Simple Cloud Cover Classification CNN

Seminar Pattern Recognition

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Introduction

GOALS OF THE PROJECT

- The aim of this project is to build a simple and effective image classifier using convolutional neural networks (CNNs).
  - Goal 1: Work with an existing dataset of sky images.
  - Goal 2: Train a CNN for multi-class classification of sky images.
  - Goal 3: Evaluate the model’s accuracy and present results .

The CNN will be used for further work in irradiance prediction.

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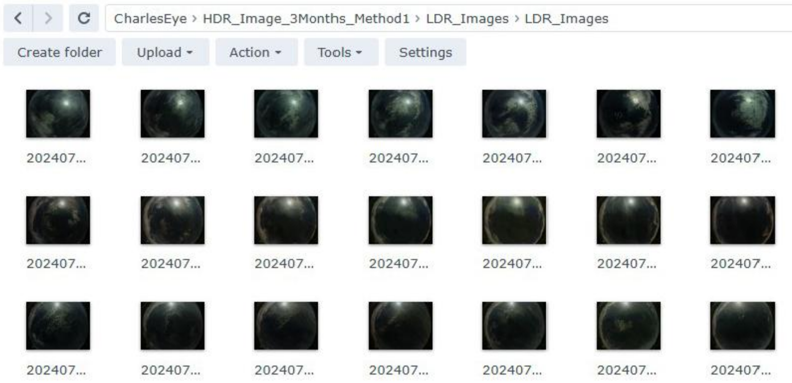
Behind the Scenes

Fereshteh’s PhD Project

Camera setup → Image Acquisition → HDR reconstruction → Image compression



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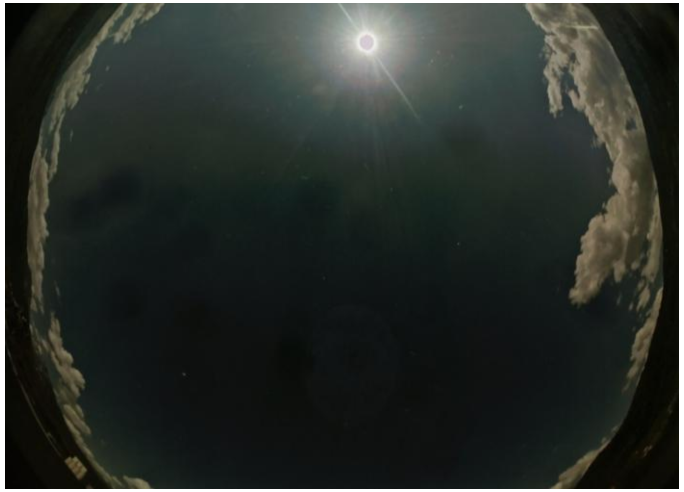
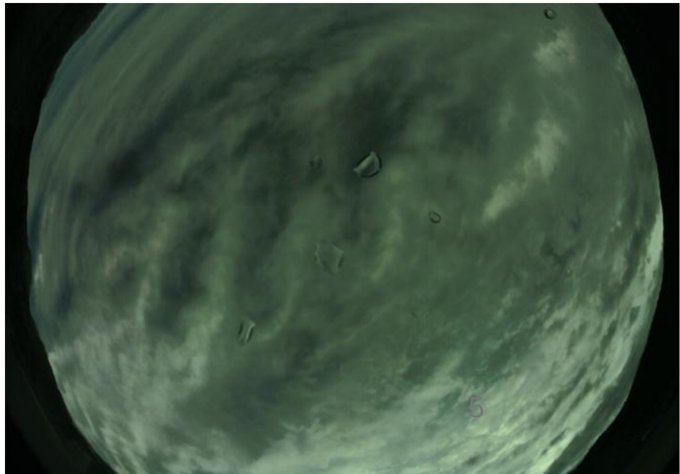
My Task: Cloud Cover Classification

- Images from July to end of September 2024 from 6am to 7.55pm
- 12GB!!
- We have a large dataset of sky images, but no automatic method to classify them into labels like
  - Clear
  - Cloudy
  - Overcast

= CLOUD COVER





Cloud cover ←→ Irradiance

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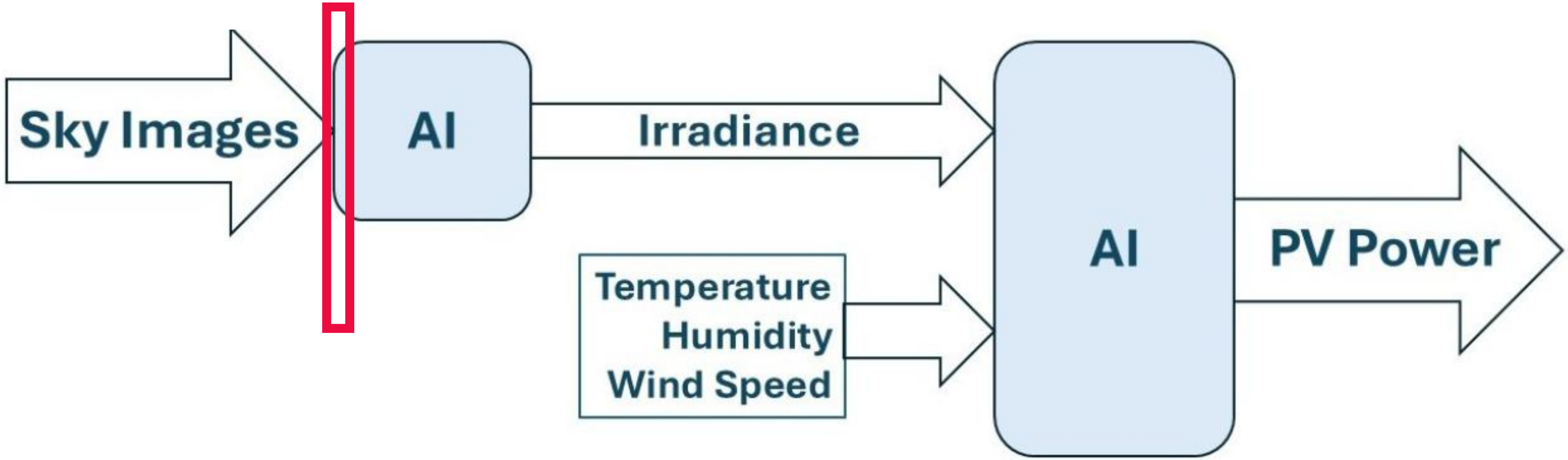
- The main source of uncertainty is cloud movement.
- Clouds dominate short-term PV variability and irradiance.
  - Classifying the sky gives immediate information about expected irradiance behaviour
  - Shadows reduce PV output by 50%-80% within minutes.
- Cloud classes describe distinct PV output patterns
  - Clear sky → smooth, high irradiance
  - Cloudy sky → rapid fluctuations, shading events
  - Overcast sky → stable but low irradiance

CNN as Preprocessing Step

- The CNN is not the final forecaster — it is the tool that turns raw images into useful inputs for downstream irradiance prediction.



Preprocessing

Preprocessing

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- **Purpose**
  - Ensure only clean, informative images enter the training dataset
  - Remove frames that would confuse or degrade the CNN – sensitive to noise

Time Window 0600 - 0620 → Raindrop CNN + SVM → Color Dominance

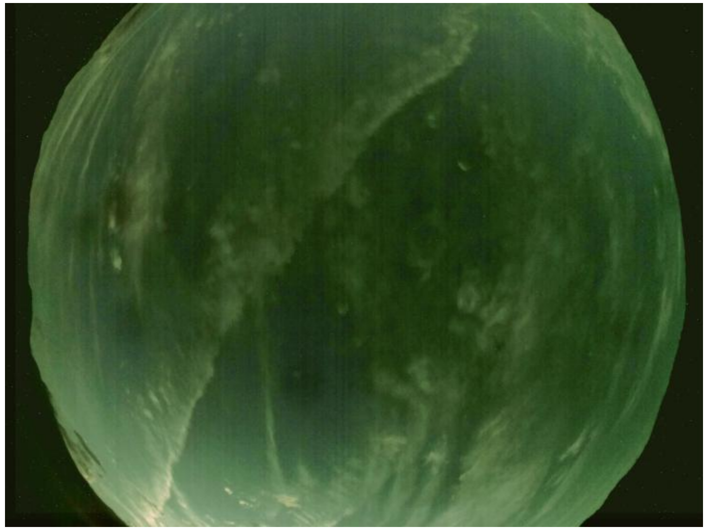
Time Window 0600 - 0620

Early morning images are often

- Heavily color-shifted (purple/blue)
- Too dark
- Clouds not visible

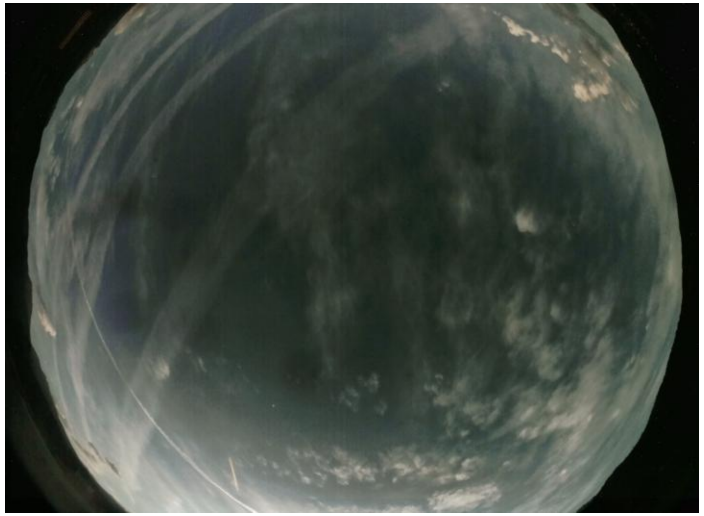
→ Can confuse CNN during training

06.07.2024 06:00



13.07.2024 06:20

06.07.2024 06:20



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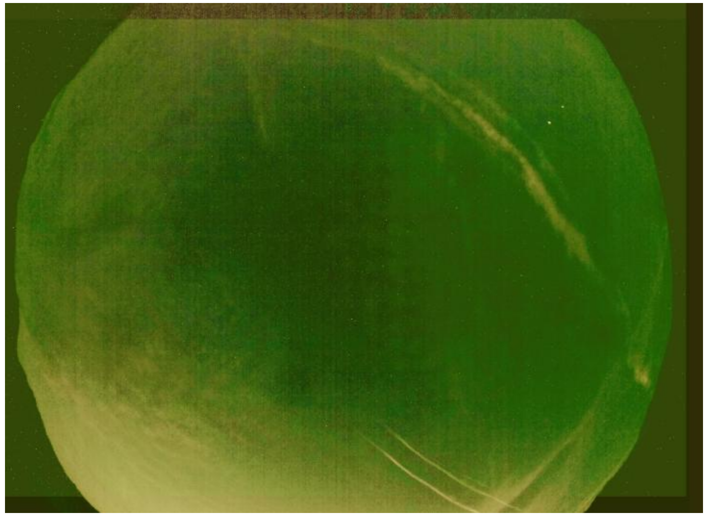
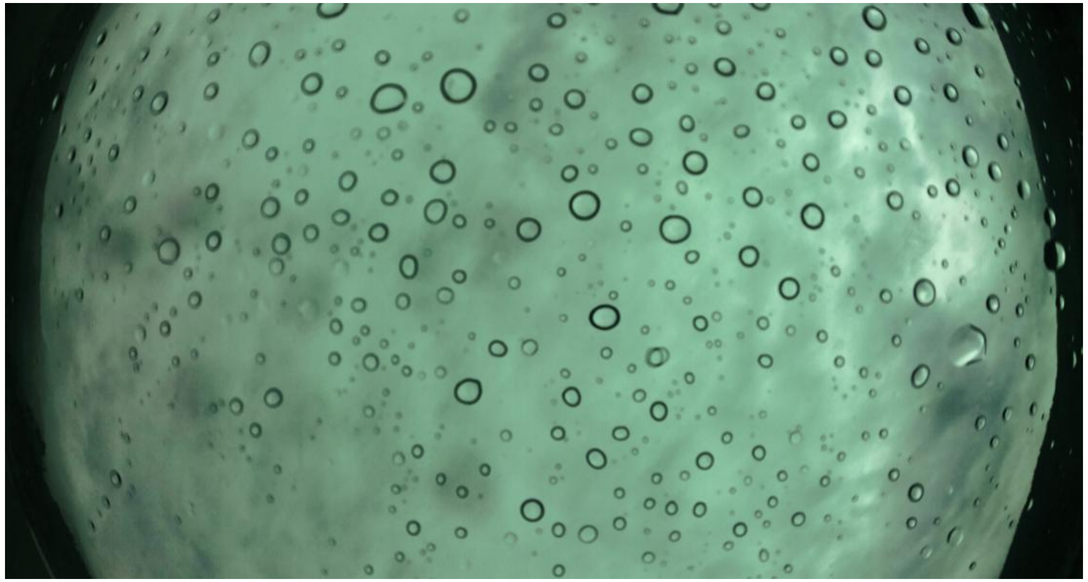
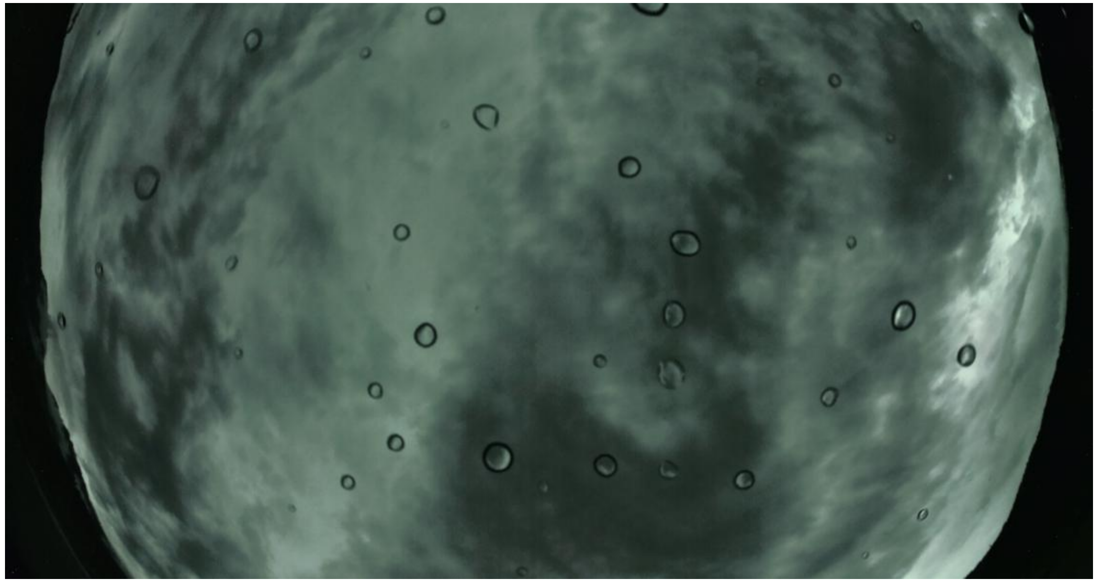
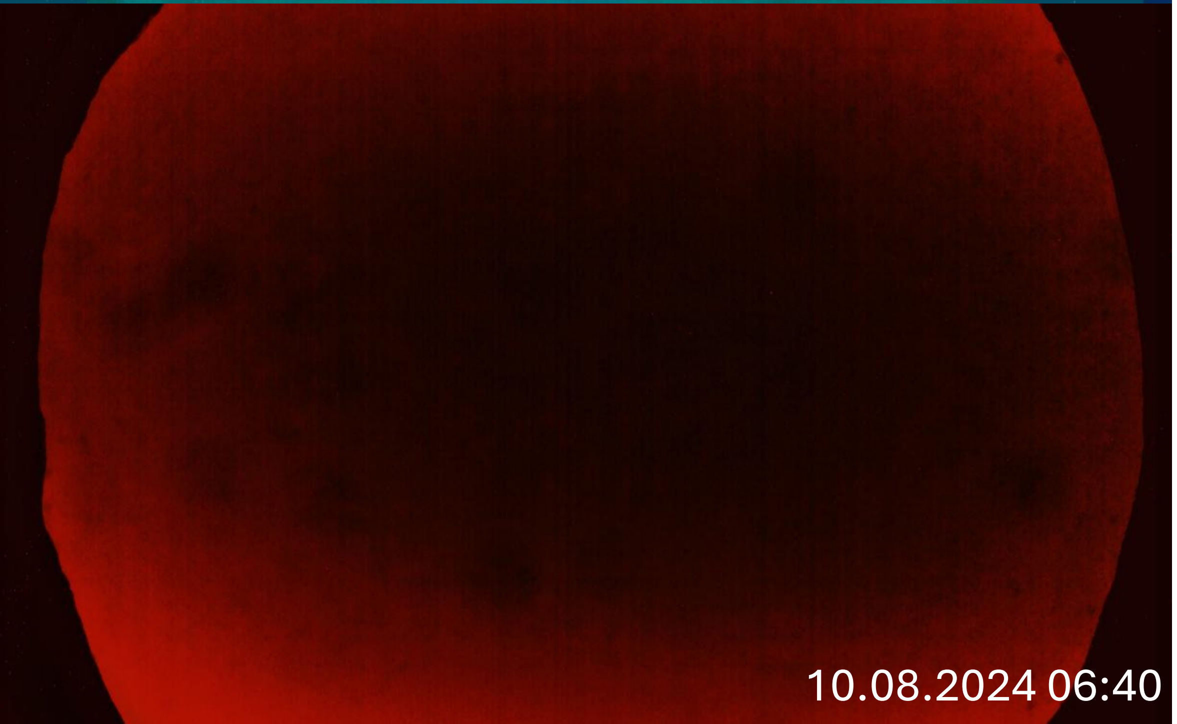


Raindrop
CNN + SVM

- Raindrops on the lens:
  - Distort the cloud structure
  - Create blurry spots unrelated to the sky
  - Can be mistaken as clouds
- Pretrained CNN + SVM classifier







Color Dominance

Algorithm:

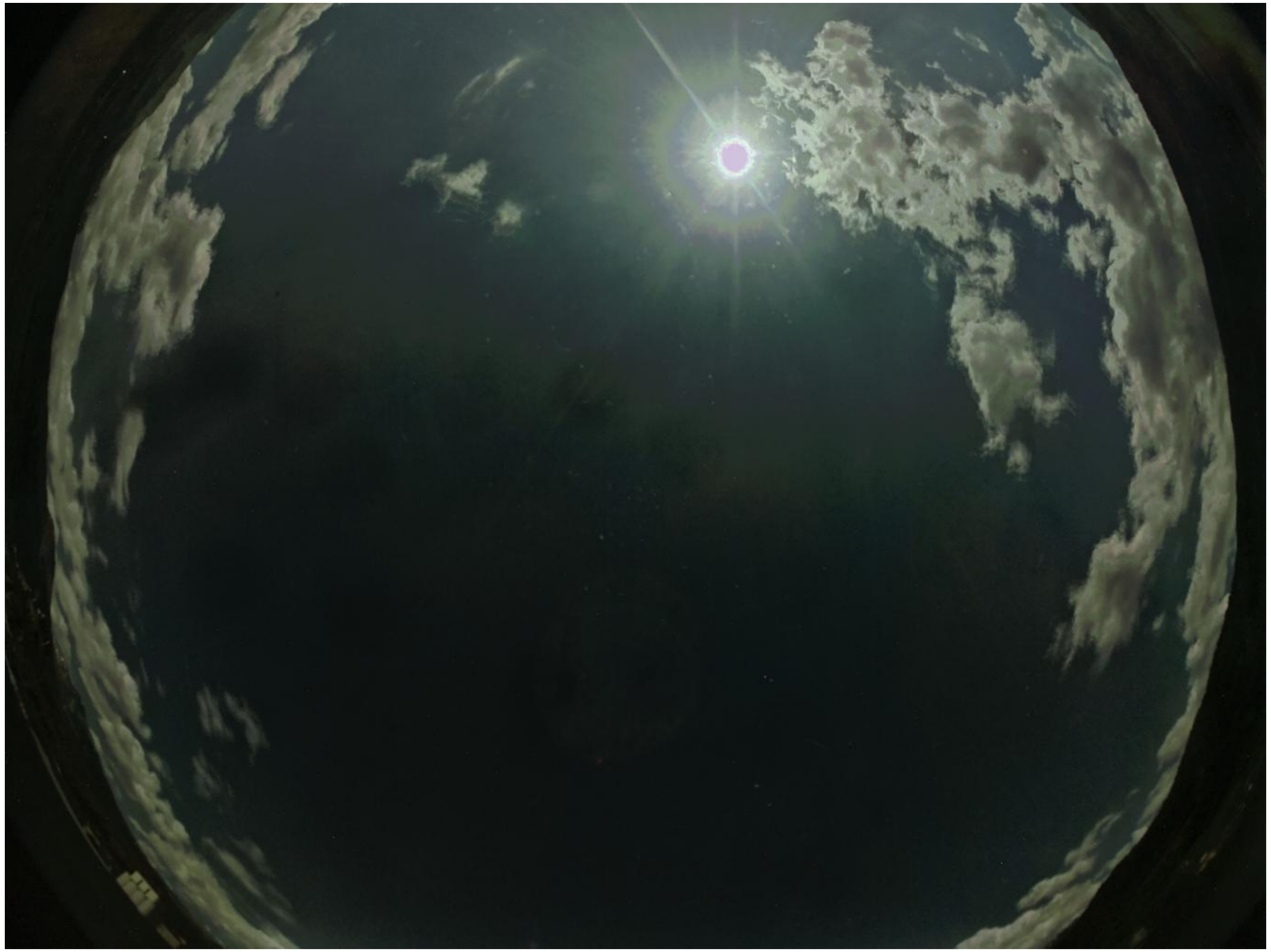
1. Compute mean color value of each channel:
   - Blue, Green, Red
2. Compute each channel’s ratio
   - ratios = [mean_B/total, mean_G/total, mean_R/total]
3. Sort the ratios
   - top_two = highest + second_highest
4. If the top two channels take **> 90%** of the total colour:
   The image is **colour-dominated**
   → move to quarantine/dark_or_tinted

Labelling

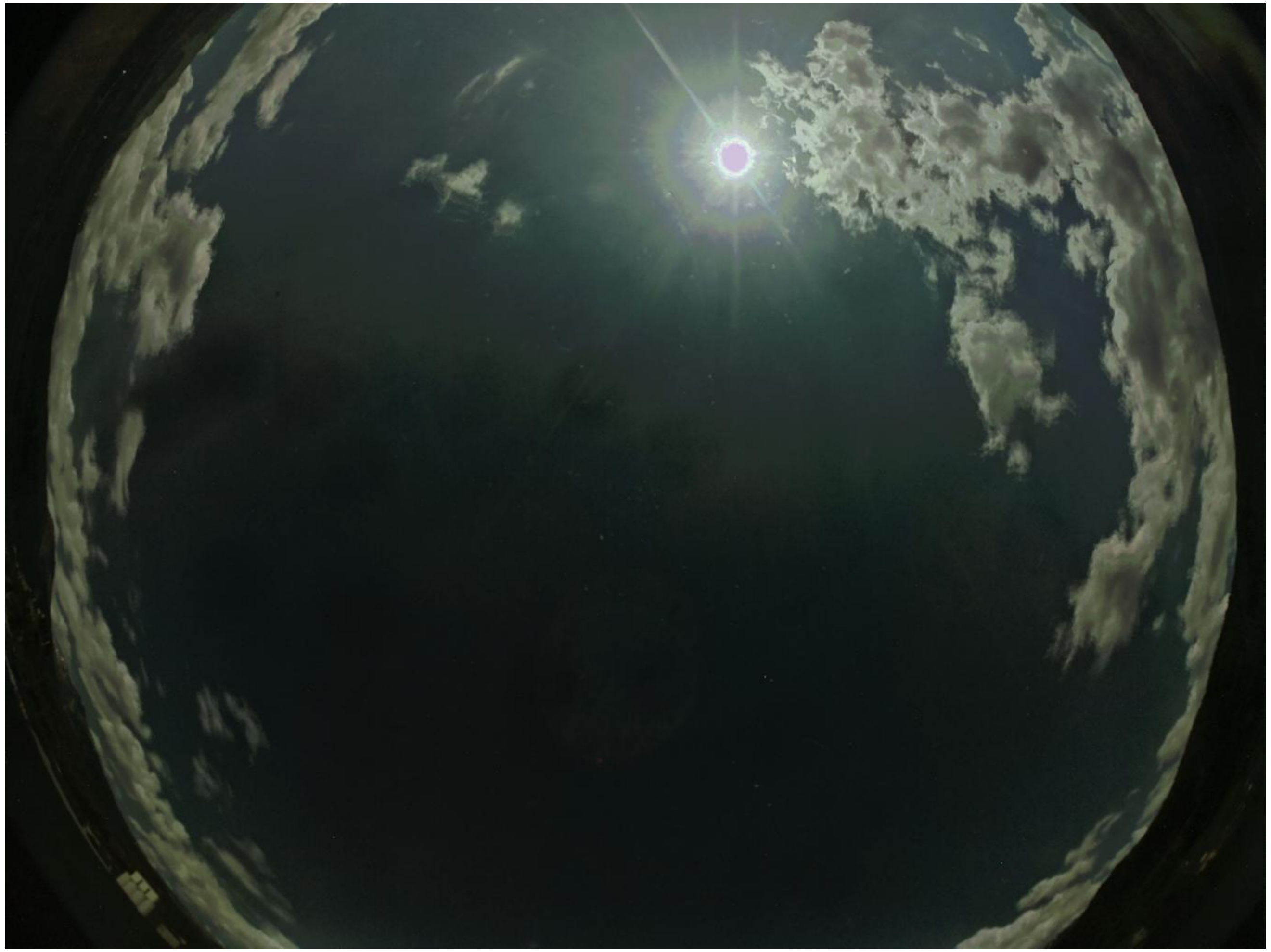
Labelling

- **Goal**
  - Assign each sky image to the correct **cloud-cover class** (Clear, Cloudy, Overcast)
- Images were labelled manually using the same labelling criteria.
- Out of 14’000 images, 3000 images were labelled → 1000 images per class.

Clear, cloudy or overcast?



Clear, cloudy or overcast?



Cloudy

Clear, cloudy or overcast?

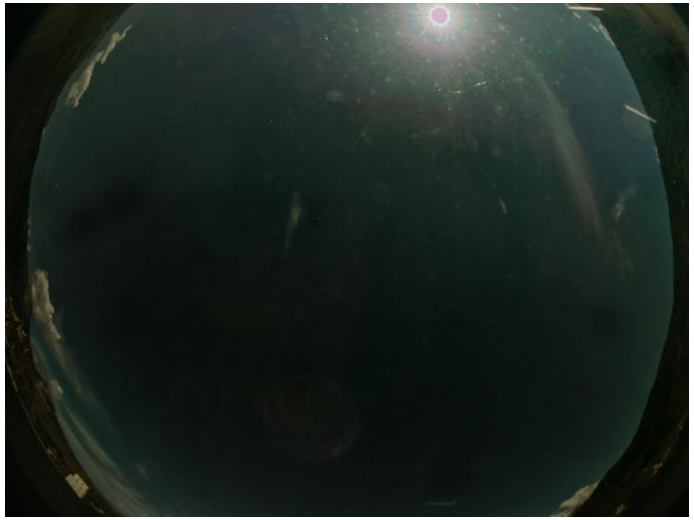
Clear, cloudy or overcast?

Cloudy

Class Clear

- Sky is almost entirely free of clouds. Direct sunlight reaches the ground with little scattering.
- Sun is visible and unobstructed – no clouds near the sun.
- 0 – 30% cloud coverage





Class Cloudy

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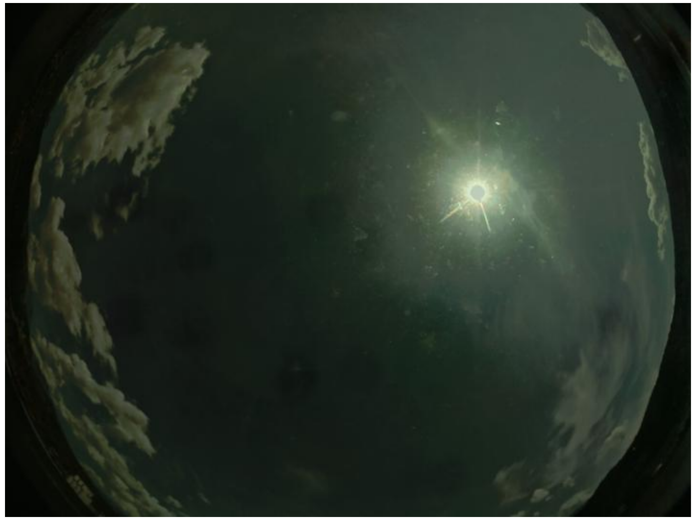
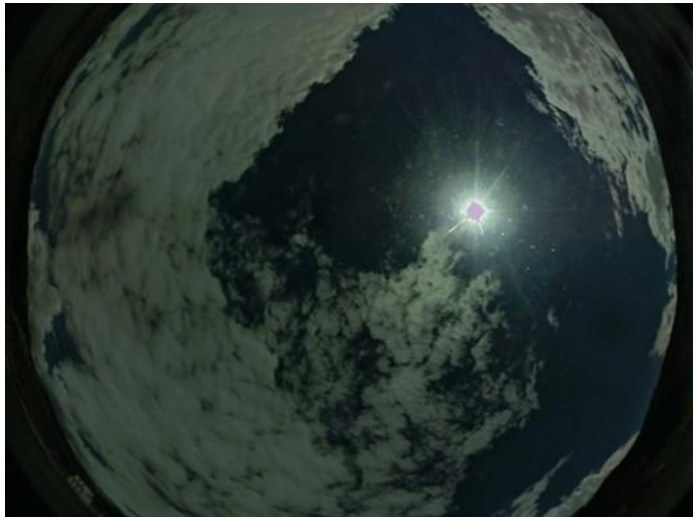
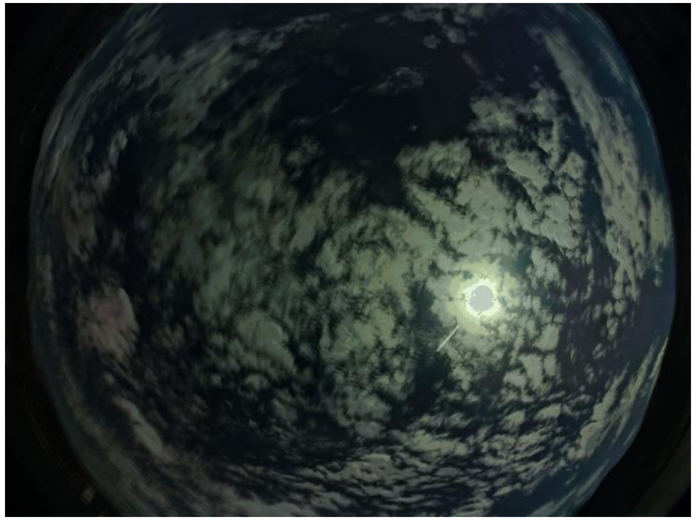
- Sky has clouds but still shows clear patches. Sunlight sometimes gets through but is partially obstructed.
- Mixture of sky and clouds - clouds near the sun
- 30 – 70% cloud coverage

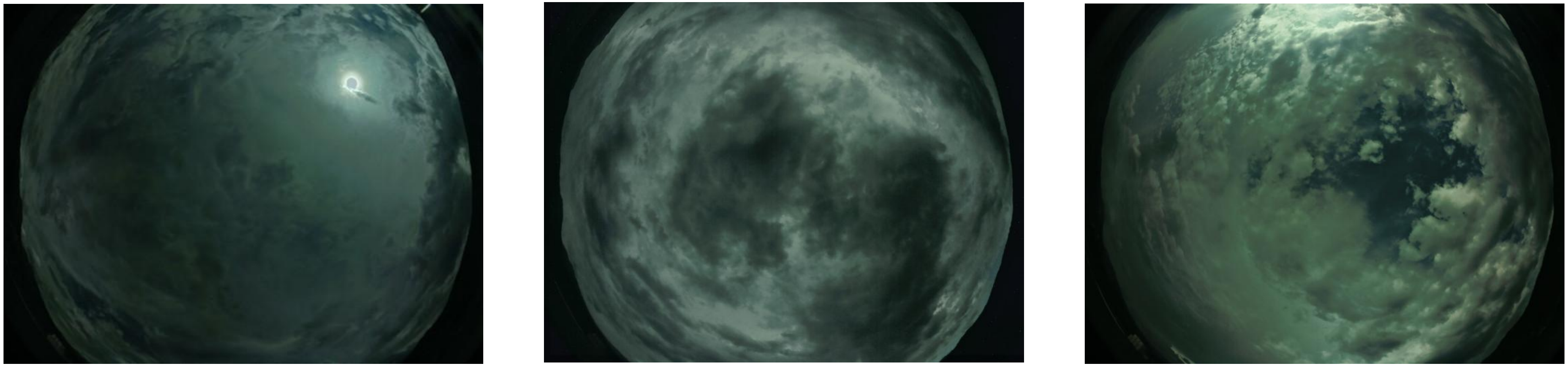






Class Overcast

- The sun is fully covered by clouds with no visible breaks around. Cloud layer blocks direct sunlight.
- No direct sunlight
- >70% cloud coverage



Definitions

Definitions

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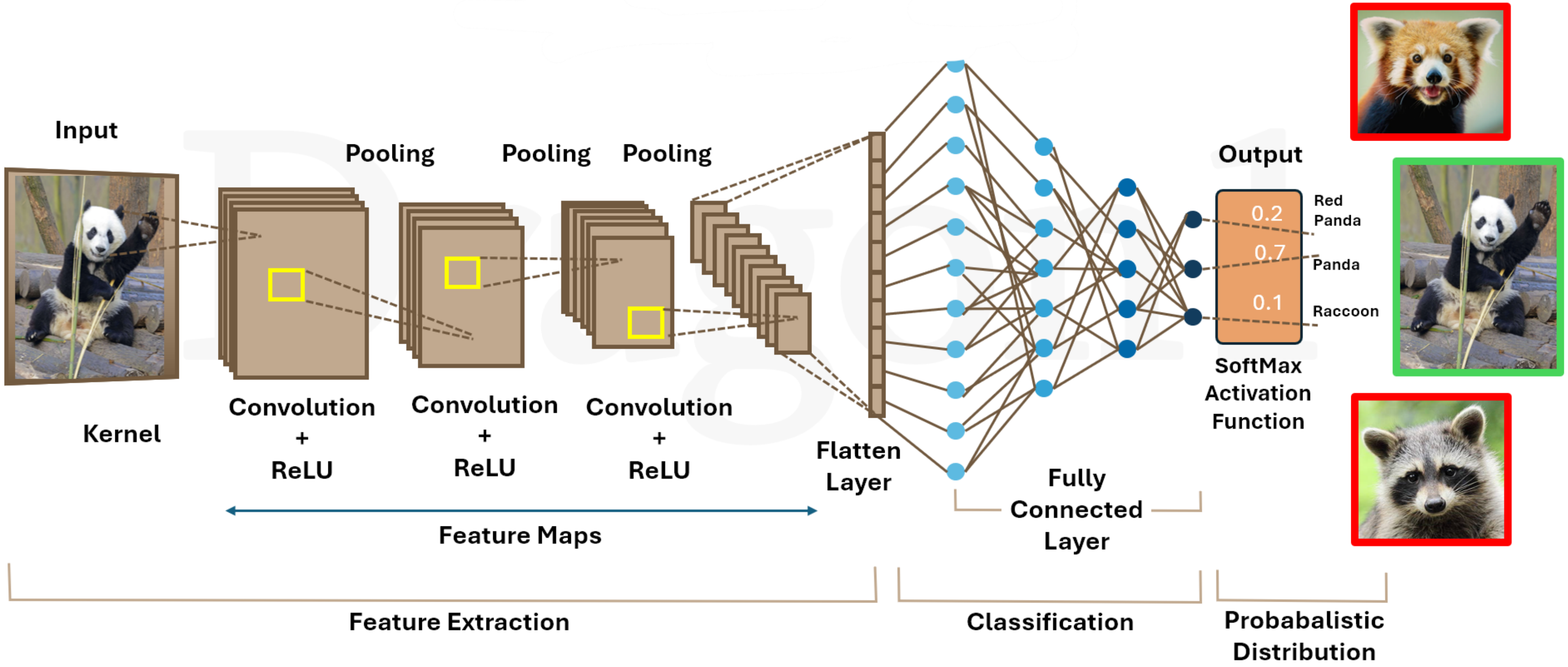
- CNN
- Transfer Learning
- Fine Tuning
- Literature Research → Model

Convolutional Neural Network (CNN)

- A CNN learns by repeatedly predicting on images, measuring how wrong it is, and adjusting its filters through backpropagation until the predictions become accurate.”

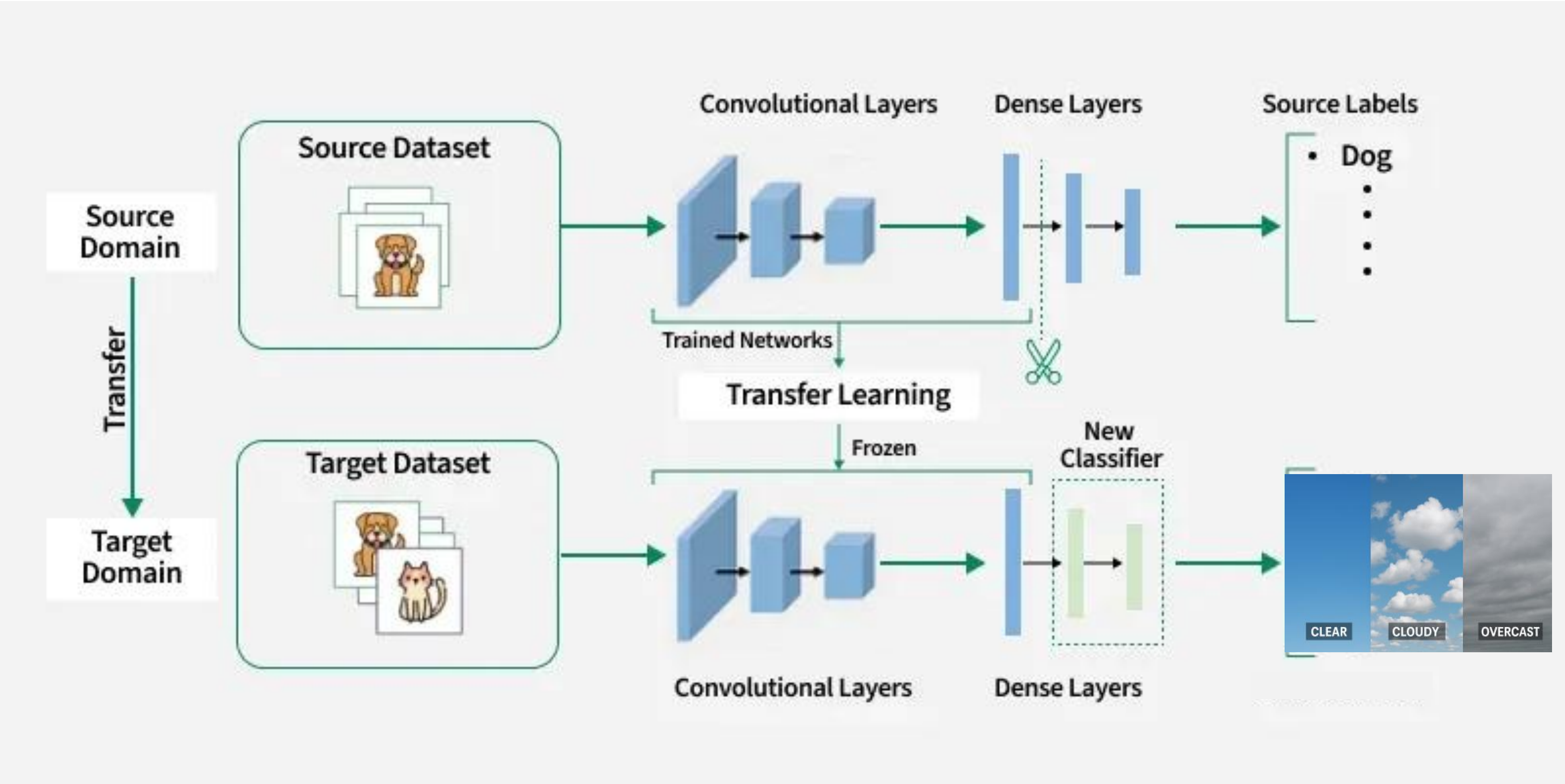


Transfer Learning

- Start with CNN trained on a large dataset

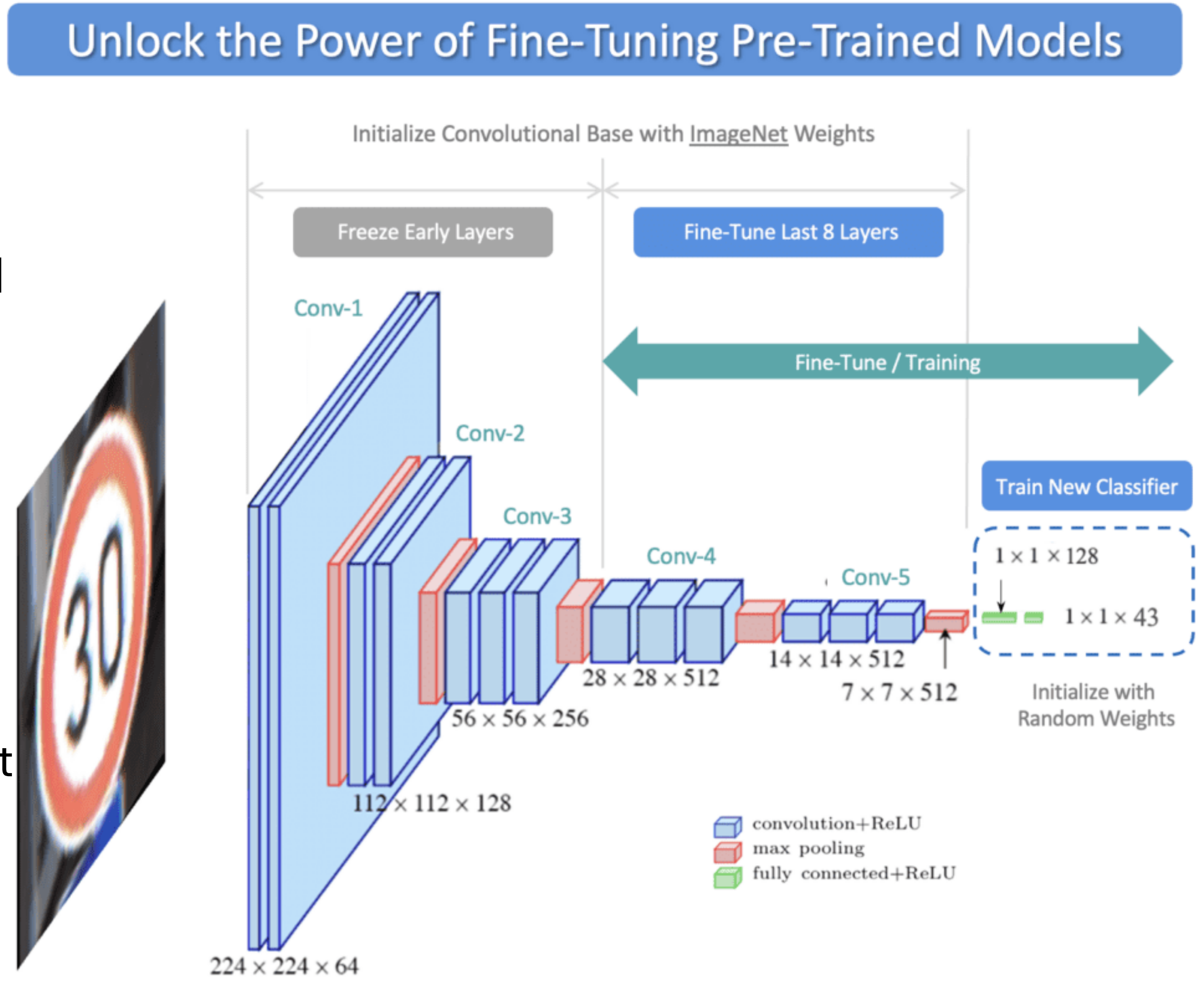
(e.g., ImageNet with 14M images and 1000 classes)

- Already knows how to detect edges, shapes, patterns like sky, tree, objects
- Cut last classification layers, keep rest **frozen**.
- add a small **new classifier** for our own categories (clear / cloudy / overcast).



Fine Tuning

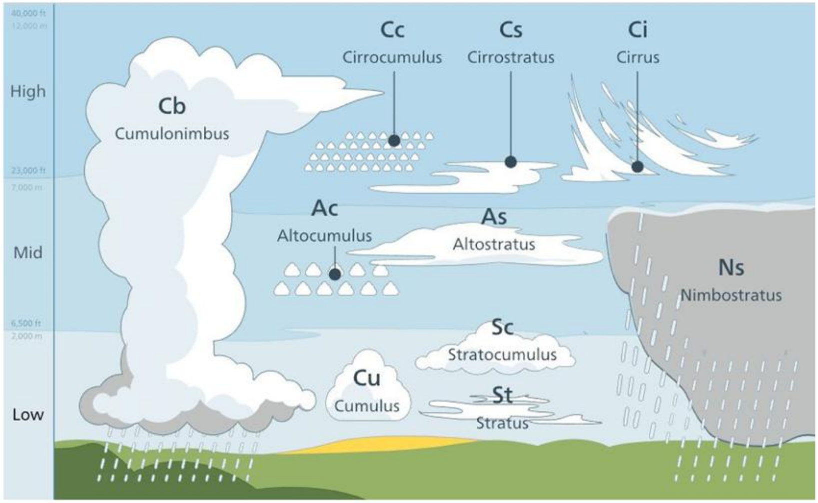
- Step 1 — Start with a Pre-Trained Model (ImageNet)
- Step 2 — Freeze the Early Layers → Keep low level features
- Step 3 — Unfreeze top M layers → to make it more task-specific
  - Layers adapt to the new dataset of clouds
- Step 4 — Replace the Classifier and train



https://learnopencv.com/fine-tuning-pre-trained-models-tensorflow-keras/

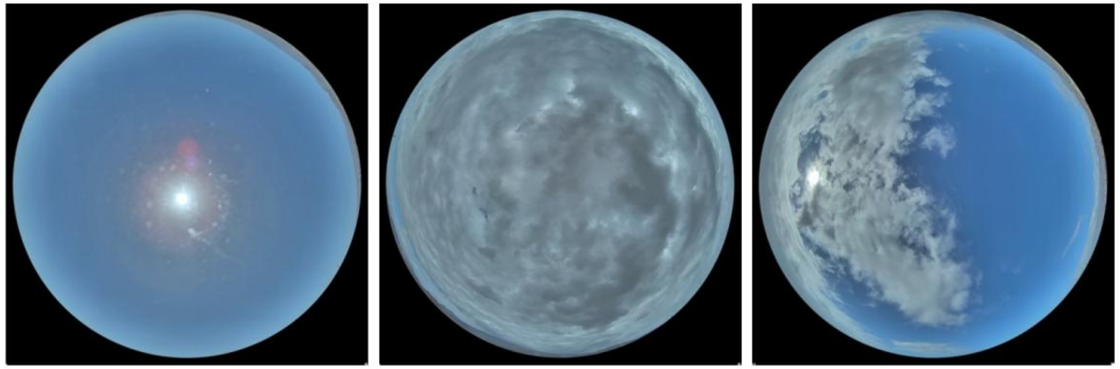
Literature Research

- Cloud Type Classification – Guzel et al. (2024)
  - 11 cloud types
  - Seven pretrained CNNs compared
  - Public Dataset: Cirrus Cumulus Stratus Nimbus
  - **Xception performed best with 97.66% accuracy**



- Weather Image Classification – Naufal et al. (2021)
  - Out of 4 CNN architectures tested, **Xception performed best with 90.21% accuracy.**

Literature Research



(a) *Clear sky* class. (b) *Cloudy sky* class. (c) *Partly cloudy sky* class.

- Sky Image Classification – Hernández-López et al. (2024)
  - Clear / Partly Cloudy / Cloudy
- Tested EfficientNet V2 (B1, B2) and ResNet models
- Best performance: **EfficientNetV2-B1/B2 with 98.09% accuracy.**

Conclusion from Literature Research

- Initially planned to compare multiple architectures, but this exceeded the scope of the project.
  - Selected **Xception**.
- Research Question

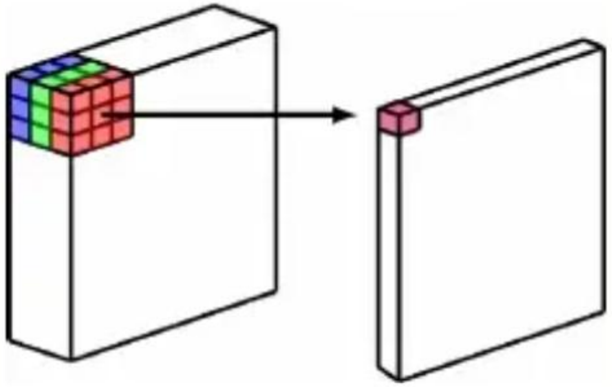
  *How effectively can a CNN based on the Xception architecture classify images into **clear, cloudy and overcast** using transfer learning?*
- Hypothesis

  Given that Xception achieved **97.66% accuracy** in cloud-type classification, it is expected to perform equally well — or better — on the simpler task of cloud-cover classification.

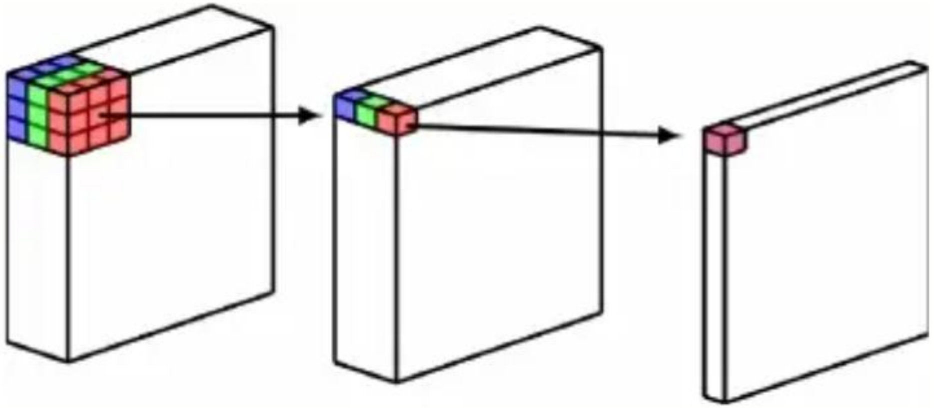
Base Model Xception

Xception

- Developed by François Chollet
  - 2017 at Google
- Uses **Depthwise Separable Convolutions**
  - First: each colour channel filtered separately (fine details)
  - Then: pointwise 1×1 convolution combines information
  - Computationally less expensive
- Pre-trained on ImageNet → strong transfer learning



(a) Conventional Convolutional Neural Network



Depthwise Convolu-
tion

Pointwise Convolution

(b) Depthwise Separable Convolutional Neural Network

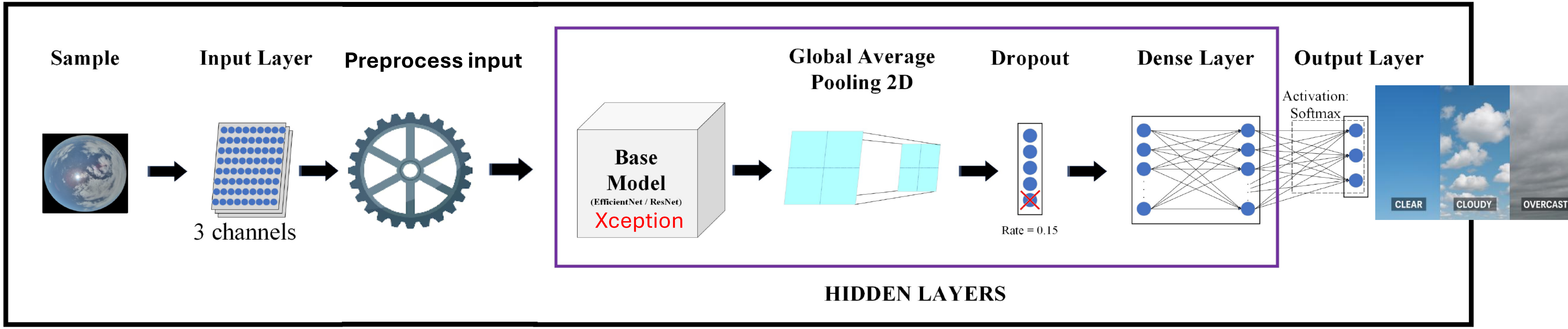
https://doi.org/10.1016/j.compag.2019.104948

Implementation Architecture


```
from tensorflow.keras.applications
import Xception


base = Xception(
   include_top = False,
   weights = "imagenet",
   input_shape=IMG_SIZE + (3,)
)
base.trainable = False
```

```
inputs = keras.Input(shape = IMG_SIZE + (3,))
x = preprocess_input(x)
x = base(x)
x = layers.GlobalAveragePooling2D()(x)
x = layers.Dropout(0.2)(x)
outputs = layers.Dense(len(CLASS_NAMES),
                 activation="softmax")(x)
```



Hernández-López, et al. Sky Image Classification Based on Transfer Learning Approaches. *Sensors* **2024**, *24*, 3726

Training and Results

Training Setup

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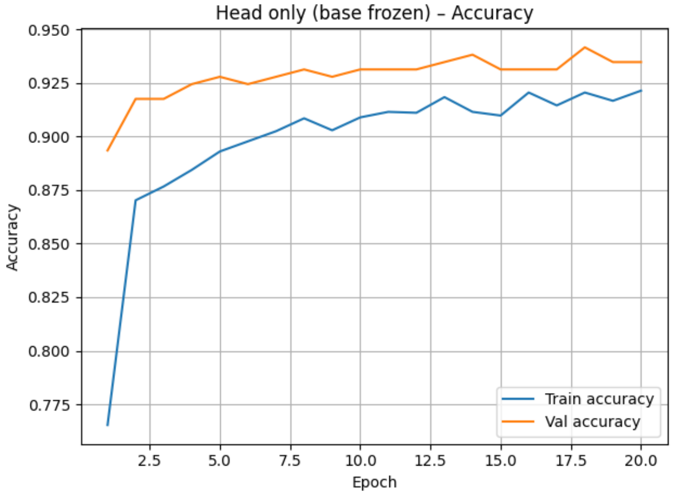
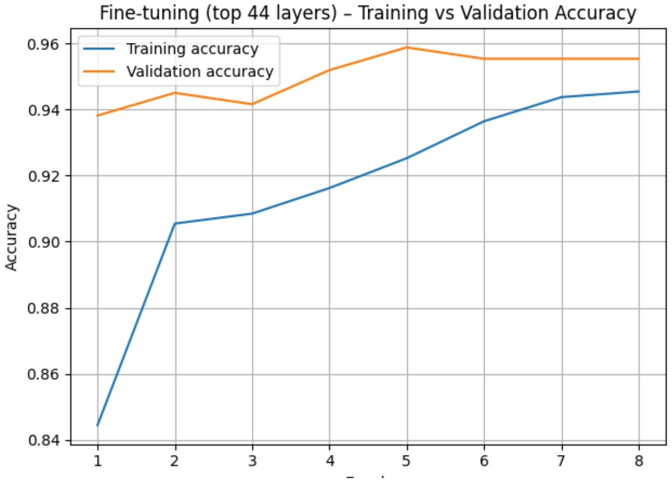
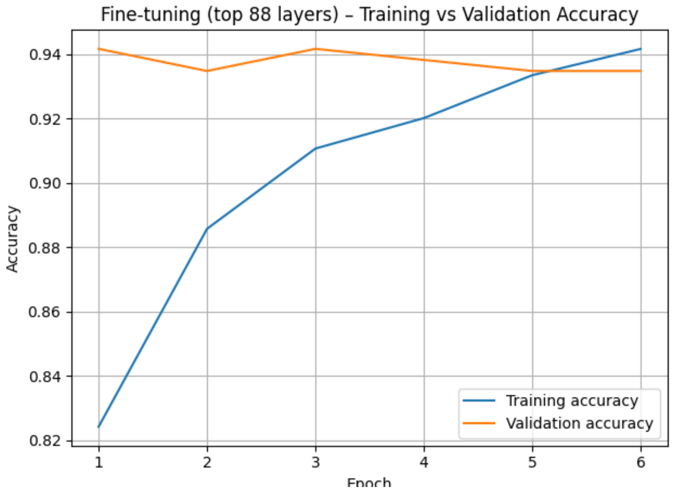
- 3 classes: **clear, cloudy, overcast**
- Split: 80% train / 10% validation / 10% test over 3000 labelled images.
- Metrics used:
  - **Accuracy** – how many images are correctly classified.
  - **Loss** – Sparse categorical cross entropy
  - **Precision / Recall / F1 (macro)** – average over the three classes, so each class counts equally.
- Two stages (20 Epochs):
  - **Stage 1:** train only the new head (Xception frozen)
  - **Stage 2: fine-tuning** with different numbers of unfrozen layers (44, 88, 132)

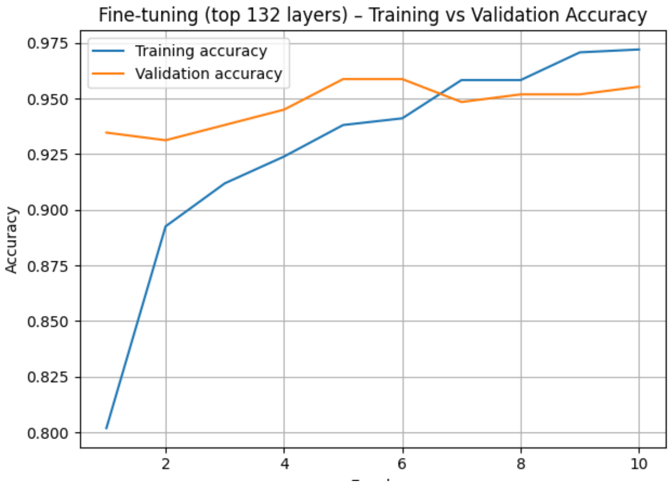
Accuracy

- Head-only training already gives strong performance
- Early stopping triggers quickly during fine-tuning
- In FT-132 and FT-88, training accuracy grows much faster than validation accuracy and even surpasses it → Overfitting
- Validation accuracy staying stable while training accuracy rises









Training set metrics

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Train set	Accuracy	Loss	Precision	Recall	F1
Base model	0.9208	0.2117	0.9219	0.9206	0.9210
FT - 44	0.9432	0.1500	0.9436	0.9437	0.9436
FT - 88	0.9367	0.1667	0.9366	0.9370	0.9366
FT - 132	0.9712	0.0891	0.9710	0.9717	0.9712

FT – 44 = Xception Fine-tuned with 44 layers unfrozen

Validation set metrics

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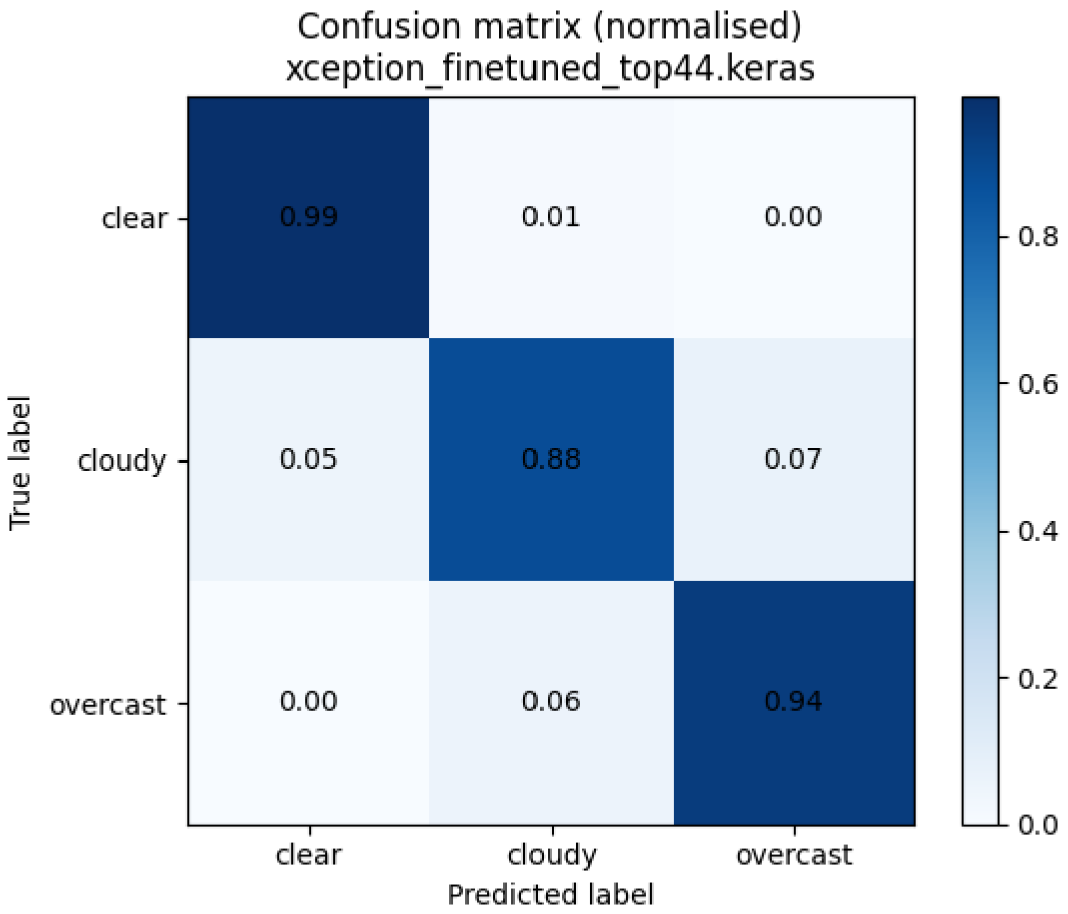
Val set	Accuracy	Loss	Precision	Recall	F1
Base model	0.9367	0.1650	0.9416	0.9347	0.9367
FT - 44	0.9588	0.1358	0.9626	0.9586	0.9599
FT - 88	0.9416	0.1792	0.9429	0.9437	0.9428
FT - 132	0.9450	0.1348	0.9484	0.9450	0.9462

Test set metrics

Test set	Accuracy	Loss	Precision	Recall	F1
Base model	0.9212	0.1981	0.9205	0.9203	0.9082
FT - 44	0.9384	0.1727	0.9374	0.9382	0.9374
FT - 88	0.9110	0.2386	0.9128	0.9128	0.9083
FT - 132	0.9315	0.1545	0.9303	0.9301	0.9230

Test set metrics



Some misclassified images

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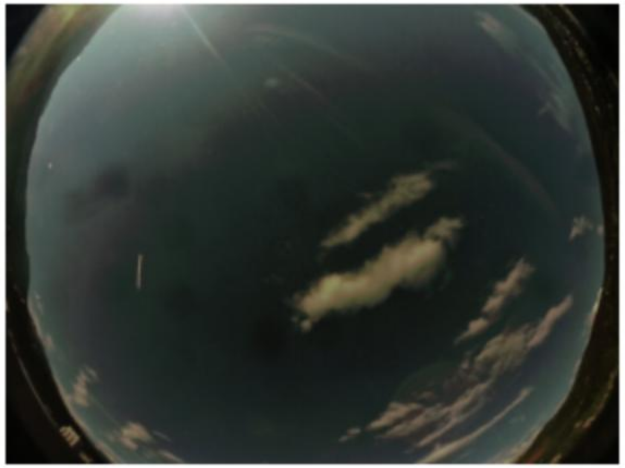
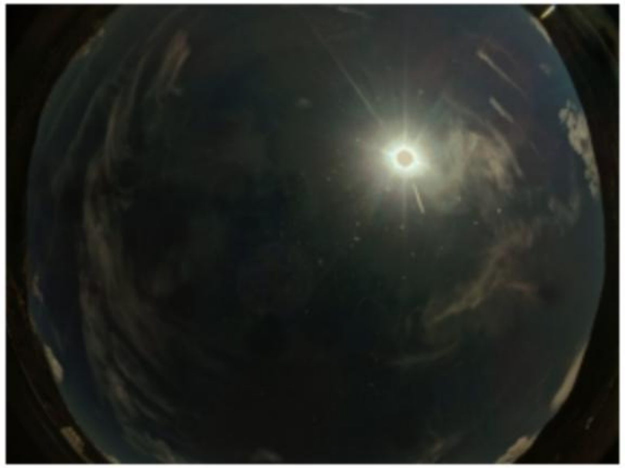
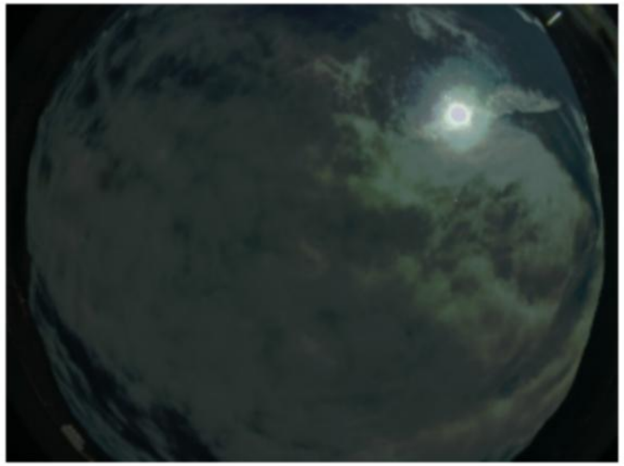
True: clear
Pred: cloudy



True: cloudy
Pred: clear



True: cloudy
Pred: overcast



Analysis of Results

- Strong classifier with all four model variants achieving high values in all metrics.
  - 91 – 97% train accuracy
  - 93 – 96% validation accuracy
  - 91 – 94 % test accuracy
  - Precision/Recall/F1 between 90% and 97%

✓The model is consistently above 90% on unseen data.

✓It correctly classifies clear / cloudy / overcast images with high reliability.

Conclusion

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- Research Question

  *How effectively can a CNN based on the Xception architecture classify images into **clear, cloudy and overcast** using transfer learning?*

- Hypothesis

  Given that Xception achieved 97.66% accuracy in cloud-type classification, it is expected to perform equally well — or better — on the simpler task of cloud-cover classification.

  → **Hypothesis Outcome:**
  Although the model did **not reach the expected 97.66%**, it still achieved a **high accuracy of 93.86%**, confirming that Xception is highly effective for cloud-cover classification.

Conclusion

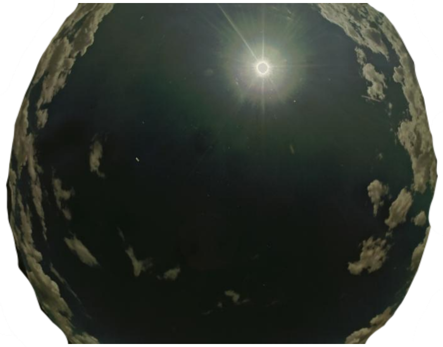
- Fine-tuning improves performance
  - **FT-44** achieves **best** result with **93.84% accuracy.**
  - **FT-88 & FT-132** show signs of **overfitting**

→ Fine-tuning increases performance by a few percentage points (92% in base model), but this comes at the cost of **higher computational load**, **longer training times**, and the risk of **overfitting**. Whether the additional accuracy is worth the extra complexity depends entirely on the application requirements.

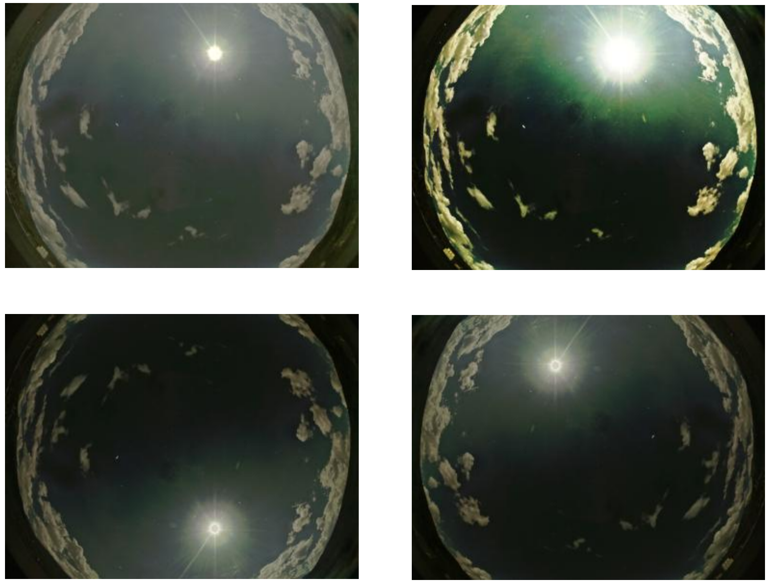
Future Work

Possible Data Preparation Steps

- **Apply circular mask and resize to 299 x 299**
  - Remove black rim
  - Cut away objects at the horizon
  - Squeeze it to 299 x 299



- **Augmentation**
  - Rotation
  - Color shifts
  - Brightness adjustments



Future Research

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- Cloudy sky → cloud type classification
- Xception very heavyweight – try base model with less parameters. Code is built very modularly, so can be easily replaced. E.g. Efficientnet V2

Model	Size (MB)	Top-1 Accuracy	Top-5 Accuracy	Parameters	Depth	Time (ms) per inference step (CPU)	Time (ms) per inference step (GPU)
Xception	88	79.0%	94.5%	22.9M	81	109.4	8.1
EfficientNetV2B2	42	80.5%	95.1%	10.2M	-	-	-
MobileNet	16	70.4%	89.5%	4.3M	55	22.6	3.4

- CNN + other model for cloud movement and irradiance prediction

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That’s it!
Thank you for your attention!

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Questions

Questions

- Do you think it was worth it to fine-tune?
- Do you have other ideas on how to predict solar irradiance? Hybrid models?
- What is the most realistic next step with the conclusions of this project?
- Do you have suggestions of other models for transfer learning?
- If you were to collect the dataset again and preprocess what would you change to make the model more robust?

References

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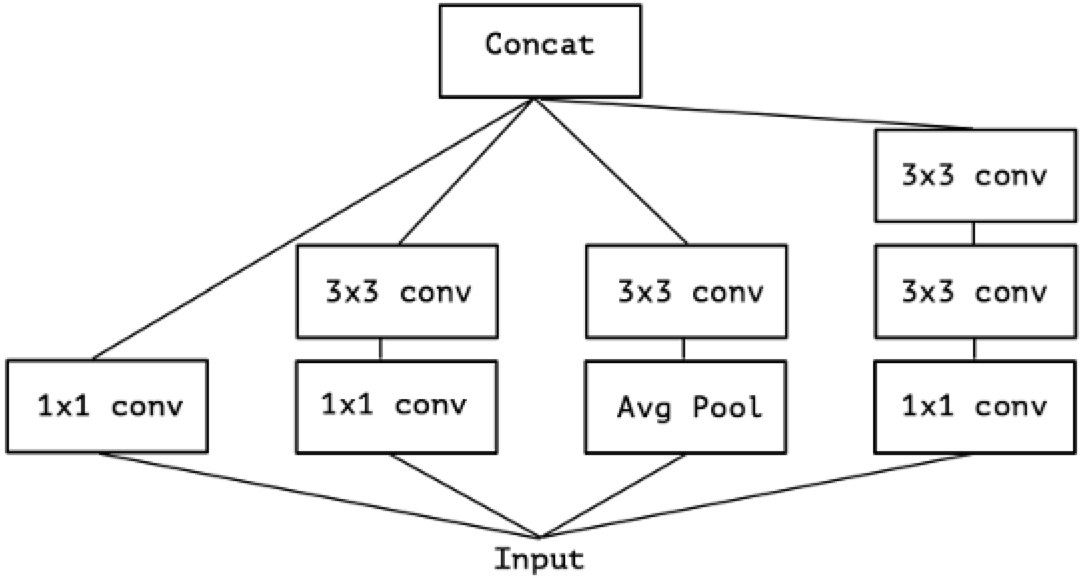
Evaluation Metrics

Metric	Definition
Accuracy	Percentage of all predictions that are correct.
Loss	Measures how wrong the model is during training (lower is better).
Precision	Of all images predicted as a class, how many are actually correct.
Recall	Of all real images of a class, how many the model correctly finds.
F1-Score	Harmonic mean of precision and recall; high only if both are high.

132 length vs 81 depth



Why SVM for Raindrop

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- Because raindrop detection is a **small, highly imbalanced, and very visual problem.**
  An SVM works better when you have:
- **few training images**
- **only two classes**
- **high-quality feature embeddings** (like MobileNetV2's 1280-D vectors)
- a **simple linear boundary** between classes
- Softmax requires more data and tends to overfit quickly.
  SVMs, especially with pre-trained embeddings, are **very strong for small binary problems**.

My journey

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- Problem description
  - Why do we need it
- Preprocessing
- Transfer Learning
  - Xception architecture (warum Xception?)
- My CNN
  - First time 87%
  - Extract wrong images and see who was right me or CNN
  - # Part 1: train only the small "head" (fast, safe).#
  - Part 2: fine-tune the top layers of Xception (better accuracy).#
  - Then: evaluate (accuracy, precision, recall, F1), confusion matrix
  - Fine tuning with different layers frozen
- How to make it better
  - Preprocessing steps
- Question round

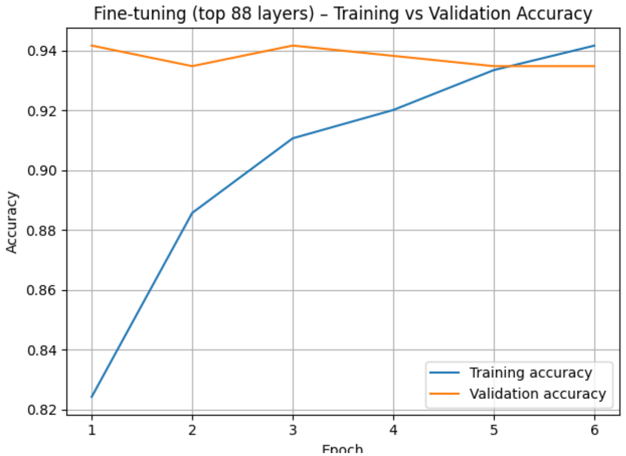
Fine Tuning – How it Works

- Freezing

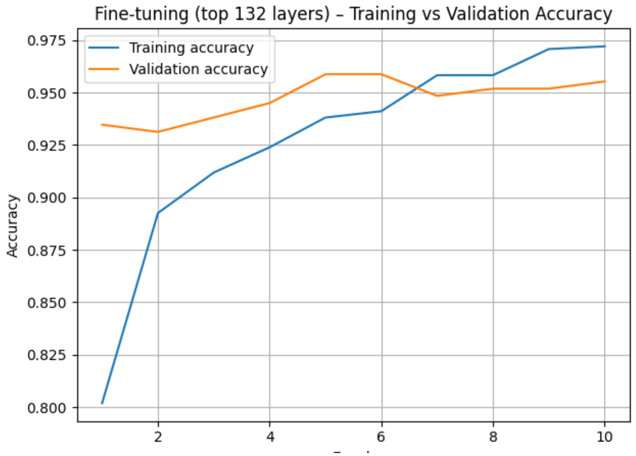
FINE TUNING

- The fine tuning process took over 1 hour
- So I split it and saved my progress in a model keras file after training the head and after fine tuning.
- Problem is fine tuning causes overfitting.
- When putting images from the new server, it might be as accuarte

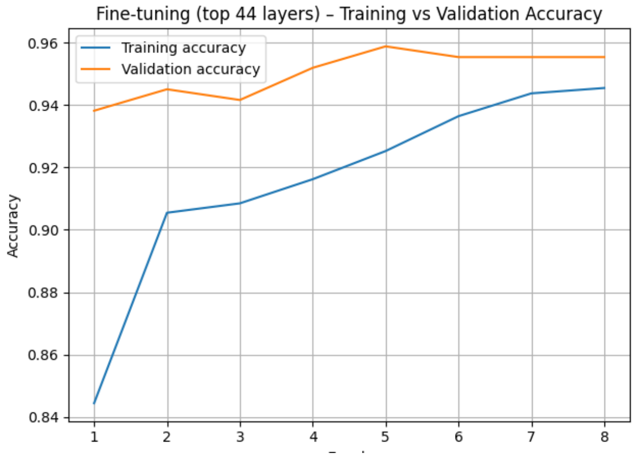
Accuracy



Fine-tuning (top 88 layers) – Training vs Validation Accuracy
Accuracy
0.94
0.92
0.90
0.88
0.86
0.84
0.82
1
2
3
4
5
6
Epoch
Training accuracy
Validation accuracy



Fine-tuning (top 132 layers) – Training vs Validation Accuracy
Training accuracy
Validation accuracy
Accuracy
0.975
0.950
0.925
0.900
0.875
0.850
0.825
0.800
2
4
6
8
10



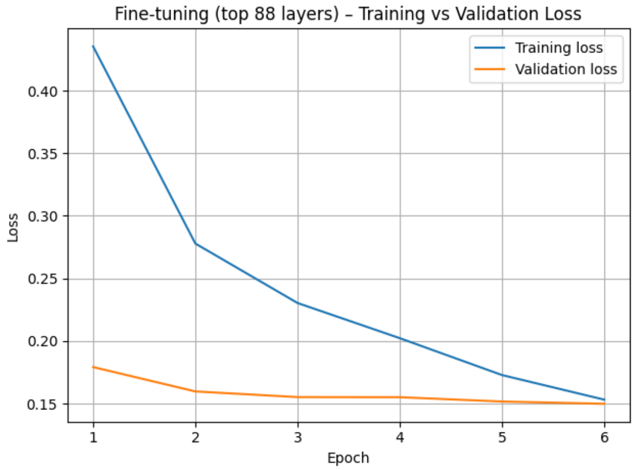
Fine-tuning (top 44 layers) – Training vs Validation Accuracy
Training accuracy
Validation accuracy
Accuracy
0.96
0.94
0.92
0.90
0.88
0.86
0.84
1
2
3
4
5
6
7
8

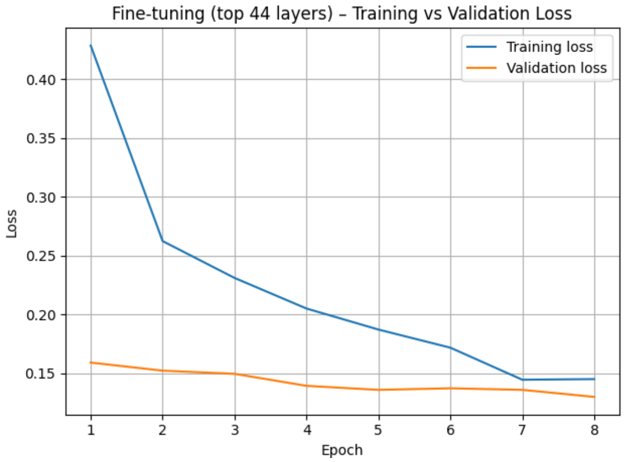
ETH Study

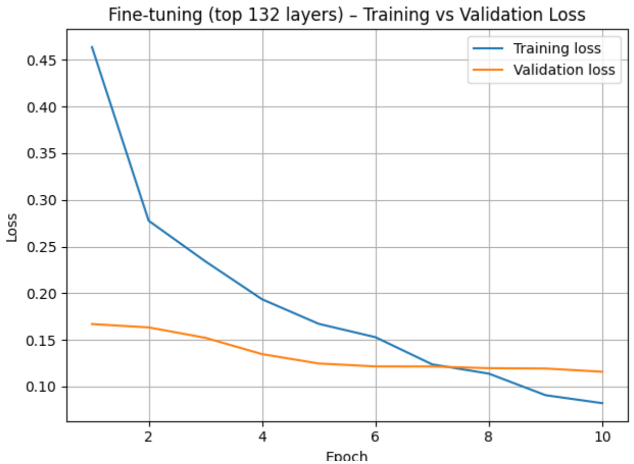
UNIVERSITÄT BERN

- https://www.research-collection.ethz.ch/server/api/core/bitstreams/47bd7a0d-5c7f-41b6-8752-7bceb3407f35/content

Loss


Fine-tuning (top 88 layers) – Training vs Validation Loss
Training loss
Validation loss
0.40
0.35
0.30
0.25
0.20
0.15
Loss
1
2
3
4
5
6
Epoch


Fine-tuning (top 44 layers) – Training vs Validation Loss
Training loss
Validation loss
0.40
0.35
0.30
0.25
0.20
0.15
Loss
1
2
3
4
5
6
7
8
Epoch


Fine-tuning (top 132 layers) – Training vs Validation Loss
Training loss
Validation loss
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
Loss
2
4
6
8
10
Epoch

In a Broader Context