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DEEP LEARNING APPROACH FOR MUSIC GENERATION USING RNN

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Abstract— Automated music composition has become a significant area of research in Artificial Intelligence. Traditional methods, such as evolutionary algorithms, often struggle to maintain long-term structural coherence in melodies. To address this, this paper proposes a Deep Learning approach using Recurrent Neural Networks (RNN) for the generation of high-quality music sequences. By leveraging the sequential processing capabilities of RNNs, the system is trained to learn complex musical patterns, note transitions, and rhythmic structures from diverse datasets. Unlike heuristic-based fitness functions, the RNN model automatically extracts features and predicts succeeding notes with high accuracy. The results demonstrate that the proposed RNN-based model can effectively compose melodies that exhibit both creativity and structural consistency, providing a robust framework for hybrid-genre music generation The research showed that each technique can promote an 86% success rate, as the SVM demonstrated when tested on the same dataset used in the research. Nevertheless, the current study does not say that a high success rate can be achieved on all datasets.

Keywords - Deep Learning, Recurrent Neural Networks (RNN), Music Generation, Artificial Intelligence, Sequence Learning, LSTM.

I. INTRODUCTION

Algorithmic music composition is the process of using automated systems to create musical pieces with minimal human intervention. recent years it has emerged as a powerful tool for this purpose, surpassing traditional rule-based and evolutionary techniques. One of the most effective architectures for handling sequential data like music is the Recurrent Neural Network (RNN).

Music is inherently a time-series sequence of notes, where each note depends on the previous ones to form a meaningful melody. Traditional algorithms often fail to capture these long-distance dependencies, leading to repetitive or chaotic outputs. RNNs, however, are designed to retain "memory" of previous inputs, allowing them to model the temporal dynamics of music more effectively.

This study focuses on developing an RNN-based framework for generating hybrid-genre music. By training the network on MIDI datasets of various genres, the model learns the underlying probability distribution of notes. This approach eliminates manual feature engineering or complex use of fitness functions in earlier genetic algorithms. The primary aim study determines how well generate visually appealing and technically sound music. A music player is designed to capture human emotions using the web camera found on computers.

II. LITERATURE SURVEY

The world of computer-generated music is broadly divided between: Methods for generating music using algorithms can generally be categorized into is Daniel Alarcon, who used predefined musical rules to guide the composition process. Those rules come from the Faxian method, which has a specific list of guidelines for composing music. Evolution-based algorithmic composition deals with optimization of any set of potential solutions or variations that result from an initial model. We then evolve the next candidate to the goal: the solution that is closest to the target.

A number of fitness functions have been studied and employed to evaluate algorithmic composition algorithms outputs. Conversely, there is as yet no definitive best way of determining fitness. It would be difficult to even contemporary studies involving computer music without a human, if any, effort or a human assessment or assistance. In-scoring systems that require human interaction are human critics, rule-based critics, learning-based critics, and global statistics. Scoring methods based on humans become less effective the more data one has to rely on. The study is currently underway on the topic of automated evaluation methods used to circumvent human limitations. Quantifiable audio data using acoustic records have been studied by Nozaki and Kameyama [8]. The spectral variation, frequency strength, and amplitude frequency were taken as data. A weight analysis was directed to ensure that an appropriate weight was assigned to each feature; the value is genre dependent. This form of acoustic analysis does not assume musical traits are essential components of musicality; the features can be lost in a process, audio, or acoustic signals. Towsey et al studies compiled and analysed features with melody using global analysing stats from a MIDI file dataset. We extracted twenty-one melodic characteristics for melodic analysis. Pitching variation, interval dissonance, and contour direction are examples of these features. Principal component analyses and clustering analyses for which significant impact of these factors on the score of melodies has been performed successfully (e.g., [7]). Another analysis of the above features (Freitas et al.), listed the melodic evaluation features relevant in the original studies and discussed their presentation [9]. In a more recent study done by Andrei Coronel, finding some combinations of features would be most appropriate for a specific melodic analysis for a genre is concerned. His work provides the essential musical quality and characteristics which can serve for melodic assessment [5]. Hence, this study aims to show the impact of different feature sets on algorithmic result compositions in the context of hybrid-genre melodies generator.

III. PROPOSED METHODOLOGY

This study explores a unique approach to music composition that leverages algorithmic features from melodies in two different genres. The goal is to define new rules for composition based on individual creativity and to use these rules to guide the creation of algorithmically generated music.

In our research, we will evaluate continuous musical works, drawing on a dataset of audio signals—either compressed musical data files or MIDI files. For this study, we will focus on MIDI, as our primary objective is to analyse melodies rather than delve into the intricacies of acoustic architecture.

It's important to clarify that our aim isn't to develop a completely new method for algorithmic composition or to explore a new set of music features. Instead, we will specify the techniques used in an evolutionary algorithm-based composition process. This involves assessing the quality of the generated music based on how well it aligns with the characteristics of the chosen genres.

1. **Collect Feature Profiles**: We will gather feature profiles from two genres, which will serve as the foundational goals for our algorithmic compositions. The resulting melodies should be able to embody elements from both genres, creating a hybrid outcome.
2. **Identify Relevant Features**: We will pinpoint specific features that are essential for crafting hybrid-genre music. This will help us create a decision tree that categorizes our dataset into the two genres.
3. **Explore Key Properties**: We will identify important properties necessary for producing music in a hybrid format. This involves selecting high-correlation filters for the genres and determining a class of features suitable for genre creation.
4. **Evaluate Feature Sets**: We will assess each feature set individually in terms of their contribution to the fitness criteria within the fitness function of our evolutionary composition algorithm. This algorithm is designed to generate musical works algorithmically.
5. **Validate Generated Music**: Finally, we will test the algorithmically generated pieces by comparing their threshold values to those of the selected musical items. This comparison will ensure that the generated music aligns closely with the characteristics of both genres, using Support Vector Machine (SVM) classification.

IV. RESULTS AND ANALYSIS

a pair of genres was executed with the methodology creating compositional which aim to target
music was collected, to which 101 features were measured by using symbolic. Prior to deciding which feature sets are extraction symbolic declared neither related nor in any way of making the music, it was done by hand removal.

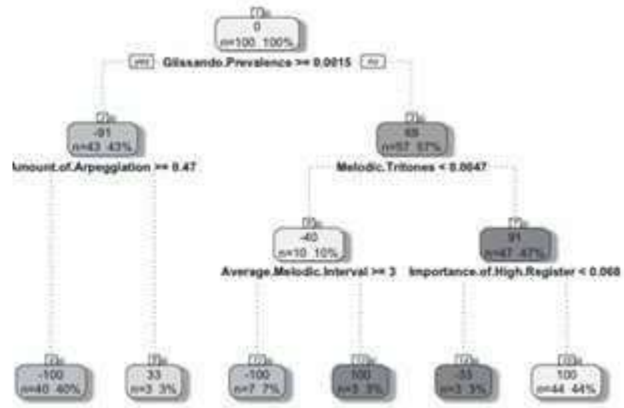

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Figure 1 shows the decision tree created using the rpart method.

TABLE I

THE HIGH-CORRELATION FILTERING TABLE

Feature	Correlation	Absolute Value
Average Range of Glissandos	-0.68221122	0.68221122
Voice Equality - Note Duration	-0.677430451	0.677430451
Voice Equality - Melodic Leaps	-0.660775304	0.660775304
Amount of Apreggiation	-0.644396901	0.644396901
Chromatic Motion	0.632214785	0.632214785
Range of Highest Line	0.619354129	0.619354129

the values via the classification up to such criteria Only chosen.
To analyse how useful the features are, three models were developed (with e1071 and 100 MIDI samples). The initial model employed all 86 features. The other two models used fewer features—one from the decision tree method and the other from
Figure 2 presents the classification results with all 86 features.
Values close to 100 represent classical music, and values close to -100. mean classic rock.
There is already a clear pattern in how the 14 test songs are classified, as most of them are close to their correct genre.
Figures 3 and 4 show the results when only the selected features from the two reduction methods are used. With these smaller feature sets for classification becomes clearer and more accurate. Most songs move closer to their actual genres.
These results suggest that using only the most important features can improve genre classification. It also helps in understanding which features are useful for creating music that blends different genres.
Figure 5 further shows that the accuracy of the SVM models improves after reducing the number of features.

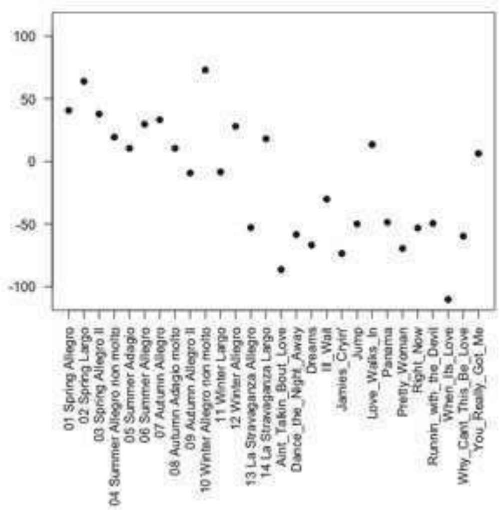

Fig. 2. SVM classification using model trained with 86 features.

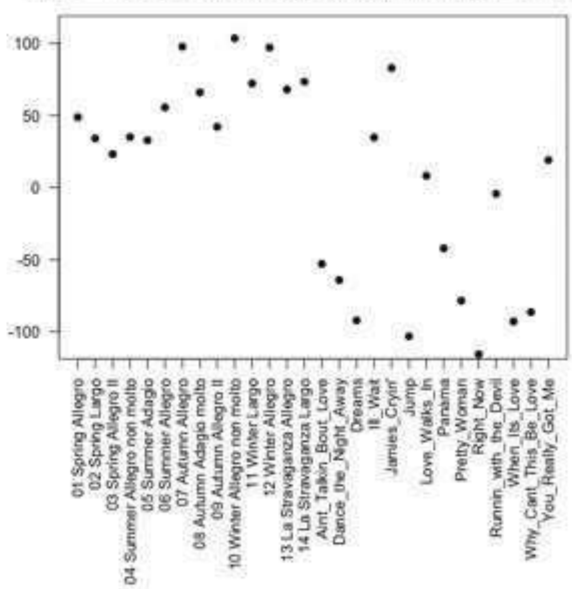

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Figure 3 shows the classification of SVM.

After we reduced the number of features, classification results improved. Average accuracy increased by 14.48% by selecting features and by 18.95% by using features chosen by the correlation filter. In this case, better accuracy means classical music and now, the results can be grouped into. If a piece has a score of more than 33.33, it belongs to Classical; if it has a score between 33.33 and -33.33, it is part of Hybrid.

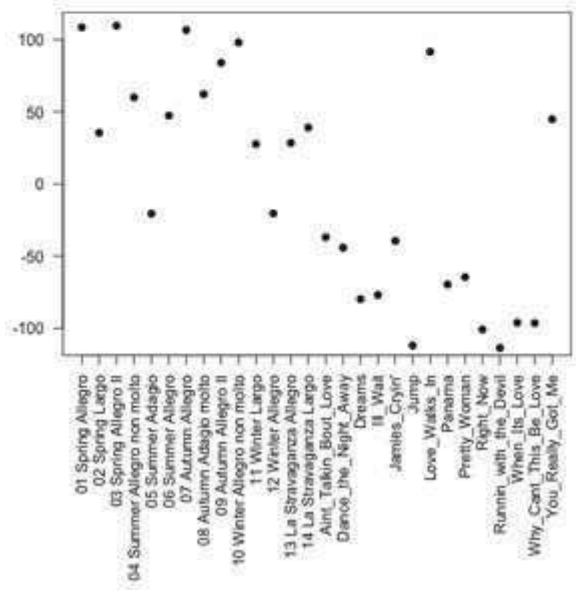

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Fig. 4. SVM classification using model trained with 6 features determined using correlation filteing.

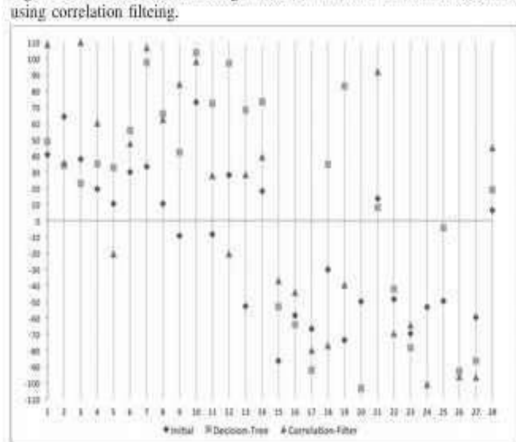

Fig. 5. Comparative plot of SVM models.

classified under Hybrid, and pieces scoring less than -33.33 classified under Classic Rock. Table II shows the performance of each feature set with classification under SVM.

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TABLE II

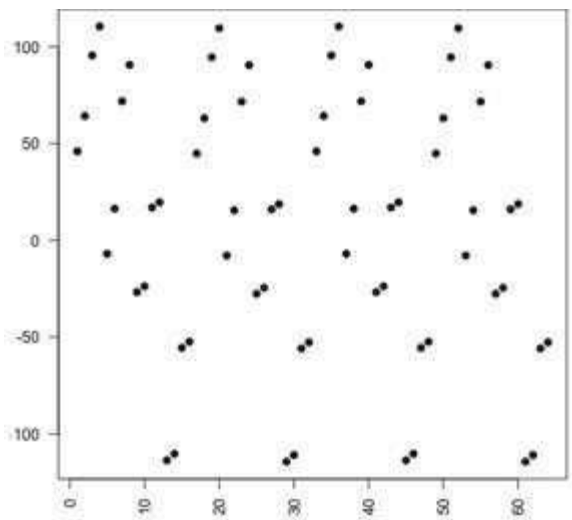
TERNARY CLASSIFICATION TABLE

Set	Classical	Hybrid	Classic Rock
Initial Feature Set	4	12	12
Decision Tree Feature Set	14	5	9
Correlation Filter Feature Set	12	4	12

there are some music pieces which in a way, fall between or towards all the genres. These were Vivaldi's Summer Allegro and Summer Adagio and Van Halen's You Really Got Me. And if you keep that in mind, there is a way to calculate how much each quality of the thing (as in its form) actually dictates something by looking at certain features of a particular thing.

Two music pieces that were most clearly classified into their genres were selected.

Using the 6 features from the correlation filter, a combination (Cartesian product) of these was created, resulting in 64 data points. This is shown in Figure 6



Based on information presented procedure might developed particular through in the direction of specific targets to a classification score. It will play a crucial role in the algorithm design for in which goal and to have target. it is straightforward which proposed and used to satisfy fitness criteria based on shows how the algorithm forms Initially, formed the sources of initial mutation. All the compositions for this study start and thus same seed was used for all. Each single seed of the initial seeds was randomly picked for one of many mutations. Table III lists the most likely mutations. The features of compositions were quantified symbolically after the mutation to compare with the criterion. follow nearer those eliminated. A mutation cycle persists indefinitely to the limit of fitness of the compositions. These feature values, on the basis of the correlation-filter feature set, for values of feature value data.

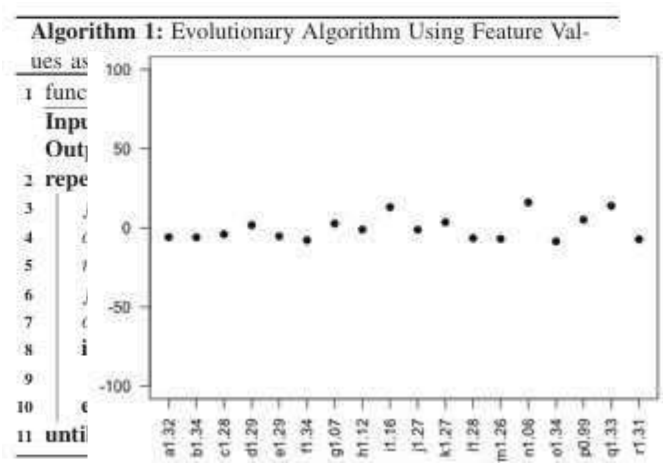
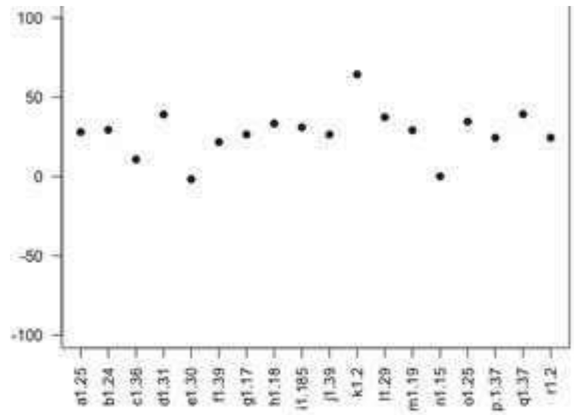


TABLE III

COMPOSITIONMUTATIONS



Mutation	Description
Shuffle	The notes for the entire composition are shuffled randomly.
Invert	The notes of the entire composition are replaced by a corresponding note of the same distance opposite from the composition's first note.
Pitch Up	A random note from the composition is increased one semitone.
Pitch Down	A random note from the composition is decreased one semitone
Split	A random note from the composition is split into two notes of the same frequency but half the duration.
Augment	A random note from the composition's duration is increased to twice it's original.

Fitness criteria aim of the evolutionary algorithm was also calculated in a specific way and such was used through selection of feature value of different hybrid node to focus fitness.

(~5.97 – the scores of this set are from the characteristics of a composition scoring 5.97).

Figure 8.it is based on the values and obtained from features of decision tree

Fig. 9. Excerpt from Bessie Smith's Lost Your Head Blues

Fig. 10. Excerpt from Joseph Haydn's Surprise

n part showing computer-generated piece of music, figure 11, shows how this is similar to two similar pieces of music by Kamien. A pattern of note repetition, consistency, this is also found in this, Haydn's composition— one that exhibits uniformity, computer-generated piece of music. Similarly, a sense of going down then moving up, seen in the Bessie Smith excerpt, alongside a lesser degree of uniformity and consistency of notation, which was seen in this computer. The Rock music mostly depicts a piece by breaking the rhythmic excitement up with respect to music by sub-breaking the beats. Usually, this kind of music that Rock music shows increased exciting:

the heightened rhythmic excitement and splitting off the beats of the two-beat subdividing the sounds into two notes [11]. to make comparison by scheme of 9 the third measure in figure 11. which common in that plus construction is used to reverse the subdividing beat illustrates a rock music's rhythmic structures. This is where one hears syncopations and a lot of switches between Long Notes on the one end and the short notes on the other. He further elaborates that classical melodies are usually utilized to They sound balanced and symmetrical as the phrases are usually comprised. Algorithmically it might as create at level 2, where points You're not always changing between long and short notes (but) both of those are also seen throughout the Haydn excerpt as well as the algorithmic generation. Referring to the Kamien, the algorithmic written piece that combines the music. The piece can be hybrid-genre composition

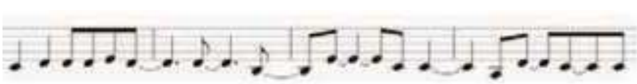


Fig. 11. Excerpt from an algorithmically generated piece.

The findings show that hybrid genre, music compositions can be produced from some specific values of feature set fitness. Both quantitatively and qualitatively, this can be confirmed. By identifying initial classification of using the same approach of SVM, using the same SVM model music pieces, which had proved their validity to algorithmic music compositions to be hybrid, which were also qualitatively reviewed from a music perspective. Algorithmically generated music displayed the features of both of the original genres used

V. CONCLUSION

music works with the help of music theory. The aim of the study is not argued that with available datasets a high success rate can be achieved. This paper suggests that a chain of research can ultimately follow this methodology and be applied further to different datasets and possibly different formats, and perhaps genres, depending upon how interesting their content or theme. The importance of using appropriate music is verified in this work. Successful hybrid genre music generation based on obtained has been applied to demonstrate that a much smaller feature set can actually be used as a criterion of any algorithm. It is found the generated music for the hybrid genre could generate a fully validated success rate using SVM, with a success rate of 72% to 100%. (i.e., with this dataset used above.) Furthermore, the hybridity of music generated by the generation process conducting analyses. The next logical step would be to compare the accuracy of the outcomes in each of the experiments. Other recommended next-step research might involve exploring other feature reduction practices and what strategies might provide further to explore approach and its application to that can used in more research on algorithmic music generation, and possibly can lead to the perceived incremental advancement of fitness functions for evolutionary algorithms.

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