



# Deep Learning: Weather Image Classification

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# Problem Statement/Abstract



# Problem Statement

We have 11 classes of weather items in image format, we then pick 4 items to perform image classification with Convolutional Neural Networks as Modeling Project

Fog vs Glaze vs Lightning vs Rainbow



# Approach Framework & EDA

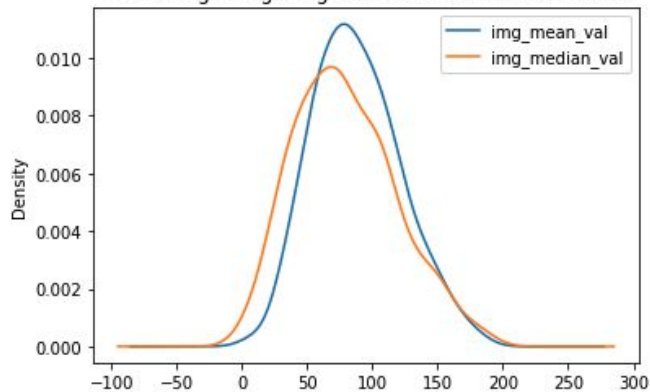


# Project Framework

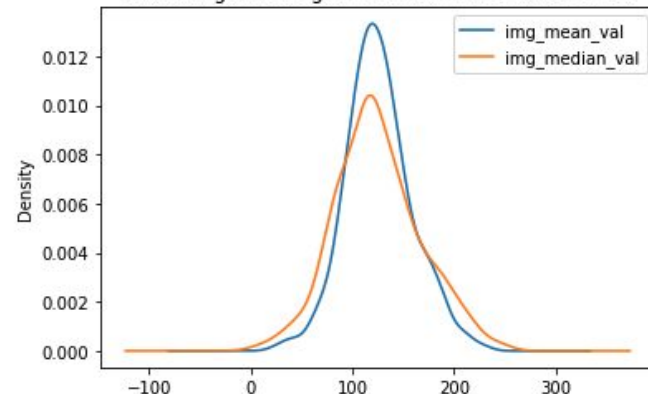
- Image Data EDA
- Image Train/Test Split : 80/20 Percentage
- Image Train/Test Images Input Generators Engineering (**from** tensorflow.keras.preprocessing.image **import** ImageDataGenerator)
- ResNet Model Direct Prediction
- CNN Baseline Model to Train/Predict
- CNN Baseline Model Validation and Over/underfitting testing
- Implement a Transfer Learning Model to Train/Predict
- Transfer Model Validation and Over/underfitting testing
- Compare CNN baseline model vs Transfer Learning Model

# EDA - classified Images density Plotting

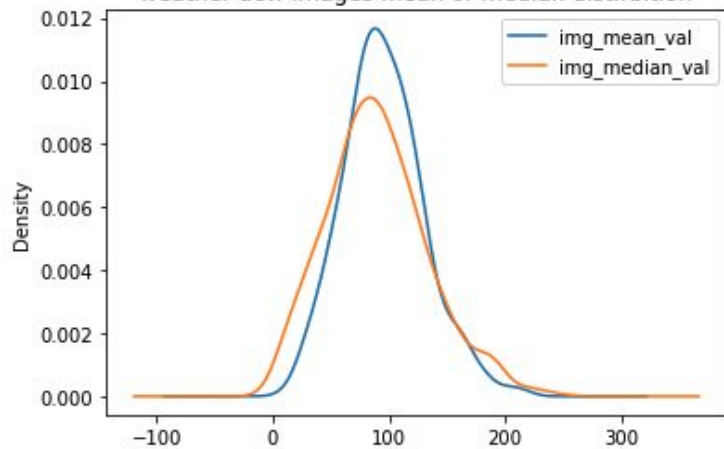
weather lightning images mean or median distirbition



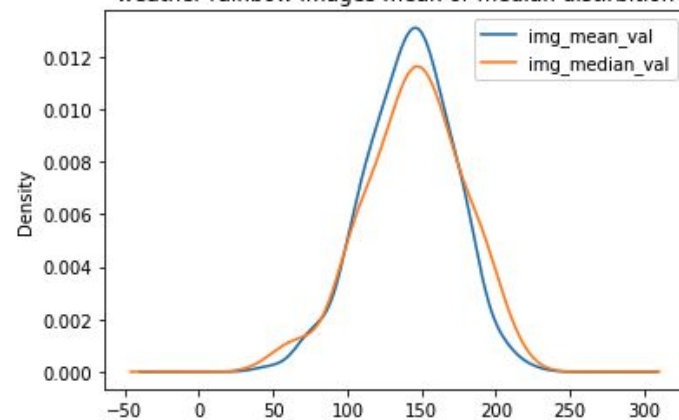
weather glaze images mean or median distirbition



weather dew images mean or median distirbition



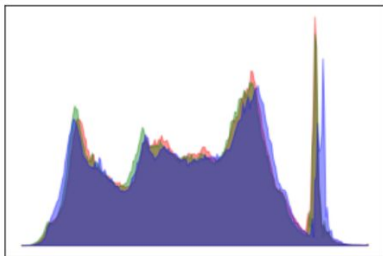
weather rainbow images mean or median distirbition



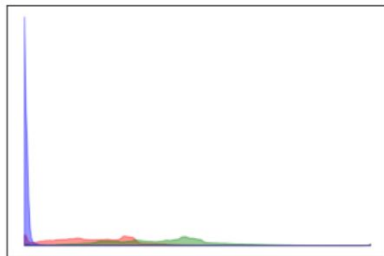


# EDA – RGB distribution

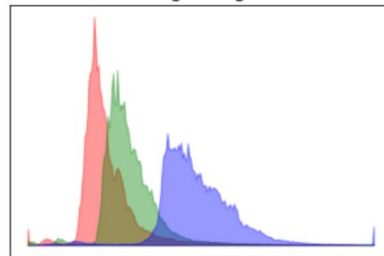
Rain



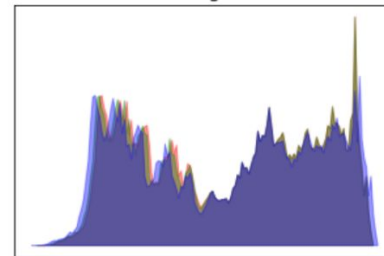
Dew



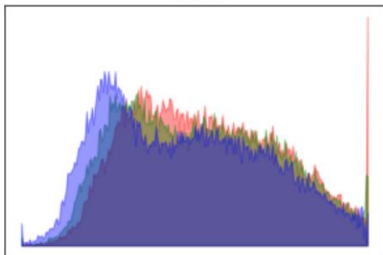
Lightning



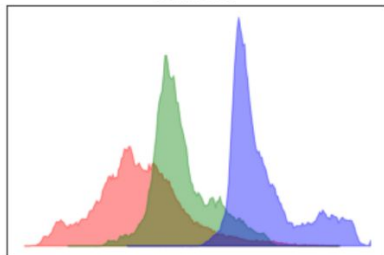
Fog



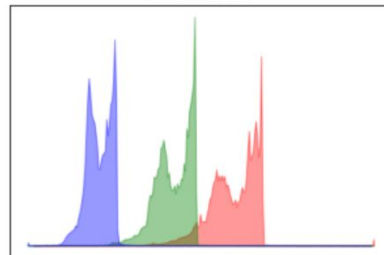
Glaze



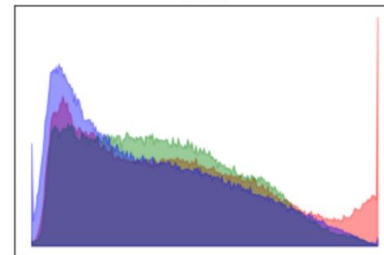
Rainbow



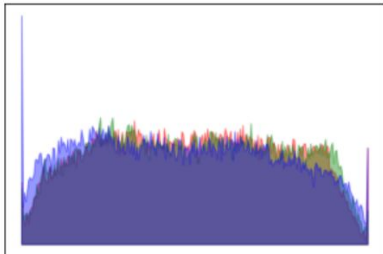
Sandstorm



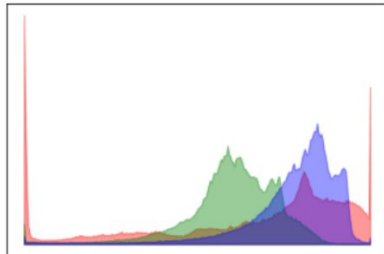
Frost



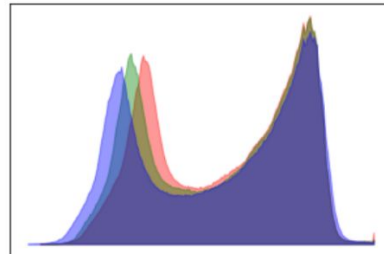
Snow



Rime



Hail



# Unsupervised Classification With ResNet

Apply ResNet Model Directly on Test Set of Data without training

## Predicted Items from Fog testset

'toilet\_tissue': 1, 'stupa': 6, 'digital\_clock': 1,  
'tub': 2, 'unicycle': 9, 'tricycle': 1,  
'crash\_helmet': 2, 'theater\_curtain': 1,  
'suspension\_bridge': 27

## Predicted Items from Lightning testset

'fountain': 53, 'geyser': 43, 'volcano': 43,  
'stage': 35, 'spotlight': 33, 'spider\_web': 31,  
'monitor': 26, 'alp': 22, 'space\_shuttle': 14,  
'fireboat': 14, 'loudspeaker': 12, 'oscilloscope':  
12, 'jellyfish': 11, 'garden\_spider': 10

## Predicted Items from Glaze testset

'coral\_fungus': 37, 'hip': 37, 'cliff': 26,  
'spider\_web': 24, 'alp': 19, 'chainlink\_fence':  
18, 'fountain': 18, 'picket\_fence': 17, 'pot': 12,  
'hen-of-the-woods': 12, 'coral\_reef': 12

## Predicted Items from Rainbow testset

'fountain': 42, 'fireboat': 34, 'geyser': 27,  
'lakeside': 18, 'bubble': 14, 'volcano': 13,  
'spotlight': 10, 'alp': 9, 'seashore': 7,  
'space\_shuttle': 6, 'wing': 5, 'sandbar': 4,  
'cannon': 4



# Model Development



## Baseline CNN Model

```
model = Sequential()
model.add(Conv2D(input_shape=(128, 128, 3), filters=64, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=64, kernel_size=(3,3), padding="same", activation="relu"))
model.add(MaxPool2D(pool_size=(2,2), strides=(2,2)))
model.add(Conv2D(filters=128, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=128, kernel_size=(3,3), padding="same", activation="relu"))
model.add(MaxPool2D(pool_size=(2,2), strides=(2,2)))
model.add(Conv2D(filters=256, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=256, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=256, kernel_size=(3,3), padding="same", activation="relu"))
model.add(MaxPool2D(pool_size=(2,2), strides=(2,2)))
model.add(Conv2D(filters=512, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=512, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=512, kernel_size=(3,3), padding="same", activation="relu"))
model.add(MaxPool2D(pool_size=(2,2), strides=(2,2)))
model.add(Conv2D(filters=512, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=512, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=512, kernel_size=(3,3), padding="same", activation="relu"))
model.add(MaxPool2D(pool_size=(2,2), strides=(2,2)))

model.add(Flatten())
model.add(Dense(units=4096, activation="relu"))
model.add(Dense(units=4096, activation="relu"))
model.add(Dense(units=4, activation="softmax"))

from tensorflow.keras.optimizers import Adam
opt = Adam(lr=0.00001)
model.compile(optimizer=opt, loss='sparse_categorical_crossentropy', metrics=['accuracy'])

model.summary()

model.save_weights("saved_models/new_initial_weights.h5")
```

# VGG16 Model

```
from tensorflow.keras.applications.vgg16 import VGG16
from tensorflow.keras.models import Model

# load the model
vgg16 = VGG16(input_shape=(128, 128, 3), include_top=False, weights='imagenet')
```

```
model_vgg16 = Sequential()
model_vgg16.add(Input(shape=(128, 128, 3)))
model_vgg16.add(vgg16)
model_vgg16.add(Flatten())
model_vgg16.add(Dropout(0.3))
model_vgg16.add(Dense(768, activation='relu'))
model_vgg16.add(Dropout(0.25))
model_vgg16.add(Dense(256, activation='relu'))
model_vgg16.add(Dropout(0.25))
model_vgg16.add(Dense(4, activation='softmax'))
model_vgg16.summary()

model_vgg16.compile( loss = 'sparse_categorical_crossentropy',
#                   loss = 'categorical_crossentropy',
                    optimizer =keras.optimizers.Adam(learning_rate=0.0001),
                    metrics = ["accuracy"])
```

Layer (type)	Output Shape	Param #
vgg16 (Model)	(None, 4, 4, 512)	14714688
flatten_3 (Flatten)	(None, 8192)	0
dropout (Dropout)	(None, 8192)	0
dense_9 (Dense)	(None, 768)	6292224
dropout_1 (Dropout)	(None, 768)	0
dense_10 (Dense)	(None, 256)	196864
dropout_2 (Dropout)	(None, 256)	0
dense_11 (Dense)	(None, 4)	1028
Total params: 21,204,804		
Trainable params: 21,204,804		
Non-trainable params: 0		

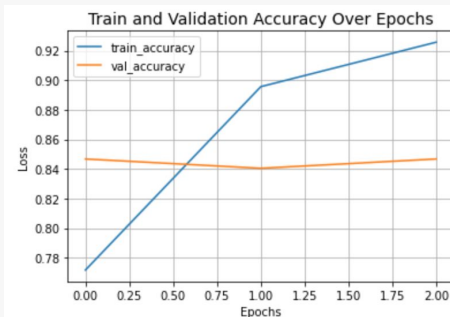
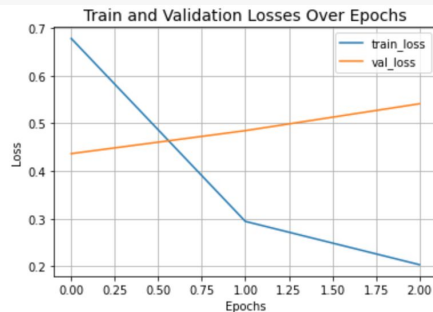
# EfficientNetV2-S

```
[61] # evaluation
test_loss, test_acc = model-fi.evaluate(x, y, verbose=2)
```

8/8 - 27s - loss: 0.5082 - accuracy: 0.8359 - 27s/epoch - 3s/step

```
# add classification head after Efficient net
inputs = tf.keras.Input(shape=(180, 180, 3))
x = preprocess_input(inputs)
x = model(x, training = False)
x = global_average_layer(x)
x = Flatten()(x)
x = Dense(1024, activation = 'relu')(x)
x = Dropout(0.2)(x)
x = Dense(1024, activation = 'relu')(x)
outputs = Dense(11, activation = 'softmax')(x)

model-fi = Model(inputs, outputs)
```



```
[ ] #model.compile(loss = "sparse_categorical_crossentropy", optimizer = 'Adam', metrics=["accuracy"])

model-fi.compile(loss = "sparse_categorical_crossentropy", optimizer = 'Adam', metrics=["accuracy"])

callbacks = [EarlyStopping(monitor = 'val_loss', min_delta = 0, patience = 2, mode = 'auto')]
```

# Model Validation



# Model Performance Validation

{'fog': 0, 'glaze': 1, 'lightning': 2, 'rainbow': 3}

Model	Fog	Glaze	Lightning	Rainbow	Overall	Over/Under-Fitting
Baseline CNN	Test F1: 0.81 Train F1:0.81	Test F1: 0.93 Train F1:0.93	Test F1: 0.55 Train F1:0.55	Test F1: 0.89 Train F1:0.91	Test Accuracy: 0.86 Train Accuracy: 0.87	N/A
Vgg16	Test F1: 0.97 Train F1:0.98	Test F1: 0.97 Train F1:0.98	Test F1: 0.92 Train F1:0.98	Test F1: 0.96 Train F1:0.98	Test Accuracy: 0.96 Train Accuracy: 0.98	Slight overfitted



Model Performance Validation with Testset

Model	Dew	Fog	Frost	Glaze	Hail	Lightning	Rain	Rainbow	Rime	Sandstorm	Snow	Overall
Accuracy		FP		FP FN			FP FN		FP		FN	0.84
F1	0.97	0.84	0.83	0.69	0.90	0.95	0.71	0.88	0.78	0.87	0.68	
Precision (TP/TP+FP)	0.95	0.78	0.86	0.71	0.88	1.00	0.67	0.92	0.71	0.91	1.00	
Recall (TP/TP+FN)	1.00	0.91	0.80	0.67	0.92	0.90	0.75	0.85	0.88	0.84	0.52	

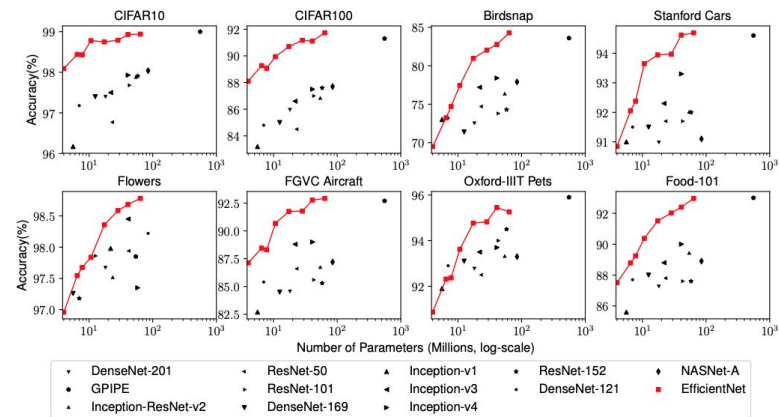


# Model Investigation



## Differences between models and effect

- Our ResNet predicting four weather types show great result and EfficientNet predicting 11 weather types is also descent
- If we want to further fine-tune our model, EfficientNet will be our choice as compared with other convolution models, EfficientNet is more accurate and smaller when trained on same dataset (Tan & Le, 2020)
- Still a lot more samples will be needed for training

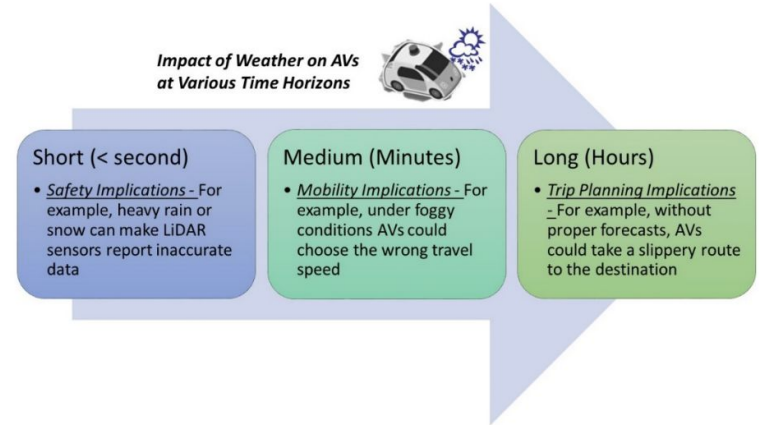


# Model Further Deployment



## API and Application

- Our project provides a base for many higher-level applications related to weather
- Video traps for footage shooting of wildlife
  - Capture weather condition for different timestamp
  - Helpful for behavioural study
- Weather identification for self-driving
  - Short-time decision making
  - Long-term trip planning



# Testing our Swin-Transformer

- Train the same data with Swin and compare with EfficientNet
- Swin has been seen efficient when train with enough data and it will be interesting to compare Swin with state-of-the-art CNN models
- Visual Transformers can be the future?

## ▸ Swin Transformer

```
class SwinTransformer(layers.Layer):  
    def __init__(  
        self,  
        dim,  
        num_patch,  
        num_heads,  
        window_size=7,  
        shift_size=0,  
        num_mlp=1024,  
        qkv_bias=True,  
        dropout_rate=0.0,  
        **kwargs,  
    ):  
        super(SwinTransformer, self).__init__(**kwargs)  
  
        self.dim = dim # number of input dimensions  
        self.num_patch = num_patch # number of embedded patches  
        self.num_heads = num_heads # number of attention heads  
        self.window_size = window_size # size of window  
        self.shift_size = shift_size # size of window shift  
        self.num_mlp = num_mlp # number of MLP nodes  
  
        self.norm1 = layers.LayerNormalization(epsilon=1e-5)  
        self.attn = WindowAttention(  
            dim,  
            window_size=(self.window_size, self.window_size),  
            num_heads=num_heads,  
            qkv_bias=qkv_bias,  
            dropout_rate=dropout_rate,  
        )  
        self.drop_path = DropPath(dropout_rate)  
        self.norm2 = layers.LayerNormalization(epsilon=1e-5)
```

# References



1. <https://medium.com/@mygreatlearning/what-is-vgg16-introduction-to-vgg16-f2d63849f615#:~:text=VGG16%20is%20a%20simple%20and,visual%20object%20recognition%20software%20research.>
2. <https://www.kaggle.com/jehanbathena/weather-dataset>
3. <https://www.kaggle.com/jiongjieta/efficientnetb4-model>
4. <https://www.analyticsvidhya.com/blog/2020/02/learn-image-classification-cnn-convolutional-neural-networks-3-datasets/>
5. <https://towardsdatascience.com/wtf-is-image-classification-8e78a8235acb>
6. <https://arxiv.org/abs/1905.11946>
7. <https://www.tensorflow.org/tutorials/images/classification>
8. [https://rosap.ntl.bts.gov/view/dot/32494/dot\\_32494\\_DS1.pdf?](https://rosap.ntl.bts.gov/view/dot/32494/dot_32494_DS1.pdf?)