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## TOPICAL REVIEW

# Mel Frequency Cepstral Coefficient and Its Applications: A Review

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**ABSTRACT** Feature extraction and representation has significant impact on the performance of any machine learning method. Mel Frequency Cepstrum Coefficient (MFCC) is designed to model features of audio signal and is widely used in various fields. This paper aims to review the applications that the MFCC is used for in addition to some issues that facing the MFCC computation and its impact on the model performance. These issues include the use of MFCC for non-acoustic signals, adopting the MFCC alone or combining it with other features, the use of time series versus global representation of the MFCC, following the standard form of the MFCC computation versus modifying its parameters, and supplying the traditional machine learning methods versus the deep learning methods.

**INDEX TERMS** MFCC, speech analysis, cepstrum analysis, feature extraction, indusial analysis.

## I. INTRODUCTION

The complexity of any system is a critical issue, though reducing it has been a promising area for researchers. One of the basic demands for any machine learning application is to have an enormous size dataset in terms of number of samples and variables. Nowadays, the size of the collected dataset tends to be larger such that it leads to the increase of the adopted system complexity. For this purpose, many approaches have been developed to reduce dimensionality [1]. Dimensional reduction helps in data compression since it reduces storage space and computation time. It is also a way to eliminate redundancies from the dataset. Dimensional reduction can be conducted in using feature extraction and feature selection techniques [2].

The feature extraction is the process of extracting and tackling hidden information in the raw data signal [3]. Data can be more manageable by applying feature extraction because it removes all ineffective features from the data without losing any important or relevant data. Moreover, feature extraction techniques help to develop a system with less machine's efforts and increase the speed of learning and generalization steps in the machine learning process [4], [5].

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Nowadays, many feature extraction techniques are available in a variety of fields based on the characteristics of the raw data. In most of the fields, finding harmonics and sidebands of signal in both time and frequency domain are important to any pattern recognition system. Power spectrum using Fast Fourier Transform (FFT) is used to capture the harmonics and sidebands of the signal in the time domain. While cepstrum; such as Mel Frequency Cepstrum Coefficient (MFCC), Gamma Tone Cepstrum Coefficient (GTCC), is capable to extract harmonics and sidebands of the spectrum version of the signal [6].

Although MFCC is used to extract feature from input data of various fields, it faces many challenges, which have not been covered comprehensively in the literature. The purpose of this paper is to conduct a comprehensive review of MFCC and its applications including speech recognition, speaker recognition, emotion recognition, bearing fault detection, gear fault detection, Electrocardiogram (ECG) and Electroencephalogram (EEG) classification. Additionally, the paper targets answering the following questions regarding the use of MFCC:

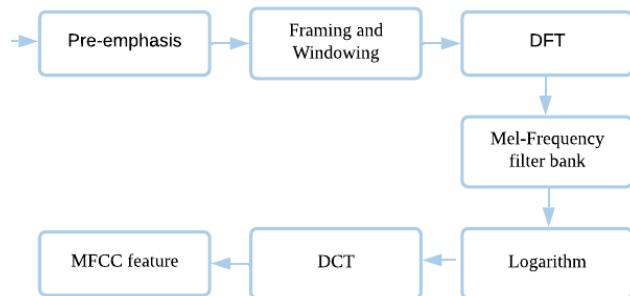
1. How wide is MFCC applied to other fields rather than acoustic signal?
2. Is the MFCC well-tuned to fit the demand of various applications?

3. Since the MFCC is computed in short term signal, has it been used more in a time-series or in a global representation?
4. Is MFCC mostly combined with other features, or it is used alone?
5. Does MFCC feed deep learning more or traditional machine learning methods?
6. What are the most well-known used windows in the data framing process?
7. Which classifier is used more frequently with MFCC and what could be the reason?

The rest of this paper is organized as follows; the computation of MFCC is explained in section 2. Section 3 introduces MFCC applications. Followed by a summarized analysis presentation in section 4, and finally the conclusion is drowned in section 5.

**II. MFCC IMPLEMENTATION**

MFCC is one of the commonly used features that has been used in a variety of applications especially in voice signal processing such as speaker recognition, voice recognition, and gender identification [6]. The MFCC can be calculated by conducting five consecutive processes, namely signal framing, computing of the power spectrum, applying a Mel filter bank to the obtained power spectra, calculating the logarithm values of all filter banks, and finally applying the DCT. Figure (1) illustrates the processes of MFCC computation [7].



**FIGURE 1. MFCC framework.**

**A. PRE-EMPHASIS**

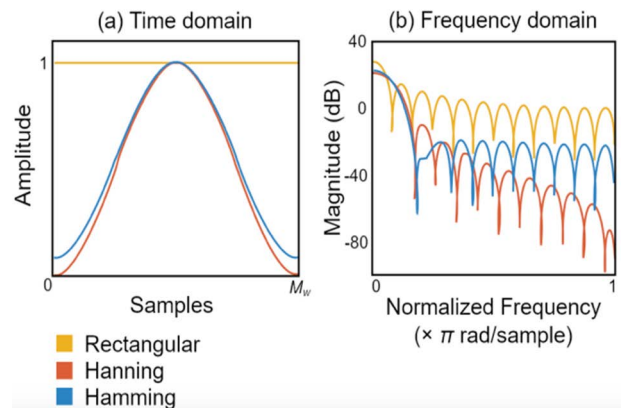
Pre-emphasis is one of the common pre-processing practices in signal processing area which is used to compensate the high frequency of the signal that was suppressed during the signal production. Pre-emphasis is the very first step during the MFCC adaptation, which can be adopted by simply applying a high-pass filter with a setting of [1, -0.97]. The filtering process alters energy distribution across frequencies, as well as the overall energy level [8].

**B. SIGNAL FRAMING AND WINDOWING**

The idea behind splitting signals into distinct “frames” is to break down the raw data signal into frames where the signal tends to be more stationary. For stable acoustic characteristics, speech needs to be examined over a sufficiently short

period of time. Regarding the speech signal, the period of 20-30ms time is reported to be a Quasi-Stationary Segment (QSS) since the time between two glottal closure is shown to be around 20ms. However, vowel voices are reported to be captured in 40ms- 80ms [9]. Hence, short-term spectral measurements are typically carried out over 20 ms windows, and each frame is overlapped by 10 ms with the next one. Overlaps of frames by 10 ms enables the temporal characteristics the speech signal to be tracked. With overlapping of frames speech, sound representation would be approximately centered at some frame.

On each frame, a window is applied to narrow the signal towards the border of the frame. In general, Hanning and Hamming windows [10] are among the most well-known nominees. These windows can enhance harmonics, smooth edges, and diminish edge effect while taking a DFT on the signal. Figure (2) illustrates the rectangular Hamming and Hanning windows in both time and frequency domains.



**FIGURE 2. The rectangular hanning and hamming windows in the time and frequency domains [11].**

**C. POWER SPECTRUM**

A power spectrum can be described as the distribution of the power of the frequency components that composes the signal [12]. Traditionally, Discrete Fourier Transform (DFT) is utilized to compute the power spectrum. The power spectrum of each of the obtained frames must be determined based on the below equation (1):

$$X(k) = \sum_{n=0}^{N-1} x(n)e^{-\frac{2\pi jnK}{N}} \quad k = 1, 2, 3 \dots N - 1 \quad (1)$$

where  $x(n)$  is discrete signal and  $N$  is the length of the signal.

**D. MEL FILTER BANK**

The Mel band-pass filter is a bank of filters, which is constructed based on pitch perception. The Mel filter was originally developed for speech analysis and like human ear perceiving of speech, it targets extracting non-linear representation of the speech signal. The convention Mel filter-bank is constructed of 40 triangular filters [13]. The transfer function

(TF) of each of the  $m$ -th filter can be computed via equation (2),

$$H_m(k) = \begin{cases} 0 & k < f(m-1) \\ \frac{k-f(m-1)}{f(m)-f(m-1)} & f(m-1) \leq k < f(m) \\ 1 & k = f(m) \\ \frac{f(m+1)-k}{f(m+1)-f(m)} & f(m) < k \leq f(m+1) \\ 0 & k > f(m+1) \end{cases} \quad (2)$$

where,  $f(m)$  is the centre frequency of the triangular filter and  $\sum_{m=1}^{M-1} H_m(k) = 1$ .

The Mel scale to the response frequency and vice versa is computed by equations (3) and (4)

$$m = 2595 \log_{10} \left( 1 + \frac{f}{700} \right) \quad (3)$$

$$f = 700 \left( 10^{\frac{m}{2595}} - 1 \right) \quad (4)$$

**E. DISCRETE COSINE TRANSFORMS (DCT)**

A Discrete Cosine transform (DCT) expresses a finite sequence of data points regarding a summation of cosine functions oscillating at different frequencies. The DCT was introduced by Nasir Ahmed in 1972. In the MFCC process, the DCT is applied on the Mel filter bank to select most accelerative coefficients or to separate the relationship in the log spectral magnitudes from the filter-bank [14]. The DCT is computed by the below equation (5)

$$X(k) = \sum_{n=0}^{N-1} x_n * \cos \left( \frac{2\pi jnk}{N} \right), \quad k = 1, 2, 3 \dots N - 1 \quad (5)$$

where  $x_n$  is discrete signal and  $N$  is the length of the signal.

**III. MFCC APPLICATIONS**

Nowadays, many huge datasets are available that have been collected in various fields. It is not applicable to deal with the whole of these datasets, which are used to develop automatic systems [15]. Mel Frequency Cepstrum Coefficient (MFCC) is a framework feature extraction technique that has been adopted in many areas and frequently reported to be useful for various applications. In this section a set of these applications are presented (see figure 3).

**A. MFCC IN ACOUSTIC ANALYSIS**

**1) SPEECH ANALYSIS**

Speech signal analysis aims to find out more informative, compact, and relevant knowledge than the speech signal raw data itself. Vocal tract features (also named as segmental, spectral or system features) [16] are one of the well-known representations of speech analysis. When the process of speaking starts, the air is traveling out from the lungs, the air movements within the vocal tract create a unique version

of the sound. Vocal tract features are well reflected in the frequency domain of the speech signal. There are various developed techniques to extract vocal tract features, one of which is the MFCC. The MFCC can capture the vocal tract features, since it extracts human ear information, which has a response of a non-linear scale instead of a linear scale [17]. Among the most well-known applications that utilize MFCC of the speech signal are emotion recognition in speech, language and dialect recognition and speech recognition as shown in the following subsections.

*a: AUTOMATIC SPEECH RECOGNITION*

The ASR model targets the recognition of four main categories, which are isolated word, connected word, continuous speech, and spontaneous speech [18]. Regarding the isolated word speech recognition, the speaker needs to pause briefly between words. While connected work recognition aims to recognize words that are separated with a minimum pause. On the other hand, a continuous speech recognition system does not require pause between words as the speech is continuous [19]. The continuous speech recognition model is dealing with an almost natural sound. However, spontaneous speech can handle natural speech in various languages. One of the shared challenges in all the models is providing a generalized and robust feature of the speech signal to achieve high recognition accuracy.

The MFCC feature is one of the well-known features especially for isolated word speech recognition for instance the MFCC feature was extracted from speech signals of spoken words (isolated) and then classified via Support Vector Machine (SVM) and Maximum Likelihood Classifier [20]. Dhingra et al. proposed a model to isolate 10 digits through their speech signal. The MFCC was extracted from the spoken words and identified based on a similarity measurement which was measured by Dynamic Time Warping (DTW) [21]. Omer et al. used MFCC with two other spectral based features to feed a pairwise SVM classifier and the model was used for isolating uttered Kurdish digits (0-9) recognition systems [22]. Author in [23] used MFCC to feed an Artificial Neural Network (ANN) classifier to identify the isolated Arabic words.

In 2019, NASSIF et al. reviewed 174 papers which were developed ASR models based on deep learning models where all the deep learning models were fed by extracting specific features. Moreover, all the papers (174) have been published between 2006 to 2018. They found that most of the researchers, which was about %69, still use MFCCs as a feature to feed the machine learning models [24].

Despite these usages of MFCC, there is a limitation of this feature for speech recognition system due to the fixed window size (20ms-30ms) and this limitation leads to two problems. Firstly, the obtained frequency resolution for the Quasi-Stationary Segment (QSS) longer than 20 ms is quite low compared to what could be achieved using longer analysis windows. Secondly, the analysis window can span the transition between two QSSs and the MFCC vectors extracted

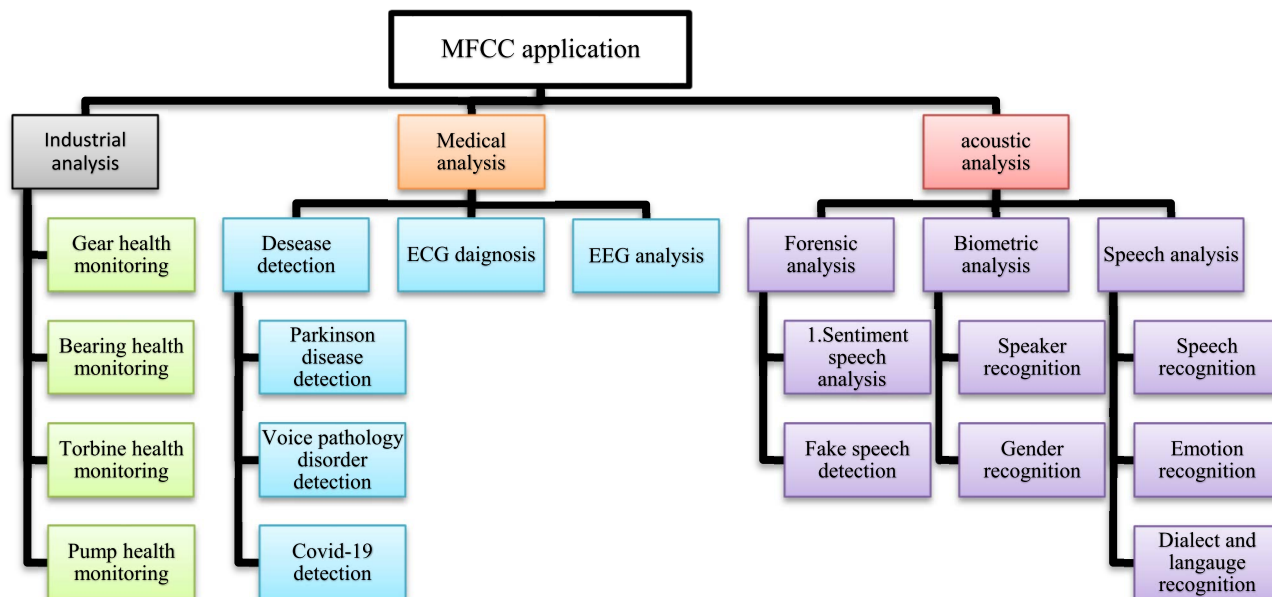


FIGURE 3. Common application of MFCC.

from such transition segments do not provide the information about a single unique (stationary) class which may lead to poor discrimination in a pattern recognition problem [9]. Table (1) summarizes some research, where the MFCC is involved in speech recognition application in the past decade.

*b: SPEECH EMOTION RECOGNITION*

Speech Emotion Recognition (SER) is the process of identifying the emotion of the human from the speech signal. Based on the existing literature, it is well understood that MFCC features for SER can reach a high recognition rate compared to other cepstrum features because it is a short-term spectral based feature that leads to extract a rich amount of information from speech signals [38]. Consequently, the MFCC is adopted frequently for SER by the researchers for instance: Aouani and Ayed examined two set of features that includes MFCCs. Features were examined using 39 MFCCs and 65 MFCCs together with the SVM classifier, which was used to evaluate both sets. The finding of this paper shows that the first set which was 39 MFCCs, can outperform 65 MFCCs [39]. On the other hand, the related information to the emotion is reported to be sparse and distributed in various features [40]. Consequently, researchers integrated MFCCs with other sort of features, for example, MFCCs and Gamma-Tone Cepstral Coefficients (GTCCs) features were fused together for SER and fed either to the GMM classifier [41] or ESN model [42]. Improvement in emotion recognition has also been noticed by hybridizing some features including formants, pitch, zero crossing, MFCC and its statistical parameters [43]. Aouani et al. studied a model for emotion recognition based on the SVM where the SVM was fed by 42 -dimensional vector which consisted

of 39 coefficients of MFCC, a Teager Energy Operator, a Zero Crossing Rate, and a Harmonic to Noise Rate. The obtained feature (42 -dimensional vector) was reduced by Auto-Encoder, the results confirmed that the reduced dimension representation effectively improved the SER accuracy [44]. However, in another study, six basic emotional states were classified based on GMM, which was fed by two sets of features, namely Sub-band based Cepstral Parameter and MFCC features. Here, the Sub-band based Cepstral Parameter features is reported to outperform the MFCC features [45]. Table (2) provides more details about other research that used MFCC for human emotion and music emotion recognition.

*c: LANGUAGE AND DIALECT RECOGNITION*

Language recognition system aims to recognize the language of the speaker, which can be developed based on the machine learning model. Dialect recognition is quite like language recognition. However, the dialect recognition focuses on categorizing the dialects or accents rather than categorizing the languages and consequently, more challenging due to the linguistic similarities among dialects. Dialect recognition is an important application, and it has been considered as one of the very first steps to speech recognition. This may be the reason for the plenty of articles that have been published. Various features for both language and dialect recognition are available in the literature such as MFCC (see table (3)), singular values decomposition and Linear Predictive Codes (LPC).

Koolagudi et al. extracted several MFCC sets, which were different in dimension (6, 8, 13, 19, 21, 29 and 35), from the speech signal for identifying a language such as Bangla, Assamese, Gujarati, Hindi, Nepali, Kashmiri, Malayalam,

**TABLE 1. Summarizing of those papers that use MFCC for automatic speech recognition.**

Classification	Feature	Advantage	Disadvantage
DTW	MFCC [25] [21] [26], Weighted MFCC[19]	Usefulness of 1-12 MFCC[25], Reasonability of use MFCC[21] [26], Weighted MFCC achieved higher recognition rate[19].	Low MFCC confidents are sensitive to noise[25], other features might be required for differentiating more spoken word[21] [26], in order to capture more patterns, MFCC coefficients need to be selected [19]
ANN	MFCC[23], MFCC+LPC[27], LPC+PLP+MFCC[28]	MFCC can improve the reliability of speech recognition	MFCC is not sufficient for speech recognition, and combination with other features might be needed[27]. MFCC cannot predict future features based on previous features[28].
SVM	Dimension of MFCC reduced by PCA[20]	Improvement in recognition rates significantly when MFCC was fed to SVM	Not all MFCC coefficients are significant for speech recognition
HMM	MFCC, LPCC, PLP, RASTA-PLP[29], Wavelet-MFCC[30]	MFCC and its delta provides the best rate of recognition rate[29], Wavelet was used to denoise the speech which leads to have better performance [30]	MFCC alone is not a robust feature[29] [30]
GMM	MFCC + DPGMM[31], MFCC[32] [33]	Fusion between (MFCC + DPGMM) improve ASR compared to original MFCC[31], MFCC is reasonable to use for speech recognition [32] [33]	MFCC extracts the characteristics from the input speech signal with respect to a particular word uttered by a particular speaker[32] [33]
Bayes classifier	MFCC-Equivalent Rectangular Bandwidth [34]	Increasing filter bandwidth improves recognition rate.	For clean speech recognition, performance of MFCC- ERB does not change when number filter increases from 40 to 80 filters
Statistical analysis	Frequency Band Energy (FBE)- MFCC[35], MFCC from vocal-tract length normalization (VTLN) and without VTLN[36], MFCC[37]	FBE-MFCC can reduce error rate by about 10.0%[35], better not to scale the bandwidth of the filters during VTLN and scaling should only be done on the filter center frequencies[36], MFCC feature is the best suitable feature for digit recognition[37]	0th coefficient of the MFCC is unreliable [35]. Center frequencies should be scaled to improve the performance for children speech recognition[36].

Marathi, Rajasthani, Odia, Punjabi, Tamil, Telugu, Kannada, and Urdu. Among these MFCC sets (6, 8, 13, 19, 21, 29 and 35) nineteen dimensions outperformed the other sets [48].

Warohma et al. developed a model for Indonesian dialect recognition based on the multilayer perceptron. The multilayer perceptron was fed by obtaining MFCC from the speech signal [49]. Tawaqal and Suyanto claimed that the use of the traditional machine learning approach gives a low accuracy for dialect recognition, and they proposed a model for increasing the performance of Indonesian dialects recognition system based on deep recurrent neural network (DRNN) where the DRNN was trained by MFCC feature [50]. Mansour et al. investigates the usage of MFCC and LPC for language identification, namely Arabic, English and French. Both features were evaluated based on the Artificial Neural Network (ANN) and as a result, MFCC shows

better performance to identify these languages compared to LPC [51].

The MFCC feature was extracted by conducting MFCC steps and fed to the GMM approach for identified dialects of Himachal Pradesh. The result shows high performance of MFCC for identification of some dialects [52]. However, Al-Talabani et al [53], evaluated three features including the MFCC, Local binary pattern (LBP), and LPC separately and as a merged form. The adopted features used to feed the SVM model to identify Kurdish dialects and distinguish between some languages including Kurdish, Arabic, Turkish, and Persian. The result shows that the LPC has better performance than MFCC and a fusion feature LBP-LPC outperformed the rest of the feature's form.

Based on the existing literature, the MFCC features do not always show capability to outperform other well-known features such as LPC. This may be due to the language and

**TABLE 2. Summarizing of those papers that use MFCC for emotion recognition.**

Classification	Feature	Advantage	Disadvantage
GMM	MFCC[41], MFCC+ Sub-band based Cepstral [45]	Influence of frame duration to MFCC performance [41], still reasonable to use MFCC [45]	The performance of SBC outperforms the MFCC, and SBC parameters are less sensitive to the noisy data compared to MFCC [45]
SVM	24 MFCC[46], 39, 65 MFCC[39], 39 MFCC, Zero Crossing Rate, Harmonic to Noise Rate and Teager Energy Operator[44], Pitch, formants, zero crossing, MFCC[43]	MFCC is one of the impactful features for emotion and highest accuracy obtained by feeding the features to SVM-RBF kernel	MFCC carry less information about fear and sadness [46]. Increase of MFCC coefficients is proportional with the performance of recognition system [39], formants feature increase the performance of MFCC for emotion recognition [43]
AANN	MFCC[38], MFCC and residual phase[47]	MFCC with AANN outperform MFCC with SVM[38], The fusion features with SVM for music emotion recognition get higher result compared to AANN and RBFNN[47]	MFCC carry out all feature regrading music emotion. So, researchers have been combined MFCC with other features.

**TABLE 3. Summarizing of those papers that use MFCC for language and dialect recognition.**

Classification	Feature	Advantage	Disadvantage
GMM	MFCC[48]	1-19 MFCC was the best set to identify languages compared to the (1 to 6,8,13, 21 and 29) set	This is for the Indian language which might change for other languages.
ANN	MFCC[49]	MFCC-ANN model shows capability in identifying the dialects	The performance of MFCC might be vary based on the dialect characterized
CNN	Examine MFCC, FBANK and spectrogram energies[54]	FBANK-CNN achieves slightly better results than MFCC-CNN	MFCC-CNN has lower performance compared to the FBANK-CNN

dialect properties in addition to the nature of collected data. However, the studies in the literature show that it is one of the informative features for language and dialect recognition.

**2) BIOMETRIC APPLICATION**

Biometric application is an application which allows to either confirm or determine the identity of a certain characteristic of an individual. The aim of these applications is to confirm that the provided services are accessed only by a legitimate user. Biometric applications can be classified into two categories based on their task such as verification and identification application, where the verification application validates a person’s identity by comparing the captured biometric information with her/his own biometric template which is stored in the database and the relationship between the objective and the database is called one to one. While, identification application is called one to many as the application tries to identify an individual by searching the templates of all the users in the

database [22]. Based on the existing literature, the MFCC has been used in two biometric applications, speaker recognition and gender recognition over the phone call.

*a: SPEAKER RECOGNITION*

Speaker recognition is the process of automatically recognizing the speaker based on their speech signal and can be classified into six categories such as speaker identification, speaker verification, speaker detection, speaker segmentation, speaker clustering and speaker diarization [55]. Speech signals contain speaker-specific information which can be extracted and fed to a machine learning algorithm to learn a specific pattern in it. MFCC and LPC are considered as the most two well-known features that have been widely used by researchers for speaker recognition applications, due to their capacity to capture the repetitive nature and efficiency of speech signals [55], [56]. Plenty of research have claimed that the MFCC is an effective feature in correctly recognizing

speakers. For instance, three features for automatic speech recognition were evaluated based on the Fuzzy approach including MFCC, dynamic time warping, and fast Fourier transform. Based on their result, the MFCC improves the performance of the fuzzy model compared to fast Fourier transformation features [57]. Al-Ali et al. enhanced forensic speaker verification based on the fusion features namely the MFCC and Discrete Wavelet Transform (DWT), where their models were evaluated in a noisy environment [58]. Abdul investigated the MFCC feature for speaker identification. He used the MFCC features to feed to the CNN and the result shows that the MFCC features could be used to train the CNN model to distinguish between speakers [7]. Despite the capacity of MFCC in capturing the characteristics of a speaker, the performance of MFCC degrades on complex speech datasets and in noise environments. For instance [59] present that the speaker recognition using MFCC and k-NN significantly degrades under noisy environment, and conclude that denoising the input signal can improve the result more when the highest MFCCs is adopted. To overcome this problem, in [60] a multi-channel training framework within the deep speaker embedding network was proposed for speaker recognition under reverberant and noisy environment. The method receives the time-, frequency-, and spatial-information from the multi-channel input to improve the robustness speaker embedding process. The work concludes that little increase in model parameters, can make the method significantly outperform i-vector with MFCC system with front-end signal enhancement. Additionally, Jahangir et al proposed fusion features based on MFCC and time-based features. The fusion features were fed to the DNN to identify speakers. The result shows that the limitation of the MFCC feature can be solved by this approach [56]. Table (4) displays the summarization of a further thirty papers that used the MFCC for speaker recognition.

#### *b: GENDER RECOGNITION OVER THE PHONE CALL*

Gender recognition is the process of identifying a speaker's gender via analysis and comparison of patterns. Gender recognition is one of the effective techniques for biometric and has been a widely interested application for forensic teams. The most Common feature for gender recognition is the pitch feature of the speech. However, the literature, refers to the use of the MFCC features for gender recognition as well. For example, MFCC features were merged with the speaker's mean pitch for gender recognition. Both features were extracted from the acoustic signal and fed to the Gaussian Mixture Model [89]. The MFCC features were extracted from telephonic speech. The MFCC features were evaluated with several machine learning algorithms such as random forest, k-nearest neighbor, multilayer perceptron, naïve Bayes, and support vector machine [90]. Kang and Chang optimized the MFCC feature based on minimum classification error "SVM" and called weighted MFCC as a weight vector of the coefficients was optimized. The weighted MFCC feature

outperformed conventional MFCC [91]. More details are shown in Table (5).

#### *3) DIGITAL FORENSIC*

Digital forensic can be defined as an application or a process which helps the forensic team to identify, analyze and extract important information regarding a specific crime or fakes from digital data. Usually, it is considered as robust evidence in court of law. Digital forensic applications vary depending on obtained information such as Network information and personal information about criminals.

##### *a: SENTIMENT SPEECH ANALYSIS*

Sentiment speech detection is the analysis of the speech signal to extract subjective information in source material for identifying the mood of the speaker and customer that helps a business understand the social sentiment of their product and service during the monitoring of online chats. Generally, sentiment speech analysis classifies acoustic data into three statuses including positive, negative, and neutral categories [94]. The MFCC feature has been used a lot for sentiment speech analysis; for instance, Amiriparian et al. trained SVM based on the bag-of-audio-words (BoAW), which was obtained from the 39-dimensional MFCC feature. The 39-dimensional MFCCs consist of 12-MFCCs, 12- $\Delta$ MFCCs, 12- $\Delta\Delta$ MFCCs, Energy(E),  $\Delta E$ , and  $\Delta\Delta E$  [95]. The 13, 65 and 130-Dimension MFCCs were also used to feed a sentiment model based on Gaussian Mixture Models (GMM) and Deep Neural Network (DNN) classifiers separately and the result shows that the 65 dimensions MFCC with the DNN outperformed the GMM model [96]. Authors in [97] studied Sentiment Analysis on Speaker Specific Speech by extracting the MFCC feature from the speech signal and feeding it to Dynamic Time Wrapping (DTW).

##### *b: FAKE SPEECH DETECTION*

Although many recent technologies have been developed for voice recognition speaker verification, it still struggles and opens issues which is having a universal fake speech and it needs to be detected. The main aim of fake speech detection is to differentiate between a fake speech and a natural speech [98]. There are plenty of features that have been used for detecting fake speech such as MFCC and LPC. Sanchez et al. in [99] proposed a model based on the statistical classifier for synthetic speech and the MFCC was used as an authorized baseline. Lui et al. in [100] developed a model for fake Stereo Audio detection where the classifier was the SVM, and the feature was MFCC. Based on their result, the MFCC can detect stereo-faking audio very effectively. Authors in [101] developed a deep learning model. which was trained by the MFCC,  $\Delta$ MFCC and  $\Delta\Delta$ MFCC, for discriminating a synthesized speech from an actual human speech. they have found that both  $\Delta$ MFCC and  $\Delta\Delta$ MFCC can improve discrimination accuracy significantly compared to the MFCC performance alone. Table (6) summarizes the use MFCC in some other studies.

**TABLE 4. Summarizing of those papers that use MFCC for speaker recognition.**

Classification	Feature	Advantage	Disadvantage
GMM	MFCC + phase information[61], MFCC + some of spectral features[62], Improved-MFCC based on Gaussian Filter[63], MFCC and it's delta [64] [65], MFCC and Bark Frequency Cepstral Coefficients[66]	MFCC combined with spectral feature leads to the reduction of error rate compared to MFCC alone[61] [62], MFCC with Gaussian Filter achieves better performance compared to triangular filter [63], suitability of MFCC and its delta [64] [65], increasing filter from 12 to 20 improves the performance of MFCC and BFCC. MFCC also has better (BFCC) by 12%[66]	MFCC does not provide a complete description of the speaker's speech system[61] [62] [63] [64] [65] [66]
ANN	Residual phase +MFCC[67], MFCC and its delta[68] [69] [70], MFCC,LPC[71]	MFCC and its delta yield better results compared to individuals[68] [69] [70], MFCC-MLP is faster and better than LPC-MLP[71]	Residual phase and deltas of MFCC are useful features since it is complementary to MFCCs[67] [68] [69] [70].
HMM	frequency band energy (FBE)-MFCC-40[72], Averaged-MFCC[73], MFCC[74] , Adaptive MFCC[75]	Larger number of filters in the filter bank and the overlapping among the neighboring filters reduces the error rate[72], MFCC is useful for identify animals[73], adaptive MFCC outperformed conventional MFCC[75].	Some parameters of MFCC need to be tuned based on the work[73] [75]
Statistical analysis	MFCC with spectral subtraction and median filter[76], GFCC and MFCC [8], Hilbert transform- MFCC[77]	MFCC reduces the error rate over a wide signal-to-noise ratio range[76]. The most effective parameter of MFCC and GTCC to noise robustness is taking the cubic root instead of log [8]. The combination of Hilbert transform and MFCC can improve the performance of speaker recognition[77]	MFCC is sensitive to noise however it might be solved by taking cubic root or change filters or taking Hilbert transform before the MFCC framework[76], [8], [77]
Deep learning	MFCC+LPC[78], MFCC+ learned feature from CNN[79]	MFCC alone is not very robust to audio degradations, but fusion of MFCC+PLC with CNN can overcome this problem[78], the hybrid feature (MFCC + other features) can reduce the impact of degradation of the speech signal[79]	MFCC alone is not very robust to audio degradations[78], [79]
SVM	Normalized MFCC[80] , MFCC with modification in windowing[81], statistical Values of MFCC[82], 12 MFCCs plus an energy[83]	22 <sup>nd</sup> -order MFCCs and SVM achieved highest accuracy rate[80], Hamming window was modified, and it leads to improvement of accuracy rate[81]. Usefulness of MFCC for speaker identification[82][83].	Number of obtained MFCC coefficient, the slope window and phase of power spectrum are impactful on the MFCC performance[80][81]
Vector quantization and I-vector	MFCC[84] [85] [86], MFCC and perceptual linear prediction [87], MFCC extracted from DWT [58]	MFCC with 32 filter and Hanning window get higher accuracy rate [85], Multi tapering using sine or multi-peak or Slepian tapers outperforms the baseline single taper[87], DWT combined with MFCCs improve the MFCC performance in noise condition [58], MFCC has good identification results as it holds the human perception of logarithmic loudness and pitch[84] [86]	The performance of MFCC feature degrade for speaker text independent compared to speaker dependent text. So that, it requires to tune some of its parameters or make a fusion with other features.
DTW	MFCC [88]	Feasibility of MFCC to extract features from voice signal	The problem with MFCC-DTW is when if constant window spacing is utilized, the lengths of the input and stored sequences is unlikely to be the same.



**TABLE 5. Summarizing of papers that are using MFCC for gender recognition.**

Classification	Feature	Advantage	Disadvantage
SVM for gender recognition	MFCC[92] [90], First four formant frequencies and 12 MFCCs[93]	SVM with RBF kernel has better performance compared to SVM with other kernels[92] [90], mid-frequency MFCC features is better for gender[93]	MFCCs become more robust when the number of MFCCs increase. However, the dimensionality keeps increasing and that leads to high complex model[92]
KNN for age recognition	First four formant frequencies and 12 MFCCs[93]	Low and high frequency-MFCCs are suitable for age recognition.	12 MFCC are also important features for age recognition. However, the drawback of these features is that they are affected by noise.

**TABLE 6. Summarizing of those papers that use MFCC for sentiment speech detection and fake speech detection.**

Classification	Feature	Advantage	Disadvantage
LDA	LDA-MFCC[102], MFCC, LPCC[103]	The LDA is applied to MFCC to improve the performance of Speech detection in noisy environments[102].	The performance of LPCC feature slightly outperformed MFCC[103]
SVM	MFCC[104] [105]	MFCC is useful for detecting voice activity	The MFCC performance to detect voice is not robust as the achieved accuracy plays between 85% – 100%.
HMM	MFCC+ MPEG[106]	Increasing the accuracy significantly	MFCCs was used as a complimentary feature, not as a main feature
DTW	MFCC with delta[107]	Feasibility of MFCC as feature for command recognition	The voice signal tends to have different temporal rate, the alignment of MFCC parameters is important to produce a better performance
Deep learning	Mod-MFCC, Log Mel-Band Energy(LMBE)[108], MFCC feature map[109]	Mod-MFCC features give decent performance at much lower costs compared to LMBE[108], MFCCs-CNN can better distinguish three kinds of sound quality noise samples: non-comfort, comfort, and very comfort[109]	Both Mod-MFCC and MFCCs-CNN are more complex compared to state of art
K-means clusters	MFCC [17] [110]	The main reason of selecting MFCC as a feature, is that the MFCC extracts human ear information, which has a response of a logarithmic scale and not a linear scale	MFCC cannot extract the whole Isolated Command feature as it is originally developed for extracting feature from human auditory
Statistical analysis	MFCC and harmonic pitch class profile (HPCP) [111]	Fusion of the feature (MFCC and HPCP) can capture complementary information	Shorter windows lead to decrease of robustness of the MFCC

**B. MEDICAL APPLICATIONS**

Nowadays, machine learning approaches have been involved in many healthcare applications and it helps to observe critical clues among huge data about the patient where the observation is beyond the scope of human capability, or it is difficult to know them in the shortest time [112]. Both traditional machine learning and deep learning approaches have been adopted by researchers to convert medical signals like ECG and EEG into clinical insight which is meaningful for the doctors. One of the crucial features is MFCC features, which

was originally developed to extract vocal track features, however, shows the ability to extract useful features from medical signals to find out a clinical insight as it is mentioned below.

**1) EEG ANALYSIS**

An electroencephalogram (EEG) is a recording of the electronic action generated by the brain. EEG has a crucial role to identify or recognize brain activities and their means as well. Plenty of research is available that focuses on brain activities and there are still many challenges in this field. One of the

TABLE 7. Summarizing of those papers that use MFCC for EEG.

Classification	Feature	Advantage	Disadvantage
ANN	MFCC[113] [115], MFCC, Spectral, Zero-crossing, Energy and Entropy of energy[116], MFCC, (LPCC) and Sequency mapped real transform (SMRT) [117]	25 MFCC components are enough to provide maximum accuracy, which was 97%[115]. These features were evaluated and MFCC features are more robust than others and shows influential impact[116]	Most of the research in this field prefers to combine MFCC with other features like Spectral, LPCC, Zero-crossing, Energy and Entropy
Deep learning	13 MFCC[3], MFCC and Mel Cepstral Distortion (MCD) extracted EEG signal[118]	EEG features can be generated from MFCC acoustic features with lower root mean square error [3],	The performance of MCD is slightly higher compared to MFCC performance[118]
SVM	MFCC [119]	The performance of MFCC-SVM model can reach up to 96.623%	The performance of the MFCC-SVM might be improved by changing hyper-parameters of SVM and MFCC
Analysis	MFCC from brain wave[120]	The ability of MFCC to show the reaction of brain for acupuncture stimulation	The MFCC for brain reaction did not show reliability using various datasets

vital challenges is obtaining a proper feature from the brain signal.

Based on the literature, some researchers proposed MFCC features for monitoring the brain activity and knowing the emotion of the patient or client, for example, Othman et al. extracted MFCC features from the EEG signal for identifying and recognizing the emotions. The MFCC feature then fed to the multi-layer perceptron to classify the emotions (happy, fear, sad and calm) based on the EEG signal and the result shows that the accuracy can gain up to 90% [113]. The performance of the EEG classification method was improved by combining 13 MFCCs with 19 articulatory features and then, the features were classified by gated recurrent unit [114]. Rajesh extracted 15, 25, and 35 MFCCs features from the EEG signal and fed them to an ANN model separately for classifying normal and abnormal activity. Based on his result, 25 MFCC components are fair enough to provide a maximum accuracy compared to 15 and 35 MFCCs [115]. Based on the information in the table (7), the MFCC is extracted from both EEG and acoustic source to diagnose brain activities.

## 2) ECG ANALYSIS

An electrocardiogram (ECG) signal is a recording of the electronic action generated by the heart. Doctors and health staff usually use ECG to check the status of the heart. An automatic ECG classification system is an experimental area and there are still many efforts and challenges in identifying and classifying several waveforms in the ECG signal [121]. Recently, the MFCC features have been widely used for this purpose; for example, Yusuf & Hidayat evaluated two well-known features which are 13 MFCCs and Discrete Wavelet transformation when fed to the kNN. The obtained

result shows that the performance of the 13 MFCCs outperformed DWT [122]. Boussaa et al. claimed that the MFCC is a robustness feature for ECG classification into normal and abnormal when it feeds into a multilayer perceptron [123]. Authors in [124] extracted two sets of features, which were MFCCs and Motifs, extracted from the ECG signal and the features were used to train the SVM individually. Based on their experiments, the best results were achieved when the MFCC trained the SVM. Table (8) shows the narration for some other research on this application.

## 3) DISEASE DETECTION APPLICATION

Nowadays, the adoption of innovative technologies has been increasing in the field of medicine rapidly to detect signs of the illness in the earlier stage or to enhance and monitor the status of the patients. Behind any modern technologies in the medical application, there are several signal processing methods as they all work on the observation data. Recently, the MFCC has shown up in the detection of some diseases such as Parkinson’s disease, voice disorder, vocal fold disorder, pathology detector, and Cough detection (see table (9)) which are described briefly below.

### a: PARKINSON DISEASE

Parkinson’s disease is known as one of the brain diseases and it was described by James Parkinson in 1817. The brain cells, which produce and store dopamine, are subjected to a gradual loss and this is also called a neurological disorder. Parkinson’s disease leads to some difficulties in the patient such as shaking, difficulty with walking, stiffness, and unbalance [129].

Plenty of intelligent systems have been developed for classifying healthy and patient people by analyzing the voice

**TABLE 8.** Summarizing of those papers that use MFCC for ECG.

Classification	Feature	Advantage	Disadvantage
HMM	MFCC[125] [126]	Extracting MFCC from ECG could have offered better accuracy at a higher sampling rate and MFCC has high potential to ECG diagnostic aid	The model in [126] requires to verify the usefulness of the proposed model in the noise environment .
KNN	MFCC approach to extract features of ECG biometric and PCA to extract features of Palm print [127], MFCC, Haar and Symlet order 7 [122]	The suitability of MFCC for extracting the constant features from the ECG[127], the performance of MFCC outperforms both Haar and Symlet[122]	Author recommends combining MFCC with the delta and delta-deltas
ANN	MFCC[123]	Advantage of combining MFCC and SVM descriptor to classify ECG using ANN	An improvement in MFCC can be developed to make it evolve into a system capable of classifying ECG signals depending on the nature of the anomalies.
SVM	Fusion motifs and MFCC[124]	The best results were achieved when the fusion features were fed to SVM	MFCC need to be combined with other feature like motifs
Deep learning	Improved MFCC[128]	MFCC can provide a comprehensive characterization of heart sound dynamics	Various heart diseases are frequently encountered and the multi-class classification problem

as the disease hits the voice in the beginning and becomes impaired [130]. So, as it is related to the voice, MFCC features have been used a lot for this purpose, for example, 1-20 coefficients of the MFCC extracted from the voice of the vowel / a / and is fed to the Linear kernels SVM to detect the PD. The consequences of the experiment shows that the first 12 coefficients of the MFCC are the best classification accuracy achieved which was 91.17% [131]. A modification of the MFCC was done by changing the bandwidth of the Mel scaled bank filter to extract the region of interest [300 Hz, 1700 Hz] that are more related to the PD and then trained a radial basis function (RBF) network to classify healthily and patient [132]. Authors in [133] used Linear discriminant analysis to reduce the dimension of the MFCC coefficients and fed it to the SVM and the result shows that 10, 12 and 18 MFCC are more related to the PD signs.

#### *b: VOICE PATHOLOGY DISORDERS*

Voice pathology disorder is a problem on the vocal track voice, which appears in pitch, volume, tone and other qualities of a voice. The problem occurs whenever the vocal cords do not vibrate normally. Computer-aided tools have played a significant role in the diagnosis and identification of a lot of diseases including voice pathology disorders [134]. The MFCC as a feature, has been adopted to train computer-aided tools for classifying normal voice and voice pathology disorders, for instance a model based on the MFCC feature was developed for the same purpose and the MFCC was extracted from the speech signal when the speech has undergone the distortion of an analog communications

channel. The performance of the MFCC is still reasonable to be conducted. However, the performance of the model was degraded because of the added distortion [135]. Ali et al. used the MFCC with the Gaussian mixture model (GMM) to develop an automatic detection system that could differentiate between normal and pathological voices [136]. Enhanced the traditional MFCC and named adaptive weighted Thomson multi-taper MFCC. The enhanced MFCC was given to the GMM model as input for differentiating normal and disorder speech, and the performance of the obtained MFCC outperformed the traditional MFCC [137]. In 2018, the 19 MFCC were extracted from the speech signal and ANN was trained for discriminating between healthy and pathological voices, and the high classification rate achieved up to 99.96% [138].

#### *c: COVID 19 DETECTION VIA COUGH*

Cough is a symptom of over thirty medical conditions including COVID-19. For more than three decades, the detection of medical conditions based on coughing has been interesting to researchers who work in this field [139], [140]. The performance MFCC feature for classifying cough and ordinary speech was reported to be better than some other features such as Short-time Fourier transform (STFT) and Mel-scale filter banks (MFB) [141]. Recently, the MFCCs have been used as a feature for detecting whether the patient has COVID-19 or not, for example, the MFCC features were obtained from cough sounds and fed to the kNN to detect COVID-19 infected patients [142]. Bansal et al. trained a CNN model by the MFCCs, which was obtained from the

**TABLE 9. Summarizing of those papers that use MFCC for disease detection.**

Classification	Feature	Advantage	Disadvantage
HMM	A dynamic MFCC using K-means cluster [144], wavelet transform (W-MFCCs)[145].	MFCC can provide a dynamic set of features for distinguishing different brain structures[144]. The performance of WMFCCs was better than MFCCs[145].	Wavelet has been used to reduce the noise sensitivity of MFCC feature[145].
ANN	Optimized MFCC using Particle Swarm Optimization (PSO) [146], MFCC [135] [138], 13 MFCC and 13 PLP features[147], modified MFCC filter bank[132]	Number of filters and coefficients were optimized by PSO[146], Reasonability of using MFCC for signal when it has undergone the distortion and best accuracy was achieved when the number of MFCCs is 39[135] [138], Modification was done by varying its bandwidth in the region of interest to compute the MFCC[132].	Modification of the MFCC parameters is very essential to be done for MFCC suitability. This might be done via optimization or trial and error method
GMM	MFCC[136], Multitier MFCC[137]	MFCC’s capability for discriminating normal and pathological voices[136], Optimal number of tapers can be chosen between 4 to 8[137]	MFCC features are usually computed from a single window (taper) characterized by large variance[137].
SVM	12 MFCC[131] [148], wavelet transform then MFCC[149] Mean of MFCCs then reduced by linear discriminant analysis[133].	12 MFCC-SVM with linear kernel can achieve better accuracy [131] [148]. Compression was done by using Daubechies wavelet transform (WT) to get better accuracy rate[149]. Mean of the 20 MFCC features hold most information related to Parkinson disease[133]	The statistical value like mean of the 20 MFCC features might lose some information about Parkinson disease
Deep learning	MFCC[150] [151] [152], MFCC delta-delta[153] [154], Fused STFT and MFCC[155]	The performance of MFCC-MLPNN is better than the performance MFCC-GRNN and MFCC-PNN[150], MFCC capability for detecting pathologies: cycle starts[151]. MFCC based high-level features carry relevant information related to depression [152], Suitability of MFCC-DNN and MFCC-LSTM model in noise environment[153] [154]. The fusion feature becomes a complement feature as the MFCC alone represents human auditory[155].	The performance of MFCC-DNN based system and MFCC-based Recurrent Neural Network for voice disorder are still low, which is up to 78%[151] [152]. DS-CNN models trained on the STFT has better performance than MFCC-CNN[155].
Statistical analysis	MFCC [156]	MFCC of voice is more robust for detecting Covid-19	There are many symptoms for Covid-19, one of them is change in voice during cough, but we cannot rely on voice analysis for Covid-19 detection

cough sound, and classified into two classes such as Covid and Non-Covid classes [143].

**C. INDUSTRY ANALYSIS**

Reliability of machines or tools is gaining importance in the industry because of the need to decrease the possible loss of production whenever the machine experiences an abnormal

situation during the working load. There is plenty of market assessment tools, which are utilized by analysts to understand the competitive dynamics of an industry, and they are used in industry [157]. A Health monitoring system is one of the well-known assessment tools that has been used to monitor a dynamic system and predict a failure in the early stage [158]. In condition monitoring systems whether it deals

**TABLE 10. Summarizing of those papers that use MFCC for fault detection.**

Classification	Feature	Advantage	Disadvantage
SVM	MFCC[163], Fusion MFCC, Wavelet Packet Decomposition Energy features and the Zero-crossing rate (ZCR) [167]. MFCC and its delta [169]	Most influential coefficients are the first three MFCC coefficients[163]. For Fusion feature, higher classification accuracy was achieved even under noisy environment[167]. Rank-based recursive feature elimination (RFE) was used to select proper feature among them and the selected feature are reliable for fault detection in electromagnetic pumps[169].	Other features like Wavelet Packet Decomposition and Zero-crossing rate were used to support the MFCC to gain better performance in the noisy background[167].
GMM	MFCC[170],MFCC+ Kurtosis[166],	MFCC can hold 95% of defect information and adding Kurtosis leads to the improvement the accuracy by 4%[166]	The model was not checked in noisy environment
XGboost algorithm	An improvement of MFCC was named adaptive frequency cepstrum coefficient (AFCC) [168].	Adaptive MFCC improves the performance of the fault detection system	MFCC method is limited for detecting bearing fault as Mel scale designed based speech signal and is not suitable for the frequency distribution of rolling bearing vibration signal
Similarities analysis	MFCC [171]	MFCC suitable to show some various faults detection	The proposed model was composed into two parts. Fault detection and fault classification. The MFCC was only used for fault classification

with vibration [159] or acoustic signal [160]. The MFCC is known as an effective feature to monitor tools or equipment and has been used quite recently for this purpose such as gear health monitoring, bearing health monitoring, turbine health monitoring, and Pump health monitoring. Table (10) provides more details on other industrial applications.

**1) GEAR HEALTH MONITORING**

A gear is a type of machine equipment that has teeth around cone-shaped or cylindrical surfaces. The teeth are designated around the shape with equal spacing. A force from one shaft, which is named the driving shaft, transmits to another shaft (driven shaft). Monitoring gears in rotation machinery devices have been focused on the industry as the failure in gear downs the entire system where the gears are involved in construction [161]. Various faults are related to the gears and many machine learning-based models have been developed to recognize these faults [162]. The MFCC has become one of the effective features in gear fault detection, for instance, Benkedjough et al. extracted the MFCC feature and fed it to the SVM and claimed that the first three MFCC components contain the most defect information of gears [163]. However, based on the research of Abdul et al, 1-13 MFCC are more effective to be taken to train LSTM [164] and Jin et al. evaluated some sets of MFCCs (16, 21, 26, 31, 36, 41 MFCCs) by feeding them into a CNN model individually and the result shows that 41 MFCCs outperformed the others for gear fault

detection. In conclusion, the dimension of the MFCC features is important for increasing the classification rate [109].

**2) BEARING HEALTH MONITORING**

Bearings are the most widely used components in industrial rotating machinery, which consists of rolling elements, inner race, outer race, and separator. The bearing is used for rotating or linear shaft applications. There are plenty of types of bearing that are available in the industry, namely Ball Bearings (like Deep-Groove Ball Bearings and Angular Contact Ball Bearings) and Roller Bearings (like Cylindrical Roller Bearings and Tapered Roller Bearings). In earlier times, researchers used some statistical features to predict how the bearing such as mean, variance, standard deviation, root mean square, skewness and kurtosis is healthy?. However, these features are not sufficient to monitor all faults that might occur in bearings [165]

So many distinctive features have been extracted to overcome this problem such as MFCC feature and gamma tone spectrum coefficients. Nelwamondo and Marwala investigated the performance of a combination of features, which consisted of the MFCC and kurtosis and gave it to the Gaussian Mixture model. Based on their result, combining the Kurtosis can improve the performance of the MFCCs features by 5% [166]. Nelwamondo et al. used the first thirteen MFCCs feature as temporal feature and hidden Markov Models (HMM) was trained to classify bearing faults. they observed that the first 13 MFCCs is the optimal for bearings fault and beyond

**TABLE 11. Summarizing of those papers that use MFCC for other industrial applications.**

Classification	Feature	Advantage	Disadvantage
HMM	MFCC [178] [179]	Improving the performance of MFCC by modifying bank filter[178], 36 MFCC hold more dynamic information compared to 24 MFCC that can be used for Drone Sound Recognition [179]	Modification of filter bank is required to identify loose particle material[178]. Decreasing the MFCC coefficient leads to the decrease of performance for detecting drone sound recognition
SVM	MFCC and it reduced by attribute subset selection[180], Dimension of MFCC was reduced by locally linear embedding (LLE) [181], MFCC+ optimized selected time and frequency domain eigenvalues[182], Improved MFCC[183].	MFCC-SVM model enables cost-effective for fault detection[180], Results show that the model(MFCC- LLE with SVM) is effective and reliable for diagnostics of solenoid pumps[181], Improved-MFCC can improve the performance to detect faults.	MFCCs feature of these pumps are effective features but it is not sufficient to obtain reliable fault detection system. To make MFCC more reliable, the LLE has been combined with MFCC[181]
Gradient Boost Decision Tree mode (GBDT)	MFCC[184]	Verified that MFCC-GBDT model is useful for fault detection in Belt conveyor systems	The performance of MFCC was not checked in strong background noise.
ANN	MFCC [185]	Provide high precision in locating faults in the simulations	Adopting MFCC can gain high precision in locating faults however the MFCC is still needed to optimize its parameters
Time Delayed Neural Networks (TDNN)	MFCC [186]	MFCC-TDNN is remarkably effective for learning features of contact events	The applicability of MFCC to fitting motions other than pen motions is not clear.
Statistical analysis	(MFCC) and/or Code Excited Linear Prediction (CELP) [174]	Using the fusion feature requires no knowledge of engine speed.	The parameters of the MFCC should be selected properly based on the model
K means cluster	MFCC is optimized by entropy weight method[175]	The effectiveness MFFCC-K means is verified by using two faulty and one faultless wind turbine	Entropy method was used to optimize the features of MFCC

13 does not increase the fault detection rate [165]. In another research, 12 MFCC coefficients were extracted from the vibration signal and then combined with both Wavelet Packet Decomposition Energy features and the Zero-crossing rate features. The mixture feature was fed to the support vector machine to classify gear faults [167]. Mingsi et al. however, studied two limitations of the MFCC to fault detection for rolling bearing fault diagnosis. Firstly the Mel scale originally developed to speech signal based on human hearing and it is not suitable for the frequency distribution of rolling bearing vibration signal and the second, the ability of the MFCC in denoising. For these limitations, the adaptive frequency cepstrum coefficient (AFCC) method was proposed by [168] and fed to the XGboost algorithm for classification bearing faults. Table (10) displays some researches in which MFCC has been used as feature.

### 3) TURBINE HEALTH MONITORING

A turbine is a set of devices that harness the kinetic energy of some liquid such as water, air, steam, and turns this into the rotational motion of the device itself [172]. The turbine plays a vital role in converting power and many application tools have been developed for monitoring the turbine [173]. The essential requirement for any monitoring system based on machine learning is a dataset as decisions come out based on the data analysis. Based on the existing literature, MFCC has been used to obtain defected features in turbines, for example the MFCC and Code Excited Linear Prediction were used to extract a feature set from the acoustic signal. Then the feature of each technique was compared into different states which were fault and non-fault states [174]. Wang et al. optimized MFCC features, which were extracted from wind turbine sound signals, based on the entropy weight method for fault

TABLE 12. Summary of papers that use various methods of MFCC for speech, medical and industrial applications.

Methods	Speech application	Medical application	Industrial application
Acoustic signal	78	25	10
Non-Acoustic signal	0	13	8
MFCC alone	40	27	12
Combined with others	38	12	6
Standard MFCC	61	28	13
Enhanced MFCC	17	11	5
Dealing MFCC as time series	15	11	3
Dealing MFCC as non-time series	63	28	15
Used 13 coefficients or less	65	35	17
Used 14 coefficients or above	13	4	1
Fed to classical machine learning	63	20	16
Fed to Deep machine learning	15	19	2

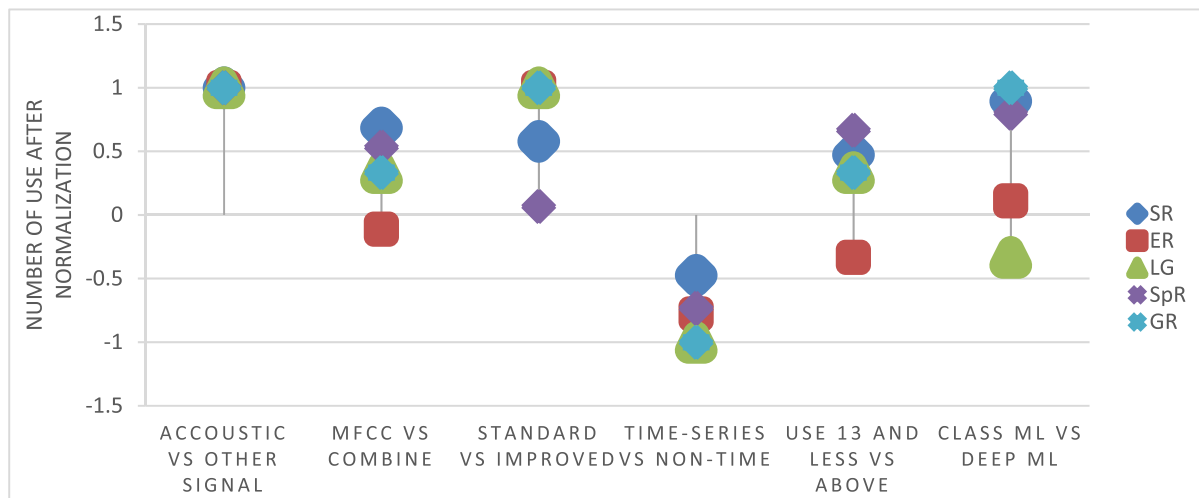


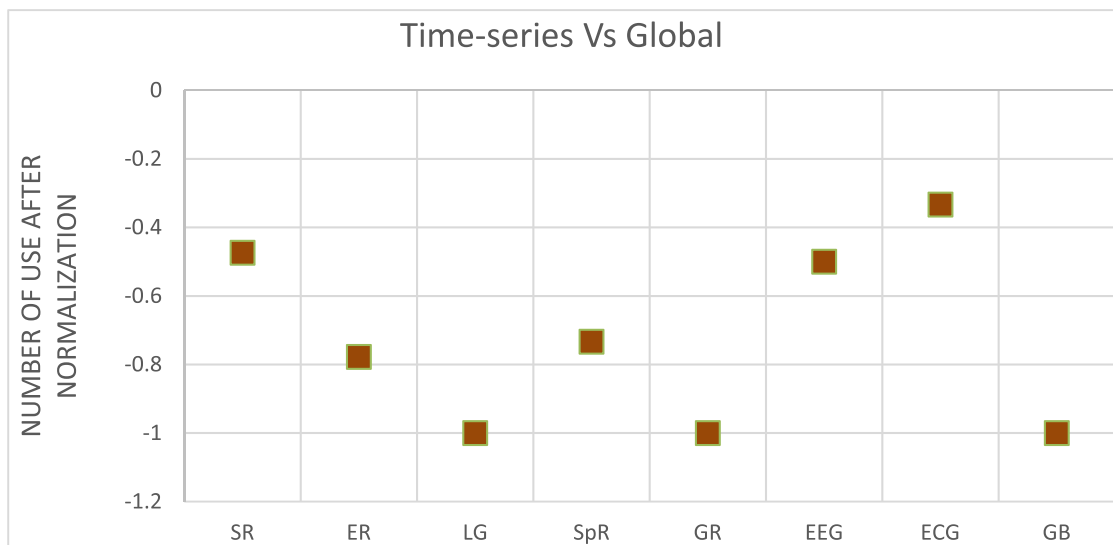
FIGURE 4. The figure shows the number of papers of the first item in each pair (acoustic input vs other signals, MFCC vs combined feature, standard MFCC vs improved version, time series vs global, using 13 MFCC vs more MFCC, using classical machine learning vs using deep learning) normalized to one. (SR: Speech Recognition, ER: Emotion Recognition, LG: Language Recognition, SpR: Speaker Recognition, and GR: Gender Recognition).

diagnosis of the wind turbine blade. The optimized feature was later clustered using the K-means clustering [175]. Kilic evaluated three sets of features, which are MFCC, spectrogram, and Mel spectrogram, by feeding them into three machine learning models such as LSTM, RNN and CNN. Based on Kilic’s result the MFCC feature with CNN can get better than the other adopted model [176].

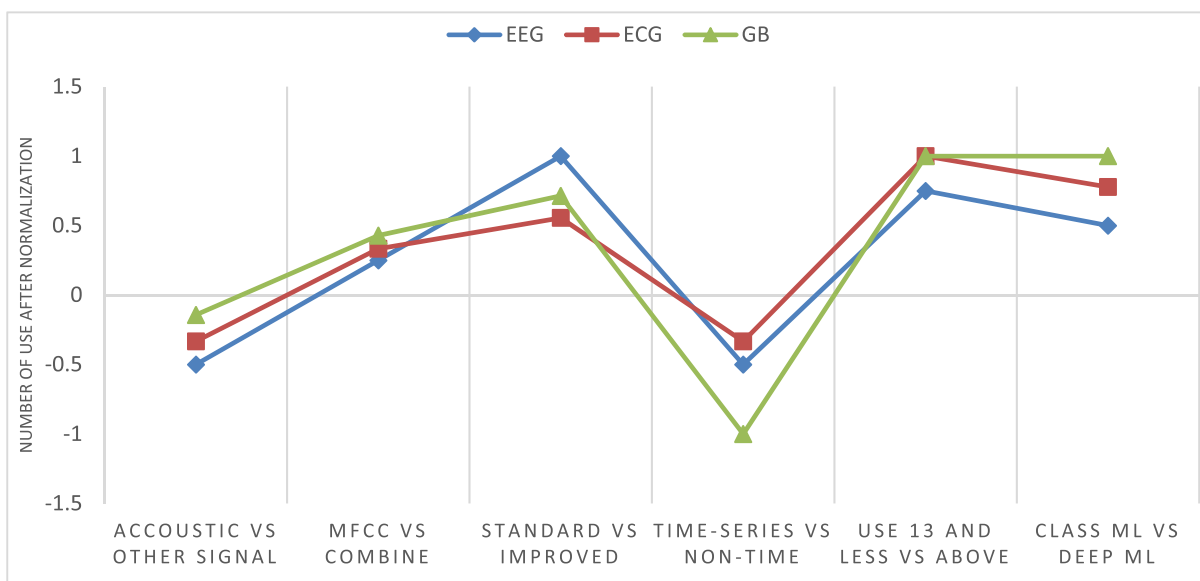
#### 4) PUMP HEALTH MONITORING

A pump is a device which moves fluids from one place to the other by mechanical action and it is particularly important to monitor it well as any failure of pump will affect productivity and safety. There are many types of pumps which are

available in the industrial field, and they are classified based work, namely dynamic, and positive displacement. MFCC as feature has been used to know the status of a pump for instance for fault isolation of Solenoid pumps, Akpudo and Hur employed a locally linear embedding (LLE) for reducing dimension of the MFCC features which obtained from vibration signal and the reduced MFCC feature fed to the SVM with Gaussian kernel [177]. In 2021, Akpudo and Hur proposed another model for Fault Detection and Isolation in Electromagnetic Pumps. They used the same feature, which was 12 MFCC (2nd to 13th MFCCs) features, with two other features namely first-order and the second-order differentials (12 Delta and 12 Delta-Delta features), which are driven from



**FIGURE 5.** The figure shows the number of papers of the first item in one pair (time series vs global) normalized to one. (SR: Speech Recognition, ER: Emotion Recognition, LG: Language Recognition, SpR: Speaker Recognition, GR: Gender Recognition and GB: Gearbox).



**FIGURE 6.** The figure shows the number of papers of the first item in each pair (acoustic input vs other signals, MFCC vs combined feature, standard MFCC vs improved version, time series vs global, using 13 MFCC vs more MFCC, using classical machine learning vs using deep learning) normalized to one.

the MFCC feature. A feature selection technique known as rank-based recursive feature elimination, was then used to select the most effective features among 36-dimension and later given to the SVM classifier [169]. Table (11) shows some other studies that MFCC has been used in the industrial field.

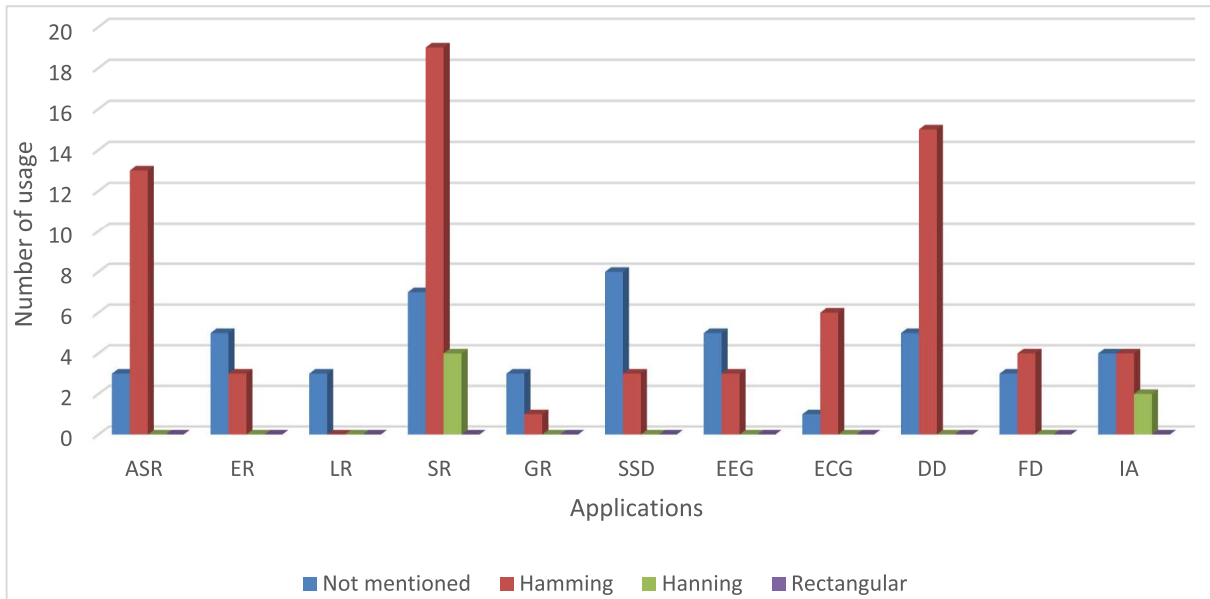
**IV. SUMMARY**

Table (12) shows a statistic obtained from the survey about the use of MFCC in various methods for different applications. Since the MFCC is mostly derived for audio-based

applications, one can clearly observe that it has been applied frequently to acoustic signals. However, despite that, this cepstral feature has recently started to be used for non-acoustic signals in various areas such as medical and industrial applications. MFCC is reported to be a powerful feature hence it has mostly been adopted alone, much less been combined with other features. The reason of combination of MFCC with other features is mostly to overcome the sensitivity of MFCC in noise environment [109].

Most of the works in the literature followed the standard approach of using MFCC. For example, the coefficient in





**FIGURE 7.** Utilized window types in various applications (ASR: Automatic Speech Recognition, ER: Emotion recognition, LR: Language recognition, SR: Speaker recognition, GR: Gender recognition, SSD: Sentiment speech detection, EEG: Electroencephalogram, ECG: Electrocardiogram, DD: Disease Detection, FD: Fault detection and IA: Industrial Application).

most of the works is adopted to be 13 or less, and third of the papers tried to enhance the MFCC computation parameters. However, the traditional way of MFCC computation followed the demand of audio signal modeling, which is not necessarily to be useful for non-audio signal such as ECG, EEG, and vibration. Even though the input signals of the adopted application in this paper are of time-series nature, most of researchers represented the MFCC in a global way by computing the statistics of the coefficients along with the signal frames. Despite the promising result of MFCC in the industrial field, table (12) shows that only around 13% of the papers that are using MFCC is applied to industrial application. This encourages more investigation of MFCC in this field.

The handcrafted features including the MFCC are mostly feeding the classical machine learning and rarely supply deep learning classifiers. The reason could be the nature of some deep learning methods that are able to extract deep features directly from the raw data.

If we take the reviewed papers as a sample of what has been conducted using the MFCC, we can observe the following:

- Most of the acoustic-based applications such as speech recognition, speaker recognition, gender recognition from speech and language recognition are using the MFCC alone more than the combination of it with other features as it is shown in the figure (4). However, the works that adopt the emotion recognition application are mostly using the combination of MFCC with other features. This could be an indication of the sparse nature of emotional information in the speech signal which may not be captured properly by the MFCC alone.

- Among the same works of acoustic application, the conducted works are mostly using the standard form of the MFCC, while around half of the works of the speaker recognition-based articles are adopting improving the MFCC parameters (see figure (4)). This may be due to the diversity of the speakers' vocal tracts, which needs MFCC computation process modification.
- Although the MFCC is computed in a short-time feature, most of the works are using the global version of the feature representation rather than the time series one as illustrated in figure (5). The reason could be the issues that may appear when using the time series version of the feature representation such as the diversity of the input signal length. Additionally, the application itself can benefit from the time series representation more than other representations.
- Works that adopt the use of non-acoustic application are mostly using the standard form of MFCC computation. Since the standard parameters of the MFCC are derived for audio applications, optimizing the MFCC parameters may have significant impact on the recognition results (see figure (6)).
- Most of the publications are using Hamming window in the signal framing step. Very little are using Hanning window, and none is adopting the use of rectangle window, however, some are not mentioning the adopted window in their work(see figure (7)).
- Based on reviewing 186 articles, the MFCC has been used with various classifiers including suitable classifiers for the global representation of features (such as SVM, kNN, ANN and MLC) and classifiers that are

**TABLE 13.** The most frequently used classifiers with MFCC features (ASR: Automatic Speech Recognition, ER: Emotion recognition, LR: Language recognition, SR: Speaker recognition, GR: Gender recognition, SSD: Sentiment speech detection, EEG: Electroencephalogram, ECG: Electrocardiogram, DD: Disease Detection, FD: Fault detection and IA: Industrial Application).

ASR	ER	LDR	SR	GR	SSD	EEG	ECG	DD	FD	IA
40%	70%	30%	23%	80%	47%	71%	37%	38%	36%	57%
DWT	SVM	ANN	ANN	SVM	Deep	ANN	ANN	deep	SVM	SVM

used with time series representation (such as DTW, HMM and LSTM). The review shows that the most used classifier with the MFCC feature depends on the application. Table (13) presents the ratio of the most used classifier for each covered application in this review. It is clearly seen that SVM, and ANN are widely adopted with MFCC for their capability to find optimum separators among classes. SVM is a high-performance classifier with representative features and is not affected by the curse of dimensionality. On the other hand, ANN has the capability to learn the linear and non-linear characteristics of various classes from their data samples. Despite its importance, deep learning classifiers such as CNN have not been widely utilized with the MFCC, because CNN is capable of extracting learned features directly from the raw data. The nature of the application has its role to choose the classifier as well. For example, the ASR is a time series-based application, therefore, classifiers that detect the characteristics of the time-varying samples such as DTW, HMM and RNNs are more adopted for such an application. One can conclude from these results that nothing special is observed about the relation between the MFCC and other classifiers since the most adopted classifiers are those that are widely used with other applications as well.

## V. CONCLUSION

This paper is a review of using MFCC in various applications and presents some issues regarding the computation of it. One can conclude from the review that covers 186 papers, that the MFCC is a widely used feature for acoustic-applications and a promising one for other applications such as EEG, ECG and industrial signals. However, there is no comprehensive investigation of MFCC for non-acoustics applications. Another finding is that most of the papers have not adapted the MFCC computation for non-acoustic applications. However, there are many indications that this modification may improve the performance of the non-acoustics models. Even though the MFCC is computed in a short time signal, however, most of the works has adopted the use of the global representation of the MFCC, which are mostly globalized by computing the statistics the features along the frames. The duality of time series versus non-time series is worth much more investigation to show their capability in modelling various applications.

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