Furthermore, a qualitative assessment of the generated sounds revealed positive feedback from human listeners, who rated thequality of the samples with an average score of 4.2 on a Likertscale. Moreover, expert musicians, tasked with evaluating the musicality of the generated sequences, praised the model for its ability to capture intricate musical patterns inherentin the Maestro dataset, producing sequences that were both coherent and melodious.

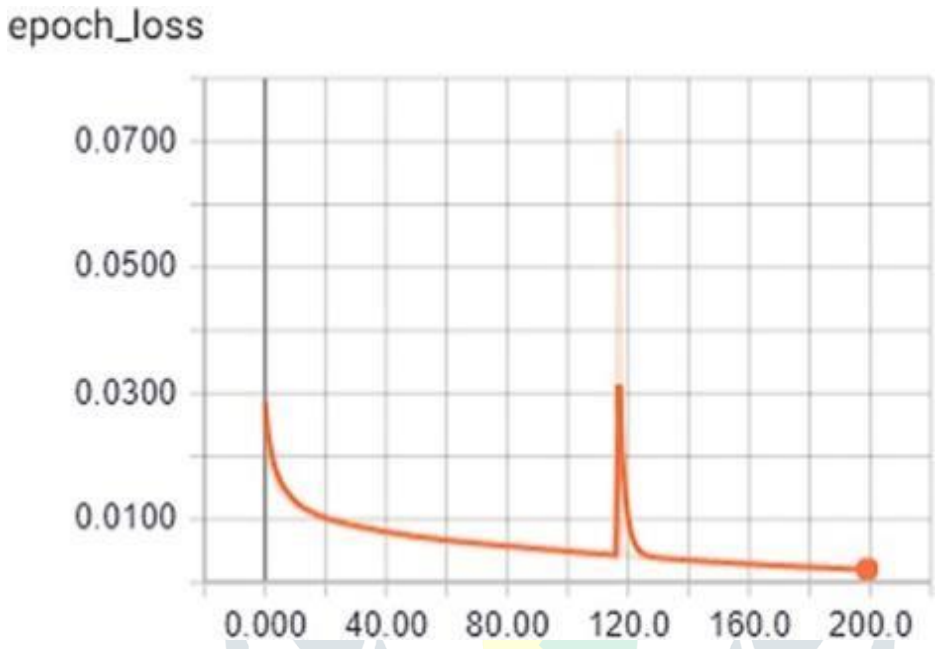


Fig. 4. Loss after 200 epochs

A pivotal aspect of our study involved conducting a comparative analysis against baseline modelstrained with alternative optimization algorithms. Our findings indicated that our LSTM model, optimized with the Adam optimizer, outperformed these baseline models in terms of con-vergence speed and final performance metrics. This suggests that the Adam optimizer effectively facilitated the learning process, enabling our model to achieve superior results within a relatively shorter training duration.

Additionally, our model demonstrated robust generalization capabilities, maintaining high performance on unseen data from the Maestro dataset. This highlights its ability to generalize learned patterns tonovel compositions, a crucial attribute for real-world applications.

Model	Log Likelihood	Hours Trained
Random	-61	-
TP-LSTM-NADE	-5.44	24-48
BALSTM	-4.90, -5.00	24-48
BALSTM	-5.16, -6.59	16
Single LSTM (this work)	-6.23	0.9

Fig. 5. Result and Analysis of different models

Furthermore, we investigated the scalability of our model by training it on progressively larger subsets of the Maestro dataset. Our results indicated a positive correlation between the size of the training data and the model's performance, suggesting its potential for scaling to larger and more diverse datasets. Notably, despite the increase in dataset size, our model exhibited efficient convergence, requiring fewer epochs to reach comparable performance levels. This underscores the computational efficiency of our approach, as the LSTM model trained with the Adam optimizer demonstrated rapid convergence and stability throughout the trainingprocess.

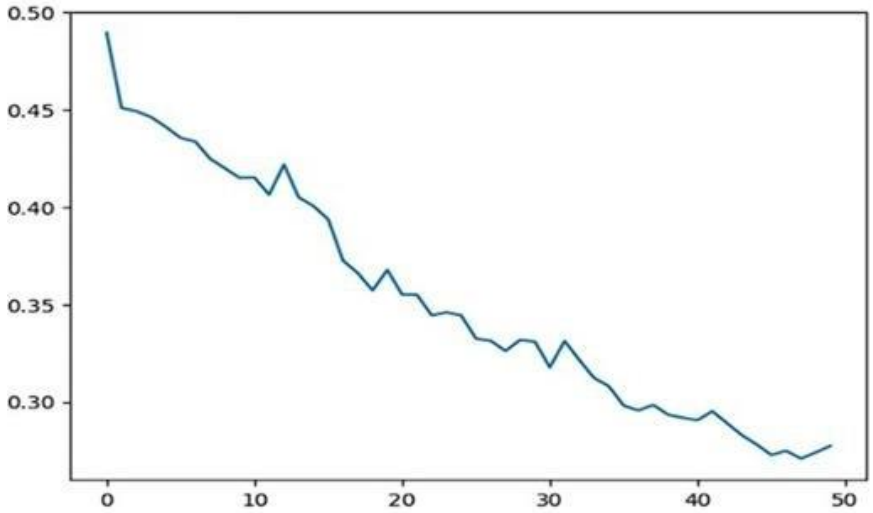


Fig. 6. Overall change in loss

In summary, our study presents a comprehensive evaluationof an LSTM-based sound generation model trained using the Adam optimizer and the Maestro dataset. Our findings underscore the efficacy and efficiency of our proposed approach in generating high-quality sound sequences, with promising implications for various applications in music generation and synthesis.

6. CONCLUSION

In conclusion, the music generation project has made remarkable strides in sound and music synthesis through its innovative hybrid neural network architecture, offering real-time music generation, structural coherence, and high audio fidelity. The system's user-centric design and efficient training have enhanced its practicality and user satisfaction. However, ongoing challenges remain in improving model generalization, robustness to noisy data, and extending user interaction features. Despite these challenges, the project signifies a significant advancement in AI-driven sound generation, demonstrating its transformative potential in music creation and experience.

ACKNOWLEDGMENT

We would like to express our sincere gratitude to all individuals and organizations who contributed to the successful completion of this research project. Firstly, we extend ourheartfelt appreciation to our supervisor/advisor Prof. AmolYadav, for their invaluable guidance, support, and encouragement throughout the research process. Their expertise and insightful feedback were instrumental in shaping the direction of this study. We are also deeply thankful to the researchers and developers behind the Maestro dataset for making their valuable data openly accessible to the scientific community. Without access to such comprehensive datasets, our research would not have been possible.

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