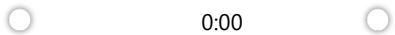


# Birdclef 2021

## Birdcall Identification



Tobias Priesholm Gårdhus & Kaare Endrup Iversen



# Motivation

## Technical

- Working with "complex" mixed data-sources including audio
- "Real world" problem

## Ethical

- Pros: Contributing to wild-life monitoring and preservation
- Cons: Enables automatic surveillance

## Fun

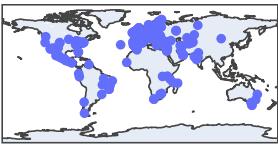
- Working in a field new to both of us

# Data

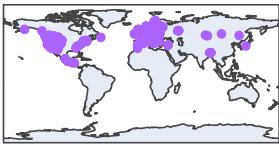
8548 Audio files containing 27 different species



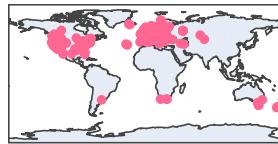
House Sparrow



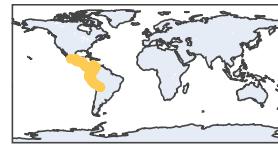
House Wren



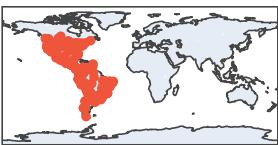
Common Raven



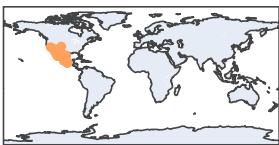
Red Crossbill



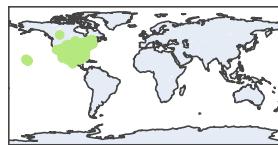
Curve-billed Thrasher



Spotted Towhee



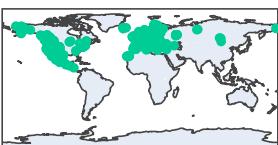
European Starling



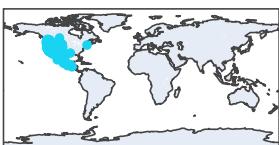
Northern Cardinal



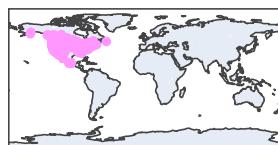
Song Sparrow



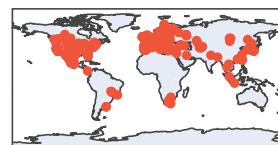
Gray-breasted Wood-Wren



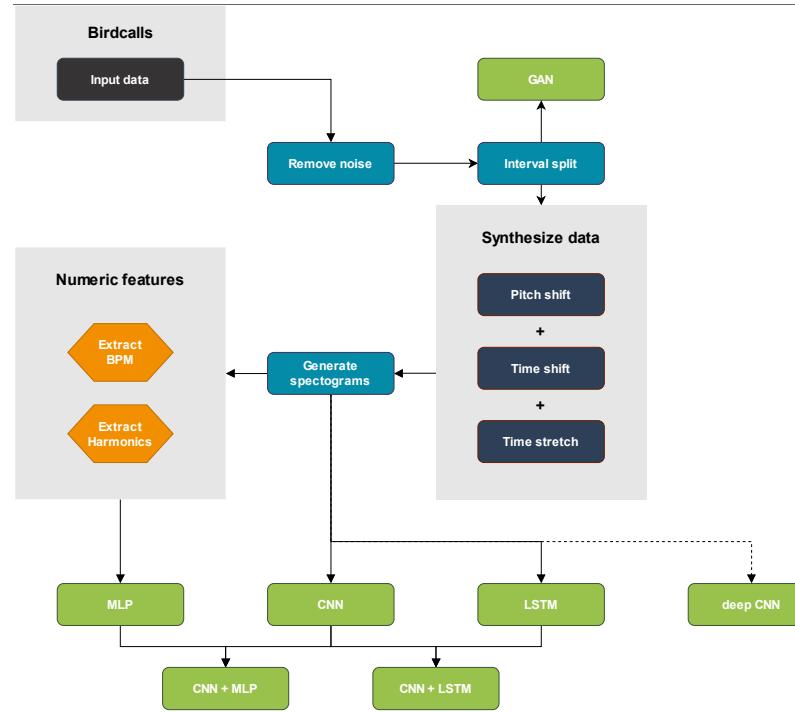
Red-winged Blackbird



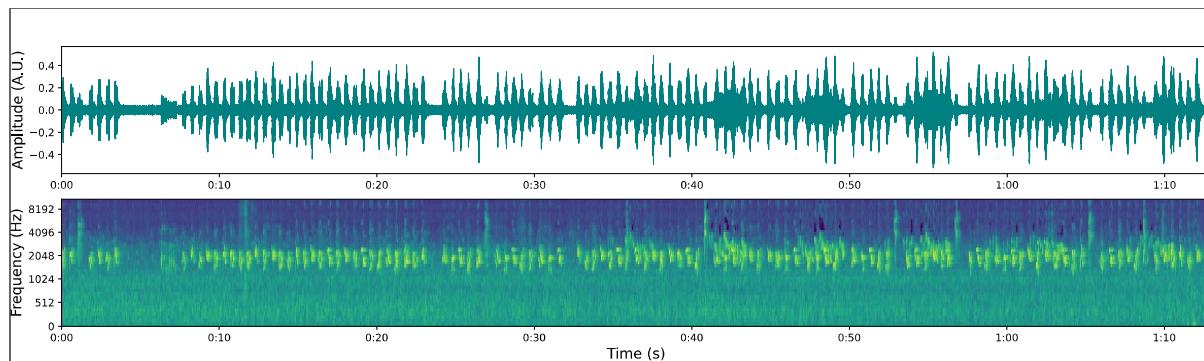
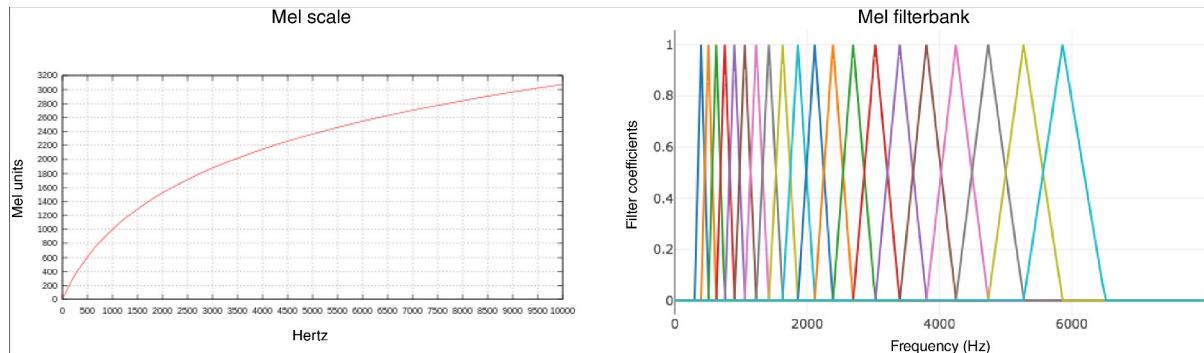
Barn Swallow



# Procedure

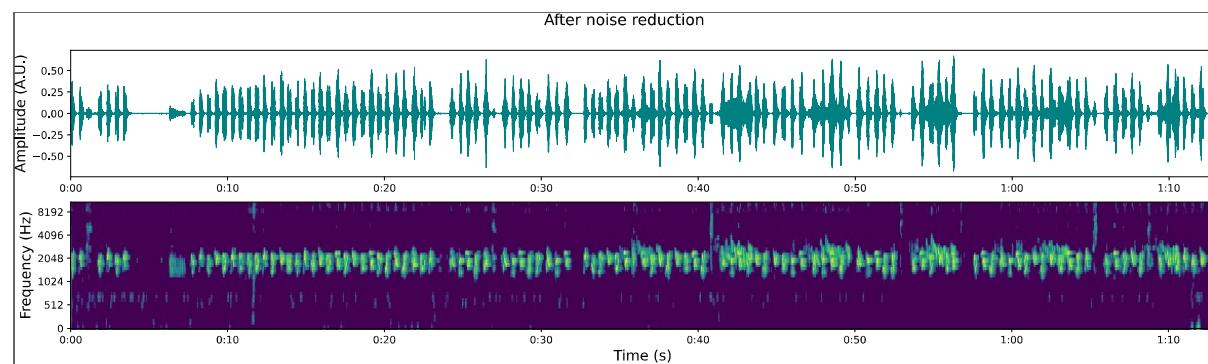
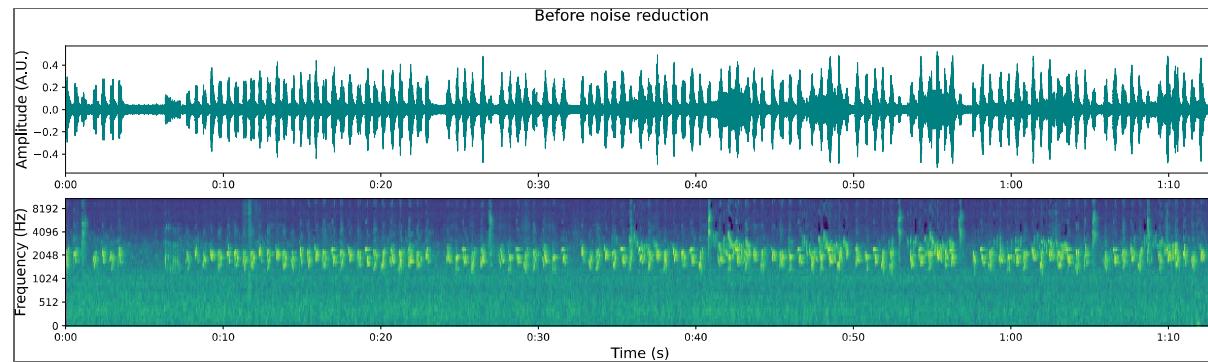


# Mel Spectograms



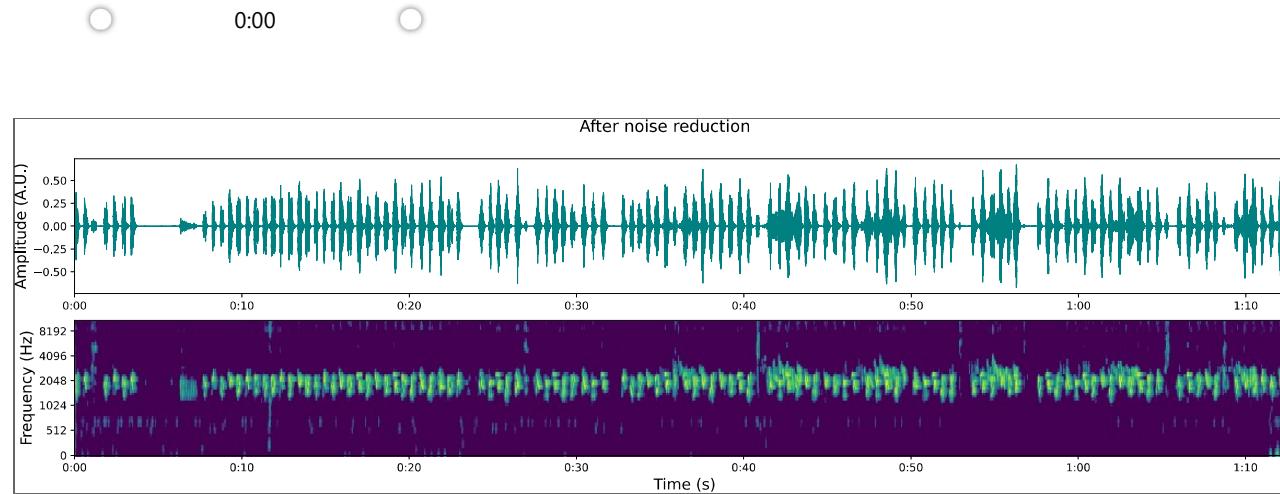
# Feature Engineering

## NOISE REDUCTION



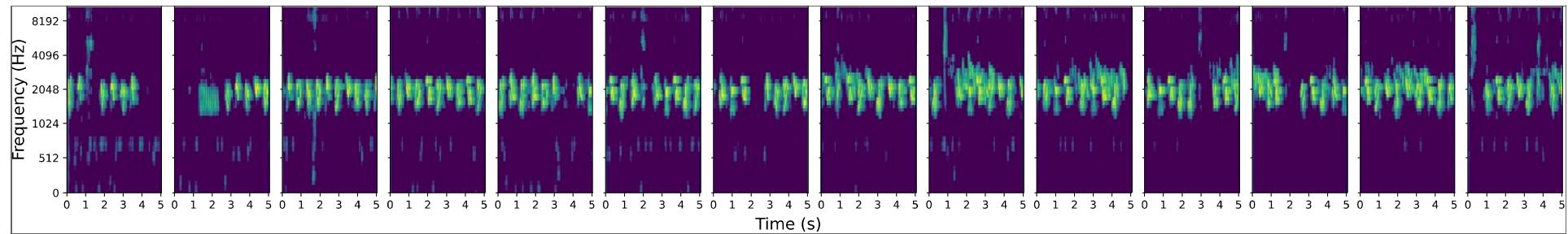
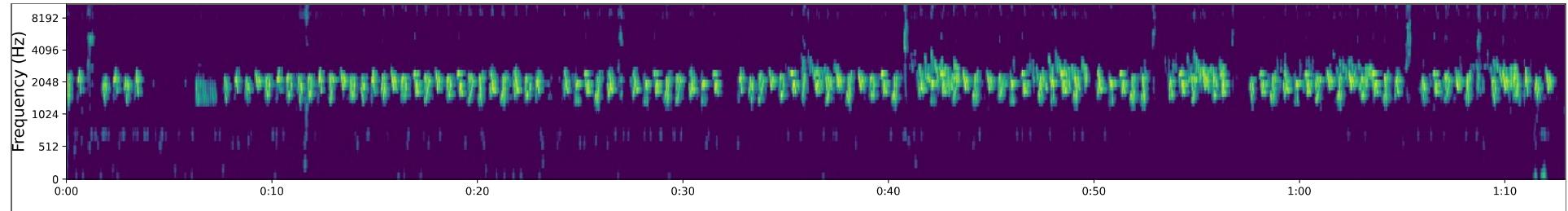
# Feature Engineering

## NOISE REDUCTION

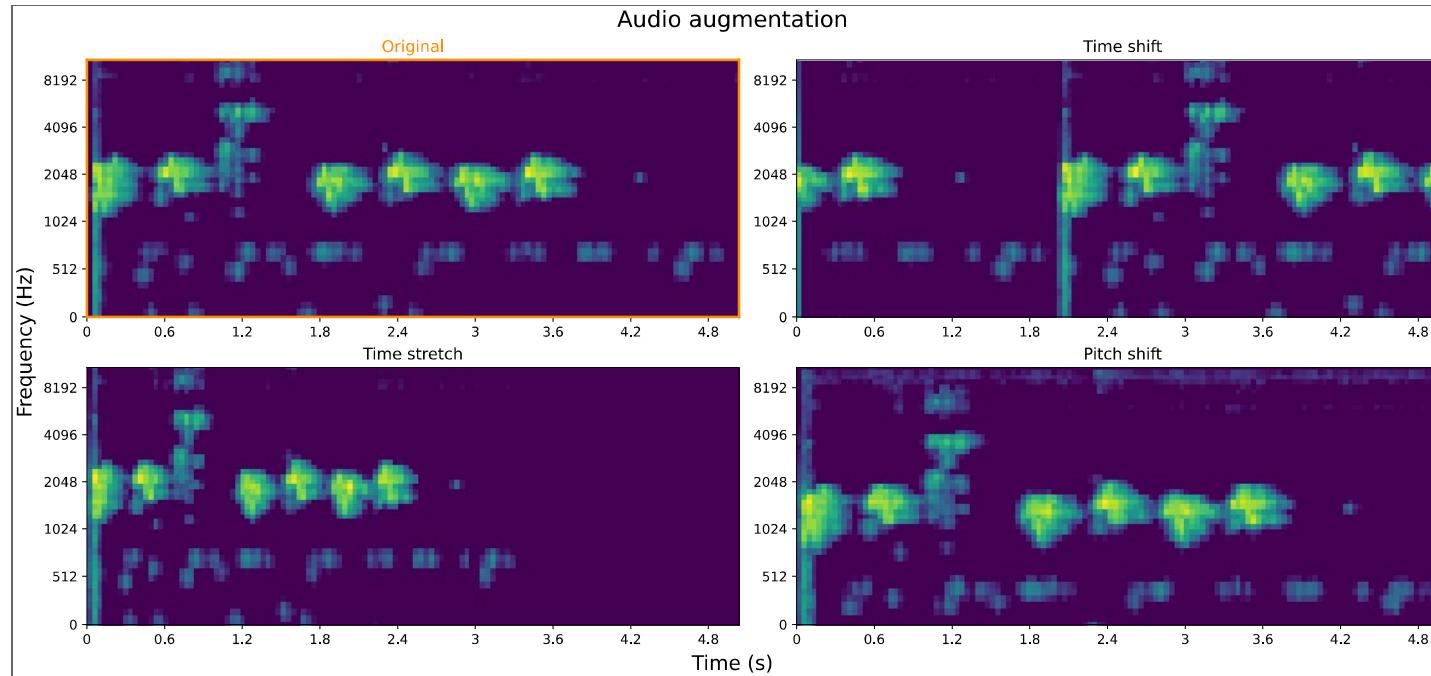


0:00:00 / 12:25:39

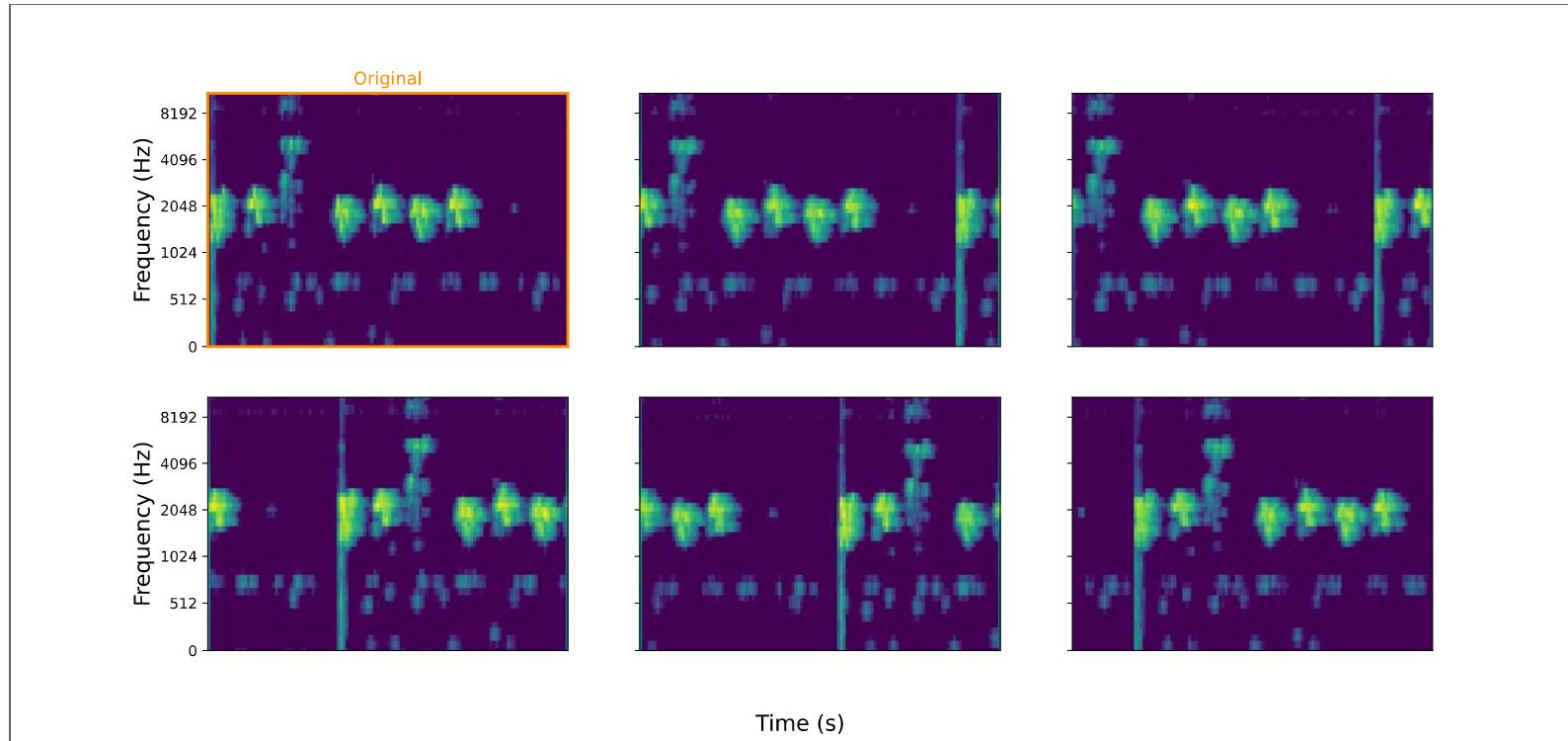
# Split



# Audio Augmentation

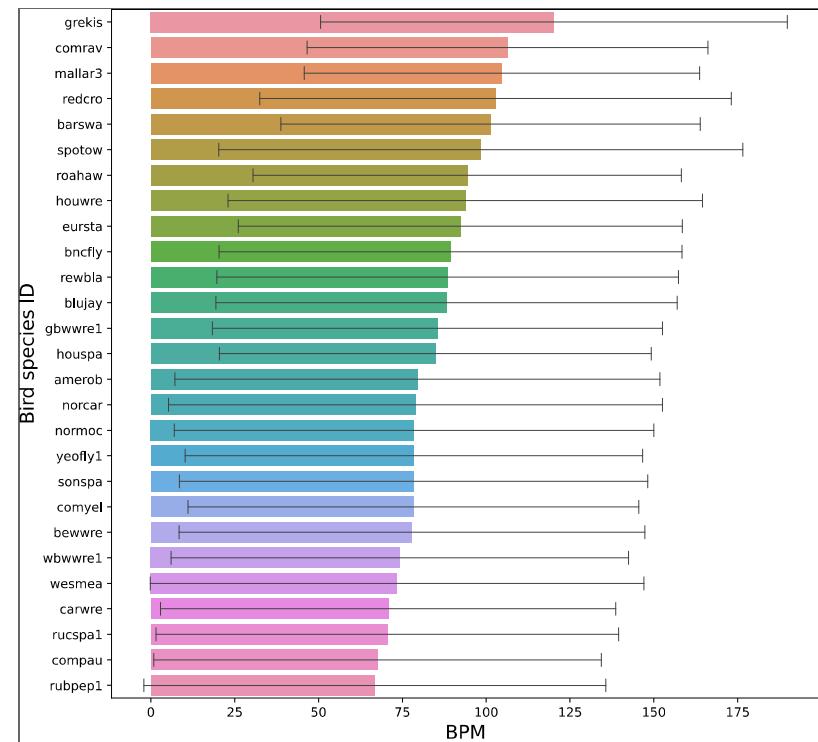


# Audio Augmentation



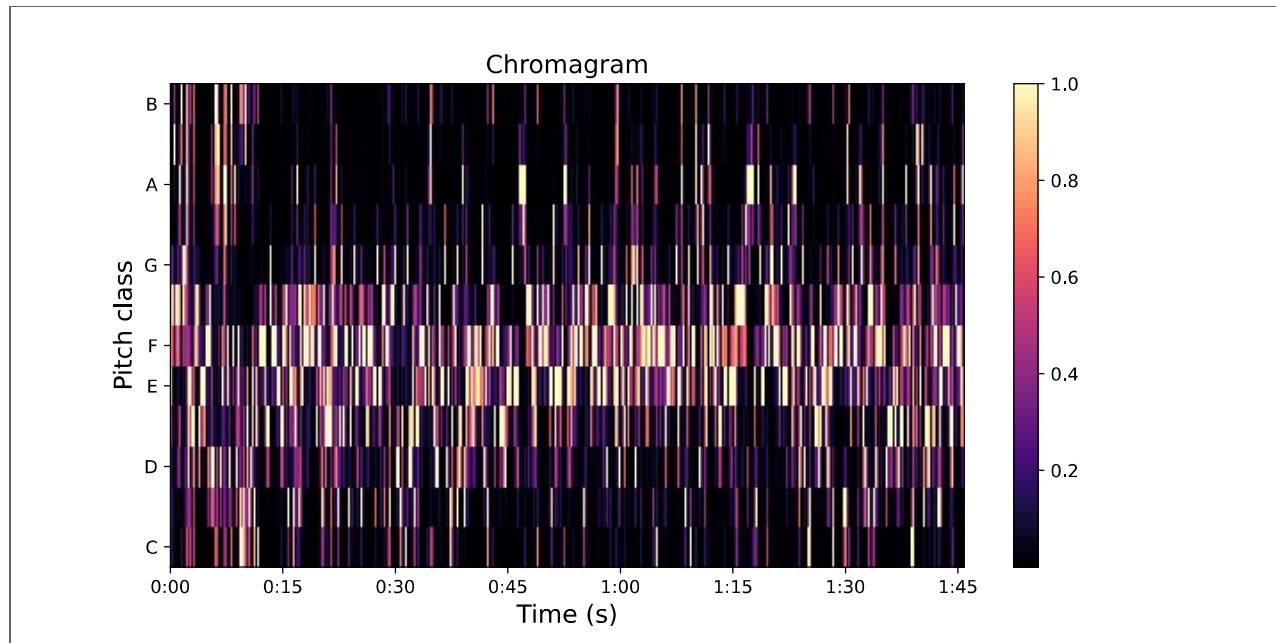
# Numeric features

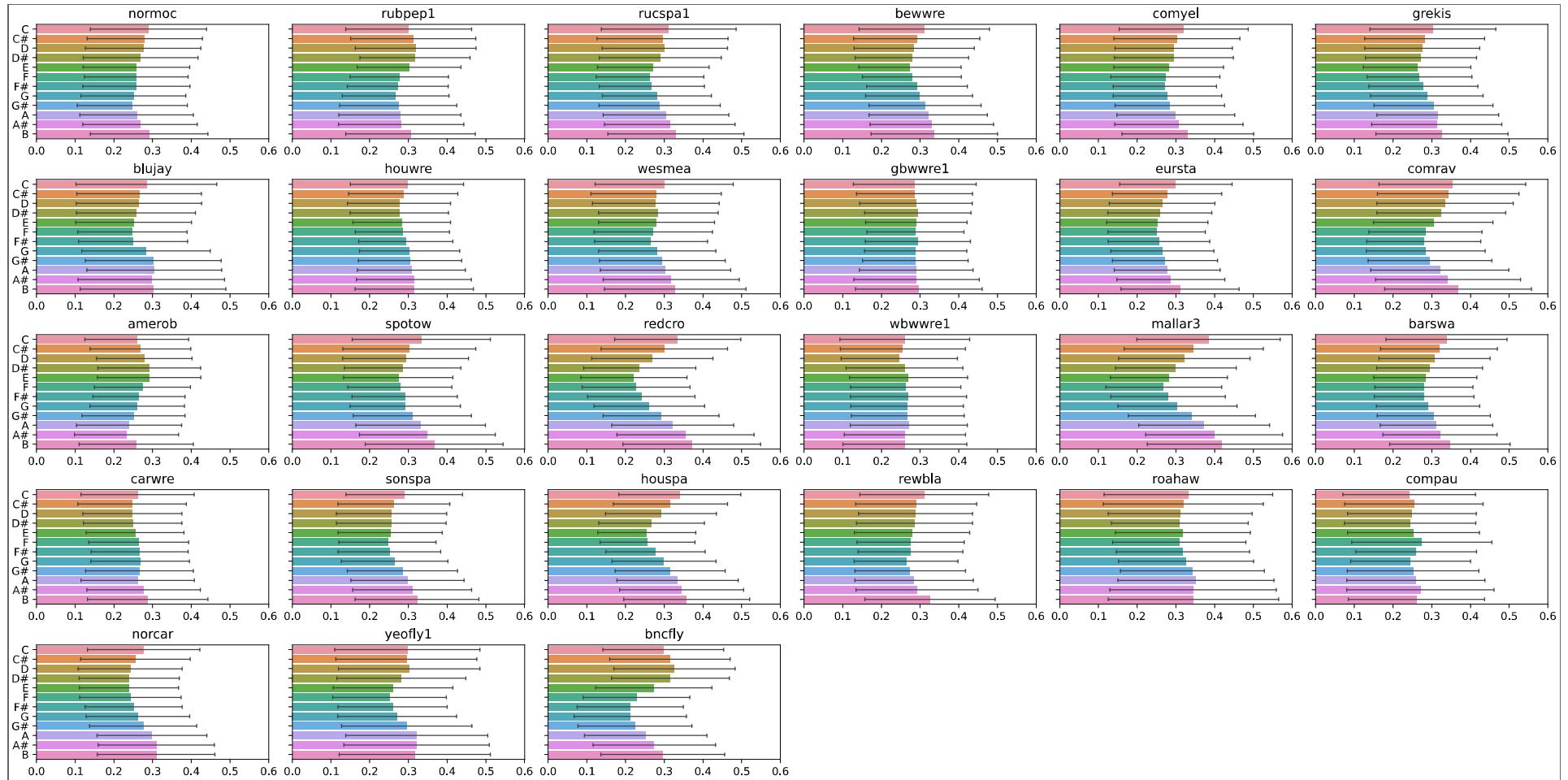
## BPM

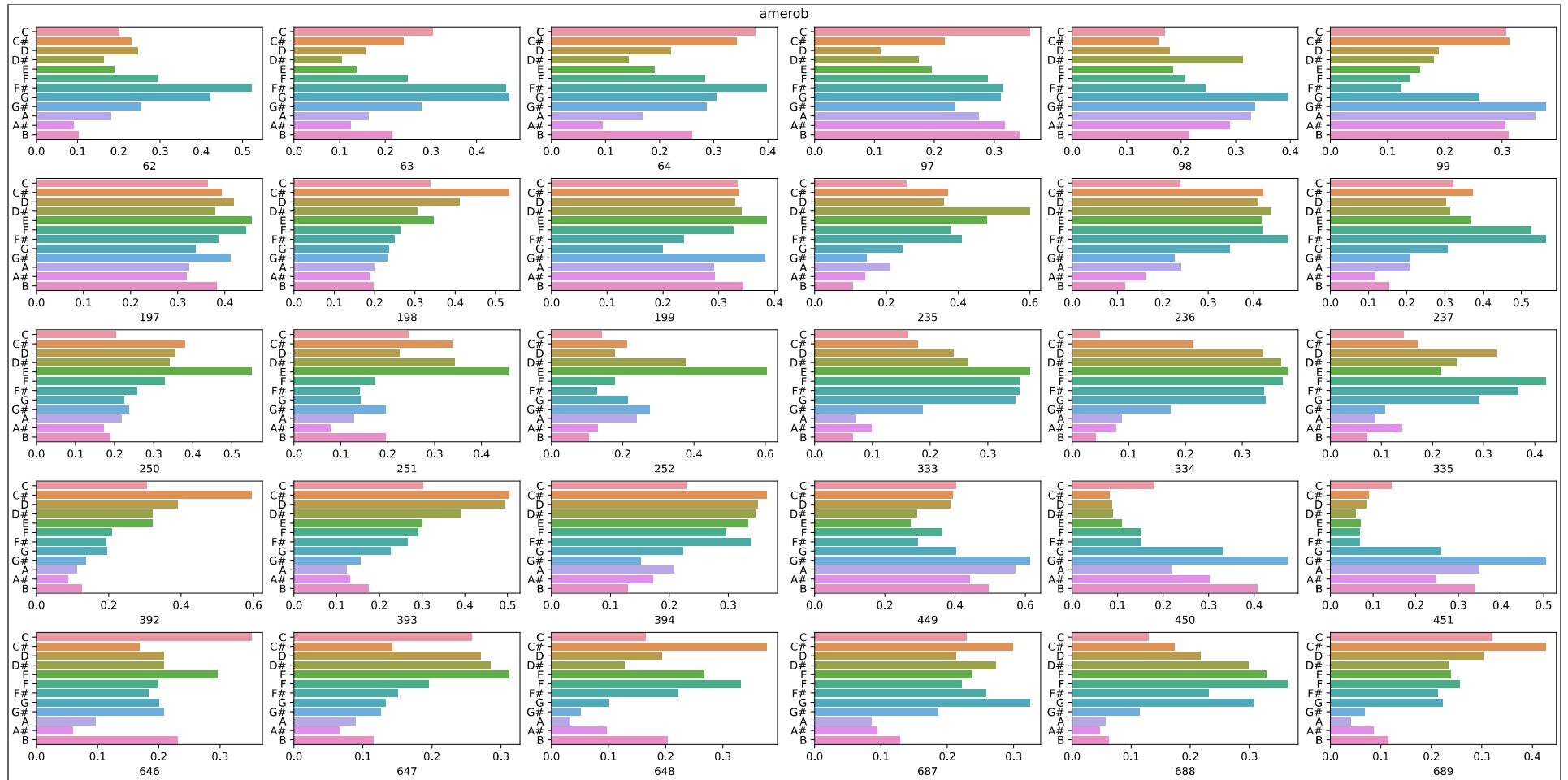


# Numeric features

## HARMONICS





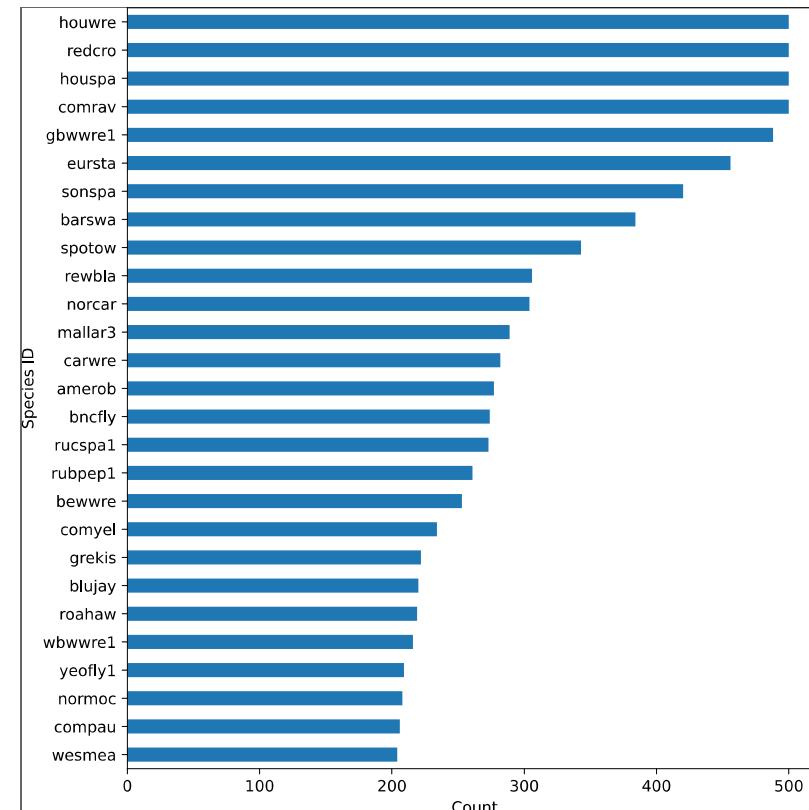
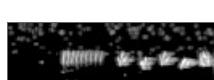
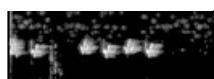
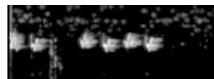


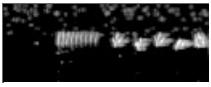
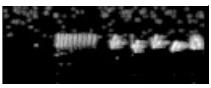
# Input data set

**Train samples:** 113568 (of which 5/6th [94640] is augmented data and 1/6th [18928] is original data)

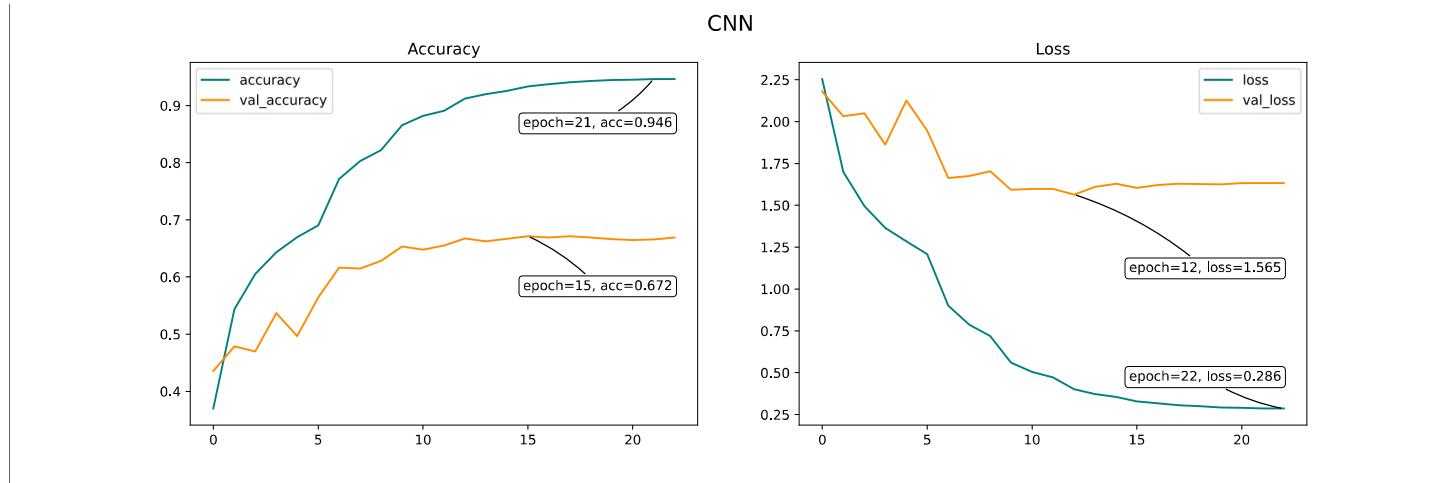
**Validation samples:** 2366

**Test samples:** 2367

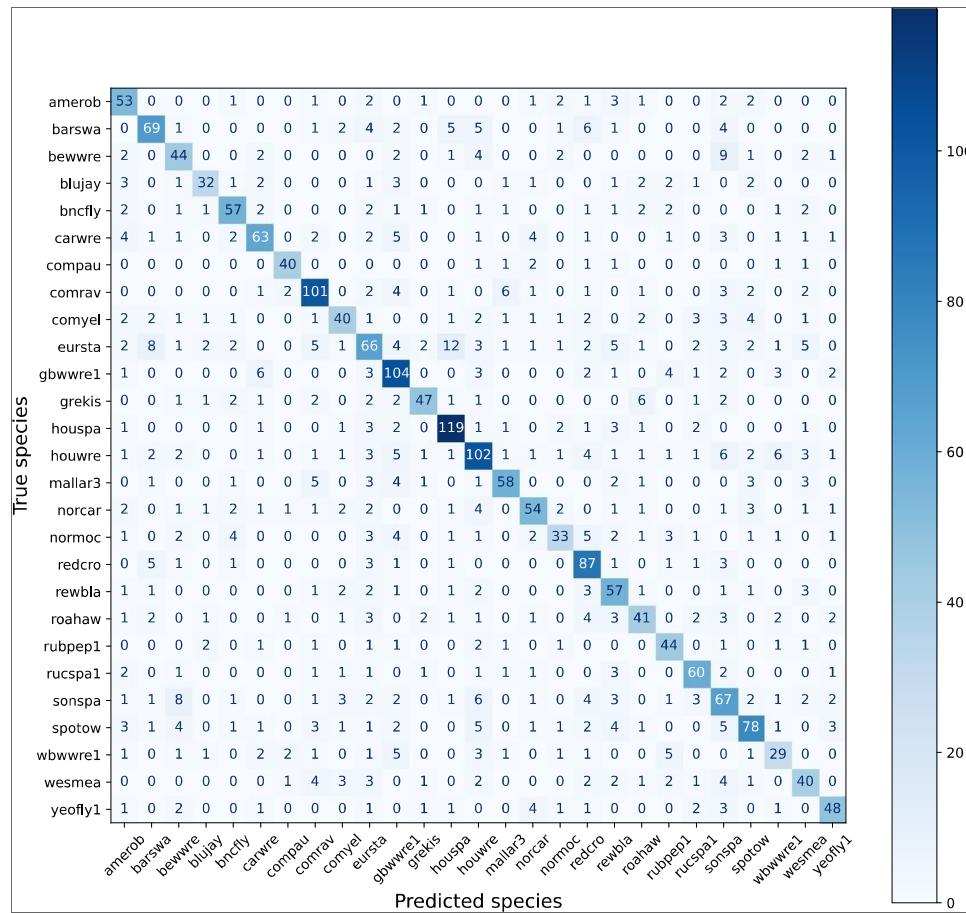




# ML Models - CNN



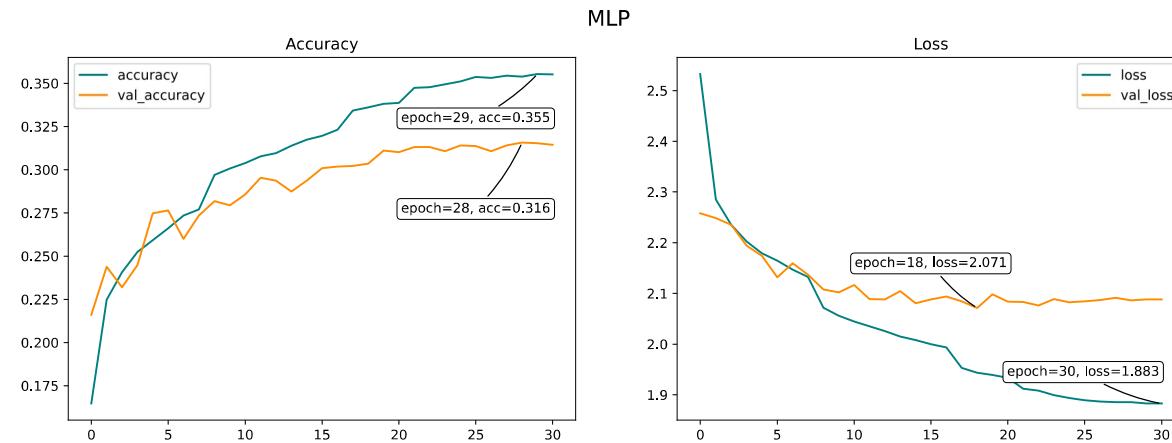
# ML Models - CNN



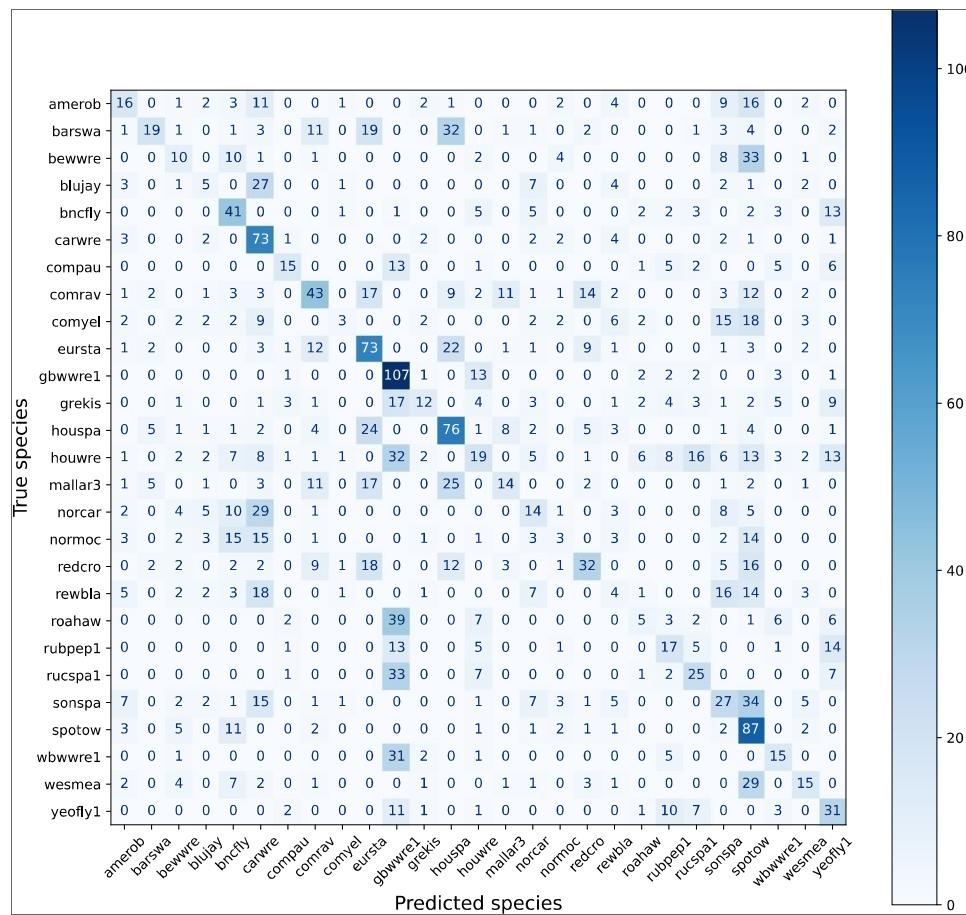
Classification report

	precision	recall	f1-score	support
amerob	0.63	0.76	0.69	70
barswa	0.74	0.68	0.71	101
bewwre	0.60	0.63	0.62	70
blujay	0.76	0.60	0.67	53
bncfly	0.75	0.73	0.74	78
carwre	0.74	0.68	0.71	93
compau	0.85	0.83	0.84	48
comrav	0.77	0.80	0.78	127
comyel	0.69	0.57	0.62	70
eursta	0.56	0.50	0.53	132
gbwwrel	0.68	0.79	0.73	132
grekis	0.81	0.68	0.74	69
houspa	0.80	0.86	0.83	139
houwre	0.67	0.68	0.68	149
malla3	0.78	0.70	0.74	83
norcar	0.71	0.66	0.68	82
normoc	0.67	0.50	0.57	66
redcro	0.66	0.83	0.74	105
rewbla	0.60	0.74	0.66	77
roahaw	0.64	0.58	0.61	71
rubpepl	0.67	0.77	0.72	57
rucspal	0.74	0.79	0.76	76
sonspa	0.53	0.60	0.56	112
spotow	0.74	0.66	0.70	118
wbwre1	0.59	0.53	0.56	55
wesmea	0.59	0.60	0.59	67
yeofly1	0.76	0.72	0.74	67
accuracy			0.69	2367
macro avg	0.69	0.68	0.69	2367
weighted avg	0.69	0.69	0.69	2367

# ML Models - MLP



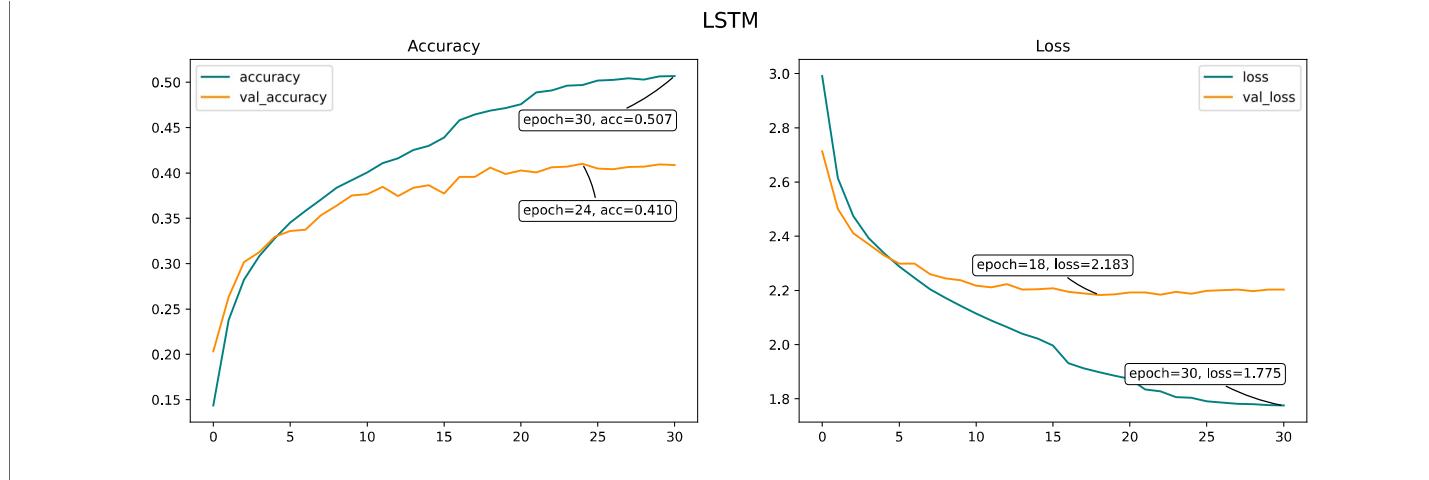
# ML Models - MLP



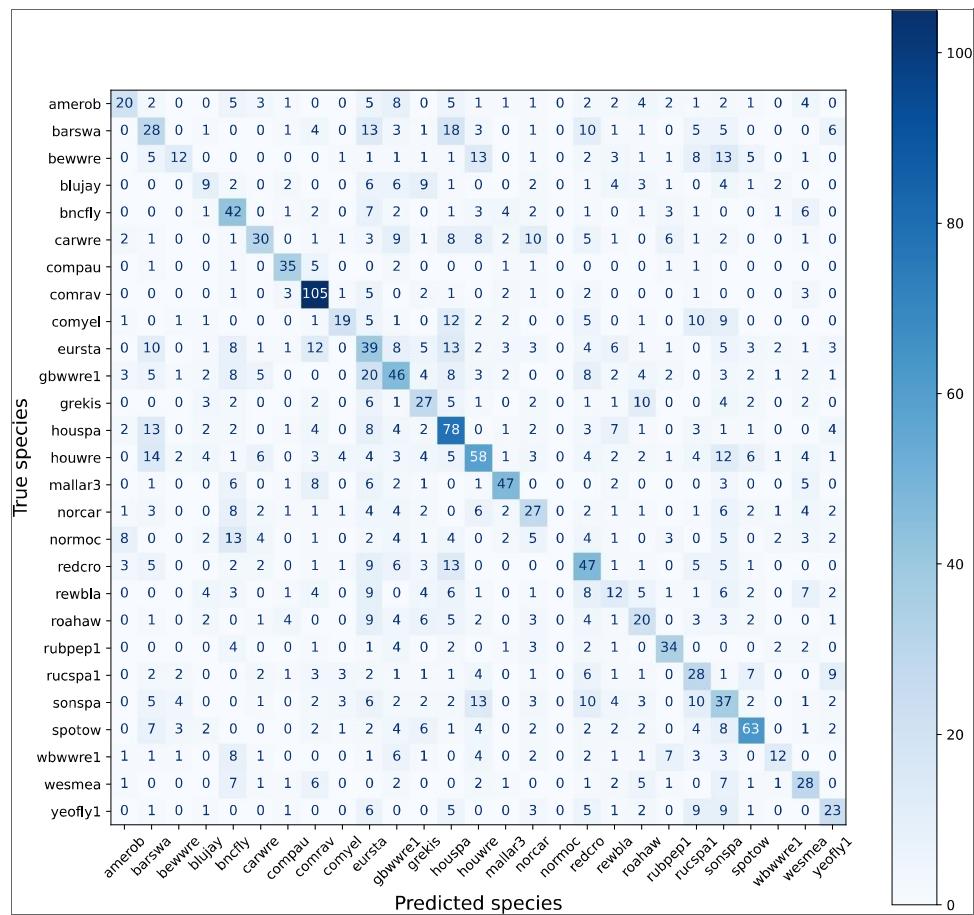
**Classification report**

	precision	recall	f1-score	support
amerob	0.31	0.23	0.26	70
barswa	0.54	0.19	0.28	101
bewwre	0.24	0.14	0.18	70
blujay	0.18	0.09	0.12	53
bncfly	0.35	0.53	0.42	78
carwre	0.32	0.78	0.46	93
compau	0.54	0.31	0.39	48
comrav	0.43	0.34	0.38	127
comyel	0.30	0.04	0.07	70
eursta	0.43	0.55	0.49	132
gbwwre1	0.36	0.81	0.50	132
grekis	0.44	0.17	0.25	69
houspa	0.43	0.55	0.48	139
houwre	0.27	0.13	0.17	149
malla3	0.36	0.17	0.23	83
norcar	0.23	0.17	0.19	82
normoc	0.14	0.05	0.07	66
redcro	0.46	0.30	0.37	105
rewbla	0.10	0.05	0.07	77
roahaw	0.22	0.07	0.11	71
rubpepl	0.29	0.30	0.30	57
rucspal	0.38	0.33	0.35	76
sonspa	0.24	0.24	0.24	112
spotow	0.28	0.74	0.41	118
wbwre1	0.34	0.27	0.30	55
wesmea	0.38	0.22	0.28	67
yeofly1	0.30	0.46	0.36	67
accuracy			0.34	2367
macro avg	0.33	0.31	0.29	2367
weighted avg	0.34	0.34	0.31	2367

# ML Models - LSTM



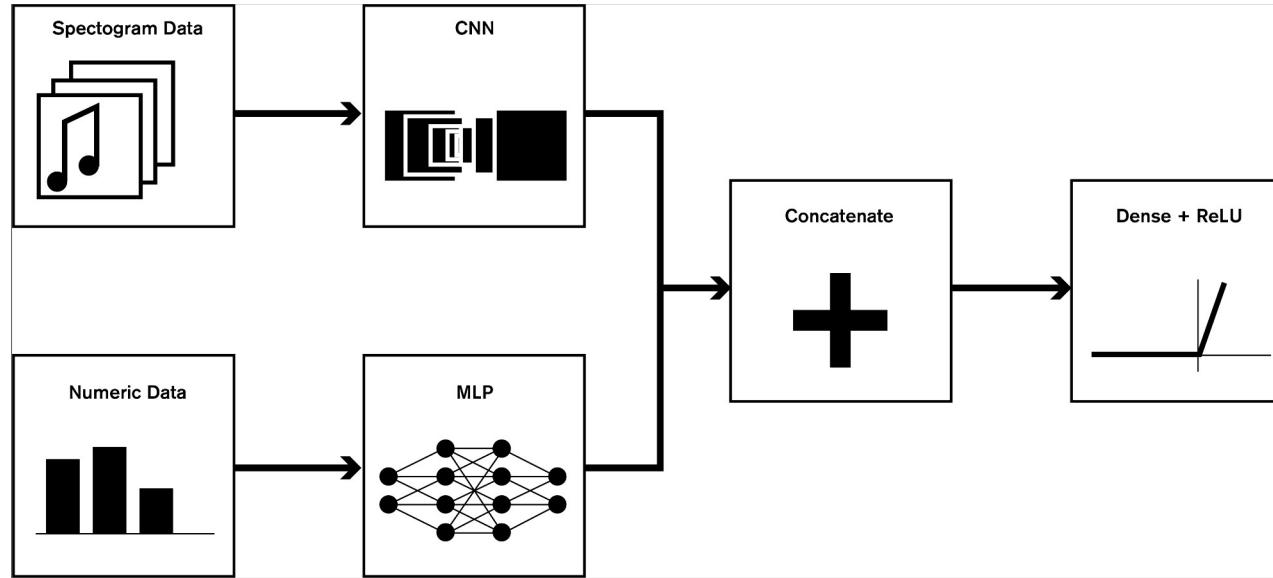
# ML Models - LSTM



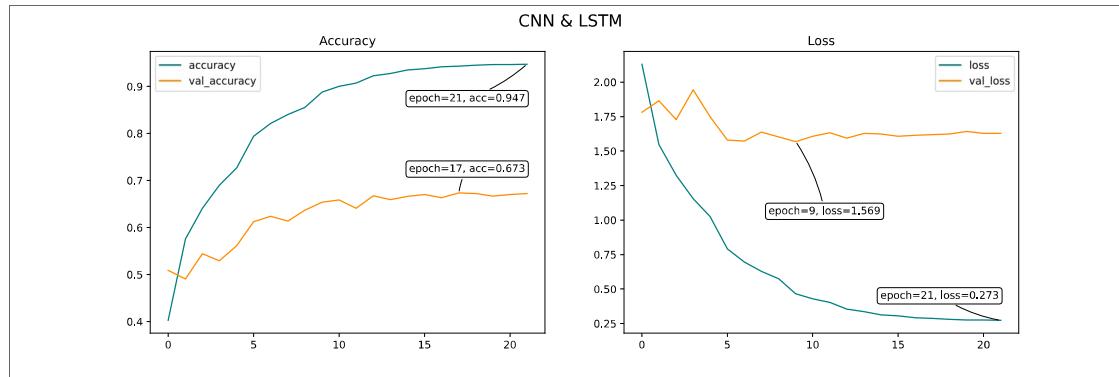
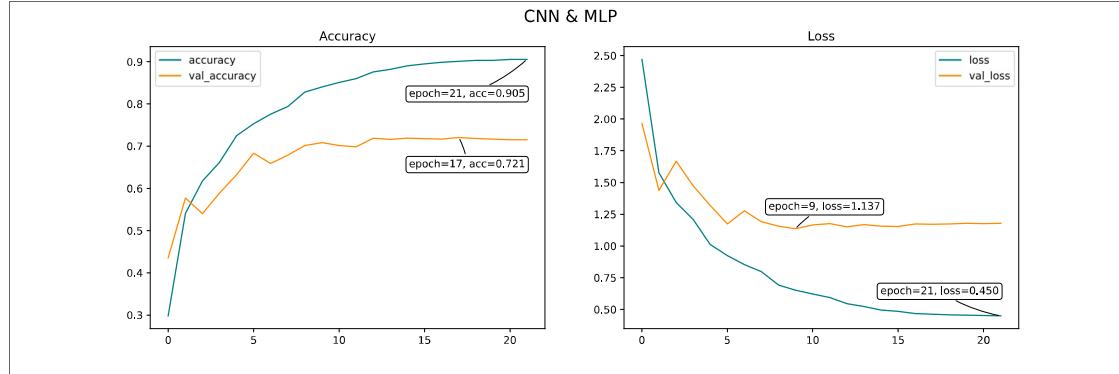
Classification report

	precision	recall	f1-score	support
amerob	0.48	0.29	0.36	70
barswa	0.27	0.28	0.27	101
bewwre	0.46	0.17	0.25	70
blujay	0.26	0.17	0.20	53
bncfly	0.34	0.54	0.42	78
carwre	0.51	0.32	0.39	93
compau	0.64	0.73	0.68	48
comrav	0.62	0.83	0.71	127
comyel	0.54	0.27	0.36	70
eursta	0.22	0.30	0.25	132
gbwwrel	0.35	0.35	0.35	132
grekis	0.33	0.39	0.36	69
houspa	0.40	0.56	0.47	139
houwre	0.44	0.39	0.41	149
malla3	0.65	0.57	0.61	83
norcar	0.34	0.33	0.34	82
normoc	0.00	0.00	0.00	66
redcro	0.33	0.45	0.38	105
rewbla	0.20	0.16	0.18	77
roahaw	0.29	0.28	0.28	71
rubpepl	0.53	0.60	0.56	57
rucspal	0.28	0.37	0.32	76
sonspa	0.24	0.33	0.28	112
spotow	0.62	0.53	0.57	118
wbwre1	0.48	0.22	0.30	55
wesmea	0.37	0.42	0.39	67
yeofly1	0.40	0.34	0.37	67
accuracy			0.39	2367
macro avg	0.39	0.38	0.37	2367
weighted avg	0.39	0.39	0.38	2367

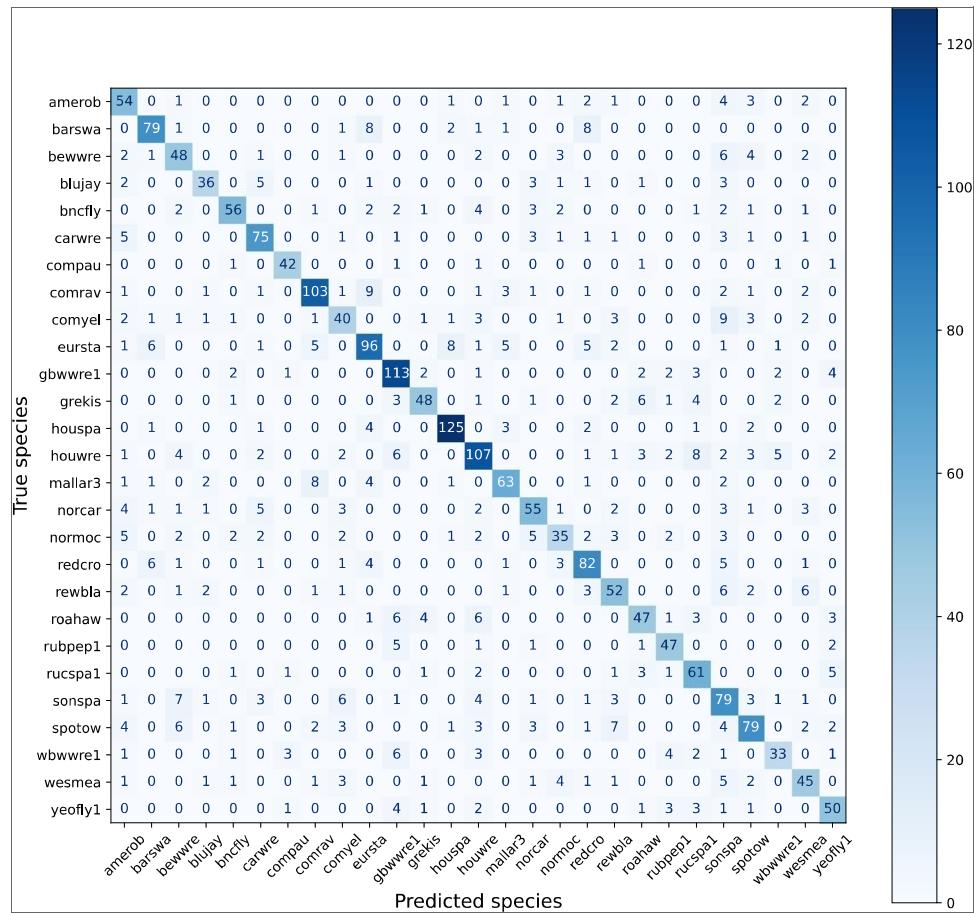
# ML Models - Mixed



# ML Models - Mixed



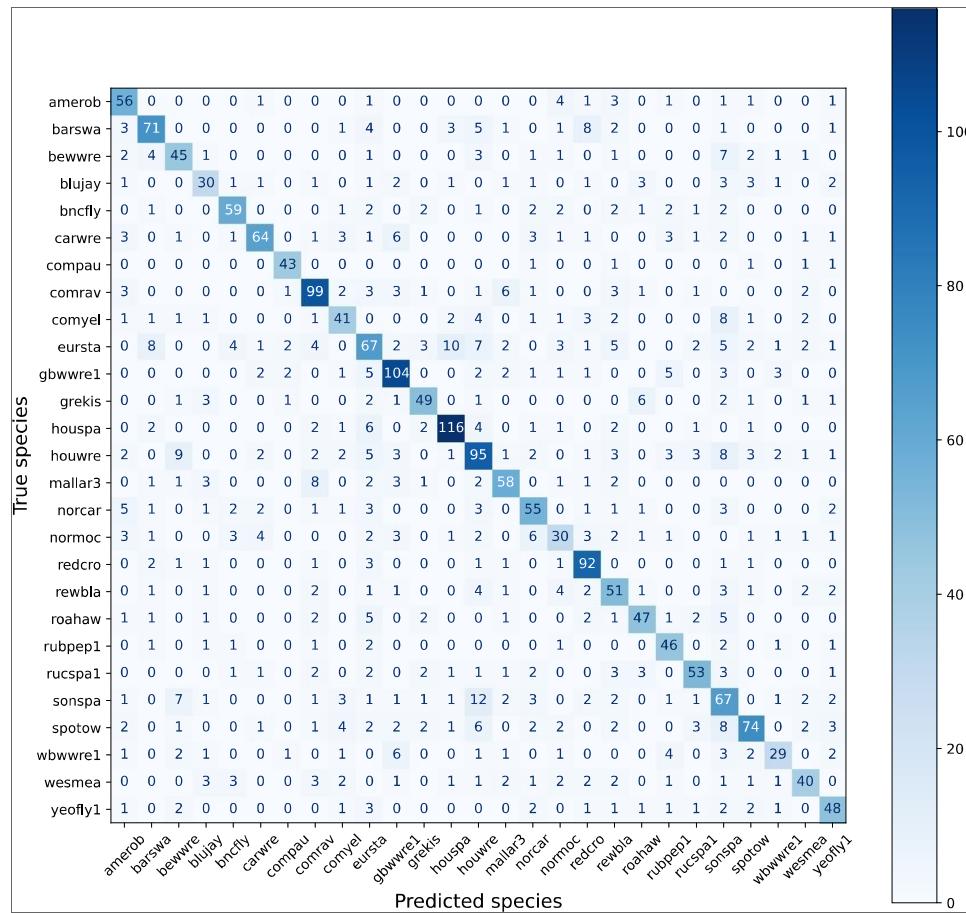
# ML Models - CNN & MLP



Classification report

	precision	recall	f1-score	support
amerob	0.62	0.77	0.69	70
barswa	0.82	0.78	0.80	101
bewwre	0.64	0.69	0.66	70
blujay	0.80	0.68	0.73	53
bncfly	0.84	0.72	0.77	78
carwre	0.77	0.81	0.79	93
compau	0.88	0.88	0.88	48
comrav	0.84	0.81	0.83	127
comyel	0.62	0.57	0.59	70
eursta	0.74	0.73	0.74	132
gbwwrel	0.76	0.86	0.81	132
grekis	0.81	0.70	0.75	69
houspa	0.89	0.90	0.90	139
houwre	0.73	0.72	0.72	149
malla3	0.81	0.76	0.78	83
norcar	0.71	0.67	0.69	82
normoc	0.67	0.53	0.59	66
redcro	0.73	0.78	0.76	105
rewbla	0.66	0.68	0.67	77
roahaw	0.72	0.66	0.69	71
rubpepl	0.75	0.82	0.78	57
rucspal	0.71	0.80	0.75	76
sonspa	0.56	0.71	0.62	112
spotow	0.75	0.67	0.71	118
wbwre1	0.73	0.60	0.66	55
wesmea	0.66	0.67	0.67	67
yeofly1	0.71	0.75	0.73	67
accuracy			0.74	2367
macro avg	0.74	0.73	0.73	2367
weighted avg	0.74	0.74	0.74	2367

# ML Models - CNN & LSTM

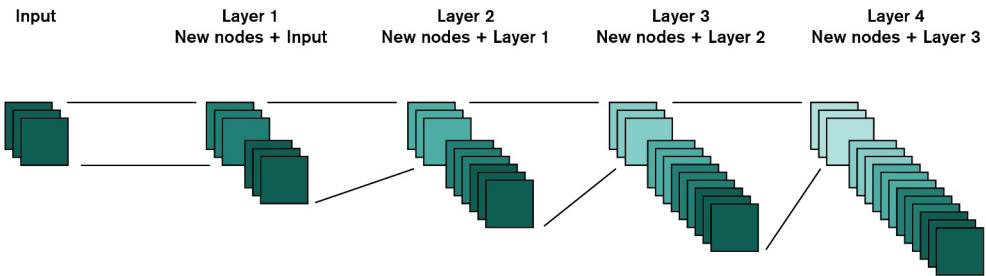


Classification report

	precision	recall	f1-score	support
amerob	0.66	0.80	0.72	70
barswa	0.75	0.70	0.72	101
bewwre	0.63	0.64	0.64	70
blujay	0.62	0.57	0.59	53
bncfly	0.79	0.76	0.77	78
carwre	0.81	0.69	0.74	93
compau	0.86	0.90	0.88	48
comrav	0.75	0.78	0.76	127
comyel	0.64	0.59	0.61	70
eursta	0.54	0.51	0.52	132
gbwwre1	0.75	0.79	0.77	132
grekis	0.75	0.71	0.73	69
houspa	0.84	0.83	0.84	139
houwre	0.61	0.64	0.62	149
malla3	0.72	0.70	0.71	83
norcar	0.65	0.67	0.66	82
normoc	0.53	0.45	0.49	66
redcro	0.75	0.88	0.81	105
rewbla	0.56	0.66	0.61	77
roahaw	0.72	0.66	0.69	71
rubpepl	0.67	0.81	0.73	57
rucspal	0.77	0.70	0.73	76
sonspa	0.48	0.60	0.53	112
spotow	0.76	0.63	0.69	118
wbwre1	0.69	0.53	0.60	55
wesmea	0.69	0.60	0.64	67
yeofly1	0.68	0.72	0.70	67
accuracy			0.69	2367
macro avg	0.69	0.68	0.69	2367
weighted avg	0.69	0.69	0.69	2367

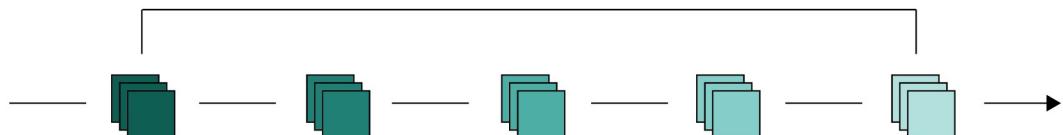
# ML Models - Transfer Learning

## DenseNet

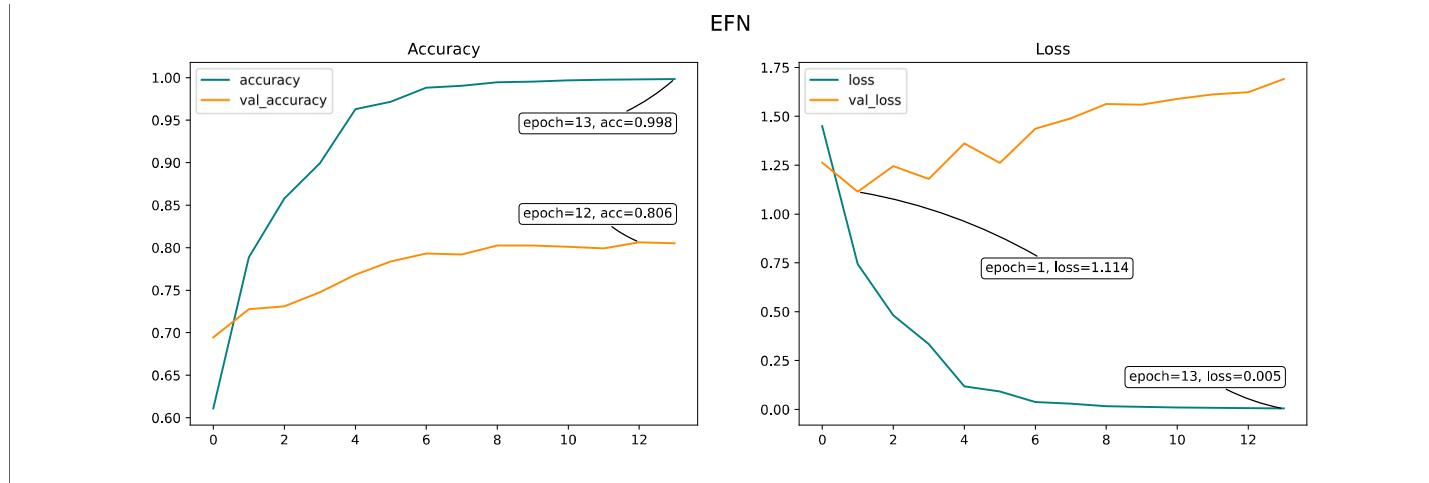


## ResNet

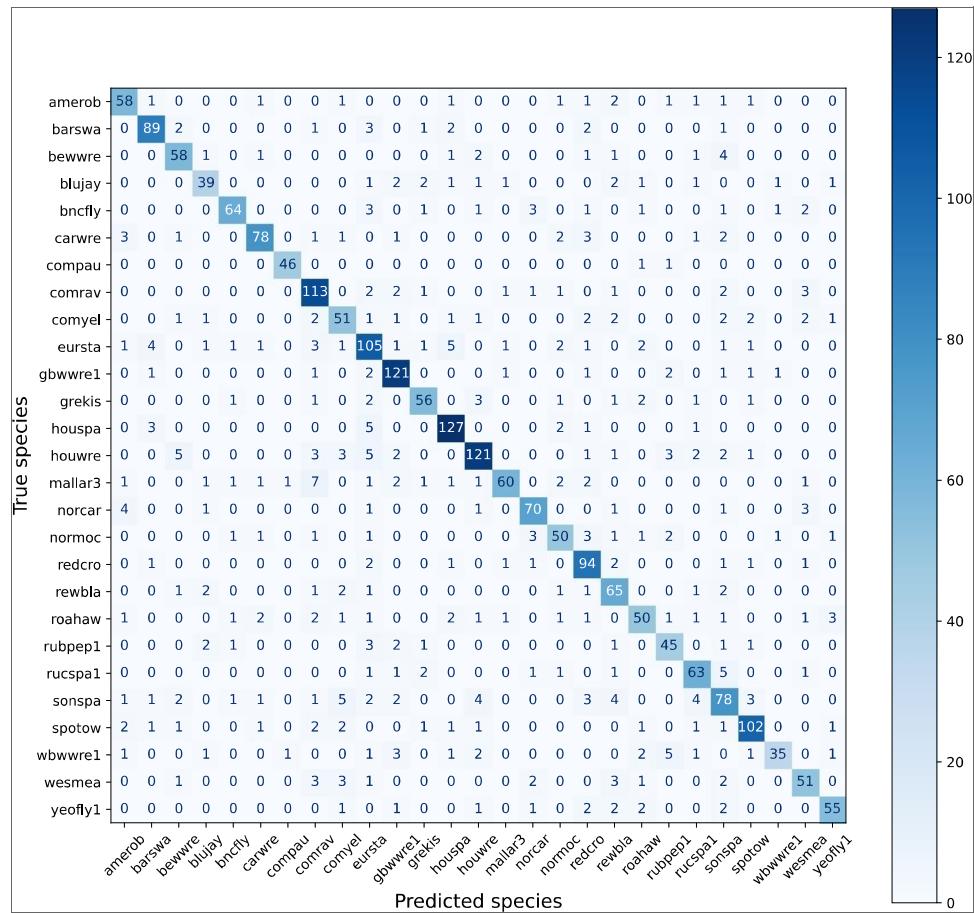
Skip connection



# ML Models - EfficientNet B1



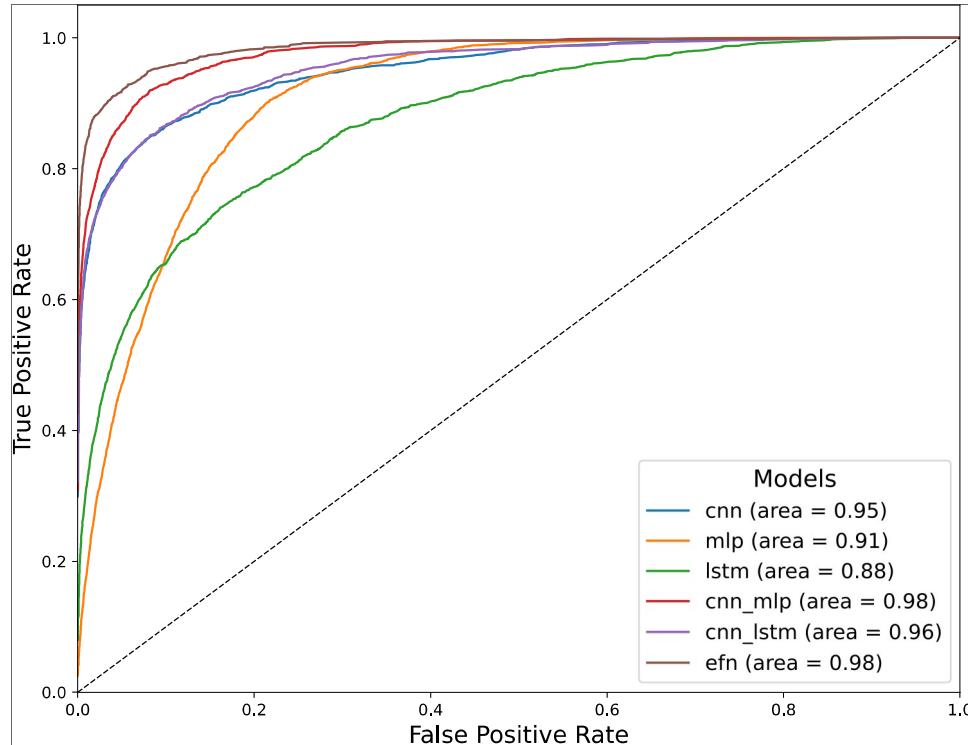
# ML Models - EfficientNet B1



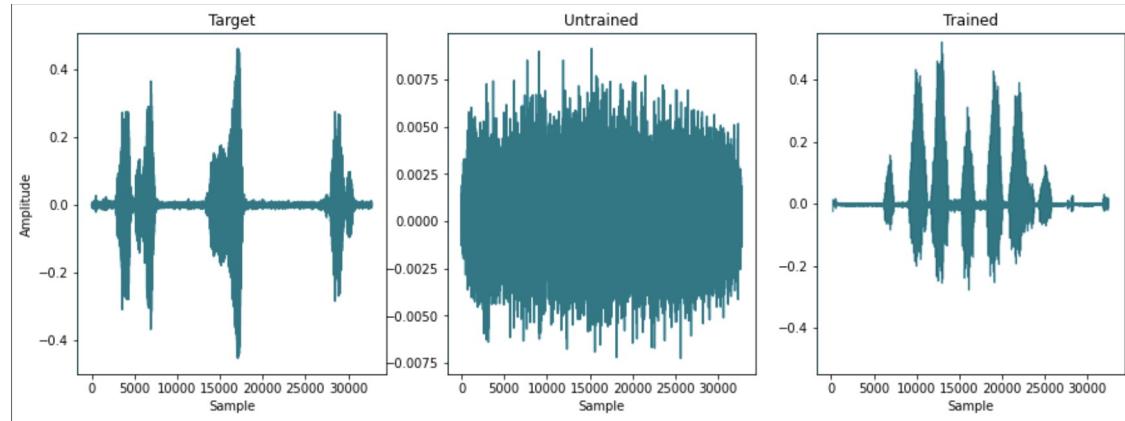
**Classification report**

	precision	recall	f1-score	support
amerob	0.81	0.83	0.82	70
barswa	0.88	0.88	0.88	101
bewwre	0.81	0.83	0.82	70
blujay	0.80	0.74	0.76	53
bncfly	0.90	0.82	0.86	78
carwre	0.90	0.84	0.87	93
compau	0.96	0.96	0.96	48
comrav	0.80	0.89	0.84	127
comyel	0.72	0.73	0.72	70
eursta	0.73	0.80	0.76	132
gbwwrel	0.86	0.92	0.89	132
grekis	0.84	0.81	0.82	69
houspa	0.88	0.91	0.90	139
houwre	0.86	0.81	0.84	149
malla3	0.91	0.72	0.81	83
norcar	0.85	0.85	0.85	82
normoc	0.78	0.76	0.77	66
redcro	0.78	0.90	0.84	105
rewbla	0.72	0.84	0.78	77
roahaw	0.78	0.70	0.74	71
rubpepl	0.75	0.79	0.77	57
rucspal	0.80	0.83	0.81	76
sonspa	0.70	0.70	0.70	112
spotow	0.89	0.86	0.88	118
wbwwrel	0.90	0.64	0.74	55
wesmea	0.78	0.76	0.77	67
yeofly1	0.87	0.82	0.85	67
accuracy				0.82
macro avg	0.82	0.81	0.82	2367
weighted avg	0.82	0.82	0.82	2367

# ML Models - Macro-average ROC curve of multi-class predictors



# ML Models - GAN



## Convolutional GAN

○ 0:00:00 / 24:16:21 ○

## WaveGAN

○ 0:00:00 / 37:16:58 ○

## Summing up

### Further challenges

- Testing on the soundscape dataset

### Methods for improvement

- Vary length of audio snippets and resolution parameters
- Use different kinds of spectrograms
- Use more numeric data
- Use a tree based algorithm on the numeric data
- Remove audio snippets without birdcalls from training data
- Distinguish between types of birdcalls
- Adjust for non-uniform class distribution
- Source separation

### If we had more time...

- Automate hyperparameter optimization
- Try unsupervised clustering
- Try self-supervised wav2vec
- Score by top 3 appearances



## References

**BirdCLEF 2021** <https://www.kaggle.com/c/birdclef-2021/overview>

**WaveGAN** <https://arxiv.org/abs/1802.04208v3>

**ResNet** <https://github.com/KaimingHe/deep-residual-networks>

**DenseNet** <https://arxiv.org/abs/1608.06993v5>

**EfficientNet** <https://arxiv.org/abs/1905.11946>

**Bird Vocalizations** [https://en.wikipedia.org/wiki/Bird\\_vocalization](https://en.wikipedia.org/wiki/Bird_vocalization)

**Very good talk about audio classification** [https://www.youtube.com/watch?v=uCGROOUO\\_wY](https://www.youtube.com/watch?v=uCGROOUO_wY)

**Good talk specifically about this subject** <https://www.youtube.com/watch?v=pzmdOETnhI0>

# Appendix

# Packages

For audio:

- Librosa (loading audio, generating spectrograms)
- noisereduce (reducing noise)
- audiomentations (augmenting audio)
- PIL (handling spectrogram images)

Machine Learning:

- tensorflow v2 (For building models)
- scikit-learn (Evaluating models)

Data:

- numpy
- pandas
- scipy

Visualization:

- matplotlib
- seaborn
- plotly

Utility:

- joblib
- tqdm

# Optimization

## Multi-processing

Loading all the audio files, preprossesing them, and saving the final mel-spectograms takes a lot of time.

In order to speed things up, we used *joblib* as to enable multi-processing for the procedure. We chose this framework because it is also what is used internally in the Librosa package, and as such yielded us the best results.

Using 6 cores as simultaneous workers, we recuded time usage by a factor 3, from 12 hours to 4 hours.

## Hardware

In order to run our models more efficiently, we took advantage of Google Colab's GPU ressourcers. This sped things up significantly, by a factor 20 from 300 seconds per epoch to 15.

Additionally, we relied on Colab's large amount of RAM (25 GB) to train the mixed models (and even then it would sometimes crash).

## Model summaries

# CNN

Model: "model\_19"

Layer (type)	Output Shape	Param #
input_22 (InputLayer)	[ (None, 48, 128, 1) ]	0
conv2d_8 (Conv2D)	(None, 46, 126, 16)	160
batch_normalization_8 (Batch Normalization)	(None, 46, 126, 16)	64
max_pooling2d_8 (MaxPooling2D)	(None, 23, 63, 16)	0
conv2d_9 (Conv2D)	(None, 21, 61, 32)	4640
batch_normalization_9 (Batch Normalization)	(None, 21, 61, 32)	128
max_pooling2d_9 (MaxPooling2D)	(None, 10, 30, 32)	0
conv2d_10 (Conv2D)	(None, 8, 28, 64)	18496
batch_normalization_10 (Batch Normalization)	(None, 8, 28, 64)	256
max_pooling2d_10 (MaxPooling2D)	(None, 4, 14, 64)	0
conv2d_11 (Conv2D)	(None, 2, 12, 128)	73856
batch_normalization_11 (Batch Normalization)	(None, 2, 12, 128)	512
max_pooling2d_11 (MaxPooling2D)	(None, 1, 6, 128)	0

# MLP

Model: "model\_20"

Layer (type)	Output Shape	Param #
=====		
input_23 (InputLayer)	[ (None, 15) ]	0
dense_58 (Dense)	(None, 64)	1024
dense_59 (Dense)	(None, 64)	4160
dense_60 (Dense)	(None, 64)	4160
dropout_32 (Dropout)	(None, 64)	0
dense_61 (Dense)	(None, 27)	1755
=====		
Total params: 11,099		
Trainable params: 11,099		
Non-trainable params: 0		

# LSTM

Model: "model\_21"

Layer (type)	Output Shape	Param #
<hr/>		
input_24 (InputLayer)	[ (None, 48, 128) ]	0
lstm_61 (LSTM)	(None, 48, 36)	23760
lstm_62 (LSTM)	(None, 48, 32)	8832
lstm_63 (LSTM)	(None, 48, 28)	6832
lstm_64 (LSTM)	(None, 48, 24)	5088
lstm_65 (LSTM)	(None, 48, 20)	3600
lstm_66 (LSTM)	(None, 16)	2368
dense_62 (Dense)	(None, 64)	1088
dropout_33 (Dropout)	(None, 64)	0
dense_63 (Dense)	(None, 64)	4160
dropout_34 (Dropout)	(None, 64)	0
dense_64 (Dense)	(None, 32)	2080
dropout_35 (Dropout)	(None, 32)	0

## Merge layers

### CNN & MLP

Model: "model\_27"

Layer (type)	Output Shape	Param #	Connected to
<hr/>			
input_27 (InputLayer)	[None, 48, 128, 1]	0	
conv2d_16 (Conv2D)	(None, 46, 126, 16)	160	input_27[0][0]
batch_normalization_16 (BatchNo	(None, 46, 126, 16)	64	conv2d_16[0][0]
max_pooling2d_16 (MaxPooling2D)	(None, 23, 63, 16)	0	batch_normalization_16[0][0]
conv2d_17 (Conv2D)	(None, 21, 61, 32)	4640	max_pooling2d_16[0][0]
batch_normalization_17 (BatchNo	(None, 21, 61, 32)	128	conv2d_17[0][0]
max_pooling2d_17 (MaxPooling2D)	(None, 10, 30, 32)	0	batch_normalization_17[0][0]
conv2d_18 (Conv2D)	(None, 8, 28, 64)	18496	max_pooling2d_17[0][0]
batch_normalization_18 (BatchNo	(None, 8, 28, 64)	256	conv2d_18[0][0]
max_pooling2d_18 (MaxPooling2D)	(None, 4, 14, 64)	0	batch_normalization_18[0][0]
conv2d_19 (Conv2D)	(None, 2, 12, 128)	73856	max_pooling2d_18[0][0]
batch_normalization_19 (BatchNo	(None, 2, 12, 128)	512	conv2d_19[0][0]
max_pooling2d_19 (MaxPooling2D)	(None, 1, 6, 128)	0	batch_normalization_19[0][0]

# CNN & LSTM

Model: "model\_33"

Layer (type)	Output Shape	Param #	Connected to
<hr/>			
input_31 (InputLayer)	[ (None, 48, 128, 1) ]	0	
conv2d_24 (Conv2D)	(None, 46, 126, 16)	160	input_31[0][0]
batch_normalization_24 (BatchNo)	(None, 46, 126, 16)	64	conv2d_24[0][0]
max_pooling2d_24 (MaxPooling2D)	(None, 23, 63, 16)	0	batch_normalization_24[0][0]
conv2d_25 (Conv2D)	(None, 21, 61, 32)	4640	max_pooling2d_24[0][0]
batch_normalization_25 (BatchNo)	(None, 21, 61, 32)	128	conv2d_25[0][0]
max_pooling2d_25 (MaxPooling2D)	(None, 10, 30, 32)	0	batch_normalization_25[0][0]
conv2d_26 (Conv2D)	(None, 8, 28, 64)	18496	max_pooling2d_25[0][0]
input_32 (InputLayer)	[ (None, 48, 128) ]	0	
batch_normalization_26 (BatchNo)	(None, 8, 28, 64)	256	conv2d_26[0][0]
lstm_73 (LSTM)	(None, 48, 36)	23760	input_32[0][0]
max_pooling2d_26 (MaxPooling2D)	(None, 4, 14, 64)	0	batch_normalization_26[0][0]
lstm_74 (LSTM)	(None, 48, 32)	8832	lstm_73[0][0]

## Species legend

Label	Name
amerob	American Robin
barswa	Barn Swallow
bewwre	Bewick's Wren
blujay	Blue Jay
bncfly	Brown-crested Flycatcher
carwre	Carolina Wren
compau	Common Pauraque
comrav	Common Raven
comyel	Common Yellowthroat
eursta	European Starling
gbwwre1	Gray-breasted Wood-Wren
grekis	Great Kiskadee
houspa	House Sparrow
houwre	House Wren
mallar3	Mallard
norcar	Northern Cardinal
normoc	Northern Mockingbird

Label	Name
redcro	Red Crossbill
rewbla	Red-winged Blackbird
roahaw	Roadside Hawk
rubpep1	Rufous-browed Peppershrike
rucspa1	Rufous-collared Sparrow
sonspa	Song Sparrow
spotow	Spotted Towhee
wbwre1	White-breasted Wood-Wren
wesmea	Western Meadowlark
yeofly1	Yellow-olive Flycatcher