# Music Generation Using Deep Learning

### Vaishali Ingale

Army Institute of Technology vingale@aitpune.edu.in

#### **Anush Mohan**

Army Institute of Technology anushmohan\_17380@aitpune.edu.in

#### Divit Adlakha

Army Institute of Technology divitadlakha\_17493@aitpune.edu.in

### Krishna Kumar

Army Institute of Technology krishnakumar\_17564@aitpune.edu.in

### **Mohit Gupta**

Army Institute of Technology mohitgupta\_17429@aitpune.edu.in

Abstract—This paper explores the idea of utilising Long Short-Term Memory neural networks (LSTMNN) for the generation of musical sequences in ABC notation. The proposed approach takes ABC notations from the Nottingham dataset and encodes it to beefed as input for the neural networks. The primary objective is to input the neural networks with an arbitrary note, let the network process and augment a sequence based on the note until a good piece of music is produced. Multiple tunings have been done to amend the parameters of the network for optimal generation. The output is assessed on the basis of rhythm, harmony, and grammar accuracy Index Terms—Music, RNN, LSTM, ABC, Adam

### I. Introduction

In today's world, it's a myth that you need to be a music expert to generate music. Even a person who likes music can produce good quality music. We all like to listen to music and if it is possible to generate music automatically then it will prove to be a new revolution in the world of music industry. Until very recently, all music generation was done manually by means of analogue signals. In recent years though music production is done through technology, assisted by humans. The task that has been accomplished in the paper is the construction of generative neural network architectures that can efficiently portray the complex details of harmony and melody without the need for human interruption. A brief summary of the precise details of music and its mechanisms has been provided in the papers with appropriate citations where required. The primary objective of the papers was to devise an algorithm that can be used to create musical notes utilising Long Short-Term Memory (LSTM) [9] networks in Recurrent Neural Networks (RNNs) [2][7]. The output data obtained is in ABC notation which is then converted into MP3. To train the model we have chosen to work on ABC notations. ABC notation is basically one of the ways to represent music. It consists of two parts. First part represents the meta data which comprises various characteristics of tines such as index, time signature, default note length and type of tune. The second part represents the actual tune which is nothing but a sequence of characters. The devised algorithm learns the sequences of monophonic musical notes over three single layered LSTM [9][10] network.

### **II. Literature Survey**

#### A. Related Work

Music generation has been at the epicentre of attention of members of the research community and has thus been studied upon a lot [1]. Many who did try to generate music have done so using different approaches. Hence there exists numerous ways in which music can be generated and an amalgamation of such approaches can be used to create and design a new yet competent model. These approaches have been divided into two main categories – Traditional and Autonomous [3]. Traditional approach uses algorithms working on already defined functions to make music, whereas Autonomous Model learn from the prior iterations of the notations and then generates new ones. Algebra founded upon the usage of the tree structure to enforce grammar constitutes one of the earlier attempts [4]. Markov chains [5] can be used to design such a model [2]. Many models and approaches have been documented in the field of artificial intelligence soon after the field experienced a massive boom. Such models include probabilistic models which use variants of RNN, namely Char RNNs, Anticipation RNNs [7] [2]. One method that is actively being used to generate musical notes is the Generative adversarial networks (GANs) which contains two neural networks – discriminator network and the generator network [8]. The generator network and the discriminator network work in tandem to evaluate authenticity of the generated data against the original dataset. Research studies reveal that LSTM outclasses the GAN in terms of fixating on certain sequences, that is, LSTM is superior when it comes to uncovering specific patterns and then recycling them throughout the course of the output sequence. The models based upon LSTM were able to get out of certain note loops and shift into other notes [9]. When it comes to GAN, it can only pick up on basic concepts, albeit better, and exhibits shorter training time [8].

### B. Survey-I: LSTM Based Music Generation System by Sanidhya Mangal, Rahul Modak, Poorva Joshi

They propose an algorithm which can be used to generate musical notes using Recurrent Neural Networks (RNN), principally Long Short-Term Memory (LSTM) networks. The model is capable to recall the previous details of the dataset and generate a polyphonic music using a single layered LSTM model, proficient enough to learn harmonic and melodic note sequence from MIDI files of Pop music.

# C. Survey-II: Towards Music Generation with Deep Learning Algorithms by Eftim Zdravevski, Petre Lameski, Andrea Kulakov

They created a multilayer Long-Short Term Memory (LSTM) Recurrent Neural Network (RNN) and feed-forward network, based on acquired dataset; and a LSTM based Encoder-Decoder architecture as baseline models. The work so far did not fulfil the set goal of generating a 60-second-long sequence of polyphonic music. They discussed the interpretation of the limitations of the models that was used. There is a need of further refinement before being able to generate actual musical sequences.

# D. Survey-III: Music Generation with Variational Recurrent Autoencoder Supported by History by Ivan P. Yamshchikov, Alexey Tikhonov

Combination of a new architecture of an artificial neural network and variational autoencoder supported by history, with filtering heuristics allows generating pseudo-live acoustically pleasing and melodically diverse music. This is the first application of VRASH to music generation. It provides a good balance between the global and local structure of the track. The proposed structure is relatively easy to implement and train. It also allows to control the style of the output and generate tracks corresponding to the given parameters

## E. Survey-IV: Deep Recurrent Music Writer: Memory-enhanced Variational Autoencoder-based Musical Score Composition and an Objective Measure by Romain Sabathe, Eduardo Coutinho, Bjorn Schuller

They created a new metric to assess the quality of generated music and use this measure to evaluate the outputs of a truly generative model based on Variational Autoencoders that will apply to automated music composition. They used it to automatically and systematically fine-tune the generative model's parameters and architectures for optimizing the musical out- puts in terms of proximity to a specific musical style.

## IV. Methodology

### A. Objectives and Technical Challenges

The first problem faced when dealing with music is that of its representation. Signals, MIDI, notations, etc. are all possible representations. Due to the higher efficacy of notations for the task at hand, the model used in this paper is fed, processes and outputs using ABC notations. The ABC notation uses 7 letters (A to G) with other symbols representing features such as - flat, sharp, note length, key, etc. to represent the given notes.

The generation of output also posed a challenge as in our model, the output has to be human compatible, that is to say that the output should be understandable by humans. The ABC notation-based sequence from the output is then converted into MIDI format which in turn is converted into MP3 for easy listening.

### B. Design

RNNs fall victim to the vanishing/exploding gradient problem due to their use of back-propagation, to remedy this we have employed the use of LSTMs. At each timestep of the RNN, the individual LSTM cell is fed a value, the cell then calculates the hidden vector and outputs is to the next timesteps. The current input, and the previous hidden and memory states are given as input to the cell. Similarly, the current hidden state and the current memory state are the outputs. Taking the current timestep as t, the current hidden vector  $h_t$  is found using the current input at and the previous timestep's hidden vector  $h_{t-1}$ . This is how RNNs process data sequentially.

### C. Data Processing

The model is designed to interpret the musical notes in the form of 87 unique characters present in a dictionary, using integer encoding. The dataset is hot-encoded as well, to convert the labels into binary vectors. This is then fed into the LSTM units in batches. The specification of the batches used here are as follows: Batch Size = 16, Sequence Length = 64.

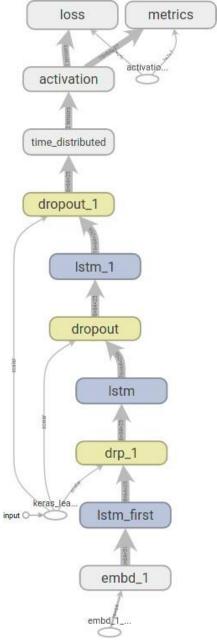


Figure 1: The figure depicts the flow of data through the layers present in the model.

### D. Architecture

The model is built around 3 LSTM layers, acting as the core. Due to the multi-class classification nature of the problem statement, the SoftMax activation function is deployed as well. Dropout layer is also present to aid in the avoidance of overfitting. The Adam optimizer is used since the model deals with RNNs. Also, to process the outputs at each timestep, Time Distributed Dense Layer is utilized here.

Laye	er (type)	Output Shape	Param #
embd	d_1 (Embedding)	(16, 64, 512)	44544
lstm	n_first (LSTM)	(16, 64, 256)	787456
drp_	_1 (Dropout)	(16, 64, 256)	0
lstm	n (LSTM)	(16, 64, 256)	525312
drop	pout (Dropout)	(16, 64, 256)	0
lstm	m_1 (LSTM)	(16, 64, 256)	525312
drop	pout_1 (Dropout)	(16, 64, 256)	0
tim∈	e_distributed (TimeDistri	(16, 64, 87)	22359
acti	ivation (Activation)	(16, 64, 87)	0

Figure 2: The figure shows the architecture, that is the different layers, their input and output sizes etc.

### IV. Result

LSTM RNNs propose a promising approach for automated sequence generation. These networks excel at predicting the next member of the sequence by making decisions based on context. The monophonic music generated here is pleasant—to the ear and has high accuracy. Training the model with polyphonic data can help make the output sequence more appreciable to the normal person.

	Epoch	Loss	Accuracy
0	1	1.435903	0.592773
1	2	1.126381	0.660156
2	3	0.943660	0.719727
3	4	0.885984	0.711914
4	5	0.805664	0.755859
85	86	0.168085	þ.937500
86	87	0.180467	0.939453
87	88	0.161075	0.947266
88	89	0.186609	0.938477
89	90	0.173722	0.941406

Figure 3: The table is the output of running the model for 90 epochs, yielding up to 94% accuracy.

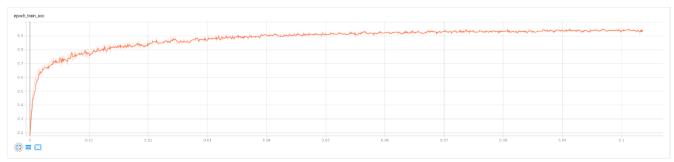


Figure 4: The graph represents the Tensorboard output of the result of the model. The variables being epoch and the corresponding training accuracy.

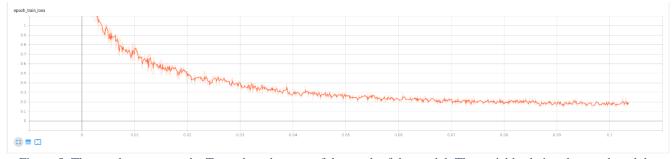


Figure 5: The graph represents the Tensorboard output of the result of the model. The variables being the epoch and the corresponding training loss.

### V. Conclusion

The paper has thus proved the efficiency of an LSTM RNN model at producing a musical sequence that matches the dataset in terms of it's the sequence's grammatical coherence. The final output, once converted into MIDI, is surreal to most casual listeners' ears. Most of the audience couldn't identify any discrepancies with the sequence generated.

## **VI. Future Scope**

This paper trains the model on monophony, that is, the dataset comprised of a single instrument. Further progressions can be made by delving into multiple instruments, that is, polyphony. The dataset can also be further expanded to comprise of more tunes, in variety, so that the model can have more robust training.

### VII. References

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