Improving Speaker Gender Detection by Combining Pitch and SDC

Aniruddha Mohanty[1[0000−0001−9799−4088]], Ravindranath C. Cherukuri[2]

[1] CHRIST (Deemed to be University), Bangalore, Karnataka, India
aniruddha.mohantyh@res.christuniversity.in
[2] CHRIST (Deemed to be University), Bangalore, Karnataka, India
cherukuri.ravindranath@christuniversity.in
[3]

Abstract. Gender Detection is helpful in various applications, such as speaker and emotion recognition, which helps with online learning, telecom caller identification, etc. This process is also used in speech analysis and initiating human-machine interaction. Gender detection is a complex process but an essential part of the digital world dealing with voice. The proposed approach is to detect gender from a speech by combining acoustic features like Shifted Delta Cepstral (SDC) and Pitch. The first step is pre-processing the speech sample to retrieve valid speech data. The second step is to calculate the pitch and SDC for each frame. The multifeature fusion method combines the speech features, and the XGBoost model is applied to detect gender. This approach results in accuracy rates of 99.44% and 99.37% with the help of RAVDESS and TIMIT datasets compared to the pre-defined methods.

Keywords: Pitch, MFCC, SDC, XGBoost, Gender Detection, and Datasets.

1 Introduction

Gender information is the voice of the speaker that helps to detect whether it is a male or female. Automatic gender detection from speech is a vital area of research used for speech segmentation, speaker identification, verification, human-machine interaction, telecom caller identification, etc. The speech-based gender detection approach is also essential for natural and personalized dialogue systems [1]. It has many practical applications, like targeting certain gender groups in commercial ads, which might enhance sales. In forensic science applications, the suspects are reduced from evidence, like telephone calls, recorded speech, etc. [2].

There is plenty of research literature on gender detection. The performance of automatic gender detection reduces due to acoustic conditions like noisy speech, compressed speech, silence, speech on the telephone, and so on. Image, audio, dressing style, and body expression help to acknowledge gender detection [3]. The change of the human vocal tract helps to detect the gender of a person. Therefore, speech is vital for gender detection. However, an approach or idea is required for better results in various acoustic conditions for gender detection.

The proposed gender recognition approach uses Pitch and SDC speech features combined with multifeature fusion [4] technique. The output of the integrated speech features is an input to the XGBoost model. TIMIT and RAVDESS are two datasets used to assess the approach that contains various speech samples of different age groups and circumstances.

The paper constitutes as follows: Section 2 is the related work that explains the preexisting techniques of gender detection. Section 3 describes the system model, called a black box constituent, which helps to get the input-output relationship in graphical representation. Section 4 describes the proposed method, which discusses the implemented idea and the designed algorithm. Section 5 demonstrates the experimental setup and result analysis, which helps to get the details of the used software, dataset, and the implication of the proposed algorithm and the obtained results. Section 6 is the conclusion and future work of the paper.

2 Related Work

Many investigations on gender detection have been done earlier with a wide range of features and classification techniques. Feature extraction is used in gender detection often. Some of the speech features used in the detection of gender are Pitch [13], Mel-frequency Cepstral Coefficient (MFCC) [20] or Mel-Frequency Spectral coefficient (MFSC), Fundamental frequency (F0), Shifted Delta Cepstral Coefficient (SDC), Linear Prediction Coefficients (LPC), Spectral Flux, Zero Crossing Rate [14]. The process also uses classification techniques like K-Nearest Neighbour[2], Hidden Markov Model (HMM) [1], Gaussian Mixture Model (GMM) [21], Logistic Regression [11], Linear Regression [25], XGBoost [23], Support Vector Machine [24], and Neural Networks [16].

In [5], the speech feature is the Fundamental Frequency used to identify and classify the gender from speech with a proposed model Backpropagation Neural Network (BPNN). BPNN has two stages, namely Feed-Forward and Feed-Backward. Feed-Forward identifies the hidden layer values and outputs, whereas the Feed-Backward compares the output and the previous target values. The verification of the performance of the existing approach uses the private dataset, Kaggle dataset, and Javanese gender dataset. Deep Learning and Support Vector Machine models can improve the model's performance with the help of large datasets.

In [6], the proposed NeuraGen is a low-resource Artificial Neural Network architecture that helps to detect genders from speech recordings. This implementation uses eight essential features to identify gender: Mel-Frequency Cepstrum Coefficient (MFCC), Root mean square (RMS), Fundamental frequency, Spectral-centroid, Spectral bandwidth, Spectral coefficient, Spectral-roll off, and Zero crossing rates. NeuraGen implementation verifies English language performance for Speaker Recognition (ELSDSR) and TIMIT datasets after fusing all the features into one dataset point. The model's performance can improve using noisy or out-of-lab audio or demographic samples.

In [7], the Generative Adversarial Network (GAN) used in synthetic spectrograms generates much train data for the experiment. The GAN is trained on a small set of speech data to generate gender-specific spectrograms, which helps to augment the actual speech samples. The generated spectrograms are used as trained data in Convolutional Neural Network (CNN) for gender classification.

In [8], proposes both gender and overlapped speech detection. MFCC and WavLM are two speech features in gender detection using two different approaches GD1 and GD2. In GD1 LSTM, a recurrent neural network is used with SoftMax layer to predict genders, whereas in GD2 first model predicts the presence of male level, and the second model predicts the presence of the female group. Finally, the model's prediction is the ArgMax between the outputs of the two models. The approach's evaluation can improve using Pitch to develop a joint gender detection model. This approach has also been extended to the Neural-on-Neural [22] approach for speaker gender protection.

In [9], Forward Rajan Transform (FRT) helps to compute the Cumulative Point Index (CPI) feature. These features help to identify the gender of the voice by using Light Gradient Boosting Machine (LightGBM). This approach performs better by using Speech Accent Archive (SAA), Common Voice (CV), TIMIT Acoustic Phonetic Continuous Speech Corpus (TIMIT-APCSC), and Voice Gender Dataset (VGD).

In [10], the voice-based Gender Recognition model extracts the MFCC spectral speech feature and uses it to implement CatBoost, XGBoost, Stochastic Gradient Descent, and Decision Tree classifiers. The performance of these four models is 90%, 89%, 88%, and 80%, respectively. The consideration of accent and vocabulary could improve the performance of the models.

Based on the above literature analysis, a few issues are associated with identifying gender from speech. The first problem is the selection of data or datasets. The second problem is momentous features of speech that influence gender detection. The third problem is dimension reduction in terms of optimizing the redundancy and projection of data. The last issue is the selection of classification algorithms. The above-listed issues are the motivation for the initiative.

3 System Model

The proposed gender detection approach uses Pitch and SDC features from speech samples. MFCC is used to estimate the vocal tract filter. SDC derived from MFCC works well in delta and acceleration feature vectors, while Pitch represents the voice source feature. Acoustic analysis and Pitch estimation are two independent approaches used to improve the accuracy of gender detection.

The proposed method comprises various blocks, as shown in Fig. 1. Speech signal is the input to the preprocessing block of the design system. The preprocessing block contains phases like pre-emphasis, framing and windowing, and voice activity detection. Pre-emphasis helps to reduce noise in the speech sample without any alteration. Framing helps to capture the information in time-varying speech samples. Voice activity detection determines the presence or absence of speech in the speech samples.

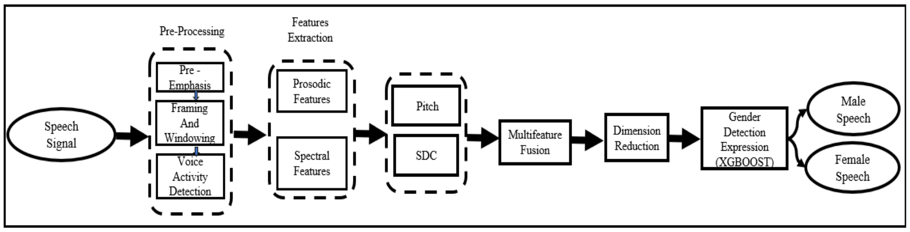

Fig. 1. Visual Illustration of Gender Detection approach

Feature extraction is the next step of the proposed approach. Prosodic features and spectral features are two types of features primarily used in the experiment. The modulation of acoustic characters generates prosodic features; Pitch is one type of prosodic feature. Spectral features help to extract human vocal tract information; MFCC and SDC are part of spectral features. Then, the speech features are combined into a single feature by multifeature fusion.

Dimension Reduction is the next step after the feature extraction. Principal Component Analysis (PCA) helps to reduce the dimension of large data points to smaller ones by minimizing information loss. PCA reduces the dimension of extracted pitch and SDC features. Finally, the combined Pitch and SDC outputs are used in XGBoost modeling to determine the gender information.

4 Proposed Method

The proposed gender detection from speech approach segregates into four parts:

- Pre-processing speech samples
- Feature extraction and fusion
- Dimension reduction
- Gender detection

4.1 Dataset

The DARPA TIMIT Acoustic-Phonetic Continuous Speech Corpus (TIMIT) [3] database contains the recordings of 6300 audio sentences. Each audio file records a 16KHz sampling rate. This data corpus includes male and female speech samples where each speaker speaks ten sentences.

Ryerson Audio-Visual Database of Emotional Speech and Songs (RAVDESS) [3] database distinguish between speaking and singing data. This dataset segregates the speech of males, the speech of females, a song sung by a male, and a song sung by a female, which can efficiently verify the genders.

4.2 Pre-processing

Pre-processing is the first step of gender detection and comprises pre-emphasis, framing, windowing, and voice activity detection.

Pre-emphasis: Speech signals have the characteristic of weakening high-frequency components. So, a pre-emphasis digital filter helps to increase the energy of the high-frequency portion of the speech sample and decrease noises with low frequency without any voice distortion [11].

$$Y(t) = X(t) - \alpha X(t-1) \tag{1}$$

Where $Y(t)$ is the pre-emphasis signal. $X(t)$ is the initial signal. α is the filter coefficient with a value of 0.95 or 0.97.

Framing and Windowing: The length of the human voice varies, so farming is necessary to keep the speech size consistent [9]. Segmenting speech samples to twenty to twenty-five milliseconds of frames with five milliseconds overlap reduces data leakage.

Applying the window function to each frame length is necessary to reduce spectral leakages or aliasing [9]. Out of multiple windowing functions, this experiment uses the hamming window.

$$W(n) = 0.54 - 0.46cos(2\pi m/(K-1)), \quad for \quad 0 \leq m \leq K-1 \tag{2}$$

Where K is the Hamming window length.

4.3 Feature Extraction and fusion

Pre-processing the speech samples follows feature extraction. Broadly, the features are of two types: Prosodic and Spectral.

Prosodic Features: Prosodic characters [12] obtained by modulation of various acoustic features help to get information like speaker characteristics, language characteristics, and recognition patterns. Many prosodic features like pitch, energy or loudness, formant, speech rate, and intensity directly influence the speaker's gender detection. This experiment uses the Pitch speech feature.

Fundamental Frequency (Pitch): Fundamental Frequency (F0) [13] is the minimum frequency of the periodic waveform. F0 is the significant parameter to differentiate male speech from female speech. Pitch helps to determine the voiced and unvoiced portion of the speech signal.

Spectral features: Spectral features [14] help to give information about the human vocal tract system. Fourier Transform helps to transform these features by converting the time-based signal into the frequency-based signal. Several spectral features like MFCC, Linear Prediction Cepstral Coefficients (LPCC), Log Frequency Power Coefficients (LFPC), SDC, and so on help to detect the gender of a human. This experiment uses the SDC feature derived from the MFCC feature.

Shifted Delta Cepstrum (SDC): Applying the time derivatives to cepstral coefficients obtained from MFCC and merging it with delta coefficients shown in Fig. 2 extracts the SDC [15]. It has four parameters: M, D, P, and K. M represents cepstral coefficients for each frame. P indicates the frames that get added from the future frame data. K represents the frames delta features append to form a new feature vector. D signifies the delta value difference.

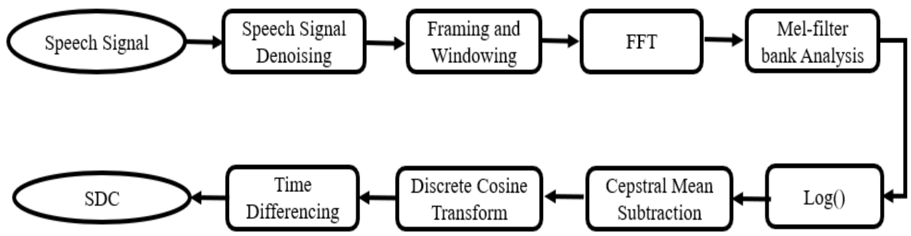

Fig. 2. Steps to extract SDC feature.

SDC and fundamental frequency are the two speech features used in this implementation. The multifeature fusion [4] technique helps to create a single set of data points as the speech features differ in their values and dimensions. Using feature proximity helps create the average dimensional spacing between the feature vectors.

4.4 Dimension Reduction

The dimension reduction method is the next step to reduce the dimensions of the extracted speech features which is helpful in modeling. High data variance is present in the extracted speech features which contain more information with random variables. This process simplifies complex modeling problems, eliminates redundancy, and reduces the probability of model overfitting. This experiment uses Principal Component Analysis (PCA) for dimensionality reduction.

Principal Component Analysis (PCA): PCA [16] is a dimension reduction technique used to reduce the dimensionality of a large dataset by transforming many variables into smaller numbers. These reductions in the number of variables help to get more accurate results and make it easier to explore the reduced dataset, resulting in easy and fast data visualization and analysis.

4.5 Gender Detection:

After dimensionally reducing the data, the XGBoost model predicts the genders from the speech samples. XGBoost is highly scalable, quick to execute, and gives a better accuracy rate than other algorithms performing parallel computations with Data files, Dense and Sparse matrices.

XGBoost: Extreme Gradient Boosting [17] is a classification algorithm that helps to detect male and female genders. This design is an end-to-end tree-boosting system that justifies the weighted quantile sketch. Sparsity-aware algorithm also helps in parallel tree learning, which allows parallel processing, fitting to memory for calculations.

The differentiable convex loss function predicts the difference between the predicted and targeted values. The additional regularized function (f_k) uses to avoid overfitting.

Algorithm 1 :Detecting Gender from Speech/Speaker based on acoustic and Pitch analysis

INPUT: Dataset (RAVDESS, TIMIT)
OUTPUT: Genders (Male, Female)

```
1: Begin:
2: Read the speech samples from Dataset
3: Pre−processing: Processed_speech = Pre−processing (Speech_Sample)
4: Feature extraction: SDC, Pitch = Feature_Extraction (Processed_speech)
5: Multifeature fusion: multi_feature = multifeatured_fusion (SDC, Pitch)
6: Dimension reduction: Dimension R = Dimension_Reduction (multi_feature)
7: Determine gender: Gender = XGBoost (Dimension R)
8: Gender (Male, Female)
9: End
```

5 Experimental Setup and Result Analysis

Python and its supported libraries help to implement the proposed gender detection approach. The pitch (Pitch 0.0.6) file helps to extract pitch from the individual speech sample files. Librosa (librosa 0.8.0) is a python file used to extract the features from the audio file and the MFCC feature from the speech files. This implementation also uses some other packages like NumPy, pandas, matplotlib, preprocessing files from Sklearn, signal files from SciPy, and Wave packages.

Each preprocessed speech file in the datasets TIMIT and RAVDESS helps to evaluate the experiment, and then the speech file extracts the Pitch, MFCC, and SDC features. Then Pitch and SDC speech features are fused with the help of multifeature fusion. PCA method dimensionally reduces the data points to get the resultant data points, Finally, all the data points are fed to XGBoost to predict the genders of each of the speech samples.

5.1 Evaluation Metrics

To assess the effectiveness of the designed gender detection approach, Accuracy, Precision, Recall, and F1-Score measurements have been used to determine all the evaluated datasets. A “confusion matrix” comprising True Positive, True Negative, False Positive, and False Negative [18] [19] helps calculate all these

measurements.
True negative: The system detects the female speaker as a female.
False negative: The system detects the female speaker as a male.
False positive: The system detects the male speaker as a female.
True Positive: The system detects the male speaker as a male.
The confusion matrix derived from RAVDESS dataset has one value for False

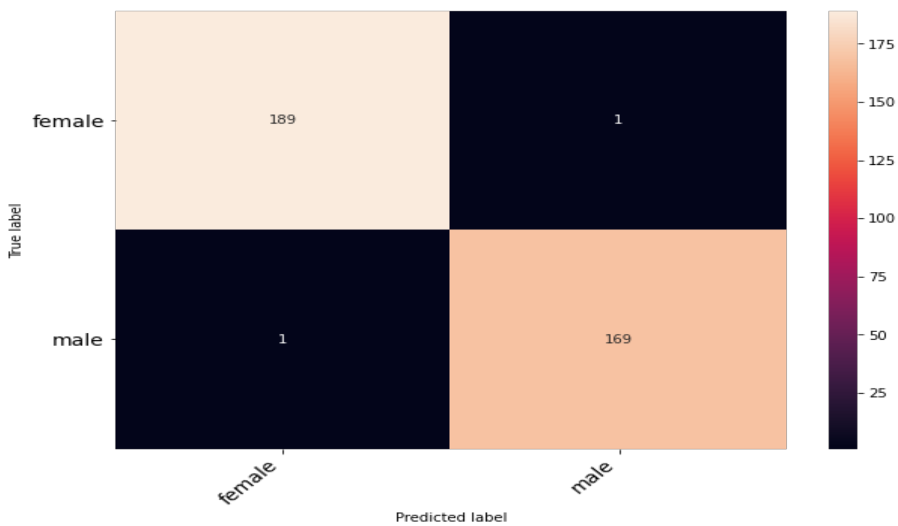

Fig. 3. Confusion Matrix of Gender for RAVDESS dataset.

Negative and True Negative, shown in Fig. 3. Hence the accuracy is 99.44 from 360 speech samples. The obtained precision, recall, f1- score, and support values are in Table 1. The precision, recall, and f1-score values for both the male and female speech samples perform an accuracy of more than 99%. The number of male and female speech samples used in the experiment are 170 and 190, respectively. Only one speech sample from each set of speech samples predicting wrongly. In this dataset, both the male and female speech samples are balanced. Therefore, the performance of the model is accurate. SDC helps to identify spoken languages and Pitch used in clustering different members as required.

The confusion matrix derived from TIMIT dataset three values for False Negative and one value for True Negative. Hence the accuracy is 99.37% from 481 speech samples. In the dataset, the accuracy of the gender detection of male samples is more than that of females. Two hundred thirty-six male samples are correctly detected compared to two hundred forty-two females. The performance of the gender prediction improves by combining SDC and Pitch features. Pitch features help to identify the rhythm of the speech samples, and SDC helps to detect gender in the presence of noise.

Table 1. Performance metrics for RAVDESS dataset

measures	precision	recall	f1 Score	Support#
female	0.99	0.99	0.99	190
male	0.99	0.99	0.99	170
accuracy	-	-	0.99	360
micro avg	0.99	0.99	0.99	360
weighted avg	0.99	0.99	0.99	360

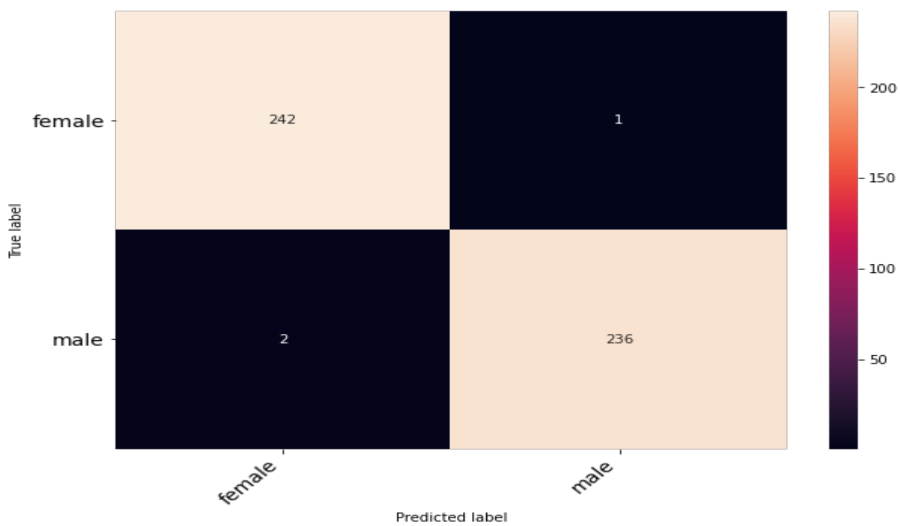

Fig. 4. Confusion Matrix of Gender for TIMIT dataset.

Table 2. Performance metrics for TIMIT dataset

measures	precision	recall	f1 Score	Support#
female	0.99	1.00	0.99	243
male	1.00	0.99	0.99	238
accuracy	-	-	0.99	481
micro avg	0.99	0.99	0.99	481
weighted avg	0.99	0.99	0.99	481

The obtained precision, recall, f1- score, and support values are in Table 2. The precision, recall, and f1-score values for both the male and female speech samples perform an accuracy of more than 99%. The number of male and female speech samples used in the experiment are 243 and 238, respectively.

5.2 Comparison

The proposed model comparison done with existing experiments is in Table 3. The performance of the proposed model is better than the previous implementations, with an accuracy rate of 99.44%

The MFCC speech feature and SVM as a model [14] give an accuracy rate of 92.73% with the RAVDESS dataset. The MFCC, RMS, Fundamental Frequency, Spectral-centroid, spectral bandwidth, spectral coefficient, spectral roll-off, ZCR as a feature, and NeuraGen as a model [5] give an accuracy rate of 91.227

Table 3. Comparision with previous implementations

Sl#	Models	RAVDESS	TIMIT
1	MFCC, SVM [20]	92.73%	NA
2	MFCC, RMS, etc. [6]	NA	91.22
3	Proposed Model (Pitch, SDC, XGBoost)	99.44%	99.37%

6 Conclusion And Future Work

In the proposed approach, both the acoustic analysis and pitch feature estimations are used to improve the performance of gender detection. The process starts with speech sample preprocessing, feature extraction, dimension reduction, multifeature fusion, and finally, the implementation of XGBoost model. TIMIT and RAVDESS databases give better accuracy compared to the traditional approaches. The implementation of this approach uses minimal resources and computations. In future enhancement, the approach can be extended and evaluated in various speech features like Spectral Centroid, Chroma frequency, Energy, Zero-Crossing, Linear Prediction Coefficients (LPC), Linear prediction cepstral coefficients (LPCC) with different machine learning concepts like Logistic Regressions, Linear Regressions, other Neural Networks. The different available databases may create an opportunity to check the accuracy of the proposed model.

References

1. Levitan, Sarah Ita, Mishra, Taniya, Bangalore, Srinivas: Automatic identification of gender from speech. In: Proceeding of speech prosody, pp. 84–88. Semantic Scholar, Boston (2016).
2. Abdulsatar, Assim Ara, Davydov, VV, Yushkova, VV, Glinushkin, AP, Rud, V Yu: Age and gender recognition from speech signals. Journal of Physics: Conference Series, 1410 (1), 012073 (2019).

3. Uddin, Mohammad Amaz and Hossain, Md Sayem and Pathan, Refat Khan and Biswas, Munmun: Gender recognition from human voice using multi-layer architecture. In: 2020 International conference on innovations in intelligent systems and applications (INISTA) , pp. 1–7. IEEE, Biarritz (2020).
4. Zhang, Shaoyun, Li, Chao: Research on feature fusion speech emotion recognition technology for smart teaching. Mobile Information Systems, 2022, (2022).
5. Liztio, Laksita Maulisa, Sari, Christy Atika, Rachmawanto, Eko Hari, others: Gender identification based on speech recognition using backpropagation neural network.. In: 2020 International Seminar on Application for Technology of Information and Com-munication (iSemantic), pp. 88–92. IEEE, Semarang (2020).
6. Ghosh, Shankhanil, Saha, Chhanda, Molakathaala, Naagamani: Neuragen-a low-resource neural network based approach for gender classification. arXiv preprint arXiv:2203.15253, (2020).
7. Bořil, Hynek and Horn, Skyler : GAN-Based Augmentation for Gender Classification from Speech Spectrograms. In: 2022 International Conference on Electrical, Computer and Energy Technologies (ICECET), pp. 1–6, IEEE, Prague (2022).
8. Lebourdais, Martin, Tahon, Marie, Laurent, Antoine, Meignier, Sylvain: Overlapped speech and gender detection with WavLM pre-trained features. arXiv preprint arXiv:2209.04167, (2022).
9. Kannapiran, Priya, Sindha, Mohamed Mansoor Roomi: Voice-Based Gender Recognition Model Using FRT and Light GBM. Tehnički vjesnik, 30(1), pp. 282–291, (2023).
10. Munoli, Bhushan Kiran and Jain, K Abheeshta Kumar and Kumar, Prem and PS, Aditya Ram and others : Human Voice Analysis to Determine Age and Gender. In: 2023 International Conference on Recent Trends in Electronics and Communication (ICRTEC), pp. 1–4, IEEE, Mysuru (2023).
11. Kone, Vinayak Sudhakar and Anagal, Atrey and Anegundi, Swaroop and Jadhav, Pranali and Kulkarni, Uday and Meena, SM: Voice-based Gender and Age Recognition System. In: 2023 International Conference on Advancement in Computation & Computer Technologies (InCACCT), pp. 74–80. IEEE, Mohali (2023).
12. Li, Aini and Lai, Wei and Kuang, Jianjing: How do listeners identify creak? The effects of pitch range, prosodic position and creak locality in Mandarin. Proceedings of Speech Prosody, 2022, pp. 480–484 (2022).
13. Ting, Huang, Yingchun, Yang, Zhaohui, Wu: Combining MFCC and pitch to enhance the performance of the gender recognition. In: 2006 8th international Conference on Signal Processing, (1). IEEE, Guilin (2006).
14. Priya, E and Reshma, Padam Satya and Sashaank, S and others: Temporal and spectral features based gender recognition from audio signals. In: 2022 International Conference on Communication, Computing and Internet of Things (IC3IoT), pp. 1–5. IEEE, Chennai (2022).
15. Sandhya, P and Spoorthy, V and Koolagudi, Shashidhar G and Sobhana, NV: Spectral features for emotional speaker recognition. In: 2020 Third International Conference on Advances in Electronics, Computers and Communications (ICAECC, pp. 1–6, IEEE, Bengaluru (2020).
16. Sefara, Tshephisho Joseph and Modupe, Abiodun: Yorùbá gender recognition from speech using neural networks. In: 2019 6th International Conference on Soft Computing & Machine Intelligence (ISCMI), pp. 50–55. IEEE, Biarritz (2019).
17. Chen, Tianqi and Guestrin, Carlos: Xgboost: A scalable tree boosting system. In: Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining. ACM, New York (2016).

18. Mohanty, Aniruddha and Cherukuri, Ravindranath C and Prusty, Alok Ranjan: Improvement of Speech Emotion Recognition by Deep Convolutional Neural Network and Speech Features. In: Congress on Intelligent Systems, pp. 117–129. Springer, Bengaluru (2022).
19. Sánchez-Hevia, Héctor A and Gil-Pita, Roberto and Utrilla-Manso, Manuel and Rosa-Zurera, Manuel: Age group classification and gender recognition from speech with temporal convolutional neural networks. Multimedia Tools and Applications, 81 (3), pp. 3535–3552, (2022).
20. Abakarim, Fadwa, Abenaou, Abdenbi: Voice Gender Recognition Using Acoustic Features, MFCCs and SVM. In: Computational Science and Its Applications–ICCSA 2022, pp. 634–648, Springer, Malaga (2022).
21. Doukhan, David and Carrive, Jean and Vallet, Félicien and Larcher, Anthony and Meignier, Sylvain: An open-source speaker gender detection framework for monitoring gender equality. In: 2018 IEEE international conference on acoustics, speech and signal processing (ICASSP), pp. 5214–5218, IEEE, Albert (2018).
22. van Bemmel, Loes and Liu, Zhuoran and Vaessen, Nik and Larson, Martha: Beyond Neural-on-Neural Approaches to Speaker Gender Protection. In: ICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 1–5, IEEE, Rhodes (2023).
23. Zaman, Syed Rohit and Sadekeen, Dipan and Alfaz, M Aqib and Shahriyar, Rifat: One source to detect them all: gender, age, and emotion detection from voice. In: 2021 IEEE 45th Annual Computers, Software, and Applications Conference (COMPSAC), pp. 338–343, IEEE, Madrid (2021).
24. Safara, Fatemeh and Mohammed, Amin Salih and Potrus, Moayad Yousif and Ali, Saqib and Tho, Quan Thanh and Souri, Alireza and Janenia, Fereshteh and Hosseinzadeh, Mehdi: An author gender detection method using whale optimization algorithm and artificial neural network. IEEE Access, 8, 48428–48437, (2020).
25. Gumina, S and Polizzotti, G and Spagnoli, A and Carbone, S and Candela, V: Critical shoulder angle (CSA): age and gender distribution in the general population. Journal of Orthopaedics and Traumatology, 23 (1), 10, (2022).