Speech Emotion Recognition Through Neural Networks

Ashapriyadarshini. M,[1]M. Harika[2], P. Sowmika[3], N. Pavan kumar[4], M. Susanna[5]

[1] Asst. Professor, Department of Computer Science and Engineering

[2,3,4,5] Students, Department of Computer Science and Engineering

[1,2,3,4,5]Vignan's Lara Institute of Technology & Science, Vadlamudi, Guntur(dt),AP, India.

Abstract-Clarity and intelligibility in speech signal demands removal of noise and interference associated with the signal at the source. This poses further challenge when the speech signal is colored with human emotions. Recognizing emotions in speech signals have always been a tough task. In this work, we have taken a different approachforpreprocessing and enhancing the emotional speech signal adaptively before classification.Artificial Neural network based Multilayer perceptron (MLP) classifier is used to recognize neutral, calm, happy, sad, angry, disgust, fear and surprise emotion as against neutral voices using Mel-frequency cepstrum coefficients (MFCC), chroma and Mel features. Ryerson Audio-Visual Database of EmotionalSpeech and Song (**RAVDESS**)The accuracy has improved to approximately 75% with enhanced signal.In this work, we would like to analyze basic emotions of a human being like calm, happy, fearful, disgust etc. from emotional speech signals. We use Multi Layer Perceptron Classifier to categorize the given data into respective groups. Mel-frequency cepstrum coefficients (MFCC), chroma and Mel features are extracted from the speech signals and are used to train the MLP classifier. For achieving this objective, we use python libraries like Librosa, sklearn, pyaudio, NumPy and soundfile to analyse the speech modulations and recognize the emotion.

Keywords—*Speech enhancement; Emotion recognition; Multilayer perceptron; Adaptive algorithm*

I. INTRODUCTION

Rapid development and applications in the area ofspeech signal processing suffers due to inherent noise associated at the source of voice pick-up. In spite ofadvanced acoustic chambers and adequate recordingenvironments used for recording speech signal, noise andinterference makes their presence felt. Hence, postprocessingat the receiver end of the channel uses some formof adaptive filtering algorithm to enhance the speech signalaffected with noise. As complete elimination of noise from asignal is not possible, it poses a challenge for speechresearchers to revive new methodology in the area of speechenhancement for better audibility.Few speech enhancement algorithms as spectralsubtraction (SS), Least mean square (LMS), Normalizedleast mean squares (NLMS), Time varying Least MeanSquare (TVLMS), Recursive least square (RLS), FastTransversal RLS have been quite effective in providingenhanced speech to some extent [1]. Single channel SSmethod of speech enhancement is suitable due its simplicity.However, the method is unable to accommodate nonstationarynoise as its accuracy depends on the accuracy ofvoice activation detector. Further, the technique tends toproduce a type of randomly fluctuating noise with narrowband spectrum. This is a musical noise with tone-likecharacteristic [2]. LMS algorithm approaches noisecancellation adaptively, using stochastic gradient descentmethod. The gradient search is accomplished based on theinstantaneous error square of the gradient at the current time[3].

It is simple and robust algorithm but sensitive to thescale factor used in its input. It makes the selection oflearning rate parameter difficult. Consequently, stabilityhampers. The drawbacks of LMS can be eliminated to someextent by normalizing the input power in NLMS algorithm[4]. Contrarily, the RLS algorithm provides optimumperformance in a dynamic environment. It recursivelyminimizes the weighted linear least squares cost function ofthe input signals to achieve the desired adaptability withfaster convergence. Hence, this method is crucial for speechenhancement application. However, the algorithm iscomputationally complex and possesses unwarrantedstability problem [5]. Bendoumia*et al.,* proposed a newalgorithm based on forward-and-backward (FB) and blindsource-separation (BSS) for noise reduction and speechenhancement [6]. The FB structures used the least-meansquare(LMS) algorithm in combination with two BSSstructures. Therefore, two new two-channel variable-stepsizeFB algorithms (2C-VSSF and 2C-VSSB) weredeveloped to improve the previous LMS-based algorithm inthe transient and the steady- state phases. These two newproposed FB algorithms were based on recursive formulas,which provide efficient estimation of the optimal step-sizesof the cross-coupling filters. In [7], a new speechenhancement method was proposed combining the statisticalmodels and non-negative matrix factorization (NMF) withKullback–Leibler divergence. Speech emotion recognition (SER) plays a significant role in human–machine interaction.

Emotion recognition from speech and its precise classification is a challenging task because a machine is unable to understand its context. For an accurate emotion classification, emotionally relevant features must be extracted from the speech data. Traditionally, handcrafted features were used for emotional classification from speech signals; however, they are not efficient enough to accurately depict the emotional states of the speaker.In time-varying noiseenvironments, both the speech and noise bases of NMF wereconsidered with the help of the estimated speech presenceprobability to get the better-enhanced speech. Threealgorithms as LMS, NLMS and RLS are compared for theirability to enhance emotional fear and neutral speech signalin this work.Speech is always associated with some form of emotions.Few basic emotions such as angry, happiness, fear, sad,surprise and so on are easily identified during conversation[6]. However, sometimes they are overlapped in anutterance making it difficult to recognize individually [7].Speech happens to play a pivot role, as it is the loneeffective channel of communication via the phone. Speechwhen colored with emotions will be associated withadditional noise due to variability in expression andenvironment at which it is exhibited. Factors such as hiss,restlessness and other physiological components duringemotional speech encounter makes the speech corrupted.Hence, in this work, we have taken a step to removeunwanted noise from fear speech emotions recorded in a reallife situation along with neutral voice.

The utterances are initially enhanced against any noise and interferences usingthe chosen adaptive algorithms. Subsequently, the enhancedemotional speech is fed as input to MLP classifier forrecognition [8-9]. A comparison between the noisyemotional speech and enhanced emotional speech has beenmade based on Signal to noise ratio (SNR), Mean squareerror (MSE) both at the filter end and classification stage. Speech emotion processing and recognition system is generally composed of three parts, the first being speech signal acquisition, then comes the feature extraction followed by emotion recognition. Artificial Neural Networks are biologically inspired tools for information processing. Speech recognition modelling by artificial neural networks doesn't require any prior knowledge of speech process and this technique quickly became an attractive substitute to Hidden Markov Models. The conventional neural networks of Multi LayerPerceptron type have been increasingly in use for speech recognition and for various other speech processing applications. Speech recognition is the process of converting an acoustic signal, captured by microphone or a telephone, to a set of characters. They can also serve as the input to further linguistic processing to achieve speech understanding, a subject covered in section. It is widely applied in human - computer interaction, interaction teaching, security fields, etc…

Speech is a natural and commonly used medium of interaction among human beings. The importance of speech in communication motivates many researchers to develop methods where speech can be used for human—machine interaction. However, the machine should be intelligent enough so that it can recognize not only speaker voices but also the emotional states of the speaker. In general, speech signals contain linguistic and paralinguistic information. Linguistic information refers to the language and context of the speech, whereas the paralinguistic information provides information about emotion in speech. In different parts of the world, people have different cultural backgrounds, local languages, speaking rates, and speaking styles. This cultural variation creates difficulties in the effective recognition of the emotional states of the speaker and makes the process of speech feature selection very challenging and complex. In the literature, acoustic features have been used by researchers for speech emotion recognition (SER) [1]. These acoustic features are further divided into four groups: continuous features (energy, pitch, formants, etc.), spectral features, qualitative features (voice quality), and Teager energy operator-based features. However, these handcrafted features mostly represent low-level features; therefore, they are not efficient for precise emotional classification in complex scenarios. Moreover, their performance degrades in complex situations, such as speaker and environment variations. Consequently, there is a need to extract the optimal and suitable features that are emotionally relevant by implementing efficient approaches for SER. For this purpose, we adopted a deep convolutional neural network (DCNN) that automatically extracts the relevant emotional features from the spectrogram of the speech signal. Several studies, such as [2,3], have been carried out in recent years, where a convolutional neural network (CNN) was implemented for feature extraction of speech. The 1-layer CNN was implemented in [2] for SER and, recently, an end-to-end SER system was implemented using a two-layer CNN followed by long short-term memory (LSTM) [3]. However, these 1-layer and 2-layer CNNs are not suitable for learning emotional discriminative features due to their shallow architectures. In [4], DCNNs, which consist of deep multilevel convolutional layers and pooling layers, were adopted. Because DCNNs involve more parameters to extract more detailed temporal frequency correlation information and have strong feature learning ability, they achieve better performance than shallow CNNs.Automatic recognition of emotion is important for facilitating seamless interactivity between a human being and intelligent robot towards the full realization of a smart society. The methods of signal processing and machine learning are widely applied to recognize human emotions based on features extracted from facial images, video files or speech signals. However, these features were not able to recognize the fear emotion with the same level of precision as other emotions.

II. RELATEDWORKS

HadhamiAouani and Yassine Ben Ayed , 2020 have proposed an approach for automatically detecting emotions in speech that explores some characteristics of how speech signals are detected and meta-information of the signals are calculated for labeling its emotion.Features like 39 coefficients of Mel Frequency Cepstral Coefficients, Zero Crossing Rate, Harmonic to Noise Rate are used. In this paper , they have used SVM algorithm for training the machine.Yogesh Kumar and Manish Mahajan, 2019 have proposed an approach to automatically detect emotions in speech of a speaker that explores some characteristics of how speech signals are detected and meta-information of the signals.In this paper , they have used KNN algorithm for detecting emotions in speech signals. Features like MFCC , LPCC are used for data preprocessing and feature extraction.Speech Emotion Recognition is one of the booming research topics in the computer science world. Emotion is a medium by which one expresses how a person feels and one's state of mind. Predicting emotions is a tough task as every individual has a different tone and intonation of speech. Thus emotions are difficult to extract using current machine learning systems easily. Therefore, many researchers have used Deep Learning and Machine Learning techniques to extract the emotions of speech signals.

Emotion plays an important role in the daily interpersonal interactions and is considered an essential skill for human communication [**1**]. It helps humans to understand the opinions of others by conveying feelings and giving feedback to people. Emotion has many useful benefits of affective computing and cognitive activities such as rational decision making, perception and learning [**2**]. It has opened up an exhilarating research agenda because constructing an intelligent robotic dialogue system that can recognize emotions and precisely respond in the manner of human conversation is presently arduous. The requirement of emotion recognition is steadily increasing with the pervasiveness of intelligent systems [**3**]. Huawei intelligent video surveillance systems, for instance, can support real-time tracking of a person in a distressed phase through emotion recognition. The capability to recognize human emotions is considered an essential future requirement of intelligent systems that are inherently supposed to interact with people to a certain degree of emotional intelligence [**4**]. The necessity to develop emotionally intelligent systems is exceptionally important for the modern society of the internet of things (IoT) because such systems have great impact on decision making, social communication and smart connectivity [**5**].

Practical applications of emotion recognition systems can be found in many domains such as audio/video surveillance [**6**], web-based learning, commercial applications [**7**], clinical studies, entertainment [**8**], banking [**9**], call centers [**10**], computer games [**11**] and psychiatric diagnosis [**12**]. In addition, other real applications include remote tracking of persons in a distressed phase, communication between human and robots, mining sentiments of sport fans and customer care services [**13**], where emotion is perpetually expressed. These numerous applications have led to the development of emotion recognition systems that use facial images, video files or speech signals [**14**]. In particular, speech signals carry emotional messages during their production [**15**] and have led to the development of intelligent systems habitually called speech emotion recognition systems [**16**]. There is an avalanche of intrinsic socioeconomic advantages that make speech signals a good source for affective computing. They are economically easier to acquire than other biological signals like electroencephalogram, electrooculography and electrocardiograms [**17**], which makes speech emotion recognition research attractive [**18**]. Machine learning algorithms extract a set of speech features with a variety of transformations to appositely classify emotions into different classes. However, the set of features that one chooses to train the selected learning algorithm is one of the most important tools for developing effective speech emotion recognition systems [**3**,**19**]. Research has suggested that features extracted from the speech signal have a great effect on the reliability of speech emotion recognition systems [**3**,**20**], but selecting an optimal set of features is challenging [**21**].

Speech emotion recognition is a difficult task because of several reasons such as an ambiguous definition of emotion [**22**] and the blurring of separation between different emotions [**23**]. Researchers are investigating different heterogeneous sources of features to improve the performance of speech emotion recognition systems. In [**24**], performances of Mel-frequency cepstral coefficient (MFCC), linear predictive cepstral coefficient (LPCC) and perceptual linear prediction (PLP) features were examined for recognizing speech emotion that achieved a maximum accuracy of 91.75% on an acted corpus with PLP features. This accuracy is relatively low when compared to the recognition accuracy of 95.20% obtained for a fusion of audio features based on a combination of MFCC and pitch for recognizing speech emotion [**25**]. Other researchers have tried to agglutinate different acoustic features with the optimism of boosting accuracy and precision rates of speech emotion recognition [**25**,**26**]. This technique has shown some improvement, nevertheless it has yielded low accuracy rates for the fear emotion in comparison with other emotions [**25**,**26**]. Semwal et al. [**26**] fused some acoustic features such as MFCC, energy, zero crossing rate (ZCR) and fundamental frequency that gave an accuracy of 77.00% for the fear emotion. Similarly, Sun et al.

[27] used a deep neural network (DNN) to extract bottleneck features that achieved an accuracy of 62.50% for recognizing the fear emotion. The overarching objective of this study was to construct a set of hybrid acoustic features (HAFs) to improve the recognition of the fear emotion and other emotions from speech signal with high precision.

III. PROPOSED SYSTEM ARCHITECTURE

Speech Emotion Recognition is one of the booming research topics in the computer science world. Emotion is a medium by which one expresses how a person feels and one's state of mind. Emotions are difficult to extract using current machine learning systems easily. Therefore, many researchers have used Neural Network and Machine Learning techniques to extract the emotions of speech signals.Our proposed system consists of MLP classifier which is shown in figure 1 and 2.In the Speech Emotion Recognition System (SER), the audio files are given as the input. The data sets travels through a number of blocks of processes which makes it executable to help for the analysis of the speech parameters. The data is pre-processed to change it to the suitable format and the respective features. This process helps in breaking down the audio files into the numerical values which represents the frequency, time, amplitude or any other such parameters which can help in the analysis of the audio files. After the extraction of the required features from the audio files, the model is trained. We have used the RAVDESS dataset of audio files which has speeches of 24 people with variations in parameters. For the training, we store the numerical values of emotions and their respective features correspondingly in different arrays. These arrays are given as an input to the MLP Classifier that has been initialized. The Classifier identifies different categories in the datasets and classifies them into different emotions.

The model will now be able to understand the ranges of values of the speech parameters that fall into specific emotions. For testing the performance of the model, if we enter the unknown test dataset as an input, it will retrieve the parameters and predict the emotion as per training dataset values. The accuracy of the system is displayed in the form of percentage which will be the final result of our project.

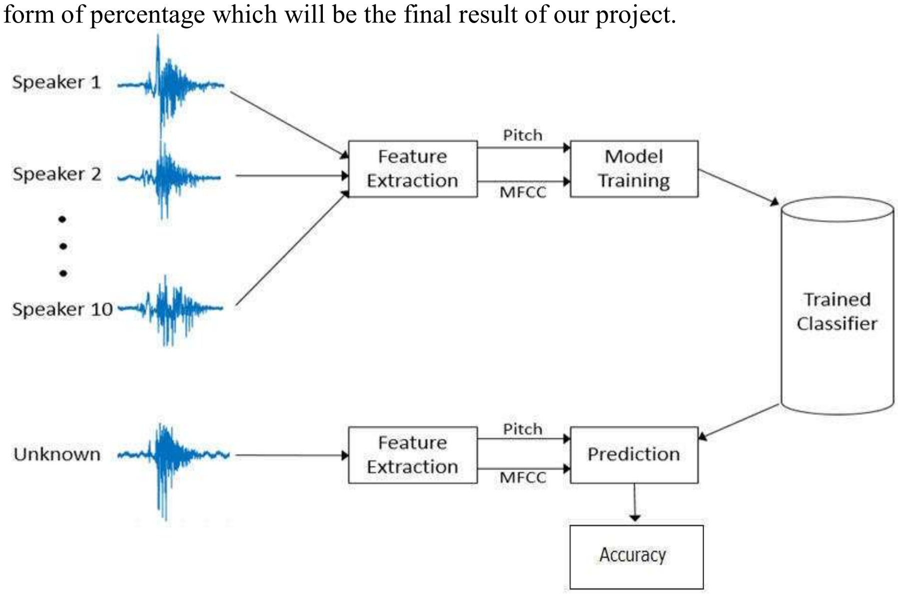

Fig.1. Proposed System Architecture

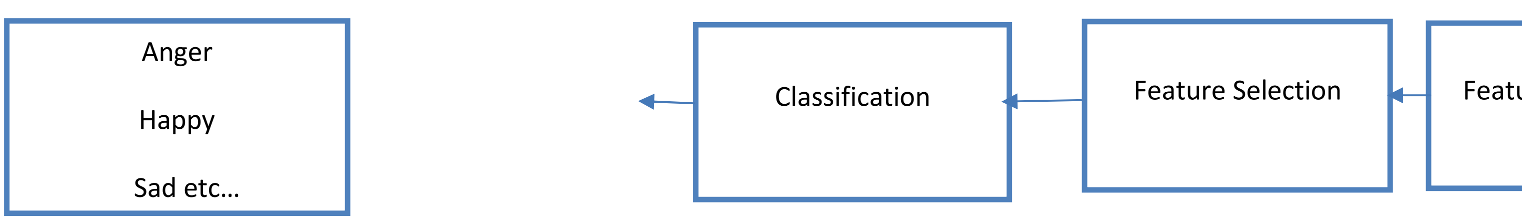

Fig.2 Framework of our system

IV. RESULTS AND DISCUSSION

The neutral, calm, happy, sad, angry, disgust, fear and surprise emotionsare recorded in a closed room.The result is highly depending on thestep size (μ) value in this case. Various μ values are testedto obtain better-enhanced result. From the experiment, it isclear that increase in μ provided faster convergence. Hence,it gives better accuracy in this case. However too large μdegraded the performance of the filter. A μ value of 0.4 and0.2 resulted in the required enhancement for MLP respectively in this experiment. For the MLPalgorithm, a forgetting factor of one and regularizing factorof 0.1 provided the desired accuracy. However, the variation in MSE founds to bedecreasing as number of iterations increase in all thesefigures mentioned. Lowest MSE has been observed between15 to 20 iteration for MLP. For MLP it alsoprovided similar results after 15 iterations.MLP algorithm provided lowest enhancement ofemotional speech signal among all discussed algorithm(Fig.2).Classificationusing MLP classifier for the clean speechand noisy speech has been discussed using LPC featureextraction techniques in Table I. Anenhancement in accuracy and decrease in MSE has beenobserved for fear utterance using MLP classifier. Highestaccuracy and lowest MSE has been observed with MLPalgorithm in our case as shown in these tables.

	anger	boredom	disgust	fear	happy	neutral	sad
anger	**91.33**	0	0	2.36	6.29	0	0
boredom	0	**96.06**	0	0	0	3.14	0.78
disgust	0	0.78	**97.63**	0	0	1.57	0
fear	3.93	0.78	0	**93.7**	0.78	0.78	0
happy	6.29	0	0.78	0.78	**91.33**	0.78	0
neutral	0	3.14	0	0	0	**96.85**	0
sad	0	0.78	0	0.78	0	0	**98.42**

Fig.2 Enhancement of neutral, calm, happy, sad, angry, disgust, fear and surprisespeech emotion using MLP algorithm

Table I. Comparison of proposed system with state-of-the-art approaches.

Dataset	Features	Accuracy
RAVDESS	MFCCs, spectral centroids and MFCC derivatives	43.8
	LLDs Stats	65.8
	Emobase feature set	72.1
	OpenSmile features + ADAN	66.1
	RESNET MODEL + Deep BiLSTM	58.9
	Complementary Features + KELM	59.3
	ADRNN	62.7
	Complementary Features + KELM	70.9
	Mel-frequency cepstrum coefficients (MFCC), chroma and Mel features	**96.5**

V. FUTURE SCOPE ANDCONCLUSION

- In this study, the main focus was on learning relevant and discriminative features from state-of-the-art speech emotional datasets, which is a critical research problem for Speech Emotion Recognition. Speech enhancement has increased the classificationaccuracy due to increase in SNR for neutral, calm, happy, sad, angry, disgust, fear and surprise speech emotion in thiswork. Ultimately, the MSE is also reduced. Among all thetested algorithms MLP provided better performance in termsof MSE and classification accuracy. This has been found truefor both enhancement and classification mode.For example, Arabic sometimes uses single words to convey ideas that are entire sentences in English. At some point in the future, speech recognition may become speech understanding. The statistical models that allow computers to decide what a person just said may someday allow them to grasp the meaning behind the words.

REFERENCES

[1] Jyoti Dhiman, Shadab Ahmad and Kuldeep Gulia, “Comparisonbetween Adaptive filter Algorithms (LMS, NLMS and RLS)”International Journal of Science, Engineering and TechnologyResearch (IJSETR), Vol. 2, Issue-5, pp.1100–1103, May 2013.
[2] AnujaChougule and V. V. Patil, “Survey of Noise EstimationAlgorithms for Speech Enhancement Using Spectral Subtraction”,International Journal on Recent and Innovation Trends in Computingand Communication, Vol.2, Issue.12, pp,4156–4160, Dec. 2014.
[3] S.Haykin, “Adaptive Filter Theory”, 3rd Edition, Prentice Hall, UpperSaddle River, 1996.
[4] Allam Mousa, Marwa Qados and Sherin Bader, “Speech SignalEnhancement Using Adaptive Noise Cancellation Techniques”, No. 7, pp.375–383, Sept. 2012.
[5] G. Iliev and N. Kasabov, “Adaptive filtering with averaging in noisecancellation for voice and speech recognition”, in Proc.ICONIP/ANZIIS/ANNES’99 Workshop, Dunedin, New Zealand, pp.71-74, 22–23 Nov.1999.
[6] RedhaBendoumia, Mohamed Djendi. “Two-channel variable-stepsizeforward-and-backward adaptive algorithms for acoustic noisereduction and speech enhancement”, Signal Processing, ElsevierJournal, pp 226-244, 2015.
[7] Meng Sun, Yinan Li, Jort F. Gemmeke and Xiongwei Zhang, “SpeechEnhancement Under Low SNR Conditions Via Noise EstimationUsing Sparse and Low-Rank NMF with Kullback–LeiblerDivergence”, IEEE/ACM Transactions on Audio, Speech, andLanguage Processing, Vol. 23, No. 7, July 2015.
[8] H.K. Palo, M.N. Mohanty and M. Chandra, “Emotion recognitionusing MLP and GMM for Oriya language”, International Journal ofComputational Vision and Robotics, Inderscience (in press), 2015.
[9] Hemanta Kumar Palo, Mihir Narayan Mohanty, Mahesh Chandra,“Efficient feature combination techniques for emotional speechclassification”, International Journal of Speech Technology, Vol.19,pp. 135-150, Jan 2016.
[10] H.K. Palo, Mihir Narayan Mohanty, “Classification of EmotionalSpeech of Children Using Probabilistic Neural Network”,International Journal of Electricaland Computer Engineering (IJECE),Vol. 5, No. 2, pp. 311–317, April 2015.
[11] S. Haykin, “Neural Networks”, 2nd Ed., Prentice Hall, 1999.
[12] Ma, Y.; Hao, Y.; Chen, M.; Chen, J.; Lu, P.; Košir, A. Audio-visual emotion fusion (AVEF): A deep efficient weighted approach. *Inf. Fusion* **2019**, *46*, 184–192.
[13] Picard, R.W. Affective computing: Challenges. *Int. J. Hum. Comput. Stud.* **2003**, *59*, 55–64.
[14] Sarker, K.; Alam, K.R. Emotion recognition from human speech: Emphasizing on relevant feature selection and majority voting technique. In Proceedings of the 3rd International Conference on Informatics, Electronics & Vision (ICIEV), Dhaka, Bangladesh, 23–24 May 2014; pp. 89–95.
[15] Li, S.; Xu, L.; Yang, Z. Multidimensional speaker information recognition based on proposed baseline system. In Proceedings of the 2017 IEEE 2nd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), Chongqing, China, 25–26 March 2017; pp. 1776–1780.
[16] Jiang, H.; Hu, B.; Liu, Z.; Yan, L.; Wang, T.; Liu, F.; Kang, H.; Li, X. Investigation of different speech types and emotions for detecting depression using different classifiers. *Speech Commun.* **2017**, *90*, 39–46.
[17] Subhashini, R.; Niveditha, P.R. Analyzing and detecting employee’s emotion for amelioration of organizations. *Procedia Comput. Sci.* **2015**, *48*, 530–536.

[18] Feinberg, R.A.; Hokama, L.; Kadam, R.; Kim, I. Operational determinants of caller satisfaction in the banking/financial services call center. *Int. J. Bank Mark.* **2002**, *20*, 174–180.
[19] Gomes, J.; El-Sharkawy, M. Implementation of i-vector algorithm in speech emotion recognition by using two different classifiers: Gaussian mixture model and support vector machine. *Int. J. Adv. Res. Comput. Sci. Softw. Eng.* **2016**, *6*, 8–16.
[20] Yu, T.-K.; Fang, K. Measuring the post-adoption customer perception of mobile banking services. *Cyberpsychol. Behav.* **2009**, *12*, 33–35.
[21] Chakraborty, R.; Pandharipande, M.; Kopparapu, S.K. Knowledge-based framework for intelligent emotion recognition in spontaneous speech. *Procedia Comput. Sci.* **2016**, *96*, 587–596.
[22] Kerkeni, L.; Serrestou, Y.; Mbarki, M.; Raoof, K.; Mahjoub, M.A. Speech emotion recognition: Methods and cases study. In Proceedings of the 10th International Conference on Agents and Artificial Intelligence (ICAART 2018), Funchal, Madeira, Portugal, 16–18 January 2018; Volume 2, pp. 175–182.
[23] Arias, J.P.; Busso, C.; Yoma, N.B. Shape-based modeling of the fundamental frequency contour for emotion detection in speech. *Comput. Speech Lang.* **2014**, *28*, 278–294.
[24] Atayero, A.A.; Olugbara, O.O.; Ayo, C.K.; Ikhu-Omoregbe, N.A. Design, development and deployment of an automated speech-controlled customer care service system. In Proceedings of the GSPx, The International Embedded Solutions Event, Santa Clara, CA, USA, 27–30 September 2004; pp. 27–30.
[25] Hess, U.; Thibault, P. Darwin and emotion expression. *Am. Psychol.* **2009**, *64*, 120–128.
[26] Ying, S.; Xue-Ying, Z. Characteristics of human auditory model based on compensation of glottal features in speech emotion recognition. *Future Gener. Comput. Syst.* **2018**, *81*, 291–296.
[27] Xiaoqing, J.; Kewen, X.; Yongliang, L.; Jianchuan, B. Noisy speech emotion recognition using sample reconstruction and multiple-kernel learning. *J. China Univ. Posts Telecommun.* **2017**, *24*, 17–19.
[28] Papakostas, M.; Spyrou, E.; Giannakopoulos, T.; Siantikos, G.; Sgouropoulos, D.; Mylonas, P.; Makedon, F. Deep visual attributes vs. hand-crafted audio features on multidomain speech emotion recognition. *Computation* **2017**, *5*, 26.
[29] Arruti, A.; Cearreta, I.; Álvarez, A.; Lazkano, E.; Sierra, B. Feature selection for speech emotion recognition in Spanish and Basque: On the use of machine learning to improve human-computer interaction. *PLoS ONE* **2014**, *9*, e108975.
[30]Altun, H.; Polat, G. Boosting selection of speech related features to improve performance of multi-class SVMs in emotion detection. *Expert Syst. Appl.* **2009**, *36*, 8197–8203.
[31] ”Prediction of Dengue Disease Cases by ML Techniques”, International Journal of Data Science and Machine Learning (IJDSML), ISSN : 2692-5141, Vol-1 Issue-1, Sep 2020, Page No: 1-6.
[32] ”An Approach For Detecting Phishing Attacks Using Machine Learning Techniques”, Journal of Critical Reviews (JCR), ISSN : 2394-5125, Vol-7 Issue-18, Jun 2020, Page No: 321-324.
[33] ”Disease Prediction and Diagnosis Implementing Fuzzy Neural Classifier based on IoT and Cloud”, International Journal of Advanced Science and Technology (IJAST), ISSN : 2005-4238, Vol-29 Issue-5, May 2020, Page No: 737-745.
[34] "Research of Feature Selection Methods to Predict Breast Cancer", International Journal of Recent Technology and Engineering (IJRTE), ISSN : 2277-3878, Vol-8 Issue-2s11, Sep 2019, Page No: 2353-2355.
[35] ,”Suicide Prediction on Social Media by Implementing Sentimental Analysis along with Machine Learning”, International Journal of Recent Technology and Engineering(IJRTE), ISSN : 2277-3878, Vol-8 Issue-2, July 2019, Page No: 4833-4837.
[36] “Issues for building an Artificial Intelligent System” JARDCS, Vol-7 Issue-13, Dec 2018, ISSN : 1943-023X, Page No: 1447-1451.