Temporal Drift Analysis With Synthetic Hit Song Feature Generation Using GANs And Hit Prediction

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***Abstract*—The prediction of music popularity has garnered significant attention in the domains of music information retrieval and data science. This study proposes a machine learning framework that integrates both real-world Spotify data and synthetically generated data to enhance classification accuracy in predicting song popularity. A comprehensive temporal drift analysis is performed to quantify how core audio features of popular music evolve between 1950 and 2023. Insights from this analysis guided the construction of our Generative Adversarial Network (GAN), which is trained on recent high-popularity tracks to generate synthetic samples that reflect contemporary hit characteristics. Random Forest classifier achieved the highest accuracy of 92.11%. Subsequently, feature importance analysis revealed the most influential audio attributes contributing to song popularity prediction. Our results demonstrate that combining GAN-based data augmentation—guided by temporal drift insights with traditional oversampling techniques can significantly improve classifier robustness and accuracy in imbalanced music datasets. This framework offers a promising approach for leveraging both synthetic and real data in music popularity prediction tasks.**

***Index Terms*—Generative adversarial networks, temporal drift, Music popularity prediction, Machine Learning, Classification.**

I. Introduction

In the rapidly developing landscape of the music industry, the ability to make an accurate prediction of potential popularity of music has adequate commercial, cultural and technical importance. The rise in digital streaming platforms such as Spotify, Apple Music, and YouTube has fundamentally changed how music is produced, distributed and consumed globally. Understanding the complex interaction of music characteristics contributing to the success of a song, with accessible billions of tracks has emerged as an important challenge for both artists and data scientists.

Traditional approaches to music popularity prediction predominantly rely on static historical datasets and conventional supervised learning models. These models typically leverage structured audio features, including danceability, energy, tempo, loudness, valence, speechiness, and acousticness to classify music into binary popularity categories or predict continuous popularity scores. While prior studies[1], [2], [3] have demonstrated promising correlations between these features and track success, such models often fail to account for two critical realities of modern music analytics: (1) temporal evolution of musical styles and listener preferences, and (2) inherent class imbalance in popularity-labeled datasets.

There are two major challenges associated with popularity prediction of music. (i) First, the phenomenon, often termed as *temporal drift*, where the defining characteristics of popular music change over time. For instance, the compositional and production features that dominated chart-topping hits in the early 2000s differ markedly from those prevalent in the post-2020 streaming era. Factors such as advancements in music production technology, shifting cultural trends, and evolving consumer tastes contribute to this drift. Static models trained on older data distributions often underperform when applied to contemporary music, as they fail to capture these subtle but impactful shifts in feature importance and interaction patterns. (ii) The second major challenge is *class imbalance*. Empirical analyses of platforms like Spotify consistently reveal that only a small fraction of tracks achieve high popularity (e.g., appearing in curated playlists or surpassing significant stream thresholds), while the vast majority languish with minimal listener engagement. This imbalance skews model training, leading to biased classifiers that exhibit poor sensitivity towards emerging or minority (high-popularity) classes.

To address these challenges, we propose a comprehensive and systematic framework that integrates temporal drift analysis with Generative Adversarial Networks (GANs) to enhance hit song prediction. Our approach focuses on both understanding how the core audio features of popular music have evolved over time and generating synthetic samples that accurately reflect contemporary hit characteristics. By curating and analyzing a large corpus of high-popularity Spotify tracks released between 1950 and 2023, we quantify trends and shifts in critical musical attributes, such as danceability, energy, tempo, and valence, over recent years. Subsequently, we design and train a specialized GAN model capable of synthesizing realistic and high-quality audio feature profiles that emulate the properties of modern hit music. These synthetic data samples are employed to augment traditional classification pipelines, addressing the class imbalance problem and enhancing model

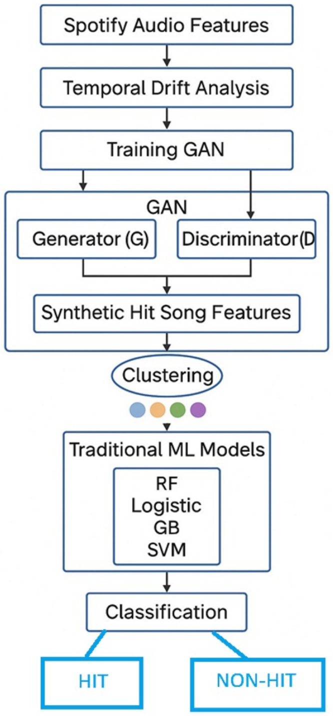

Fig. 1: Flow chart of the methodology

robustness against temporal drift. In addition, through the application of unsupervised clustering techniques and dimensionality reduction methods such as Principal Component Analysis (PCA), we explore latent subgenre patterns within the generated data and trace their temporal dynamics. Furthermore, to rigorously evaluate the effectiveness of our proposed framework, we benchmark multiple machine learning classifiers—including Logistic Regression, Random Forest, Gradient Boosting, and Support Vector Machine (SVM)—on both real-world and GAN-augmented datasets. Our experimental results demonstrate that incorporating GAN-generated synthetic samples into training datasets consistently improves classification accuracy, recall, and generalization performance, particularly for high-popularity song prediction.

The main contributions of this work are:

- Integration of temporal drift analysis on high-popularity Spotify tracks musical features from 1950 to 2023 with GANs for generating synthetic hit-like audio feature profiles to enhance hit song prediction.
- Comparative analysis of ML classifiers on real and synthetic-augmented datasets to assess the performance of ‘hit’ prediction.
- Incorporation of K-means clustering and PCA to visualize and interpret latent subgenres structure and emerging musical trends in the generated data.

II. Literature Review

To ground this project in prior work, a range of relevant studies are reviewed. These papers provide critical insights into music mood classification, recommendation systems, and the application of machine learning for emotion modeling in music. In paper[1] the authors introduced a multi-modal attention-based architecture to improve music mood classification, emphasizing the fusion of various data modalities (audio, lyrics, and metadata) for better performance. In paper [2] authors proposed a supervised learning system that leverages both song features and user emotional states to generate personalized music recommendations. Paper [3] demonstrated how national mood can be quantified using audio features extracted from popular music, offering a novel socio-emotional application of machine learning. The authors in [4] evaluated multiple classifiers on mood prediction tasks using COVID-19 datasets, providing methodological benchmarks for mood-based classification. Paper [5] presents an interactive system that combines user interface design with mood-based filtering for enhanced music discovery. In paper [6], the authors explored predictive features associated with music’s calming effects, contributing to studies on music-induced emotional regulation. The authors in paper [7] developed a personalized recommendation model aimed at fulfilling users’ emotional and mental well-being through adaptive music selection. An Automatic Music Emotion Classification Model for Movie Soundtrack Recommendation is reported in paper [8] that combines audio feature extraction and machine learning to classify music emotions, focusing on its application to soundtrack and cinematic contexts.

Research gap and Goal of the current study: The main limitations of these existing works are, they majorly focus on static, emotion-driven, or personalized music generation and prediction without accounting for temporal dynamics, or concept drift. Most prior models lack adaptability to changing trends and offer limited interpretability. Contrary to these works reported in literature, in the present study we proposed a drift-aware, generative, and interpretable methodology for advancing music popularity prediction. By bridging the gap between static historical modeling and adaptive, forward-looking analytics, our framework leverages deep generative models to provide actionable insights into emerging musical trends and enhances predictive capabilities in imbalanced, temporally dynamic datasets. The code of this work is available at Github Repository[1].

III. Methodology

Our proposed methodology integrates temporal drift analysis, generative modeling, clustering, and machine learning classification to predict hit music in a dynamic, evolving musical landscape. The complete workflow is composed of dataset preparation, temporal trend analysis, unsupervised style clustering, GAN-based synthetic data generation, classifier training, and interpretability analysis. The block diagram

[1]https://github.com/abhyudk/spotify-temporal-drift-along-with-GAN-based-hit-classifier?classId=024d6218-fc0e-41d7-aed7-a09abf7038ee&assignmentId=b4124866-3fe8-4d01-8653-2616d6b53f61&submissionId=1da1cabf-5bd9-eff8-31a2-5a6993ef9d26

of the proposed methodology is shown in Figure 1. The details of each step is elaborated in the subsequent subsections.

A. Dataset description

The publicly available spotify music dataset is used in the current study[2]. The dataset represents hit music with Spotify popularity scores above a predefined threshold as well as non-hit or underperforming tracks with lower popularity scores. We focused on tracks released between 1950 and 2023 to capture contemporary musical characteristics and mitigate long-term stylistic shifts. Each track entry includes 12 standardized Spotify audio features: danceability, energy, valence, tempo, loudness, speechiness, instrumentalness, acousticness, liveness, duration, key, and mode. Any incomplete or anomalous records are filtered out. All numerical features are normalized using z-score to ensure comparability across attributes.

B. GAN Architecture and Training for Synthetic Hits

A Generative Adversarial Network (GAN) is designed using PyTorch to synthesize realistic hit song feature profiles, guided by insights from the temporal drift analysis. To ensure that the generated samples reflect contemporary musical trends (such as the observed rise in energy, tempo, and danceability from recent years), the generator is explicitly conditioned on temporal information. The 'Generator' maps a concatenated input of a 64-dimensional noise vector and a scalar representing the normalized release year to a 10-dimensional feature space. This conditioning allows the generator to produce feature profiles that correspond to stylistic trends from specific time periods, focusing primarily on the modern era 2023. The 'Discriminator' takes as input both the feature vector and the corresponding release year and attempts to distinguish between real high-popularity samples and fake ones generated by the Generator. The model is trained exclusively on high-popularity tracks from 1950–2023. The training objective is to minimize the classification error of the Discriminator while encouraging the Generator to produce indistinguishable, temporally coherent feature vectors. This drift-aware GAN framework helps ensure that the synthetic samples emulate modern hit song profiles aligned with evolving listener preferences. Both networks consist of fully connected layers with LeakyReLU activations and batch normalization. The GAN is trained exclusively on high-popularity music (1950–2023) to ensure generation fidelity towards contemporary hits. The GAN is trained for 500 epochs using Adam optimizer (learning rate $= 0.0002$, $\beta_1 = 0.5$) and a batch size of 64. Label smoothing and noise injection techniques are used to stabilize adversarial training and prevent mode collapse. Upon convergence, we sampled 5000 synthetic high-popularity feature vectors.

C. ML Classification for hit prediction

The final prediction models are trained on an augmented dataset consists of real hit music, GAN-generated synthetic hits music, and real non-hit music. We benchmarked the following classifiers for hit prediction. These are Logistic Regression (with balanced class weights), Random Forest Classifier, Gradient Boosting Classifier, and Support Vector Machine (SVM-RBF Kernel). To address class imbalance, the Synthetic Minority Over-sampling Technique is applied to the training dataset. All models are trained using a 70:30 stratified train-test split. Hyper-parameters are tuned using grid search with 3-fold cross-validation. Performance measures such as, precision, recall, F1-score, and accuracy are evaluated from confusion matrices.

[2]https://www.kaggle.com/datasets/solomonameh/spotify-music-dataset

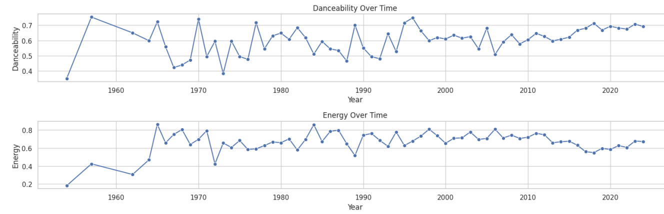

Fig. 2: Illustration of temporal drift of the two key music features Danceability (row-1) and Energy (row-2) from 1950 to 2023, showing noticeable increase in recent years, reflecting evolving listener preferences.

IV. Results and Discussion

The proposed framework is rigorously evaluated through a comprehensive set of experiments to validate its effectiveness across multiple dimensions: classification performance, quality and realism of GAN-generated data, latent stylistic structure discovery, and feature importance interpretability. This section presents the detailed results derived from these analyses.

A. Temporal Drift Analysis

To analyze how hit song features have evolved over time, we performed temporal drift analysis by calculating yearly averages of each audio feature from 1950 to 2023. This allowed us to visualize long-term shifts in musical trends such as rising energy, tempo, and danceability in recent years — factors frequently associated with modern pop hits. This is shown in Figure 2

B. Evaluation of GAN Output Realism

A critical component of our framework involves generating synthetic hit-like feature vectors using a Generative Adversarial Network (GAN). To quantitatively assess the realism of these generated samples, a binary classification experiment is conducted wherein a Logistic Regression model is trained to distinguish between real hit music and GAN-generated samples. The classifier achieved an accuracy of 57.33%, which is only marginally better than random guessing (50%). This result indicates that the synthetic data closely mirrors the statistical distribution of real hit song features, rendering it difficult to differentiate between real and synthetic examples.

For visual interpretation, PCA is employed to qualitatively assess the distributional similarity between real and synthetic feature vectors. The PCA visualization is shown in Figure 3 where the non-separability clearly depicts the closeness of

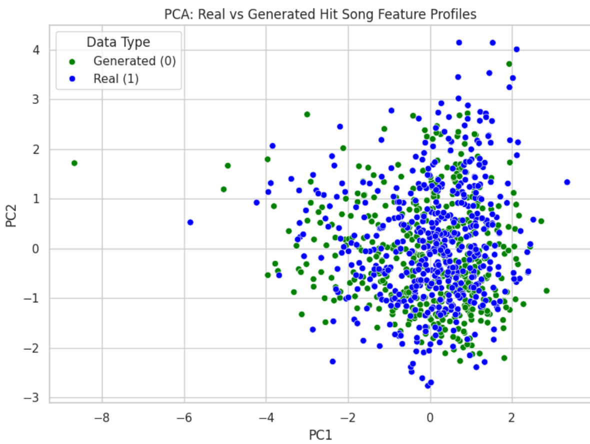

Fig. 3: PCA plot showing real vs. GAN-generated hit song feature vectors. The visual overlap indicates successful learning of feature distributions.

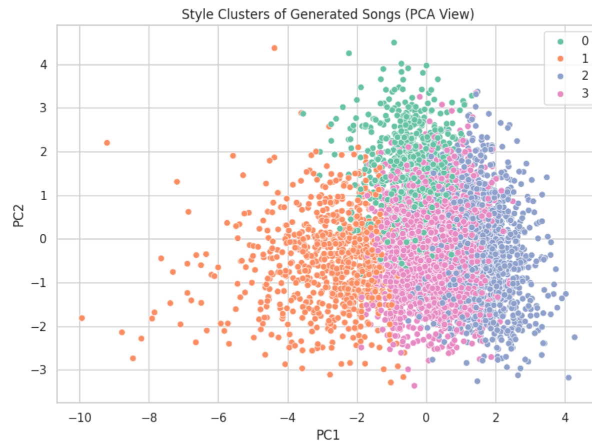

Fig. 4: Visualization of clustered GAN-generated hits using PCA. Four stylistic groups: Dance-pop (*Blue*), Rock (*Orange*), Classical tracks (*Pink*), and Rhythm-centric spoken-word styles (*Green*) emerged clearly in feature space.

the GAN-generated samples with the real hit song data. This indicates that GAN has effectively captured and repeated the underlying data distribution which supports the success of the GAN model in learning the complex structure of the original dataset, showing the ability to generate the music with realistic and stylistically coherent compositions.

Thus, the combination of quantitative classification results and qualitative PCA visualization validates the effectiveness of the GAN in synthesizing realistic and high-quality feature vectors that augment traditional datasets.

C. Style Clustering and Latent Structure

To explore latent stylistic patterns within the GAN-generated samples, KMeans clustering is performed on the synthetic feature vectors. Using the elbow method, we determined an optimal cluster count of $k = 4$. This resulted in four stylistic groupings that broadly represent categories. These are (i) dance-pop, (ii) Rock, (iii) classical tracks, and (iv) rhythm-centric spoken-word styles. The resulting clusters revealed four distinct stylistic groups. PCA is used to visualize the separability of these clusters in reduced dimensional space, as shown in Figure 4. The clear separation between clusters confirms the presence of meaningful sub-genres or latent styles within the generated data. A downstream style classification model, trained on these cluster labels, achieved over 98% accuracy in predicting the correct cluster, thereby confirming the coherence and consistency of the discovered stylistic categories. This clustering analysis not only enriches interpretability but also opens avenues for understanding emerging musical trends within synthetic hits.

Additionally, We analyzed the temporal distribution of each cluster to examine how the prominence of different hit styles evolved across the study period. This is shown in Figure 5

D. Classifier Performance on GAN-Augmented Dataset

To assess the impact of augmenting real-world data with GAN-generated synthetic samples, four supervised machine

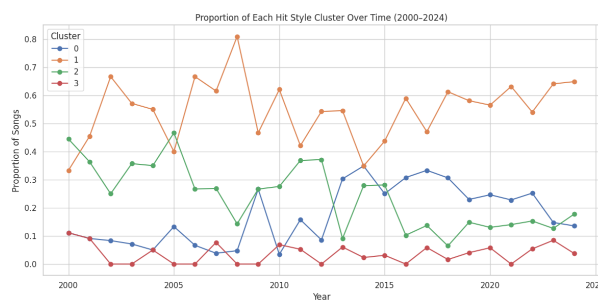

Fig. 5: Trend in GAN generated hit music in Dance-pop (*Green*), Rock (*Orange*), Classical tracks (*Purple*), and rhythm-centric spoken-word styles (*Blue*) categories, showing between years 2000 to 2024. The plot suggests a rise in energetic, rhythm-driven tracks.

learning classifiers—Logistic Regression, Random Forest, Gradient Boosting, and SVM with an RBF kernel are trained on the composite dataset containing real hits, real non-hits, and GAN-generated hits. Table I summarizes the results of all ML classifiers. As seen from the table, the Random Forest classifier achieved the highest classification accuracy of 92.11%, outperforming all other models. This highlights the ability of ensemble-based models to leverage both real and synthetic feature distributions effectively. The introduction of GAN-generated data contributed to increased class diversity, which allowed models to generalize better to unseen examples. Although the remaining classifiers like Logistic Regression, Gradient Boosting, and SVM achieved comparable accuracies around 90%, Random Forest's superior result underscores its robustness and resilience to overfitting in high-dimensional feature spaces.

The confusion matrix for Random forest classification is shown in Figure 6. The confusion matrix demonstrates a strong balance between true positive and true negative rates. The

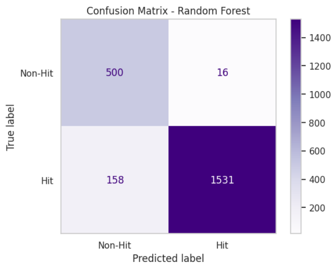

Fig. 6: Confusion matrix of the best-performing Random Forest model on GAN-augmented dataset. As seen, Random forest performs well in classifying hits and non-hits.

TABLE I: Performance measures obtained from different ML classification models

Model	Precision	Recall	F1-score	Accuracy
Logistic Regression	0.93	0.90	0.91	90%
Gradient Boosting	0.93	0.90	0.90	90.2%
SVM (RBF Kernel)	0.93	0.90	0.91	90.5%
Random Forest	**0.94**	**0.92**	**0.92**	**92.11%**

relatively low incidence of false positives and false negatives indicates that the classifier not only detects hit music accurately but also minimizes incorrect misclassifications, making it highly reliable in practical deployment scenarios for hit prediction.

E. Feature Importance Analysis

In order to enhance interpretability and uncover which audio characteristics are most influential in determining the classification performance, we extracted feature importance scores from the trained Random forest model. The analysis revealed that duration, tempo, and loudness are the most influential factors in distinguishing hit music. The resulting ranking, visualized in Figure 7, highlights the top contributing features. These features align with intuitive musical expectations, where timing, pace, and perceived energy strongly correlate with listener engagement and commercial success. Secondary features such as danceability and valence also contributed meaningfully, underscoring the multi-faceted nature of what constitutes a hit song. Overall, these results demonstrate the robustness, interpretability, and practical applicability of the proposed framework for drift-aware, generative hit song prediction.

This study presented a comprehensive, data-driven framework that integrates temporal drift analysis, unsupervised clustering, generative modeling, and supervised classification to enhance hit song prediction. By leveraging both real-world audio feature datasets and synthetically generated samples via Generative Adversarial Networks (GANs), the proposed approach not only addressed the evolving nature of musical trends but also enriched the diversity of training data to improve model generalization. Firstly, temporal drift analysis illustrated how key musical attributes—such as energy, danceability, and tempo have undergone significant evolution over the decades, reflecting shifts in listener preferences and pro-

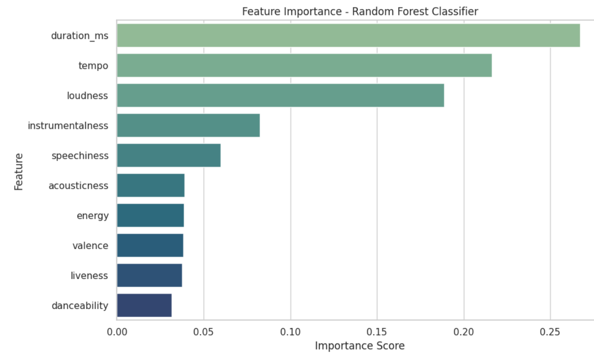

Fig. 7: Feature importance scores derived from the Random Forest classifier. Duration, tempo, and loudness are found to be the most influential features in hit prediction.

duction styles. These insights validated the need for temporal awareness in modeling hit song potential, especially when considering contemporary datasets spanning 1950 to 2023. Secondly, the introduction of a GAN to synthesize realistic hit-like feature vectors proved highly effective. Quantitative evaluations showed that the GAN-generated samples closely mirrored real hits, as evidenced by the difficulty in distinguishing them via logistic regression and substantial distributional overlap in PCA visualizations. This synthetic data is instrumental in expanding the training set and introducing greater feature variability. Moreover, the clustering using Kmeans revealed distinct stylistic groupings within GAN-generated hit music, and subsequent analysis demonstrated how the prevalence of these styles has been fluctuated over time. This reinforced the notion that hit song success is not monolithic but also influenced by multiple latent stylistic archetypes. Finally, the results obtained from supervised ML classification models suggest that augmenting real datasets with GAN-generated samples improved predictive performance. The Random Forest classifier, in particular, achieved the highest accuracy of 92.11%, reliably identifying both hits and non-hits. Additionally, feature importance analysis highlighted certain music attributes such as duration, tempo, and loudness that are critical in determining hit potential, aligning well with music industry insights about listener engagement.

V. Conclusion

The study demonstrates the potential of combining temporal context, stylistic understanding, synthetic data generation, and robust classification methods for powerful and interpretable hit prediction system. The GAN-augmented approach not only mitigates issues related to data scarcity and evolving trends but also provides valuable interpretability for stakeholders in the music industry, such as producers, marketers, and artists.

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