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Group Project

TIME FREQUENCY ANALYSIS

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PROBLEM STATEMENT

Spotify has hired us at FCEA Analytics as they want to develop a music genre classification model that can better organize the works of smaller or independent artists who may not accurately classify their music.
To achieve this, our team will conduct studies using web scraping data from Spotify and audio files from GTZAN dataset transformed into images to build a classification model. We aim to develop the best model to predict the genre of music.

TODAY'S AGENDA

01 Background

02 Study 1
(tabular audio feature data)
SPOTIFY API

RESEARCH PROCESS

- DATA COLLECTION
- DATA PREPROCESS
- DATA MODELING & EVALUATION

03 Study 2
(raw audio)
GTZAN DATASET

04 Conclusion & Recommendations

01

BACKGROUND

BACKGROUND

- Spotify face some challenges when it comes to classify music genre:
  - Genre Ambiguity: Many songs contain elements of multiple genres, making it difficult to assign them to a specific category.
  - Genre Evolution: Music genres evolve over time, with new sub-genres emerging, making it challenging to keep up with the latest trends and accurately classify songs.

We at FCEA Analytics is here to build a model that ensures accurate classification and organization of their vast libraries of songs.

02

Study 1 (tabular audio feature data):

SPOTIFY WEB API

DATA COLLECTION

Data source: Spotify Web API

- Rate limiting impacted the possibility of creating a fresh data set
- Implemented: Cameron Watt’s Dataset on the same API

Datasets

- 32,200 rows x 11 columns
- 8,576 rows x 21 columns once cleaned
- Features: danceability, energy, key, loudness, mode, acousticity, instrumentalness, liveness, balanca, tempo

Music Genre:

Dance Pop	Contemporary Country	Alternative Metal	Alternative Hip Hop
Album Rock	Alt Rock	Adult Standards	Alt Dance

DATA PREPROCESS

- Removal of genres with less than 500 appearances
- Removal of unknown columns
- Encoding of key as a categorical variable
- Transforming the list of genres into one genre per entry

Study 1 (tabular audio feature data): Spotify Web API

CLASSIFICATION METHODS

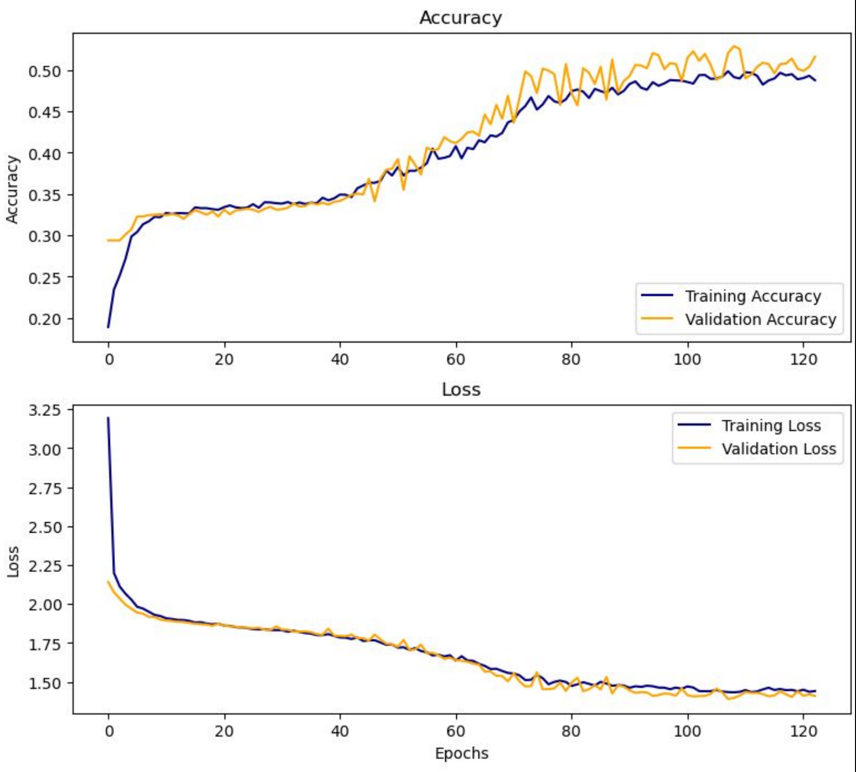
01

LOGISTIC REGRESSION

02

DENSE NEURAL NETWORK

DENSE NEURAL NETWORK



Multiple dense Layers:

- 256/ 128/ 64 neurons
- 'ReLU' activation

Dropout regularization (0.3 & 0.1)

L2 regularization

Output layer:

- 8 neurons
- 'Softmax' activation
- Early Stopping Regularization

Test Loss: 1.404
Accuracy: 0.515

MODEL PERFORMANCE EVALUATION

STUDY 1: SPOTIFY WEB API	
Model	**Test Accuracy**
Logistic Regression	.532
Dense Neural Network	.515

Baseline: .125

03

Study 2 (raw audio):

GTZAN DATASET

DATA COLLECTION

Data source: GTZAN Dataset From Kaggle

Genres original

- 10 genres with 100 audio files per each genre
- Each having a length of 30 seconds (wav.file) and classified as one of the following genres:

Music Genre:

Blues	Classical	Country	Disco	Hiphop
Jazz	Metal	Pop	Reggae	Rock

DATA PREPROCESS

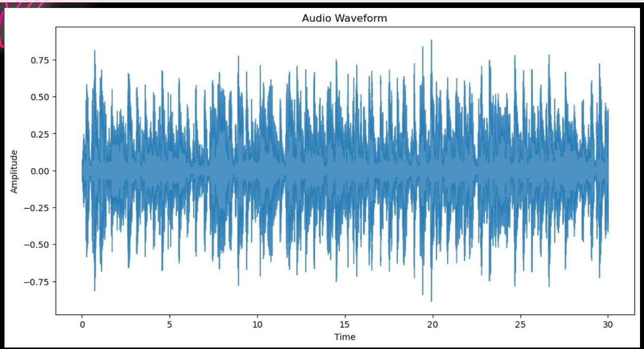
WHAT IS LIBROSA?

Librosa is used for analyzing processing audio signals, particularly for music and speech-related applications. It provides a variety of tools including:

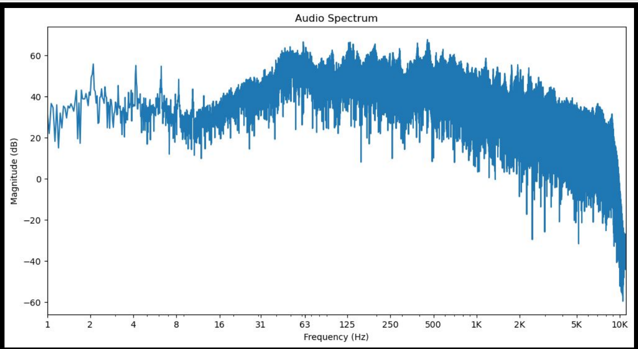
- Loading and playing audio files in various formats (WAV, MP3, etc.)
- Extracting various features from audio signals
- (time-series waveforms, spectrum, spectrograms)
- Visualizing audio data and features
- Transforming audio data for machine learning algorithms for music analysis and classification tasks

Study 2 (raw audio): GTZAN Dataset

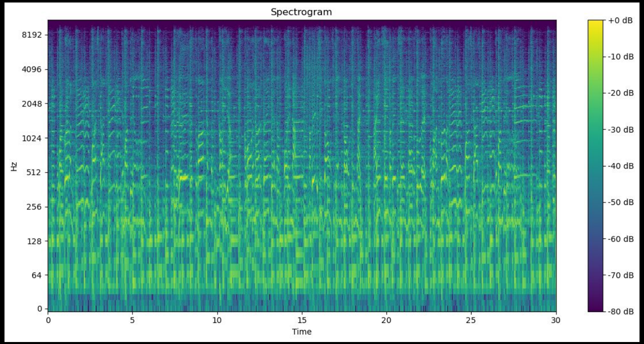
SOUND VISUALIZATION



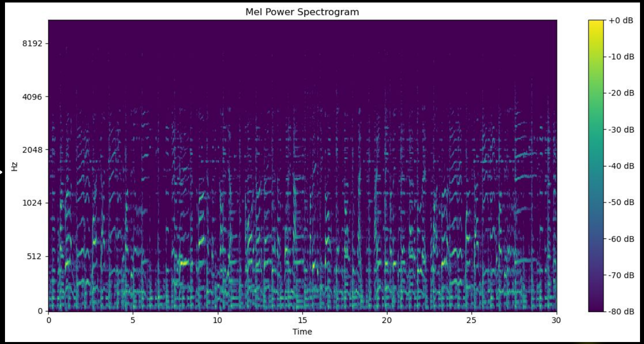
01 Waveform



02 Spectrum



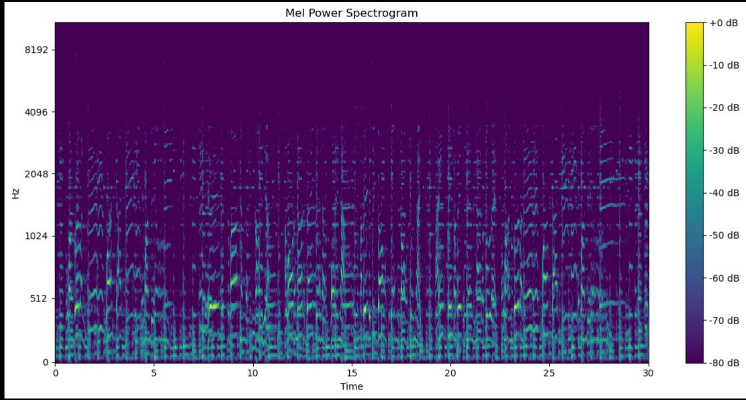
03 Spectrum



04 Mel Spectrogram

WHAT ARE MEL-SPECTROGRAMS?

- A mel-spectrogram is a visual representation of the frequency spectrum of an audio signal over time that has been transformed via a mel-scale.
- The mel scale is a non-linear frequency scale that is more perceptually relevant for human hearing than a linear or logarithmic dB scale used in traditional spectrograms.



CLASSIFICATION METHODS

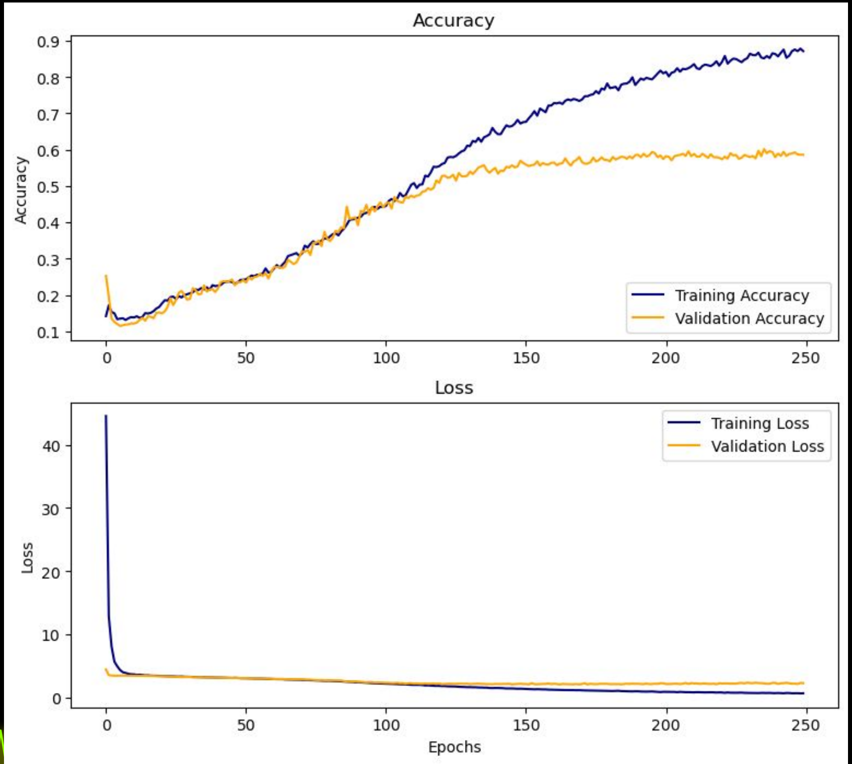
01

DENSE
NEURAL NETWORK

02

CONVOLUTIONAL
NEURAL NETWORK

DENSE NEURAL NETWORK



Multiple dense Layers:

- 512 / 256 / 64 neurons
- ‘ReLU’ activation

Dropout regularization (0.3)

L2 regularization

Output layer:

- 10 neurons
- ‘Softmax’ activation

Test Loss: 2.415
Accuracy: 0.578

CNN : KEY FEATURES THAT HELP IMPROVE OUR MODEL PERFORMANCE

BATCH NORMALIZATION

IMPROVED OUR MODEL'S OVERALL ACCURACY BY 5%

DROPOUT

IMPROVED OUR MODEL'S OVERALL ACCURACY BY 6%

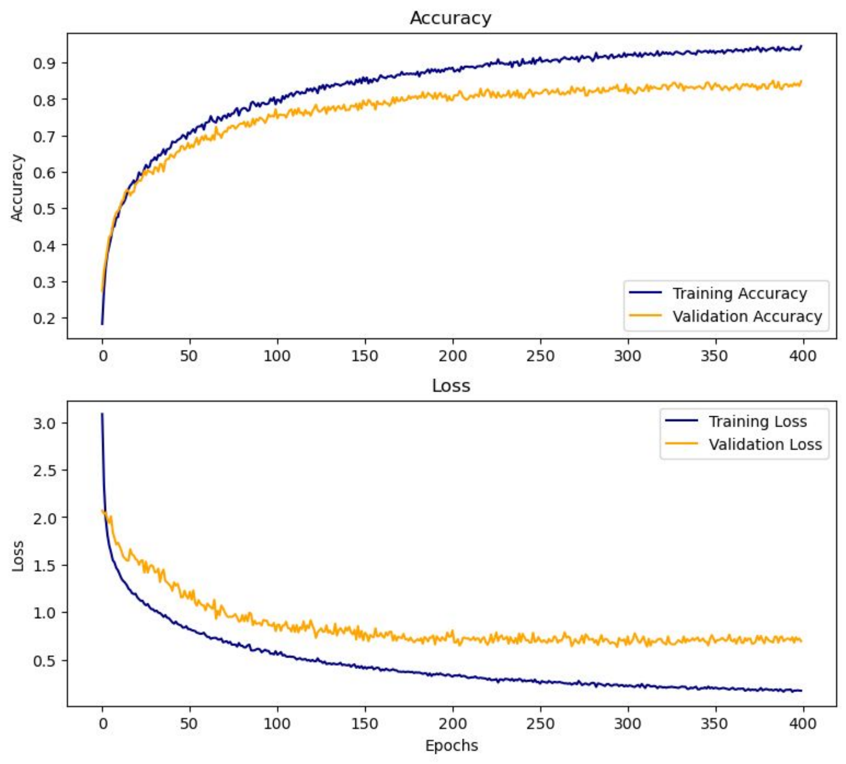
EPOCHS

INCREASED EPOCHS FROM 50 TO 400

AUDIO "IMAGE" DATA AUGMENTATION

IMPROVED OUR MODEL BY SENDING AUDIO FORWARD AND REVERSED AUDIO THROUGH THE MODEL

CONVOLUTIONAL NEURAL NETWORK



Multiple convolutional blocks:

- Conv2D: 32 / 64 / 64 filters
- Kernel size (3x3 / 3x3 / 2x2)
- 'ReLU' activation
- Maxpooling2D layer
- Flatten layer

Dense layer

- 128 neurons
- 'Relu' activation
- Dropout regularization (0.5)

Output layer:

- 10 neurons
- 'Softmax' activation

Test Loss: 0.634
Accuracy: 0.838

MODEL PERFORMANCE EVALUATION

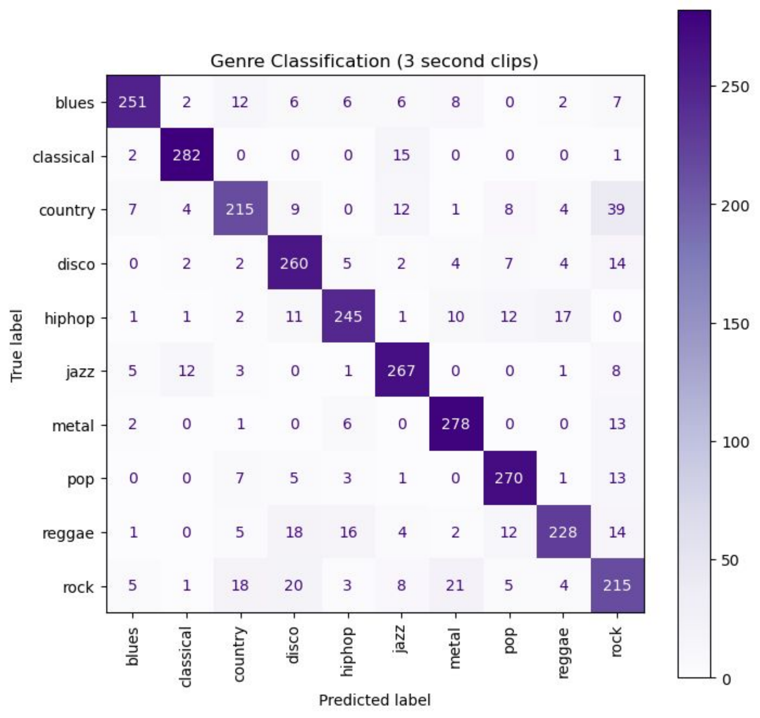
STUDY 2: GTZAN DATASET	
Model	**Test Accuracy**
DNN	0.578
CNN (without regularization)	0.691
CNN (with regularization)	0.801
CNN (with regularization and data manipulation)	**0.838**

Baseline: 0.100

Study 2 (raw audio): GTZAN Dataset

Music Genre		Blues	Classical
Hiphop	Jazz	Hiphop	Jazz
Metal	Pop	Reggae	Rock

CONFUSION MATRIX



04

CONCLUSION & RECOMMENDATIONS

CONCLUSION

- In this project, we explored different audio data and built music genre classification models.
- The model that used pre-engineered features from Spotify's API achieved an accuracy of 0.532. However, using raw audio files and transforming them into Mel-spectrograms resulted in better classification models. In fact, the top performing model was a convolutional neural network (CNN), achieving an accuracy of 0.838.
- The CNN model performance was significantly improved by using batch normalization, dropout, increasing the number of epochs, and data augmentation.
- This project demonstrated the ability to learn complex audio patterns in audio features and build a successful model for music genre classification.

RECOMMENDATIONS

- Additional areas of exploration for genre classification optimization:
  - Increase the size of the datasets, collect more diverse samples
  - Conduct additional data augmentation techniques such as altering the tempo
  - Add time-series features such as zero-crossing rate, amplitude envelope, etc.
  - Experiment with different hyperparameters such as batch size, dropout rate, number of layers, and number of epochs
  - Test different lengths of audios
- The best performing model could be leveraged for recommendation systems to provide personalized music recommendations to Spotify users.

THANKS!

Any questions?