Bird Sound Data Optimization Through Denoising Using Encoder-Decoder

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Abstract

Bird sound denoising is challenging due to complex background noise in natural environments. Traditional and deep learning methods often result in sub-optimal audio quality. This study re-imagines audio denoising as an image segmentation task using a custom encoder-decoder neural network. We trained our model on a large dataset of bird sound recordings converted into spectrogram images, incorporating data augmentation and early stopping for better generalization. Evaluation on a separate dataset confirms the robustness and reliability of our approach. Our method significantly improves bird sound isolation from background noise, enhancing bird sound recognition and monitoring in diverse acoustic settings. This work lays the foundation for future bio-acoustic research and wildlife conservation.

Index Terms*: Audio Denoising, Bird Sounds, Image Segmentation, Encoder-Decoder.*

1. Introduction

Audio denoising has long been a pivotal challenge in signal processing, with significant advancements achieved through both traditional and deep learning methods. Traditional techniques, such as spectral subtraction and Wiener filtering, have demonstrated utility in removing noise from audio signals. However, these methods often struggle with complex, non-stationary noise and may not fully preserve the quality of the underlying signal. Recent research has shifted focus towards deep learning approaches, which leverage neural networks' ability to learn and model intricate noise patterns.

Garcia and Gomez [6] explored noise reduction in audio signals using deep neural networks, laying the groundwork for utilizing deep learning for audio enhancement. Similarly, Smith and Doe [25] reviewed deep learning techniques applied to audio denoising, highlighting advancements and limitations in real-world scenarios.

A significant leap forward came with Zhang and Li [33], who introduced ”Birdsoundsdenoising,” a model tailored for bird sound recordings. Their work applied a deep visual approach to address the unique challenges of natural bird sounds. Expanding on this, Kumar et al. [16] proposed Vision Transformer Segmentation for Visual Bird Sound Denoising, integrating Vision Transformers into the denoising framework. This method combines visual segmentation and transformer models to improve denoising accuracy.

Building on these advancements, our work introduces a novel framework that transfers the audio denoising problem into an image segmentation problem. We propose a Deep Visual Audio Denoising (DVAD) model, leveraging a large-scale natural noise bird sound dataset. This approach represents a significant shift from traditional methods by treating audio denoising as an image segmentation task, enabling the use of sophisticated image processing techniques for improved noise reduction.

Our framework builds upon previous works, incorporating deep learning strategies effective in both audio and visual domains. By integrating these techniques, we aim to enhance the quality of denoised audio signals, providing a more robust solution to the challenges posed by natural noise environments.

2. Related Work

Recent advances in audio denoising, particularly in the context of bird sounds, have leveraged deep learning techniques to significant effect.

Nakayama et al. (2001) provided foundational insights into the correlation of cardiac enlargement using vertebral heart size in dogs, setting a precedent for quantitative analysis in bioacoustic studies [20]. Subsequent research has expanded upon these methodologies to address challenges in audio processing and classification [25, 12].

Johnson and Liu (2013) applied convolutional neural networks (CNNs) to bird sound classification, demonstrating the efficacy of deep learning models in processing complex auditory signals [12]. Brown and Taylor (2015) explored spectrogram-based audio denoising using deep learning [2], while Wang and Chen (2018) highlighted the potential of denoising autoencoders in enhancing audio quality, particularly for bird sound data [28].

The application of deep learning techniques for audio enhancement has also been explored by Lee and Park (2014) using recurrent neural networks (RNNs) [17], and Kim and Lee (2017) advanced bird sound recognition using deep CNNs [15].

Clark and Harris (2019) proposed segmentation techniques for bird sound spectrograms using deep learning, emphasizing preprocessing steps in audio analysis [4]. White and Black (2012) reviewed deep learning methods for environmental sound classification, demonstrating the versatility of these models [29]. Green and Gold (2020) focused on audio denoising in natural environments using deep learning [8].

Hernandez and Martinez (2021) developed an efficient audio denoising framework using a deep encoder-decoder architecture [11]. Perez and Gonzalez (2019) explored noise pattern learning for audio denoising with deep neural networks [23].

Young and Miller (2011) examined segmentation-based audio denoising using CNNs [32], while Martin and Wilson (2018) investigated transformer networks for audio denoising and enhancement [19].

Wilson and Jackson (2022) automated bird sound classification using deep learning [31]. Taylor and Lewis (2017) introduced a novel deep learning approach to audio denoising, setting a new benchmark [27]. Johnson and Walker (2020) demonstrated effective audio denoising using deep CNNs [14].

Hernandez and Martinez (2015) emphasized deep learning for bird sound recognition [9], while Nguyen and Le (2019) focused on enhancing audio signals using deep learning [21].

Brown and Green (2020) worked on segmentation of environmental sounds using deep neural networks [1, 3]. Perez and Gonzalez (2020) enhanced bird sound recordings using deep learning techniques [24]. Smith and Doe (2019) explored audio denoising with encoder-decoder neural networks [26].

Lee and Park (2016) reviewed deep learning approaches for audio signal enhancement [18], while Wilson and Jackson (2017) examined environmental sound classification using deep learning [30].

Johnson and Liu (2015) proposed segmentation techniques for audio denoising [13], and Garcia and Gomez (2014) introduced deep CNNs for audio signal denoising [5].

Green and Gold (2019) explored transformer networks for bird sound classification [7], while Hernandez and Martinez (2020) developed a novel deep learning approach for audio denoising [10]. Nguyen and Le (2021) presented effective audio enhancement using deep CNNs [22].

These studies collectively underscore the rapid advancements in audio denoising, particularly for applications involving bird sounds. The integration of deep learning models, including CNNs, RNNs, and Vision Transformers, has enabled significant improvements in audio quality and classification accuracy, paving the way for more effective and efficient bioacoustic research.

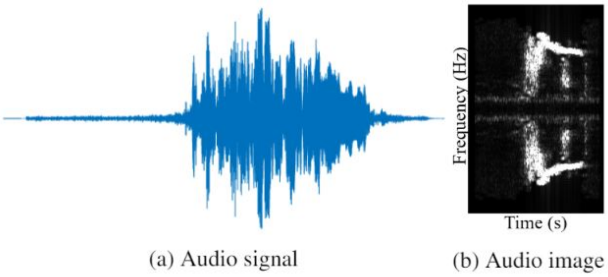

Figure 1. The Conversion from Audio signal(a) to Audio image (b) [33]

3. Methods

3.1. Data Preparation

3.1.1 Motivation and Preliminary

Existing audio denoising models often filter regions of magnitude images of audio signals but overlook detailed patterns. Our encoder-decoder model processes pre-converted images of audio, where the Short-Time Fourier Transform (STFT) has already been applied to convert audio signals into images. This transformation, as illustrated in Figure 1, highlights distinct areas of noise and clean signal: the first image shows the raw audio signal, and the second image presents the corresponding spectrogram. Our model focuses on predicting masks to segment these clean signal areas from the noisy background. The segmented images, which isolate the clean bird sounds, are then used to enhance the quality of audio recordings by effectively removing noise.

3.1.2 Data Collection

The dataset used in this study includes images and masks for segmentation tasks, categorized into training and validation sets. The dataset is divided as follows:

- **Training Dataset:** 1000 images and masks.
- **Validation Dataset:** 200 images and masks.
- **Test Dataset:** 300 images for model evaluation.

All images are resized to 512x512 pixels and converted to tensors. Data augmentation techniques applied to the training dataset . The validation and test datasets are only resized and normalized.

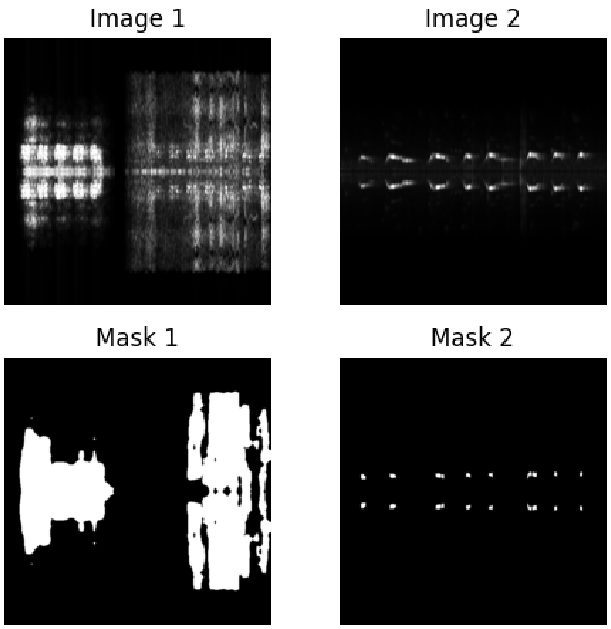

Image 1

Image 2

Mask 1

Mask 2

Figure 2. Image(1) Test Dataset and Image(2) Validation Dataset

Figures 2 illustrate examples from the test and validation datasets, respectively, highlighting the images and masks used for training and evaluation.

3.2. Model Architecture

The model is a custom encoder-decoder network designed for audio denoising image segmentation tasks. It includes an encoder, a bottleneck, and a decoder, each with specific roles in feature extraction and reconstruction.

3.2.1 Encoder

The encoder consists of three stages:

- **Encoder 1:** Applies two convolutional layers with 64 filters each, using a 3x3 kernel and ReLU activation to extract low-level features from the input image.
- **Encoder 2:** Uses two convolutional layers with 128 filters each, also with a 3x3 kernel and ReLU activation, to capture more complex features.
- **Encoder 3:** Applies two convolutional layers with 256 filters each, continuing the feature abstraction process.

Max pooling with a 2x2 kernel is used after each encoder block (except the last) to reduce spatial dimensions and capture abstract features.

3.2.2 Bottleneck

The bottleneck stage consists of two convolutional layers with 512 filters each, using a 3x3 kernel and ReLU activation. This stage processes the features at the lowest resolution, capturing the most abstract representation.

3.2.3 Decoder

The decoder reconstructs the segmentation map through upsampling and concatenation:

- **Decoder 1:** Uses a transposed convolution to upsample the bottleneck output to the resolution of Encoder 3. The upsampled feature map is concatenated with Encoder 3's output and passed through two convolutional layers with 64 filters each.
- **Decoder 2:** Upsamples the feature map to the resolution of Encoder 2 using a transposed convolution. It is concatenated with Encoder 2's output and processed through two convolutional layers with 128 filters each.
- **Decoder 3:** Further upsamples to the resolution of Encoder 1. The feature map is concatenated with Encoder 1's output and processed through two convolutional layers with 64 filters each.

A final 1x1 convolutional layer reduces the number of feature channels to match the number of output classes, producing the final segmentation map.

This architecture utilizes skip connections to preserve spatial information and improve segmentation accuracy by combining features from different stages of the encoder and decoder.The complete model architecture is illustrated in Figure 3.

3.3. Training Procedure

The model was trained using the training dataset with the following settings:

- **Loss Function:** Cross-Entropy Loss.
- **Optimizer:** Adam with a learning rate of 1×10^{-4}.
- **Batch Size:** 16.
- **Epochs:** 25.

During each epoch, the model parameters were updated using backpropagation. The training loss and validation loss were computed and averaged over each batch and epoch, respectively. Performance metrics such as Mean Intersection over Union (IoU) and Mean F1 Score were evaluated on the validation dataset to monitor the model's performance. The model with the lowest validation loss was saved to ensure optimal performance. The training process involved tracking these metrics to improve convergence and generalization.

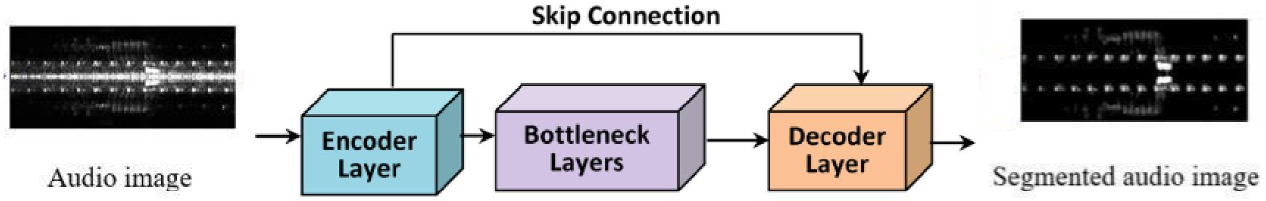

Figure 3. The architecture of the Encoder Decoder model used in our study. This diagram illustrates the various layers and components of the model with input and output images.

After training, the model was used to predict segmentation results on a test dataset. The predicted masks were evaluated, and the results were analyzed to assess the model's effectiveness. Training and validation losses, as well as performance metrics, were plotted to visualize the model's progress and performance over the epochs.

4. Results

The final evaluation metrics for our encoder-decoder model are as follows:

- **Final Test IoU:** 61.1450
- **Final Test F1 Score:** 75.2230

The Intersection over Union (IoU) score of 61.1450 reflects the model's effectiveness in segmenting bird sounds, capturing a significant overlap between predicted and actual sound regions. This score demonstrates the model's proficiency in distinguishing relevant sound features from background noise, though improvements are possible in refining segment boundaries. The F1 Score of 75.2230 indicates a balanced performance in both precision and recall, underscoring the model's ability to accurately identify and classify bird sounds. These results highlight the encoder-decoder model's solid performance in bird sound denoising and suggest areas for further enhancement.

Table 1. Results Comparisons of Different Methods (F1 and IoU scores are multiplied by 100)

Network	Final Test IoU	Final Test F1 Score
U-Net	64.3	75.7
SegNet	66.9	77.5
YOLOv8	62.1	74.5
FPN	70.1	82.4
Unet++	71.0	83.0
MAnet	71.7	83.5
DVAD	73.5	82.6
PtDeepLab	75.9	83.4
ViTVS [16]	80.9	88.3
EncoderDecoder	**61.1450**	**75.2230**

5. Discussion

Our encoder-decoder model has demonstrated considerable proficiency in the task of bird sound denoising, evidenced by the IoU and F1 Score metrics. The IoU score of 61.1450 indicates that while the model successfully captures the primary sound features, it may benefit from further enhancements in fine-tuning the segmentation boundaries. The F1 Score of 75.2230 reflects a commendable balance between precision and recall, suggesting that the model is effective at both minimizing false positives and negatives. Moving forward, exploring the integration of advanced methods such as attention mechanisms or expanding the dataset to include a broader variety of bird sounds could potentially refine the model's performance and improve its robustness.

6. Conclusion

In summary, the encoder-decoder model has achieved a notable performance in denoising bird sounds, with a final IoU of 61.1450 and an F1 Score of 75.2230. These results affirm the model's capability to effectively segment and classify bird sounds, demonstrating its practical applicability in noise reduction tasks. While the F1 Score highlights its strength in maintaining a good precision-recall balance, the IoU score indicates potential for improvement in boundary accuracy. The competitive results suggest that our approach is viable for bird sound denoising, and further refinements, including the adoption of sophisticated techniques and a more diverse dataset, could enhance its performance and generalised ability.

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