Accent Recognition of Speech Signal Using MFCC-SVM and k-NN Technique

Mahesh K. Singh
Department of ECE, Aditya University

D. Kishore
Department of ECE, Aditya College of Engineering & Technology

R. Anil Kumar
Department of ECE, Aditya College of Engineering & Technology

https://doi.org/10.5109/7183440

出版情報：Evergreen. 11 (2), pp.1305-1312, 2024-06. 九州大学グリーンテクノロジー研究教育センター
バージョン：

Accent Recognition of Speech Signal Using MFCC-SVM and k-NN Technique

Mahesh K. Singh[1*], D. Kishore[2], R. Anil Kumar[2]

[1]Department of ECE, Aditya University, Surampalem, India

[2]Department of ECE, Aditya College of Engineering & Technology, Surampalem, India

Corresponding Author's E-mail: mahesh.singh@adityauniversity.in

(Received September 14, 2022; Revised April 8, 2024; Accepted June 14, 2024).

Abstract: The accent dependent recognition system is substantially more difficult in speech processing. The accent-dependent identification system had several steps. Pre-processing, a feature extraction method, feature reduction, feature categorization, and feature selection were among them for calculating efficiency. The SVM and k-NN classification algorithms, along with the MFCC feature extraction methods, are presented in this article for accent-dependent speaker recognition systems. The classification task is achieved using two training and testing stages. In the training stage, the parameter of speaker-specific features is calculated and different speaker statistical model is generated. In the testing stage, the unknown speaker's speech sample is compared with the speaker's statistical model and then classified using different classifiers. If the amount of accent is dependent on language, then it is becoming more crucial accent recognition. In the Indian language southern part of India is extensively spoken. It has dissimilar accents. The spoken languages of Rayalaseema, Telangana, and coastal Andhra are the most prominent accents. A sample of speech is collected from resident speakers of the Telugu language in three distinct accents as part of the technique that has been proposed. It is used for both training and testing features.

Keywords: Accent recognition, GMM, k-NN classifier, MFCC features, the SVM classifier

1. Introduction

MSP is an important technique to understand the major attention for improvement of voice recognition is expected to interfacing and the adequate conversion for human-machine[1, 2]. At a time to pursue the dispense for recognition of accent in recognition of speech expressed by the spoken conversion in an accurate aspect. The voice tone masks the ability to respect dialect in a period dependent on the speakers belongs from a particular region.

Recognition of accent supports the speaker identification system[3, 4]. The efficiency of an automatic recognition system for speech may be increased. The dialect or accent of the speaker could be exposed prior the speech recognition through the accommodating convenient Automatic speaker recognition (ASR) acoustic model[5, 6]. The Telugu language is a specific language that is spoken in the large locality in south India[7, 8].

So there are many dialect/accents in the Telugu language. Despite, particularly three accents are to be acknowledged in this article that is Telangana (TG), Rayalaseema (RS), and Coastal Andhra (CA)[9, 10]. The contrasting dialects organized in the Telugu accent are commenced the territorial perception. The consequences of the different neighbored states are language to which person deliver in contrasting accent[11, 12]. The different accents information is accessible at other matches in the voice signal. In the direction of the dialect or accent specialized information could be recognized with the form[13]. The exclusive progression of the architecture of the articulation state for hearing the sound system[14]. Towards the prior segmental level, the accent particular ability that is entrenched in that duration[15]. A general voice sample used for scent recognition shown in Fig. 1. The design of the speech sound sequence as well as the motion of the tilt and their efficiency counters. Each contributor has their belonging to an individual speech ratio[16]. Through which the individual speaker could be stabilized.

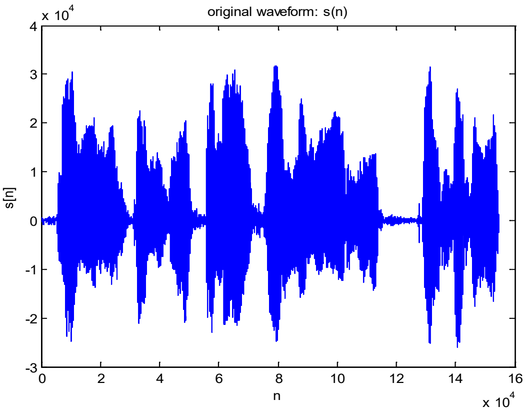

Fig. 1: Recorded speech sample for accent recognition

The numerous characteristics are deliberated as accent and speech recognition system or typical autocorrelation [17]. The immediate spectrum covariance matrix for the histogram of the fundamental frequency, Mel-frequency cepstrum coefficients, and LPCC. In MFCC, the frequency scale is placed frequency on a direct measure smaller than 1 kHz. While the frequency of more than 1 kHz has been deliberated in log scale[18]. The MFCC coefficients are in complex form. This similarity for the linear and non-linear MFCC is composed significantly in speech processing the following challenges illustrated in the present draft.

1. Non-availability of Telugu speech sample for the standard database.
2. Accent dependent identification in the results of the literature review informed the decision to focus on Telugu speeches for future.

2. Related Work

Some research has been described towards decreased recognition accurately. The inconsistency concerning English dialect of British and American dialect for speech model in the input speech [19, 20]. The pitch quality and inflection prototype of speech or exploit as reduced the feature in fault rate of dialect-based accent recognition[21]. The probability-based Gaussian controls the complete computational complexity. While the development in speech processing depended on the training statistics quantity, this is essential to choose the accurate Gaussian mixture model (GMM)[22]. Due to the volume of database accessible intended for Indian languages are small, for the upper assortment GMM could not be relevant. English sentence dialect recognition shows the importance of representation for a superior match up with the acoustic method[23].

The competency intensifies towards the human being settlement approximately 86% recognition of an approach in favors of English speech or object by obtains dialogues commencing from a citizen from English speakers of two child groups as well as Japanese speakers among this similar stage of ability in English language[24]. These consequences have an inaccuracy scale estimated 13% on origin data as well as 20% on Japanese non-origin data. The impact study of origin accent for provincial Indian dialect or selected file provincial. Indian dialects like Hindi, Urdu, Kashmiri, Manipuri, and Bengali[25]. The GMM and spectral characteristics have been employed. Next to the result, transfer out the accent and language recognition task.

It is identified that the extension for the influence of three origins accept accents between them Hindi was little different Kashmiri language more influenced on the accent that was more than Manipuri and Bengali[1]. Many methodologies have been offered that employ a quantity of stream for data in auditory signal. This methodology recognized regional accents or dialects. Phonetic features, frame-based acoustic features, high-level prosodic features, and overall speech characteristics can be used to identify the speaker's dialect phonetic by using discriminate and generative techniques[2]. It was described the advantages of speech recognition and speaker identification in the Mel-wrapped cepstral coefficient as well as fluctuated LPC parameter.

An acoustic-based algorithm for feature extraction has been projected in that the feature secondhand for Cochlear filter cepstral coefficients (CFCC)[4,5]. It is described as built by the recently expanded transformation called the acoustic transform. The situation of the component which, follow the signal processing purpose in the CFCC [7,8]. The performances have been demonstrated in CFCC. Below the quiet situation, the CFCC and MFCC feature's characteristics are approximately identical. The contributed speech signal through the SNR ratio with 6 dB is deliberated. By this approach, efficiency decreased by 41.20% using MFCC feature extraction. The reason behind CFCC illustrates the efficiency of 88.30% [2, 4].

Investigations based on accents were performed with the help of MFCC as well as RASTA-PLP algorithms. For a short time, feature spectrum is extracted for each speech fragments dependent on organized information. The experimentation outcomes show that the MFCC and sub-division merging features extraction technique of RASTA-PLP[12]. Show it can be detected Chinese dialect recognition, analyzed with efficiency relatively 82.1%. The recognition of the speakers, an algorithm had been proposed that the MFCC features accents. It was reported by the K-NN efficiency with elevated standard test precision related to SVM[25].

The automated classification method depended on dialect similar phonetic identification for foreign dialect in Australian English speech. These efforts utilized in continuous speech and discriminated against the classifier with two migrated speakers and Australian English using HMM statistical model. The preeminent accent identification efficiency described 85.3% and 76.6% for three dialects and these dialects put together for classification tasks[24].

2.1 MFCC feature extraction

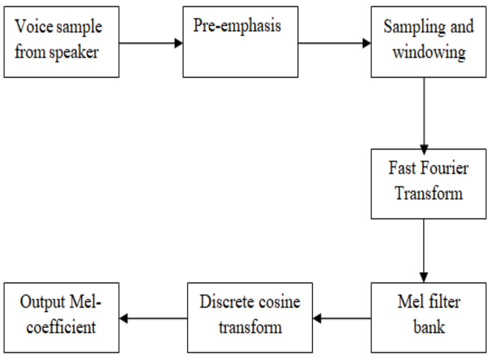

Fig. 2: MFCC feature extraction technique.

Human's speech observations are non-linear. MFCC feature extractions are related to a person's speech observation techniques. MFCC feature extraction coefficients are non-linear and linear speech signal properties. The estimated method, to calculate MFCC cepstrum 'Mel' to frequency 'f' in Hzs. The process for achieving the MFCC feature coefficients are given in the following block in Fig. 2.

Decimation in many stages is improved than the single-phase decimation[14, 15)]. For the reason that the filter coefficients are also reduced[17, 18)]. Other than it ensures with the intention of rejection the anti-aliasing occur within the on the whole decimation process. This can be designed for every phase to keep away from anti-aliasing contained by the frequency band of attention exposed in Fig. 3.

2.2 Pre-emphasis

To compensate for the higher frequency component of the speech stream, the pre-emphasize is used. Systems that convey it have effectively tamed the human voice. The digital voice is given more prominence by the use of a digital filter that employs explicit transmission functions. The contribution of the voice signal (n) is assigned a preserved value. Equation 1 displays the high pass filtering computational equation for all users.

$$y(n) = s(n) - d \times s(n-1) \qquad (1)$$

Where 'd' is the coefficient for pre-emphasized. It can be changed between 0.1 to 0.9, where 'y(n)' is the output speech signal.

2.3 Framing

We will therefore assume that the signal is reasonably stable over extremely short time scales in order to keep things simple. The voice signal's intrinsic dynamic nature is the explanation behind this. Each lasting between twenty and forty milliseconds [23)]. When the size of the contained frame is significantly smaller, a sufficient number of samples are needed to produce a reliable spectral approximation.

2.4 Windowing

The windowed function is shown in equation (2) where y'(n) filtered output, s(n) input speech signal, and w(n) windowed function.

$$y'[n] = s[n] \times w[n] \qquad (2)$$

2.5 Fast Fourier Transform (FFT)

At this stage, we extract our windowed signal's spectrum-specific properties. The quantity of energy included in the signal at various frequency components must be understood.

$$X_i(k) = \sum_{n=1}^{N} x_i(n) e^{-j2\pi kn/N} \qquad 1 \le k \le K \quad (3)$$

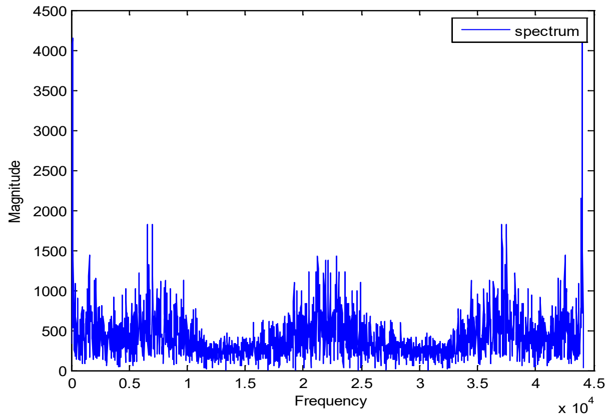

Fig. 3: Speech signal frequency spectrum using FFT

2.6 Frequency warping

In human perception, neither the spoken signals nor the pure tones can be represented by a linear scale. Every vocal stream has a subjective pitch (P) and frequency (f) assigned to it by the 'Mel' scale. This scale is called the 'Mel' scale. Thus, the relationship between the perceived pitch frequency and the original pitch frequency is depicted in this graph. For frequencies higher than one thousand hertz, the scale is logarithmic; for frequencies lower than one thousand hertz, it is linear. The effects on the human auditory system are depicted in Fig. 4.

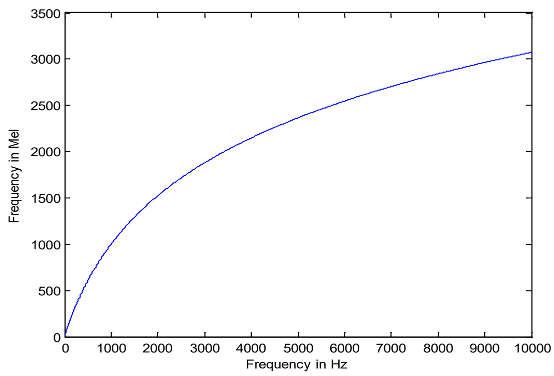

Fig. 4: Mel scale representation

2.7 Mel Filter banks

Beginning at the first frequency point, the first filter bank is positioned in its original position. When the first filter reaches its peak, the second frequency point will begin, and by the time the third frequency point appears, the filter will have returned to its initial value of zero.For the purpose of obtaining Mel filter banks, ten filters are positioned logarithmically above frequencies of 1000 Hz, while ten filters are separated linearly at frequencies that are lower than 1000 Hz. To get the intended outcomes, this is done. Each band of filters contributes energy that these filters gather.

The above figure contains 20 triangular bandpass filters shown in Fig. 5. The filters are placed at regular intervals along with the Mel scale frequency.

$$\boldsymbol{Mel\,(f) = 2595 \times log_{10}\left(1 + \frac{f}{700}\right)} \qquad \textbf{(4)}$$

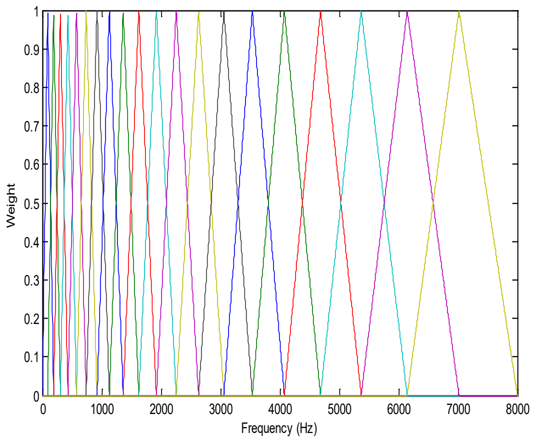

Fig. 5: Mel filter bank

2.8 Logarithmic compression

After that, the logarithm of each and every value in the Mel filter banks is calculated. In humans, the response to a stimuli is logarithmic because they are less reactive than other species. They are unable to predict even the slightest shift in the voice's level. The utilisation of log is beneficial in this situation as it enables the extraction of the most effective component for evaluating.

2.9 Cepstrum with DCT

Then, for each value in the Mel filter banks, the logarithm is computed. Due to their lower reactivity compared to other animals, humans exhibit a logarithmic response to stimuli. They have no idea what the next smallest change in volume will be. In this case, log is useful since it minimizes output and allows the extraction of the most effective component for evaluating the less sensitive input.

It is finally possible to restore the original shape of the logarithmic representation of the Mel spectrum. The establishment of the MFCC is predicated on this response.

It is the cepstral domain that MFCC represents for speech spectra. This sample displays the MFCC spectrum plot. Frame analysis alone takes the twelve most significant cepstral coefficients into account. In most cases, these cepstral coefficients do not correlate with spectrum [23, 24].

Here, the DCT is the process of transforming it into the time domain was applied. In terms of mathematics, MFCC can be represented as follows:

$$c[n] = \sum_{n=0}^{N} \log\left(\left|\sum_{n=0}^{N} x[n] e^{-\frac{j2\pi kn}{N}}\right|\right) \cos\left(\frac{k(n-0.5)\pi}{N}\right) \qquad (5)$$

Testing and training data for SVM classifier as an example: taken dataset (x1, y1)…………..(xn, yn)

The collection of training feature vectors is denoted by x_1, and the corresponding testing feature vectors are denoted by y_1. Each experiment i:

$$x_i=(x_i^{(1)}\ldots\ldots\ldots\ldots x_i^{(d)}) \qquad (6)$$

'xi' is This demonstrates whether the feature is present or not present xi(j) is real value

$$W{*}x=\sum_{j=1}^{d} w^j x^j \qquad (7)$$

'w' the most efficient linear separator is the weight of each vector, which is used and 'x' is the features vector.

determining each vector's margin: The nearest point's distance to 'x'is a primal form of SVM shown in Fig. 6.

- (Coefficients of training class)
- (Coefficients of testing class)

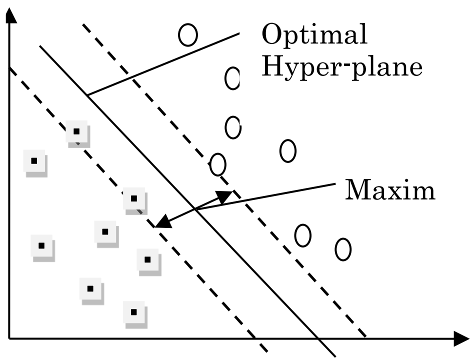

Fig.6: SVM classifier for training and testing class.

2.10 Speech database

Table 1. Speech sample collection details

S.No.	Speech pattern	Setting
1	Genders	Male
2	Total Speaker	13

3	Frequency	8000 Hz
4	Recording Language	Telugu
5	Recording Condition	Enclosed Room
6	Recording time	≥ 3.5 Sec
7	Sound Recorded	"Somebody ate food but I haven't seen anybody"
8	Accents	Rayalaseema, coastal Andhra and Telangana
9	Total utterance used	39

The pre-liminary work in the improvement of this planned technique of tone of voice identification scheme. It is collected information commencing Telugu speakers from the dissimilar region. The regions are RS, CA, and TG. For investigational assessment forty confined citizen speakers from each one area are recognized. The speech was recorded Audacity recording tool (https://www.audacityteam.org/) in a closed room. Speaker's voice was recorded and stored in ''.wav'' format. The recorded speeches are done by the smartphone. The voice preferred for recording is based on text-dependent accents identification. The text speech selected in English ''somebody ate food but I haven't seen anybody'' in RS, CA, and TS accent format. In the subsequent step, each accent model is transformed commencing ''.wav format. The ".wav recording format" is the most important hearing voice sentence for every speaker. It is a useful processing tool for proposed algorithms simulated by Mat lab software. For classification and development of database compared by the training and testing database. The recorded speech samples of twenty speakers are collected from TG, RS, and CA for accent recognition techniques. The speech collection details are given in Table 1.

3. Methodologies

A block diagram of accent recognition methodology is proposed in Fig, 2. The database collecting method used in this method is explained in the section before. The database gathered through individual testing and training for the suggested approach. The testing and training accent is taken in three accent formants as Telugu, Rayalaseema, and coastal Andhra of all twenty speakers. For all twenty speakers voice feature extracted using the MFCC feature extraction technique for all accents separately. The GMM approach is using for all extracted speaker's voice. Here the proposed method for speaker classification using MFCC-SVM and MFCC-k-NN methods is used. It is shown in Fig. 7.

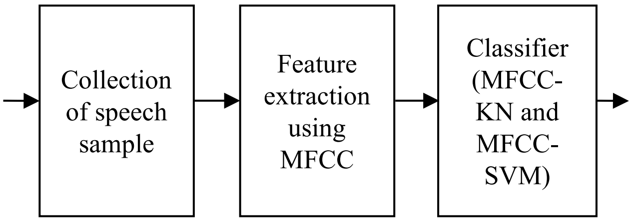

Fig.7: Accent recognition approach.

Subsequently, the importance of the arithmetical moment of every illustration is inserting in the database. That is supported by testing data and training data. Different two types of the classifier are used such as SVM and k-NN to classify the speech data after MFCC features. The different classifier performance is described in a relative- measurements of the classification method. The performance of speech identification is evaluated with previous techniques MFCC-GMM, Prosodic-NNC Vs MFCC-k-NN, and MFCC-SVM classification techniques.

4. Results and discussions

An entire of three utterances of each speaker's commencing the composed database was measured in the pronunciation appreciation method. Beyond the three utterances of every speaker's, three-voice samples are measured to test and train the classification, while an additional two voice sample is used for training identification efficiency of this system. So 13*3 = 39 In order to train the algorithm, we use a sample that contains all three accents. The remaining thirteen samples of the 39 speakers' voices are measured to see how well the identification process worked. You can see this in Table 2 down below. Using these voice signals as quality vectors, the MFCC feature was retrieved. Additionally, the technique presented in this research was trained using these vectors. We used these characteristic vectors for both training and recognizing the unique accents, as they were acquired from the voice samples. The methodologies of extracting the MFCC features are described in feature in the earlier part. Subsequent to extract the MFCC's features, SVM and k-NN classifiers are used to representation as well as recognize the accents of the test and train voice signal.

Table 2. Voice sample measured for an accent identification system

Accent	RS	CA	TG
No. of speaker	13	13	13
Training samples	26	26	26
Testing samples	13	13	13

The identification efficiency of MFCC-SVM and MFCC-k-NN dependent accents identification method for English in every accent are representing in Fig. 8.

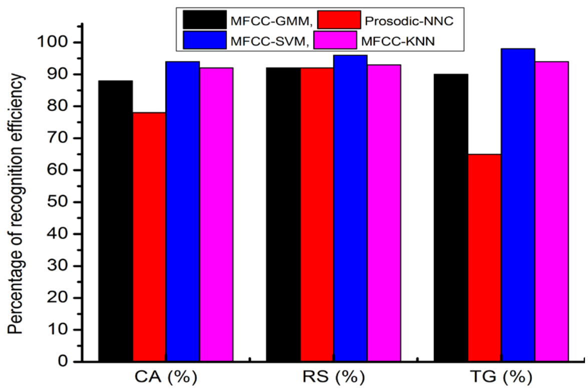

Fig. 8: Comparisons of accent recognition efficiency for the existing and proposed method

The effectiveness of the accent identification method by using, MFCC-GMM method and the Prosodic-NNC method are reported 91% and 78 % efficiency respectively. Therefore, by using this approach, and development of 5% by using the MFCC-SVM system and 2% by using the MFCC-k-NN method with respect to the MFCC-GMM method. The Prosodic features used by the Prosodic-NNC method for classification. The dataset used for the previous method (MFCC-GMM and Prosodic-NNC) as well as MFCC-SVM and MFCC-k-NN proposed method in Table 3. The comparison result is shown in table 3 that compares the previous (MFCC-GMM methods and Prosodic-NNC) with respect to proposed MFCC-SVM and MFCC-k-NN methods.

Table 3: Comparison result of the previous method and the proposed method

Specification	**Existing method**		**Proposed method**	
	Prosodic-NNC	**MFCC-GMM**	**MFCC-SVM**	**MFCC-kNN**
Feature Used	Prosodic features	MFCC features	MFCC features	MFCC features
Classification Method	NNC	GMM	SVM	k-NN
No. of speakers	13	13	13	13
Recognition rate (%) Coastal Andhra	77	88	94	92
Recognition rate (%) Rayalaseema	92	92	96	93
Recognition rate (%) Telangana	78	91	98	94
Overall (%) recognition accuracy	**78**	**91**	**96**	**93**

The comparison results between the previous method and the proposed method shown as well. The identification efficiency increased by 6% intended for coastal Andhra inflection using the MFCC-SVM technique and 4% inflection changed by the MFCC-k-NN method in comparison to MFCC-GMM method. The identification efficiency increased by 17% intended for coastal Andhra inflection using the MFCC-SVM technique and 15% inflection changed by the MFCC-k-NN method in comparison to Prosodic-NNC method. On the other hand, the identification efficiency increased by 4% intended for Rayalaseema accent using the MFCC-SVM technique and 1% accent changed by the MFCC-k-NN method in comparison to MFCC-GMM method. The identification efficiency increased by 4% intended for Rayalaseema inflection using the MFCC-SVM technique and 1% inflection changed by the MFCC-k-NN method in comparison to the Prosodic-NNC method. In the general efficiency of the MFCC-SVM system efficiency is 96 % and MFCC-k-NN system efficiency is 93% as shown in Fig. 8. Figure 8 represents the similarity among the general efficiency of Prosodic-NNC, MFCC-GMM, MFCC-SVM, MFCC-known methods. The identification efficiency increased by 6% intended Telangana accent inflection using the MFCC-SVM technique and 2% inflection changed by the MFCC-k-NN method in comparison to the MFCC-GMM method. The identification efficiency increased by 23% intended for Telangana accent inflection using the MFCC-SVM technique and 19% inflection changed by the MFCC-k-NN method in comparison to Prosodic-NNC method.

In general, the identification efficiency obtained using the MFCC-SVM technique is 96% performance enhancement of 6% evaluated to the MFCC-GMM method, and using the MFCC-k-NN technique is 93% efficiency improvement of 3% compared to MFCC-GMM. It is also found that the identification efficiency obtained using the MFCC-SVM technique is 96% performance enhancement of 18% evaluated to the Prosodic-NNC method and using the MFCC-k-NN technique is 93% efficiency improvement of 15% compared to Prosodic-NNC.

5. Conclusion

This article suggests an algorithm to determine the significance of accent recognition using a range of methods. The training and testing databases provide a uniformly distributed diversity of accents, which facilitates the effective extraction of accent-based MFCC feature extraction techniques. Additionally, this paper investigates two different strategies for accent identification. Based on two distinct classifiers, MFCC-k-NN and MFCC-SVM, these systems are constructed. This article is carried out to create a classification to find the speaker's accent at a different stage. This is carried out by using dissimilar feature extraction techniques of speech, one of them MFCC. It is the speaker's pitch and formants that have a significant impact on the auditory characteristics. The combination of MFCC with the sensing characteristic of speech makes acoustic feature extraction an effective method for accent recognition. This is due to the fact that it is paired with features of speech. The identification rate of TG pronunciation using the MFCC-SVM technique is 98% performance an improvement of 6% evaluated to the MFCC-GMM method and 23% performance improvement evaluated to over Prosodic-NNC technique. The accent identification rate of RS accent using MFCC-SVM also has shown a very good performance rate. The MFCC-SVM techniques have a recognition accuracy of 94 % for the costal Andhra accent, that's how the development of 6%. The overall identification rate using MFCC-SV and MFCC-k-NN method is 96 % and 93% respectively.

References

1) Singh, Mahesh K., A. K. Singh, and Narendra Singh. "Multimedia analysis for disguised voice and classification efficiency." *Multimedia Tools and Applications* 78.(20): 29395-29411(2019). doi: 10.1007/s11042-018-6718-6.
2) Singh, Mahesh, Durgesh Nandan, and Sanjeev Kumar. "Statistical Analysis of Lower and Raised Pitch Voice Signal and Its Efficiency Calculation." *Traitement du Signal* 36.(5): 455-461 (2019). doi: 10.18280/ts.360511.
3) Hamzah, N., et al. "Identification of CNT growth region and optimum time for catalyst oxidation: experimental and modelling studies of flame synthesis." *Evergreen Jt J Novel Carbon Resour Sci Green Asia Strategy* 6: 85 (2019). doi:10.5109/2328409.
4) Satya, P. Mohana, et al. "Stripe Noise Removal from Remote Sensing Images." *2021 6th International Conference on Signal Processing, Computing and Control (ISPCC)*. IEEE, 2021. **doi:** 10.1109/ISPCC53510.2021.9609457.
5) Syahrul, Azwan Shaedi, et al. "Entropy generation minimization of two-phase flow in a mini channel with genetic algorithm." *Evergreen, Joint Journal of Novel Carbon Resource Sciences & Green Asia Strategy* 6.01: 39-43 (2019). doi:10.5109/2321004.
6) Nandini, A., R. Anil Kumar, and Mahesh K. Singh. "Circuits Based on the Memristor for Fundamental Operations." *2021 6th International Conference on Signal Processing, Computing and Control (ISPCC)*. IEEE, 2021. **doi:** 10.1109/ISPCC53510.2021.9609439.
7) Wulan, P. P. D. K., Juli Ayu Ningtyas, and Miranda Hasanah. "The effect of nickel coating on stainless steel 316 on growth of carbon nanotube from polypropylene waste." *Evergreen* 6.1: 98-102 (2019) doi:10.5109/2328411.
8) Anushka, R. L., et al. "Lens less Cameras for Face Detection and Verification." *2021 6th International Conference on Signal Processing, Computing and Control (ISPCC)*. IEEE, 2021. doi: **doi:** 10.1109/ISPCC53510.2021.9609392.
9) Balaji, V. Nithin, P. Bala Srinivas, and Mahesh K. Singh. "Neuromorphic advancements architecture design and its implementations technique. "*Materials Today: Proceedings* (2021). doi: 10.1016/ j.matpr. 2021.06.273.
10) Wong, Keng Yinn, et al. "Effects of surgical staff turning motion on airflow distribution inside a hospital operating room." *Evergreen* 6.1 52-58 (2019). doi:10.5109/2321008.
11) Alhamid, M. I., et al. "Study on the Effectiveness of Ozonation Technique in Preventing Scale Precipitation on Closed System Cooling Towers." *Evergreen* 6.1: 65-70 (2019). doi:10.5109/2321013.
12) Singh, Mahesh K., Narendra Singh, and A. K. Singh. "Speaker's voice characteristics and similarity measurement using Euclidean distances." *2019 International Conference on Signal Processing and Communication (ICSC)*. IEEE, 2019.doi: 10.1109/ICSC 45622. 2019. 8938366.
13) Veerendra, G., et al. "Detecting plant Diseases, quantifying and classifying digital image processing techniques." *Materials Today: Proceedings* (2021). doi: 10.1016/j.matpr. 2021.06.271.
14) Syahrudin, Muhamad Fuad, Muhammad Arif Budiyanto, and Muhammad Aziz Murdianto. "Analysis of the Use of Stern Foil on the High-Speed Patrol Boat on Full Draft Condition." *Evergreen* 7.2 (2020): 262-267. doi:10.5109/4055230.
15) Padma, Uppalapati, Samudrala Jagadish, and Mahesh K. Singh. "Recognition of plant's leaf infection by image processing approach."*MaterialsToday: Proceedings* (2021). doi: 10.1016/j.matpr. 2021. 06.297.
16) Berawi, Mohammed Ali, et al. "Determining the Prioritized Victim of Earthquake Disaster Using Fuzzy Logic and Decision Tree Approach." *Evergreen* 7.2: 246-252 (2020). doi:10.5109/4055227.
17) Daud, Dalina, et al. "Radical Scavenging Activity Assay and Red Fluorescence Microscopy Studies: Antioxidant Properties of Selected Young and Mature Leaves for Application in Pharmaceutical Industry." *Evergreen* 7.2: 216-220 (2020). doi:10.5109/4055222
18) Punyavathi, G., M. Neeladri, and Mahesh K. Singh. "Vehicle tracking and detection techniques using IoT." *Materials Today: Proceedings* (2021). doi: 10.1016/j.matpr. 2021.06.283.
19) Singh, Mahesh K., A. K. Singh, and Narendra Singh. "Multimedia utilization of non-computerized disguised voice and acoustic similarity

measurement." *Multimedia Tools and Applications* 79.(47), 35537-35552 (2020). doi: 10.1007/s11042-019-08329-y.

20) Akbar, Lasta Azmillah, et al. "Method development of measuring depth of burn using laser ranging in laboratory scale." *Evergreen* 7.2: 268-274 (2020). doi: 10.5109/4055231.
21) Balaji, V. Nithin, P. Bala Srinivas, and Mahesh K. Singh. "Neuromorphic advancements architecture design and its implementations technique." *Materials Today: Proceedings* (2021). doi: 10.1016/j.matpr. 2021.06.273.
22) Syahrudin, Muhamad Fuad, Muhammad Arif Budiyanto, and Muhammad Aziz Murdianto. "Analysis of the Use of Stern Foil on the High Speed Patrol Boat on Full Draft Condition." *Evergreen* 7.(2): 262-267 (2020). doi:10.5109/4055230.
23) M.A. Lambert, and B.J. Jones, “Automotive adsorption air conditioner powered by exhaust heat. part 2: detailed design and analysis,” *Proc. Inst. Mech. Eng. Part D J. Automob. Eng.*, **220** (*7*) 973–989 (2006). doi:10.1243/0954 4070 JAUTO222.
24) M. Elimelech, and W.A. Phillip, “The future of seawater desalination: energy, technology, and the environment,” *Science (80-.).*, **333** (*6043*) 712–717 (2011). doi:10.1126/science.1200488.
25) Amiruddin, Hilmi, et al. "CNGDI Engine Performance Using a Vaned Diffuser Turbocharger Compressor with Varying Injection Timings.". 414-420 (2021). doi: 10.5109/4480723