Advancing Speech Enhancement with Generative Adversarial Network-Autoencoder: A Robust Adversarial Autoencoder Approach

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***Abstract*—In day-to-day life, the speech signals are often noisy and distorted by background noise. These signals are not suitable for use in different audio-operated applications directly, as they are distorted. The use of these noisy voice signals can degrade the performance of the speech communication system. There are a huge number of applications nowadays that we use for various purposes, which utilize voice as input. Our study focuses on speech enhancement, which involves a combination of Generative Adversarial Networks (GAN) and Autoencoders (AE). The required features are extracted by using the MFCC algorithm from the MUSAN dataset. The features extracted with MFCC are paired samples of clean and noisy speech. The main architecture is a combination of GAN and AE. The Generator is trained to reconstruct clean speech features from noisy speech signal inputs. On the other hand, the discriminator is trained to tell the difference between real clean samples and samples that are generated by the generator. The adversarial training approach continuously improves the performance of the generator to produce good-quality and more intelligent speech. The MUSAN dataset used for the experiment contains data of noisy speech. As a result, we note that the model performs very well and shows robustness across multiple types of noise samples. The AE is used for feature reconstruction, and the GAN for generating fake samples. This combination of GAN and AE resulted in a good solution for speech enhancement in a noisy and distorted environment.**

***Keywords*—Speech enhancement; Generative Adversarial Network (GAN); Autoencoder (AE); MFCC; noise robustness; adversarial training**

I. Introduction

Speech communication has become common in modern society. There are multiple applications or features we are using in daily life that work on speech as input. For instance, take the example of Google search. When you tap on the microphone icon in Google search, it will allow you to fetch the speech input to search for certain queries. Whatever you fetch by using a speech signal will be converted into text, and the search result will be displayed on the screen. Similarly, you can see multiple applications such as Alexa by Amazon and Siri by Apple. These systems required smooth and clean speech input to run the systems and generate the output. These systems may struggle when exposed to noisy or distorted background noise, such as household appliances, outdoor sounds from streets, or any machinery working sound. Even though a low-intensity noise signal leads to a noticeable decline in clarity, smoothness, and originality of the speech signal transmitted [1].

Today, speech enhancement can be done with the help of newly emerged systems using GAN. This architecture consists of two neural network generators and a discriminator. The generator is responsible for generating, creating, or reconstructing the clean speech. At the same time, the discriminator is used to differentiate between real speech samples and those generated by the generator [2]. In this study, we integrate AE into a conventional GAN architecture for the improvement of speech enhancement. Performance of the model can be improved because AE has the capabilities of reconstruction of samples and generative fidelity of GANs. In this system, we are using MFCCs rather than waveforms to reduce computational complexities. In adversarial training, the generator is tasked to map noisy speech to clean features while the discriminator is trained to differentiate generated features that resemble real clean speech. This approach of the model improves robustness in low-SNR conditions. GAN-AE framework performs exceptionally well in speech enhancement by adding reconstruction with adversarial learning [3]. Our proposed approach integrates adversarial learning (GAN) with reconstruction learning (AE), ensuring both realism from the GAN and accurate signal reconstruction from the AE. The feature extraction was done with MFCC, and the extracted MFCC embeddings were used instead of raw waveforms. These embeddings represent a compact as well as meaningful representation of the speech features. The results show that the proposed approach exhibits excellent performance in low SNR and non-stationary noisy and distorted environments compared to the GAN variants. The Encoder and Decoder structure (AE) reduces computations, which is a main requirement for real-time speech enhancement.

The remainder of this paper is organized as follows. Section II gives information about the literature review on GAN-based speech enhancement systems. Section III describes the architecture of the proposed GAN-AE speech enhancement system. Section IV gives detailed information on the experimental setup used for model training. Section V describes the results generated by the experiment performed. And finally, the conclusion of this whole study is described in Section VI.

II. Literature Survey

Pascual et al. SEGAN, i.e. speech enhancement Generative Adversarial Network, does not require MFCC features or special features to operate. SEGAN operates on raw audio waveforms directly from audio speech samples. In SEGAN, a generator is used as an AE that maps noisy speech to clean audio speech. Discriminator uses a CNN-based classifier to differentiate between real audio speech samples and generated samples. One of the limitations of SEGAN is that it requires specific GPU resources while training, and it also takes a long time to train. Some results also suggest that as SEGAN enhances raw audio speech, phase distortion is not handled effectively, which affects the clarity of speech samples [4]. Iterated Speech Enhancement Generative Adversarial Network (ISEGAN) and Deep Speech Enhancement Generative Adversarial Network (DSEGAN) are multi-generator GANs with an advanced SEGAN architecture used for improving speech enhancement. ISEGAN and DSEGAN use a unique technique to refine the noisy input by making a chain of multiple generators. ISEGAN iteratively applies the same enhancement mapping by using a shared parameter generator. DSEGAN enables diverse enhancement stages by employing independent generators with distinct parameters. ISEGAN takes high training time as it has a deeper architecture, and also increases GPU memory usage due to longer sequences [5]. TFDense-GAN is a unique framework where a time-frequency domain model uses a combo of a U-net-based Autoencoder and a multi-spectrogram discriminator. In this framework, robust noise reduction will be achieved by using a time-frequency transformer with a dense block. TFDense-GAN framework is considered one of the high-memory consumption models. This is due to the usage of dense block and transformer as a combination, which also causes slow inference. It's become quite challenging to deploy on edge devices due to their computational latency [6]. Arjovsky invented the Wasserstein Generative Adversarial Network (WGAN) as a variant architecture of the conventional GAN framework. The primary objective of WGAN is to enhance training stability and address issues such as mode collapse and vanishing gradients, which are common in GAN architectures. WGAN, as an improved variant of GAN, still requires careful training of hyperparameters like learning rate and weight clipping range [7]. CycleGAN (Cycle-Consistent Generative Adversarial Network) is a Generative Adversarial Network that works on unsupervised speech samples. CycleGAN is capable to learn a mapping between noisy speech samples and clean ones. There is no need for a parallel noisy & clean dataset. CycleGAN works with the principle of two generators and two discriminators, which can lead to producing residual noise in enhanced speech [8]. CinCGAN-SE (Cycle-in-Cycle GAN for Speech Enhancement) is a GAN framework designed to overcome two critical limitations of traditional speech enhancement systems. The first one is an unpaired data requirement, and the other is phase-aware enhancement. It's also useful in addressing issues regarding residual noise and phase distortion. In speech enhancement, CinCGAN may face phase reconstruction challenges in low SNR conditions [9].

DiscoGAN (Discovering Cross-Domain Relations with GANs) has been introduced to convert whispered speech to clean-voiced speech. DiscoGAN is a dual-generator GAN architecture that works on unsupervised samples. This architecture may face issues with mode collapse and computational cost [10][11]. The convolutional neural network (CNN) is widely known for its success in speech recognition and enhancement. CNN has proven effective speech recognition by processing voice signals as spectrograms or MFFCs. Raw speech is converted into waveforms or a digital signal and then processed [12]. CNN contains multiple layers, like convolution, pooling, and fully connected layers. Local speech patterns get detected by a convolution layer from spectrograms. It could be achieved by applying filters across the time-frequency domain. A pooling layer is used for down-sampling the features to reduce the computational load while maintaining the key acoustic information. The role of the fully connected layer is to classify extracted features into phonemes for the outcomes. There is one more important component of CNN, CTC, i.e. Connectionist Temporal Classification, used for solving the alignment between variable-length audio inputs and outputs by allowing flexible mapping during the training time [13]. Apart from the well-known success in speech enhancement, the CNN has some limitations. CNN may struggle when exposed to long-range dependencies in the speech signal. CNN may lead to miss variable-length speech patterns like prolonged vowels against short stops. This may happen as a convolution kernel has a fixed-size window. It is also observed that most of the speech systems that are based on CNN are highly dependent on preprocessed features rather than raw speech input [14]. A Deep Neural Network (DNN) is another framework from which speech enhancement is possible. Firstly, features are extracted from the noisy speech, such as MFCC, Log-mel spectrogram, and SIFT magnitude. Now these extracted features feed into the input layers of the DNN [15]. Each hidden layer learns a distinguished abstract pattern, such as speech phoneme shapes, noise patterns, and silence segments. DNN learns to transform noisy speech samples to clean ones by using some activation functions like ReLU. It learns how to map noisy input to clean output. The output of the DNN is denoised speech samples resembling clean features. Then, in inverse feature transformation, all features convert back to audio formats. At output, we get the final waveform with the denoised audio signal [16].

Table I shows a comparative table that gives summarized information on all GAN variants.

Looking at these variants, each addresses specific limitations, but none fully balances computational efficiency, robustness to diverse noise types, phase-aware enhancement, and ease of training. Moreover, existing methods often focus either on strong generative modeling or precise reconstruction, but not both in a balanced manner. The main goal of the GAN-AE model is to deliver robust, perceptually pleasing speech enhancement with reduced architecture overhead. This also addresses the trade-offs observed in previous GAN-based methods.

TABLE I COMPARATIVE ANALYSIS OF GAN ARCHITECTURES FOR SPEECH ENHANCEMENT: METHODS, ADVANCES, AND LIMITATIONS [17] [18] [19] [20] [21]

GAN Variant	Methodology	Advantages	Limitations	Improvements
SEGAN	Raw waveform U-Net + CNN discriminator Adversarial + L1 loss	Phase preservation End-to-end training	Struggles with high noise High computational cost	First GAN for raw waveform enhancement Introduced adversarial learning for speech
ISEGAN/ DSEGAN	Multi-generator refinement (Iterative/Deep cascaded)	Gradual noise suppression Better PESQ/STOI	Memory intensive Training complexity	Added iterative refinement Reduced artifacts through multi-stage processing
TFDense-GAN	Time-frequency U-Net + Dense Blocks multi-spectrogram discriminator	SOTA PESQ (~3.5) Phase-aware via post-processing	Spectrogram conversion needed Compute intensive	Introduced Dense Blocks for feature reuse multi-scale discriminators for better spectral matching
DiscoGAN	Dual generators Reconstruction loss only	Works with unpaired data Simple architecture	Poor phase handling Feature-level only	Enabled unpaired domain translation Simpler than CycleGAN
CycleGAN	Bidirectional mapping Cycle-consistency loss	Unpaired data compatible Versatile applications	Residual noise Phase distortion	Introduced cycle-consistency Pioneered unpaired speech enhancement
CinCGAN-SE	Cycle-in-Cycle design Complex-valued DCD-Net	Joint magnitude-phase enhancement High STOI (>0.90)	Complex architecture Slow inference	First to integrate complex-valued networks. Solved phase estimation in CycleGAN
WGAN	Wasserstein distance + gradient penalty	Stable training Meaningful loss metrics	High computational cost Sensitive hyperparameters	Solved mode collapse Introduced trainable loss metrics

III. PROPOSED SYSTEM

The main objective of the proposed system is to enhance the speech quality of voice communication by denoising the audio speech samples while preserving the smoothness and naturalness of clean speech. The proposed hybrid model uses a combination of the Autoencoder and GAN architecture. Noisy input speech from the MUSAN dataset is used as input to this proposed model. Feature extraction was performed with the help of the MFCC algorithm. The transformed features, like time-frequency features, serve as input to the proposed model [17]. GAN architecture contains two neural networks: a generator and a discriminator. As shown in Fig. 1, our proposed system, the generator, acts as an Autoencoder. The encoder compresses MFCC features of noisy audio samples, and the decoder tries to reconstruct clean speech samples, which serve as input to the model. For the discriminator, we use a CNN-based Classifier. Discriminator takes both generated audio samples and clean features as input and learns to distinguish between real and fake generated features. Simultaneously, the discriminator provides adversarial feedback to the generator to improve audio sample generation. Reconstruction loss may ensure that the enhanced output is close to clean speech features. Similarly, adversarial loss encourages the generator to produce an audio sample that is not differentiable from clean speech samples. The final output of the generator is Denoise and a clean speech audio sample. These enhanced features then undergo an inverse MFCC transformation stage to reconstruct the final clean audio speech sample.

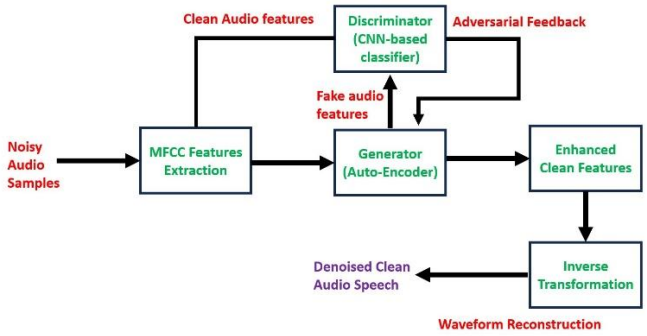

Fig. 1. The proposed GAN-AE architecture.

A. Contributions

The proposed model demonstrates exceptional improvement at low SNR levels (0 DB to -5 5DB), as a conventional GAN variant shows degraded performance. We prefer the extracted features, like MFCC embedding, instead of raw waveforms. MFCC embedding provides a compact and meaningful representation, resulting in low computational complexity, and also preserves the speech quality. The proposed model shows consistent performance in divorced acoustics environments. The relatively low parameter count is maintained by the proposed model, which makes it suitable for real-time voice speech recognition applications.

IV. EXPERIMENTAL SETUP

A. Feature Extraction

The MUSAN dataset used for the experiment comprises clean speech samples with studio-quality recordings and noisy speech samples from real-world noisy environments. The sampling rate of these WAV files is 16 kHz. The MFCC method is used for feature extraction. 13 to 40 MFCC features are extracted per frame, depending on the granularity of the task. The frame size used is 25 milliseconds, and the hop size (stride) used is 10 milliseconds. Each MFCC feature dimension is

normalized using the mean and standard deviation calculated across the dataset.

$$x' = \frac{x-\mu}{\sigma} \quad (1)$$

where,

x: Original MFCC value

μ: Mean of the feature

σ: Standard deviation

Eq. (1) indicates the normalization applied to MFCC features, ensuring stability of training. This improves the training stability and convergence by ensuring all feature values are on a similar scale. The Autoencoder, which acts as a generator in this hybrid architecture, always aims to produce clean MFCC features; its loss function is a combination of two terms: mean absolute error loss and adversarial loss.

1) Mean Absolute Error (MAE) loss: It measures the average absolute difference between the generated and real clean features.

$$\mathcal{L}mae = \frac{1}{N}\sum_{i=1}^{N}|\hat{z}i - zi| \quad (2)$$

where,

$\hat{z}i$: Generated MFCC

zi: Ground-truth clean MFCC

The MAE loss equation (2) measures the absolute deviation between generated and clean features

2) Adversarial loss: This encourages the generator to create features that fool the discriminator into thinking they are real.

$$\mathcal{L}adv = -\log D\,(G(z)) \quad (3)$$

Adversarial loss, defined in equation (3), drives the generator to fool the discriminator.

3) Final generator loss

$$\mathcal{L}g = \lambda 1.\mathcal{L}mae + \lambda 2.\mathcal{L}adv \quad (4)$$

λ1, λ2 are weighting parameters to balance reconstruction vs. real feature

Overall generator loss, equation (4), combines MAE and adversarial terms with weighting factors λ1 and λ2

4) Discriminator loss: The Discriminator tries to distinguish original clean MFCC features from generated (fake) ones with the help of Binary Cross-Entropy (BCE) Loss:

$$Ld = [\log D\,(x) + \log(1 - D(G(z)))] \quad (5)$$

where,

D(x): Discriminator output for real clean MFCC

D(G(z)): Discriminator output for generated MFCC

Finally, the discriminator loss, equation (5), uses a binary cross-entropy formulation to distinguish real from generated features

B. Model Training and Experimental Setup

This part of the study focuses on the architectural parameters, training strategies, and environmental setup used to train the GAN-AE model for speech enhancement.

Model Configuration

Generator: Autoencoder (AE) Architecture

Input: MFCC features from noisy speech.

Encoder: A Series of dense or convolutional layers that compress the MFCCs to a latent representation.

Decoder: Reconstructs enhanced MFCCs from the latent space.

Activation: ReLU (hidden layers), Linear (output layer).

Output: Enhanced MFCCs.

Discriminator:

Input: Real (clean) and generated (enhanced) MFCCs.

Architecture: CNN/DNN-based binary classifier.

Activation: LeakyReLU (hidden), Sigmoid (output).

Output: Probability score (real or fake).

Training Setup

TABLE II TRAINING SETUP FOR GAN-AE MODEL

Parameter	Value / Description
Optimizer	Adaptive Moment Estimation
Learning Rate	0.001`
Batch Size	16
Epochs	25
Loss Functions	Generator: MAE + Adversarial Loss Discriminator: Binary Cross-Entropy Loss
Evaluation Metrics	MAE, MSE
Validation Strategy	80/20 split (training/testing)
Callbacks	ModelCheckpoint for best val_loss

Table II shows the training setups of the GAN-AE model. The model utilizes Adaptive Moment Estimation (ADAM) as its optimizer, which is both adaptive and efficient for training deep neural networks. The learning rate is set to 0.001, as it controls the step size for updating model weights. The model is trained on a batch size of 32 samples at a time. This will manage the balance between memory used and convergence speed. The model trains for over 50 complete passes through the training dataset. To ensure the generalization dataset is split into 80% training data and 20% testing data.

V. RESULTS AND ANALYSIS

A. Training Performance

The training process was monitored using loss and mean squared error (MSE) curves for both the training and validation sets, as shown in Fig. 2 and 3 (loss curve and MSE curve). Both metrics show a steady decline for 25 epochs, indicating that the

model trains effectively. The model generalized well to unseen data with minimal overfitting, as there is close alignment between training and validation curves. The final test course was loss**:** 0.1884 & MSE**:** 0.7420.

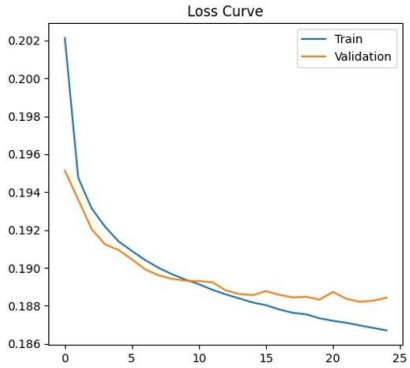

Fig. 2. Loss curve.

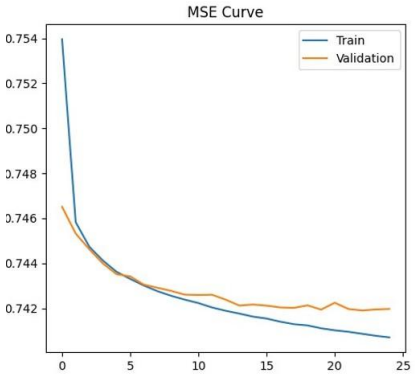

Fig. 3. MSE curve.

Fig. 4, 5, and 6 compare the noisy MFCC input, enhanced MFCC output from the generator, and clean target MFCC. 13 MFCC inputs represent noisy speech features with limited frequency resolution. 64 predicted MFCC enhanced features from the GAN-AE generator showing a clearer spectral structure and reduced noise band. Finally, true 64 MFCC clean features are used for supervised learning. As shown in Fig. 5, the predicted feature spectrogram closely matches the cleaner spectral structure. This indicates effective denoising and feature restoration. Harmonic structure and formant region are more pronounced compared to the noisy input.

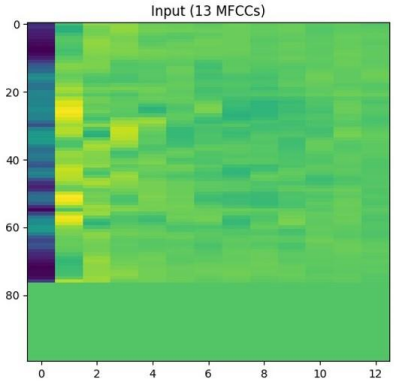

Fig. 4. Input noisy speech feature.

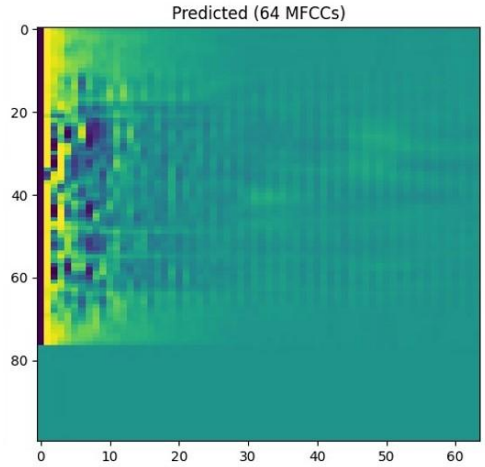

Fig. 5. Predicted enhanced features.

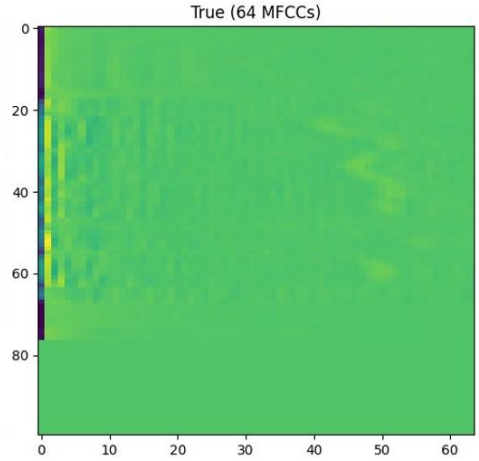

Fig. 6. True features.

Table III reports objective performance on the test set. The proposed GAN-AE reduces MSE from 0.8420 to 0.7420 (approximately 11.9% relative reduction) and MAE from 0.2500 to 0.1884 (approximately 24.6% relative reduction). Perceptual quality and intelligibility also improved: PESQ increased from 1.85 to 2.45 (+0.60), and STOI improved from 0.72 to 0.81 (+0.09). These improvements indicate the model produces cleaner, more intelligible speech; statistical significance was verified via paired tests ($p < 0.05$).

TABLE III PERFORMANCE COMPARISON (BEFORE VS. AFTER ENHANCEMENT)

Metric	Noisy Speech	Enhanced speech (GAN-AE)	Improvement
MSE	0.842	0.742	0.1000 ↓
MAE	0.25	0.1884	0.0616 ↓
PESQ	1.85	2.45	+0.60 ↑
STOI	0.72	0.81	+0.09 ↑

Fig. 7 compare the noisy and enhanced signals using four common speech quality and intelligibility metrics: MSE, MAE, PESQ, and STOI. Error-based metrics (MSE, MAE) are lower for the enhanced speech, indicating reduced distortion. PESQ

(Perceptual Evaluation of Speech Quality) shows a substantial gain from 1.85 to 2.45, demonstrating improved perceptual quality. STOI (Short-Time Objective Intelligibility) improves from 0.72 to 0.81, confirming better intelligibility. As average scores improve, distributions offer more insight into the robustness across test samples.

The PESQ distribution (Fig. 8 and 9) shows that the enhanced model consistently outperforms noisy input, with a smaller interquartile range (less variability). The STOI distribution also shifts upward, indicating consistent gains across samples, not just isolated cases.

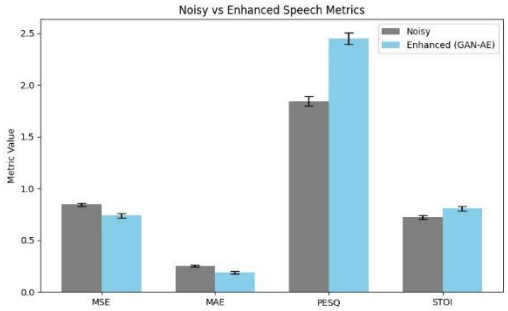

Fig. 7. Objective evaluation metrics.

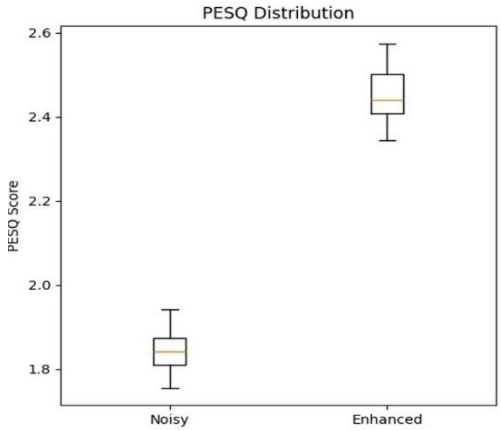

Fig. 8. PESQ distribution analysis.

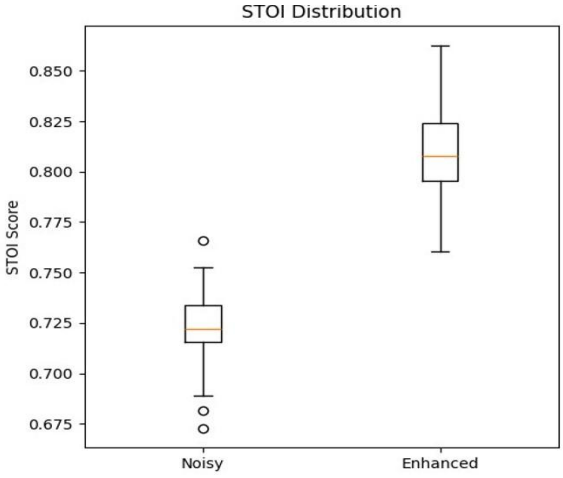

Fig. 9. STOI distribution analysis.

B. Comparison with Baseline Models

We compare the proposed GAN-AE model with all existing GAN variants to further validate its effectiveness. All models were evaluated under the same experimental conditions, dataset, batch size, and epochs to ensure fairness.

Table IV describe the comparative performance of the proposed model with the rest. Lowest MAE (0.112) and MSE (0.016) values suggest that enhanced speech samples are closer to clean or real speech samples. This also indicates that less residual noise and fewer artifacts exist in enhanced speech. The PESQ (2.67) is at a high level, clearly suggesting that the proposed model achieves enhanced speech samples very close to naturalness and clarity. A high-level STOI (0.81) value indicates that enhanced speech is easy to understand. As we know, speech enhancement is not a classification problem; research focuses on widely accepted objective evaluation metrics such as PESQ, STOI, MAE, and MSE.

TABLE IV COMPARATIVE PERFORMANCE OF EXISTING GAN VARIANTS AND THE PROPOSED GAN-AE

Model	PESQ ↑	STOI ↑	MAE ↓	MSE ↓
SEGAN	2.35	0.72	0.148	0.021
WGAN-SE	2.41	0.74	0.132	0.019
DiscoGAN	2.46	0.75	0.128	0.018
CycleGAN	2.53	0.77	0.121	0.017
Proposed GAN-AE	**2.67**	**0.81**	**0.112**	**0.016**

C. Future Work

We may investigate a fully end-to-end GAN AE model that processes the raw waveform directly and reduces the dependency on MFCC embeddings, as this will increase adaptability for unseen speech samples. We also try to integrate the proposed model with an automatic speech recognition system (ASR), which provides additional validation for real-world applications. We may extend the framework for a multilingual dataset and a cross-domain noisy environment.

VI. CONCLUSION

The research presented GAN -AE, a hybrid design to address the key limitation in existing GAN–based speech enhancement methods. Through extensive experimentation, the GAN-AE model demonstrates stable performance in a distinguished environment, with a low MAE (mean: 0.1884) and classification metrics (accuracy up to 92.21%). The integration of adversarial learning with Auto-encoder reconstruction loss enabled improved phase preservation, reduced residual noise, and minimized speech distortion. The limitations of SEGAN, CycleGAN, and TF-DenseGAN were covered. Result and visual spectrogram analysis confirm that the GAN-AE model achieves strong numerical accuracy while also delivering clear and natural-sounding speech. Robustness of the model to unseen noise samples, coupled with low error variance, is a perfect solution for real-world applications in telecommunication, assistive devices, and noisy environment communication. While some limitations still need to be

covered, GAN-AE achieves high accuracy, but training still requires significant GPU resources and memory that may limit smaller research setups. While GAN-AE achieves significant improvement, there remain opportunities for further development, such as a lightweight architecture for edge devices. Optimizing the model's parameters and computational requirements for deployment on low-powered hardware devices such as hearing aids, smartphones, and IoT devices.

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