

# Tuning In $\|\cdot\|_1$ : Analysis of Audio Classifier Performance in Clinical Settings with Limited Data

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## Abstract

This study assesses deep learning models for audio classification in a clinical setting with the constraint of small datasets reflecting real-world prospective data collection. We analyze CNNs, including DenseNet and ConvNeXt, alongside transformer models like ViT, SWIN, and AST, and compare them against pre-trained audio models such as YAMNet and VGGish. Our method highlights the benefits of pre-training on large datasets before fine-tuning on specific clinical data. We prospectively collected two first-of-their-kind patient audio datasets from stroke patients. We investigated various preprocessing techniques, finding that RGB and grayscale spectrogram transformations affect model performance differently based on the priors they learn from pre-training. Our findings indicate CNNs can match or exceed transformer models in small dataset contexts, with DenseNet-Contrastive and AST models showing notable performance. This study highlights the significance of incremental marginal gains through model selection, pre-training, and preprocessing in sound classification; this offers valuable insights for clinical diagnostics that rely on audio classification.

**Data and Code Availability** In this research, in addition to patient data, we utilized publicly available datasets such as ImageNet (Deng et al., 2009), AudioSet (Gemmeke et al., 2017), US8K (Salamon et al., 2014) and ESC50 (Piczak), alongside a proprietary clinical dataset. Due to confidentiality, patient privacy regulations, and local research ethics board (REB) constraints, the clinical portion of the dataset cannot be shared at this time. We are committed to open-source all code soon. We are working with our local data-sharing hub at our university institute to make the clinical data available in the near future through an REB amendment and the framework the institute has in place for such purposes.

**Institutional Review Board (IRB)** The study involving human subjects received approval by the Research Ethics Board at Sunnybrook Health Sciences Center. Throughout, we ensured compliance with local institution guidelines. All individuals or substitute decision makers (SDMs) participating in the study provided their written consent.

## 1. Introduction

Auditory biomarkers have been widely incorporated as the first line of assessment in medical applications, especially non-speech and non-semantic sounds have been used for decades to detect respiratory problems (Pahar et al., 2021). Modern tools for collecting and analyzing audio data have revolutionized the diagnosis of common symptoms like coughing, making voice analysis a critical first step in the diagnostic process. (Larson et al., 2012; Tracey et al., 2011). Furthermore, clinical problems rang-

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ing from continuous health monitoring (Alqudaihi et al., 2021), stroke (Saab et al., 2023), psychiatric conditions (Moedomo et al., 2012; Fagherazzi et al., 2021), neurodegenerative diseases (Fagherazzi et al., 2021; Vizza et al., 2019) to cardiac applications (Dwivedi et al., 2018; Emmanuel, 2012) and lung pathology detection (Gavriely et al., 1994; Sello et al., 2008; Aykanat et al., 2017; García-Ordás et al., 2020) among others have adopted non-speech health acoustic data as an important biomarker. However, understanding the clinical effect of different preprocessing and modeling techniques for the audio domain is a longstanding challenge.

The domain of modeling auditory data borrows heavily from the advances made in sequential and vision models. Such auditory models have greatly progressed through the development of large-scale unsupervised pre-training for audio encoders (Baevski et al., 2020; Valk and Alumäe, 2021). This transposition is usually facilitated by the conversion of audio signals into log-mel spectrograms or superlets, which are then analyzed using algorithms originally designed for vision or sequential data (Radford et al., 2023; Choi et al., 2018). Such approaches for modeling auditory data leverage the significant progress made in the vision and sequence modalities.

Among the techniques for transforming audio into such formats for learning representations from, log-mel spectrograms and superlets (Moca et al., 2021) represent two leading methodologies. Log-mel spectrograms are widely recognized for their ability to approximate the human auditory system’s response to sound. This method converts audio signals into a spectrogram using the Mel scale. This results in a compact, yet effective representation of sound, which highlights the elements most relevant to human auditory perception and have been widely used for acoustic problems (Böck and Schedl, 2011; Radford et al., 2023; Choi et al., 2018). Superlets (Moca et al., 2021), include a set of wavelets that are iteratively applied across different cycles with a specific central frequency, potentially capturing more nuanced information within complex audio signals. We were particularly interested in the comparative efficacy of these methods for downstream clinical applications in neurology and beyond, which remains a subject of ongoing research.

Audio data is increasingly used as a biomarker in clinical settings for disease classification and assessment, and our aim was to expand on the range of possibilities for both analysis and characterization of

changes using different modeling techniques and at different stages of processing. Our analysis focuses on clinical data, in a neurologic setting but with broader applications, and in comparing different model approaches. Using prospectively collected first-of-their-kind datasets, Dataset NIHSS and Dataset vowel aim to expand the existing area of research in the context of disease state classification when starting with limited real-world data. This opens the way for use in other clinical settings (neurologic and beyond), where audio data can be used as a disease biomarker, and in settings where limited data is available. This also includes clinical settings and datasets where data is limited to not only collection ability but also rare diseases where data availability is an intrinsic factor.

**Key Contributions.** Acoustic-based clinical diagnosis (or prognosis) has gained popularity in medical applications leading the way to consider audio data as a biomarker in disease classification, risk prediction, and monitoring. However, the impact of modeling decisions on these medical tasks remains largely unexplored, with one variable being limited datasets. There are also implications for rare diseases that intrinsically have this limitation. In this work, we focused on stroke as a neurovascular disease process and utilized speech as a biomarker and surrogate for swallowing difficulty (dysphagia).

- Introduced Dataset NIHSS: A novel dataset capturing continuous speech, sentences, and words based on the National Institutes of Health Stroke Scale (NIHSS) (Kwah and Diong, 2014), an internationally established neurologic assessment scale for stroke emergencies.
- Introduced Dataset vowel: A unique dataset of sustained vowel sounds from patients, further aiding in the analysis of swallowing disorders.
- Analyzed Model Training Impact: Evaluated how training health acoustic models with different preprocessing techniques—mel RGB, log-mel mono, and superlet—affects clinical data representation and classification based on a defined clinical outcome state of dysphagia.

## 2. Related Work

Categorizing acoustic data is a problem that has been well explored throughout the years, and many deep-learning-based methods have recently performed very

well in classifying acoustic data, which has led to exploration of application in clinical settings. Often directly analyzing raw audio leads to improper learned representations and acoustic data needs to be preprocessed first. We provide a brief overview of acoustic classification and acoustic event detection approaches. We are particularly interested in analyzing the downstream clinical effects of such approaches. We also provide a brief overview of analysis done previously in these areas.

## 2.1. Audio Classification

Audio event detection and classification historically relied on simple representations to transform the audio based on Dynamic Time Warping (DTW) which allowed algorithms to measure spectral variability [Sakoe and Chiba \(1978\)](#); [Salvador and Chan \(2007\)](#). Following this Hidden Markov Models (HMM) started gaining popularity for discrete speech and soon became the dominant technique for all audio-based applications and also outperformed early neural approaches ([Juang, 1984](#); [Raphael, 1999](#)). Following this, the task of audio classification was mainly addressed by features such as Mel-frequency cepstrum coefficients (MFCC) and classifiers based on Gaussian Mixture Models (GMM) ([Nilsson et al., 2002](#)), Hidden Markov Models (HMM) ([Juang, 1984](#); [Raphael, 1999](#)), Nonnegative matrix factorization (NMF) ([Holzapfel and Stylianou, 2008](#); [Ozerov and Févotte, 2009](#)) or Support vector machine (SVM) ([Dhanalakshmi et al., 2009](#)). Soon these models transitioned to a discriminative training strategy ([Hermansky et al., 2000](#)), which led to weighted finite-state transducers (WFSTs) becoming increasingly common and Restricted Boltzmann Machines (RBMs) becoming the first popular neural component of acoustic models. Following this, [Seide et al. \(2011\)](#) led to neural architectures becoming the dominant approach for modeling audio after demonstrating 30% RER on the Switchboard benchmark.

Modern neural-network-based models for acoustic tasks have demonstrated significant performance increases over previous approaches with ConvNets ([Hershey et al., 2017](#); [Schmid et al., 2023](#); [Gong et al., 2021b](#)), RNNs ([Phan et al., 2017](#); [Gimeno et al., 2020](#)), Transformers ([Koutini et al., 2021](#); [Jaegele et al., 2021](#); [Chen et al., 2022](#)) often trained with Self-supervised learning ([Gong et al., 2022](#); [Georgescu et al., 2023](#); [Huang et al., 2022](#)), and for some tasks

Diffusion ([Kong et al., 2020](#); [Lee and Han, 2021](#)) models.

The gain offered by early DNN, HMM, and hybrid models could be attributed mainly to the wider frame windows they took into account. While these features are valuable, they are highly correlated, and neural networks become prominent for this task by building specialized acoustic architectures as opposed to building language models over acoustic frames like most of the early neural approaches.

An important milestone in the development of acoustic event detection and classification has also been some form of feature extraction, that transforms raw waveforms into a sequence of feature vectors that can be used as inputs to deep models ([Radford et al., 2023](#); [Gong et al., 2021a](#); [Chen et al., 2022](#); [Georgescu et al., 2023](#)). While, MFCC spectrograms were demonstrated to work very well for shallow models, modern deep models mainly utilize mel-spectrograms and very recently superlets ([Moca et al., 2021](#)).

## 2.2. Downstream Effects of Transforms

There has been a significant shift from traditional, hand-crafted audio features such as MFCCs to the use of raw audio waveforms and spectrogram representations as inputs for neural networks. [Wyse \(2017\)](#) showed the advantages of spectrogram representations for deep neural networks, particularly their ability to capture both time and frequency information, which is crucial for effectively modeling and generating complex audio signals. Furthermore, multiple works have employed spectrogram-based representations, coupled with convolutional neural networks and have shown that these work particularly well together ([Hershey et al., 2017](#); [Schmid et al., 2023](#); [Gong et al., 2021b](#)).

A class of models is also based on directly processing raw audio ([Verma and Berger, 2021](#)). These often involve segmenting the audio input with some window length before converting it into an embedding compatible with the models, rather than producing spectrograms. However, this class of models has seemed to work rather well for generative applications ([Gardner et al., 2021](#)). We do not focus on this class of models for our analysis.

While there have been works exploring the classification power from these transforms ([Wyse, 2017](#); [Ji et al., 2020](#); [Moysis et al., 2023](#)), none of these works demonstrate the downstream clinical effects of

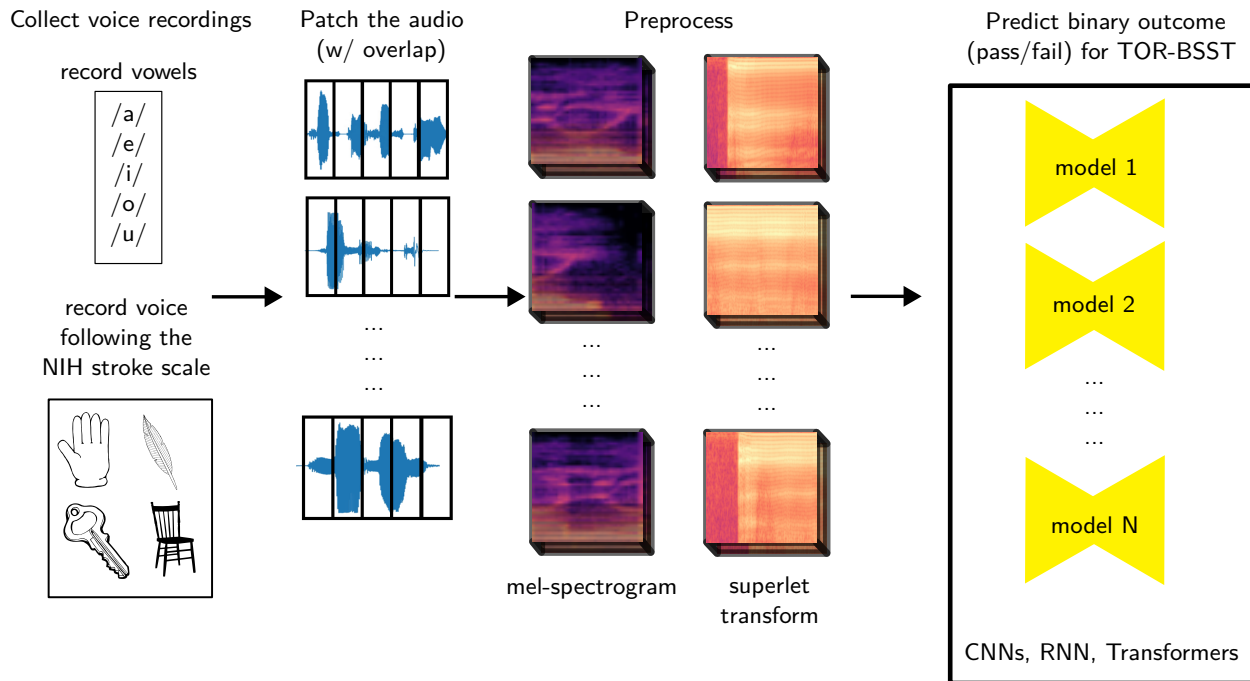


Figure 1: Schematic Overview of the Audio Classification Workflow for Stroke Assessment. The process begins with the collection of voice recordings, including both sustained vowel sounds (/a/, /e/, /i/, /o/, /u/) and speech following the NIHSS, represented by icons for hand, feather, key, chair, etc. These recordings are then segmented using an overlapping patch method to prepare for preprocessing. Subsequently, audio segments are transformed into two types of visual representations: mel-spectrograms and superlet transforms. The final stage involves inputting the processed spectrograms into an array of machine learning models—CNNs, transformers, and RNNs—to predict the outcome of the TOR-BSST© as either “pass” or “fail”.

preprocessing techniques that we focus on. Furthermore, we also analyze more transforms like superlets in this work.

### 3. Method

The prospective human patient audio data was collected at a Sunnybrook Health Sciences Center, a comprehensive stroke center, and Ontario’s highest volume thrombectomy site. The study was approved by the local Research Ethics Board. Subjects were anonymized and computation occurred locally as per local institution guidelines.

#### 3.1. Participants

We enrolled 70 individuals from a comprehensive stroke center, affiliated with the University. These participants were selected during two periods: from

June 13, 2022, to January 19, 2023 (epoch 1) and from January 24 to March 4, 2023 (epoch 2), to form training and testing datasets, respectively. Technical issues with the audio recordings resulted in the exclusion of two participants during epoch 1. Therefore, a total of 68 participant audio samples (with 94% inter-rater agreement on audio quality by AB and HM) were incorporated into our study. The Toronto Bedside Swallowing Screening Test (TOR-BSST©) was administered to all participants as part of standard care, evaluating voice changes, repetitive swallows, and dysphonia. Based on this assessment, 27 participants were marked as “fail” and 41 as “pass”. The study split these participants into two groups: 40 (58.9%) for training and 28 (41.1%) for testing. Enrollment was ongoing and based on a randomized approach, targeting admissions to the stroke unit within 72 hours of entry. Every participant gave informed consent, and the research was sanctioned

by the stroke center’s REB. Inclusion criteria were recent stroke patients proficient in English, able to follow instructions, and without severe aphasia. Exclusions comprised non-English speakers, those with major speech impairments, or medically unstable individuals.

### 3.2. Data Collection

Speech data was categorized into two: a) National Institutes of Health Stroke Scale (NIHSS) speech segments and b) sustained vowel pronunciations. The NIHSS, was utilized to negate bias in choosing speech tests due to its prevalent use in stroke evaluations. NIHSS language tests were further broken down into continuous speech, sentences, and individual words. The second data set was vowel sounds, where participants pronounced each vowel (/a/, /e/, /i/, /o/, and /u/) for an intended span of 3 seconds, thrice. This was based on evidence highlighting the distinctiveness of vowel sounds in discerning swallowing abnormalities. Data was collected via an encrypted iPhone 12 using Voice Recorder app. Recordings took place in real-world hospital setting. Investigators overseeing data collection, segmentation, and model testing were intentionally kept unaware of each other’s activities.

### 3.3. Data Analysis

The initial step involved quality assessment. A three-stage data processing method was adopted, which included segmentation, transformation, and the use of machine learning. Audacity© software was employed for data segmentation, and a customized Python program transformed segmented audio into Mel-spectrogram image representations (see Figure 1). Given the varied audio durations, a windowing approach ensured consistent Mel-spectrogram image scaling. The Mel-spectrograms, renowned for their accuracy in replicating human auditory perception, were critical for our model’s success, particularly when benchmarked against evaluations by speech-language professionals. Two distinct Mel-spectrogram images were created for separate machine learning classifier training: RGB and Three-channel Mel-spectrograms. The latter blends monochrome versions with different FFT lengths. Additionally, Superlet Transform (SLT) was used to create spectrogram images, to assess their performance against mel spectrograms.

### 3.4. Pre-training on Public Datasets

This study delves into the performance enhancement of various networks on a downstream dataset through diverse pre-training scenarios.

Pre-training on public datasets is crucial for developing machine learning applications tailored to clinical needs, especially when working with small datasets. This strategy addresses the significant challenge clinicians face in gathering large datasets.

**Imagenet** is a widely recognized dataset crucial for training and evaluating computer vision models.

**AudioSet** is a comprehensive database featuring 632 categories of audio events across 2,084,320 human-labeled, 10-second clips from YouTube. It presents a hierarchical categorization of diverse sounds including those from humans, animals, musical instruments, genres, and everyday life.

**US8K** is a dataset of 8732 labeled sound excerpts that are up to 4s in length and are taken from (Salamon et al., 2014). The sounds are composed of urban sound clips with labels such as air conditioner, car horn, children playing etc.

**ESC50** consists of 2000 audio clips of 5-second-long recordings categorized into 50 classes. These classes fall into the following major categories: animals, natural soundscapes, water sounds, human, non-speech sounds, domestic sounds, urban noises.

### 3.5. Exploring Network Architectures for Audio Analysis

In this section, we explore various neural network architectures, including ConvNeXt and DenseNet for CNN-based models, ConvLSTM2D for temporal data analysis, and Vision Transformer (ViT) and SWIN Transformer for transformer-based models. Additionally, we introduce pre-trained audio feature extractors such as YAMNet, VGGish, and Trill. To address classification tasks, we employ different loss functions and optimizers. For CNN-based models, particularly DenseNet, we implement a hybrid loss function that combines Cross-Entropy and Contrastive Loss. We also incorporate class weights to handle dataset imbalances. Transformer-based models are trained using Cross-Entropy Loss with the inclusion of class weights. The Adam optimizer is chosen for its adaptive learning rate capabilities. Our preprocessing methods involve the use of grayscale audio spectrograms and the conversion of spectrograms into RGB



images for select models. Additionally, we explore the use of Superlet transforms in preprocessing. Finally, we evaluate our classifiers using per-participant prediction aggregation (Majority Voting).

### 3.5.1. CONVOLUTIONAL NEURAL NETWORKS (CNNs)

**ConvNeXt** is a recent adaptation of the CNN architecture that has shown impressive results in image classification tasks. Although primarily designed for typical image classification applications, it can be adapted for audio spectrogram analysis, offering potentially more effective feature extraction in sound-based medical diagnostics.

**DenseNet** is known for its densely connected convolutional networks, where each layer is connected to every other layer in a feed-forward fashion (Huang et al., 2018). In the context of audio analysis, DenseNet can potentially enhance the detection of intricate patterns in sound data that are indicative of specific medical conditions. The strong performance of the basic DenseNet architecture, as detailed in Table 1, encouraged us to explore its various adaptations, namely:

- DenseNet with binary cross entropy loss, pre-trained on ImageNet (referred to as **DenseNet**).
- DenseNet with a hybrid loss (contrastive loss and binary cross entropy), pre-trained on ImageNet (referred to as **DenseNet Contrastive**).
- DenseNet pre-trained on ImageNet, then on US8K, and applied to our dataset using the hybrid loss (referred to as **DenseNet Contrastive US8K**).
- DenseNet pre-trained on ImageNet and ESC50, later trained on our dataset with the hybrid loss (referred to as **DenseNet Contrastive ESC50**).

#### *Pre-trained Audio Feature Extractors:*

**YAMNet** is a CNN that uses the popular MobileNetV1 architecture for audio event detection (Howard et al., 2017). It’s pre-trained on AudioSet to classify various sounds. This pre-training approach streamlines the creation of spectrogram-based filters without requiring extensive proprietary data.

**VGGish** (Hershey et al., 2017) is a variant of the VGG model (Simonyan and Zisserman, 2014), adapted for audio processing. Initially developed for image classification, the VGG architecture’s adaptation to audio allows it to extract meaningful features from sound waves. Like YamNet, it is pre-trained on AudioSet.

**Trill** “TRIPlet Loss network” is designed for sound event detection and is particularly effective in distinguishing fine-grained acoustic differences. Trill is based on the ResNet50 architecture (He et al., 2015) and has shown clear improvements over popular sound classification models (Shor et al., 2020).

### 3.5.2. RECURRENT NEURAL NETWORKS (RNNs)

In this paper, we utilized ConvLSTM2D, an amalgamation of CNNs and Long Short-Term Memory (LSTM) networks, designed to capture spatial and temporal relationships in data (Shi et al., 2015). This is particularly effective for our use case, which involves generating a series of consecutive spectrograms by splitting a single audio file into multiple fixed-length segments and then producing a spectrogram for each segment.

### 3.5.3. TRANSFORMERS

**Vision Transformer (ViT)** is tailored for adaptation from large-scale pre-training to fine-tuning on smaller datasets, a process that involves replacing the original MLP head with a new linear layer tailored to the specific class size of the task at hand (2 in our case). This adjustment allows ViTs to be customized for new tasks efficiently, without complete retraining (Dosovitskiy et al., 2020). ViTs utilize self-attention to capture long-range dependencies, a feature that, while powerful, necessitates extensive training data to achieve the innate perceptual capabilities of CNNs (Zhang et al., 2023).

**SWIN Transformer**, a variant of ViT, features a unique “shifted window” self-attention mechanism. Unlike ViT, which applies self-attention to the entire sequence of tokens, Swin Transformer performs attention over square-shaped blocks of patches, each block being analogous to a receptive field in convolutional layers. This method enhances hierarchical feature processing with less computational demand. The SWIN Transformer architecture integrates “merge layers” for efficient token downsampling and incorporates advanced features like layer normalization and

Method	AUC 95% CI	ST (Recall)	SP	Precision	F1 score
ConvNeXT(RGB)	0.77 - 1.0	0.78	0.89	0.78	0.84
DenseNet(RGB)	0.73 - 1.0	0.89	0.79	0.67	0.81
SWIN Transformer(mono)	0.5-0.9	0.6	0.83	0.55	0.57
AST(mono)	0.68 - 0.98	0.89	0.60	0.80	0.84
DenseNet-Contrastive US8K(mono)	0.76-1.0	0.78	1.0	1.0	0.88

Table 1: Detailed comparison of model performance on participant level classification task (AUC=Area Under the ROC Curve. ST = Sensitivity. SP = Specificity).

scaled cosine attention, significantly boosting performance and adaptability in transfer learning scenarios (Liu et al., 2021).

#### *Pre-trained Audio Feature Extractors:*

**AST** is a convolution-free, purely attention-based model designed for audio classification (Gong et al., 2021a). We used the ast-finetuned-audioset-10-10-0.4593 version, pre-trained on the AudioSet dataset. Exploring this model represents a shift from our previous approach, which was more image classification-centric, to one that is specifically designed for audio classification.

**BEATs** model, designed for audio feature extraction, incorporates 12 Transformer encoder layers, 768-dimensional hidden states, and 8 attention heads. Pre-trained on AudioSet, BEATs has been evaluated across various audio (AS-2M, AS-20K and ESC-50) and speech (KS1, KS2 and ER) classification tasks, demonstrating its versatility and effectiveness in processing and understanding complex audio data (Chen et al., 2022).

### 3.6. Loss functions and optimizers

For our CNN-based models, particularly DenseNet, we implemented a hybrid loss function combining Cross-Entropy and Contrastive Loss, incorporating class weights to address the imbalance in our dataset, notably the underrepresentation of the “fail” class (27 patients) compared to the “pass” class (41 patients). Similarly, for Transformer-based models, we applied Cross-Entropy Loss, ensuring class weights were also used. The Adam optimizer was chosen for its adaptive learning rate (Kingma and Ba, 2014), optimizing efficiency across models with varied learning rates. This approach was uniformly applied to all trainable parameters to ensure balanced learning dynamics.

### 3.7. Preprocessing

Given the large search space of the many options we wanted to explore in this paper, we chose to approach the problem strategically starting with the most popular approach in literature—Grayscale (referred to as Mel mono in Table 2) audio spectrograms. In order to take advantage of ImageNet pre-training, we ran spectrograms at three different settings as described in this section, and concatenated the three spectrograms into a single three-channel image. This was then used as input and compared across all models except ConvLSTM2D. The “Mel mono” method allowed us to establish a baseline to compare across all feasible models which we then used to refine our training approach and model selection strategy.

For select models, we converted a single-channel spectrogram into an RGB three-channel (“Mel RGB”) image using color-maps and tried this approach on ConvNeXt, Densenet, ViT, Swin Transformer, and ConvLSTM2D network architectures (see Table 2). The strategy here was to make use of the RGB feature extraction abilities of models trained on ImageNet-an RGB-image dataset. Additionally, Palanisamy et al. (2020) discussed a similar approach of converting spectrogram to an RGB image or choosing different window sizes and hop lengths to create three distinct channels that are concatenated into a single image. They found that based on the baseline model experiments, using mel-spectrograms with different window sizes and hop lengths in each channel yielded better performance. Another preprocessing approach used in this study, is Superlet transforms which is a relatively recent method to transform time-series data into spectrogram that preserves both time and frequency resolution. Similarly, the grayscale Superlet spectrogram was converted into an RGB image. This approach was only applied to the best performing models, namely ConvNeXt, Densenet and Swin Transformer.

Method	Mel RGB	Mel mono	Superlet
YAMNet		✓	
VGGish		✓	
Trill		✓	
BEATS		✓	
ConvNeXT	✓	✓	✓
DenseNet	✓	✓	✓
DenseNet-Contrastive		✓	
DenseNet-Contrastive US8K		✓	
DenseNet-Contrastive ESC50		✓	
ConvLSTM2D	✓		
ViT	✓	✓	
SWIN	✓	✓	✓
AST		✓	

Table 2: List of models evaluated for performance comparison alongside the different pre-processing options used for each.

### 3.8. Evaluation of classifiers

We evaluated each classifier using per-participant prediction aggregation (Majority Voting), treating each participant as a single data point, regardless of the number of associated clips. The majority vote across a participant’s clips determines their overall prediction. Various performance metrics including F1 Score, Precision, Recall (Sensitivity), and Specificity, both at the validation and test stages were calculated. The Receiver Operating Characteristic (ROC) curve and confusion matrices were also plotted to visually assess performance of models.

## 4. Results

The evaluation of various models on a participant-level classification task reveals performance differences measured by AUC, Sensitivity (ST), and Specificity (SP).

The ConvNeXt model showcased a robust performance across all three metrics in the “Mel RGB” category, achieving an AUC of 0.91, ST of 0.78, and SP of 0.89. It maintained this strong performance in the “Mel mono” category, with an AUC of 0.86, ST of 0.78, and SP of 0.79, and in the “Superlet” category,

with slightly lower scores of 0.74 for AUC, 0.68 for ST, and 0.66 for SP.

DenseNet models also performed well, with the standard DenseNet achieving an AUC of 0.89, the highest ST of 0.89, and SP of 0.79 in “Mel RGB”. In “Mel mono”, it scored an AUC of 0.88, ST of 0.78, and SP of 0.74, with consistent performance in “Superlet” (AUC 0.74, ST 0.67, SP 0.67). Interestingly, the DenseNet Contrastive model excelled in “Mel mono” with an AUC of 0.82, ST of 0.86, and SP of 0.78, suggesting its effectiveness in monochrome settings.

In contrast, the ConvLSTM2D model underperformed in the “mel RGB” category, with an AUC of only 0.52, although it had a satisfactory ST of 0.78. However, its SP of 0.11 was notably low, indicating a high rate of false positives.

The SWIN Transformer model demonstrated versatility with competitive scores across all categories. It achieved an AUC of 0.801, ST of 0.78, and SP of 0.68 in “Mel RGB”, and showed improvement in “Mel mono” with an AUC of 0.83, ST of 0.6, and SP of 0.83. In the “Superlet” category, it scored an AUC of 0.78, ST of 0.67, and SP of 0.79.

The performance of the AST model in “Mel mono” was notably effective, with an AUC of 0.83 and ST of 0.89, but its SP of 0.60 suggests a significant trade-off, with a higher tendency for false positives. According to [Gong et al. \(2021a\)](#), the AST model does not require as many epochs to train as the CNN-attention hybrid models, which needed significantly more number of epochs. It’s worth noting that the AST model required only 6 epochs training on our dataset to achieve these metrics, which is fewer compared to the CNN-attention hybrid models and other Transformer models explored in this study that needed significantly more epochs to train.

Other models such as YAMNet, VGGish, Trill, and BEATS were assessed only in the “Mel mono” category. VGGish showed promising results with an AUC of 0.82, ST of 0.71, and the highest SP of 0.93 among the CNN-based feature extractors, benefiting from its pre-training on AudioSet.

Finally, a detailed comparison of the top-performing models (Table 1) in terms of their statistical performance metrics provides a deeper understanding of their predictive capabilities. The ConvNeXt (Mel RGB) model’s AUC confidence interval ranged from 0.77 to 1.0, indicating a high degree of certainty in its classification performance, with a commendable F1 score of 0.84, balancing precision



Method	Mel RGB			Mel mono			Superlet		
	AUC	ST	SP	AUC	ST	SP	AUC	ST	SP
YAMNet	-	-	-	0.69	0.71	0.79	-	-	-
VGGish	-	-	-	0.82	0.71	0.93	-	-	-
Trill	-	-	-	0.71	0.57	0.86	-	-	-
BEATS	-	-	-	0.44	0.57	0.55	-	-	-
ConvNeXt	0.91	0.78	0.89	0.86	0.78	0.79	0.74	0.68	0.66
DenseNet	0.89	0.89	0.79	0.88	0.78	0.74	0.74	0.67	0.67
DenseNet Contrastive	-	-	-	0.82	0.86	0.78	-	-	-
DenseNet Contrastive US8K	-	-	-	0.89	0.78	1.00	-	-	-
DenseNet Constrastive ESC50	-	-	-	0.75	0.71	0.78	-	-	-
ConvLSTM2D	0.52	0.78	0.11	-	-	-	-	-	-
ViT	0.79	0.67	0.89	0.84	0.40	0.94	-	-	-
SWIN Transformer	0.80	0.78	0.68	0.83	0.60	0.83	0.78	0.67	0.79
AST	-	-	-	0.83	0.89	0.60	-	-	-

Table 3: Overview of model performance on participant level classification task (where AUC represents Area Under the ROC Curve, ST represents the Sensitivity, and SP represents the Specificity).

and sensitivity. This model’s precision and recall rates, both at 0.78, suggest a harmonious balance between the positive predictive value and the true positive rate.

In contrast, DenseNet (“Mel RGB”) displayed a wider AUC confidence interval of 0.73 to 1.0, reflecting more variability in its performance. Despite this, it had the highest sensitivity of 0.89, showing its strength in identifying true positives. However, the trade-off is evident in its precision of 0.67, which is lower compared to ConvNeXt, leading to an F1 score of 0.81 that, while high, indicates room for improvement in precision.

The SWIN Transformer (“Mel mono”) had a narrower confidence interval for AUC, ranging from 0.5 to 0.9. This range suggests more uncertainty in the model’s performance, which is also reflected in the lowest F1 score of 0.57 among the evaluated models. A sensitivity of 0.6 and a specificity of 0.83 show an imbalance, with the model favoring the correct identification of negatives over positives, as also implied by a lower precision rate of 0.55.

AST (“Mel mono”) showcased a strong performance with an AUC confidence interval between 0.68 and 0.98 and an F1 score equal to ConvNeXt at 0.84. The model’s high sensitivity at 0.89 is on par with DenseNet (“Mel RGB”), but a lower specificity of 0.60 points to a higher false positive rate.

The DenseNet-Contrastive US8K (“Mel mono”) model stood out with an AUC confidence interval of

0.76 to 1.0 and perfect scores for both specificity and precision, both at 1.0. This exceptional performance resulted in the highest F1 score of 0.88, indicating a very strong predictive power where the model excelled in both recognizing true positives and avoiding false positives.

## 5. Discussion

Our study examines the associations between spectrogram preprocessing techniques and the ensuing performance of audio classification models, underscoring an important consideration for clinical applications: the nuanced efficacy of preprocessing approaches has significant bearing on leveraging transfer learning. Our works suggests that while RGB preprocessing exhibits superior performance in conjunction with ImageNet pre-training, the “Mel mono” approach, when pre-trained on expansive public audio datasets, surpasses RGB’s effectiveness. This insight is crucial, suggesting that in clinical settings, where data limitations and intrinsic differences are prevalent, adopting a more standardized and contextually tailored approach to preprocessing could significantly enhance the performance of deep learning models. Moreover, the observed variances in model architecture performance, particularly the robustness of transformer-based models versus traditional CNNs in handling limited training epochs, offer a promising avenue for refining audio classification frameworks.

This suggests that through strategic selection of pre-processing techniques and models there may be more optimal audio classification strategies that can improve diagnostics in with heightened accuracy and efficiency in clinical environments. This has implications for voice as a biomarker in stroke and other neurologic conditions in addition to other disease states where data limitations may be intrinsic to the health condition including rare diseases.

The DenseNet model, particularly with its Contrastive US8K variant, excelled by leveraging a hybrid loss combining cross-entropy with a supervised contrastive loss, significantly enhancing specificity and yielding the highest F1 score of 0.88 among the evaluated models. The pre-training and fine-tuning process, progressing from general large-scale audio datasets to specialized clinical data, proved crucial in developing effective feature extractors for audio spectrogram classification.

The transformer-based approach, relatively new in the field of audio analysis, demonstrates the potential of adapting architectures originally designed for other domains, like natural language processing, to audio classification. The AST model’s substantial sensitivity score suggests a strong grasp of relevant audio spectrogram features. It showed training efficiency, achieving optimal results with just 6 epochs, contrasting with CNN-based models requiring more epochs for similar performance. This highlights the potential of transformer pre-trained models in audio classification, even with limited training epochs.

Expectantly, we observed variations in performance, partly explained by intrinsic differences and model architecture’s ability, within limited data, to classify spectrogram images.

Surprisingly, the RGB preprocessing approach outperformed the grayscale triple channel approach when using the ImageNet pre-training. Theoretically, concatenating three grayscale spectrograms constructed from different mel transform settings should outperform a single mel spectrogram transformed into an RGB image through color mapping. However, our results suggest that the convolutional layers of models pre-trained on ImageNet might be better attuned to the features present in RGB images. This had not been widely discussed in the literature before and we noticed some variations where some papers use grayscale images (Chen et al., 2022; Gong et al., 2021a; Howard et al., 2017; Mu et al., 2021) , and some would use RGB representations of

the spectrograms (Aykanat et al., 2017; Zaman et al., 2023).

## 6. Conclusion

In summary, our study underscores the effectiveness of modern CNN architectures, such as DenseNet and ConvNeXt, in the field of clinical audio classification. These architectures demonstrate robustness, often rivaling or even surpassing the capabilities of transformer models, particularly in scenarios involving small datasets. A key factor in this success is the strategic use of open-source pre-trained weights, which not only accelerates the development process but also significantly enhances model accuracy.

A cornerstone of our research involved the prospective collection of two first-of-their-kind patient audio datasets from stroke patients. We introduce use of a NIHSS-based audio dataset, a novel collection capturing continuous speech, sentences, and words based on the NIHSS. This well-established test for stroke assessment in emergency departments provides invaluable data for developing audio classification models tailored to clinical needs. Additionally, we presented the Vowel dataset, a unique compilation of sustained vowel sounds from patients, offering new insights into the analysis of swallowing disorders.

Leveraging open datasets for pre-training allows for generalized feature learning, which is crucial before fine-tuning models on specific datasets. Our findings show that a multi-stage training and fine-tuning process is highly effective, enabling gradual adaptation of the model and thus improving its performance.

The impact of preprocessing techniques, such as Mel RGB, Mel mono, and Superlet, on model performance appear to be nontrivial. These techniques require careful selection as they significantly influence the outcome.

Ensuring a chronological separation of training and testing sets is paramount to prevent data leakage, thereby enhancing the generalization capabilities of the models. Moreover, our study reaffirms the potential of audio as a potent predictor of clinically relevant information. This highlights the promise of audio-based diagnostics and monitoring in clinical settings.

Through nuanced consideration in data handling and model training, our research contributes to the advancement of clinical audio classification, with promising implications for its application in various conditions both in neurologic conditions and beyond.

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