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Leveraging Transformer Architecture and Deep Learning Models for Plagiarism Prevention in Music Composition

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ABSTRACT: Advancements in Artificial Intelligence have brought many new changes in numerous fields, including digital media, content creation, visual arts, and music, by empowering translation, composition, and originality evaluation. However, with the rise of AI generating creative content, such as musical compositions, it has demonstrated the ability to imitate human works. This capability is causing concern for almost inadvertent plagiarism, highlighting a need for building strategies and support that can guarantee the creativity of AI-driven compositions. This paper explores the application of deep learning models and, by extension, transformer architectures to avoid literary theft in music composition and generation. This paper also evaluates strategies for music transcription, originality assessment, and multimodal music modeling, leading to an analysis of existing approaches to propose a comprehensive framework for plagiarism detection and prevention. This paper leverages transformer-based architecture and other various techniques, including sequence-to-sequence, data augmentation, and self-supervised learning, to ensure creativity and ethical compliance in AI-generated content. By analyzing and comparing findings from multiple studies and integrating advanced AI methodologies, this work expects to highlight the potential for multi-disciplinary applications of these models. Furthermore, this study underscores the importance of originality assessment tools in safeguarding intellectual property rights while fostering innovation in the music industry.

KEYWORDS: Robotics And Intelligent Machines, Machine Learning, Transformer Technology, Deep Learning, Plagiarism Detection.

Introduction

As AI is rapidly growing and expanding in all fields, artificial intelligence-generated content (AIGC) is found everywhere. With the application of AI in fields such as music, many concerns have been raised about the content and legalities it produces, leading to plagiarism of younger or newer artists' work as a byproduct of AIGC.[1] Recent research highlights the role of transformer technology in generating new music using AI, while still safeguarding the intellectual property of the original composition. Studies in this field have explored methodologies such as multimodal music representation modeling, sequence-to-sequence architectures, and data augmentation to protect the original composition.[2]

Numerous models are built and enhanced to create new and innovative solutions in the field of AI and Machine Learning. Transformer models and deep learning technologies have revolutionized how data is processed and generated, particularly in the field of music. Transformers, such as Google's Music Transformer and OpenAI's MuseNet, utilize multi-layered neural networks to analyze patterns and relationships in data to compose new music.[3] The deep learning networks and transformer models are able to learn complex structures from large datasets, gaining the ability to generate highly original outputs, though their reliance on existing works also raises concerns about unintentional plagiarism.[4]

This paper explores how transformer-based models and deep learning technologies can be enhanced and utilized to avoid copyright infringement in music generation. By analyzing recent studies and leveraging on the modern methodologies, this article aims to propose a framework that balances innovation and ethical compliance, ensuring that AI-generated music contributes to the evolving creative landscape while protecting the original content.

Discussion

1. Overview of Transformer Technology and Deep Learning in Music Composition:

1.1 Deep Learning Models:

Deep Learning, at its core, is a multi-layered neural network that learns directly from data without any manual feature extraction to find patterns and make predictions (Figure 1). Various deep learning architectures exist, such as Convolutional Neural Networks (CNNs), which are effective at analyzing spatial data like images, and Recurrent Neural Networks (RNNs), which are designed for sequential data like music or text. A transformer is another multi-layered neural network architecture that can learn complex patterns and hierarchical features from data. Applications like OpenAI's MuseNet and Google's Music Transformer have used some proprietary transformer-based mechanisms to analyze and compose new music on request, often proving their capability of mimicking specific styles or genres.[5] However, this capability also introduces significant challenges like plagiarism.

In the context of music composition, the model must read vast amounts of publicly available datasets for musical notes and audio & video files and go through multiple layers to identify underlying patterns such as melody, rhythm, and harmonic structure.[6] Each layer performs a specific function and feeds the output to the next connected layer. While the model and tools are built to expand possibilities, concerns have arisen about the ethical and legal implications of the outcome. Models are being trained on existing and original musical works, so any output is some form of reproduction of original work's patterns and melody fragments that might closely resemble copyrighted compositions and unintentional plagiarism. In the creative industries, particularly music generation, deep learning has been used to create original compositions, generate harmonies, and even mimic the styles of specific artists.[7]

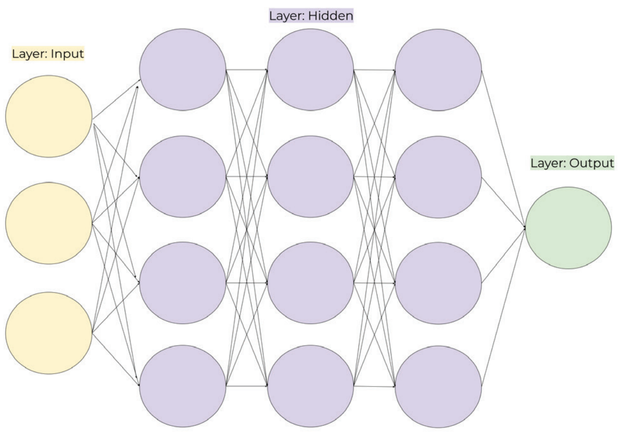

Figure 1: A graphical image of a deep learning model shown as layers of connected nodes. The model shown has an input layer that takes in the data, then processes the data through the interconnected series of hidden layers, and sends a result at the output layer.

1.2. Transformer Models:

The transformer model is an enhanced machine learning neural network model that uses a self-attention mechanism to efficiently process entire sentences in parallel and understand the context of the sentence. This mechanism understands and preserves the meaning of each element in the sequence, unlike recurrent neural networks (RNNs) and long short-term memory networks (LSTMs),[8] which process one word at a time (Figure 2). The model is built from two key components, the encoder and decoder. An encoder reads input sequences and is able to create contextual representations of the sequences. A decoder uses the representations to generate the output sequence. This architecture allows for the transformer to preserve the meaning of each element and model short-term and long-term dependencies with high accuracy. This model has been effectively used in the field of music composition to capture the intricate structure and flow of music notes & text and identify more patterns and significantly improve the quality of output. We could efficiently use this model for composing new music without copyright infringement or for checking if the composition is plagiarized. OpenAI's MuseNet and Google's Music Transformer use this model and capture both short-term and long-term dependencies to generate music.

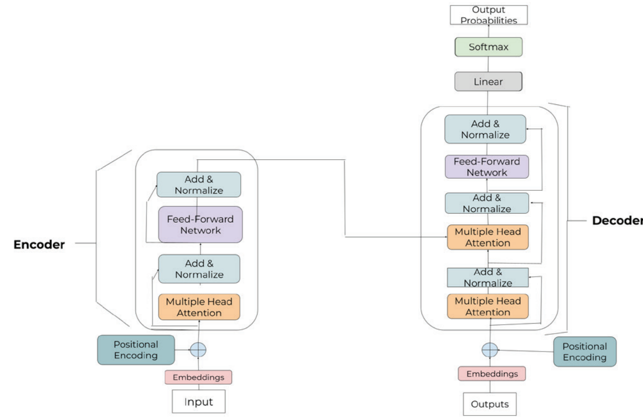

Figure 2: Transformer architecture showing information flow. The beginning input sequence goes through an encoder, which extracts the context of each element. The encoder then sends the information to the decoders, which use the information to create an output probability. This lets the Transformer keep relationships across entire sequences efficiently and preserve meaning from input to output.

1.3. Summary of Models and Impact:

While AI applications in the field of music expand the possibilities of music composition, it intricately brings issues regarding the ethical and legal implications of the compositions it generates. Learning from existing datasets of music and related files, these models can generate highly convincing compositions. However, the output may often overlap with the original works they were trained on. It could be a complete overlap or slight modifications in melody and chord progressions, and could bring considerable intellectual property violations. Deep learning models are often described as "black boxes" due to the difficulty in assessing their decisions.[9] This creates a bigger issue as it becomes harder to determine whether the generated piece is indeed original or subtly plagiarized. While AI has revolutionized music composition and helped in curating more musicians, specifically newcomers, it is vital to have a progressive development in complementary technologies like plagiarism detection for ensuring that AI-driven creativity remains both ethical and legally compliant.

2. Current Applications in Music Generation and Originality Assessment:

2.1. Originality Assessment Tools in AI Music Generation:

Originality Assessment Tools are critically important to prevent unintended plagiarism.[10] They use implementations of similarity scoring techniques, like cosine similarity or dynamic time warping, to compare generated output against available datasets. These tools often rely on symbolic representations of music such as MIDI data (Musical Instrument Digital Interface), a digital standard that stores musical information not as sound, but as instructions, such as which notes are played, how long they last, and how hard they are pressed on a keyboard. Because MIDI files capture the structure of music rather than including recordings of instruments, they are useful for training machine learning models and comparing sequences for melodic similarity, harmonic overlap, and rhythmic patterns.[11] The goal of these tools is to measure and ensure the generated music diverges sufficiently from the model data. MuseNet, an originality assessment tool, typically uses similarity scoring techniques to compare the works.

2.2. Integration of Originality Scoring with Generation:

Modern transformer models are sophisticated and have originality scoring integrated in the process. Due to its multi-layered neural network, adding the scoring as one of the layers is not a surprise feature. For example, we could have a model that can be trained with constraints and penalize the generation of highly similar melodic fragments during output synthesis (Figure 3).[12] Some post-generation tools evaluate for the uniqueness score after its creation, flagging sections that may require revision to avoid potential infringement. This dual-layered approach ensures a balance between creative flexibility and the protection of intellectual property.

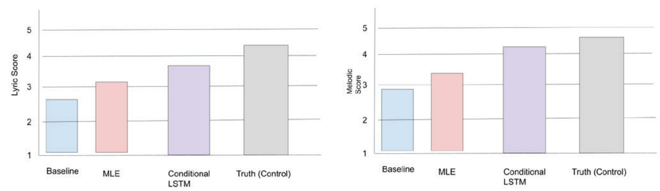

Figure 3: Tables of lyrical and melodic scoring between different model generations and analysis on a scoring of 1-5. The table consists of four bars: Baseline, MLE (Maximum Likelihood Estimation), Conditional LSTM, and Truth (control). Each bar represents the lyric or melodic score, depending on the graph, of the model generations, with higher values indicating more corresponding accuracy between generated melodies and lyrical input. The Baseline and MLE models show lower scores due to more generic melodic outputs. However, the Conditional LSTM shows improved coherence between the generated melody and lyrical text when compared to the Truth control bar. These graphs show researchers a visualized effectiveness between human creativity and originality in melody generation.

3. Challenges in Music Plagiarism Detection:

3.1. What is Plagiarism in Music?:

The topic of defining plagiarism in music becomes complex when considering topics like multi-dimensionality and substantial similarity. Some topics needed to be analyzed more than the multi-dimensionality of the music and its plagiarism: melodic similarity, note-for-note copying, checking for repeating specific note sequences and chord progressions, resemblance to other harmonies, structural overlap, and even checking for broader patterns in music, such as phrasing, tempo, and song structure.[13] The complexity and multidimensionality of the topic make defining and identifying plagiarism in music fundamentally challenging. Music often could rely on shared harmonics, cultural motifs, themes, and classical rhythms. Some may often credit the original composer for using their rhythms, while some may inadvertently include them in their compositions. So, plagiarism in music is as important as protecting any intellectual property. It helps in the longevity of the original composers and the entire musical industry. We may notice some of our favorite tunes sound very similar to other hit songs. It is challenging to identify plagiarism in music, especially with a limited set of defined chords and progression sequences. An example of this may be the well-known song "Flowers" by Miley Cyrus, allegedly plagiarizing Bruno Mars's "When I Was Your Man" in terms of lyrics and melodies.[14] While they may both sound the same in terms of lyrics, message, and melody, these are both still enjoyable songs that happen to share defined chords and progression, leading to prime research issues regarding how machines should analyze and detect plagiarism in pieces. For the focus of the article, plagiarism is simplified into the fact of analyzing melodic, harmonic, and the structural integrity of AI-driven compositions and focusing on if the models can pick up on existing motifs that may be prominent in other pieces, thus being plagiarized, or if the themes are too broad to be relatively close to any existing pieces, thus being somewhat original.

3.2. Limitations of Existing Detection Tools:

Traditionally, plagiarism detection has been based on certain rules. While these rules have led to innovations that could catch and flag some works, they struggle to handle the nuances of creativity. Historically, rule-based checks were built to check exact note sequences or chord patterns, leading towards potential failure to capture certain methods of variations like a model using live transpositions or rhythmic modifications that alter surface details yet maintain the musical essence of a piece to avoid plagiarism detection.[15] For example, tools like Melisma Music Analyzer rely on symbolic pattern matching, which has the limitations of overlooking abstract similarities between pieces. Other AI-driven models, on the other hand, offer more enhanced pattern recognition for users but can ultimately overflag legitimate creative overlaps due to the models' extreme sensitivity towards data similarities. Ultimately, plagiarism detection reaches a standstill. Too many flags can make a piece uninteresting and spread heightened fear across the music industry. However, multiple false positives may result in low trust in the checking process of plagiarism detection and may cause inconvenience to both parties.

3.3. Balancing Originality Enforcement and Creative Freedom:

As discussed, there are multiple challenges with the pressing issue of creative freedom with the application of machine learning models. The issue essentially is with using models ethically, especially in plagiarism detection. The models need to be within a state to balance creative freedom with the power to enforce originality. Music, by nature, involves innovative and continuous repetition of harmonic and melodic patterns to create a work of art adorned by all. An example of the continuous repetition in patterns is seen in common chord progressions like the I-V-vi-IV progression sequence, being extremely versatile and used across multiple genres of music throughout time.[16] The example shows that imposing rigid detection standards, such as strict rules on how plagiarism should be detected, could lead to a reduction in creativity because artists are discouraged from using shared musical language, such as chord progressions. However, models that use a more moderate approach towards detection risks would also not be very beneficial, as it allows for subtle bits of plagiarism to go undetected. Therefore, there is an urgent need to develop an effective detection system that must account for both musical innovation and traditionally accepted pattern repetition, distinguishing between influence and infringement.

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4. Methods for Plagiarism Prevention Using Transformer Models:

4.1. Sequence Comparison, Feature Extraction, and Self-Supervised Learning:

Multiple studies have proven that transformer models utilize techniques such as feature extractions and sequence to show promising results in the fields of plagiarism detection and even prevention. For example, the use of feature extractions in systems such as the chroma vectors and Mel-Frequency Cepstral Coefficients (MFCCs) has allowed for a deeper and more accurate analysis within patterns beyond the basic note-for-note comparisons.[17] The technique of sequence comparisons means using functions that involve breaking down information into usable data for models, or in this case, breaking down parts of musical pieces, such as rhythm, pitch, and intervals, into usable data for symbolism and detection models. This data is then sent into the model to be analyzed with pre-made similarity metrics to analyze plagiarism.[18] Both the techniques of sequence comparison and feature extraction can be used to allow transformer models to identify structural similarities within certain musical elements, such as key or tempo differences, helping models study and accurately describe plagiarism better.

Other transformer models, such as self-supervised learning (SSL), have been proven to be a strong and accurate plagiarism detection tool. SSL has shown potential in plagiarism detection, especially in musical generation, as seen in many studies.[19] SSL has taken the approach of training a model on large datasets without many labels, allowing for the development of identifying patterns and relationships in data more efficiently than other models. Contrastive learning and other learning patterns have proven to be distinguished techniques to allow the model to differentiate the original and plagiarized compositions by generating negative samples during training. Other forms of learning, such as data augmentation, can improve a model's ability to detect similarities across datasets, utilizing tempo and transposition alterations to reduce bias in originality assessment.[20]

4.2. Hybrid Approaches: Similarity Detection and Creative Constraints:

Checking and preventing plagiarism involving hybrid approaches that would combine similarity detection with creative constraint mechanisms has shown promising results. A multi-layer transformer model could generate music while continuously evaluating the similarity of each segment against a reference dataset and generating similarity scores. If the generated similarity score exceeded a predefined threshold, the multi-layer transformer model could alter its generation process in real time through certain methods, such as adjusting melodic intervals or rhythmic patterns to create and protect the original composition.[21] Moreover, certain creative constraint mechanisms, like forcing the generation of non-repetitive motifs and limiting the reuse of particular harmonic patterns, can be integrated during music generation. This hybrid of using mechanisms and models ensures that the generated compositions remain both innovative and compliant with intellectual property standards.

5. Case Studies and Results:

5.1. Deep Learning in Music Similarity Detection:

Several studies have applied various deep learning models to detect similarities, with notable success in advancing plagiarism detection in music. For instance, a study employing convolutional neural networks (CNNs) trained on spectrograms demonstrated how visual representations of audio can effectively capture melodic and harmonic features (Figure 4).[22] CNNs were chosen because they are especially good at recognizing patterns within images, and they can use spectrograms to turn sounds into a form of visual output to show how frequencies change over time. This, overall, makes the CNNs more practical than models like transformers, as models like transformers require larger datasets and more computational power. The study tested with CNNs on a variety of music genres found high accuracy in distinguishing musical styles and detecting similarities, showing that using spectrograms can reliably capture the "fingerprint" of a music piece. Another successful example is the use of Siamese networks, which compare pairs of musical inputs and measure their similarity scores is another successful example.[23] These approaches enable us to go beyond simple symbolic representations in identifying similarities in the music.

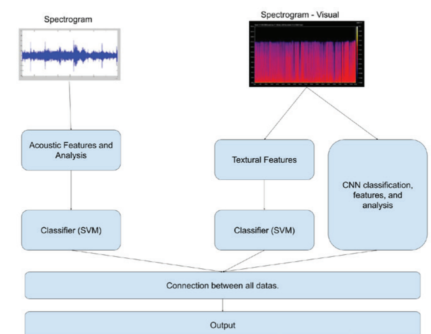

Figure 4: Diagram of CNN trained on spectrograms and how it can capture and evaluate melodic and harmonic features.[22] This diagram shows the pipeline of audio processing by converting audio signals to spectrograms. The spectrograms are then used within CNNs to identify recurring spectral patterns relating to melodic and harmonic structures. The CNN then pools the layers to compress the data while maintaining key features of the frequency. It then connects all the data from classifiers to evaluate whether the two inputs share overlap in melodic and harmonic content.

5.2. Metrics for Plagiarism Prevention:

If detecting plagiarism in music is a daunting task by itself, the performance of achieving such a feat with the best score is yet another. Performance in plagiarism is often evaluated using: precision, which measures how accurately the system identifies plagiarism cases without over-flagging original work; recall, which assesses its ability to detect all instances of plagiarism in a dataset; and F1 score, which provides a single performance indicator while balancing the metrics.[24] In one of the benchmark studies, models like Music Transformer achieved precision rates exceeding 85% for melodic similarity detection, underscoring their effectiveness.[25] However, achieving high recall remains a challenge due to the subtlety of variations in musical compositions.

5.3. Impact of Case Studies on Practical Application:

Our case studies demonstrate the potential of deep learning based applications for music originality assessments. Integrating metrics with qualitative analysis, like human evaluations of flagged outputs, researchers can refine models to better align with creative and cultural contexts. This balance of human interpretability and technical accuracy is vital for the advocacy of AI tool usage and legitimacy in creative industries and continues to support creativity.

6. Ethical and Legal Implications:

6.1. Intellectual Property in AI-Generated Music and Transparency:

Protecting intellectual property rights from AI-generated music is an important task and comes with a lot of intricate questions. Determining liability is equally challenging from AI-generated tunes. Does the responsibility fall on the developer, the user, or the AI system itself? Current copyright laws, often designed for human creators, struggle to address these ambiguities.[26] As with time and technology, the binding legal frameworks need some updates to consider the unique nature of AI creativity. Transparency in how AI systems that generate and evaluate music is crucial for their ethical use. Explainable AI, or XAI, shows insights into the decision-making processes of models, enhancing trust and accountability.[27] For example, an AI tool that flags potential plagiarism should clearly state which elements of a composition, melody, harmony, or rhythm triggered the flag. Providing this level of detail can help creators address issues proactively and avoid unnecessary legal disputes.

6.2. Balancing Innovation and Ethics:

People must create a balance between ethical standards and innovation to grow and change AI technology. AI tools have unlocked unparalleled levels of creativity for audiences, but have also brought about the risks of intellectual property theft, raising alarm for concerned people. Fixing this issue would require policymakers, researchers, and legalists to collaborate and establish new guidelines that could promote responsibility in AI development with the mindset of protecting intellectual rights.

7. Future Directions and Innovations:

7.1. Advances in Model Architecture:

Future advancements in transformer models could focus on enhancing their ability to multi dimensional analysis and provide more insights into explainability. Techniques that could combine audio, text, and symbolic data could improve the precision of similarity detection.[28] Additionally, advancements in sparse and adaptive-based attention mechanisms may allow models to process longer compositions without compromising computational efficiency, enabling more detailed analysis. Collaboration between technologists and musicians will play a pivotal role in shaping the future of plagiarism prevention.[29] Exchanging valuable insights into the nuances of creativity and originality would help technologists design better mechanisms to validate the composition. Hackathons and joint research projects are some of the initiatives that can accelerate innovation in the field.

7.2. Expanding Ethical and Cultural Contexts:

Cultural and historical knowledge has become so advanced and critical that integrating it with AI systems may allow for better originality and credibility of AI-generated music. As an example, a model study trained on a diverse knowledge set of global musical traditions could analyze and understand that certain cultural overlaps and shared motifs can be avoided as plagiarism.[30] For instance, recognizing that melodies like national anthems or folk songs carrying deep cultural meaning in the world would help an AI avoid misclassifying them as plagiarized content, which would also ensure that generated music shows accuracy and cultural respect for world traditions.

■ Conclusion

With the trending and growing innovations in transformer and deep learning models, artificial intelligence has expanded and evolved in creating music and other artistic expressions that seem almost life-like and man-made, shifting attention towards the overall originality, ethical, and legal debates of AI. Transformer and deep learning models have expanded the field of creativity towards a wider span of artists and can even play a critical role in helping copyright protection and originality enforcement. This article leverages multi-layer neural networks and their functionality to bring about examples of transformer models improving and safeguarding intellectual property rights. This article raises awareness towards originality assessments in order to further protect and preserve the ethics of AI-generated music. There are many tools available to the general public, which are all capable of generating compositions, and many techniques, such as self-supervised learning, which have shown effectiveness in evaluating plagiarism. The challenges of defining plagiarism boundaries by balancing between creativity and originality highlight the inherent complexity and limitations of the systems. With the expansion of AI, ethics and legalities must stand as a top priority, along with accountability and transparency being within the purview of artists, technologists, and legal experts to address these concerns. Research must also focus on refining models and architectures to improve plagiarism detection accuracy, fostering an innovative future for AI-driven music composition.

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