SWIN Transformers and transfer learning for EuroSAT classification

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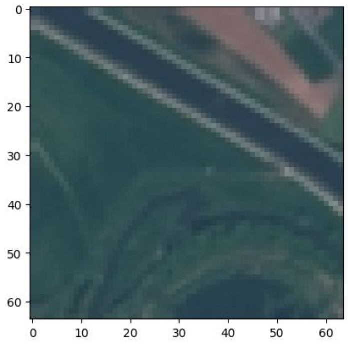
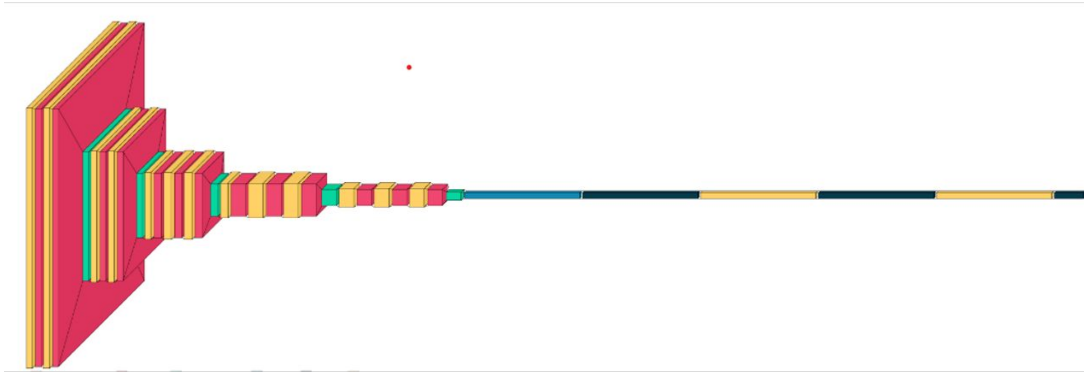
Problem Statement





River

Classification using Eurosat data

Input data visualization

ConvNets (pretrained)

Pros:

- Less parameters and computational complexity

Cons:

- Require Resampling to standard input data size
- Extra Compute required without adding any extra information

Vanilla vision transformers (pretrained)

Pros:

- Can handle arbitrary image size

Cons:

- Quadratic computational complexity of the attention mechanism
- Would not scale to large images
- Pretrained models are available on large patches

Proposed solution

SWIN transformers

- Hierarchical structure like CNNs with small patch sizes and linear attention

Implementation details and hyperparameter

Our model is developed using pytorch, timm and pytorch lightning

Hyperparameters

min_epochs=10

max_epochs=200

batch_size =1000

Initial learning_rate=0.01

Model Details

Loss function is categorical cross entropy

Optimizer RMSprop

Learning rate scheduler reduces the accuracy if accuracy on test set doesn’t increase for 10 epochs (reduce LR on plateau)

Early stopping if accuracy doesn’t improve for 30 epochs

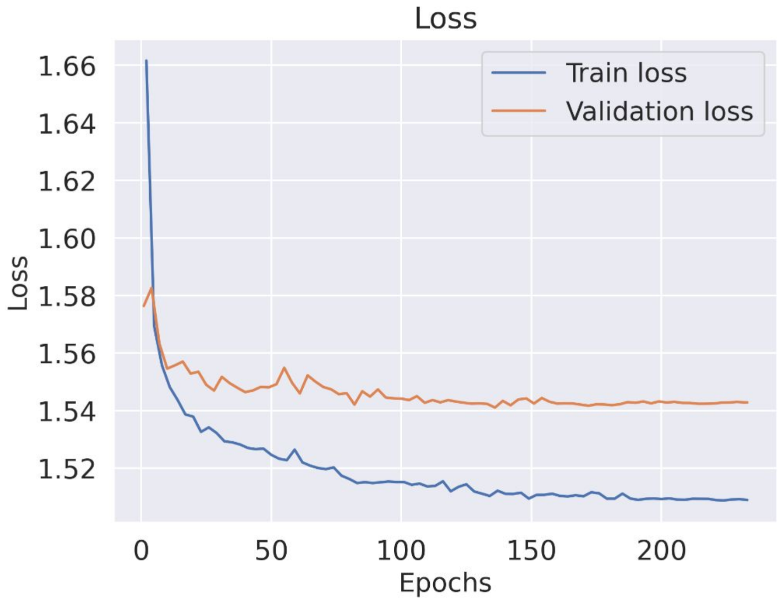
Model parameters - 27.5 million trainable 7700 (head)

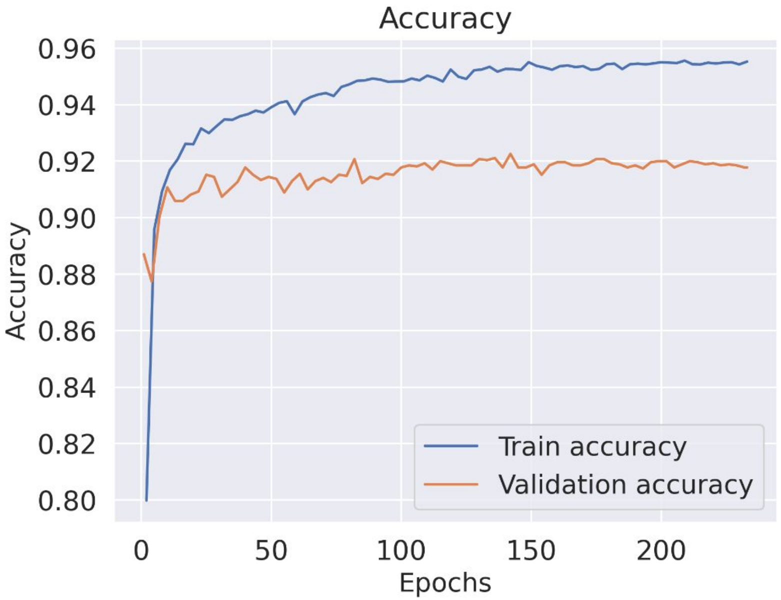
Hardware details

GPU - Nvidia RTX4090

Train time 6 mins

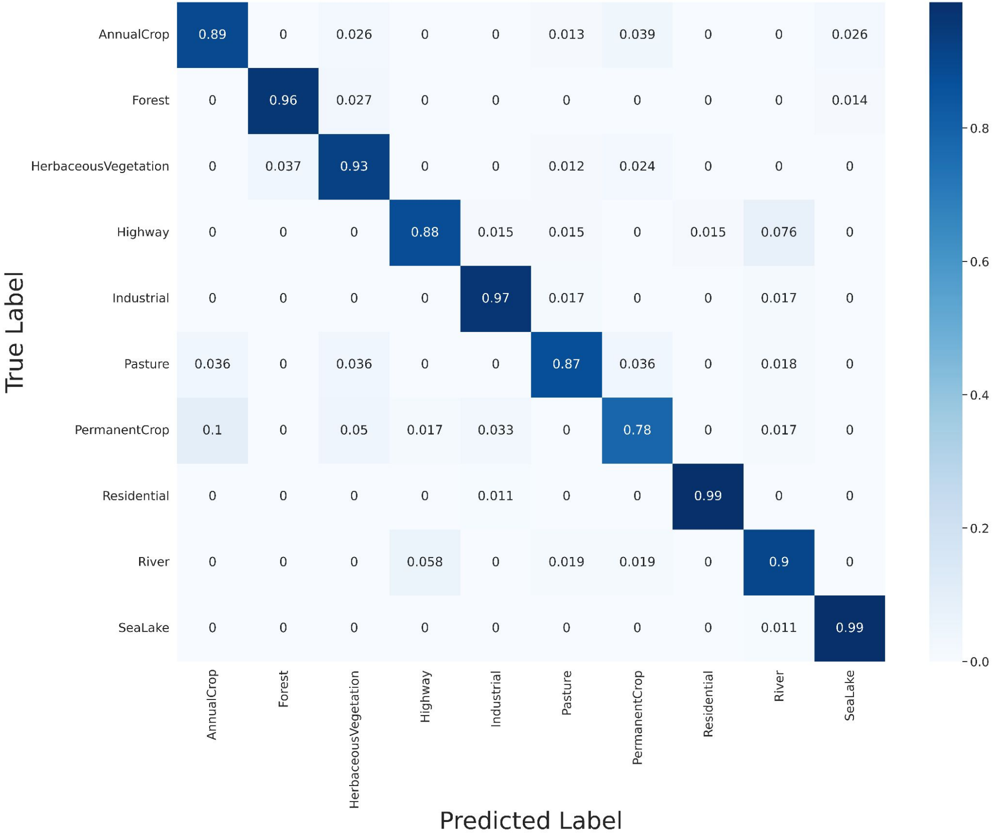
Training plots





The model has 92.30% accuracy on test set, showing model has not overfitted

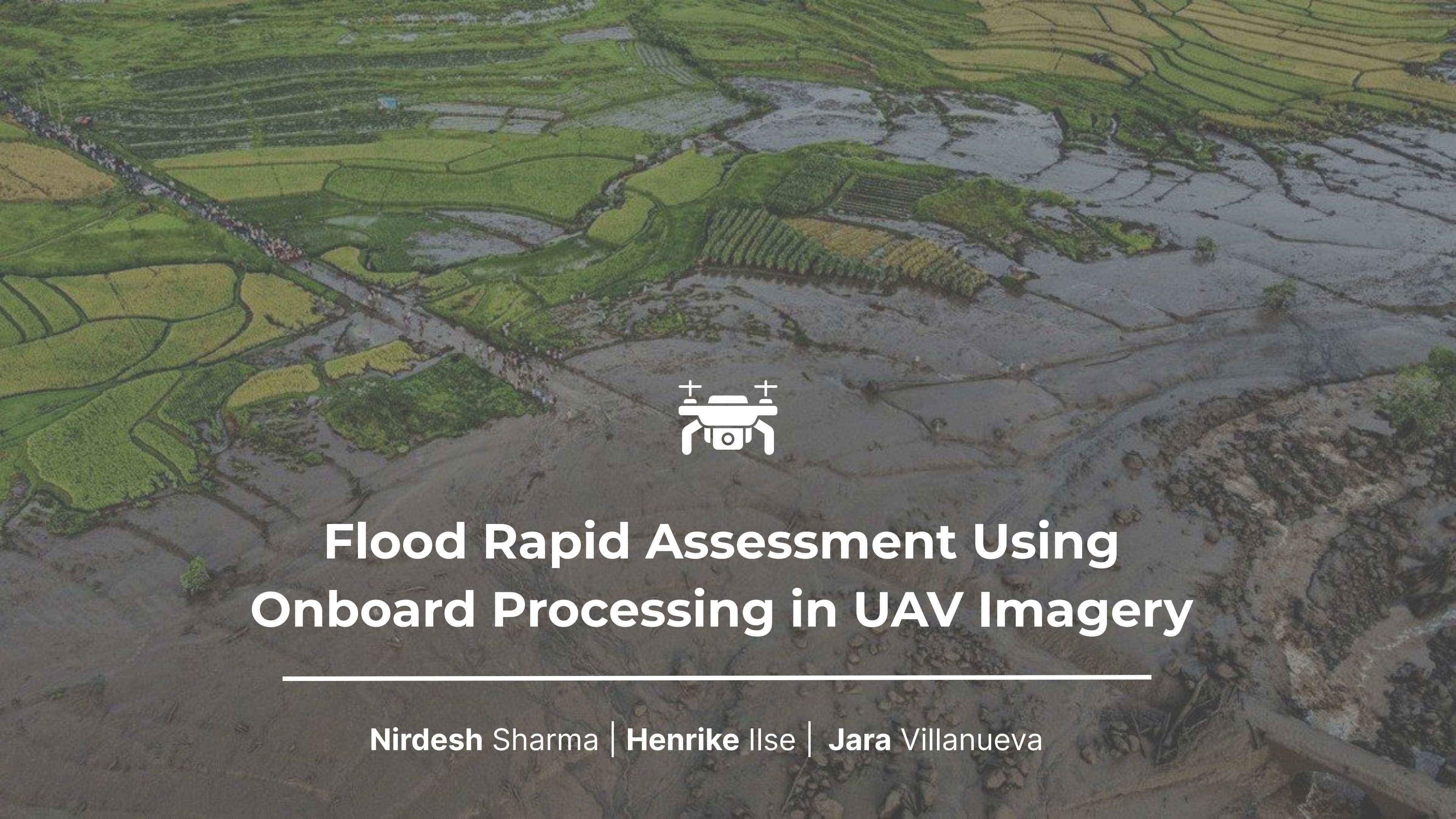
Confusion matrix for Validation set



- The model has similar results on test and validation set
- The model confuses pasture permanent crops as annual crops
- The model has high accuracy for residential areas and sea lakes since they have a distinct spectral signature

Test plot


Label:Pasture,Prediction:AnnualCrop
Label:Pasture,Prediction:River
Label:Pasture,Prediction:Pasture
Label:SeaLake,Prediction:SeaLake
Label:HerbaceousVegetation,Prediction:HerbaceousVegetation
Label:Residential,Prediction:Residential
Label:AnnualCrop,Prediction:AnnualCrop
Label:Pasture,Prediction:HerbaceousVegetation
Label:Highway,Prediction:Highway
Label:Industrial,Prediction:Industrial
Label:Residential,Prediction:Residential
Label:Forest,Prediction:Forest



Flood Rapid Assessment Using Onboard Processing in UAV Imagery

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“Flooding is a global recurring problem causing destructive impacts on communities.”

50K

Flood-related deaths over the last decade

$66B

Economic losses in 2022

“Flooding is a global recurring problem causing destructive impacts on communities.”

Disaster Response Operational Flow

Existing operations

Flooding event → **Response** → **End-user**

Step 1:
UAV data acquisition
(T = 4h)

Step 2:
Data Downloading
(T = 1h)

Step 3:
Data Analysis
(T = 4h)

Emergency planning & disaster response

Emergency flooding events need urgent & real-time response.

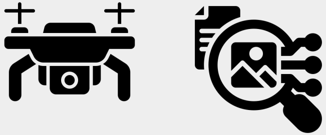
Flood Rapid Assessment Using Onboard Processing in UAV Imagery

Disaster Response Operational Flow

Proposed operations

Flooding event

Response

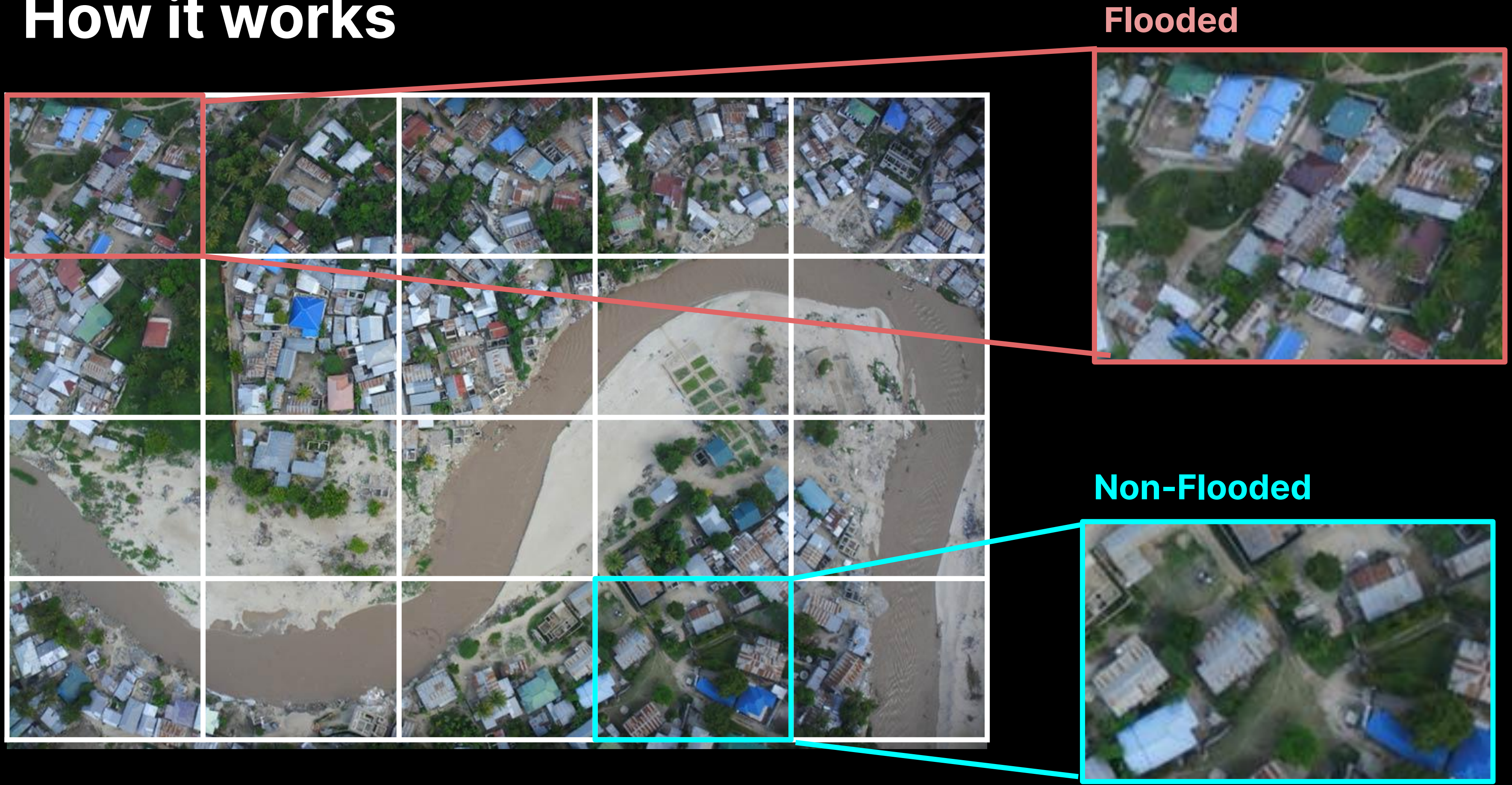


Single step process:
UAV data acquisition + mobile nets + Data analysis on device
(T = 4h (real-time analysis) / Simultaneous process)

End-user

Emergency planning & disaster response

How it works



IMPACTS

Fast and reliable technologies are increasingly becoming more important as a reaction to the climate change

Economical

- Cost and time efficient
- Reduction in flood-related financial losses

Social

- Reduction in casualties
- Enables remote data collection in inaccessible areas

Political

- Faster and more informed decision-making

Thank you for your attention.

The model code can be found at

https://github.com/der-knight/IGARSS2024_summer_school

Sources

- https://www.mdpi.com/2624-6511/4/3/65
- https://onlinelibrary.wiley.com/doi/10.1155/2022/6155300
- https://ieeexplore.ieee.org/document/8517946