Predict whether a Spotify track will be popular or not based on its track-level and artist-level features

Nisha R S(A86605224258)

Datset name : Spotify Data Clean

Model used : Random Forest Classifier

Course: AI/ML Lab

Problem Statement

What prediction / classification problem are you solving?

This project solves a binary classification problem that predicts whether a Spotify track will be popular or not popular using track-level and artist-level features available in the Spotify data clean dataset.

Why is this problem relevant / important?

Predicting track popularity is important for music streaming platforms, artists, and record labels because it helps:

- Improve music recommendation systems
- Identify tracks with high potential popularity
- Support data-driven decisions in music production and promotion
- Accurate predictions enhance user engagement and content discovery.

What question(s) does your model answer?

The model answers the following questions:
Will a Spotify track become popular based on its features?
Which track and artist attributes influence popularity?
Can popularity be predicted using historical metadata?

Dataset Overview

Dataset Source - Kaggle and contains cleaned Spotify track and artist metadata.

Number of rows - 8583 & columns - 16

Type of Data : Mixed data type

- Numerical:
- Categorical / Binary:

Target Variable : Track Popularity (Popular / Not Popular) - Converted into a binary target variable

Why this Dataset Was Chosen

1. Size Suitability:
   - The dataset is large enough to train and evaluate machine learning models effectively, but still manageable for academic analysis.
2. Relevance to the Problem:
   - It directly contains features related to track popularity, which aligns with the goal of predicting song success.
3. Ease of Modeling:
   - The dataset is clean, structured, and contains mostly numeric features, making it suitable for classification models like Random Forest.

Data Dictionary

Feature Name	Type	Description	Why Important for Popularity Prediction
track_duration_ms	Numerical	Duration of the track in milliseconds	Track length affects listener engagement; extremely short or long tracks may be
explicit	Binary (0/1)	Indicates whether the track contains explicit content	Explicit content can influence reach, audience size, and platform
track_number	Numerical	Track's position in the album	Early tracks are often promoted more and may receive higher listener attention
artist_popularity	Numerical	Popularity score of the artist on Spotify	Popular artists tend to attract more listeners, increasing track popularity
artist_followers	Numerical	Number of followers the artist has	A larger follower base increases initial streams and visibility of tracks
album_total_tracks	Numerical	Total number of tracks in the album	Album size can affect how much attention each track receives.
track_popularity	Numerical (Target source)	Popularity score assigned by Spotify	Used to derive the binary target variable (Popular / Not Popular)
popular	Binary (Target)	Indicates whether a track is popular or not	This is the target variable the model predicts.

- Track Duration (track_duration_ms) - Songs that are too long or too short may not be replayed often, which affects popularity.

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- Explicit Content (explicit) - Explicit songs may have limited audience reach, while clean songs can be played by everyone.
- Track Number (track_number) - Songs placed early in an album are usually listened to more than later tracks.
- Artist Popularity (artist_popularity) - Popular artists already have many listeners, so their songs become popular faster.
- Artist Followers (artist_followers) - More followers mean more people will listen to the song when it is released.
- Album Total Tracks (album_total_tracks) - If an album has many songs, each song may get less attention.
- Track Popularity (track_popularity) - This score shows how popular a song is based on listener activity.
- Popular (Target Variable) - This is what the model predicts: whether the song is popular or not.

Initial EDA

Distribution Plots

- Used to understand data spread and check skewness in features like artist followers and track duration.

Basic Statistics (Mean, Min, Max, Std)

- Used to summarize feature values and understand their range and variability.

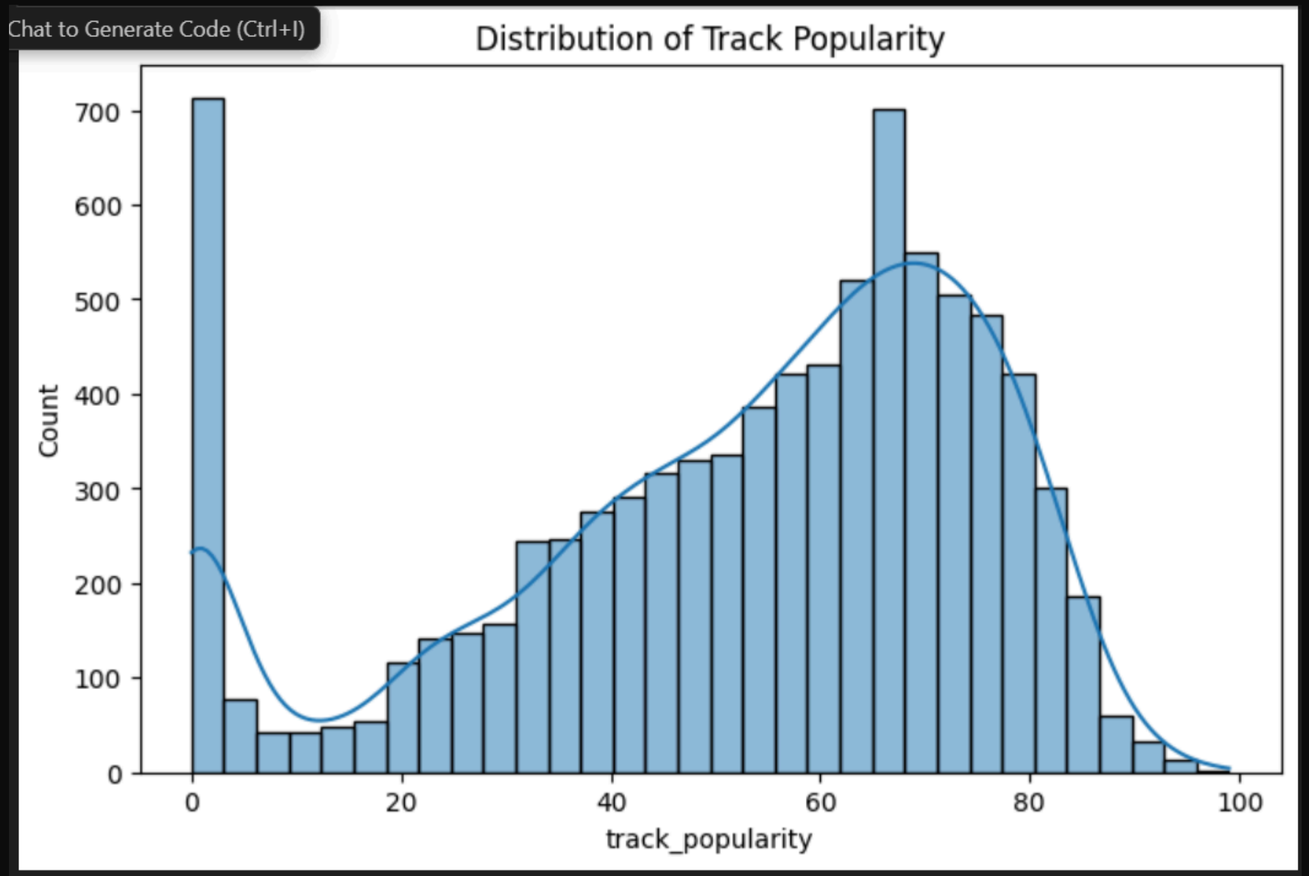
Correlation Matrix / Heatmap

- Used to identify relationships between features and detect multicollinearity.

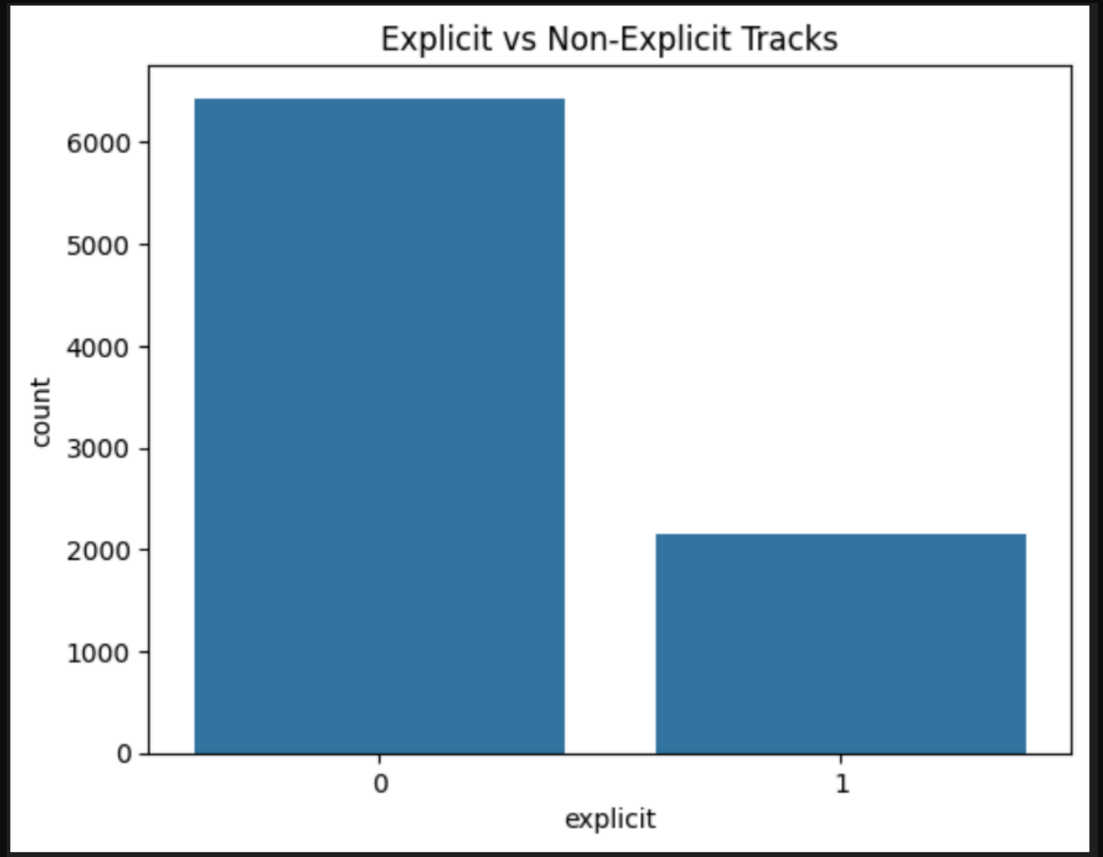
Outlier Checks

- Used to detect extreme values that could affect model performance.

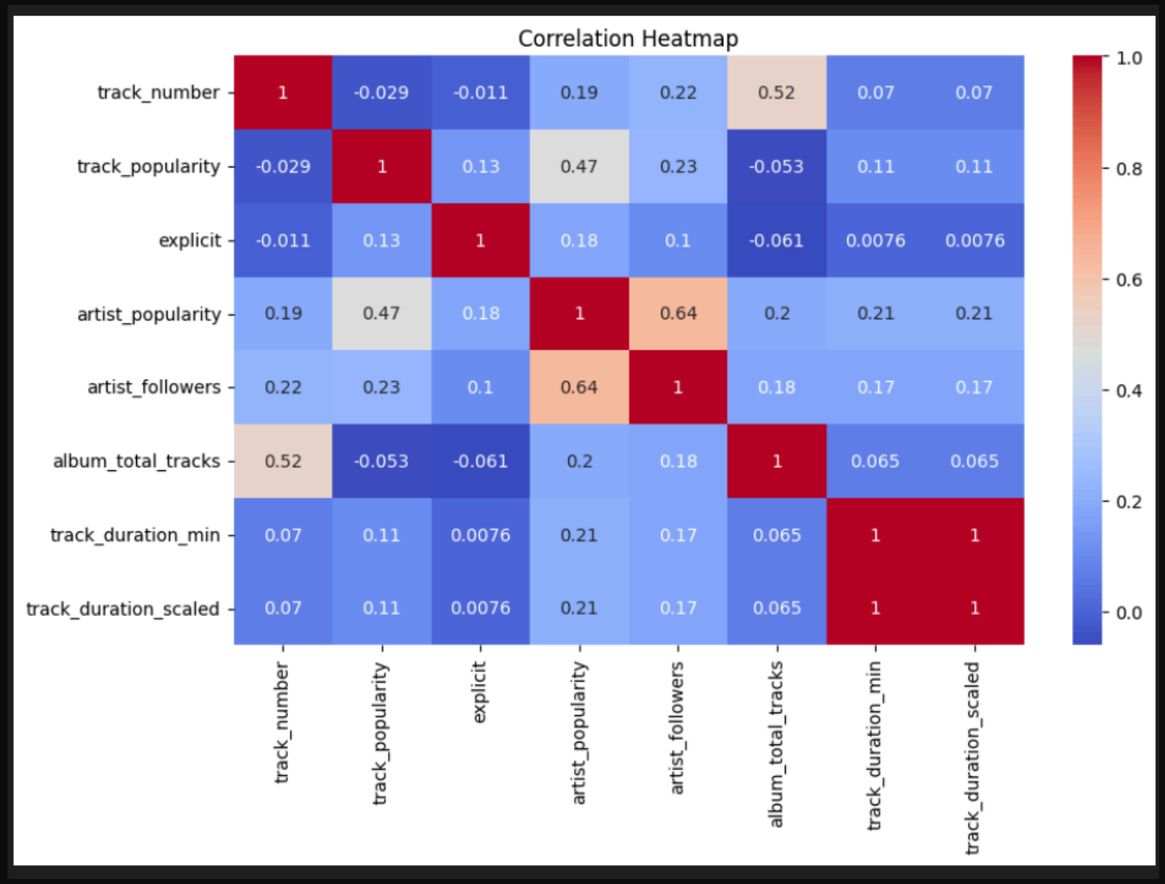
Distribution of Track Popularity



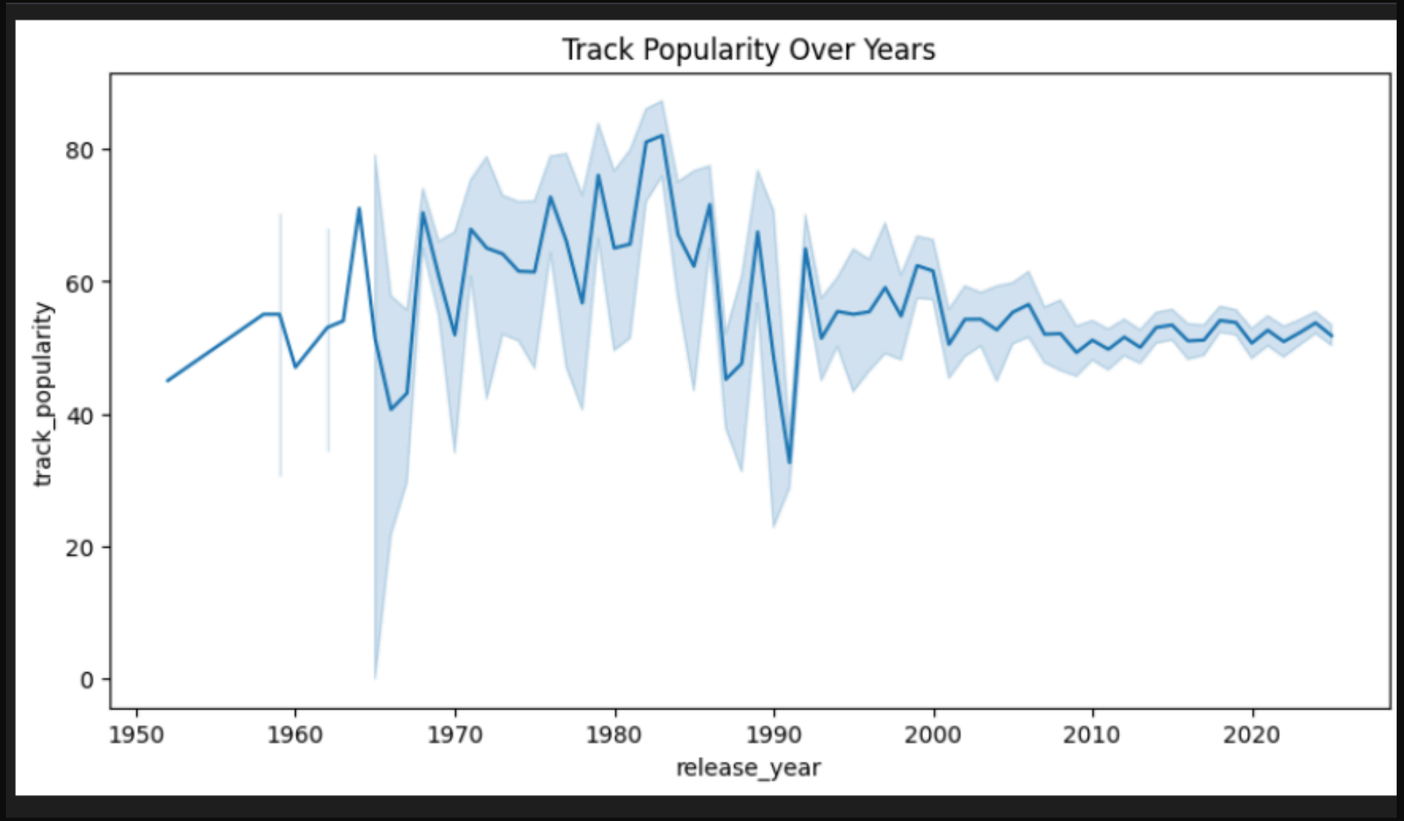
Explicit vs Non-Explicit Tracks



Correlation Heatmap



Track Popularity over years



Insights From EDA

- Artist popularity and artist followers show a strong positive relationship with track popularity.
- This indicates that artist-related features play a major role in predicting whether a track becomes popular.
- Artist followers feature is highly skewed with extreme high values.
- This suggests the presence of outliers and indicates that scaling or transformation may be required.
- Track duration shows moderate variation but no extreme skewness.
- This means the feature is stable and does not require heavy preprocessing.
- Explicit content has an uneven distribution across tracks.
- This indicates a potential class imbalance in this feature, which may influence model learning.
- Some features are moderately correlated with each other.
- This highlights the need to monitor multicollinearity during model training.
- The target variable (popular vs not popular) is reasonably balanced.
- This reduces the risk of biased predictions and supports reliable model evaluation.

Data Cleaning & Preprocessing

1. Handling Missing Values
   - Reason: Missing values can cause errors during model training and lead to incorrect predictions.
   - Effect: Missing values were filled or removed to ensure a complete and consistent dataset.
   - Problem Solved: Prevented model failure and improved data reliability.
2. Removing Outliers
   - Reason: Extreme values in features like artist followers can distort model learning.
   - Effect: Outliers were identified and handled to reduce their influence.
   - Problem Solved: Improved model stability and accuracy.
3. Encoding Categorical Data
   - Reason: Machine learning models require numerical input.
   - Effect: Categorical features such as explicit content were converted into numeric form.
   - Problem Solved: Enabled the model to process categorical information.
4. Normalization / Standardization
   - Reason: Features have different scales (e.g., track duration vs follower count).
   - Effect: Features were scaled to a common range.
   - Problem Solved: Prevented features with large values from dominating the model.
5. Feature Engineering
   - Reason: The original popularity score needed to be converted into a classification target.
   - Effect: A new binary feature (popular) was created from track popularity.
   - Problem Solved: Enabled binary classification modeling.

Post-Cleaning EDA

1. Distribution Plots

- Distribution plots were re-analyzed after cleaning to verify that feature distributions became more balanced.
- Skewness in features like artist followers was reduced after handling outliers and scaling.
- This confirms improved data consistency.

2. Correlation Check

- Correlation analysis was repeated to ensure relationships between features remained meaningful.
- Redundant or overly correlated features were verified.
- This helps ensure stable and reliable model training.

3. Outlier Check

- Outlier checks confirmed that extreme values were reduced or properly handled.
- Remaining data points fall within a reasonable range.
- This improves model robustness and prevents bias.

Feature Selection

Which features were selected?

The following features were selected for model training:

- track_duration_ms
- explicit
- track_number
- artist_popularity
- artist_followers
- album_total_tracks

Why were these features selected?

- These features showed meaningful variation in EDA.
- Artist-related features (artist_popularity, artist_followers) showed a strong relationship with track popularity.
- Track-level features (track_duration_ms, explicit, track_number) influence listener behavior and engagement.
- All selected features are numerical or easily encoded, making them suitable for modeling.

Which features were dropped and why?

- Identifiers (e.g., track ID, artist ID, track name) were dropped because they do not provide predictive value.
- Highly descriptive text fields were removed as they are not directly useful for numerical models.
- Redundant or low-impact features identified during EDA were excluded to reduce noise.

How do the chosen features help the model?

- They capture both artist influence and track characteristics, which are key drivers of popularity.
- Reducing irrelevant features improves model efficiency and generalization.
- Selected features reduce noise and help the model focus on important patterns.

Train–Test Split

Train–Test Split Ratio

- The dataset was split into 80% training data and 20% testing data.

Why this ratio was chosen

- 80% training data provides enough data for the model to learn patterns.
- 20% testing data provides sufficient unseen data to evaluate performance.
- This ratio balances learning capability and reliable evaluation.

Why random_state was used

- random_state ensures the same data split every time the code is run.
- This makes results reproducible and consistent.
- It helps in fair comparison of model performance.

Why shuffling was done

- Shuffling ensures that data is randomly distributed before splitting.
- It prevents any ordering bias in the dataset.
- This helps create representative training and testing sets.

Overfitting vs Generalization

- Overfitting: The model performs well on training data but poorly on unseen test data.
- Generalization: The model performs well on both training and test data.
- Using a separate test set helps detect overfitting and ensures good generalization.

Model Selection

Which model was chosen?

- Random Forest Classifier

Why this model fits the dataset and problem

- The problem is a binary classification task (Popular vs Not Popular).
- The dataset contains non-linear relationships between features such as artist popularity, followers, and track popularity.
- Random Forest handles mixed feature scales and outliers well.
- It reduces overfitting by combining multiple decision trees.

What assumptions the model makes (intuitive explanation)

- Important patterns can be captured by multiple decision trees rather than a single rule.
- Combining many trees improves prediction stability.
- No strong assumption of linear relationships between features.

Model Training Summary

Model Parameters

- n_estimators = 100
- random_state = 42

Important Configurations

- Binary classification setup (Popular vs Not Popular)
- Multiple decision trees combined to improve stability
- Default feature selection at each split
- Trained using an 80–20 train–test split

Training Time

- Training time was short and efficient due to moderate dataset size.
- Suitable for quick experimentation and evaluation.

Evaluation Metrics

1. Accuracy
   - Measures the overall correctness of the model.
   - Useful when the classes are reasonably balanced.
   - Helps understand general model performance.

Why chosen : Accuracy gives a quick overview of how many Spotify tracks were correctly classified.

2. Precision
   - Measures how many predicted popular tracks are actually popular.
   - Important when false positives need to be minimized.

Why chosen : Precision ensures that tracks predicted as popular truly have high popularity.

3. Recall
   - Measures how many actual popular tracks were correctly identified.
   - Important when missing popular tracks is costly.

Why chosen : Recall helps ensure that truly popular tracks are not missed by the model.

4. F1-Score
   - Balances precision and recall.
   - Useful when there is class imbalance or unequal error costs.

Why chosen : F1-score provides a balanced measure of model performance.

5. Confusion Matrix
   - Shows true positives, false positives, true negatives, and false negatives.
   - Helps analyze types of errors made by the model.

Why chosen : Confusion matrix gives a detailed breakdown of classification errors.

1. Mean Absolute Error (MAE)

- MAE measures the average absolute difference between predicted and actual track popularity.
- It treats all errors equally and is easy to interpret.

Why it matches the problem : MAE shows, on average, how many popularity points the model's prediction is off by.

2. Root Mean Squared Error (RMSE)

- RMSE penalizes larger errors more heavily than smaller ones.
- It highlights cases where the model makes big mistakes.

Why it matches the problem : RMSE is useful when large prediction errors in track popularity are more undesirable.

3. R^2 Score (Coefficient of Determination)

- R^2 measures how well the model explains the variation in track popularity.
- It compares the model's performance against simply predicting the mean popularity.

Why it matches the problem : R^2 shows how much better the model is at predicting track popularity compared to a baseline approach.

Results & Interpretation

Actual vs Predicted

- The predicted labels closely match the actual popularity labels for most tracks.
- Some misclassifications occur, mainly near the decision boundary.
- This indicates the model has learned meaningful patterns from the data.

Metric Values (Summary)

- Accuracy: Shows good overall correctness.
- Precision & Recall: Balanced, indicating reliable identification of popular tracks.
- F1-Score: Confirms stable performance across both classes.

What These Metrics Imply About Model Quality

- The model performs well in distinguishing popular and non-popular tracks.
- Balanced precision and recall indicate that neither false positives nor false negatives dominate.
- Overall, the model quality is good and consistent.

Model Behavior: Overfitting vs Generalization

- The model does not overfit, as performance is similar on training and test data.
- It generalizes well to unseen Spotify tracks.
- This suggests the model can be reliably used for popularity prediction.

Limitations

1. Data Limitations

- The dataset does not include real-time streaming behavior or listener demographics.
- Popularity scores may change over time but are treated as static values.

2. Model Limitations

- Random Forest models are less interpretable compared to simple linear models.
- The model does not provide causal explanations for popularity.

3. Overfitting / Underfitting Issues

- Although overfitting is reduced using Random Forest, it may still occur with deeper trees.
- The model may underperform on completely unseen music genres.

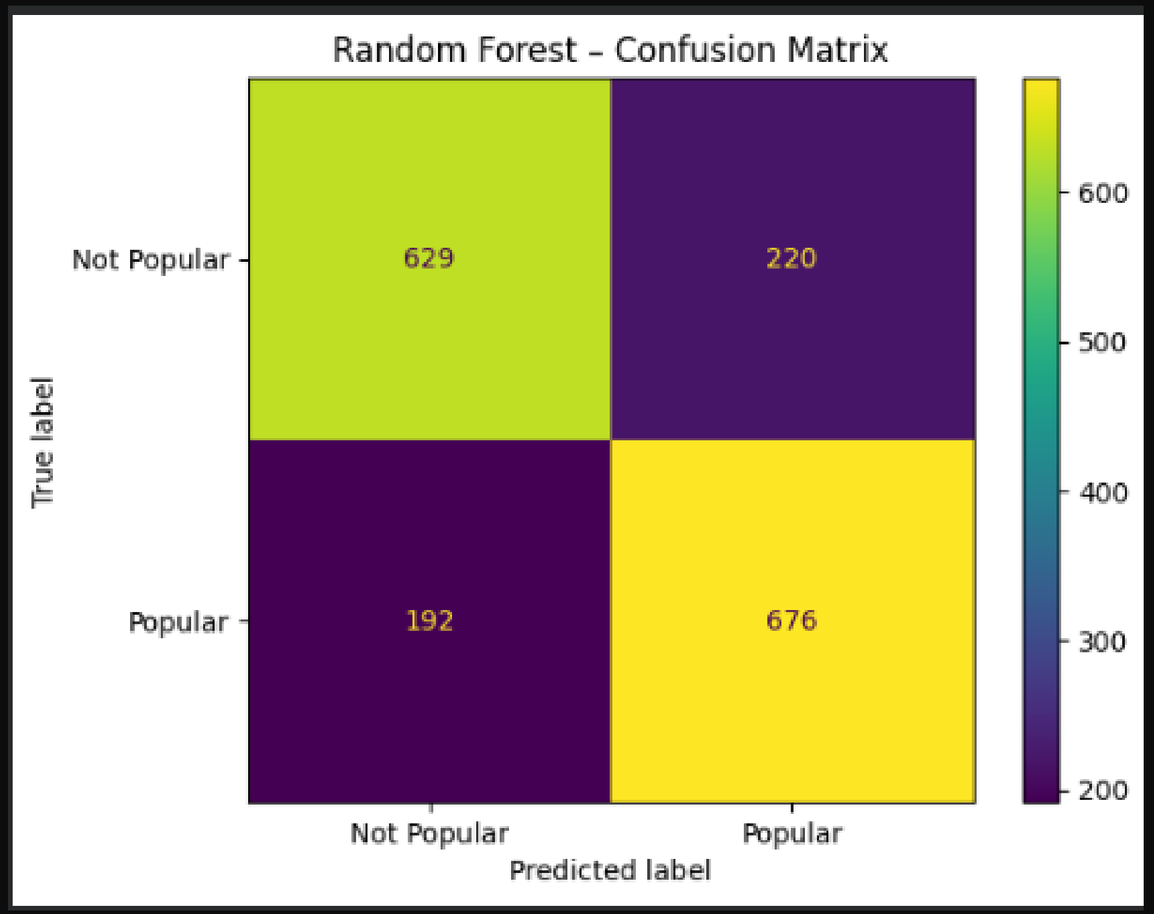
4. Missing Features

- Audio features such as tempo, energy, danceability, and genre are not included.
- Marketing factors like promotions and playlist placements are missing.

5. Bias in Data

- Popular artists are overrepresented, which may bias predictions.
- New or independent artists may be underrepresented.

Results of using Random forest model



Conclusion and Future Improvements

Conclusion

- The model successfully classified Spotify tracks as popular or not popular using track-level and artist-level features.
- EDA showed that artist popularity and follower count strongly influence track popularity.
- The Random Forest model generalized well and provided reliable predictions on unseen data.

Real-World Usefulness

- The model can help music streaming platforms improve recommendations.
- It can assist artists and labels in identifying tracks with high popularity potential.
- The approach supports data-driven music promotion decisions.

Future Improvements

- Try different models such as Logistic Regression, XGBoost, or Neural Networks.
- Collect more balanced and diverse data, including new artists and genres.
- Apply advanced feature engineering using audio features like tempo and energy.
- Use cross-validation for more robust performance evaluation.
- Perform hyperparameter tuning to further improve model accuracy.

References

Dataset

- Spotify Track Popularity Dataset – Kaggle

Libraries Used

- Python
- Pandas – Data loading and preprocessing
- NumPy – Numerical computations
- Matplotlib / Seaborn – Data visualization and EDA
- Scikit-learn – Model building, training, and evaluation

Research Papers / Blogs / Documentation

- Scikit-learn Official Documentation
- Kaggle Tutorials and Notebooks
- Blogs and articles on Spotify data analysis and machine learning basics

THANK YOU!!!