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Robust dual-tone multi-frequency tone detection using k-nearest neighbour classifier for a noisy environment

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Abstract

Purpose – Due to the continuous and rapid evolution of telecommunication equipment, the demand for more efficient and noise-robust detection of dual-tone multi-frequency (DTMF) signals is most significant.

Design/methodology/approach – A novel machine learning-based approach to detect DTMF tones affected by noise, frequency and time variations by employing the k-nearest neighbour (KNN) algorithm is proposed. The features required for training the proposed KNN classifier are extracted using Goertzel's algorithm that estimates the absolute discrete Fourier transform (DFT) coefficient values for the fundamental DTMF frequencies with or without considering their second harmonic frequencies. The proposed KNN classifier model is configured in four different manners which differ in being trained with or without augmented data, as well as, with or without the inclusion of second harmonic frequency DFT coefficient values as features.

Findings – It is found that the model which is trained using the augmented data set and additionally includes the absolute DFT values of the second harmonic frequency values for the eight fundamental DTMF frequencies as the features, achieved the best performance with a macro classification F1 score of 0.980835, a five-fold stratified cross-validation accuracy of 98.47% and test data set detection accuracy of 98.1053%.

Originality/value – The generated DTMF signal has been classified and detected using the proposed KNN classifier which utilizes the DFT coefficient along with second harmonic frequencies for better classification. Additionally, the proposed KNN classifier has been compared with existing models to ascertain its superiority and proclaim its state-of-the-art performance.

Keywords Dual-tone multi-frequency, KNN classifier, DFT coefficients, Goertzel's algorithm

Paper type Research paper

1. Introduction

While telecommunication receivers have gotten exceedingly better with time, there is still a degree of unreliability associated with analog detectors. This is due to various factors such as the circulation of outdated transmitters alongside noise and frequency variations that are extant in analog signals. Previously, single tone frequency line pulsing was used in telephone equipment [1], however, thanks to rapid technological advancements in the recent past, wireless networks have been moving towards digitization where all signals are considered equal. It is therefore financially prudent to replace analog receivers with their digital equivalents which are found to be far less susceptible to noise as well as more reliable and cost-effective. Also, the dual-tone multi-frequency (DTMF) signal is utilized in many applications in recent past [2–7]. Mobile and remote controlled automatic agricultural devices utilized the principle of DTMF signal for controlling [3, 4]. Even during the night time also spy robots are deployed in military applications to monitor [5]. The night vision camera has been controlled by DTMF signal and Global

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Positioning System (GPS) system. The automation plays the vital role in industrial application. The DTMF signalling helped to automate the industrial control in an efficient way [6, 7]. The brief specifications required for DTMF and R2 signal suggested by International Telecommunication Union-Telecommunication (ITU-T) is presented [8]. The detailed surveys of various decoding techniques that have been applied in practice are also discussed. In [9, 10], a new computationally efficient method has been proposed and experimentally verified. They have developed a DTMF detection model involving lesser area and power in field-programmable gate array (FPGA) using the split Goertzel process and claim that the suggested resource allocation process consumes less power whilst still detecting DTMF efficiently.

A new method for performance evaluation for a DTMF receiver employing quick Fourier transform (QFT) has been proposed in [11]. The symmetric properties of the QFT method lead to better performance in terms of lower memory occupation and good real-time deployment as compared to DFT, FFT and Goertzel's method with fewer floating-point processes [12]. Cheng-Yu Yeh, Shaw-Hwa Hwang [13] investigated a multi-frequency detecting (MFD) method to replace the traditional single-point method. It was found to be a suitable way to reduce computational load even further for DTMF detection. Dabbabi Karim *et al.* [14] presented a new method to optimize audio classification and segmentation by utilizing the Genetic Algorithm using Self-Orga-nizing Maps (GASOM) algorithm for their multimedia data set. Audio coding using empirical mode decomposition has been presented in [15]. In this method, the audio signal has been broken down into intrinsic oscillatory components and encoded. The investigation on audio encoding and lossless audio codec has been compression presented [16]. The advancements made in machine learning algorithms and the technology to implement these algorithms is a tool that is being implemented everywhere [17–19]. Recognition of DTMF tones is yet another avenue where ML/AI can be employed. There is a need to make the recognition system immune to the presence of unwanted elements like speech, noise and frequency variations. These reasons have led to the employment of artificial intelligence (AI) for the reception of DTMF signal tones in the most efficient way possible.

Nagi *et al.*, [20] proposed the AI-based method to detect DTMF signals which are contaminated by white Gaussian noise (WGN) using support vector machines (SVM). Pao *et al.*, [21] assigned three weighting functions and compared the performance of weighted k-nearest neighbour (KNN), weighted D-KNN and conventional KNN to identify ten digits in Mandarin database. To retrieve content-based audio, a genetic algorithm with KNN based approach has been suggested [22]. The audio files fed at the input of the system have been ordered by their similarity at the output of the system using varying features. Ali *et al.*, [23] investigated the performance of the KNN classifier to classify heterogeneous data by measuring the resemblance between the distance for binary and numerical data. Daponte *et al.*, [24] depicted a new method to decode DTMF tones efficiently using an artificial neural network (ANN) and implemented the same on a digital signal processor (DSP). After a suitable training phase, the ANN can relate an output about the DTMF signal. Salamon *et al.* [25] proposed a convolutional neural network (CNN)-based architecture to classify environmental sounds. Also, they have demonstrated the importance of data augmentation in avoiding the problem of data scarcity.

1.1 Research contribution

The major contributions of the proposed research are:

(1) Proposed a machine learning-based DTMF detection technique for identifying the DTMF signals which have been affected by subjected additive white Gaussian noise and also huge frequency and time variations.

(2) Goertzel's algorithm is developed to model the proposed KNN DTMF detection technique for computing the absolute DFT values of the fundamental DTMF frequencies and their second harmonics.

(3) The performance is analysed and compared with existing detection models using the classification precision, recall and F1 score combined with the five-fold stratified cross-validation accuracy to measure the efficacy.

2. Materials and methods

2.1 DTMF tones

DTMF tones are generated by adding two sinusoidal signals from the predefined eight fixed frequencies set. The predefined set contains both low and high-frequency groups which are mutually exclusive. When a DTMF tone is generated for an element from the table, the frequencies corresponding to the row-column intercept are generated and summed. The formula for the generation of pure DTMF signal is given by

$$x(t) = A_m \cos(2\pi f_L T + \theta) + A_m \cos(2\pi f_H T + \theta) \tag{1}$$

where A_m is the amplitude for each DTMF waveform. The higher and lower frequencies are given by f_H and f_L respectively. T is the sample rate. The keypad formed by this combination of frequencies is given in Table 1.

The Bell System Inc, US developed the standards for DTMF signals. The standards have been specified in the ITU-T Recommendation Q.23 [26] are used in this research article.

2.2 Computation of DFT coefficients using Goertzel's algorithm

The absolute value of the DFT coefficients in Goertzel's algorithm has been computed using a second-order recursive digital resonance system [12] and it is shown in Figure 1. In place of solving for all N-point DFT values, this algorithm obtains the values pertinent to the DTMF frequencies by using eight/sixteen banks of filters, depending upon the inclusion of second harmonics. The index value k for the DFT is defined as $k = N*f/f_s$, where f, N and fs are frequency of DTMF signal, length of the block and sampling frequency respectively.

Frequency (Hz)	High frequency group (f > 1kHz)			
Low frequency group (f < 1kHz)	1209	1336	1477	1633
697	1	2	3	A
770	4	5	6	B
852	7	8	9	C
941	*	0	#	D

Table 1.
DTMF signals–Touch keypad

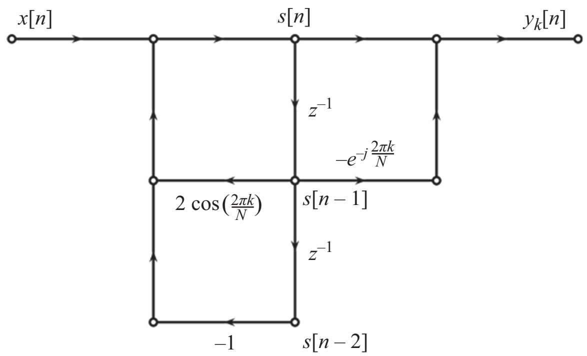

Figure 1.
Second order digital resonance system–Goertzel's algorithm

The process of this algorithm is depicted using

$$q_k(n) = x[n] + 2\cos(w_k)q_k[n-1] - q_k[n-2] \tag{2}$$

$$y_k(n) = q_k[n] - q_k[n-1]e^{-jw_k} \tag{3}$$

where $x[n]$ represents the samples of the input signals, n refers to the number of samples and w_k is the kth DFT sample obtained. This recursive aspect of Goertzel's algorithm is shown in (2). This algorithm is tested for each input signal. The non-recursive aspect of the algorithm is represented in (3). It is executed at a rate that is $1/N$ times the sampling rate.

3. Proposed KNN classifier

In recent past, KNN models are widely used to classify, detect or recognize patterns amongst other similar applications where a high accuracy is required but not a human-readable model. In this section, the various preprocessing required for the proposed model is explained.

3.1 Data acquisition and augmentation

The data sets used for training, validation and testing of the KNN classifier models consist of audio files with a tone duration of 100 ms and a sampling frequency of 8000 Hz consistent with the standard audio specifications of DTMF tones used for modelling generators and decoders. The clean/non-augmented data set consists of 2032 DTMF signal audio files which were downloaded from the online dual-frequency audio tone generator tool offered by the website "audiocheck.net" by creating multi-frequency tones whose low and high-frequency components were chosen as specified by the ITU-T Q.23 recommendation [20]. To eliminate the process of filling out the form at audiocheck.net and downloading each of the 2032 audio files, a python-based Selenium (an open-source web-based automation tool) script was written and deployed. These audio files were then respectively annotated to create a total of 16 different categorical classes, one for each keypad character/DTMF tone.

The lack of the amount of required data is one of the most prevalent issues in data science problems. Data augmentation assists in the generation of synthetic data from existing data sets such that the generalization capability of the classifier model can be enhanced. The proposed method for the detection of DTMF tones is designed to be robust to all noise, frequency and time variations corrupting audio signals during the transmission of these DTMF tones over a telecommunication network channel. To incorporate this, the clean data set comprising 2032 audio files was augmented such that each audio file is made into 10 corrupted audio files with different random errors therefore, creating a final data set of 20,320 audio files. Audio file corruption was done by the addition of additive white Gaussian noise (AWGN), time-stretch, time-shift and volume control.

3.2 Data exploration, feature extraction and standardization

In any automated audio-recognition/classification system, the arguably most important step is to extract features that can be used to train the classifier model. These features must be unique and should be useful to identify and differentiate the spectral content in the audio file while ignoring redundant information such as background noise etc. Our approach involves the extraction of the absolute value of the DFT components of the 8 frequencies, namely the 4 higher frequencies and the 4 lower frequencies used in DTMF tones along with their second harmonics. Therefore, a total of 16 computations are required. Goertzel's algorithm has been employed to compute the magnitude of these 16-individual DFT coefficients. Through data exploration, it was inferred that Goertzel algorithm's coefficients computation serves as viable features for training the model to produce accurate predictions.

After the features were extracted from the DTMF tone data sets, each column of the entire table was centered and scaled by the column mean and standard deviation, respectively, such that the range of values is not disturbed. This normalizes the impact of each feature/attribute. This was done by subtracting each cell (x) of every column with its column-mean (μ) and dividing each column by its column-standard deviation (σ).

$$z = \frac{x - \mu}{\sigma} \tag{4}$$

3.3 Proposed classifier model

The proposed machine learning-based KNN classifier is shown in Figure 2. As discussed in previous section, the data set is acquired by web scraping by the prevalent technical specifications for DTMF tones. Next, the data set is augmented with noise and other channel discrepancies to make the model more robust to noise and other interferences. For training and testing the KNN classifier model, the data set is divided randomly into a ratio of 4:1. 80% of the data set was used for training the model and the balance is used to test the model's accuracy. Over or under-fitting of the model was avoided this way.

The characteristics and features utilized in each models are shown below.

KNN Model A: The model is trained using the clean/non-augmented data set consisting of 2032 audio files. However, it is tested with the augmented data set to simulate real-word environments. The DFT coefficient values about the second harmonics are not considered in this model.

KNN Model B: The model is trained with the clean/non-augmented data set consisting of 2032 audio files. It is tested with the augmented data set. The DFT coefficient values about the second harmonics are considered in this model.

KNN Model C: The model is trained and tested with the augmented data set consisting of 20320 audio files. The DFT coefficient values about the second harmonics are not used in this model.

KNN Model D: The model is trained and tested with the augmented data set consisting of 20320 audio files. The DFT coefficient values about the second harmonics are considered in this model.

Training the model with the augmented data set makes the model more robust to noise and other signal interferences. Moreover, the inclusion of second harmonic frequency values as features also enhances the model's ability to distinguish and isolate DTMF tones from noise. We proceed with the intuition that the employment of both these methods would create a model less susceptible to noise which as the results prove, is a valid hypothesis.

3.3.1 Hyperparameter tuning. The hyperparameters for the KNN model are procured by employing the Bayesian optimization algorithm to solve the minimization problem of the five-fold cross-validation classification loss/error by optimally varying these hyperparameters. The Bayesian optimization algorithm aims at minimizing a scalar objective function $f(x)$ for x in a bounded domain. In our case, the objective function is the five-fold stratified cross-validation loss/error. The value for $y_i = f(x_i)$ is evaluated for four values of x_i, taken at random within the variable bounds. In the event of evaluation errors, more random points are taken until there are four successful evaluations. The probability distribution of each component is either uniform or log scaled. The acquisition function calculates the expected amount of

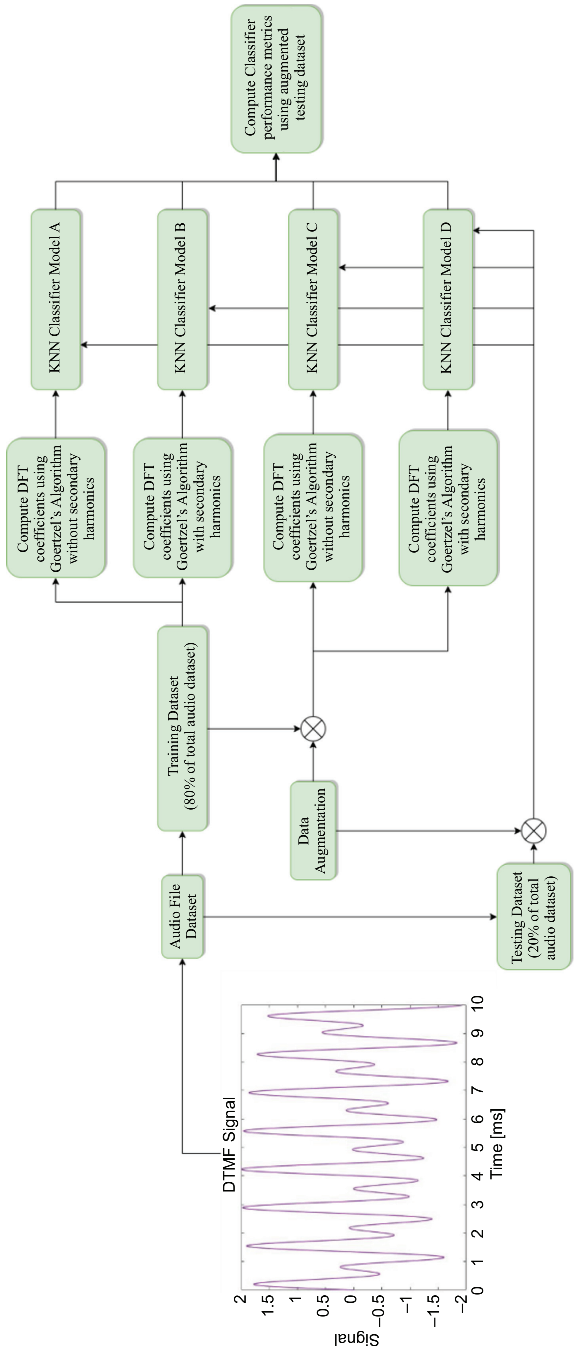

Figure 2.
The proposed KNN classifier model

improvement in the objective function, while ignoring values that cause an increase in the objective. The expected improvement (acquisition function) is defined as:

$$\mathrm{EI}(x, Q) = E_Q \max[(0, u_Q(x_{\mathrm{best}}) - f(x))] \tag{5}$$

where Q represents the posterior distribution over function obtained after updating the Gaussian process model of $f(x)$, x_{best} is the location of the lowest posterior mean and $\mu_Q(x_{\mathrm{best}})$ is the lowest value of the posterior mean. To avoid a local objective function minimum, the acquisition function modifies its behaviour when it estimates that it is overexploiting an area. If $\sigma_F(x)$ is the standard deviation of the posterior objective function at x and σ the posterior standard deviation of the additive noise, then:

$$\sigma^2{}_Q(x) = \sigma^2{}_F(x) + \sigma^2 \tag{6}$$

Let t_σ be the value of the exploration ratio (0.5). After each iteration, the acquisition function evaluates whether the next point x satisfies:

$$\sigma_F(x) < t_\sigma \sigma \tag{7}$$

If so, the algorithm deems that x is overexploiting. The exploration ratio, therefore controls a trade-off between exploring new points for a better global solution versus concentrating near points that have been examined already. The resulting optimizing hyperparameter values for each KNN model are shown in Table 2.

4. Results and discussions

The proposed KNN classifier models are created and compared based on the reported performance metrics. The results are evaluated to choose the best model amongst them. To impartially judge the performance of all the models, a test data set created by randomly taking 20% of the augmented data set which best simulates the real-word telecommunication channel scenario is given as input to the models, and the predicted responses are then used to plot the confusion matrix/chart. This confusion chart is used for computation of the performance metrics as it shows how well the model will perform on unseen and new data. The performance metrics such as macro-precision classification score, macro-recall classification score, macro F1 classification score and overall test data set detection accuracy are analysed. The proposed KNN model is simulated and validated using MATLAB R2019.

4.1 KNN classifier model A, B, C

The first three models showcased results that are inferior to the final model (KNN Model D). Since these models are not the focus of our research article, we will refrain from discussing their results in great detail. Their macro precision, recall and F1 classification score along with their test dataset detection accuracy have been generated and discussed in the following subsection.

4.2 KNN classifier model D

The confusion charts for the five-fold stratified cross validation accuracy and the test accuracy of the KNN model D are generated and shown in Figures 3 and 4, respectively.

Table 2.
KNN classifier model parameter values

KNN classifier model	Number of neighbours (K)	Distance measure	Distance weight
A	31	Cosine	Equal
B	29	Cosine	Equal
C	16	Correlation	Inverse
D	138	Correlation	Squared inverse

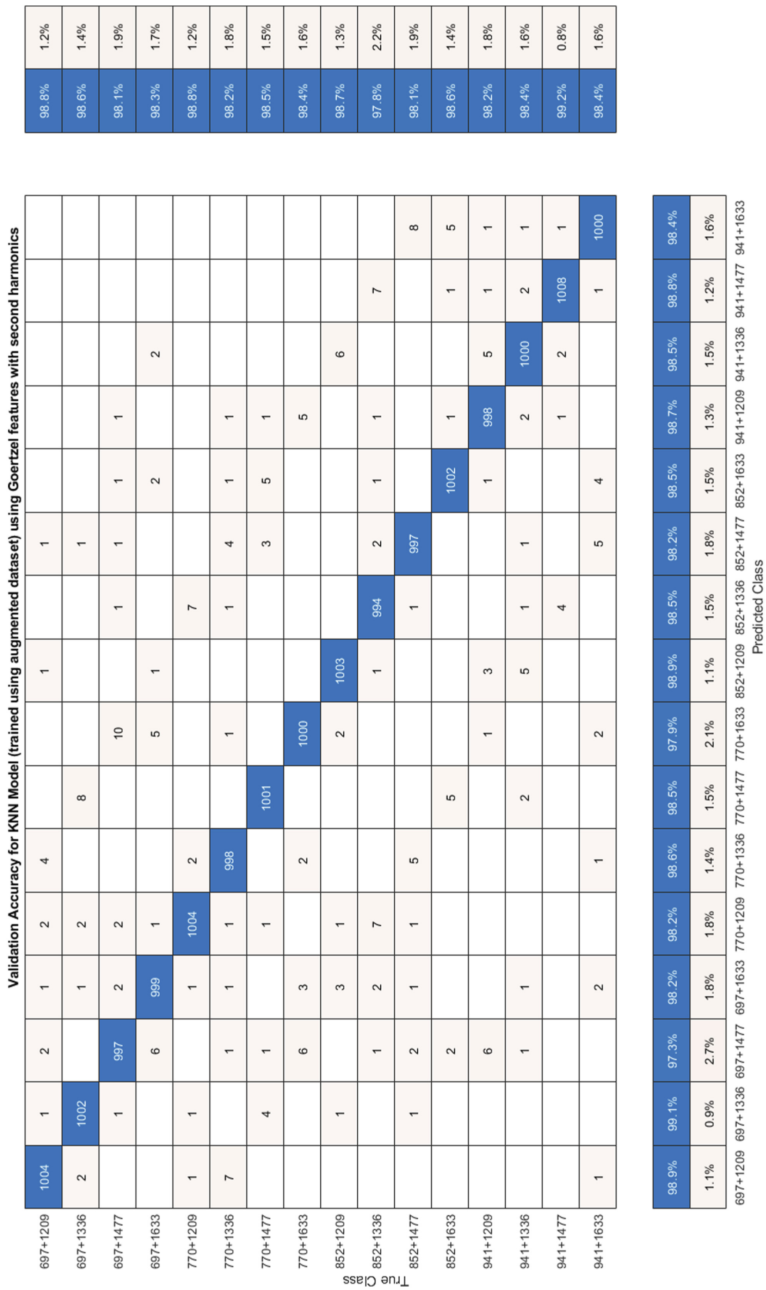

Figure 3.
Confusion chart for five-fold stratified cross validationaccuracy for KNN model D

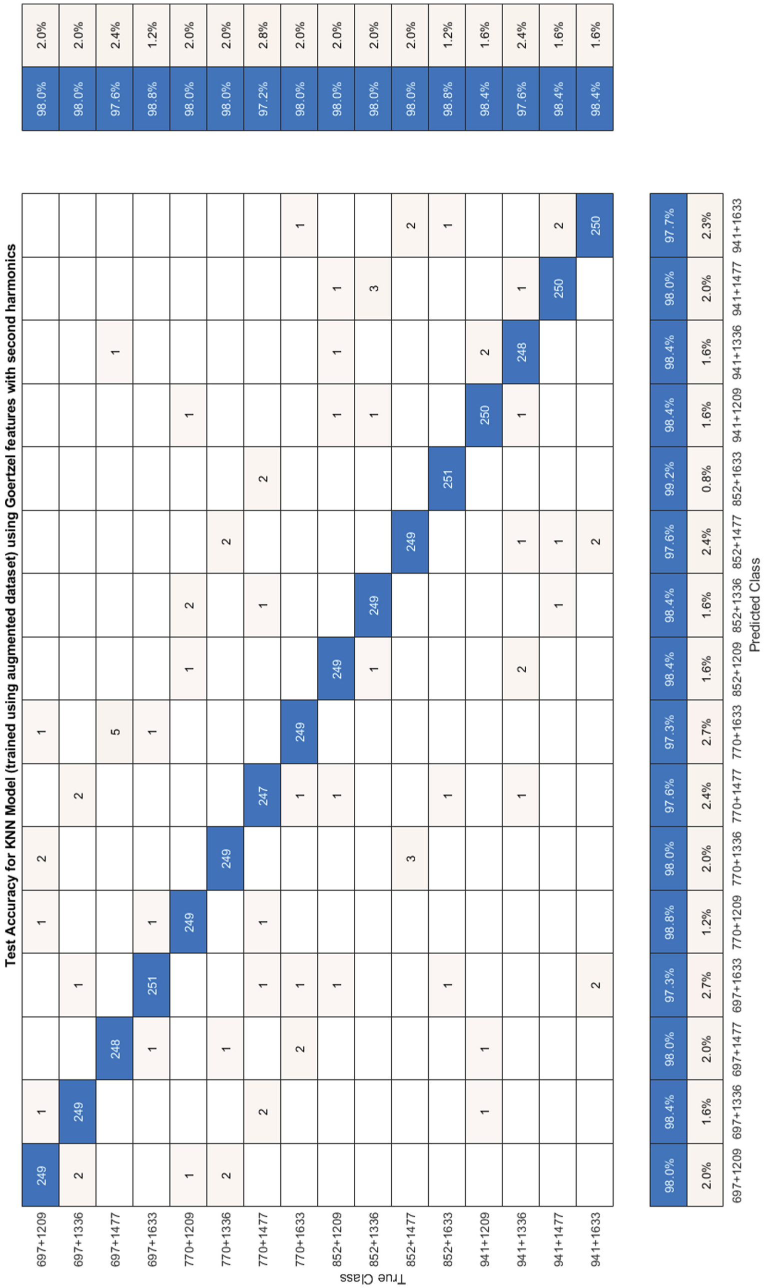

Figure 4.
Confusion chart for test dataset detection accuracy for KNN model D

The computed individual categorical class recall, precision and F1 score for the test data set are tabulated in Table 3.

From Figure 3, it is observed that the proposed KNN model D achieved a mean five-fold stratified cross-validation detection accuracy of 98.47%. Moreover, Figure 4 shows that the proposed model is able to detect the DTMF signals in the test data set with an overall detection accuracy of 98.1053%.

The value for macro-precision and macro-recall is found to be 0.980938 and 0.98075, respectively. The value of the macro F1 classification score is obtained as 0.980835. The performance metrics obtained for the four proposed KNN models have been tabulated in Table 4.

From Table 4, it is observed that the proposed KNN classifier model D which utilizes Goertzel's algorithm to compute DFT values at all the 16 frequencies, involving the 8 fundamental frequencies as well as their second harmonics values, has the highest metrics and is thus the most optimum model to decode DTMF signals. Since the model is tested using an augmented and noisy data set, the accuracy achieved can be considered robust and reliable. The data set is indicative of the noise one may face in real-world environments i.e. the telecommunication channels.

4.3 Performance analysis

The detection accuracy of the proposed KNN model is compared with existing models and it is shown in Table 5.

Frequencies	Recall	Precision	F1 score	Frequencies	Recall	Precision	F1 score
697 + 1209	0.98	0.98	0.98	852 + 1209	0.98	0.984	0.981996
697 + 1336	0.98	0.984	0.981996	852 + 1336	0.98	0.984	0.981996
697 + 1477	0.976	0.98	0.977996	852 + 1477	0.98	0.976	0.977996
697 + 1633	0.988	0.973	0.980443	852 + 1633	0.988	0.992	0.989996
770 + 1209	0.98	0.988	0.983984	941 + 1209	0.984	0.984	0.984
771 + 1336	0.98	0.98	0.98	941 + 1336	0.976	0.984	0.979984
770 + 1477	0.972	0.976	0.973996	941 + 1477	0.984	0.98	0.981996
770 + 1633	0.98	0.973	0.976487	941 + 1633	0.984	0.977	0.980488

Table 3. Performance metrics for KNN model D

Proposed KNN classifier	Test dataset detection accuracy	Metrics values with augmented (test) data set Macro-recall	Macro-precision	Macro-F1 score
KNN model A	97.5639%	0.97556	0.97562	0.97555
KNN model B	97.7854%	0.97768	0.97793	0.97775
KNN model C	97.81003%	0.97781	0.97825	0.97798
KNN model D	*98.1053%*	*0.98075*	*0.980938*	*0.980835*

Table 4. Comparison of performance metrics of proposed KNN models

Model/ Algorithm/Classifier	Detection accuracy
SVM classifier [20]	97.72%
Counter propagation neural network [27]	97.9%
DFT & modified Goertzel algorithm [28]	97%
ANN model [24]	97%
Proposed KNN classifier model	*98.1053%*

Table 5. Comparison of the DTMF detection accuracy

The various detection/classification models considered are SVM classifier [20], counter propagation neural network model [27], DFT & modified Goertzel algorithm [28] and artificial neural network (ANN) model [24]. It is observed that the proposed KNN classifier achieved the maximum classification accuracy of 98.1053% whilst attempting to detect DTMF signals in a noisy environment. This proves the superiority of the proposed model. This higher accuracy is mainly due to training the KNN model with an augmented noisy data and including second harmonic DFT values as features since they help in isolating noise components.

5. Conclusion

In this research, a machine learning-based approach for the detection of DTMF tones with and without noise and frequency disturbances has been presented. Within the proposed models, two are trained using non-augmented data set and the remaining two models are trained with a noisy augmented data set. All the models have been evaluated with five-fold stratified validation accuracy, precision, recall as well as the F1 score with the help of the plotted confusion matrices. From the experimental analysis, it is observed that KNN model D attained the highest F1 score of 0.980835, and a test data set detection accuracy of 98.1053%. Hence, this proposed model will be more suitable for real-time DTMF detection given that it is robust to noise and being a light-weight model is frugal with computational resources. The obtained solution is a significantly faster decoder which is much less affected by noise and sound interference when compared to the traditional approaches. This model is sufficiently complex and is not as computationally demanding as other approaches such as ANN, SVM and deep neural networks. It is also relatively smaller in size which implies that most micro-controllers will be able to run it without additional modifications.

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