Melody Generation using Deep Learning: Unleashing the Power of RNN and LSTM

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Abstract:- This project aims to develop a novel approach for piano melody generation using Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) models in deep learning.The suggested models will be trained on a dataset of MIDI files with piano melodies to use sequential learning capabilities and capture the complex patterns and relationships present in musical compositions. [1] The project aims to generate a variety of melodies that are both musically coherent and diverse by experimenting with various network designs, hyperparameters, and training procedures. The developed tunes will be evaluated primarily on their originality, conformity to stylistic elements, and general quality. The results of this study could lead to new developments in AI-driven music composition as well as opportunities for computational creativity in the music industry.

Keywords:- *Measurement; Recurrent Neural Networks; Instruments; Music; Reinforcement Learning; Signal Processing; Generative Adversarial Networks; Music Generation; Melody; GAN; LSTM.*

I. INTRODUCTION

The combination of technology and creativity in music com- position has resulted in ground-breaking developments. Deep Learning, a subclass of artificial intelligence, has emerged as a powerful tool for producing music autonomously. This study article explores the use of Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks in melody generation, revealing the intricacies and promise of these technologies in redefining the creative environment. [2]

➢ *Background*

Music creation has always been a highly human endeavour, informed by emotions, experiences, and cultural influences. However, with the introduction of computational approaches, composers have increasingly relied on technology to help, augment, and occasionally even replace conventional creative processes. Deep Learning, in particular, has received attention for its capacity to understand patterns and structures inside data, making it an attractive contender for music creation jobs.

➢ *Objective*

- Construct a deep learning model that can produce melodies on the piano.
- Using a dataset of MIDI recordings with piano melodies, train the model.
- Learn long-term dependencies and capture the sequential nature of music using RNN and LSTM architectures.
- Investigate various network topologies, training methods, and hyperparameters to maximize melody creation effi- ciency.
- Check the produced melodies for stylistic fidelity, origi- nality, and musical coherence. [3]

➢ *Understanding RNN and LSTM:-*

Recurrent Neural Networks (RNNs), like its more ad- vanced sibling, Long Short-Term Memory (LSTM) net- works, are neural network topologies that handle sequen- tial input. Unlike classic feedforward neural networks, RNNs and LSTMs include internal memory, allowing them to record temporal relationships and produce out- puts depending on input sequences. This intrinsic aptitude makes

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them ideal for jobs involving sequential data, such as music production. [13]

- *Music Composition using RNN and LSTM:-*

In the domain of music creation, RNNs and LSTMs may be trained on enormous datasets of musical sequences to learn about the underlying structures, patterns, and gen- res. By feeding a model a corpus of melodies, harmonies, and rhythms, these networks may internalise the subtle connections between musical elements and develop new compositions that are similar to the training data.

- *Scope:-*

It can, first and foremost, completely transform the pro- cess of writing music by giving songwriters access to AI-powered instruments that produce a wide variety of unique tunes. It may also improve education by providing music students with a tool to master composition tech- niques and explore their creative side. It may also be used in the entertainment sector to provide background music for commercials, video games, and movies. The project's overall goal is to promote innovation in the fields of entertainment, education, and music production by providing fresh opportunities for both technology innovation and creative expression. [14]

- *Challenges: -*

- Data Quality and Quantity:- It is difficult to obtain a varied and sizable enough dataset of excellent piano tunes for model training.
- Model Complexity: It is a technological challenge to design and optimize RNN and LSTM architectures to capture the subtleties of musical compositions without overfitting.
- Evaluation criteria: Because musical enjoyment is subjective, it might be difficult to develop reliable criteria that objectively evaluate the inventiveness and quality of created tunes.

- *Opportunities: -*

- Creative Exploration: Using AI-generated tunes, com- posers and musicians are given the ability to experiment with new ideas and genres. [15]
- Providing interactive venues for music students to explore composition techniques and experiment with musical concepts is an educational tool.
- Collaborative composition is the process of enabling AI systems and human composers to work together to create unique music for a variety of applications, including game development and film soundtrack.

II. LITERATURE SURVEY

- *Music Composition with Deep Learning: A Review*

This research focuses on using deep learning techniques, especially long short-term memory (LSTM) networks, to analyse, model, and synthesise new music from current transcriptions. The study tackles issues such as inflating and disappearing gradients during training by including clever activation algorithms. [4] Recent advances in train- ing algorithms have made it possible to successfully apply recurrent networks to music transcription modelling and creation. To generate music transcriptions, models are built using thousands of units trained on large datasets including tens of thousands of samples. This study ex- pands on prior research on using RNN and LSTM net- works to music composition, demonstrating the promise of deep learning in the field of music transcription and composition.

- *Music Transcription Modeling and Composition using Deep Learning-VAE Architecture*

The study digs into Music Composition inside Music Information Retrieval, namely melody creation, multi-track composition, style transfer, and harmonisation. It exam- ines the move from Algorithmic Composition to Deep Learning approaches in music production, including top- ics about AI-generated music originality, comparisons to human compositions, and data needs for DL models. [5] DL-based music creation employs a variety of approaches like as VAE, GAN, and Transformer architectures to handle difficulties such as producing organised music, harmony and melody conditioning, and style transfer. Evaluation measures like as loss, perplexity, and BLEU score are used to analyse the performance of DL models in music generation, offering insights into the changing environment of AI-powered music composition.

- *Deep Learning for Music-RNN NADE*

This work sought to create a generative model for music using deep learning techniques. The method required training models on midi files and piano-roll represen- tations to capture musical structure. Experiments com- paring the created music to an RNN-NADE sequence yielded encouraging results. However, more assessment is required to determine the musical quality. The study emphasised the potential of deep neural networks for music creation, as well as the significance of adding musical aesthetics into model evaluation. [6]

- *Music Generation using Bidirectional Recurrent Network*

In this study, a neural network-based music generational model is proposed, which learns the conditional proba- bility from time and pitch dimensions by analyzing the intricate interaction between notes. The paper's thesis revolves around the introduction of a bidirectional re- current network that processes a musical track as time series data, with each note's probability in the sequence determined by both its predecessor and its successor. A bidirectional recurrent neural network is an exten- sion of a recurrent neural network, with the ability to train in both the positive and negative time directions concurrently.This idea is mostly taken into consideration since, while writing a song, composers view notes from a global viewpoint, in which neighboring notes and harmonics influence each note individually. [16] The study includes input data in time and note directions, as well as chord and nearby contexts. In note direction, researchers take time direction and prior note output as input. The architecture is separated into two

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parts: time and note direction, with final activations decided by context, previous and next activations in each timestep. The model, which employs customized loss functions and sampling algorithms, achieves quicker convergence and produces harmonic results by evaluating forward and backward notes. The researchers intend to cooperate with musical specialists to improve the model for long-term musical composition structure.

➢ *Polyphonic Music Composition with LSTM Neural Networks and Reinforcement Learning*

Artificial Neural Networks (ANNs) have been used in algorithmic music creation, with the goal of producing creative compositions that resemble human-composed music. A new representation for polyphonic music has been developed to minimise sparsity and streamline the learning process. [7] Training ANNs with this rep- resentation resulted in considerable gains in rhythm, melodic complexity, and harmonic variety. Reinforcement learning was used to determine high-level network con- figurations, which improved the quality of algorithmic music. Future study will focus on establishing higher- level musical features, such as organised repetition and climactic sequences, in order to increase the potential of AI-generated music compositions.

➢ *Temporally Conditioning of Generative Adversarial Networks with LSTM for Music Generation*

The research introduces a hybrid model that uses CNN, RNN, and GAN to determine the underlying distributions of musical melodies while preserving temporal infor- mation. The model includes a generator, conditioner, LSTM, skip connections, and discriminator. Using LSTM and DC-GAN, the generator generates new data that is similar to existing data, while the conditioner arranges the data to simulate genuine music. LSTMs are used to store previous information, whereas skip connections increase learning by resolving degradation difficulties. The discriminator inspects the created data to ensure its legitimacy. The model is assessed using objective measures such as the percentage of notes with more than three timesteps, unique notes, and matching training data. The C-RNN-GAN model surpasses the cutting-edge Midinet model but falls short of MuseGAN. [17]

➢ *Generation of Music Pieces using Machine Learning: Long Short-Term Memory Neural Networks Approach*

The research investigates the use of Long Short-Term Memory (LSTM) neural networks in producing music compositions, with an emphasis on Bach's compositional style. The study emphasizes the rising relevance of au- tomated music creation in both commercial and artistic settings. LSTM neural networks are favored because they can learn complex patterns. [18]The paper goes into detail into technical topics such the MIDI file format and augmentation methods, as well as optimization tests. The authors discover that particular settings produce the greatest outcomes, but with some restrictions such as intermittent output discrepancies and short melodies. The report finishes by addressing difficulties, proposing poten- tial solutions, and outlining areas for further research.

➢ *The Bach Doodle: Approachable Music Composition with Machine Learning at Scale*

The paper announces the availability of a dataset includ- ing 21.6 million examples of human-computer collabora- tive music compositions for ethnomusicological research and machine learning advancements. It explores the use of machine learning to boost creativity in music composi- tion, user testing to improve design and user experience, and the usage of Coconet to generate music compositions. The article also discusses adapting Coconet to the web using TensorFlow.js, load balancing tactics, analysing user sessions and compositions, and examining model outputs for musical patterns. It also cites comparable works in algorithmic music composition, demonstrating the convergence between technology and music produc- tion. [10]

➢ *Music Generation using Deep Learning- Gaussian Process*

The study in music composition focuses on using deep learning models to improve the creative process by producing, suggesting, and controlling. AdaptiveKnobs, ChordRipple, Music Transformer, and Coconet are exam- ples of projects that use sophisticated techniques such as Gaussian Processes, Chord2Vec, and self-attention pro- cesses to generate music. [11]These initiatives try to cap- ture nonlinear connections, learn chord embeddings, and create coherent musical compositions. Future research in this topic will focus on higher-level controls, adaptive suggestions, and mixed-initiative music composition to increase AI's skills in music production.

➢ *Generating Music with Data:Application of Deep Learning Models for Symbolic Music Composition*

The study looked at the musical quality of snippets created by deep learning models vs human composi- tions. Data wrangling techniques were used to optimise processing, converting MIDI data into a language that included pitch dynamics, time shifts, and performance start and stop tokens. The models, including Custom GRU and Custom GPT2, were trained and tested, and MuseNet and Music Transformers outperformed human- origin extracts. The results revealed a link between musi- cal sensitivity and the capacity to appropriately recognise musical passages. Data on musical quality and com- poser model rating were collected, offering insights into how musicality is perceived. Overall, the study found disparities in musical appraisal between AI-generated and human compositions, emphasising the necessity of musical sensitivity when judging musical samples. [12]

➢ *Tools and Libraries: -*

- Keras/TensorFlow - Keras is a high-level neural network API that makes it easier to work with TensorFlow. It was designed with the goal of facilitating rapid experimentation.We will design and train an LSTM model using the Keras framework. Once trained, we will utilize the model to produce musical notation for our song.

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- Music21 is a Python framework designed for computer- aided musicology. It enables us to teach the principles of music theory, create musical examples, and study music. The toolkit provides a simple interface for acquiring musical notation from MIDI files. It also allows us to build Note and Chord objects, making it easy to generate our own MIDI files. We'll utilize Music21 to extract the contents of our dataset and transform the neural network's output into musical notation.

- MuseScore is a free, open-source music notation software that enables musicians, composers, and educators to create, modify, and print sheet music. MuseScore, with its user-friendly interface and extensive functionality, allows users to produce musical scores utilizing a broad range of instruments, genres, and notation symbols. It has MIDI input and output, so users can play back their songs and hear how they would sound when performed. MuseScore also offers an online platform for sharing and collaborating on musical compositions, which fosters a thriving community of musicians and composers throughout the world.

III. METHODOLOGY

A. *Data Collection: -*

In this experiment, we used almost 5,000 songs from the ESAC dataset, which is a comprehensive database of musical descriptors. These songs come from a variety of genres, styles, and eras, offering a wide and rich supply of musical data for our neural network models to train on. Using this huge dataset, we want to capture the intricacies and patterns inherent in musical compositions, allowing our models to produce melodies that are both varied and musically cohesive.

B. *Data Preprocessing: -*

➢ *Tracks Feature Extraction:*

We use Music21's objects and libraries to extract features from our input MIDI tracks. [19]

- *Note:-*

A note in music signifies a certain pitch and duration. It refers to the fundamental building block of a melody or chord. There are seven notes (C, D, E, F, G, A, and B), with the exception of note E, which can be flat or major. The following properties of the note object have been extracted:

✓ Pitch-It relates to the perceived frequency of a sound, which determines whether it is high or low. In piano music, each key represents a distinct pitch, with lower keys creating lower sounds and higher keys producing higher pitches.
✓ Offset- It is the time or position of a note in a musical composition relative to the beginning. It shows when the note begins to play following the piece's opening or the preceding note.
✓ Quarter Length-It is the duration of a note relative to a quarter note, which is used as a reference duration in music notation. It specifies the length of time a note is held, with larger durations denoted by multiples of the quarter note (half note, whole note).
✓ Octave-An octave is a musical interval of eight notes, with the eighth note having twice the frequency of the first. In piano music, each octave is made up of twelve keys, including white and black keys, with higher octaves producing higher sounds and lower octaves creating lower pitches.

- *Chords:-*

They are described as a group of notes per- formed simultaneously. The following properties are taken from the chord object:

✓ NormalOrder- It returns the Chord's normal order/form as a list of numbers.
✓ Quarterlength- It is the duration of each chord. If a measure includes four quarters and the chord's quarter length is 2.0, it will be played throughout the measure.
✓ Pitch- It is the pitch of each note in a chord.
✓ Octave- It is the octave of each note in the chord.

We encode each chord by combining the IDs of its constituent notes into a single string, where each note is delimited by a dot.

- *Rest:-*

A rest in music notation denotes a time of silence or pause in which no sound is performed or sung. Rests describe the amount of time between notes or phrases in a musical composition. The rest object has a quarterlength connected with it, which we extract for training data. Rest values include entire rest, half rest, quarter rest, one-eighth rest, and one-sixteenth rest.

To ensure accurate music generation, our neural network must effectively predict the subsequent note or chord in a sequence. This necessitates that our prediction array encompasses every encountered note and chord object from our training set. In our training data, we would ob- serve a total of 1600 distinct notes and chords. While this might seem daunting for the network, LSTM architectures are well-equipped to handle such complexities. Moreover, we can simplify the data and model by disregarding the varying offsets between notes in the MIDI files, which commonly have intervals of 0.25. This simplification streamlines the model without significantly impacting the musical output's fidelity.

➢ *Model Input Preparation:*

After evaluating the data and deciding on notes and chords as input and output characteristics for our LSTM network, we prepare the data for the network. Each file is loaded into a Music21 stream object, which allows us to generate lists of all notes and chords. We use string notation to append notes' pitches since it captures the most important information. Chords are encoded by grouping the IDs of their constituent notes into a single string

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separated by dots. These encodings make it easier to decode the network's output into the right notes and chords. [20]

We create input sequences for the network using a list of all notes and chords sorted sequentially. First, we provide a mapping function that converts string-based categorical data into integer-based numerical data, therefore improving network performance. Subsequently, we produce input sequences and outputs. In our list, each output represents the first note or chord that comes after the input sequence. In our approach, each sequence consists of 64 notes or chords, which provides the network with enough information to anticipate the following element.

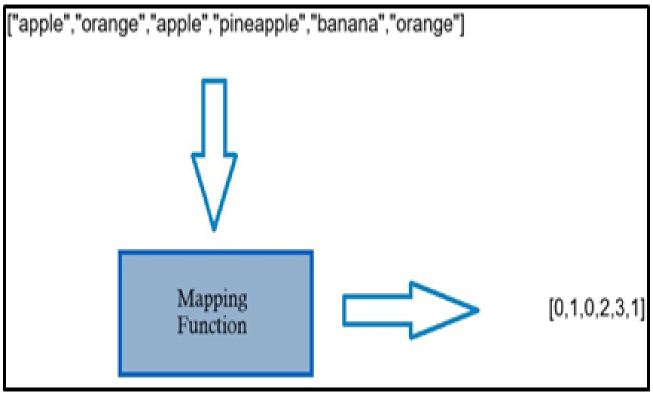

Fig 1 Converting Categorical Data to Integer Data using a Mapping Function

C. Model Architecture: -

Our model includes four different sorts of layers:

➢ *LSTM (Long Short-Term Memory) Layers:*

These recurrent neural network layers analyze sequential data while retaining long-term dependencies. They can return sequences (with'return sequences=True') or matrices.

➢ *Dropout Layers:*

These act as a regularization approach, reducing the likelihood of overfitting. During training, a random percentage of input units is set to zero based on a layer-specific parameter.

➢ *Dense Layers (or Completely Linked Layers):*

These neural network layers connect each input node to every output node, allowing for thorough data processing.

➢ *Activation Layers:*

They define the activation function that the neural network uses to compute the output of each node. The initial layer requires a unique parameter, input shape. This parameter informs the network about the data shape that will be processed.The final layer should have the same number of nodes as our system's total outputs, guaranteeing that the network's output maps directly to our classes.

In this project, we use a basic architecture consisting of three LSTM layers, three Dropout layers, two Dense layers, and one Activation layer.

D. Training: -

After finalizing the architecture of our network, we proceed to initiate the training phase. Leveraging the 'model.fit()' function in Keras, we commence the training process. The function requires two main parameters: the input sequences prepared earlier and their corresponding outputs. In this tutorial, our training regimen spans 100 epochs (iterations), with each batch containing 64 sam- ples propagated through the network. [21]

To ensure flexibility during training and prevent loss of progress, we implement model checkpoints. These checkpoints enable us to save the network's weights to a file after each epoch. Consequently, we can halt the training process once satisfactory loss values are attained, without concerns about losing weight data. Without such checkpoints, we would need to await completion of all 100 epochs before safeguarding the weights.

E. Generation of Music: -

The process of creating musical tracks requires a mix of several metrics:

➢ *Maximum Probability Selection:*

First, a random be- ginning note is chosen from the note vocabulary. Then, at each time step, a probability distribution of notes is generated, and the note with the highest probability is chosen as the next note in the series.

➢ *Multinomial Distribution picking:*

This creates diver- sity by randomly picking the next note from a multino- mial distribution rather than selecting the note with the highest probability. A temperature parameter governs the unpredictability of sampling, with higher values produc- ing more randomness and lower values producing more predictable results.

➢ *Musical Constraints:*

Incorporating parameters or func- tions removes unwanted sequences from the created track, guaranteeing that the music follows preset musical rules or qualities.

➢ *Iterative Refinement:*

Instead of creating music from a random beginning point, common starting notes or tiny structures from human songs might be used as input. The model then creates further sequences based on the first input, allowing for iterative refining and cooperation of human creativity with AI-generated output.

We opted to generate a musical sequence comprising 1600 notes using the neural network. Each note generation requires submitting a sequence to the network. Initially, we provide the sequence of notes at the starting index. For subsequent inputs, the first note is removed, and the output from the previous iteration is appended to the sequence. [22]

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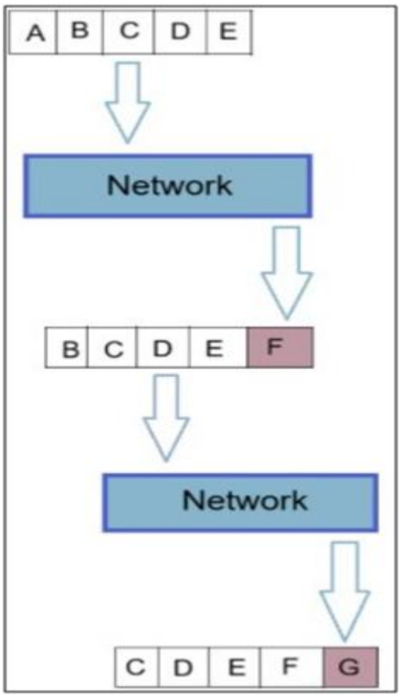

Fig 2 In the initial input sequence, denoted as ABCDE, the output generated by the network after processing this sequence is the note F. Moving to the next iteration, we exclude the first note, A, from the sequence and append the output note, F, resulting in the updated sequence BCDEF. This process of updating the sequence by removing the first element and adding the output note is iteratively repeated to generate subsequent notes in the sequence.

To determine the most probable prediction from the network output, we extract the index with the highest value, where each index corresponds to the probability of the next note. With the encoded representations of notes and chords consolidated into an array, decoding and creation of Note and Chord objects commence. When decoding a chord pattern, the string is split into an array of notes, with each note used to create individual Note objects. [23]These Note objects are then aggregated to form a Chord object. In the case of a single-note pattern, a Note object is created using the pitch represented in the pattern.

After each iteration, the offset is incremented by 0.25, and the created Note/Chord object is appended to a list. With a list of generated Notes and Chords, a Music21 Stream object is constructed, utilizing the list as a parameter. Finally, the generated musical sequence is written to a MIDI file using the write function in the Music21 toolkit.

IV. RESULTS

The result of this project is a neural network model capable of generating musical melodies.The model was trained using a dataset of over 5,000 songs from the ESAC dataset, representing a variety of genres and styles. The model is capable of producing different and musically coherent tunes by using LSTM layers for sequence prediction and applying musical restrictions.

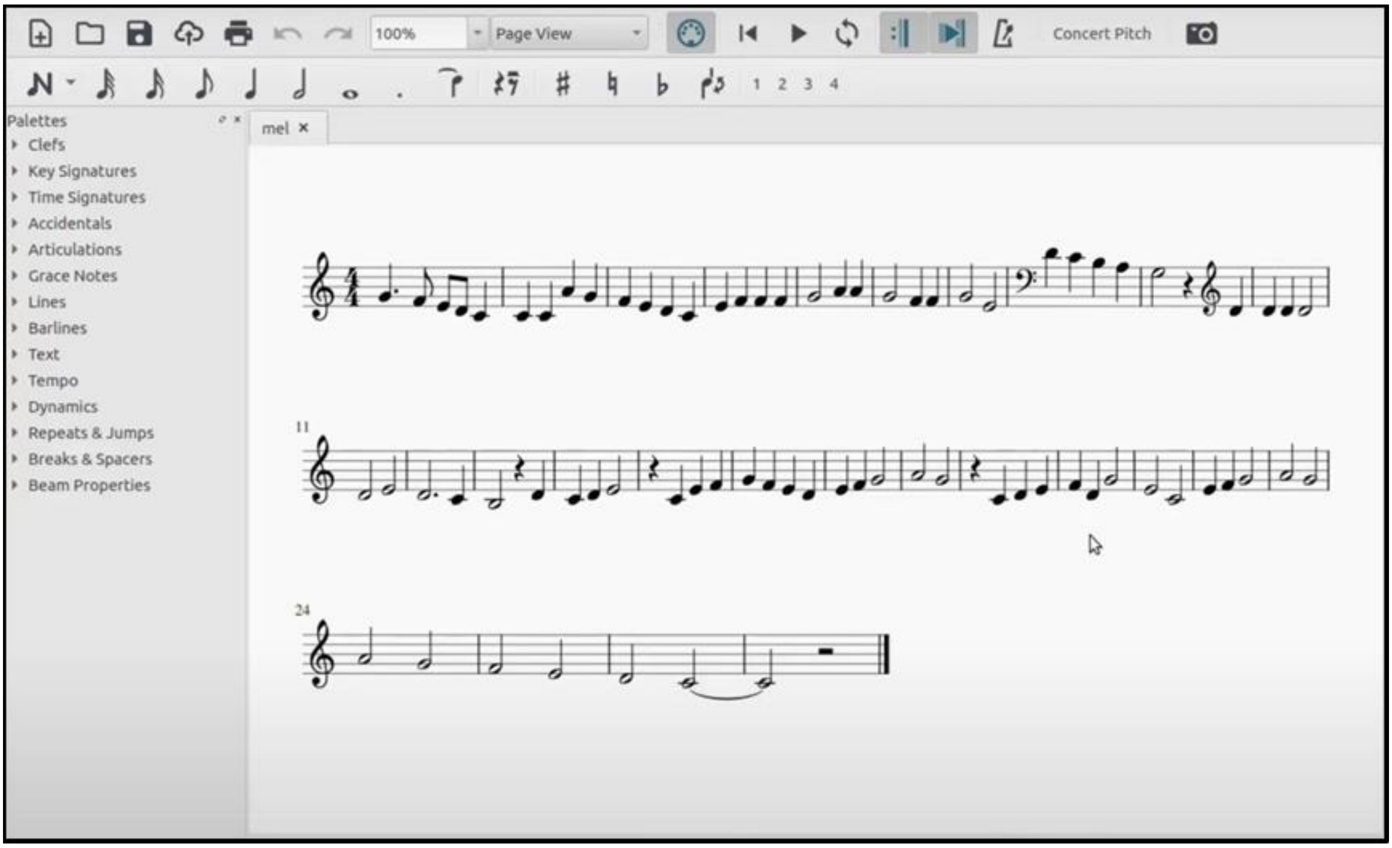

Fig 3 Example of Sheet Music Generated by LSTM Network

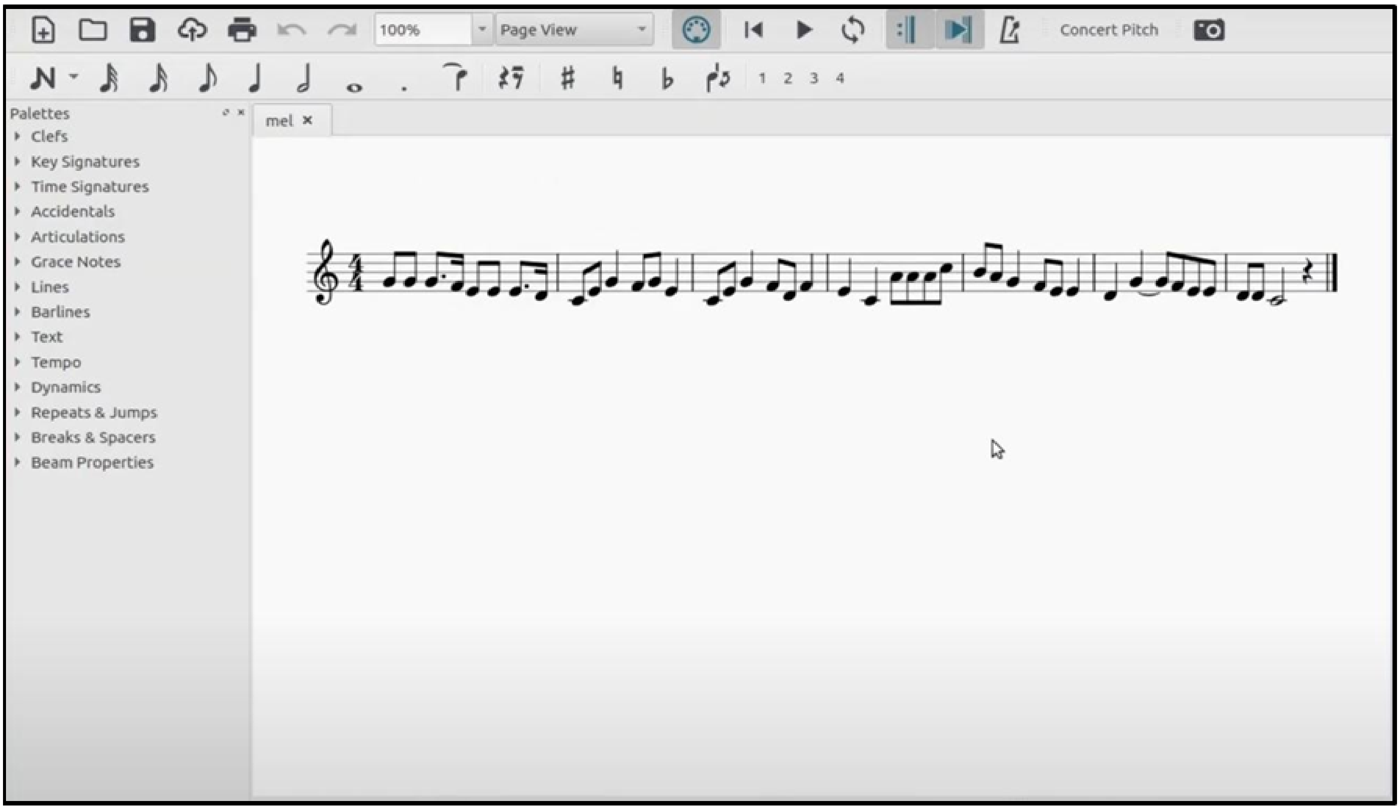

Fig 4 Example-2 of Sheet Music Generated by LSTM Network

V. CONCLUSION

Finally, we successfully developed a neural network model capable of producing musical tunes. By training on a vast dataset of songs, the machine learnt to produce melodies in a variety of styles and genres. We ensured that the model's melodies were different and musically consistent. We built a tool that may stimulate creativity and help musicians with their composing process by carefully tweaking and training. Overall, this research showcases AI's intriguing potential for music production.

FUTURE WORK

Looking ahead, further study might go beyond single-instrument music production to include the development of dual-instrument compositions. This breakthrough en- tails harmonizing melodies from two different instru- ments and exploring the complex interaction and dynam- ics between them. This attempt involves both technical and artistic aspects, demanding a thorough understanding of musical theory and the harmonies that support musical beauty.

Expanding on our successes in single-instrument music production, the next phase of investigation is creating dual-instrument compositions that go beyond technical proficiency and encompass a greater range of musical tracks.

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