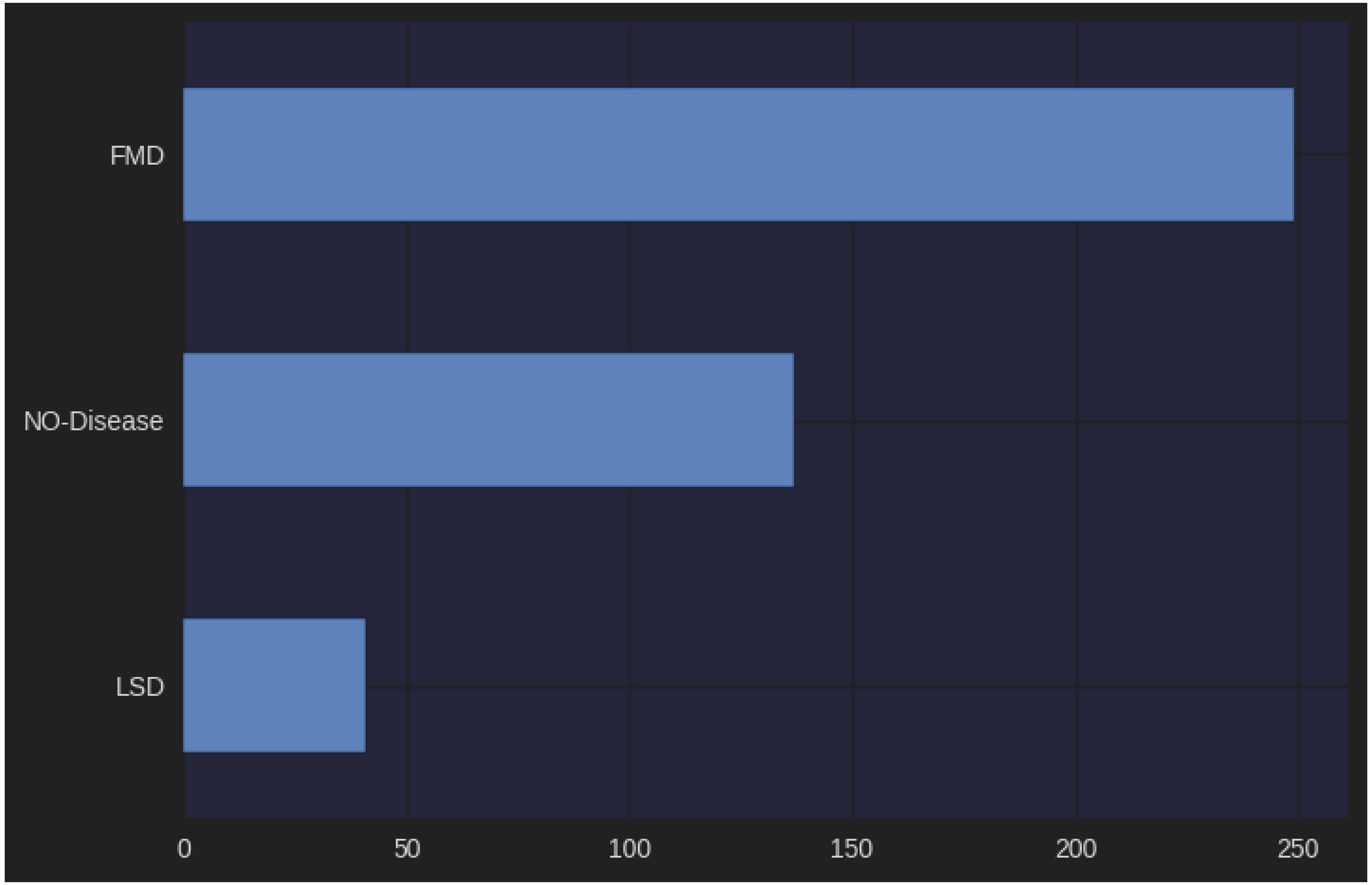
REMOTE VET<>AIML

Akide Liu – Research Assistant, AIML, UofA
Dr. YiFan Liu – Assistant Professor, AIML, UofA
{akide.liu,yifan.liu04}@adelaide.edu.au

PREVIOUS WORKS

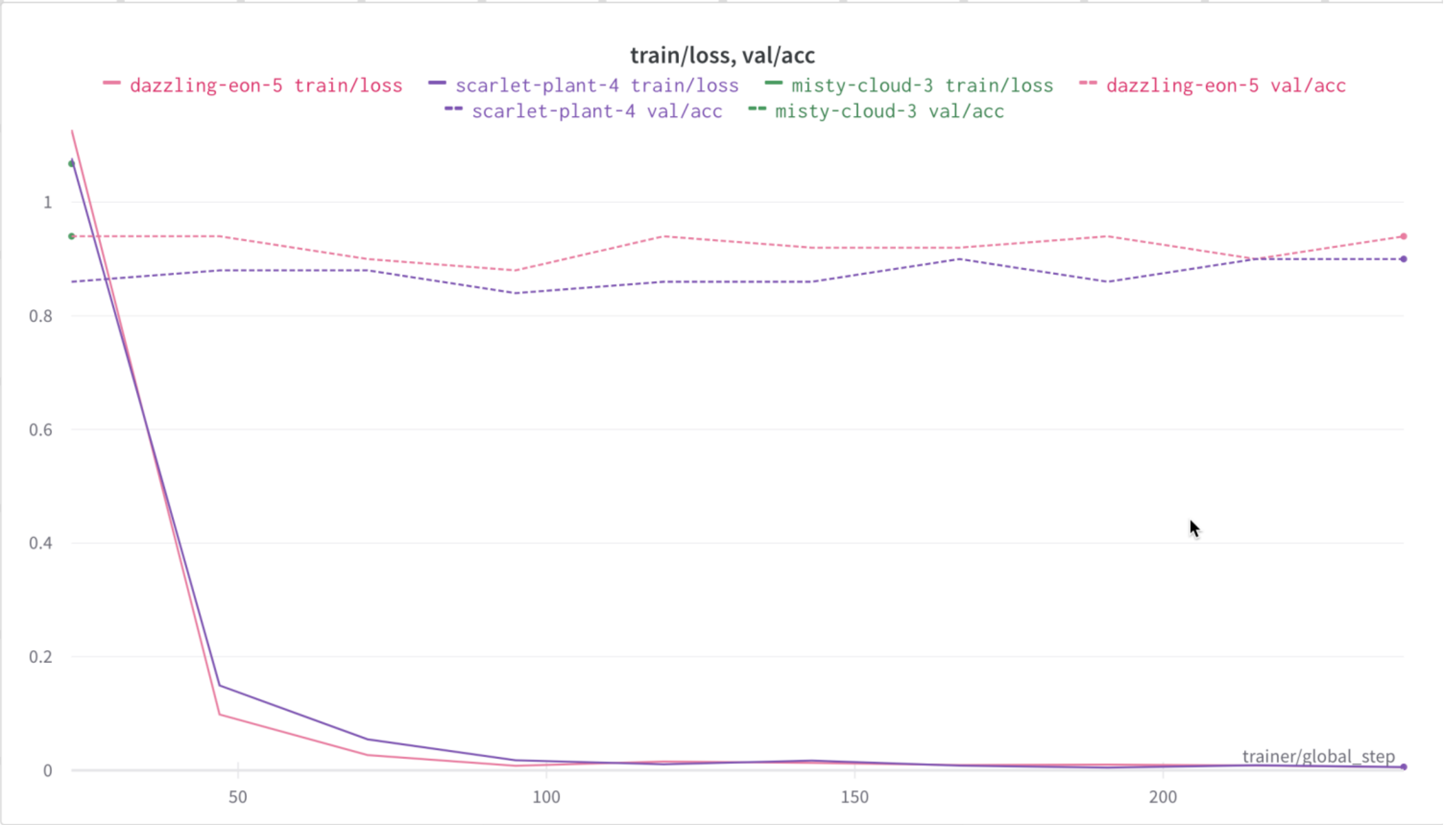
- Model Development
- Web / Mobile Application Proof of Concept



Class Distribution

MODEL DEVELOPMENT

- Dataset Version 1
- 249 FMD, 137 No Disease, 41 LSD
- Long Tail Problem
- Dataset are highly imbalanced



MODEL DEVELOPMENT

- Weak Data Augmentation, Such as Resize, Flip, Rotate
- Model Sections, Such as ResNet, Vit, MobileNet, EfficientNet
- Hyper-parameter section, such as, LR, Optimizer, Scheduler
- Obtained Perfect Performance, 96% in validation set.

MODEL DEVELOPMENT

EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks

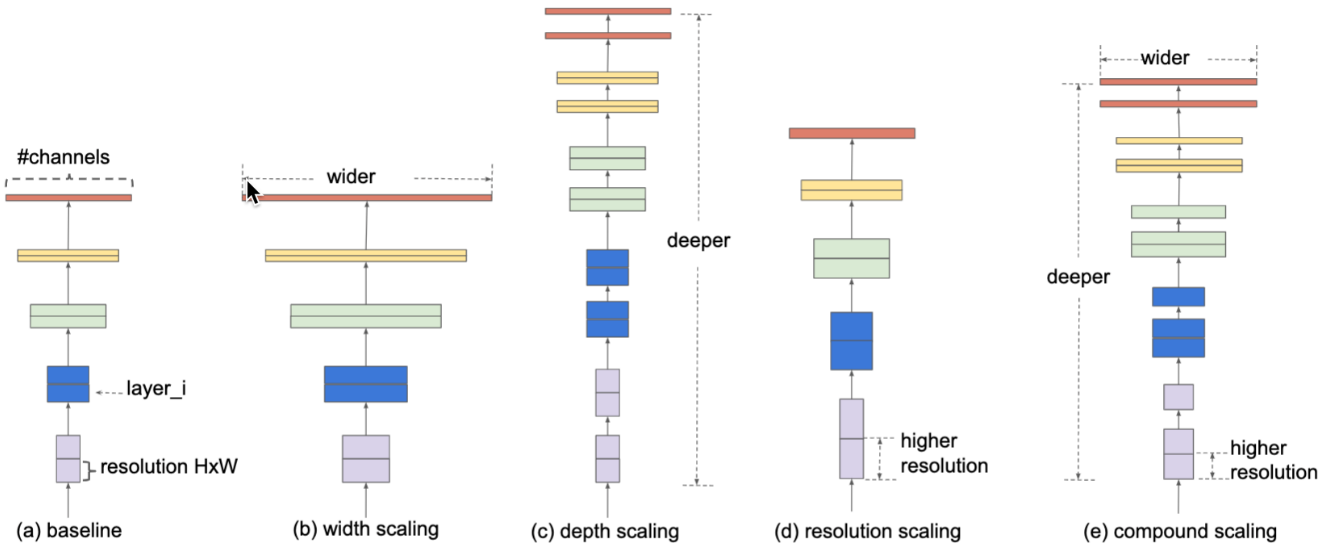
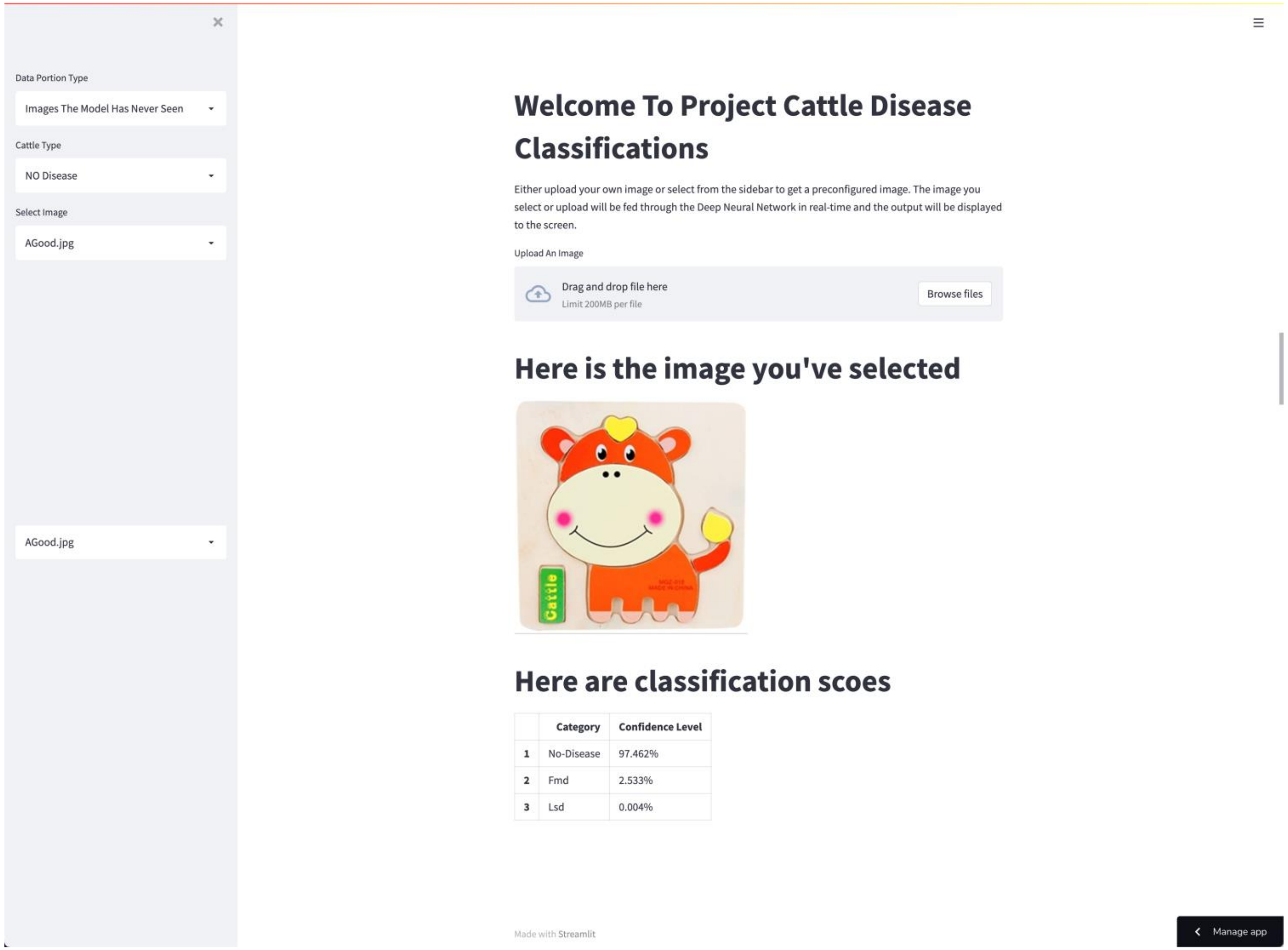


Figure 2. **Model Scaling.** (a) is a baseline network example; (b)-(d) are conventional scaling that only increases one dimension of network width, depth, or resolution. (e) is our proposed compound scaling method that uniformly scales all three dimensions with a fixed ratio.

Mingxing Tan and Quoc V. Le. "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks" (2019).

- EfficientNet Proposed by Google Research. A comprehensive study to explore the scalability of CNNs.
- Depth Scaling: Capture Richer and more complex features, and improve generalization with domain shift. ImageNet -> Our DS.
- Width Scaling: Capture fine-grained features and improve efficiency. Mobile Deployment.
- Resolution Scaling: Capture more fine-grained patterns. Leverage details of images. Diseases are in a small region.
- NAS: neural architecture search.



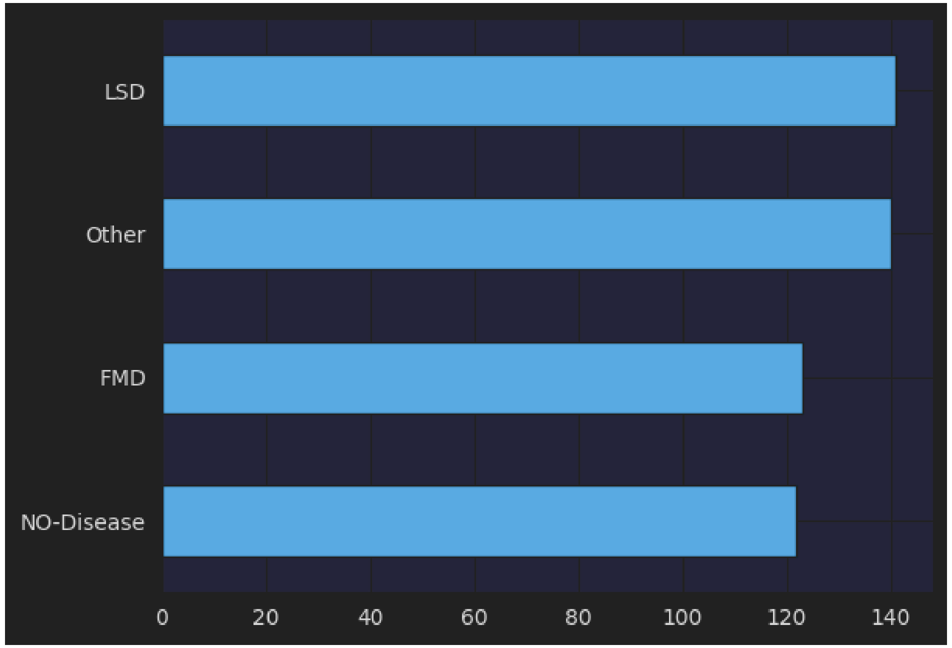
http://vmv.re/8Yno0

WEB / MOBILE APPLICATION

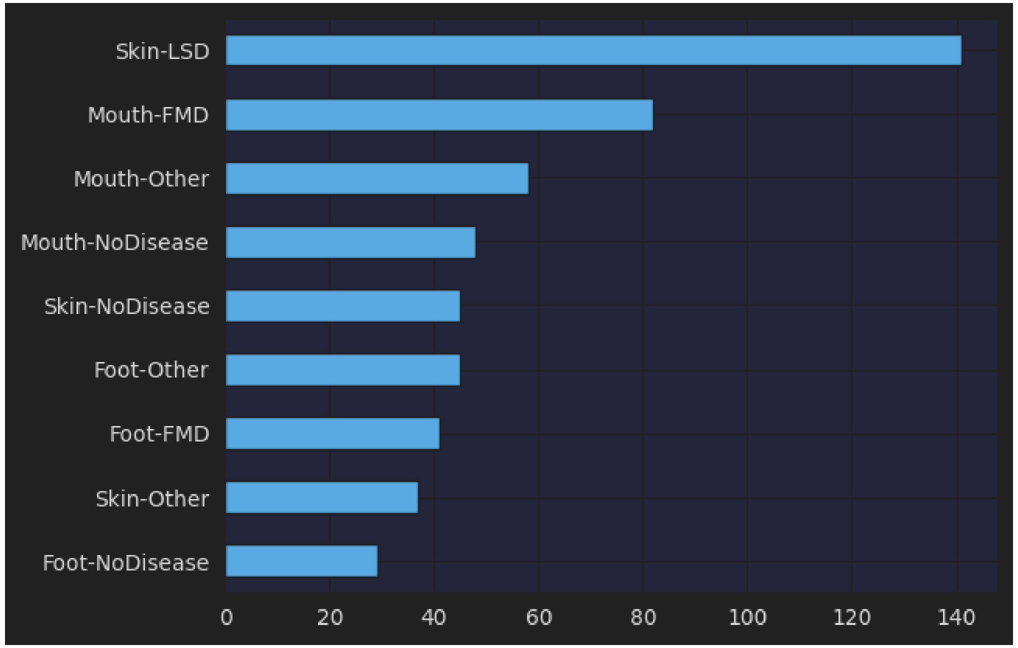
- PyTorch Oriented
- Build on streamlit.io
- Lightweight and mobile friendly
- Cloud Deployment friendly

CONTINUOUS DEVELOPMENT

- Dataset v1 -> Dataset v2
- efficient v1 small → efficient v2 small
- enhanced data augmentation
- carefully selected hyper-parameters



4 Class Split

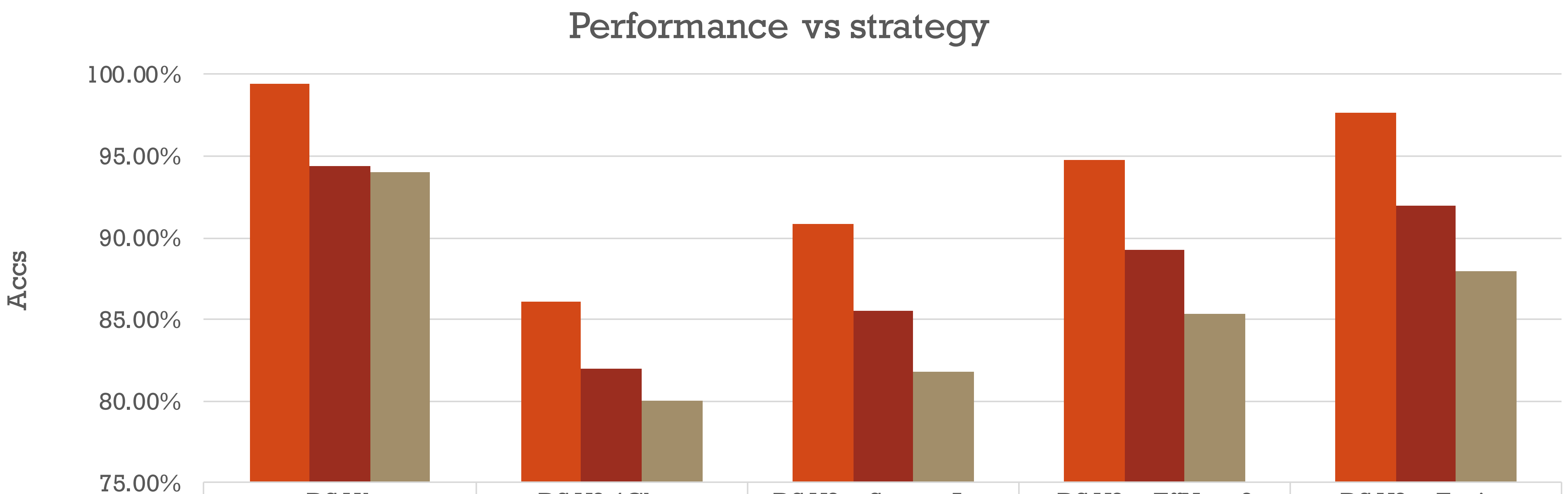


9 Class Split

NEW DATASET SPLIT POLICY

- We change the 4 classes classification problem to 9 classes. Leads to increased complicity and more accurate localization.

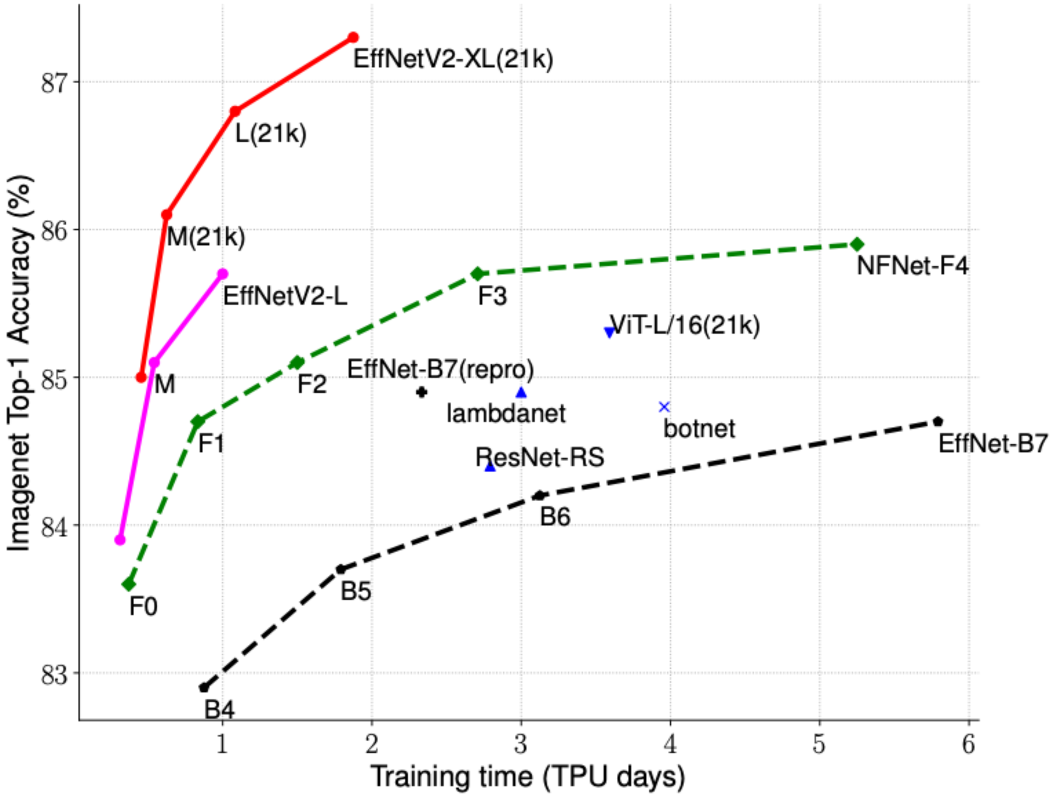
PERFORMANCE VS STRATEGY



	DS V1	DS V2 4Class	DS V2 + Strong Aug	DS V2 + EffNet v2	DS V2 + Tuning
Train Acc	99.47%	86.13%	90.84%	94.75%	97.68%
Validation Acc	94.40%	81.99%	85.56%	89.24%	92.00%
Test Acc	94.00%	80.00%	81.83%	85.35%	87.99%

EFFICIENT V1S → EFFICIENT V2S

- Smaller, Faster by training-aware NAS and scaling.
- Adaptive Image Size regularization.
- UP to 11x faster speed
- Up to 6.8x better parameter efficiency.



(a) Training efficiency.

	EfficientNet (2019)	ResNet-RS (2021)	DeiT/ViT (2021)	EfficientNetV2 (ours)
Top-1 Acc.	84.3%	84.0%	83.1%	83.9%
Parameters	43M	164M	86M	24M

(b) Parameter efficiency.

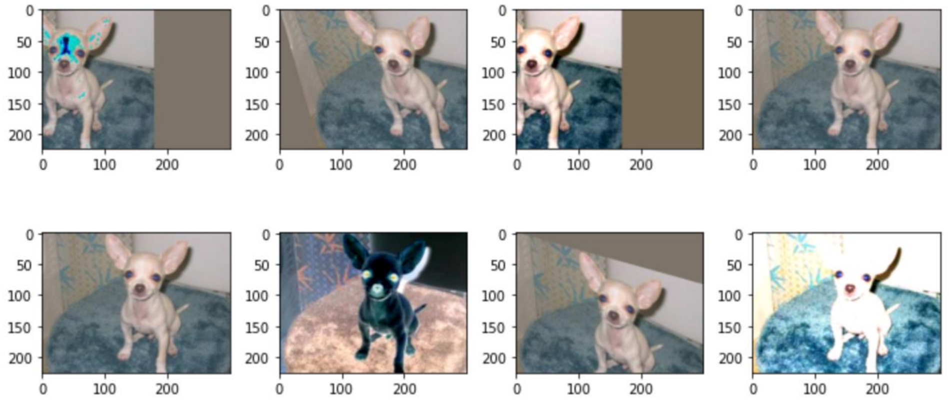
Mingxing Tan and Quoc V. Le. "EfficientNetV2: Smaller Models and Faster Training" (2021).

```python
from timm.data.auto_augment import rand_augment_transform
```

```python
tfm = rand_augment_transform(
    config_str='rand-m9-mstd0.5',
    hparams={'img_mean': (124, 116, 104)}
)
```

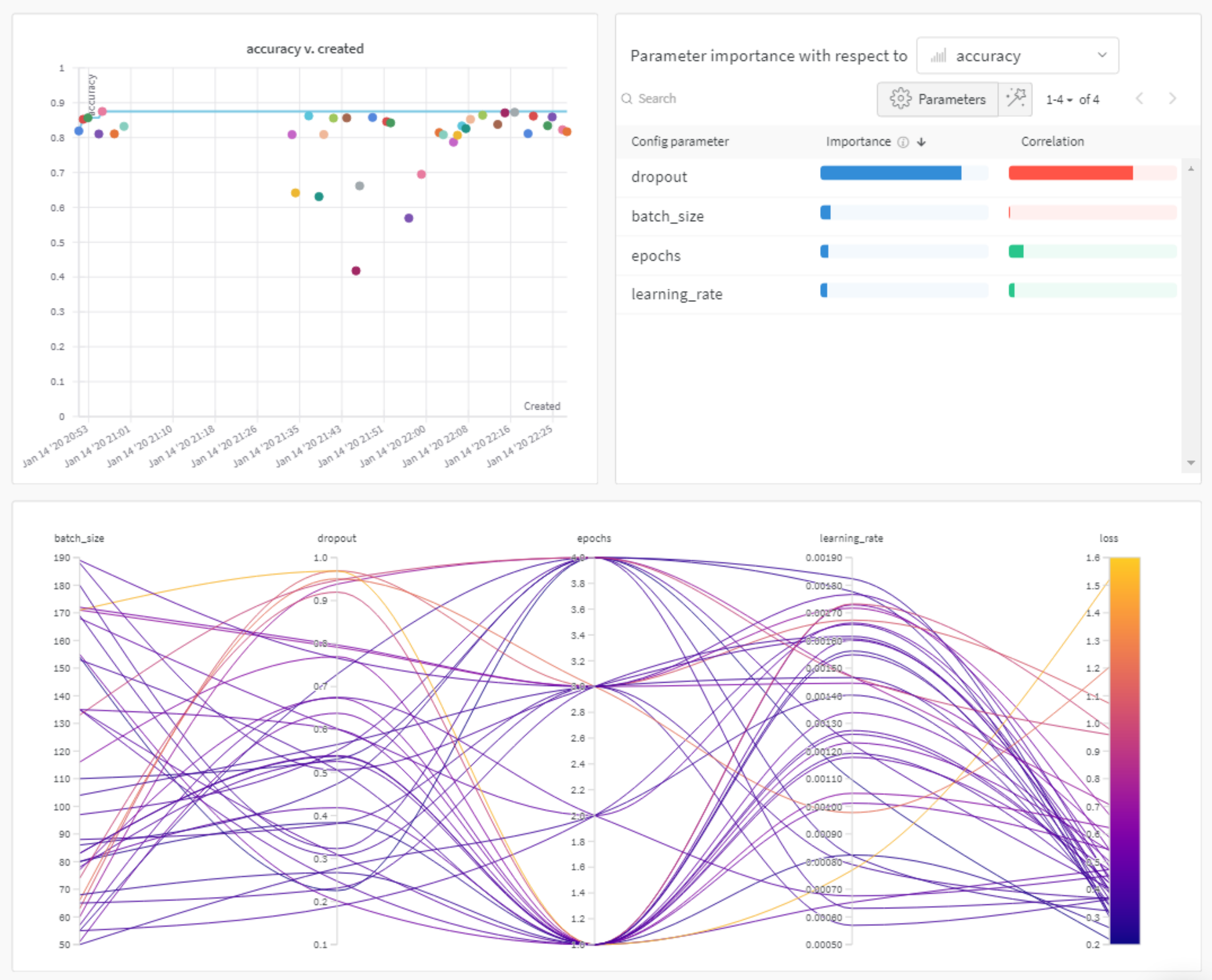
```python
tfm
```

```
RandAugment(n=2, ops=
        AugmentOp(name=AutoContrast, p=0.5, m=9, mstd=0.5)
        AugmentOp(name=Equalize, p=0.5, m=9, mstd=0.5)
        AugmentOp(name=Invert, p=0.5, m=9, mstd=0.5)
        AugmentOp(name=Rotate, p=0.5, m=9, mstd=0.5)
        AugmentOp(name=Posterize, p=0.5, m=9, mstd=0.5)
        AugmentOp(name=Solarize, p=0.5, m=9, mstd=0.5)
        AugmentOp(name=SolarizeAdd, p=0.5, m=9, mstd=0.5)
        AugmentOp(name=Color, p=0.5, m=9, mstd=0.5)
        AugmentOp(name=Contrast, p=0.5, m=9, mstd=0.5)
        AugmentOp(name=Brightness, p=0.5, m=9, mstd=0.5)
        AugmentOp(name=Sharpness, p=0.5, m=9, mstd=0.5)
        AugmentOp(name=ShearX, p=0.5, m=9, mstd=0.5)
        AugmentOp(name=ShearY, p=0.5, m=9, mstd=0.5)
        AugmentOp(name=TranslateXRel, p=0.5, m=9, mstd=0.5)
        AugmentOp(name=TranslateYRel, p=0.5, m=9, mstd=0.5))
```



ENHANCED DATA AUGMENTATION

- RandAugment, an automated data augmentation method that uniformly samples operations from a set of augmentations — such as equalization, rotation, solarization, color jittering,, changing contrast, changing brightness, changing sharpness, and translations.



CAREFULLY SELECTED HYPER-PARAMETERS

- PlateauLRScheduler
- Adam -> AdamW
- Auto LR Search
- Increase training schedule.
- Sweeps Hyper-Parameter Search (Planned) (High Computational Overhead)

CHALLENGES & PERSPECTIVE

- The dataset is still under development, and data imbalance issues are still encountered
- Unified pipelines have been built, and are ready to retrain the more powerful model with incoming data.
- The Web / Mobile Application has been built for proof of concept.