Best Practices for Noise-Based Augmentation to Improve the Performance of Emotion Recognition “In the Wild”

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Abstract

Emotion recognition as a key component of high-stake downstream applications has been shown to be effective, such as classroom engagement or mental health assessments. These systems are generally trained on small datasets collected in single laboratory environments, and hence falter when tested on data that has different noise characteristics. Multiple noise-based data augmentation approaches have been proposed to counteract this challenge in other speech domains. But, unlike speech recognition and speaker verification, in emotion recognition, noise-based data augmentation may change the underlying label of the original emotional sample. In this work, we generate realistic noisy samples of a well-known emotion dataset (IEMOCAP) using multiple categories of environmental and synthetic noise. We evaluate how both human and machine emotion perception changes when noise is introduced. We find that some commonly used augmentation techniques for emotion recognition significantly change human perception, which may lead to unreliable evaluation metrics such as evaluating efficiency of adversarial attack. We also find that the trained state-of-the-art emotion recognition models fail to classify unseen noise-augmented samples, even when trained on noise augmented datasets. This finding demonstrates the brittleness of these systems in real-world conditions. We propose a set of recommendations for noise-based augmentation of emotion datasets and for how to deploy these emotion recognition systems “in the wild”.

1 Introduction

Emotion recognition is considered a low resourced domain due to the limitations in the size of available datasets. As such, the performance of emotion recognition models is often improved when techniques such as data augmentation or transfer learning are applied. Accurate performance is critical because the predictions made by emotion recognition models are often used for downstream applications such as advertising, mental health monitoring (Khorram et al., 2018), hiring (emo) and surveillance (Martin, 2019). However, when used in such sensitive human-centered tasks, incorrect emotion predictions can have devastating consequences.

Data used to train emotion recognition systems are often collected in laboratory environments designed to avoid as much noise variation as possible. This collection method ensures that the collected data are variable only due to the presence of emotion or predefined control variables. This ensures that the trained models avoid spurious correlations between noise and emotion labels, which results in datasets that are usually clean and small.

However, these pristine conditions generally do not hold in the real world. Researchers have addressed this concern by augmenting emotion datasets via signal manipulation to enhance generalizability to real-world noise conditions or avoid overfitting of ML models as is common in other speech domains (Zheng et al., 2016). For example, many speech domains, such as speech recognition and speaker identification, tackle this challenge by manipulating training samples to encourage models to learn only salient features (Mošner et al., 2019). But, unlike these tasks, where the desired output remains consistent in the presence of noise, this same consistency cannot be assumed for emotion labels. This paper investigates how common sources of noise affect both human and machine perception of emotion.

Prior researchers has analyzed robust augmentation methods for automatic speech recognition (Li et al., 2014). The results have shown that humans have surprisingly robust speech processing systems that can easily overcome the omission of letters, changes in the speed of speech, and the presence of environmental noise through psychoa-
cousic masking (Biberger and Ewert, 2016) during speech comprehension. However, the same analyses have not been completed within the domain of computational paralinguistic applications. While it is known that the comprehension of lexical content in noisy data examples is not significantly affected, the same effect in emotion perception is understudied. Instead, previous works have focused on other confounders, ranging from distribution shift (Abdelwahab and Busso, 2018) to physiological factors such as stress (Jaiswal et al., b), or have studied how pink or white noise affects emotion perception (Parada-Cabaleiro et al., 2017; Scharenborg et al.). Important outstanding questions include the impact of real world noise, e.g., footsteps, running water, and how variation across both type and loudness impacts human and machine perception.

In this paper, we study how human’s emotion perception changes as a factor of noise. We find that multiple commonly used methods for speech emotion dataset augmentation that assume consistent ground truth, like, speeding of the utterance or the adding fillers and pauses, actually alter human emotion perception. We show how the addition of noise, such as, footsteps, coughing, rain, clock ticks, that does not alter human emotion perception, do result in incorrect emotion recognition performance. This is critical because these types of noise are common in real world applications (e.g., in inputs to virtual agents such as Siri or Alexa). The fragility of these models can pose a security risk, especially when the change in signal isn’t perceived by humans. Adversarial attacks are designed to test the robustness of model. They might be inaccurately evaluated if they introduce noise that do change the perception of human, but are also considered as successful if the model output changes. We end the paper with a set of recommendations for emotion dataset augmentation techniques and deployment of these emotion recognition algorithms. We investigate the following research questions:

- **Q1**: How does the presence of noise affect the perception of emotions as evaluated by human raters? How does this effect vary based on the utterance length, loudness and the added noise type, and the original emotion?
- **Q2**: How does the presence of noise affect the performance of automatic emotion recognition systems? Does this effect vary based on the type of the added noise in agreement with changes in human perception?
- **Q3**: Does dataset augmentation or sample denoising help improve ML models’ robustness to unseen noise?
- **Q4**: How does difference in allowed set of noises for adversarial perturbation change evaluation of adversarial attack efficiency?
- **Q5**: What are the best practices for speech emotion dataset augmentation and model deployment, based on crowdsourced experiments on human perception?

Our findings suggest that human emotion perception is usually unaffected by the presence of environmental noise or common modulations such as reverberations and fading loudness. We find that human perception is changed by signal manipulations such as speed, pitch change, and even the presence of pauses and fillers, and hence are not good noise augmentation methods. We show that the trained models though, are brittle to the introduction of various kinds of noise, which do not change human perception, especially reverberation. We show that some kinds of noise can help through either dataset augmentation or sample denoising, or a combination of both, but, the performance still drops when an unseen noise category is tested. We finally show how noise augmentation practices can lead to a false improvement in adversarial test efficiency, thus leading to an unreliable metric. We end the paper with a set of augmentation and deployment suggestions.

## 2 Relation to Prior Work

Previous work focused on understanding how noise impacts machine learning models can be classified into three main directions: (a) robustness in automatic speech recognition or speaker verification; (b) noise-based adversarial example generation; and, (c) improvement in performance of machine learning models when augmented with noise.

Previous work has looked at how speech recognition systems can be built so that they are robust to various kinds and levels of noise (Li et al., 2014). The most common themes in these papers are to concentrate on either data augmentation or gathering more real-world data to produce accurate transcripts (Zheng et al., 2016). Other lines of work have looked into preventing various attacks, e.g., spoofing or recording playback, on speaker verification systems (Shim et al.). Noise in these systems is usually considered to be caused by reverberations...
or channel-based modulations (Zhao et al., 2014). Researchers have also looked into building noise robust emotion recognition models, using either signal transformation or augmentation (Aldeneh and Provost, 2017). But data augmentation in this analysis was formulated in a similar manner to those for speech recognition, or, speaker identification systems, which have a fixed ground truth and are independent of human perception. This paper attempts to establish methods for noise-based data augmentation of emotion datasets that are grounded in human perception.

Previous works have also investigated adversarial example generation that aims to create audio samples that change the output of the classifier. However, these methods usually assume white-box access to the network and create modifications in either feature vectors or actual wave files (Carlini and Wagner; Gong and Poellabauer, 2017). This generally results in samples that either have perceivable differences when played back to a human, or are imperceptible to a human but fail to attack the model when played over-air (Carlini and Wagner).

The line of work closest to ours is data augmentation aimed for training more generalizable models. Noise and manipulation-based data augmentation is a prime research field in the space of vision and text. (Sohn et al., 2020) have looked at how rotating and blackening out random pixels in images to create augmented datasets leads to better performance on the test set for digit and object recognition. Authors (Sohn et al., 2020) have also looked at how data augmentation can help with zero shot object recognition in sparse classes of the dataset, providing new options for sub sampling of classes. In the field of NLP, researchers have looked at how replacing words with their semantic synonyms can lead to better performance on tasks such as POS tagging and semantic parsing (Wallace et al., 2019). Researchers have also looked at techniques for data augmentation using noise augmentation (Kim and Kim), mostly focusing on how model training can be improved to yield better performance. However, these augmentation techniques are mostly used for acoustic event detection, speaker verification or speech recognition (Ko et al., 2015; Rebai et al., 2017), and has been sparingly used in audio classification tasks.

To the best of our knowledge, this is the first work that looks at the effect of different kinds of real world noise and varying amounts of noise contamination on the human perception of emotion and its implication for noise-based augmentation for emotion datasets.

3 Datasets And Network

3.1 Dataset

For our study, we use the Interactive Emotional MOtion Capture (IEMOCAP) dataset (Busso et al., 2008), which is commonly used for emotion recognition. The IEMOCAP dataset was created to explore the relationship between emotion, gestures, and speech. Pairs of actors, one male and one female (five males and five females in total), were recorded over five sessions (either scripted or improvised). The data were segmented by speaker turn, resulting in a total of 10,039 utterances (5,255 scripted turns and 4,784 improvised turns). It contains audio, video, and associated manual transcriptions.

3.2 Network

To focus on the effect of types of noise contamination on performance of emotion classifiers, we use the state-of-art single utterance emotion classification model which has been used in previous research (Khorram et al., 2017; Krishna et al.).

Acoustic Feature. We extract 40-dimensional Mel Filterbanks (MFB) features using a 25-millisecond Hamming window with a step-size of 10-milliseconds. Each utterance is represented as a sequence of 40-dimensional feature vectors. We standardize the acoustic features by each speaker.

Emotion Labels. The target emotion labels represented in a dimensional format are binned into three classes to represent \{low, medium, high\} for both activation and valence.

Architecture. The extracted MFBs are processed using a set of convolution layers and Gated Recurrent Units (GRU), which are fed through a mean pooling layer to produce an acoustic representation which is then fed into a set of dense layers to classify activation or valence.

Training. We implement models using the Keras library (Chollet, 2015). We use a subject independent five-fold cross validation scheme to select our train, test and validation sets. We generate corresponding noisy examples for each sample in the test using the method described in Section 4. We use a weighted cross-entropy loss function for each task and learn the model parameters using the RMSProp optimizer. We train our networks for a
maximum of 50 epochs and monitor the validation loss from the emotion classifier after each epoch for early stopping, stopping the training if the validation loss does not improve after five consecutive epochs. Once the training process ends, we revert the network’s weights to those that achieved the lowest validation loss on the emotion classification task. We measure performance using Unweighted Average Recall (UAR) (chance is 0.33). We report averaged performance over all samples considered as test in multiple runs.

**Sample Selection.** We select 900 samples from the IEMOCAP dataset for the human perception part of the study. The sample size is far larger than the ones used for previous perception studies (Parada-Cabaleiro et al., 2017; Scharenborg et al.). To ensure that the 900 samples covered multiple variations, we select 100 samples from each activation and valence pair bin, i.e., 100 samples from all the samples that have activation bin low, and valence bin low; 100 samples which have activation bin low, and valence bin mid, and so on.

We ensure that out of the 100 samples, 30 of them are shorter than first quartile or greater than fourth quartile of utterance length in seconds to cover both extremities of the spectrum, and the rest of the 70 belong in the middle. We also ensure that the selected samples had a 50-50 even split amongst gender.

### 4 Noise

#### 4.1 Environmental Noise

We define environmental noises (ENV) as additive background noises. These noises are obtained from the ESC-50 dataset (Piczak), which has often been used for both, noise contamination and environmental sound classification, out of which, we choose:

- Natural soundscapes (Nat), e.g., rain, wind.
- Human, non-speech sounds (Hum) for e.g. sneezing, coughing etc.
- Interior/domestic sounds (Int) for e.g. door creaks, clock ticks etc.

These environmental sounds are representative of many factors in “in the wild” audio, especially in the context of virtual and smart home conversational agents. We manipulate two factors in addition to noise:

- **ENVPos:** We vary the position of the introduction of sound that (i) starts and then fades out in loudness, represented by St, or (ii) occurs during the entirety of the duration of the utterance, represented by Co. Complete additive background would represent a consistent noise source in real world, e.g., fan rotation.
  - **ENVdB:** We vary the signal to noise ratio (SNR) of additive background noise for the Co method at levels of 20dB, 10dB and 0dB.
  - **ENVLen:** We vary the length of the introduced background noise, from a short blip to covering the entire clip. Short length is represented by Sh, medium length by Me, and complete length by Co. A complete additive background represents a consistent noise source in real world (e.g. fan rotation).

#### 4.2 Synthetic Noise

We define synthetic noise as modulations that aren’t additive in background. These kinds of noises in audio signal can occur from linguistic/paralinguistic factors, room environment, internet lags, or the physical locomotion of the speaker. We add ten variations of synthetic noise in our dataset.

- **SpeedSeg:** We speed up a random segment of the utterance by 1.25×.
- **Fade:** We fade the loudness of the utterance by 2% every second, which emulates the scenario of a user moving away from the speaker. We increase the loudness for fade in, and decrease for fade out.
- **Filler:** Insertion of non-verbal short fillers such as ‘uh’, ‘umm’ (from the same speaker) in the middle of a sentence. The insertion is either just the filler (S) or succeeded and preceeded by a long pause (L).
- **DropW:** Dropping all non-essential word belonging to the set: {a, the, an, so, like, and}.
- **DropLt:** Phonological deletion or dropping of letters has been widely studied as a part of native US-English dialect (pho; Yuan and Liberman). Hence, we drop letters in accordance with various linguistic styles chosen from the set: /b/+vowel, vowel+/nd/+consonant(next word), consonant+/l/+consonant(next word), vowel+/r/+consonant, /ihng/.
- **Laugh/Cry:** We add “sob” and “short-laughter” sounds obtained from AudioSet (Gemmeke et al., 2017) to the end of utterance.
- **SpeedUtt:** Speed up the entire utterance by 1.25× or 0.75×.
5 Analysis

5.1 Qualitative human study

For the human perception part of the study, we introduce noise into the selected 900 samples in ten ways each, leading a total of 9000 samples for comparison. Each sample is introduced to the four kinds of environmental noise and six out of ten randomly chosen synthetic noise methods to create ten noisy samples.

Crowdsourcing Setup. We recruited annotators using MTurk from a population of workers in the United States who are native English speakers, to reduce the impact of cultural variability. We ensured that each worker had > 98% approval rating and more than 500 approved Human Intelligence Tasks (HITs). We ensured that all workers understood the meaning of activation and valence using a qualification task that asked workers to rank emotion content, as in previous work of (Jaiswal et al., a). All HIT workers were paid a minimum wage ($9.45/hr), pro-rated to the minute. Each HIT was annotated by three workers.

For our main task, we created pairs of samples, i.e., the original and modulated version. For each pair, we asked three workers to annotate if they thought that the samples contained the same emotional content. If the worker selected yes for both activation and valence, the noisy example was labeled same and they could move to the next HIT. If the worker selected no, the noisy example was labeled different. If a clip was labeled different, the annotator was asked to assess the activation and valence of the noisy sample using Self Assessment Manikins (Bradley and Lang, 1994) on a scale of one to five (as in original IEMOCAP annotation).

We ensured the quality of the annotations by paying bonuses to the workers based on time (removing the incentive to mark same every time) and by not inviting annotators to continue if their level of agreement with our attention checks was low.

We created final labels for the noisy examples by taking the majority vote over each pair. The final label was either same emotion perception or different emotion perception and an averaged valence and activation score. The annotators agreed in 79% of the cases. All the samples along with the paired noisy examples and their annotations will be made available for further research.

Table 1: The original activation (Act) and valence (Val) performance is 0.67 and 0.59, respectively. The table shows the change in UAR on IEMOCAP (Iem) and the Augmented IEMOCAP (Iem(Aug)) datasets. The rows are augmentation methods that were evaluated as imperceptible for emotion by human annotators.

| Environmental Noise | UAR       | Iem | Iem(Aug) |
|----------------------|-----------|-----|----------|
|                      | Act       | Val | Act      | Val      |
| NatSt                | -.25      | -.24| .22      | .18      |
| NatdB (Co)           | -.33      | -.34| .22      | .13      |
| 10dB                 | -.37      | -.41| .33      | .31      |
| 0dB                  | -.40      | -.41| .27      | .26      |
| HumSt                | -.22      | -.24| .15      | .13      |
| HumdB (Co)           | -.33      | -.37| .16      | .16      |
| 10dB                 | -.37      | -.42| .21      | .26      |
| 0dB                  | -.40      | -.42| .25      | .21      |
| IntSt                | -.21      | -.25| .15      | .18      |
| IntdB (Co)           | -.31      | -.39| .20      | .22      |
| 10dB                 | -.34      | -.39| .23      | .19      |
| 0dB                  | -.40      | -.41| .30      | .26      |

| Synthetic Noise      | UAR       |       |          |
|----------------------|-----------|-------|----------|
|                      | Act       | Val   |          |
| SpeedSeg             | -.09      | -.12  | .03      | .02      |
| Fade                 | In        | -.07  | -.10     | .05      | .04      |
|                      | Out       | -.09  | -.14     | .02      | .06      |
| DropW                | -.04      | -.05  | .02      | .00      |
| DropLt               | -.03      | .02   | .06      | .03      |
| Reverb               | -.36      | -.37  | .05      | .04      |

Human Perception Study Results. We report our human perception results below. The values represent the ratio of the utterances that were marked as different based on majority vote amongst all the utterances introduced with that noise. We also find that the presence of environmental noise, even when loud, rarely affects human perception, verifying our initial judgement that humans are able to psycho-acoustically mask the background noise. We verify expected patterns, such as the presence of laughter or crying often changes human perception. The results for the five synthetic modulations that significantly change human perception of either activation or valence are as follows:

- Filler(L)- Act: 0.10, Val: 0.06
- Filler(S)- Act: 0.06, Val: 0.03
- Laugh- Act: 0.16, Val: 0.17
- Cry- Act:0.20, Val: 0.22
- SpeedUtt (1.25x)- Act: 0.13, Val: 0.03
- SpeedUtt (1.25x)- Act: 0.28, Val: 0.06
This suggests that modifications that do not change human perception and wouldn’t raise suspicion, should ideally not impact performance of an ideal machine learning model.

5.2 Variation in changes in human perception

In further experiments, we aim to find if there is a notable difference in human perception of emotion based on the original length of utterance, original emotion classification and gender of the speaker. We find that the original emotion of the utterance, the gender of the speaker, or the length of the utterance, plays no significant role in predicting if the perception of noisy example would change. In line with the hypothesis tested by Parada et.al in (Parada-Cabaleiro et al., 2017), we test how noise shapes the direction of perception change.

We find that the addition of laughter or crying increases perceived activation while laughter increases perceived valence and crying decreases it. We also find that increasing the pitch usually increases perceived activation and vice-a-versa. Further, increases in the speed of an utterance increases activation and vice-versa (Busso et al., 2009). This evaluation gives us an insight into what methods can be used for robust data augmentation, which, unlike for speech recognition, do not always convey the same material.

5.3 Model performance

We study how introducing varying kinds of noise affects the performance of the model trained on a clean dataset. The test samples of each fold are introduced to all the types of noise (Section 4), except those that were also found to often affect human perception (Pitch, SpeedUtt, Laugh, Cry, Filler), which are then used to evaluate the performance of the trained network. Given that, the domain of the trained network, the speaker independent fold distribution remains the same, a drop in performance can be singularly attributed to the addition of a particular noise.

We report the performance of emotion recognition model trained as described in Section 3 in Table 1. We find that the machine learning model’s performance decreases greatly given environmental noise, fading, and reverberation. There is also a smaller drop in performance for speeding up parts of the utterance and dropping words, showing the brittleness of these models.

5.4 Denoising Algorithms and Model Performance

The common way to deal with noise in any audio signal is to use denoising algorithms. Hence, it is a valid counterpoint to understand how machine learning models trained to recognize emotions perform if they are tested on denoised samples. To this end, we look at two major approaches to denoising algorithms in the audio space: Denoising Feature Space (Valin, 2018) and Speech Enhancement (Chakraborty et al., 2019). Denoising feature space algorithms seek to remove noise from the extracted front end features. Speech enhancement algorithms seek to convert noisy speech to more intelligible speech. Both techniques are associated with known challenges, including signal degradation (Valin, 2018) to harmonic disintegration (Valin, 2018).

We use the most common denoising methods from each category, Recurrent Neural Network Noise Suppression (RNNNoise, denoising feature space) (Valin, 2018) and Vector Taylor Series (VTS, speech enhancement) (Chakraborty et al., 2019).

We train a system composed of the emotion recognition models, described in Section 3.2. We then create two separate denoising approaches, one that combines the emotion recognition model with RNNNoise and the other with VTS. In both cases, we refer to the different approaches using RNNNoise and VTS, respectively. We then use these denoising algorithms on the extracted features for the noise augmented samples as shown in Section 4. The combination ensures that the models are trained to maximize the probability of predicting the correct emotion as well as maximizing the speech quality.

We use the noise augmented training, validation, and testing datasets, described in Section 5.5. We then evaluate the performance of pre-trained emotion recognition models from Section 3.2 on the denoised test samples using a leave-one-noise-out cross-validation approach. This assumes that the system doesn’t have an individual sample of noise prototype introduced in the sample, akin to real world conditions. We do not compare with other denoising algorithms that assume a priori knowledge of noise category (Tibell et al., 2009).

We find that the addition of a denoising compo-
nent to the models leads to significant improvement (average of 23% \pm 3% across all environmental noise categories) in continuous noise introduction at 20dB SNR as compared to when there is no denoising or augmentation performed. We observe a decline in performance when dealing with other signal to noise ratios of continuous noise additions, possibly due to masking of emotional information from the speech to maintain legibility. We further show that the addition of a denoising component didn’t significantly improve performance when samples were faded in or out or segments were sped up. While we did see an improvement in performance for unseen reverberation contaminated samples as compared to data augmentation, the performance is still significantly lower (−28%) than when tested on a clean test set. Finally, we observe an increase in emotion recognition performance, compared to when the model is trained on a clean training set, which supports the findings from dataset augmentation.

5.5 Model performance with augmentation

We then augment the dataset with noise to increase the robustness of the trained model. Hence, we test environmental and synthetic noise separately. We perform leave-one-noise-out cross-validation, augmenting each fold with one kind of noise from the set: \{Hum, Int, Nat\}. We train on two kinds of environmental noise and test on the third. We do the same with synthetic noise, performing leave-one-noise-out cross-validation, augmenting each fold with the most impactful augmentations from the set: \{SpeedSeg, Fade and Reverb\}.

We find that data augmentation improves performance, especially when the environmental noise is introduced at the start of the utterance, e.g., when the test set is introduced with NatSt and the train set is introduced with HumSt and IntSt, we see a performance jump of 22%, compared to when the model is trained on clean data and tested on noisy samples. We can speculate that the network learns to assign different weights to the start and end of the utterance to account for the initial noise.

Though the performance increase on test data when introduced to continuous background noise is aided by addition of training samples that have a continuously present background noise as well, the performance is still affected due to introduction of new noise in the test set.

We also find that it is hard to improve performance on utterances contaminated with reverberation, a common use case, even when the training set is augmented with other types of noise. This can be because, reverberation adds a continuous human speech signal in the background delayed by a small period of time. None of the other kind of noises have speech in them, and hence augmentation doesn’t aid the model to learn robustness to this kind of noise.

5.6 Use Case: Adversarial Attack Evaluation

The common way to evaluate the robustness of a model to noise or an attacker with malicious intent, is adding noise to the dataset and testing performance of the model. This method is commonly used for various tasks, such as, speech recognition, or, speaker identification (Abdullah et al., 2019), which aren’t perception dependent as discussed before. The closest task to ours where the ground truth varies based on noise introduction is sentiment analysis. In this case, the adversarial robustness is usually tested by flipping words to their synonyms, such that the meaning of the text remains the same, and analyzing how the predictions of the model change. Unlike the lexical modality, speech cannot be broken down into such discrete components with obvious replacements while maintaining speech feature integrity, and hence, introduction of noise for emotion recognition while assuring that the perception remains the same is more difficult.

Instead, we formulate the problem as a decision boundary untargeted attack, which tries to find the minimal amount of noise perturbation possible in k-queries such that the decision of a model changes, while having no knowledge about the internal workings of the model (probabilities or gradients). A decision-based attack starts from a large adversarial perturbation and then seeks to reduce the perturbation while staying adversarial. In our case, because we are considering noise augmentations, we define the distance between an adversarial sample and the original sample as the degradation in signal to noise ratio (SNR). The input to this attack model is a set of allowed noise categories (e.g., white, gaussian, or categorical), and the original signal. We also modify the decision boundary attack to first use the any random sound from four categories at lowest SNR. If the attack model is successful, it then shifts to using other additive noise options from that category. In case, the attacker has knowledge about the relation between noise category and performance degradation, we also provide an ordering
Table 2: Attacker efficiency \( (P_{IF}) \) using noise-based adversarial methods. \( k \) refers to the number of black box queries an attacker can access, whereas, Corr refers to the knowledge of correlation between performance deterioration of emotion recognition and noise category, and Eval refers to whether the attack efficiency is evaluated only on those noise categories that human perception doesn’t change. Bold shows significant improvement. Higher values are better. Significance is established using paired t-test, adjusted p-value < 0.05

| Corr: No, Eval: No | Corr: Yes, Eval: No | Corr: No, Eval: Yes | Corr: Yes, Eval: Yes |
|-------------------|-------------------|-------------------|-------------------|
| \( k=5 \)         | \( k=15 \)        | \( k=25 \)        |
| 0.22              | 0.32              | 0.31              | **0.34**          |
| 0.29              | 0.38              | 0.36              | **0.43**          |
| 0.39              | 0.53              | 0.45              | **0.58**          |

6 Recommendations

We propose a set of recommendations, for both augmentation and deployment of emotion recognition models in the wild, that are grounded in human perception. For augmentation, we suggest that:

1. Environmental noise can be added to datasets to improve generalizability to varied noise conditions, whether using denoising or augmentation method or a combination of both.
2. It is good to augment datasets with fading loudness of segments, dropping letters or words, and speeding up small (no more than 25% of the total sample length) segments of the complete sound samples in the dataset. But it is important to note that these augmented samples should not be passed through the denoising component as the denoised version loses emotion information.
3. One should not change the speed of the entire utterance more than 5% and to not add intentional pauses or any background noises that elicit emotion behavior, e.g., sobs or laughter.

Regarding deployment, we suggest that:

1. Noisy starts and ends of utterances can be handled by augmentation, hence, if the training set included these augments, there is no issue for deployed emotion recognition systems.
2. Reverberation, in its various types is hard to handle for even augmented emotion recognition models, and hence, the samples must either be cleaned to remove reverberation effect, or must be identified as low confidence for classification.

7 Conclusion

In this work, we study how the introduction of real world noise, either environmental or synthetic, affects human emotion perception. We identify noise sources that do not affect human perception, and hence can be used for data augmentation, leading to more robust models. We then study how models trained on the original dataset are affected in performance when tested on these noisy samples and if augmentation of the training set leads to improvement in performance of the machine learning model. We conclude that, unlike humans, machine learning models are extremely brittle to the introduction of many kinds of noise. While the performance of the machine learning model on noisy samples is aided from augmentation, the performance is still significantly lower when the noise in the train and test environments does not match. In this paper, we demonstrate fragility of the emotion recognition systems and valid methods
8 Ethical Considerations

Data augmentation is often applied to speech emotion recognition to improve robustness. Better augmentation methods are an important way to not only ensure reliability and robustness of these models, but also improve the real-life adoption in high-stakes downstream applications. Knowing when human perception of emotion can change in the presence of noise is needed to design better model unit tests and adversarial tests for verifying the reliability of the system. However, emotion variability is often dependent on multiple factors, such as, culture, race, gender, age etc, some of which are highly protected variables. These models can also encode stereotypical expected behavior from a certain group, and hence have a higher error rate for other groups. It is important to note that this paper considers a small set of crowd-sourced workers as human raters of emotion perception, who belong to US and are well versed in English, the language this dataset is collected in, and the model is trained on.

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