Leveraging Artificial Intelligence for Predicting Music Popularity Using Social Media

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Recommended citation:

Wu, Yingchun (2024). "Leveraging Artificial Intelligence for Predicting Music Popularity Using Social Media". *Profesional de la información*, v. 33, n. 5, e330522.

https://doi.org/10.3145/epi.2024.ene.0522

Manuscript received on 6th March 2024
Accepted on 4th October 2024

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Abstract

Music industry has been remarkably influenced by artificial intelligence (AI) due to the ability of the latter to predict song popularity based on social networking sites data, though it is rather difficult to predict the success of a song in any given scenario. This study is based on the premise that improved accuracy in prediction can be achieved by developing adaptive algorithms sensitive to changing trends of data. Therefore, this study proposes a new approach called Dynamic Honey Badger Optimization-Driven Intelligent Long Short-Term Memory (DHB-ILSTM), a model that can enhance music popularity forecasting with social media metrics, incorporating audio features. Features were extracted from audio sources like Spotify and social media metrics, genre-wise on newly released music tracks. During pre-processing, Min-Max normalization technique was utilized, and inputs standardized, while missing values were filled in. Feature extraction and dimensionality reduction used LDA. It was found that DHB-ILSTM algorithm in Python was superior, regarding the model without social media data in comparison, because it yielded an accuracy of 93% for audio features, recall of 90%, and an F1-score of 91% with a precision value of 88%. The findings underscore the versatility of the model in integrating heterogeneous data sources and adapting to dynamic trends, meaning that it is a strong solution to music popularity prediction using AI and advance optimization techniques.

Keywords

Popularity of Music, Social Media, Predictive Model, DHB-ILSTM.

1. Introduction

The music industry has been remarkably influenced by artificial intelligence (AI). **Aum *et al.*** (2023) asserts that one of the most interesting applications of AI in music industry is its ability to predict song popularity based on social networking records. **Goel *et al.*** (2022) reiterate and confirm that AI can predict which pieces, artists, or styles will be popular by looking at the huge amounts of data that are created on social media sites. **Su and Sun** (2023) opine that this combination of technology and cultural trends gives valuable information about how people behave, which helps artists, record labels, and other professionals in the field to make smart choices in this fast-changing world. Modern music industry is very dynamic with new songs and acts coming out all the time. Conventional methods of assessing popularity, such as radio airplay and album sales, are now being replaced by digital metrics and streaming numbers

Chakrabarti *et al.* (2023) observe that social media has revolutionized how users interact and share information online. Platforms like Twitter, Facebook, Instagram and TikTok see immense levels of user engagement each day as people connect, post updates and trade thoughts. This treasure trove of public interactions provides a real-time look into what individuals are listening to, sharing or discussing—insights that can help predict emerging music trends (**Aboualola *et al.***, 2023). AI is perfectly suited to use this social media flow of data because it has the ability to look at huge amounts of data and find trends within them. Machine learning algorithms which is a type of AI, are also shown to be very effective and precise for pattern finding when working on big amount of historical data. **Taherdoost** (2023), suggests that these algorithms help in detecting the popularity reasons for songs in different social media platforms and network. Statistics and metrics such as shares, likes, comments and tweets on musical posts help in detections for AI to find out what makes the song popular and hits among the users and listeners. The main significant part is performed by the analysis of sentiments, which reads social media posts to find out how people are feeling. If musical notes and lyrics are getting positive attention, it is probably becoming more famous. On the contrary, negative feelings may reflect problems or a loss of interest. More advanced schemes tend to highlights on small things like humour, which makes it easier to analyse current trends (**Terroso-Saenz *et al.***, 2023).

Natural Language Processing (NLP) helps AI to identify trends by summarising and sorting large amounts of text. Predicting music popularity with AI is a crucial task. The enormous amount and unpredictability of social media data make it difficult to focus on what matters. Other exogenous factors that are quite unpredictable, like viral challenges and celebrity endorsements, also drive social media trends (**Xue *et al.***, 2023). In the domain of NLP, social media posts are interpreted. **Zhang *et al.*** (2023) mention that with the help of NLP, one will be able to recognize hashtags or terms pointing toward the release of music that may become a hit in certain genres. By mixing current social media buzz with past streaming data, AI would be able to trace back a song's peak, fall, and rise, suggesting more precise predictions. AI also finds the trend of genres that are going to get big and famous—not just which songs. This helps record labels and marketers to be up-to-date by recognizing early talent and trends, but it also avails the artist some insight into and relationship with their audience (**Simay *et al.***, 2023).

A lot of data about social issues is also updated regularly such as: proper usage of AI, protection of privacy, and non-bias in data analysis. Even with these problems, AI has huge benefits when it comes to forecasting music trends. The music business can manage its resources better, apply more effective marketing strategies, and have better decision-making options. AI-based data may help artists perform better by enabling them to reach their audiences. The ability of AI to predict the trend of music through analysis on social media is quite a leap forward in music. With tools like machine learning, sentiment analysis, and NLP, AI can turn huge amounts of raw data into meaningful insights, as pointed out by **Li *et al.*** (2023). In addition, AI makes it possible for people to easily discover new songs they like, according to **Tiwari *et al.*** (2023). This allows the industry professional to stay up-to-date and continue bringing new music into the light of public eyes.

Previous studies have exploited machine learning methods that consisted of GNNs, PEIA models, and XGBoost for music popularity prediction. These methods have faced drawbacks and shortcomings such as poor real-time processing ability, failure to adapt and change in accordance with dynamic social media trends, and generalization issues in various datasets. In this regard, this study fills these gaps by introducing the DHB-ILSTM algorithm that integrates social media metrics and audio features, and shows the best possible optimization of hyperparameters, yielding better performance than traditional models. This innovation fills a gap in accuracy, adaptability, and provides a general framework for the music popularity forecasting framework. This new algorithm of DHB-ILSTM has the potential to improve music's popularity forecast by combining both social network data and audio features. This method takes into account the difficulties involved with the integration of dynamically changing social media trends along with the sound data in order to achieve high accuracy and adaptability. Such audio data is a huge one combining features from streaming sites, with metrics on social media and processes this huge dataset on data pre-processing as well as reduction via Min-Max normalization and Linear Discriminant Analysis. Social interaction features complement audio data to predict trends in music while justifying a clear reason for using Honey Badger Optimization techniques to strengthen the model. Besides, aggressive testing is also performed to further confirm that the DHB-ILSTM algorithm is capable of use in an integrated highly sophisticated AI and optimization techniques toward achieving accurate music popularity forecasting.

This approach adopted in this study would fill research gaps in current methodologies and enable the model to accommodate changes in trends, and provide superior prediction outcomes. Further, the study would also help artists like lyricists and musicians to align their creations with market trends, record labels through targeted promotions, and stream platforms through fine-tuning recommendation systems. In addition, marketers and advertisers can also optimise campaigns, and event organisers might get ideas about audience preferences. This study thus provides a data-driven decision-making framework that empowers all stakeholders in the music industry.

2. Literature Review

Recent research in music analytics has increasingly focused on the identification of the most important driving factors of music popularity, using data-driven methods that enable the discovery of patterns in this type of data. These studies underline the critical role that data analysis plays in making predictions with respect to which tracks will be a success. In this regard (**Xing**, 2023), designed a model on a diversity of music attributes and listener preferences for what elements make up a catchy song. This study mainly applied machine learning models in Python, such as Pandas, Scikit-learn, and XGBoost, to construct methods for predicting the popularity of a song and determine which of them fits best for that purpose. Results provide a backbone for future studies on determinants of music success and hence add value to available knowledge. Similarly, **Arora and Rani** (2024) contribute to the debate on the role that music streaming services play in retaining musical authenticity against algorithmic recommendations. The study is dedicated to the enhancement of prediction models with respect to the popularity of music through feature engineering techniques applied to Spotify data. This study also examines how advanced models of machine learning—Linear Regression, Random Forest, and neural networks—are applied to predict the likelihood that a track will get into the Spotify Hit-50 list, with a view into a statistical analysis of key predictive features.

Recent research has trailed different methods of predicting user dynamics and content popularity on social media platforms with more advanced machine learning, and data analysis tools (**Rompolas *et al.***, 2024; **Musa; Dollmat**, 2024). These studies have extended field areas such as music recommendation systems, event popularity forecasting, fashion trend prediction and sentiment analysis. **Musa and Dollmat** (2024), for instance, have worked on various machine learning techniques: K-Nearest Neighbours Classifier, Logistic Regression, Support Vector Machine with the kernel RBF, Gradient Boosting Classifier, Random Forest Classifier. These methods were then applied with the goal of establishing their effectiveness in predicting music popularity. In most cases, Random Forests were used as a baseline to compare results. The objective set by the study was to achieve a prediction accuracy of at least 90%, beating performance previously reported. Their study contributes to this very fast-growing literature by providing an all-inclusive analysis of the audio features that may turn out to be relevant in predicting a piece of music's popularity. This hints at improvements in predictive modelling that have made it much easier to make predictions about what material will be popular and what market trends will be in different areas. These new ideas use complex methods to make things more accurate and able to change to changing conditions. In the domain of music popularity prediction, the area has grown a lot due to the prospect of assisting artists and composers in composing songs that appeal to larger audiences.

Likewise, **Rompolas *et al.*** (2024) analysed audience involvement and emotional response in the music industry through sentiment evaluation and internet-based data. Their model, which integrates social media features, proved effective in forecasting track popularity, offering artists and industry stakeholders valuable insights. Thus, there is a clear trend towards the inclusion of diverse user characteristics, emotions (e.g., sentiment analysis), personality and social media activity being frequent ingredients in subsequent works which all attest to personalization through context-rich models as important enablers for more accurate predictions and better user experiences. Researchers have also been focusing on improving prediction models to make them more accurate and better at handling new challenges, such as predicting events, recommending music, and monitoring social media. In line with this, **Kamal *et al.*** (2021) focused on predicting music popularity using various machine learning algorithms and exploring the effectiveness of feature engineering in enhancing prediction accuracy. Their study underscored the value of integrating sentiment analysis, song information, and demographic data in improving music recommendation systems. In addition to this, **Madisetty and Desarkar** (2021) discussed the importance of early event popularity prediction, particularly for events like sports, concerts, and conferences. Their deep learning-based model, which forecasts event popularity on social media prior to the event, outperformed baseline techniques, demonstrating its efficacy in practical applications.

Furthermore, **Verma *et al.*** (2022) proposed the UCred methodology to classify user accounts on Online Social Networks (OSN) as authentic or fraudulent. By combining multiple machine learning models, UCred achieved high precision in classification, emphasizing the importance of accurate user profiling in combating misinformation. This suggests that state-of-the-art research relies on machine learning algorithms analysing a number of audio features in order to predict the possible success of tracks. Studies have used a dataset containing only songs from Spotify, filtered on the basis of genre and popularity rate for recognizing important features in making the track popular. It is also evident that advent of sophisticated machine learning algorithms has completely transformed the way personalized content and social media analytics were done. **Ampountolas and Legg** (2021) applied a segmented machine learning approach to predict hotel demand through text analysis of social media-derived words. The incorporation of social media data into the model improved forecast accuracy and stability, offering hospitality firms a valuable tool to mitigate the negative impacts of market shifts such as the COVID-19 pandemic. Machine learning has thus facilitated improving prediction accuracy by utilizing user behaviour and network dynamics turned out to provide large gains in multiple domains. **Cao *et al.*** (2020) for example, used the coupled graph neural network (GNN) to propose a new approach for network-aware popularity prediction. This particular method explained how people are activated according to their connections in different states of social networks and are able to model the cascading nature of information spread.

Haimovich *et al.* (2020) focused on predicting the popularity of social media content in real-time using a feature-based approach. Using an ecstatic Hawkes point process model, the method was able to accurately predict how popular content would be across billions of views on Facebook public page content. This method worked well with strong baselines, showing that it could be used for real-time tasks. **Ding *et al.*** (2021) introduced the Relation Enhanced Attention Recurrent (REAR) network, designed to forecast fashion trends by capturing complex correlations among fashion elements and user groups. This model surpassed existing methods in predicting fashion trends, as demonstrated through experiments on the Fashion Innovation and Trend (FIT) and Geo-Style datasets. These recent advances in music analytics have progressively focused on the place of technology at the crossroads of creative industries, in which artificial intelligence becomes instrumental in defining outcomes. Studies have been conducted to probe into a number of data-driven methods with a view to enhancing the accuracy of music popularity prediction through the integration of AI enabled data sources in order to get more reliable results. **Rompolas *et al.*** (2024) give a complex review of the junction of technology, music, and success with emphasis on the use of machine learning algorithms in song popularity prediction. Their findings show how advanced technologies could offer both artists and fledgling performers, together with the players in that industry, reliable tools to make informed decisions. Hence, by encapsulating the features of the audio, social media data, and emotion analysis into one framework, this study stands uniquely detailed in making music success predictions.

These studies collectively illustrate the growing importance of artificial intelligence and social media data in predicting user behaviour and content popularity for communication purpose among the people. The implications for industries ranging from music and fashion to hospitality and social media are significant, offering new avenues for enhancing user engagement, improving forecast accuracy, and addressing challenges related to market shifts and content personalization.

3. Methodology

The current study introduced a new DHB-ILSTM algorithm to increase predicting music popularity, by merging audio features with social media data. A dataset of recently released tracks was used from which audio features were extracted, available on streaming platforms as direct video content metrics using social media. The data was prepared by standardizing it and dealing with any missing entries using Min-Max normalization. This was followed by dimensionality reduction using LDA, which helped bringing focus on the most impacting features for music popularity. By preparing data in this way and extracting features, the predictive model used in this study was enabled to accurately analyse music trends with respect to audio characteristics as well as widespread social media peer influences. The process of methodology is shown in Figure 1.

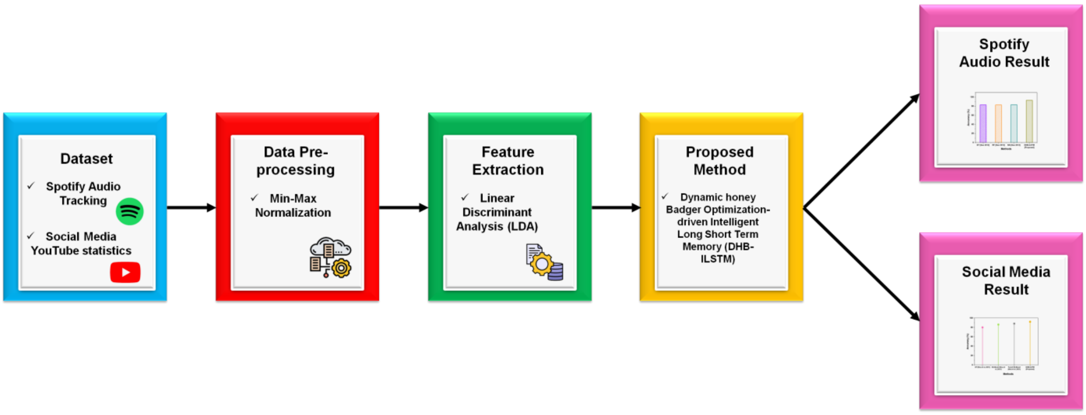

Figure 1: Process of Methodology.

3.1. Dataset

3.1.1. Spotify Audio Tracking

This dataset contains Spotify tracks that include a total of 125 genres and, correspondingly, inclusive audio features of each track. Key columns are Track ID, which uniquely identifies each track, while the Artists, Album Name, and Track Name portray information about the artists, album name, and the track name, respectively. Column Popularity rates, on a scale of 0 to 100, how popular each track is in the current moment. Other columns will include duration per minute. It also includes the length of the track in milliseconds and whether the lyrics are explicit. Many audio features are available in this dataset, including Danceability, which describes how well a track is suited for dancing, while Energy represents intensity and activity. The next step setting the Key, which represents the musical key. Other features include Loudness, general loudness in decibels; Mode representing major and minor; Speechiness, the presence of spoken words; Acousticity, the probability of a track being acoustic; Instrumentality (much of the track is instrumental), liveness (presence of an audience or live environment), valence (musical mood or positivity), tempo (speed in beats per minute), and time signature (the track's time signature). The column classifying every track into its respective genre is provided in the track genre column, therefore making dataset (S1) very useful for recommendation systems and genre classification.

3.1.2. Social Media YouTube Statistics

The dataset (S2) includes two files for analysing video popularity and comments: videos-stats.csv and comments.csv. The videos-stats.csv file provides basic video information such as the title, video ID, publication date, keyword, likes, comments, and views. The comments.csv file contains details on individual comments, including video ID, comment text, likes, and sentiment, where 0 indicates negative sentiment, and 1 or 2 denotes neutral and positive sentiments.

3.2. Data Pre-Processing

3.2.1. Min-Max Normalization

The Min-Max normalization procedure standardizes the input data, handling missing values. One of the most used techniques for normalizing data is to convert the values for the feature under consideration to new, smaller values within a pre-set range, often [0–1]. All of the associations in the examined data are acknowledged to be preserved by min-max normalization.

3.3. Feature Extraction

3.3.1. Linear Discriminant Analysis (LDA)

The transformation matrix converts the initial data with high dimensions into low-dimensional data in the feature extraction process known as Linear Discriminant Analysis (LDA). The alteration procedure equation is,

$$z = X^S w \quad (2)$$

The students in the class were scattered matrix T_x, between-class dispersed matrix T_a, and the entire group separated. Matrix T_s has the subsequent definition.

$$T_x = \sum_{l=1}^{d} \sum_{w_j \epsilon \pi_l} \left(w_j - \overline{w}_l\right)\left(w_j - \overline{w}_l\right)^S \quad (3)$$

$$T_a = \sum_{l=1}^{d} m_l (\overline{w}_l - \overline{w})(\overline{w}_l - \overline{w})^S \quad (4)$$

$$T_s = \sum_{w \epsilon \pi} (w - \overline{w})(w - \overline{w})^S \quad (5)$$

Let $W = \{w_j \epsilon \mathbb{R}^c | j = 1, \dots, m\} \epsilon \mathbb{R}^{c \times m}$ represent the provided instruction data set, where d is the dimensions of the input items and m is the total number of samples. The examples are divided into c classes, with a label for every category. $l(1 \leq l \leq d). \pi_l$ Corresponding to a particular piece of data (w_j). The class l dataset is represented by π_l, where the class l number of data points is denoted by ml. The median of class $l's$ data points is denoted by the phrase $\overline{w}_l$, while the overall mean of the data points is represented by $(w - \overline{w})^S$ represents the matrix's transpose. This problem is resolved by the conventional LDA:

$$X = \underset{X}{\arg\max}\, tr((X^S T_X W)^{-1} X^S T_a X) \quad (6)$$

Least squares regression was used to construct the discriminant analysis technique for the extraction. The squared loss function in this feature selection technique is defined as:

$$\varepsilon(X) = \|Z - S\|^2 \quad (7)$$

Where in $Z = X^S W, W = [w_1, w_2, \dots, w_m], S = [s_{d1}, s_{d2}, \dots, s_{dm}] \epsilon \mathbb{R}^{c \times m}$ and $s_l = X^S \overline{w}_l. \|\cdot\|$ The identical norm, denoted as $l \cdot l$, is defined as $\|N\|^2 = tr(N^S N)$. The objective is to use the linear transformation to minimize Equation (7). X is the related optimization issue.

$$X = \underset{X}{\arg\min} \|Z - S\|^2 \quad (8)$$

Equation (8) can be solved by defining a weighting matrix B_X as:

$$B_X(ji) = \begin{cases} \frac{1}{m_{d_j}}, & d_j = d_i \\ 0, & otherwise \end{cases} \quad (9)$$

Since B_X is an autonomous matrix, we get $B_X = B_X^2$ and $(J - B_X)^2 = J - B_X$, where J is the true nature matrix. Consequently, we may rewrite Equation (9) as $T_X = W(J - B_X)W^S$, and subsequently rewrite the optimal solution issue related to the equation 10.

$$X = \underset{X}{\arg\max}\, tr(X^S T_X W) \quad (10)$$

It is necessary to confine the undertaking matrix to prevent simple solutions. The requirement of the perpendicular requirement is the main topic of this investigation. As a result, the problem of optimization in (11) turns into the solution.

$$X = \underset{X^S X = J}{\arg\max}\, tr(X^S T_X W) \quad (11)$$

3.4. Dynamic Honey Badger Optimization-Driven Intelligent Long Short-Term Memory (DHB-ILSTM)

Leveraging artificial intelligence to enhance social media analysis can be greatly improved through a hybrid approach that combines DHB with ILSTM. DHB excels in optimizing feature selection and hyperparameters, dynamically adapting to the complex nature of data characteristics (**Huang *et al.***, 2025). ILSTM captures the complex timing and connections in social media interactions. By combining this with DHB's optimization abilities, which helps in deeper understanding of how social media trends relate to music popularity, leading to more accurate and useful predictions. This approach creates a strong framework for recognizing and predicting changes in music trends.

3.4.1. Intelligent Long Short-Term Memory (ILSTM)

To handle the timing in the interactions on social media, an ILSTM model is needed (**Lin *et al.***, 2018). First, it computes which parts of the previous cell state need an update using a sigmoid activation function. Then, using the tanh function, it creates a new vector for the values to be added or removed. The Forget Gate, however, decides on which information is to be remembered and which one is to be forgotten. It does this by utilizing the newest input and prior data. That way, it prevents the model from using irrelevant information and keeps only what is important for memorizing key features. By putting all of this together, the ILSTM model would do an even better job of keeping vital data across long sequences, as well as adjusting to changeable patterns from social media conversations (**Gao; Gao**, 2023).

The model has a sigmoid function filtering noise data from the cell state and an output gate, which regulates the information passed through to the next layer. Its sigmoid activation function details which parts of the cell state are relevant to the output and applies the tanh function to scale the output values. The input data entered at present and the momentary outputs are passed to the forget gate layer, the first interaction layer. After that, the disregarding gateway evaluated the output e_s, whose rate is a quantity between 0 and 1, positively associated with the current importance. B applicant value D_s is produced to change the present state the D_s gates considered validates into the general order of the memory unit, and the storage device is updated. The input gate layer, which is part of the interaction layer, processes the data at the preceding second and the current contribution to determine the data that should be updated into the storage unit. The updated value can be determined by adding the input gate's and forget gate's computation results together. A multiplied element is indicated by the symbol. Combining the data from the previous instant with the currently selected input, the ILSTM generates its output value in the present state of the captured the temporal patterns and developments in social media interactions. The concluding output assessment of the ILSTM algorithm is calculated using the update from the stored information unit for using the model to expect future music reputation based on incoming social media information, constantly applying DHB to refine and optimize the version as new data becomes available.

Figure 2 illustrates the architecture of the ILSTM network. Panel (a) showcases the basic structure of a standard ILSTM, while Panel (b) highlights the configuration of an intelligent LSTM with dropout applied. In the intelligent LSTM, neurons in the hidden layer are randomly dropped out during training according to a predefined probability. This dropout process temporarily removes certain neurons, with the training continuing as usual. During forward propagation, input values move through the network, while loss values are propagated backward. After each training iteration, the dropped-out neurons are reinstated, and the weights and biases of the remaining neurons are adjusted. This process is repeated iteratively until the model converges.

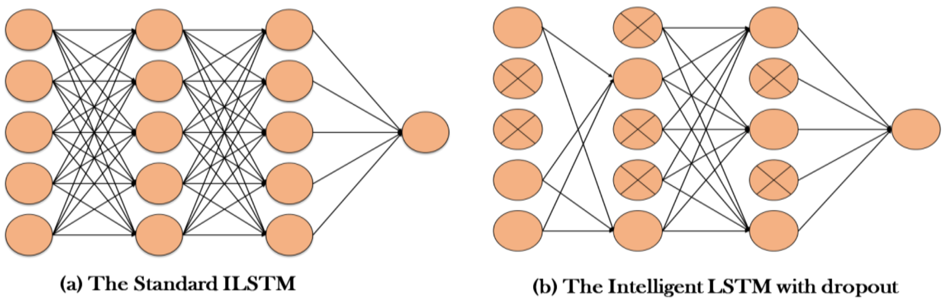

Figure 2: Structure of ILSTM.

Following the dropout layer, each neuron that was randomly deactivated during training is connected to a neuron in the dense layer through the output of the hidden layer in the ILSTM architecture. This connection is established by a dense layer that is fully linked to the hidden layer. To predict the assessment of heave motion after deactivation, the activation function multiplies the output of the hidden layer by a weight matrix and adds a bias term. The inclusion of the fully connected dense layer is crucial as it helps capture the distinctive characteristics of the predicted values related to heave motion.

3.4.2. Dynamic Honey Badger Optimization (DHB)

A DHB is developed by the need to create a higher performance algorithm which includes tents random maps, enhanced controlling measure, contribution towards composite mutations followed by an enhanced swarm-informed approach (**Hassan *et al.***, 2024). Algorithm 1 shows the process of DHB-LSTM.

Algorithm 1: Process of DHB-ILSTM

```
import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense
from honeybadger_optimizer import DHBOptimizer
def load_and_preprocess_data(file_path):
data = pd.read_csv(file_path)
features = data[['audio_features', 'social_media_metrics']]
labels = data['popularity']
features.fillna(features.mean(), inplace = True)
scaler = MinMaxScaler()
return scaler.fit_transform(features), labels
def build_lstm_model(input_shape):
model = Sequential([
LSTM(50, input_shape = input_shape, return_sequences = True),
LSTM(50), Dense(1, activation = 'linear')])
model.compile(optimizer = 'adam', loss = 'mean_squared_error')
return model
def objective_function(params):
model = build_lstm_model((timesteps, num_features))
model.set_params(params)
model.fit(train_data, train_labels, epochs = 50, batch_size = 32, validation_spl = 0.2)
return model.evaluate(validation_data, validation_labels)
def optimize_hyperparameters():
dhb_optimizer = DHBOptimizer(objective_function)
return dhb_optimizer.optimize()
if __name__ == "__main__":
data, labels = load_and_preprocess_data('music_data.csv')
 lda = LDA(n_components = 10)
 lda_features = lda.fit_transform(data, labels)
 best_params = optimize_hyperparameters()
 model = build_lstm_model((timesteps, num_features))
 model.set_params(best_params)
 model.fit(train_data, train_labels, epochs = 50, batch_size = 32)
 model.save('dhb_ilstm_model.h5')
```

4. Results

This study applied various ensemble methods to improve the DHB-ILSTM algorithm in predicting music popularity by fusing both audio and social media features. For audio features, we compared our approach with BT, RF, and NN as in **Gao** (2021). For social media features, we evaluated DT, XG-Boost, Tuned XG-Boost in the light of **Nisa *et al.*** (2021). The study further assessed the efficacy of DHB-ILSTM against these traditional approaches using performance metrics: precision, recall, accuracy, F1-score. The results obtained in this study indicate that DHB-ILSTM outperforms the established methods significantly in all aspects which shows its better predictive accuracy.

4.1. Music Popularity Prediction Using Audio Features

4.1.1. Accuracy

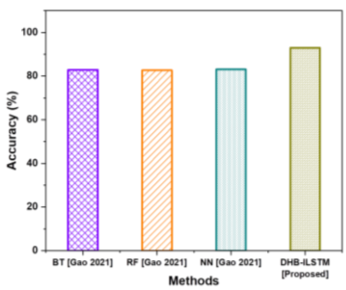

Figure 3: Performance of Accuracy.

The accuracy metric measures how well the model correctly predicts outcomes. Figure 3 and Table 1 show the accuracy of our DHB-ILSTM method compared to existing methods. The accuracy levels for methods like BT, RF, and NN were 82.9%, 82.7%, and 83.1%, respectively. The proposed method (DHB-ILSTM) achieved 93% accuracy. This shows that the proposed method had superior performance than the existing methods in music popularity forecasting in audio features.

Table 1: Result of Spotify Audio Popularity Prediction.

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
BT [Gao 2021]	82.9	82.3	84	83.2
RF [Gao 2021]	82.7	81.9	84.3	83.1
NN [Gao 2021]	83.1	82.8	84	83.4
DHB-ILSTM [Proposed]	93	88	90	91

4.1.2. Precision

The precision and dependability with which music popularity may be utilized to figure out people is known as the precision of music popularity prediction assessment, followed by Figure 4 and Table 1 showing the precision result. The precision level of existing methods BT, RF, NN achieved 82.3%, 81.9%, and 82.8%, respectively. Compared to the methods of existing, the proposed method (DHB-ILSTM) achieved a result of 88% precision. Compared to the existing methods, our proposed method delivered outperformance in music prediction on Spotify. Figure 4 presents the outcomes of this precision.

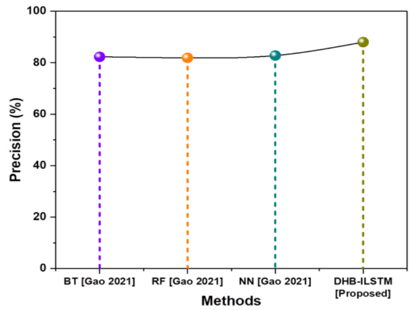

Figure 4: Outcomes of Precision.

4.1.3. Recall

A classification model's recall is a measure of efficiency that evaluates how well the model finds pertinent samples inside a given class. It is computed as a proportion of positive estimations to the sum of false negatives and true positives. Figure 5 and Table 1 depict the recall process. The Recall level of existing methods BT, RF, and NN achieved 84%, 84.3%, and 84%, respectively. Compared to the method of existing, the proposed (DHB-ILSTM) method obtained an outcome of 90% recall. Compared to the existing methods, our proposed method delivers outperformance for music popularity forecasting in audio features.

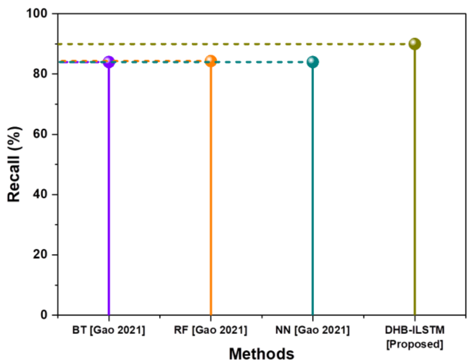

Figure 5: Outputs of Recall.

4.1.4. F1-Score

When assessing the effectiveness of a model of classification in music popularity prediction, the F1 score is a parameter that is frequently employed in machine learning and statistics. Figure 6 and Table 1 display the output of the F1 score. The F1 score level of existing methods like BT, RF, and NN achieved 83.2%, 83.1%, and 83.4%, respectively. Compared to the methods of existing, our proposed method (DHB-ILSTM) achieved a 91% result in the F1 score.

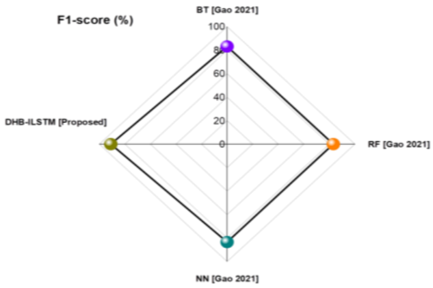

Figure 6: Performances of F1-Score.

4.2. Music Popularity Prediction using Social Media Features

4.2.1 Accuracy

The percentage of correctly estimated samples among the actual cases is measured by the accuracy metric. The accuracy performance compared the features of the present methodology with our proposed (DHB-ILSTM) method, as illustrated in Figure 7 and Table 2. The accuracy level of existing methods DT, XG-Boost, and Tuned XG-Boost achieved 80%, 86%, and 88%, respectively. The proposed method (DHB-ILSTM) achieved 92% accuracy. Our proposed method has superior performance than the existing methods in music popularity prediction on social media.

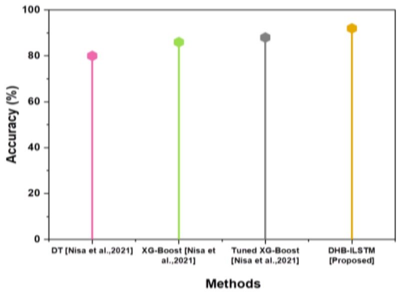

Figure 7: Result of Accuracy.

Table 2: Performances of Social Media Popularity Prediction.

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
DT [Nisa et al.,2021]	80	64	63	63
XG-Boost [Nisa et al.,2021]	86	84	63	63
Tuned XG-Boost [Nisa et al.,2021]	88	84	63	72
DHB-ILSTM [Proposed]	92	90	82	84

4.2.2. Precision

The precision and dependability with which social media prediction may be utilized to figure out people is known as the precision of YouTube video statistics followed by Figure 8 and Table 2 show the precision result. The precision level of existing methods DT, XG-Boost, Tuned XG-Boost achieved 64%, 84%, and 84%, respectively. Compared to the methods of existing, the proposed method (DHB-ILSTM) achieved a 90% result in precision. Compared to the existing methods, our proposed method delivers performance prediction of social media popularity.

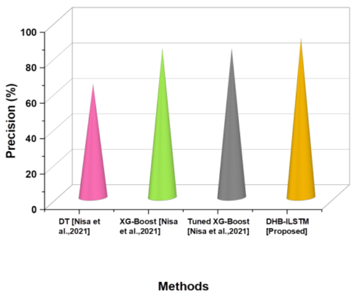

Figure 8: Result of Precision.

4.2.3. Recall

A classification model's recall is a measure of efficiency that evaluates how well the model performs inside a given class. It is computed as a proportion of positive estimations to the sum of false negatives and true positives. Figure 9 and Table 2 depict the recall process. The recall level of existing methods DT, XG-Boost, Tuned XG-Boost achieved

63%, 63%, and 63%, respectively. Compared to the method of existing, the proposed (DHB-ILSTM) method achieved an 82% outcome of recall. Compared to the existing methods, our proposed method delivers a better result of music popularity prediction in social media.

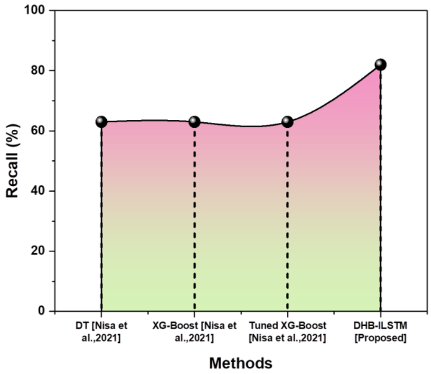

Figure 9: Outcome of Recall.

4.2.4. F1 Score

When assessing the effectiveness of a model of classification, the F1 score is a parameter that is frequently employed in machine learning and statistics. Figure 10 and Table 2 display the output of the F1 score. The F1 score level of existing methods: DT, XG-Boost, Tuned XG-Boost achieved 63%, 63%, and 72%, respectively. Compared to the methods of existing, our proposed method (DHB-ILSTM) achieved 84% of the F1 score.

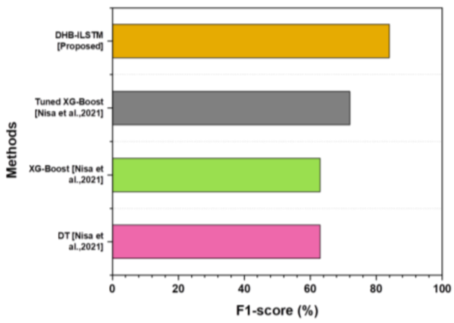

Figure 10: Performances of F1-Score.

5. Discussion

The DHB-ILSTM is a major step toward music popularity forecasting, particularly when exploited with information and communication technologies. It achieves the objective by incorporating audio specific features with social media cloud cover counts. Our results demonstrate that in different performance aspects DHB-ILSTM outperforms the preceding methods. DHB-ILSTM has an accuracy of 93% in contrast to BT, RF and NN that scored 82.9%, 82.7%, and 83.1%. The correct prediction proportion of the popularity trend underscores DHB-ILSTM's capacity for conceptualizing and capturing intricate patterns in music popularity better. On the other hand, DHB-ILSTM outperformed BT (82.3%), RF (81.9%) and NN (82.8%) in terms of precision. That is, DHB-ILSTM proves to be better in eliminating false positives and locating popular track precisely. The high precision of the model underlines its ability to analyse and interpret data for accurate predictions (**Hizlisoy *et al.***, 2021).

Furthermore, DHB-ILSTM achieved better recall (90%) than BT (84%), RF (84.3%), and NN (84%) in terms of both the average ranking scheme as well as every type-specific ranking from all four types combined. A higher recall rating which shows that the model is able to identify more of these true positive instances, a feature vital in detecting impactful trends and making sure no key patterns are overlooked. It is for these reasons that advanced behaviour capturing data integration and analysis tools in DHB-ILSTM make them a more reliable avenue toward predicting music popularity compared to the traditional method. On the F1-score, such a great example, this balance between precision and recall was better at 91% compared to BT, RF, and NN at 83.2%, 83.1%, and 83.4%, respectively. This F1-score is a strong score with respect to the model's efficiency and reliability, which is a result, of course, of its ability to interconnect and adjust several sources of data correctly in order to determine the popularity of music. As to the analysis of the features of social media, the DHB-ILSTM model had an accuracy rate of 92%, showing a very strong capacity to work with real-time data in communication. It has greatly improved from DT at 80%, XG-Boost at 86%, and Tuned XG-Boost at 88%. This high accuracy goes on to prove that the model can handle social interactions regarding social media very well, which is important in predicting music trends (**Li**, 2024).

The DHB-ILSTM model significantly improves performance, especially in social media data analysis, with an accuracy rate of 90%. This is much greater than the DT, with an accuracy of 64%, the XG-Boost with an accuracy of 84%, and even the Tuned XG-Boost, which also stands at 84%. This substantial increment underscores that it is much better in accurately analysing and giving meaningful interpretations to social media data, a critical component in modern music popularity prediction. As evident, this model identifies very famous tracks from social media, with the recall rate at 82%, way above DT, XG-Boost, and Tuned XG-Boost at 63%. With regard to this high recall rate, it clearly shows the ability of DHB-ILSTM in the recognition of music tracks that are popular, hence highly performing above the baseline models. Improved recall, especially in discovering emerging trends in music with the help of social media data, is very strong evidence for a model's effectiveness and reliability. Another important metric, balancing precision and recall, known as the F1-score, reaches 84% for social media features of the model. This high F1-score reflects the model's balanced performance, which means that DHB-ILSTM can boast a pretty low false positive rate while at the same time having excellent performance for classifying relevant tracks. This is very important, for instance, in such tasks as popularity prediction of music where precision and recall are very important to get accurate and actionable insights (**Liu *et al.***, 2018).

The high performance in three major indicators, including accuracy, recall, and F1-score, showed that DHB-ILSTM is the most powerful and flexible algorithm to deal with complex social media data. This efficacy keeps it at a potential of beating the challenging task of music popularity prediction with much more reliability and comprehensiveness than traditional models. This clearly shows the stability of the DHB-ILSTM model in outperforming other methods and hence state-of-the-art tool in music analytics with the potential of providing very accurate and enlightening predictions in an industry where the trend is highly dynamic and unpredictable. In a nutshell, the DHB-ILSTM model is more accurate than the traditional methods, aside from recall and F1-score, making it an efficient music popularity prediction tool. This model is a new frontier in the application of AI to music trend analysis, which provides a reliable framework that adapts itself to the ever-changing dynamics of the music industry (**Civit *et al.***, 2022).

Some of the drawbacks of traditional BT, RF, and NN methods are as follows. While BT and RF do an excellent job on structured data, they normally cannot pick up any complicated data interactions or subtle trends inherent in the more intricate data sets. On the other hand, NN models, though powerful, often suffer from overfitting and might not generalize quite so well to different distributions. These challenges underline the need for more advanced models like DHB-ILSTM, which actually help overcome these deficiencies. The DHB-ILSTM model improves the incorporation of audio and social media features through dynamic honey badger optimization in the tuning of hyperparameters and hence provides reliable predictions in music popularity prediction, therefore going out of reach from the traditional methods. For instance, decision trees often suffer from overfitting and handling complex interactions, while XG-Boosting is effective but can turn very demanding in terms of hyperparameter adjustments. Another major advantage of the DHB-ILSTM model is that it helps surmount the barriers above by using more advanced optimization techniques. By integrating advanced AI methodologies with a deep analysis of different features, DHB-ILSTM is a more precise way of predicting the popularity of songs than the traditional models. Combination of state-of-the-art optimization techniques with deep feature analysis makes DHB-ILSTM special and much improved compared to earlier practices. The research demonstrates how sophisticated AI techniques, combined with huge data analyses, could work out for better predictions against the fast-changing landscape of music.

As a concluding remark, the ability of the algorithm, DHB-ILSTM, to combine audio features and social media metrics provides significant value to the attempt to abate music popularity prediction complexities. Compared to the traditional methods, BT, RF, and NN, it has shown better accuracy, recall, and F1-score, which asserted the robustness as well as adaptability of this algorithm to changes in trends. The integration of Min-Max normalization and LDA strengthened pre-processing data to emphasize high-impact features, while DHB optimization helped improve the tuning of hyperparameters. Overall, these developments demonstrate the prospects for the algorithm in real-time music analytics application. Some of the potential issues, however, include biases due to trends taken from a time when the offline state could be found, inflexibility across genre types, and dependence on hyperparameter tuning. Future work would most likely delve into adding user demographics, historical trends, and real-time data to make the model more adaptive. Expanding its usage across multiple genres of music and international markets will help strengthen its diversity. If these above gaps are filled, the DHB-ILSTM algorithm is ready to perform in ways that will benefit artists, record labels, and streamers, thus changing the face of AI-driven innovations in the creative industries.

6. Conclusion

This paper introduces a robust algorithm - DHB-ILSTM-to predict the popularity of music using audio features integrated from streaming platforms and social media metrics. The algorithm performs well even in dynamic environments, as found by achieving an accuracy of 93%, recall of 90%, F1-score of 91%, and precision of 88% for predicting the popularity of music using audio features. Incorporating social media data further enhances its predictive capability, achieving an accuracy of 92%, recall of 82%, F1-score of 84%, and precision of 90%. These results outperform traditional methods, showcasing the effectiveness of the proposed approach in integrating advanced artificial intelligence and optimization techniques. Although the results prove to be promising, the DHB-ILSTM algorithm faces many limitations. It may be said that generalizability of the function for all types of music is limited since it fails to capture factors of trends in offline media and personal listening experiences. The quality and amount of used data may play an influence on the performance of this model, and reliance on hyperparameter tuning brings in risks of overfitting and reduced flexibility for genres or shifts in trends. It puts more research needs to develop more forceful and adaptable algorithms. This involves bringing in more features like listener demographics and trends over time, embedding real-time data into more dynamic forecasting models, and studying many relationships across different genres of music and international markets.

The great performances of the DHB-ILSTM algorithm indicate that it can easily overcome flaws in traditional BT, RF, and NN algorithms, which often cannot operate well with complex interactions between variables and subtle trends. The approach taken here sets a benchmark for future models in terms of predictors, integrating advanced optimisation techniques with diverse data sources. Its potential applications extend beyond the music industry into business, finance, and other areas where sophisticated algorithms can inform smarter decisions. Further theoretical research on individualisation of hyperparameters and its application in predictive modelling promises to increase the utility and impact of such methodologies across domains.

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