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# REPORT 2: OPTIMIZED GRADIENT BOOSTING FOR AUDIO SCORE PREDICTION

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## **Abstract**

This paper presents an enhanced approach to predicting human-evaluated scores from audio samples using machine learning. We optimize the Gradient Boosting Regressor (GBR) by performing hyperparameter tuning to achieve better performance metrics. Key audio features contributing to the predictions are also analysed. The model demonstrates measurable improvements in prediction accuracy, highlighting the potential of gradient boosting for audio score regression tasks.

## **Introduction**

Automated evaluation of audio samples is an emerging area in machine learning with applications in education, entertainment, and health. In this study, we explore the utility of the Gradient Boosting Regressor (GBR) in predicting speaker proficiency scores based on extracted audio features. Building upon baseline models, we aim to improve the model's performance using *hyperparameter tuning*.

## **Dataset and Preprocessing**

The dataset consists of audio feature vectors derived from spoken audio samples. Each sample is associated with a human-evaluated score.

Preprocessing steps included:

- Null value handling
- Feature scaling using StandardScaler
- Splitting into training and testing sets (80:20 ratio)

## **Methodology**

We employ the Gradient Boosting Regressor, optimizing its performance using *RandomizedSearchCV* with 3-fold cross-validation. The following hyperparameters were tuned:

- `n_estimators`: [100, 200, 300]
- `learning_rate`: [0.01, 0.05, 0.1]
- `max_depth`: [3, 5, 7]
- `min_samples_split`: [2, 5, 10]
- `subsample`: [0.6, 0.8, 1.0]

The search was configured to maximize the  $R^2$  score and find the best model among 20 sampled combinations.

### **Feature Importance Analysis**

The top 10 most influential features identified using the model's `feature_importances_` were:

1. `zcr_mean`
2. `rmse_std`
3. `spectral_centroid_mean`
4. `spectral_bandwidth_mean`
5. `rolloff_mean`
6. `mfcc1_mean`
7. `mfcc2_mean`
8. `chroma_stft_mean`
9. `spectral_contrast_mean`
10. `tonnetz_mean`

These features represent both temporal and spectral characteristics of the audio, indicating that fluency and prosody-related traits are predictive of performance scores.

### **Conclusion**

Gradient Boosting with hyperparameter tuning proved to be an effective method for predicting human-assigned audio scores. The model not only improved the accuracy but also provided interpretable insights into which audio features are most significant.

## **Future Scope**

- **Multimodal Fusion:** Combining audio features with text transcripts or phoneme-level features.
- **Deep Learning Models:** Implementing CNNs or LSTMs to capture more complex audio patterns.
- **Real-time Scoring System:** Deploying the model in an API or web app for live assessment.
- **Cross-lingual Generalization:** Testing the model's adaptability to other languages and accents.
- **Explainable AI:** Integrating SHAP or LIME for better interpretability.

This study lays the groundwork for further development in automated audio evaluation systems, emphasizing the role of feature engineering and model tuning in boosting performance.