Machine Learning Project Presentation

Title:Gender and Emotion Classification by Voice

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Motivation

Voice: used for human communication.

- Audio categorization
- Speech emotion recognition
- Mental Health and Well-being Monitoring

Emotion: used for expressing feelings.

- Enhancing Human-Computer Interaction
- Education and Training
- Automotive Industry

Literature Review (1/2)

- Voice based Age, Accent and Gender Recognition [1]
  - Utilizing five hidden layers for gender (91% accuracy) and grid search pipeline for age (59% accuracy).
  - Mel-Frequency Cepstral Coefficients (MFCCs) and Spectrogram analysis are the major features extracted for model training.
  - Potential applications could be biometric identification and NLP.
  - Challenges in enhancing age detection accuracy and handling various accents.

Literature Review (2/2)

- Emotion Recognition using pitch , tone and rate.[2]
  - The paper discusses extracting features like pitch, tone, and rate for emotion detection.
  - It reviews several classification schemes, including hidden Markov models (HMMs) and neural networks.
  - Other classification methods mentioned include support vector machines (SVMs) and decision trees.
  - The study also discusses publicly available databases used for training and testing emotion recognition systems.

Dataset Description – Voice Gender Dataset

- Dataset consists of 3168 supervised learning samples where each voice recording is labeled with either male or female gender.

- Acoustic properties that help in distinguishing male and female voice are:
    - Mean frequency (Hz)
    - Standard Deviation of frequency
    - Median Frequency
    - Skewness of Frequency Distribution etc.

- [Kaggle Link]

Dataset Description – Emotion Gender Dataset

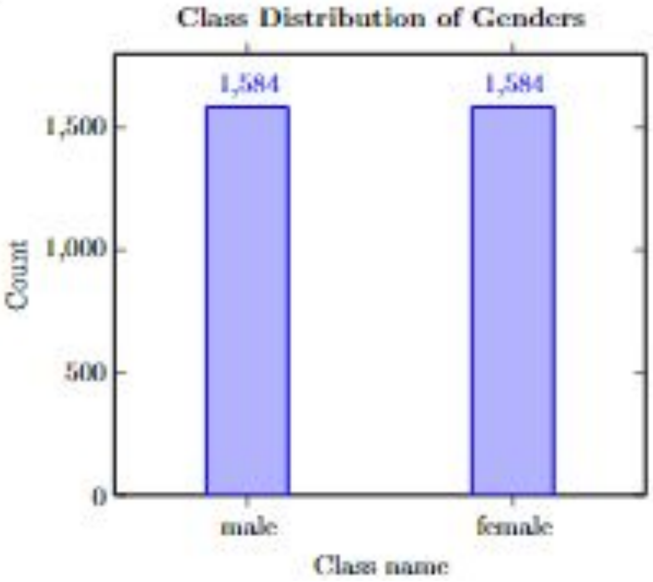
- Consists of 1440 supervised audio samples from 24 actors (12 male + 12 female), capturing a diverse range of emotions.

- Encompasses 8 distinct emotions:

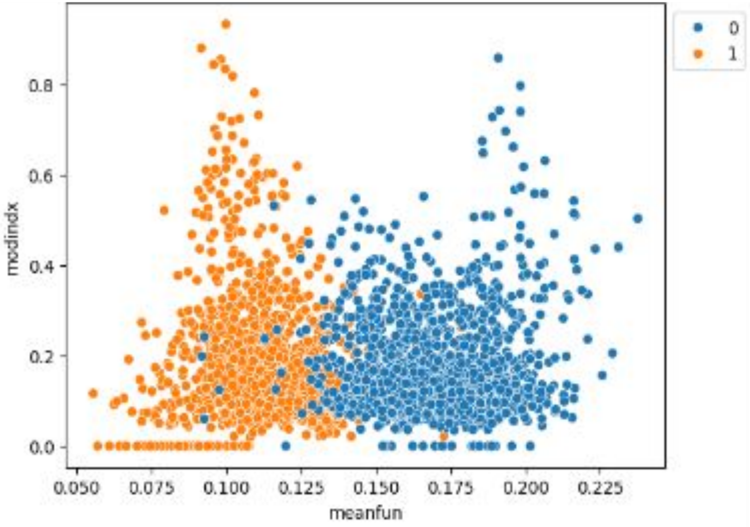
  neutral, calm, happy, sad, angry, fearful, disgust, and surprised.

- [Kaggle Link]

Visualizations



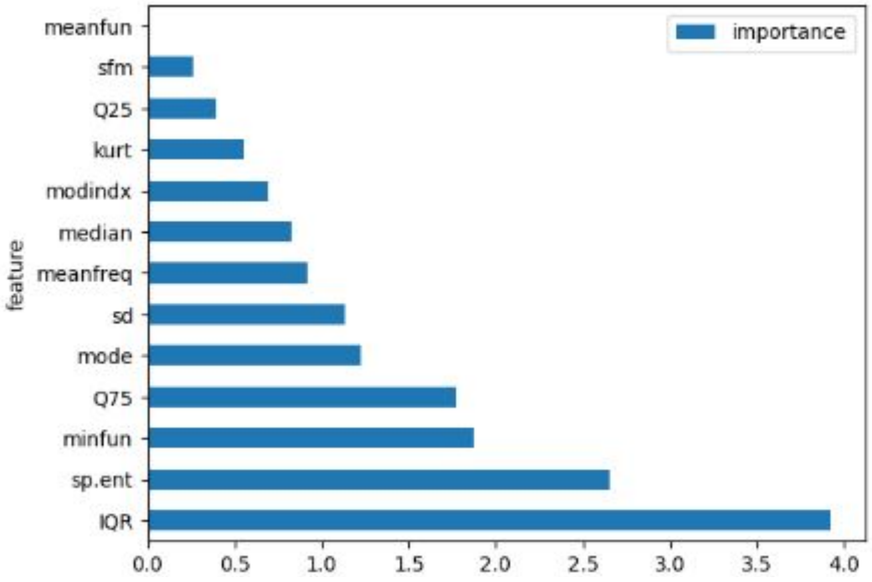
Class Distribution for output label



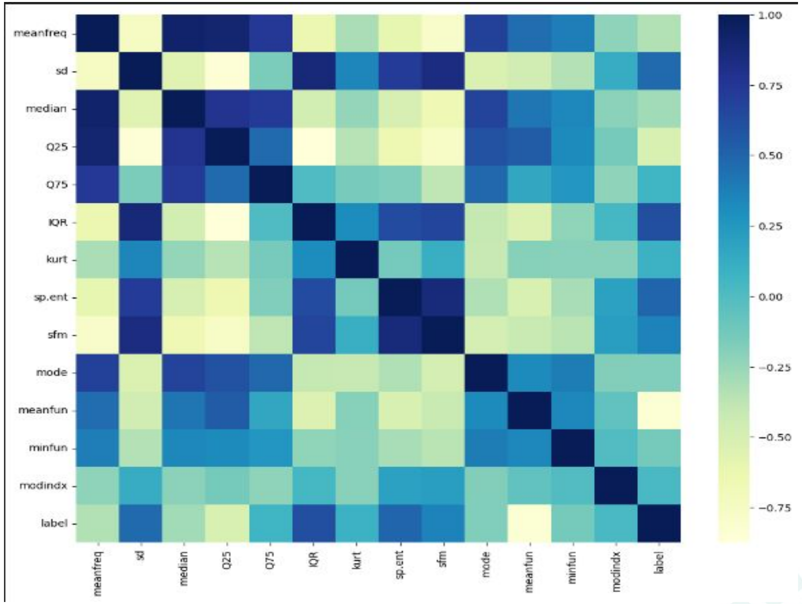
Scatter plot for correlation

Visualizations

Feature Importance Graph



Heatmap for highly correlated columns



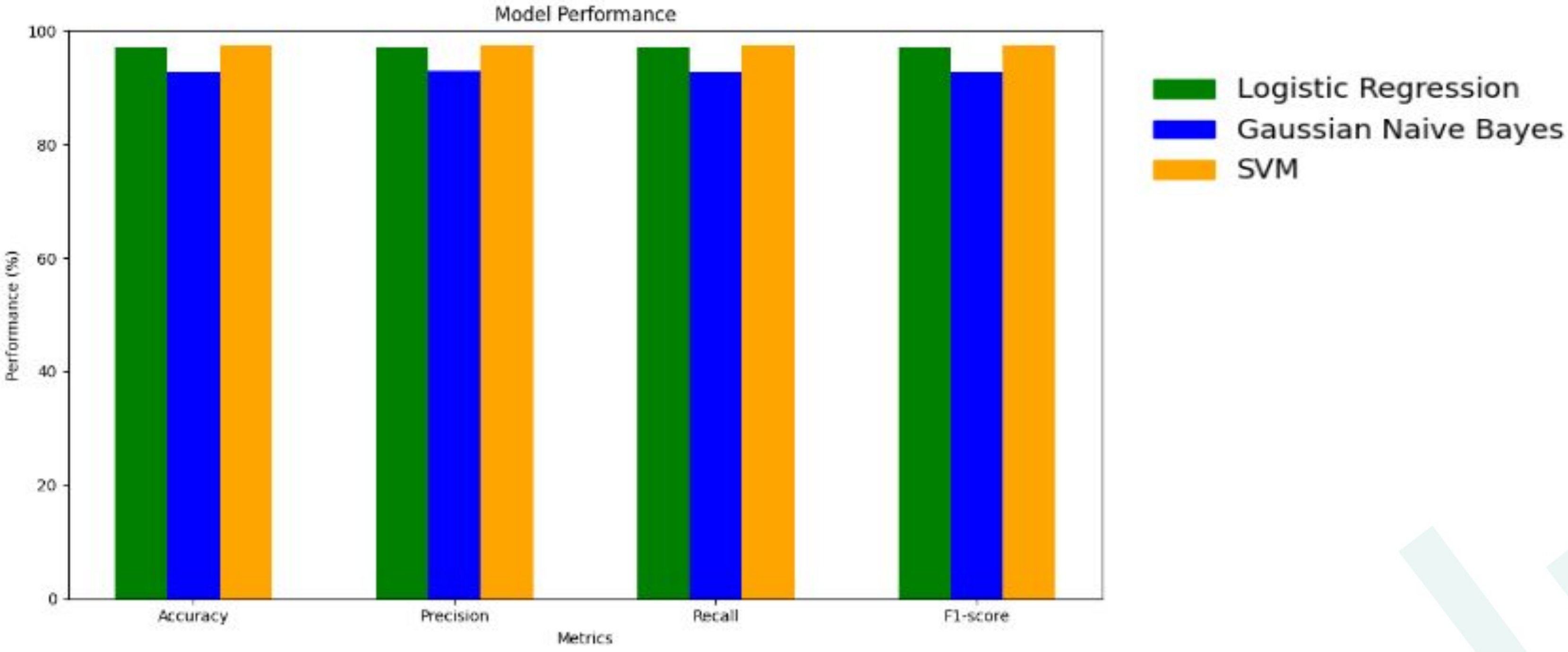
Methodology – Gender Recognition

- Preprocessed and cleaned data by normalizing, null checking, duplicate handling etc.
- Classified the speaker’s gender using selected voice attributes.
- The speaker's voice was categorized as either 'male' or 'female.'
- Three different models/methodologies were used for classification:
    - Logistic Regression
    - Naive Bayes:
        - Gaussian
        - Bernoulli
    - Support Vector Machine

Methodology – Emotion Recognition

- Filtered relevant .wav files based on predefined categories and then split the dataset into training (75%) and testing (25%).
- Extracted audio features such as: MFCC (Mel-Frequency Cepstral Coefficients), Chroma Features, Mel Spectrogram Frequency etc.
- Trained Random Forest Classifier with 100 estimators on extracted audio features and implemented OOB accuracy training.
- Decision Tree and SVM models were also trained but Random Forest was the best suited.
- Integrated speech-to-gender and speech-to-emotion models, implementing a test script for both the models.
- Libraries used: numpy, librosa, soundfile etc.

Results – Gender Recognition



Results – Emotion Recognition

Conclusions

● In Gender Recognition , Logistic Regression provided good results for each of the metrics chosen to judge the model.

● Gaussian naive bayes also reported good accuracy and other performance metrics, therefore, it implies that:

- The Gaussian Naive Bayes model fits perfectly to the data.
- The voice dataset is produced according to the Gaussian distribution for male and female categories.

● In SVM model, linear kernel was observed to be the best one.

● In Emotion Recognition , RF outperforms DT and SVM across indicating it is the most effective model among the three.

Conclusions

- In Emotion Recognition , RF outperforms DT and SVM across indicating it is the most effective model among the three.
- SVM achieves higher scores than DT in all metrics, showing it is a more reliable choice compared to DT.
- DT underperforms in comparison to RF and SVM in all the evaluated metrics, suggesting it is less suitable for this task.
- All three models show relatively high scores for Recall and F1-score, which might indicate a focus on minimizing false negatives or balancing precision and recall.
- The similar trends across Precision, Recall, and F1-score suggest that the models maintain consistent performance in handling imbalanced data.

Timeline

Timeline followed:

- Week 1-2: Data Collection , Pre-processing and Data Visualization for Gender Recognition.
- Week 3-4: Logistic Regression, Naïve Bayes, Support Vector Machine.
- Week 5: EDA, Feature Analysis, Heatmaps, PCA, TSNE (Analysis of Models).
- Week 6: Feature Selection and Observing the performance of each model .
- Week 7(after midsem):Data Collection for Emotion Recognition.
- Week 8:Progress Report and PPT , Pre-processing and Data Visualization for Emotion Recognition.
- Week 9 : Decision Trees , Support Vector Machine models for Emotion Recognition.
- Week 10: Random Forest and Integration of Gender and Emotion Recognition models .
- Week 11:: Analysis and Performance of models for Emotion Recognition
- Week 12:Final Report and PPT.

Contributions

Abdullah Shujat: Pre-processing and Data Visualization, Logistic Regression, Naive Bayes, Random Forests, Report

Anant Kaushal: Data Collection and Visualization, SVM , Decision Trees, Feature Extraction , PPT

Anikait Agrawal: Data Collection, Logistic Regression, Naive Bayes , Decision Trees, Report

Ansh Varshney: Pre-processing and Data Visualization , Feature Extraction , SVM , Random Forests, PPT

THANK YOU! 😎💪