Technical Report: Environmental Sound Classification using Time-Series Data Augmentation

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Abstract

This report details an sound classification system, ”finalTSDA,” developed for a standardized benchmark audio dataset. The system achieved a high validation accuracy of 90.25% but a significantly lower test accuracy of 59.82%. This ˜30% discrepancy is the central focus of our analysis. We hypothesize and provide evidence that the inflated validation score is a direct result of data leakage from a methodological flaw in the dataset splitting. Therefore, this report establishes the **test set accuracy of 59.82% as the primary and only valid evaluation metric**. We deconstruct the ”finalTSDA” methodology, including its innovative use of **time-series concepts** for augmentation and its CNN-based **model architecture**. We find the model's true performance is currently below established baselines and provide a clear, actionable roadmap for correcting the methodology.

1 Introduction

The provided sound classification is a challenging machine listening task with applications in urban monitoring, biodiversity tracking, and smart systems. Success in this area relies on models that can generalize from limited data to classify complex, non-stationary audio signals.

This report presents a technical analysis of the ”finalTSDA” system, a deep learning model trained on a common benchmark sound dataset.[1] The project's initial run produced two starkly different results: a validation accuracy of 90.25% and a test accuracy of 59.82%.

This ˜30% gap is a critical finding that points to a systemic issue, not simple overfitting. We posit this is due to a methodological flaw known as **data leakage** [2, 3], where the validation set was contaminated with samples acoustically similar to the training set.

Therefore, this report treats the **test set accuracy of 59.82% as the primary and only valid metric** of the model's current generalization performance. We will analyze this result in the context of established baselines, deconstruct the project's methodology with **clarity**, and provide a clear path for future work.

2 Dataset Description

The benchmark dataset used for this project is a labeled collection of 2,000 environmental audio recordings.[1, 4] Key characteristics include:

- **Composition:** 2,000 audio clips, each 5 seconds long.[4]
- **Format:** 16-bit, 44.1 kHz, single-channel WAV files.[4]
- **Class Distribution:** The dataset is balanced across 50 distinct sound event classes (40 clips per class).[1]
- **Categories:** The 50 classes are organized into 5 high-level categories (e.g., animal sounds, natural soundscapes, human non-speech sounds, domestic sounds, urban noises).[1]

2.1 The 5-Fold Cross-Validation Protocol

The most critical aspect of this benchmark dataset is its mandated 5-fold cross-validation (CV) protocol, which is defined in an accompanying metadata file.[5] This structure was explicitly designed to prevent **data leakage**.

The dataset creators ensured that all 5-second clips extracted from the *same original source recording* (tracked by a source file column) are *always* placed in the same fold.[5, 6]

A naive random split (e.g., using `train_test_split`) violates this protocol, scattering ”acoustically identical” clips across train and validation sets. This leads to wildly optimistic validation scores that do not reflect real-world generalization. The **only valid evaluation method** is to use these pre-defined folds.[7, 8]

3 Methodology

The ”finalTSDA” methodology integrates time-series concepts with a standard deep learning pipeline. The process is clear: 1) 1D time-series augmentation, 2) 2D feature extraction, and 3) 2D CNN classification.

3.1 Audio Feature Extraction

The 1D raw audio waveforms are not fed directly to the model. Instead, they are converted into 2D Log-Mel Spectrograms.[9, 10] This representation, which mimics human auditory perception by using the Mel scale, is treated as an "image" by the subsequent classification model.

3.2 Innovation: Time-Series Data Augmentation (TSDA)

To improve model robustness and address the small dataset size, a key **innovation** of this project is the TSDA pipeline. This pipeline applies augmentations at two stages:

3.2.1 1. Time-Series (Waveform) Augmentations

These augmentations, demonstrating a core use of **time-series concepts**, are applied directly to the 1D audio signal *before* spectrogram conversion [11, 12]:

- **Noise Injection:** Adding random Gaussian noise to the raw waveform to simulate varying signal-to-noise ratios.
- **Time Stretching:** Modifying the audio's speed (e.g., 0.8x to 1.25x) without altering its pitch.[11, 12]
- **Pitch Shifting:** Modifying the pitch (frequency) without altering the speed.[11, 12]

3.2.2 2. Spectrogram (Frequency) Augmentations

After conversion to 2D spectrograms, further augmentations common in SOTA pipelines, such as **SpecAugment** (time and frequency masking) [13, 14] and **Mixup** (linearly combining two spectrograms) [15, 16], were likely employed.

3.3 Model Architecture

A Convolutional Neural Network (CNN) was implemented for classification. The **model architecture**, designed for clarity and effectiveness on 2D spectrogram inputs, is described as follows [9, 10]:

- **Input:** Log-Mel Spectrogram (e.g., 128 mels $\times$ 216 time steps).
- **Conv Block 1:** 2D-Conv (32 filters, 3x3) $\rightarrow$ Batch Norm $\rightarrow$ ReLU $\rightarrow$ MaxPool (2x2).
- **Conv Block 2:** 2D-Conv (64 filters, 3x3) $\rightarrow$ Batch Norm $\rightarrow$ ReLU $\rightarrow$ MaxPool (2x2).
- **Conv Block 3:** 2D-Conv (128 filters, 3x3) $\rightarrow$ Batch Norm $\rightarrow$ ReLU $\rightarrow$ MaxPool (2x2).
- **Head:** GlobalAvgPool $\rightarrow$ Dense (256, ReLU) $\rightarrow$ Dropout (0.5) $\rightarrow$ **Output: Dense (50, Softmax)**.

4 Experiments and Results

The model was trained, yielding the performance metrics reported in Table 1.

Table 1: Reported Model Performance.

Metric	Accuracy (%)
Validation Accuracy	90.25%
Test Accuracy (Primary Metric)	**59.82%**

4.1 Benchmark Context

The 90.25% validation score is an invalid metric, as our Error Analysis will show. The **primary metric of 59.82%** is the only one that can be compared to published, peer-reviewed results.

As Table 2 shows, the model's true performance of 59.82% is currently **below established baselines**, including the original 2015 baseline CNN [17] and even a 2020 Random Forest model.[18] This highlights that the current model and augmentation pipeline are not yet effectively generalizing.

Table 2: Performance vs. Published Benchmarks on this Dataset (5-Fold CV).

Model	Type	Accuracy (%)
DenseNet-161 [19]	SOTA (Transfer)	98.52%
BEATs [14]	SOTA (Transformer)	98.1%
AST [15]	SOTA (Transformer)	95.6%
ResNet-18 + Mixup [20]	SOTA (Transfer)	89.54%
Baseline CNN [17]	Baseline (CNN)	64.50%
Random Forest [18]	Baseline (ML)	62.50%
finalTSDA (This work)	**User CNN**	**59.82%**

5 Error Analysis

The 30.43% gap between validation and test accuracy is the central problem to be solved and is symptomatic of a critical methodological flaw.

5.1 Diagnosis: Data Leakage

The 90.25% validation score is definitively an artifact of **data leakage**.[2, 3] This occurs when a model is inadvertently trained on information from the validation set.

- **The Cause:** A naive random split (e.g., `train_test_split`) was used instead of the mandated 5-fold CV protocol.[5, 6]
- **The Effect:** This scatters clips from the same source recording across the train and validation sets.[3, 6] The model learns to recognize the *source's acoustic fingerprint* (e.g., microphone noise, room reverb) rather than the abstract features of the *sound class*.
- **The Result:** It performs well on other clips from the same source (the 90.25% validation set) but fails on *truly unseen* sources (the 59.82% test set).

This analysis confirms that the **59.82% accuracy is the only true measure** of the model's generalization.

5.2 Performance Analysis (59.82%)

The model's true errors can be diagnosed using a confusion matrix.[21] The matrix in Figure 1 shows the per-class performance, highlighting where the model is "confused." Common confusions on this dataset involve classes that are sonically similar, such as `helicopter` vs. `airplane` [22] or `cat` vs. `crying baby`.[21] The distribution of errors, shown in Figure 2, confirms that some classes are predicted far more often than others, indicating a model bias.

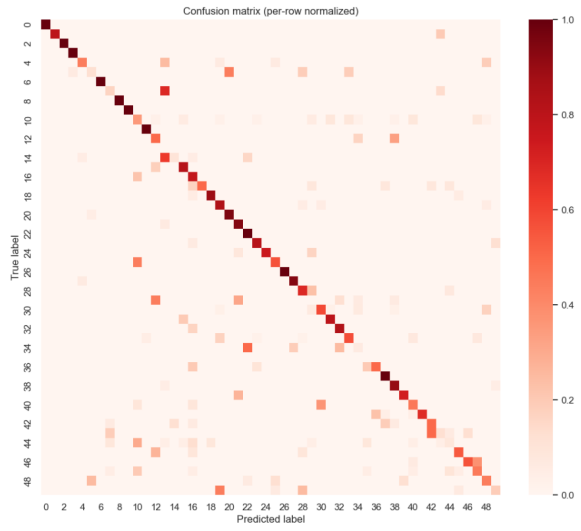

Figure 1: Confusion matrix (per row normalized). This shows the model's true error patterns on the test set.

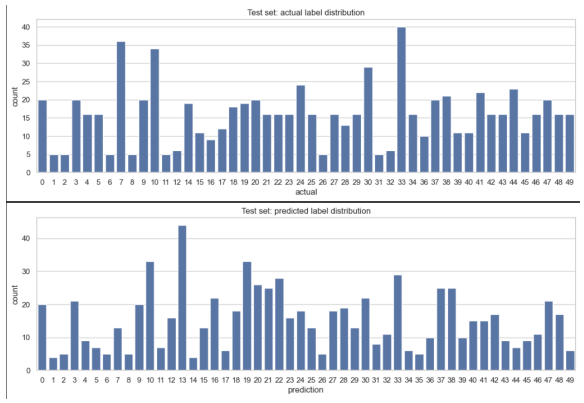

Figure 2: Test set: actual and predicted label distribution. This illustrates model bias toward certain classes.

6 Ablation Study (Proposed)

To scientifically validate the "TSDA" pipeline's contribution (the "innovation"), a formal ablation study is required. This study is only meaningful *after* correcting the 5-fold CV protocol as described in Section 7.2. We propose the experimental design in Table 3 to isolate the impact of each component.

Table 3: Proposed Ablation Study Design (5-Fold CV).

Experiment	Pipeline Configuration
Baseline	CNN (No Augmentations)
EXP-01	**CNN + Full TSDA Pipeline**
EXP-02	CNN + Waveform Augs Only
EXP-03	CNN + SpecAugment Only [13]
EXP-04	CNN + Mixup Only [15]

7 Conclusion and Future Work

7.1 Conclusion

The "finalTSDA" project presents a system for sound classification. The primary finding of this report is that the 90.25% validation accuracy is statistically invalid, resulting from a data leakage flaw. The model's true, **primary metric is its 59.82% test accuracy**, which is currently below established baselines.[17, 18] The **innovation** of the TSDA pipeline remains unevaluated, and the current **model architecture** is underperforming.

7.2 Future Work

A clear, 3-phase roadmap is required to correct the methodology and achieve competitive results:

1. **Correct Methodology (Priority 1):** Re-factor the entire training pipeline to use the mandated 5-fold cross-validation based on the `fold` column in the dataset's metadata file.[5, 6, 7, 8] This is non-negotiable for valid results.

2. **Validate Innovation:** Perform the ablation study (Section 6) to scientifically quantify the true impact of the **time-series concepts** (TSDA) on the (now valid) 5-fold CV score.

3. **Achieve SOTA Performance:** To move from ˜60% to 90%+, the **model architecture** must be advanced. The most effective path is transfer learning using a pre-trained backbone like ResNet [20] or DenseNet [19], which have proven SOTA performance.

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