Abstract—Speech emotion recognition systems have high prediction latency because of the high computational requirements for deep learning models and low generalizability mainly because of the poor reliability of emotional measurements across multiple corpora. To solve these problems, we present a speech emotion recognition system based on a reductionist approach of decomposing and analyzing syllable-level features. Mel-spectrogram of an audio stream is decomposed into syllable-level components, which are then analyzed to extract statistical features. The proposed method uses formant attention, noise-gate filtering, and rolling normalization contexts to increase feature processing speed and tolerance to adversity. A set of syllable-level formant features is extracted and fed into a single hidden layer neural network that makes predictions for each syllable as opposed to the conventional approach of using a sophisticated deep learner to make sentence-wise predictions. The syllable level predictions help to achieve the real-time latency and lower the aggregated error in utterance based cross-corpus predictions. The experiments on IEMOCAP (IE), MSP-Improv (MI), and RAVDESS (RA) databases show that the method archives real-time latency while predicting with state-of-the-art cross-corpus unweighted accuracy of 47.6% for IE to MI and 56.2% for MI to IE.

Index Terms—Speech, Emotion Recognition, Real-time, Cross-corpus, Speech processing, Syllables.

I. INTRODUCTION

Speech Emotion Recognition (SER) technology has applications ranging from digital assistants to automotive safety. SER is one of the aspects of affective computing in which the speech signal from a human speaker is used to measure the emotional state of the speaker. Up until now, the SER has been used and tested within experimental bounds by many researchers. Nonetheless, now the focus is shifting towards the real-world applicability of the technology [1]. Especially with a drastic increase in online remote collaborations, there is a need for automated applications that can analyze human speech beyond just the lingual content. This transition of SER technology from experimental to maturity faces many challenges such as the distribution shift caused by the uncontrollable and unpredictable variables, e.g., environment, speaker’s identity, and the content of the language itself [2]. In this work, we also address this challenge and propose a new method that can be used to gauge emotions in the ever-shifting real world. The basic idea is systematic standardization of as many variables as we can recognize and minimize the variation at the neural network’s inputs to prevent the learning of anomalies instead of general but subtle trends.

The generally expected use of SER is as a complementary task to the primary task of speech recognition. Therefore, using the same method for both tasks would disregard the diversity of information channels. A change in the temporal order of semantics of a word can result in a different word but it might still convey the same emotion. Similarly, keeping the same semantic order, a slight change in the trailing amplitude might change the emotional overtone. If spoken words are the drawing and emotions are the texture then by the same logic we can hypothesize that speech emotions are conveyed at a granular level instead of at the utterance level. This hypothesis can be partly rejected because there have been some researches that have used only the word-based emotion hypothesis can be partly rejected because there have been some researches that have used only the word-based emotion recognition to perform a considerably accurate speech emotion recognition [3], [4]. However, the more channels of information we keep in our inventory, the more we will be able to perform well in cross-corpus and cross-lingual scenarios. The channel of information we use in this work is syllable-level speech features, that disregard the semantic order of words or sentences. An important advantage of syllable-level prediction is that the wisdom of the crowd (i.e., average is more accurate than individual guesses) helps to increase generalization at the utterance level. Moreover, syllable level features extraction helps us to predict emotions for voiced speech segments as small as 0.2 s, therefore predicting the emotion as soon as a word is uttered.

In this paper, we propose a method for real-time SER that decomposes the Mel-spectrogram of an incoming audio stream into frame-level formants that are temporally reassembled to create word-level speech segments and then segmented again into syllables. Then statistical features of syllables are extracted as input features for a single layer neural network that predicts emotional category for each syllable. This whole process chain is implemented by multiple asynchronous processing threads to predict emotion as soon as a word break is detected in the audio stream.

The contributions of this paper are two folds. Firstly, a
method for syllable-wide recognition of formant features is proposed. Syllable level features have been proposed by earlier works, however, the method of using only the formants to calculate syllabic features is the novel part. Using only the formants reduces, simplifies, and filters the information that reaches the neural network-based classifier. Furthermore, syllables are not integrated to extract higher-level features, instead, a single layer neural network is trained to predict for individual syllables regardless of what’s outside the bounds of syllable’s temporal boundaries. Secondly, a framework of real-time SER prediction with an easily reproducible design is presented and exhibited. All the constituent parts of the framework that includes a noise gate, context-based normalization, shallow neural network, and formant attention mechanism make it possible to achieve a negligible latency of prediction. While other works focus on maximizing the accuracy, this work focuses on minimizing processing cost and latency without compromising the cross-corpus accuracy. Moreover, the whole process is standardized from end to end in such a way that allows for ubiquitous usage as long as the user has a compatible computer with a microphone. The experiment results show two advantages of the proposed method, i.e., real-time prediction and increased generalizability.

The rest of this paper is organized as follows. Some of the works related to this study are given in Section II A new syllable-based SER model is proposed in Section III. Experiments and the analyses of results are given in Section IV. Then the results are concluded in Section V.

II. RELATED WORKS

The problems caused by the mismatch between the source and target domains are at the forefront in the affective computing field. Many researchers have tried to implement or invent different tools and techniques that result in marginal improvements. The bulk of the papers tackling the cross-corpus SER problem are not focused on the nitty-gritty of speech preprocessing, instead most of the work has been in the optimization and generalization techniques that build upon the Mel-spectrum or widely used feature extractors.

There are few recent works on the feature extraction process that closely relate to our work. Such as Alex et al. proposed a combined set of 15 utterance features and 10 syllable level features [5]. Their results support that the hand-engineered prosodic features are relevant for emotion recognition. Their results show a significantly low accuracy with syllable-level features as compared to the utterance-level or frame-level features. Another similar work by Origlia et al. presented a system for automatic emotion regression that extracted features for phonetic syllables and weighs their importance based on their relative duration of syllables’ nuclei [6]. Deb et al. proposed a multi-scale amplitude features extraction method that decomposes the speech signal into several subband signals for better speech emotion recognize accuracy [7].

Real-time SER has two kinds of challenges addressed by other works, i.e., decreasing the latency and reducing the noise or transmission effects. Among the works on decreasing the prediction latency, Vryzas et al. used a CNN-based deep learning model to learn features in frame-by-frame Mel-spectrograms [8]. According to their results, the CNN-based automatic feature learning method performed better than the SVM with handcrafted input features. In earlier work, a quick emotion prediction speed was reported using a simple CNN [9], thus presenting an argument that the latency is caused by the pre-processing and feature extracting blocks. Similarly, another work presented a real-time SER solution by using a simple deep neural network for predicting emotions just from 1 second long segments of speech [10].

On the other hand, the denoising of speech signals has been a challenge since the invention of the phone. Real-time SER prediction was tested for its applicability after a speech signal goes through rough transmission channels [11]. The microphones and the telecom processing modules lower the bandwidth and compand the speech signal, which affects the accuracy of SER prediction. Moreover, real-time speech applications have the issues caused by frame loss, which has been addressed by packet loss concealment while using an RNN to continuously predict speech emotions [12]. Pohjalainen et al. [13] showed that signal denoising by temporal smoothing in cepstral and log-spectral domains outperforms the standard techniques of noise reduction (spectral subtraction and MMSE [14]). Another work demonstrated the benefit of feature selection applied to the non-MFCC high-level descriptors using the Vector Taylor Series and root compression [15]. Tamulevicius et al. presented a comparison between different types of input features that can be used with CNN [16]. Their cross-lingual analysis showed the superiority of cochleagrams (gammatone filter-based spectrum) over spectrogram and Mel-spectrogram.

The research on the cross-corpus SER system focuses on adapting to the differences in the feature distributions and eliminating anomalies to create adversarial systems that can function in multiple domains [17]. A triplet network-based domain generalization method was proposed that uses 1582 static features to minimize a triple axes loss instead of single-dimensional loss, thus improving the cross-corpus accuracy [18]. Liu et al. showed the cross-corpus SER performance of the CNN model can be improved by recalibrating a domain adaptive layer based on the mean differences of the features between different corpora [19].

There is an unsettled debate among related works on which type of neural network architecture works better for cross-corpus SER. Parry et al. tested the cross-corpus generalization capabilities of various deep learning models [20]. Their analysis showed that architectures based on RNNs tend to overfit the training set, while architectures based on CNNs show better generalization capabilities for predicting categorical emotions. On the other side, a work published a year later by [21] concluded that the RNN is more robust than CNN for continuous arousal-valence regression task. The discrepancy between the conclusions could be for different emotional measures used by both of these works. Tripathi et al. gave a very good comparison of single-corpus SER performance of neural networks compromised of different combinations of MLP layers, LSTM layers, and attention layers, suggesting that the merging multiple types of models work better than the single types of model [22]. One of the reasons that different
works are reaching different conclusions is that no one method works best for all the domains or corpora.

Multi-task learning by incorporating other tasks such as gender, speaker ID, language ID, and/or other affective labels has shown to enhance the generalization capabilities of the emotion prediction model[23], [24]. Interestingly, using a training set compromised of diverse languages seems to increase the generalizability [25]. Similarly, an ensemble of different kinds of classifiers was used as a way to accommodate diverse languages in a single SER model [26].

III. SPECTRAL DECOMPOSITION AND FORMANTS ASSEMBLY

In this paper, we present a feature extraction method that converts Mel-spectrum into constituent syllable level components that are designed to focus on the important parts of Mel-spectrum and recognize the aspects that are of affective importance. The cross-corpus experiments performed on IEMOCAP database [27], MSP-Improv [28], and RAVDESS [29] using 4-class emotion classification show the improved generalizability of the method as compared to the state-of-the-art methods. An overview of the method is shown in Fig. 1.

![Diagram](image-url)

Fig. 1. An overview of the proposed method for real-time SER.

The basic core of the proposed feature extraction method is founded on a previously introduced formant extraction method for the same purpose of speech emotion recognition [30]. The formant extraction method is essentially an attention mechanism that extracts formants from a Mel-spectrum. The formants are usually the most noticeable pattern in the speech spectrum which are caused by the harmonics of vowel sounds. The tonal and timbre characteristics of sounds can be detected by analyzing the shapes and characteristics of formants. In speech recognition, consonants are as useful as vowels, therefore focusing the attention only on the formants is not useful in lexical recognition. However, in the case of speech emotion recognition, the formants of speech are as important as in music analysis. If we assume that the arbitrariness of language affects consonants more than the vowels, then by focusing the attention on vowels we can minimize the effects of language arbitrariness to achieve better cross-corpus results. The case of disregarding the consonant sounds is argued in detail in our previous paper [30], as it achieved a similar accuracy as the state-of-the-art results while using fewer input features.

There are three steps in the formant extraction algorithm. 1) Mel-spectrum extraction. 2) Peaks and valleys of spectral power bins for each frame. 3) Conjoining the formants of adjacent frames to link formants across multiple frames (time axis).

The process starts from a windowing function. A 25 ms (recommended value) sliding hamming window with a stride of 15 ms is applied to the raw time-domain sound signal. Each sampling window (frame) goes through an FFT function and Mel-filter. The Mel-filter maps the power-spectrum on a Mel-spectrum, which helps to create a similar auditory tuning response similar to the human ear perception. The Mel spectrum has a non-linear frequency scale on which the triangular-shaped Mel bins are equidistant, but they are not equidistant to the Hertz scale. The Mel scale frequency corresponds to the Hertz scale by

$$f_m = 2596 \log_{10}(1 + \frac{f_{hz}}{700})$$  \hspace{1cm} (1)

where $f_m$ is the value on the Mel scale and $f_{hz}$ is the value on the Hertz scale for the same frequency. Since there are discrete bins of frequencies instead of a continuous scale after the Mel-filter is applied, we can use the central frequency $f$ in hertz of a bin as the face value for a discrete bin calculated as

$$f(l) = 700(10^{\frac{m_l-m_{l+1}}{5190}} - 1)$$  \hspace{1cm} (2)

where $l$ is the index of a Mel-filter bin and $m$ is the lower limit of that bin on the Mel scale. The Mel-filter is usually applied to a sampling window frame of a few milliseconds audio signal (15 - 100 ms). We can create a Mel-spectrogram for the whole length of the signal by temporally adjoining Mel-filter outputs of each time step. In our experiments, we used 128 Mel filter bins that covered the frequencies from 50 to 4k Hz sampled with 25 ms frames and 15 ms steps.

A. Formant Features Extraction

Formants are the representations of the harmonics in the spectrograms. They appear as a recognizable pattern in the spectrum because they have a significantly higher amplitude as compared to the rest of the frequency bands across a sizable duration. If there are no particular formants then it’s an indication of noise instead of a single source of the voice.
There can be up to dozens of formants appearing the spectrum for a speech signal for a certain time step, however, most of the information about the quality of the speech can be gathered by just considering the top 3 formants by amplitude. Formants are easy to detect when there are clearly separated from each other by gaps of low energy bands. The band-like formation gives formants a peaks-and-valleys like structure with maxima as

$$p_h = \max_{h=0 \rightarrow p(l) \leq p_{h-1}} p(l)$$

where $p_h$ is the power amplitude of $h^{th}$ highest amplitude formant and $p(l)$ is the amplitude of filter bank $l$. The frequencies of the formants are the frequencies at the peaks, i.e.,

$$f_h = \arg \max_{h=0 \rightarrow p(l) \leq p_{h-1}} f_m(l)$$

where $f_h$ is the Mel-scale frequency of $h^{th}$ highest amplitude formant and $f_m(l)$ is the index number of the filter bank $l \in \{1, \ldots, N_m\}$. The peak frequencies of formants don’t cover all the information about their shape because they cover a band of frequencies instead of a singular discrete frequency. The bandwidth of a formant is important to distinguish the narrowband tone like that of an oboe from a wideband tone like that of a truck horn. It is a measure of the sharpness of voice. We calculate it in terms of a frequency range (from minima to minima) as

$$w_h = |\arg \min_{l \leq f_h} f_m(l) - \arg \min_{l > f_h} f_m(l)|$$

where $w_h$ is the bandwidth of formant $h$.

### B. Real-time Noise Gate

One of the major challenges for real-time speech processing is the environment adaption in the wild because of the compromise that a speech preprocessing unit has to make between white noise and silence threshold. The amplitude of speech is an important factor for predicting the emotional arousal of the speaker, therefore normalizing it would compromise the useful information. On the other hand, the distance between speaker and microphone causes uncertainty in arousal signatures. The dilemma is to choose between normalizing to solve the speaker distance problem versus preserving the useful amplitude information for the next stage. Almost all known mechanisms to adapt to the microphone volume require a compromise (except for the multi-microphone inputs). In the proposed method, we decided to compromise the distance-amplitude uncertainty and preserve the amplitude information for feature learning. This is not a big issue because corpora are generally standardized to a normal-hearing amplitude. However, differences between corpora create a different issue of uncertain silence threshold between the words. To counter the differences between environments or speaker distances, we use a long-term mean normalization in the final stage of feature extraction.

Since the proposed method is not based on deep learning or any complex language learning methods, the syllable separations have to be detected based on unintelligent signatures such are pauses or formant breaks. In this case, the silence threshold becomes an important factor to control to precisely detect pauses in multiple databases. For this purpose, we propose using a noise gate algorithm that dynamically adapts the silence threshold based on amplitude impulses rather than the constant highs. The silence ceiling or the minimum voiced amplitude $A_{\text{min}}$ is reset by a decaying impulse amplitude value calculated as

$$A_{\text{min}} = 10^{(\log_{10} A_{\text{imp}} - 3)/2}$$

where $A_{\text{imp}}$ is the decaying the highest peak amplitude of any Mel-spectrum bin in recent frames, that is consistently updated by any new peak in the incoming frames higher than the current decaying value. Then the decay rate is set such as the $A_{\text{imp}}$ drops to its hundredth in 0.5 seconds (or 30 frames) then it stops decreasing further. It is to be noted that the $A_{\text{imp}}$ is not in decibels, so the perceived drop of 99/100 in the impulse peak threshold will be equivalent to a 3/4 drop. Moreover, a bandpass filter only allows a certain range of frequencies (100 – 1200 Hz because most of the voiced formants lie in this range) to be used for setting the $A_{\text{min}}$. This noise gate filter plays an important role in filtering out the formants from the rest of the spectrum in the next stage.

### C. Formants Assembly

The decomposition of the speech signal into formant properties allows us to cherry-pick the formants that fit well with the adjacent frames. This allows the system to filter out anything that does not have a shape of a formant, i.e., a horizontal pattern on the Mel-spectrum. The formants of supra-segments (25 ms frames) have to be linked across multiple adjacent to coalesce the formants back to their original temporal length. The sampling window helps to create digestible chunks for spectral processing, but the natural length of formants can be spread across a variable length of time, therefore the spectral chunks have to be stitched together to recreate the formant with its original duration. This can be achieved by spectral clustering or any clustering method that recognizes the clusters based on the agglomeration in the temporal neighborhood. We perform this task by calculating a matching index that measures the proximity for formants of the new incoming frame with the formants of recent frames. The formants of the new frame are assigned the formant labels $(h_0, h_1, h_3, \ldots, h_{\text{max}})$ with the highest matching index value. The proximity between formants $h_a$ and $h_b$ at time steps $t_a$ and $t_b$, respectively, is measured as

$$I_{a,b} = \frac{K_t}{t_b - t_a} + (K_f - (f_b - f_a))^2 + L_a \min_{p_a, p_b} \max_{p_a, p_b}$$

where $I_{a,b}$ is the matching index. The first two terms measure distance on the frequency and time axes. The third term multiplies the current length of the formant $a$ in frame count ($L_a$) to the ratio of power of formants given that the $t_a < t_b$, $t_b - t_a < K_t$, and $f_b - f_a < K_f$. $K_t$ and $K_f$ are Manhattan distance constants that depend on horizontal and vertical unit distances on the formant spectrum. The recommended value for 25:15 ms window and 128 Mel-bins are $K_t = 10$ and...
$K_f = 10$, respectively. These constants define the proximity neighborhood in which the unit formants can be connected to each other on a syllable or word level.

D. Syllable Segmentation

Syllable isolation is a tricky task because syllables are usually glued together in the spectrogram without any boundaries between them [31]. Even the words are not easy to isolate from a speech segment especially when someone is speaking fast. A small pause in speech is one of the clear signals of syllable separations, however, most of the prominent pauses are often the indication of the conclusion of sentences or utterances. To tackle this challenge of syllable separation, we present a strategy using the peaks and minima of the amplitude of the formants. Our method uses three amplitude thresholds that are calculated ad-hoc during three stages that divide the syllable into three parts, i.e., rising edge, plateau, and cut-off.

Amplitude thresholds are not applied to the overall sound signal, instead only the amplitude of the top three major formants at each frame $t$ are taken as

$$p_c(t) = \sum_{h=0}^{3} p_h(t)[1 + f_h(t)E_c]$$

(8)

where $p_c$ is the combined amplitude of the top three formants and $E_c < 0.1$ is a higher frequencies emphasis constant. The higher frequencies tend to have higher attenuation but their apparent amplitude is perceived higher by humans than their relative amplitude compared to the lower frequencies’ amplitude. The emphasis is used to geometrically increase the power of higher frequencies to mimic human perception. The algorithm starts the first stage with the rising edge of $p_c(t)$. The threshold for the rising edge is the same $A_{min}$ as long as there is a continuous rise for two or more frames. After the peak is reached, the plateau stage uses a threshold of 50% drop in $p_c$ to move to the third stage. Once $p_c(t)$ reaches below 50% of its local peak, the cuff-off boundary is marked at the next minima. An example of marked syllable boundaries are shown in Fig. 4.

The reason for using just the top three formants is that it reduces the likelihood of noise or background echoes to blur the syllable boundaries. A similar approach is used by [5] for syllable separation based on the vowel onset points (VOP) proposed by [32]. Their method follows three steps thus adding extra checks for syllable boundaries, which is perhaps a more rigorous approach. In our method, we use only one condition ($e_c(t) < 3A_{min}$ for 2 or more frames) to perform a quick separation while not being highly precise.

E. Syllable Statistical Features

Individual syllables can be observed in spectrograms to have a pattern with more or less similar features. There are variances caused for other factors such as noise, distance, speaker, or mood. Even the two repetitions of a same syllable by a same person will probably have some minor variations. We aim to quantify features of syllables in a statistical way such that the shape of formants instead of defining the exact shape in a matrix. This is different from CNN-based methods because CNN looks for the exact shape match in the spectrogram, where our proposed method gives measures the similarity even if the shape doesn’t match exactly. CNN might work better for the language processing tasks to recognize words more accurately because slight changes in the shape of formants can completely change words. However, for SER there are only a few output categories of emotions, while the underlying words have indefinite possibilities. Therefore a broad view of formants is more likely to generalize over a large sample without confusing the minor difference caused by unknown words.

We propose using six types of syllables with a total of 53 features. They essentially measure formant frequencies, accent (as in slope of the pitch), metallicity (lengths of formants), power, stress (pressure points in formants), and SNR. Each feature is measured within the time-axis bounds of $t_{s0} \geq t < t_{sn}$, where $t_{s0}$ and $t_{sn}$ are the first and last frame indices of the syllable in the context of the whole utterance. All 6 types of features are listed below.

- Frequency tones of top 3 formants ($h_0, h_1, h_2$):
  
  - **Freq A**: Frequency mean $\mu(f_h(t))$ of formant $h$ for $t_{s0} \geq t \leq t_{sn}$.
  
  - **Freq B**: Frequency standard deviation $\sigma(f_h(t))$ of formant $h$ for $t_{s0} \geq t \leq t_{sn}$.
  
  - **Freq C**: Frequency mean bandwidth $\mu(w_h(t))$ of formant $h$ for $t_{s0} \geq t \leq t_{sn}$.

- **Accent for top 3 formants ($h_0, h_1, h_2$):
  
  - **Accent A**: Rising accent: Increments in formant's mean frequency along the syllable length.
  
  $$X_{h,\text{rise}} = - \sum_{t=t_{s0}}^{t_{sn}} |f_h(t) - f_h(t-1)| \cdot \text{rise}_{h,t}$$

  (9)

  where,

  $$\text{rise}_{h,t} = \begin{cases} 1 & \text{if } |f_h(t) - f_h(t-1)| \geq 1 \\ 0 & \text{otherwise} \end{cases}$$

  (10)

  - **Accent B**: Falling accent: Decrements in formant’s mean frequency along the syllable length.
  
  $$X_{h,\text{fall}} = - \sum_{t=t_{s0}}^{t_{sn}} |f_h(t) - f_h(t-1)| \cdot \text{fall}_{h,t}$$

  (11)

  where,

  $$\text{fall}_{h,t} = \begin{cases} 1 & \text{if } |f_h(t) - f_h(t-1)| \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

  (12)

- **Metallicity for top 3 formants ($h_0, h_1, h_2$):**
  
  - **Metal A**: Total number of frames where formant $h$ is voiced (i.e., $p_h > A_{min}$).
  
  $$X_{h,voiced} = - \sum_{t=t_{s0}}^{t_{sn}} (f_h(t) > 1)$$

  (13)
Metal B: Count of breaks in the formant connectivity along the time-axis. This can be taken as a measure of jitters in speech

\[ X_{h, \text{breaks}} = - \sum_{t=i_{0}}^{f_{n}} (f_{h}(t) < 1) \cap (f_{h}(t - 1) > 1) \]  

(14)

Metal C: Ratio of \( X_{h, \text{voiced}} \) by total numbers frames of syllable.
- Power for top 3 formants \((h_0, h_1, h_2)\):
  - Power A: Syllable mean power in dB.
  - Power B: Standard deviation of power in dB as a measure of shimmering in speech.
  - Power C: Energy per total frames of the syllable relative to the rolling \( \mu_{\text{imp}} \).
  - Power D: Energy per total voiced frames of the syllable relative to the rolling \( \mu_{\text{imp}} \).

- Phoneme-level stress in top 3 formants \((h_0, h_1, h_2)\):
  - Stress A: Count of formant power peaks along the syllable time-axis.
  - Stress B: Mean of formant power peaks (dB) values \((\mu_{\text{peaks}})\).
  - Stress C: Standard deviation of formant power maxima (dB) values \((\sigma_{\text{peaks}})\).
  - Stress D: Relative ratio of \( \mu_{\text{peaks}} \) to average power (dB) of the formant \( \mu_{\text{amp}} \).

- SNR and threshold limits for the whole syllable:
  - SNR A: Ratio of energy of the bins detected as top three formants over the total energy of the spectrum.
  - SNR B: Utterance amplitude maximum in decibels.
  - SNR C: Noise gate voiced formant minimum limit.

F. Long-term Normalizer

Normalization contexts can cause huge shifts in the SER accuracy if it is not taken into account during the training process. It is analogous to the deep-learning-based augmentation used by comparative works which augment the samples from a new context to the contexts of the training samples, then use a deep neural network to predict emotions [33], [8], [34]. The augmentation process needs to predict some factors and values which are estimated. Augmentation needs a considerable amount of test domain data to estimate context parameters on which augmentation is performed. Since in real-time SER, the test sample is limited, context normalization is the proposed solution to adapt the new context to the training context.

This is a simple yet very important block of the framework for increasing the performance over multiple corpora. The term ‘long-term’ does not correspond to any specific context because our experiments didn’t show any specific context that works significantly better than others. Context could be each gender, each session, each speaker, each utterance, or each corpus. For a context sample set \( S_{\text{ctx}} \), the mean normalization of a feature \( q \) of a sample \( i \) is performed as

\[ X_{q}(i) = \frac{X_{q}(i) - \min_{\forall i \in S_{\text{ctx}}} X_{q}(i)}{\sigma_{\forall i \in S_{\text{ctx}}}} \]  

(15)

where \( X_{q} \) is first standardized within the context set \( S_{\text{ctx}} \) and then min-max rescaled relative to the training sample set \( S_{\text{train}} \) as \( X_{o} \). The mutable parameters in this equation are the size and limits of \( S_{\text{ctx}} \), which will be tested at different conditions in Section IV The challenge with using this method is that there will be a cold-start error in any new context. Unless the new context is very similar to the generalized normalization parameters, the cold start without the knowledge of the new domain’s expected mean, reduces the accuracy by up to 30%. The best but not conclusive results were produced with individual speakers normalization. The same conclusion has been reported by other works [35], [18].

G. Single Hidden Layer Classifier

The next stage of the proposed method is to use a machine-learning algorithm to predict the emotional category for a syllable using the 53 syllable features as input. After testing different machine learning classifiers with various parameters, we concluded that most of the complicated classification methods are unnecessary when it comes to cross-corpus SER. As we have shown in a previous paper sophisticated classifiers such as SVM (Support Vector Machine) or RF (Random Forest) perform reasonably better than relatively simple classifiers such as KNN (K-Nearest Neighbors) or MLP (Multi-Layer Perceptron) for within-corpus classifiers [30]. However, with the method proposed in this paper, SVM or RF does not seem to have any superiority over a small single neural network as shown in Section IV Even multiplying the number of units or adding extra layers was detrimental to the cross-corpus performance of the classifier. To give an example, a simple single-layer MLP with only 4 units worked better than the three layers of \( \geq 8 \) units, whereas results varied only \( \pm 2\% \) when we increased the number of units from 4 to 32 in each layer. Another advantage of using a single-layer neural network is the real-time prediction speed because a small MLP will have to do only a few hundred dot products. Based on the observations collected by experiments (given in Tables III, IV, and V), we propose to use the simplest form of Multi-Layer Perceptron with only one hidden layer as shown in Fig. 1.

The loss function we used for training the network in our experiments was the categorical cross-entropy loss function that can be given as

\[ Loss = - \sum_{v=1}^{N_{V}} y_{v} \cdot \log \hat{y}_{v} \]  

(17)

where \( N_{V} \) is the number of the emotional categories, \( \hat{y}_{v} \) is the \( v^{th} \) scalar value in the model’s output (softmax classification probabilities), and \( y_{v} \) is the corresponding known labeled value for the input sample.

H. Utterance-level Confidence Aggregation

The last block of the framework is necessary only when a single label for the whole utterance is needed. Since the
model is optimized to decrease the loss at syllable level instead of utterance level, the utterance level predictions are not optimized by any machine learning classifier. However, we can estimate it with a comparison to the start-of-the-art method by simply taking weighted sums of the class probabilities of syllables as

\[ C_{u,c} = \frac{1}{\sum_{s=0}^{N_s} T_s^{1/2} \sum_{c=0}^{T_s} P_{s,c} T_s^{1/2}} \]

where the weight is the square-root of the duration \( T_s \) of syllable at index \( s \), \( P_{s,c} \) is the predicted probability of class \( c \), \( \bar{P}_s \) is the mean of prediction probabilities of all classes for the syllable, \( C_{u,c} \) is the class confidence of the utterance \( u \), and \( N_s \) is the total number of syllables in the utterance.

### IV. Experimentation

The objective of the proposed method was to decrease prediction latency while increasing the cross-corpus SER accuracy. Based on the method described in Section III, we developed a web-based real-time SER system with the optimum parameters that were estimated by performing several experiments for the following purposes:

1) The effect of raters’ agreement on the cross-corpus UAR.
2) The effect of the normalization context on the UAR at utterance level and syllable level.
3) The comparison between the classifiers (MLP, SVM, KNN, RF) at utterance level and syllable level.
4) Measurement of real-time prediction latency on a general-purpose computer.
5) Comparison of the within-corpus UAR and WAR (Weighted Average Recall) with other works.
6) Comparison of the cross-corpus UAR with other works.

To perform these experiments, first, we designed an SER system that can work in real-time using a web-based framework. Then we used several training sets to train the system. It took a few hours to train (5 hours for IEMOCAP’s in-browser training on an Intel-i7-8550U CPU) because the system reads raw files, extracts features, and trains a neural network during training. Then finally we used the trained neural network to make predictions for a test set or to predict emotions in real-time. Since some emotions are easier to detect (e.g., anger) than others (e.g., neutral), the imbalance in the training dataset can cause a significant bias. Therefore, in our experiments, we used data boosting to balance the class samples. The classification accuracy is measured and compared using the Unweighted Average Recall (UAR), as it is a better measure than the weighted average when some classes have more samples than others.

### A. Corpora

We used three corpora with different sizes. Two of the corpora are of intermediate size and have been widely used by other researchers, therefore, allowing us to compare our approach to other methods. The third corpus has a few hundred samples collected in a highly controlled manner. Using these two different types of sample sets allows us to judge the cross-corpus performance when the model is trained with a very small (but highly controlled) sample. All the databases have emotional labels including but not limited to 4 basic categorical emotional labels i.e., Happiness, Sadness, Anger, and Neutral rated by multiple human annotators. Sample counts and duration of utterances and syllables after the syllable segmentation are given in Table I.

1) IEMOCAP (IE): The IEMOCAP database is an audio-visual English database [27] which is composed of five sessions with each session including two actors. In each session, a scripted and improvised dialog between a male/female pair was recorded. At least three annotators labeled each utterance for categorical and dimensional emotional labels. The consensus label is calculated when a certain label crosses the limit of at least 50% agreement among the raters. Some very small utterances were skipped by the formant extractor because of the lack of enough information to calculate the noise gate threshold \( A_{min} \). The total sum and duration of the selected utterances are given in Table I. The default lower limit for raters’ agreement for all experiments except for the one in Fig. 2 was set to 66.67%, i.e, only the utterances for which at least 2/3 raters agree on the same emotional label were selected.

2) MSP-IMPROV (MI): The MSP-IMPROV database is an acted audiovisual corpus in English [28], that consists of 6 sessions with pairs (a male and a female) of a total of 12 individual actors. There are three scenario labels in MSP-Improv. We only selected the scripted and improvised recording for most of the experiments because the third scenario (labeled as ‘natural’) is heavily biased towards the neutral and happy labels, thus making it difficult to balance the dataset. For example, there are 46.7 minutes of happiness and only 0.8 minutes of anger left after the syllable separation (because naturally, negative emotions are far less frequent [36]). There was an average 3% drop in accuracy when the model was trained on MSP-Improv and tested on IEMOCAP with ‘natural’ recordings included in the training set. The only exception where we included the natural scenario is in Table VII and Table VIII where we used all the use-able utterances to make the sample size big enough (6907) for a proper comparison with other works.

3) RAVDESS (RA): RAVDESS database [29] is an acted audiovisual corpus recorded with relatively a higher number of controlled factors. Each utterance in it is one of the two sentences spoken twice by 24 speakers (gender-balanced) with 8 different emotional intents and two levels of intensity (neutral has only one level of intensity). This makes it an ideal database for small-sample testing. There are 8 emotional categories in this database total consisting of 1440 utterances, but we only considered the 4 basic emotions for our experiments. We didn’t perform any reliability selection on this corpus because of the lack of individual raters’ ratings. The measure of inter-rater agreement among 20 annotators was 0.61 as reported by the data collectors [29].
**TABLE I**

Selected sample counts and total duration (minutes) for utterances (ΣN_u and ΣT_u) and separated syllables (ΣN_s and ΣT_s) for four labels Anger (A), Happiness (H), Neutral (N), and Sadness (S) with raters’ agreement > 66% in three databases. The last row shows the average duration for utterances and segmented syllables in each database.

| Label    | IEMOCAP (IE) | MSP-Improv (MI) | RAVDESS (RA) |
|----------|--------------|-----------------|--------------|
|          | Utterances   | Syllables       | Utterances   | Syllables       | Utterances   | Syllables       |
|          | ΣN_u | ΣT_u | ΣN_s | ΣT_s | ΣN_u | ΣT_u | ΣN_s | ΣT_s | ΣN_u | ΣT_u | ΣN_s | ΣT_s |
| Anger (A) | 971  | 66   | 5994 | 44.7 | 504  | 33   | 2883 | 17.1 | 192  | 6.1  | 839  | 4.3  |
| Happiness (H) | 1342 | 95   | 8723 | 56.7 | 975  | 54   | 5196 | 30.5 | 192  | 5.3  | 747  | 4.4  |
| Neutral (N) | 1458 | 87   | 8654 | 50.7 | 1451 | 82   | 7676 | 40.6 | 96   | 2.2  | 414  | 1.7  |
| Sadness (S) | 891  | 66   | 6137 | 32.9 | 570  | 46   | 4220 | 20.8 | 572  | 5.7  | 2876 | 1.5  |
| Train:IE/Test:MI | UAR | Train:MI/Test:IE | UAR |
|          | 42.3 | 41   | 55.8 | 37.5 | 54.8 |

**TABLE II**

Cross-corpus UAR% for the MLP-4 model trained and tested with various normalization contexts.

| Train/Test | IE/MI | IE/RA | MI/IE | MI/RA | RA/IE | RA/MI |
|------------|-------|-------|-------|-------|-------|-------|
| Norm space | Syl. Utt. | Syl. Utt. | Syl. Utt. | Syl. Utt. | Syl. Utt. | Syl. Utt. |
| Speaker | 40.2 | 44.7 | 43.6 | 43.4 | 48 | 53 | 43.2 | 44 | 41.9 | 43.5 | 48.2 | 32.8 | 34.4 |
| Session | 38.9 | 42.7 | 43.9 | 44.3 | 49.3 | 52.1 | 42 | 41.9 | 43.5 | 48.2 | 32.8 | 34.4 |
| Gender | 37.9 | 40.3 | 45.2 | 44.1 | 46.9 | 51.3 | 43.2 | 44.8 | 39.2 | 40.8 | 32.5 | 35.1 |
| Corpus | 35.7 | 36.7 | 39.3 | 38.6 | 43.3 | 46.9 | 43.2 | 44.8 | 39.2 | 40.8 | 32.5 | 35.1 |
| Utterance | 34 | 34.1 | 39 | 42.6 | 36.7 | 40.2 | 33.9 | 37.1 | 34.2 | 37.8 | 30.4 | 32.9 |
| None | 31.1 | 31.7 | 44.5 | 46.9 | 39.7 | 40.4 | 35.2 | 36.8 | 43.6 | 47.3 | 30.4 | 31.9 |

**TABLE III**

UAR% for different classifiers when trained on IEMOCAP (IE) in cross-corpus (CC) scheme and LOSO scheme. Leave one speaker out from the same corpus for test. The column-wise color intensity illustrates classifier performance differences at a glance.

| Classifier | MI/IE | RA/IE | IE (LOSO) |
|------------|-------|-------|-----------|
|           | Syl. Utt. | Syl. Utt. | Syl. Utt. |
| MLP-4 | 47.5 | 43.6 | 43.6 | 43.6 |
| MLP-8-4 | 47.5 | 43.6 | 43.6 | 43.6 |
| MLP-16-4 | 47.5 | 43.6 | 43.6 | 43.6 |
| MLP-53-32-8 | 47.5 | 43.6 | 43.6 | 43.6 |
| SVM | 47.5 | 43.6 | 43.6 | 43.6 |
| RF | 47.5 | 43.6 | 43.6 | 43.6 |
| KNN | 47.5 | 43.6 | 43.6 | 43.6 |

**TABLE IV**

UAR% for different classifiers when tested on MSP-Improv (MI) in cross-corpus (CC) scheme and LOSO scheme.

| Classifier | IE/MI | RA/MI | MI (LOSO) |
|------------|-------|-------|-----------|
|           | Syl. Utt. | Syl. Utt. | Syl. Utt. |
| MLP-4 | 40.9 | 44.4 | 43.5 | 38.6 | 42.1 | 47.7 |
| MLP-8-4 | 40.5 | 44.3 | 35 | 36.5 | 42.3 | 48.2 |
| MLP-16-4 | 40 | 43.9 | 36.4 | 38.5 | 40 | 46.3 |
| MLP-53-32-8 | 36.3 | 41 | 33.4 | 35.2 | 36.8 | 42.3 |
| SVM | 37.5 | 43.9 | 34.8 | 40.1 | 38.5 | 45.2 |
| RF | 40 | 41.8 | 37.1 | 38.2 | 40.7 | 44.4 |
| KNN | 37.1 | 42.2 | 35.7 | 35.5 | 37.3 | 45.9 |

**TABLE V**

UAR% for different classifiers when tested on RAVDESS (RA) in cross-corpus (CC) scheme and 5-folds scheme.

| Classifier | IE/RA | MI/RA | RA (5-folds) |
|------------|-------|-------|-------------|
|           | Syl. Utt. | Syl. Utt. | Syl. Utt. |
| MLP-4 | 43.6 | 43.4 | 41.6 | 43.5 | 48.1 | 53 |
| MLP-8-4 | 43.5 | 42.8 | 40.8 | 42.7 | 47 | 47.8 |
| MLP-16-4 | 43.5 | 42.8 | 40.8 | 42.7 | 47 | 47.8 |
| MLP-53-32-8 | 43.5 | 42.8 | 40.8 | 42.7 | 47 | 47.8 |
| SVM | 43.1 | 45.6 | 38.4 | 42.4 | 46.1 | 56.4 |
| RF | 41.4 | 41.2 | 38.5 | 40.6 | 48.8 | 50.4 |
| KNN | 41 | 44.6 | 39 | 39 | 46 | 52.6 |

**B. Real-time SER system design**

The real-time SER prediction has two additional challenges that needed to be addressed other than being real-time and accurate. The user interface (UI) had to be limited to the normal computing power that an everyday user is expected to have and the system had to be a pre-assembled end-to-end system so that the user doesn’t need to get professional help to initialize. To solve these challenges, we used web-based frameworks to develop the SER system assuming that everyone is familiar with the modern web browsers. The development of the system was made possible mainly because of the recent development of Web Audio API [37] and TensorFlow JS [38]. The process flow of the system is given in Fig. 3. The system compromises a lot of small parts that are already standardized by the Web API, thus simplifying the stack of parameters that
need to be accommodated on various devices. Figure 4 shows
the screenshot of the web interface, showing the formants in
different colors, the predicted label for each syllable, and the
predicted cumulative probabilities of the utterance*.

The main goal of decreasing latency is at odd with using the
widespread platforms because web browsers use script-based
JavaScript (JS) that is a lot slower than the alternatives such as
Python, R, or C. However, with JavaScript, the multi-threaded
approach helps to increase the processing speed because most
modern UI devices are capable of multi-threading. Figure 3
also shows the processing load of all the processes and their
division across multiple threads. FFT is the heaviest process
because of the high number of for-loops in it per each 25
ms window. There is a faster alternative available for FFT
that uses the built-in FFT module of Web-API but that lacks
sampling parameter configurations that we needed to make our
system work. Therefore, we programmed the FFT at the JS
level without using native libraries of web browsers.

The average delay between the word-end detection and
prediction was 85 ms for a word of 0.5 s duration of voiced
speech on Chrome browser (v91) running on an iPhone 8. The
latency is highly dependent on the system being used, that’s
why during our experiments we could achieve a latency of
130 ms for 0.5 s speech on Mozilla Firefox (v96) running on
an Intel i7 system clocked at 3.7 GHz. Table VI shows the
mean delays caused by the individual steps for the IEMOCAP
database. These measurements do not show the interval for all
processes combined because asynchronous calculations start
as soon as the audio stream enters the input node of the Web
API. The multi-threading streamlines a lot of processes while
the speaker is speaking that’s why it’s difficult to estimate
the latency of calculations that happen before the word-end.
When a word ends, formants have already been extracted and
assembled in memory, only the syllable segmentation, syllable
feature extraction, normalization, and MLP prediction happen
after that.

| Method                  | Prediction step                | Latency (seconds) |
|------------------------|-------------------------------|-------------------|
|                        | FFT and Mel filter            | 0.04 ± 0.02       |
|                        | Assembly and Segmentation     | 0.02 ± 0.02       |
|                        | Syllable Features Extraction  | 0.03 ± 0.01       |
|                        | MLP-4 prediction              | 0.052 ± 0.01      |
|                        | MLP-8-4 prediction            | 0.055 ± 0.01      |
|                        | MLP-16-4 prediction           | 0.056 ± 0.01      |
|                        | MLP-53-32-8 prediction        | 0.14 ± 0.04       |
| Proposed               | MFCC-13 extraction            | 0.05 ± 0.3        |
| Conventional           | LSTM-16-8 prediction          | 0.6 ± 1           |
|                        | LSTM-32-16 prediction         | 2 ± 2             |
|                        | LSTM-64-64 prediction         | >3                |

Since there are no comparisons publicly available to com-
pare the prediction latency of the proposed method and the
conventionally used methods, we created a comparative
demo application* using an LSTM based model from the Tensor-
flowJS library. We tested different models with different layer
structures, but those which performed well on accuracy were
too slow to be tested in real-time. The biggest model (LSTM-
16-8) that could perform with a real-time latency gave an
accuracy of 33%. Adding more layers and units did increase
the accuracy but it didn’t perform in real-time.

C. Discussion

As explained in Section III-F, the proposed approach for
context adaptation is the context bounds normalization. The
exact boundary of the context is one of the variables in our
proposed method that we tested in our experiments. Table
II shows the utterance level and syllable level UAR using
5 types of normalization contexts and without any context
normalization. The results show that there is no particular
textual normalization space that works significantly better
than others. However, it can be observed in Table II that
the upper three rows have higher UARs compared to the
lower three rows, which shows that the contexts in which
the speakers are differentiated are better than contexts where
speech segments are differentiated.

The IEMOCAP and MSP-Improv have one male and one
female speaker in each session. Assuming that we don’t
want to add speaker recognition or gender recognition as the
additional tasks, the normalization by a session can be taken
as the best approach for speech emotion recognition in new
test contexts. The results in all other experiments are reported
using session normalization. The purpose of using long-term
normalization instead of augmentation was to avoid cold-start
problems in scenarios where the sample size was only a few
seconds. For that case, there is no definite best option because
there were mixed results as given in the last two rows of Table
II, therefore no definite conclusion can be drawn.

Tables III, IV, and V show the comparison between the
performance of different classifiers (the best of various pa-
rameter settings) when cross-tested on three databases. At a
glance, it can be seen that the MLP classifiers work better
for all the test sets as compared to SVM, RF, and KNN. All
the MLP classifiers were constructed using the TensorFlow JS
library, whereas the SVM, RF, and KNN were tested using the
scikit-learn (v0.24) library after parsing the feature set from
JS to Python. Among the four types of MLPs given in tables,
we tested the simplest network with only 4 units in a single
hidden layer, two double hidden layers MLPs, and one triple
hidden layers MLP. There was no clear winner among the
MLPs i.e., the biggest neural network with 3 hidden layers
(MLP-53-32-8) had almost the same accuracy as the smallest
one (MLP-4). In the rest of the paper, we use only one ReLU
activated hidden layer with 4 units as the default classifier
since it is the best option if we judge by the prediction speed
without compromising the accuracy. All of the MLP models
were trained using the Adam optimizer with an L2 penalty of
0.001, 200 epochs, and mini-batches of 1000 syllable samples.

*Real-time SER demo at https://realtime-speech-emotion.netlify.app

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were trained using the Adam optimizer with an L2 penalty of
0.001, 200 epochs, and mini-batches of 1000 syllable samples.
Fig. 3. Multi-threaded system design for real-time speech emotion recognition. The Web Audio API [37] interfaces the audio inputs from different types of sources at 48 kHz (usually), then passes it to the output node (i.e., plays on speakers) and to a customized Audio Worklet [39] in a separate thread. The worklet asynchronously performs the hamming window, FFT, and Mel-filter functions on each 25 ms frame with a 15 ms stride. The async arrows show asynchronous connections between processes i.e., one does not wait for the next task to finish and moves on to the next job without waiting. Threads 3 and 4 operate asynchronously until all the preceding buffers are consumed. The orange color tones represent the processing load of each block with FFT being the highest.

Fig. 4. A screenshot of the web UI for the real-time SER. The plot shows 3 formants in different colors extracted from a 17.58 s long speech segment. The gaps between the black horizontal bars at the bottom of the formant spectrum show the detected syllable separations. The vertical lines show the detected pauses between words, that’s when the prediction for each syllable in a word is made. The higher the magenta-colored part of the vertical line, the higher the confidence of prediction for that word.

Figure 5 shows the violin plots of syllable features extracted from the 4 emotional categories of IEMOCAP. The differences between the means of features are subtle, but the deviation from means is more noticeable. The power-based features show more differences between emotions than the frequency-based features.

D. Comparative Analysis

A comparison of methods and their accuracies (UAR and WAR) are given in Table VII. The best UAR achieved by a work that used human raters was 70%, whereas all other machine learning methods performed with lower accuracy than humans (However, this is not always the case for other modalities and databases [40]). The UAR of our method for IEMOCAP was relatively the same as the state-of-the-art methods, but since the real-time prediction was the primary goal, the time and processing cost benefits of the proposed method over state-of-the-art can be taken as unique selling points. The prediction latency is difficult to compare because other works did not report any comparable measurements. Even in this study, the UAR is subject to the size of the context, which means that the UAR is better for complete session normalization instead of just single utterance normalization. It should be noted in Table VIII that the best prediction UAR for the IEMOCAP database is for our SVM-based method, which uses the scikit-learn’s SVM library in python after features are extracted instead of using the client side’s end-to-end JavaScript application.

The results of cross-corpus experiments cannot be conclusively compared with the existing literature based on a single metric due to the differences in emotion labeling structure and differences in train-test splits. Table VIII shows the comparison of the cross-corpus UAR for IEMOCAP and MSP-Improv database. The numbers of samples reported in the comparative works are mismatched with ours because of the Noise-gate filter that rejects some of the quiet and very short-utterances (it needs at least 0.2 s long voiced speech segment to adjust threshold, a 0.5 s utterance might have only 0.25 s voiced segments). For the purpose of the same sample size comparison, we tweaked our speech segmentor and the noise gate to consider the shorter quieter segments for processing, which inadvertently ended up being predicted as sadness or neutral. However, assuming that the sample space isn’t that big a factor if the total count is nearly the same, then the cross-corpus performance of our method is slightly higher than state-of-the-art methods with an added benefit of being a simpler and faster method.

V. CONCLUSION

As opposed to the automatic feature extraction strategy of throwing everything at the wall and hoping that something
would stick, we proposed a method that uses handcrafted syllable-level feature engineering to such an extent that the machine learning part of the method was minimal. Our objectives were to achieve real-time prediction speed and to improve the generalizability of SER. Based on our results, we can draw two conclusions. Firstly, the reductionist approach of simplifying features, classifiers, and operating systems does help to create a real-time application not just as a concept on paper and lab settings, but also as an easily accessible application for everyone to use. Secondly, the cross-corpus accuracy of the proposed method was the same as other state-of-the-art methods. There was a marginal improvement in the cross-corpus accuracy. Nonetheless, the more important conclusion to draw here is that the syllable level features are...
more generalizable and they allow us to predict emotion in real-time, without waiting for an utterance to complete. As opposed to the conventionally used deep learning methods, this work shows that cross- corpus generalizability can be achieved when a single-layer neural network is used as opposed to a deep neural network.

In the future, we plan to improve the cross-corp ser prediction with more emotional categories or dimensions, as well as languages, so that the system is capable of understanding human speech with greater precision and confidence. It is well established that SER generalizability is highly dependent on the non-emotional factors such as the language or speakers, therefore integrating the auxiliary tasks would probably help to improve the domain adaption in either long or short-term context. Using knowledge-based systems or deep neural networks trained on a variety of subjects can solve the coldstart issues, but the latency may go up due to the increased complications. Therefore, we plan to find a way to perform the auxiliary tasks in such a way that does not require high computation in real-time. With the increased demand for remote collaborations and online communications software, the automated real-time analysis of human speech and behavior will be useful to improve human-computer interaction [50]. We hope that speech emotion recognition technology will soon be realized as an essential tool for machines to understand humans beyond the lexical content of speech in the near future.

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