Music Genre Recognition

Machine Learning
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May 10, 2025

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- How to classify music genres?
  - By musical elements (e.g rhythm, melody, harmony, texture, style)
  - By instruments (e.g guitar, piano, violin, saxophone, or synthesizers)
  - By themes (e.g love, protest, party, religion, or politics)
  - By cultural origins (e.g country, ...)
  - By more advanced features(e.g MFCC, chroma, spectral contrast, etc.)

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- What are the challenges?
  - Overlapping acoustic features between genres and subjective boundaries

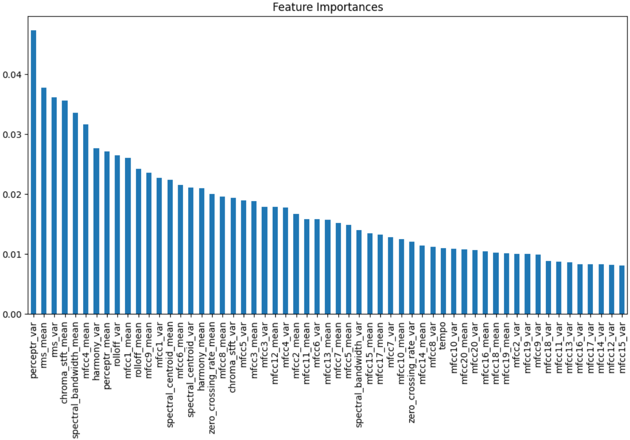
Dataset

For the project GTZAN dataset was used.
It contains:

- 100 tracks per genre
- 10 genres: Blues, Classical, Country, Disco, Hip-hop, Jazz, Metal, Pop, Reggae, Rock
- .wav files, 30 seconds each
- Spectograms of each .wav file
- Augmented dataset: 3-second segment dataset for better generalization

Features

Initially the dataset contained too many features, so we had to reduce the number of features, as the research showed that some of them were useless in Classical ML models.



Feature Extraction

How to extract features?
Use librosa library!
These can be integrated into software applications for real-time music genre classification.
`https://librosa.org`

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- Logistic Regression
- Random Forest
- SVM
- HistGradientBoostingClassifier
- VotingClassifier (Combination of all models)

Evaluation

- Train-test split
- Evaluation metric: F1 score as it is the harmonic mean of precision and recall

Evaluation Results

Rank	Model	F1 Score
1	VotingClassifier	0.935
2	SVM (Tuned)	0.932
3	HistGradientBoostingClassifier (Tuned)	0.921
4	k-NN (Tuned)	0.891
5	Random Forest (Reduced Features)	0.865
6	QDA (Tuned)	0.768
7	Logistic Regression (Tuned)	0.714
8	LDA (Tuned)	0.661
9	Gaussian Naive Bayes	0.481

Error Analysis/Confusion Matrix

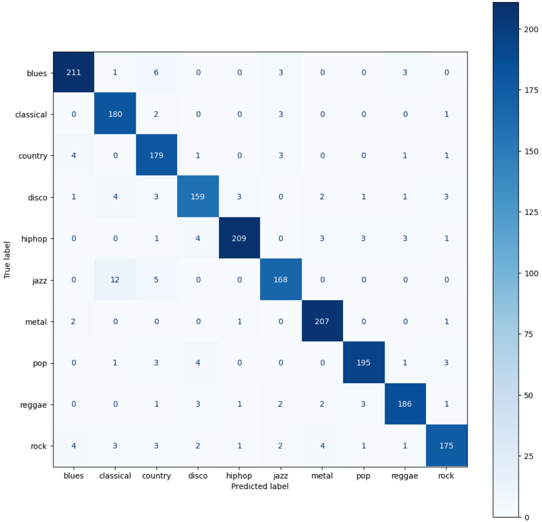

Figure 1: Confusion Matrix for VotingClassifier

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- The best model was the VotingClassifier, which combined all models
- The model can be improved by using more data and better features
- The model can be used in real-time applications
- Acoustic similarity remains a challenge
- Deep learning is the next logical step

Thank you for your attention!

Questions?