WIND FIELD ESTIMATION FROM SENTINEL-1 IMAGES USING DEEP LEARNING

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PROJECT OVERVIEW

Understand The Problem

How To Solve The Problem

Conclusion

Understand the problem: The Five W's

What

When

Wher
e

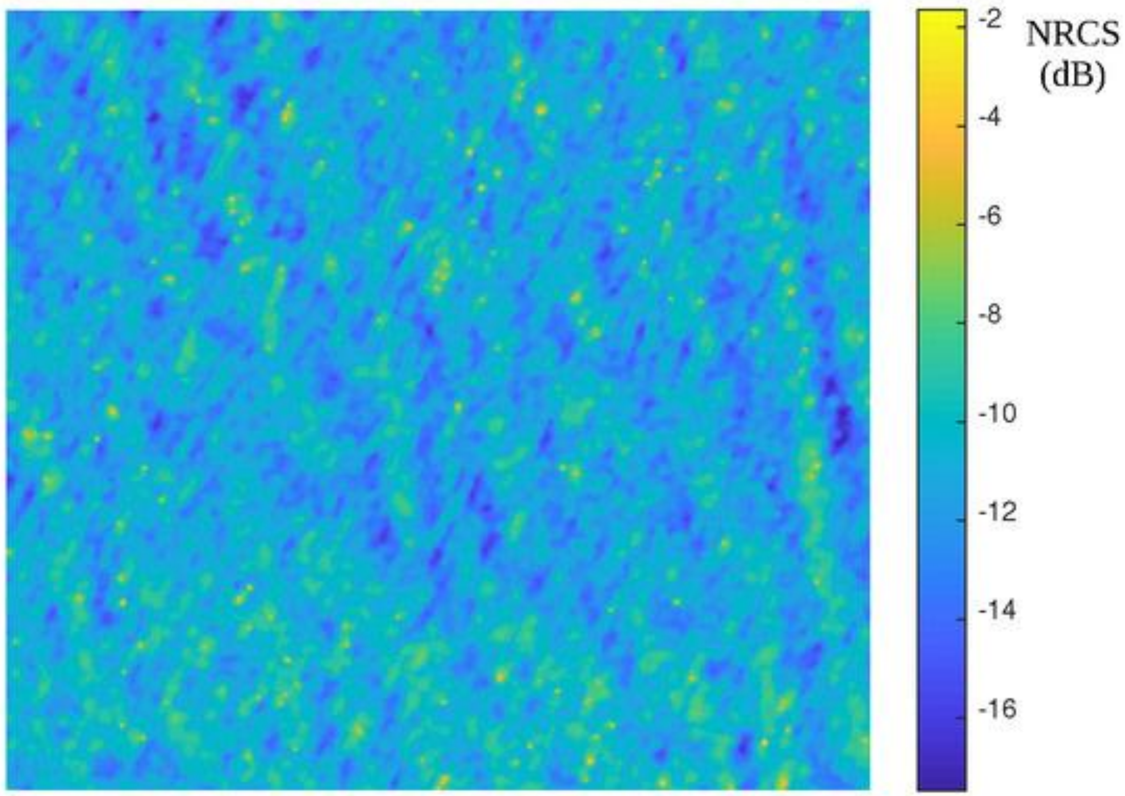
Who

Why

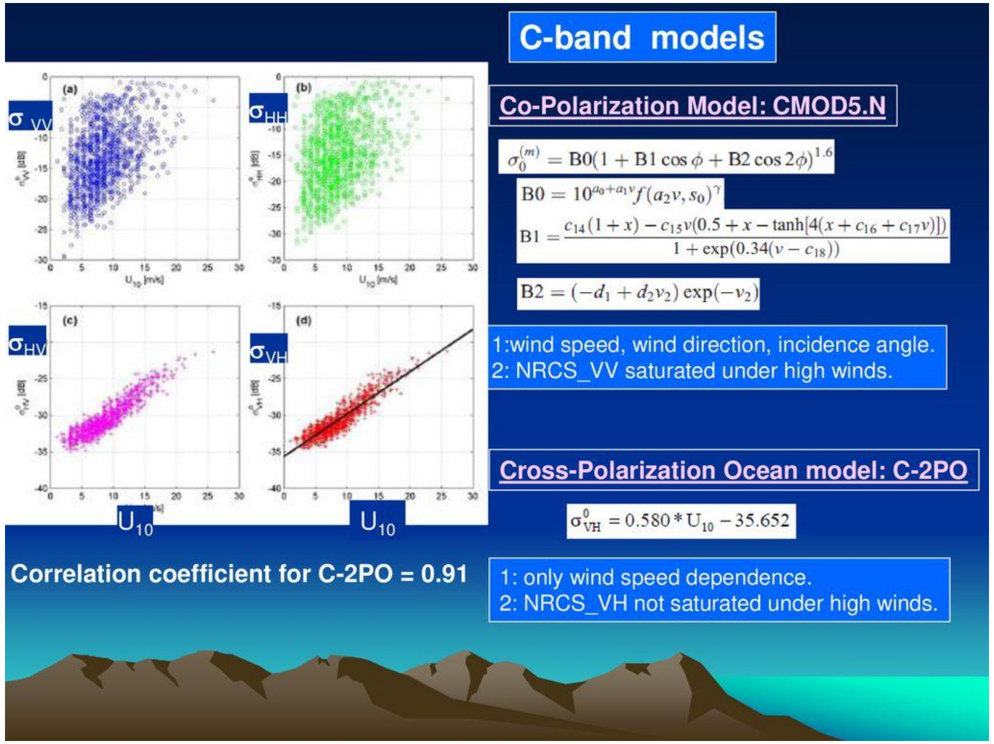
I-What?

- ❑ What is the project about?

- Traditional methods for wind field estimation using SAR images rely on handcrafted features and are often limited by the complexity and noise of the images. This project addresses the problem of wind field estimation using Sentinel-1 SAR images by proposing a deep learning-based approach that can automatically learn and extract complex features from the images.



2-when?



❑ when it become a problem?

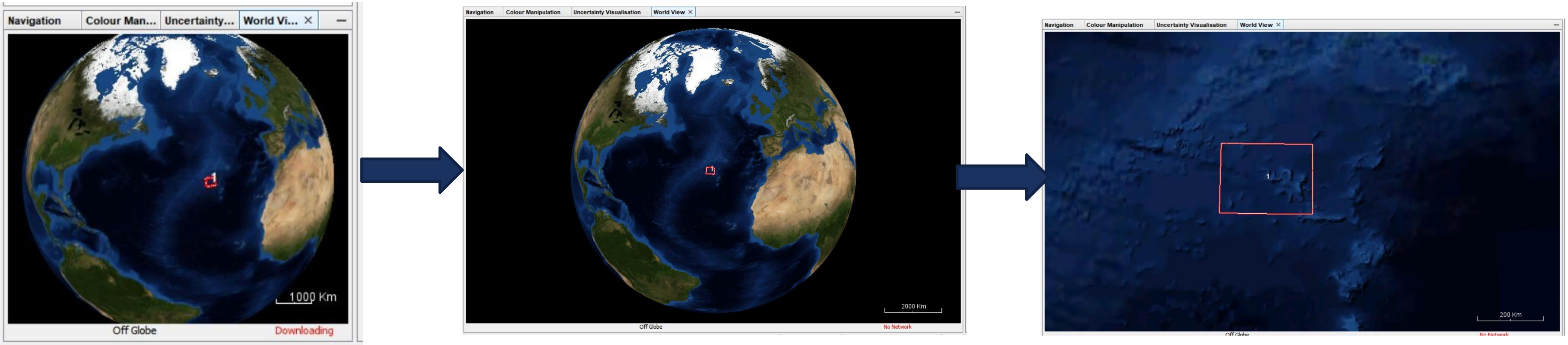
- Wind field estimation from Sentinel-1 images may encounter challenges when limitations arise in the estimation process, such as the prolonged time required for calculating wind speed and direction using the CMOD5.n algorithm.
- The use of this algorithm for wind field estimation can lead to increased computational complexity, resulting in longer processing times and slower data analysis.
- These challenges can affect the efficiency and accuracy of wind field estimation, which can impact the reliability of the results. As a result, alternative methods and algorithms may need to be explored to improve the speed and accuracy of wind field estimation from Sentinel-1 images.

3-Where?

- **Where is the project being implemented ?**

- The challenge of estimating wind speed and direction in marine environments is a pervasive issue. Our efforts to address this challenge in Egypt were impeded by the need for extensive water bodies to generate the necessary data. Consequently, we determined that an oceanic setting was a more suitable and convenient environment for our research purposes.

Location of the chosen Sentinel-1 Data



4-Who?

Who is involved in the project ?

Mohamed Fahmy

Mohamed Shaban

Ahmed Abdelaziz

Emad ali

Hassan Salah

Hassan Gommaa aa

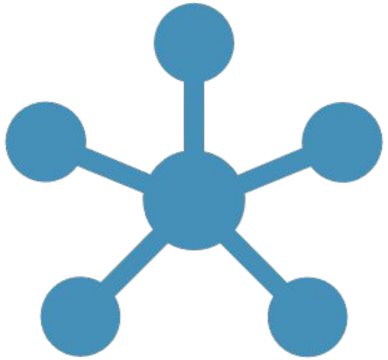
IN COLLABORATION WITH THE NATIONAL AUTHORITY FOR REMOTE SENSING AND SPACE SCIENCES (NARSS),

THE PROJECT IS BEING SUPERVISED BY DR. SALWA.

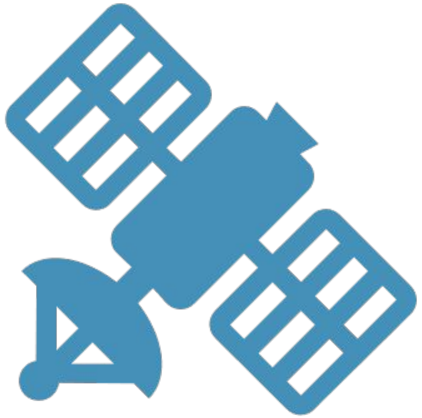
5-why?

- why to solve with Deep Learning?

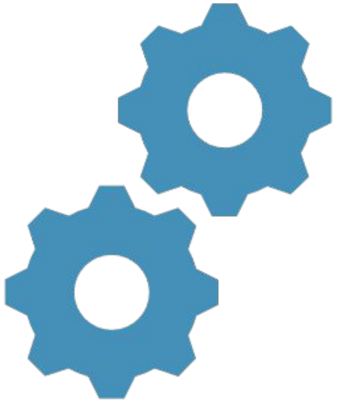
  - The application of deep learning for wind field estimation from Sentinel-1 images has gained attention due to its ability to capture complex patterns and relationships in the data.
  - Traditional methods for wind field estimation using SAR data typically rely on empirical or physical models that may not fully capture the complexity of the data, and can be limited by prior assumptions and parameterizations.
  - In contrast, deep learning models can autonomously learn the underlying patterns and relationships in the data, enabling more accurate and flexible modeling of the wind field, while also improving the efficiency of the estimation process.
  - The use of deep learning for wind field estimation from Sentinel-1 images has demonstrated promising results in terms of accuracy, efficiency, and flexibility, and is emerging as a viable alternative to traditional methods.



Network



Satellite



infrastructure

TECH REQUIREMENTS FOR TRADITIONAL WIND ESTIMATION

Just a computer

REQUIREMENTS FOR DEEP LEARNING-BASED-MODEL

Related works

- Wind Direction Retrieval Using Dl: ResNet-based Approach

By : Andrea Zanchetta, Stefano Zecchetto

- What algorithm they used ?

ResNet-based neural network

- Why they used it ?

The advantage of using a ResNet-based model is its ability to handle more complex relationships in the data and learn detailed features

- Why we can not use it ?

They can be computationally expensive and require significant computing resources for effective training.

- What it the results ?

the comparisons with ECMWF and scatterometer data indicated that the ResNet-based neural network model was effective for wind direction retrieval from scatterometer data, particularly in regions with complex wind patterns and high variability.

Related works

- A novel forecasting model for wind speed assessment using sentinel family satellites images and machine learning method

By: M. Majidi Nezhad , A. Heydari , E. Pirshayan , D. Groppi , D. Astiaso Garcia

- What algorithm they used ?

The hybrid model combines the generalized regression neural network (GRNN) and the whale optimization algorithm (WOA).

- Why they used it ?

The model takes into account parameters such as wind speed, water depth, and distance to the shoreline to assess the wind energy, the hybrid model include its ability to handle noisy data and its computational efficiency. The GRNN's radial basis function enables it to approximate the relationship between input and output variables even in the presence of noise.

- Why we can not use it ?

Data Requirement: The model needs a significant volume of high-quality data to be trained properly. Acquiring this data, especially when depending on remote sensing data, can be a challenging and resource-intensive task.

Parameter Tuning: The whale optimization algorithm (WOA) incorporated in the model requires precise parameter tuning to perform optimally. This can consume a lot of time and computational resources, which could be problematic for real-time applications or situations with resource limitations.

- What it the results ?

The paper emphasizes the ability of Sentinel-1 and Sentinel-2 satellite images to provide reliable data for near and offshore wind speed assessment and bathymetry detection.

How ?

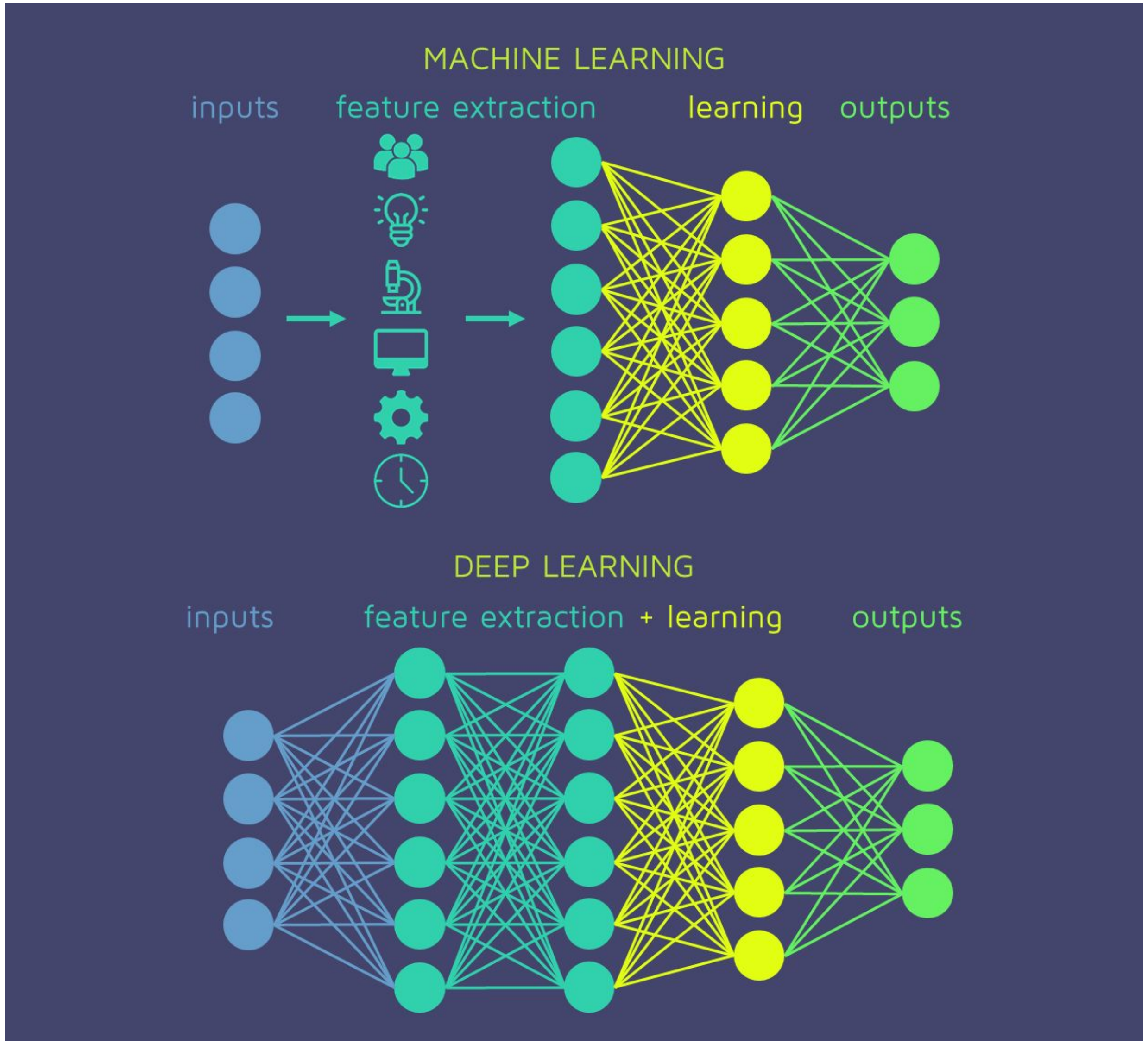
ML vs DL: Understanding the Differences and Applications

❑ applications of ML

- ML algorithms can be used for image classification, land cover mapping, and feature extraction from remote sensing data.
- ML models can be applied to wind estimation using traditional features extracted from remote sensing data, such as meteorological variables.

❑ applications of DL

- DL enables more accurate and automated feature extraction, allowing for improved classification and segmentation of remote sensing images.
- DL models, such as Convolutional Neural Networks (CNNs), can directly learn from raw remote sensing data for wind estimation, capturing complex patterns and spatial dependencies.


MACHINE LEARNING
inputs
feature extraction
learning
outputs
DEEP LEARNING
inputs
feature extraction + learning
outputs

So it’s deep learning !

1. **Improved Accuracy**: DL outperforms traditional models with superior pattern recognition, enabling precise analysis and better predictions.
2. **Scalability**: DL efficiently manages high-dimensional datasets, allowing for rapid expansion and accommodating large data volumes.
3. **Complexity Management**: DL thrives on processing complex, multi-sensor data, offering a sophisticated approach to environmental modeling.

STEPS TO BUILD A DEEP LEARNING MODELS

Problem Definition

Data Collection

Data Preprocessing

Model Selection

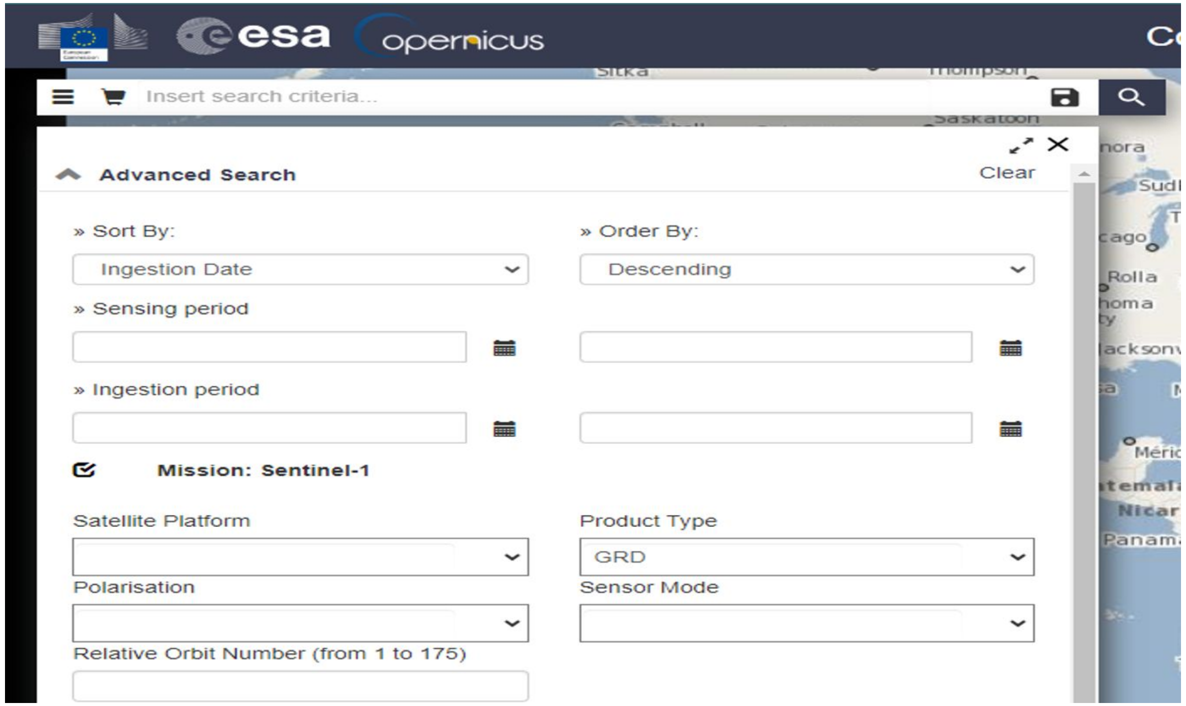
Model Building

Model Training

Our Dataset

- You can obtain Sentinel-1 data from the European Space Agency (**ESA**) Sentinel Scientific Data Hub

Link: https://scihub.copernicus.eu/dhus/#/home



preprocessing the data

- **A lot of code and GIS study !**
  - Apply orbit file
  - S-1 Thermal Noise Removal
  - Radiometric calibration
  - Terrain Correction
  - Speckle Filtering

Get the processed data ready to DL

- **A lot of code again !**
  - Matching CSV File and Image Filenames
  - Point Verification within Image
  - Image EXIF Metadata Extraction
  - Image Grouping for Efficient Data Management

Finally we have a complete dataset!

	A	B	C	D	E	F	G	H	I
1	imageFilename	WindField	geometry_x	geometry_y	speed	direction	dx	dy	ratio
2	wind_field_estimation_Orb_tnr_spk_TC_images.2425.tif	wind_0	-29.82981486	34.99740858	18.5	-11.712	-20.3	97.92	0.76
3	wind_field_estimation_Orb_tnr_spk_TC_images.2560.tif	wind_1	-29.83616272	34.97038405	9.2	-11.198	-19.42	98.1	0.72
4	wind_field_estimation_Orb_tnr_spk_TC_images.2002.tif	wind_10	-30.24979298	35.06253189	9.1	-19.335	-33.11	94.36	0.8
5	wind_field_estimation_Orb_tnr_spk_TC_images.1145.tif	wind_100	-31.32468278	35.19428689	17	-13.309	-23.02	97.31	0.68
6	wind_field_estimation_Orb_tnr_spk_TC_images.1907.tif	wind_1000	-32.41987317	35.06930431	14.3	-16.851	-28.99	95.71	0.8
7	wind_field_estimation_Orb_tnr_spk_TC_images.1906.tif	wind_1001	-32.45231148	35.07368716	9.3	-26.416	-44.49	89.56	0.78
8	wind_field_estimation_Orb_tnr_spk_TC_images.1776.tif	wind_1002	-32.34945684	35.0874732	9	-19.718	-33.74	94.14	0.76
9	wind_field_estimation_Orb_tnr_spk_TC_images.1774.tif	wind_1003	-32.38191393	35.09188596	11.9	-15.527	-26.77	96.35	0.72
10	wind_field_estimation_Orb_tnr_spk_TC_images.1910.tif	wind_1004	-32.35498045	35.06047702	17.2	-11.958	-20.72	97.83	0.73
11	wind_field_estimation_Orb_tnr_spk_TC_images.1909.tif	wind_1005	-32.38742682	35.06489067	15.2	-16.271	-28.02	96	0.84
12	wind_field_estimation_Orb_tnr_spk_TC_images.4312.tif	wind_1006	-29.9059036	34.67310336	17.2	-10.032	-17.42	98.47	0.6
13	wind_field_estimation_Orb_tnr_spk_TC_images.4447.tif	wind_1007	-29.91222677	34.6460757	12.3	-17.775	-30.53	95.23	0.78
14	wind_field_estimation_Orb_tnr_spk_TC_images.1633.tif	wind_1008	-32.51171381	35.10942601	13.8	-16.362	-28.17	95.95	0.78
15	wind_field_estimation_Orb_tnr_spk_TC_images.1768.tif	wind_1009	-32.51718319	35.08243385	16.6	-14.874	-25.67	96.65	0.74
16	wind_field_estimation_Orb_tnr_spk_TC_images.1144.tif	wind_101	-31.35713101	35.19895249	12.6	-7.909	-13.76	99.05	0.67
17	wind_field_estimation_Orb_tnr_spk_TC_images.4450.tif	wind_1010	-29.84159841	34.66296585	0.1	0	0	0	0
18	wind_field_estimation_Orb_tnr_spk_TC_images.4313.tif	wind_1011	-29.873751	34.66803461	12.1	-18.397	-31.56	94.89	0.87
19	wind_field_estimation_Orb_tnr_spk_TC_images.4584.tif	wind_1012	-29.84794245	34.6359379	0.1	0	0	0	0
20	wind_field_estimation_Orb_tnr_spk_TC_images.4448.tif	wind_1013	-29.8800846	34.6410068	7.3	-9.921	-17.23	98.51	0.67
21	wind_field_estimation_Orb_tnr_spk_TC_images.4170.tif	wind_1014	-30.06672102	34.69833322	19.9	-19.749	-33.79	94.12	0.77
22	wind_field_estimation_Orb_tnr_spk_TC_images.4305.tif	wind_1015	-30.07299186	34.67130581	11.4	-10.283	-17.85	98.39	0.66
23	wind_field_estimation_Orb_tnr_spk_TC_images.4310.tif	wind_1016	-29.93805619	34.67817211	14.5	-10.463	-18.16	98.34	0.82
24	wind_field_estimation_Orb_tnr_spk_TC_images.4309.tif	wind_1017	-29.97021294	34.68323213	13.9	-14.206	-24.54	96.94	0.67
25	wind_field_estimation_Orb_tnr_spk_TC_images.4445.tif	wind_1018	-29.94436892	34.6511446	13.5	-12.703	-21.99	97.55	0.79
26	wind_field_estimation_Orb_tnr_spk_TC_images.4444.tif	wind_1019	-29.97651522	34.65620473	4.9	-21.531	-36.7	93.02	0.78
27	wind_field_estimation_Orb_tnr_spk_TC_images.1008.tif	wind_102	-31.38374517	35.2306295	11.6	-12.627	-21.86	97.58	0.72
28	wind_field_estimation_Orb_tnr_spk_TC_images.4173.tif	wind_1020	-30.00238229	34.68826583	8.6	-20.561	-35.12	93.63	0.78
29	wind_field_estimation_Orb_tnr_spk_TC_images.4171.tif	wind_1021	-30.03455166	34.69329952	11.6	-26.078	-43.96	89.82	0.7
30	wind_field_estimation_Orb_tnr_spk_TC_images.4442.tif	wind_1022	-30.00867409	34.66123842	13.6	-18.029	-30.95	95.09	0.77

updated_wind_field_estimation_O

Let’s build a solution !

Dr. Salwa suggest that we try RNN or LSTM so we did !

hybrid LSTM

hybrid LSTM

- This model architecture is chosen because:
  1. LSTM layers: They are well-suited for capturing temporal dependencies in sequential data, making them suitable for wind field estimation tasks where time plays a crucial role.
  2. Reshape layer: It transforms the input shape to match the requirements of the LSTM layers, allowing the model to process the SAR image data effectively.
  3. Dense layers: They introduce non-linear transformations and learn complex patterns from the LSTM outputs, enabling the model to capture intricate relationships between the input features.

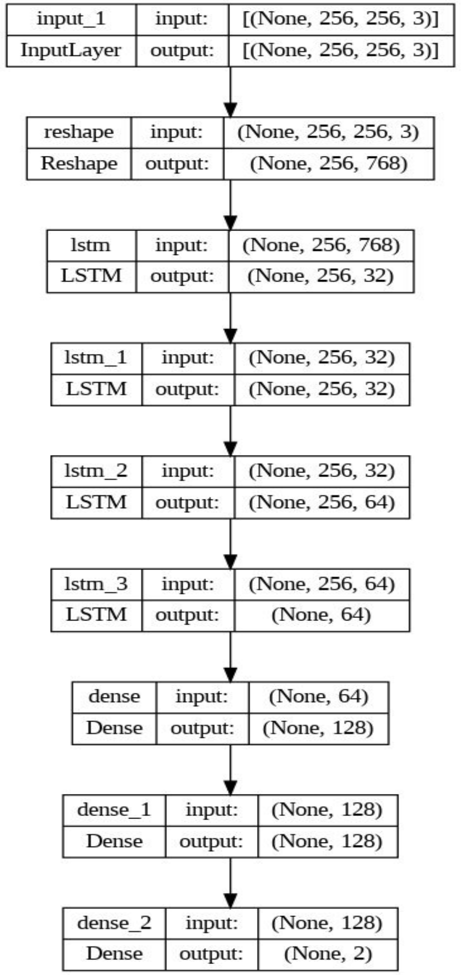
Hypered LSTM : actual and predicted wind speed

```
# Compile the model
model.compile(optimizer='adam', loss='mse',metrics='accuracy')
history = model.fit(
    train_images,
    validation_data=val_images,
    epochs=100,
    callbacks=[
        tf.keras.callbacks.EarlyStopping(
            monitor='val_loss',
            patience=10,
            restore_best_weights=True
        )
    ]
)
```

accuracy	Val loss
98%	12.7734

record	Actual	Predicted
1	15.3	20
2	12.6	17.78
3	15.8	30.9
4	12.19	7.3
5	8.0	14.9
6	14.3	16.28

hybrid LSTM structure




```python
inputs = tf.keras.Input(shape=( 256, 256, 3))

# Convert the input shape from (batch_size, 120, 120, 3) to (batch_size,
sequence_length, input_dim)
x = tf.keras.layers.Reshape(target_shape=( 256, 256*3))(inputs)

# Replace the Conv2D and MaxPool2D layers with recurrent layers
x = tf.keras.layers.LSTM(units= 32, return_sequences=True, activation='tanh')(x)
x = tf.keras.layers.LSTM(units= 32, return_sequences=True, activation='tanh')(x)

x = tf.keras.layers.LSTM(units= 64, return_sequences=True, activation='tanh')(x)
x = tf.keras.layers.LSTM(units= 64, return_sequences=False, activation='tanh')(x)

x = tf.keras.layers.Dense( 128, activation='tanh')(x)
x = tf.keras.layers.Dense( 128, activation='tanh')(x)

outputs = tf.keras.layers.Dense( 2, activation='linear')(x)

model = tf.keras.Model(inputs=inputs, outputs=outputs)
# Compile the model
model.compile(optimizer='adam', loss='mse',metrics='accuracy')
```

Overfit of : hybrid LSTM

- Possible reasons for model overfitting:
  1. Limited dataset: Insufficient data to capture the full range of patterns.
  2. Model complexity: Large number of parameters or layers leading to overfitting.
  3. Lack of regularization: Absence of techniques like dropout or weight decay.
  4. Training duration: Model trained for too long, fitting noise instead of patterns.
- Strategies to address overfitting:
  1. Increase dataset size or use data augmentation.
  2. Simplify model architecture to reduce complexity.
  3. Apply regularization techniques.
  4. Monitor training progress and use early stopping.
  5. Consider ensemble learning or transfer learning.

How to improve LSTM

- Ensure a representative and diverse dataset covering various wind conditions and geographic regions.
- Implement more sophisticated model optimization techniques and hyperparameter tuning.
- Evaluate the model's performance using additional metrics relevant to wind field estimation, such as root mean square error (RMSE) or mean absolute error (MAE).
- integrate visualization techniques to interpret and analyze the model's predictions.

FNN

Strengths, Limitations, and Suitability of FNNs

Strengths:

- Less computationally intensive compared to CNNs.
- Simplicity makes it easier to train and interpret.

Limitations:

- Struggle with complex patterns and high-dimensional data.
- Lack spatial recognition, crucial for image-based tasks.

Suitability for Project:

- Used as a baseline model due to its simplicity and ability to handle regression tasks.
- The model can also provide a reference point for the comparative performance of more complex models.

Feedforward Neural Networks (FNNs)

This architecture is chosen because:

- **Dense layers**: They allow every neuron in a layer to be connected to every neuron in the next layer, enabling the network to learn complex patterns in the input data.
- **ReLU activation:** It is a common choice for hidden layers due to its simplicity and efficacy in mitigating the vanishing gradient problem.
- **Dropout layers:** They help in preventing overfitting by randomly ignoring some neurons during training, thus forcing the data to spread across all neurons and making the model more robust.
- **Batch normalization:** It accelerates training, provides some regularization and noise robustness, and reduces the sensitivity to the initial weights.
- Linear activation function in the output layer: It is ideal for regression tasks where the output is a single continuous value.

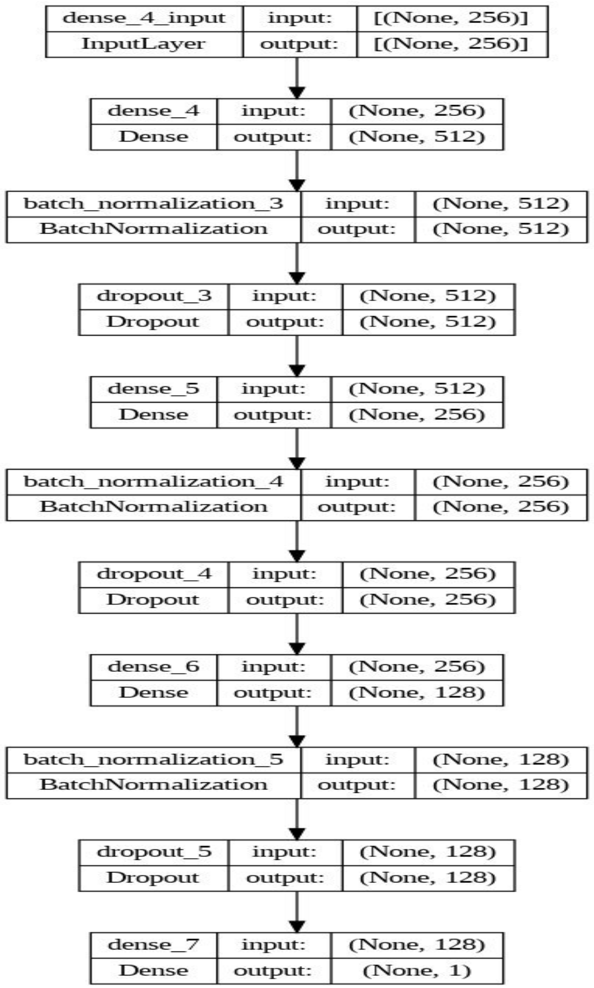
Advantages:

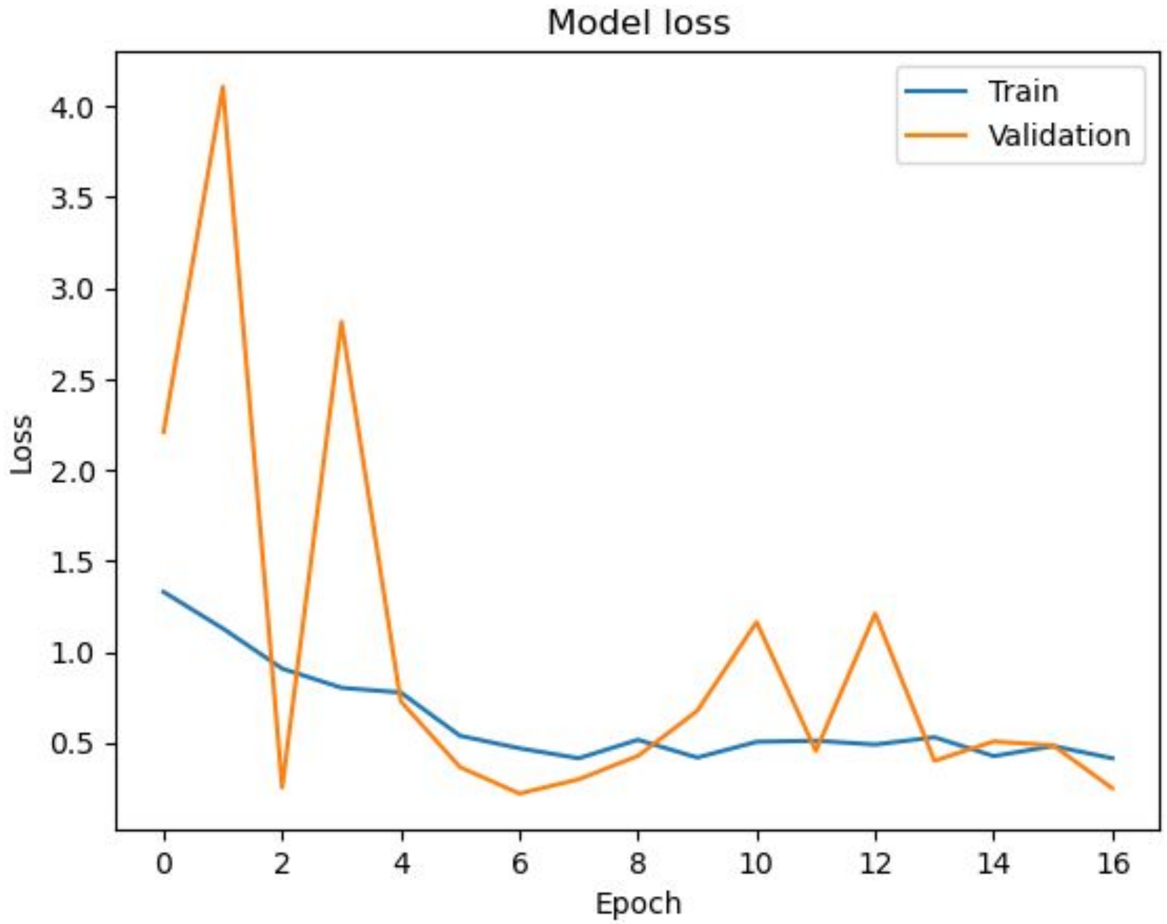
- Easier to implement, interpret, and train compared to CNNs.

Disadvantages:

- May struggle with complex image data, not inherently designed for spatial data.

FNN Architecture





FNN : actual and predicted wind speed

MSE	MAE
0.0910	0.2494

record	Actual	Predicted
1	15.3	12.82
2	12.6	12.78
3	15.8	12.91
4	12.19	14.18
5	9.0	12.96
6	14.3	13.28

CNN

Strengths, Limitations, and Suitability of CNNs

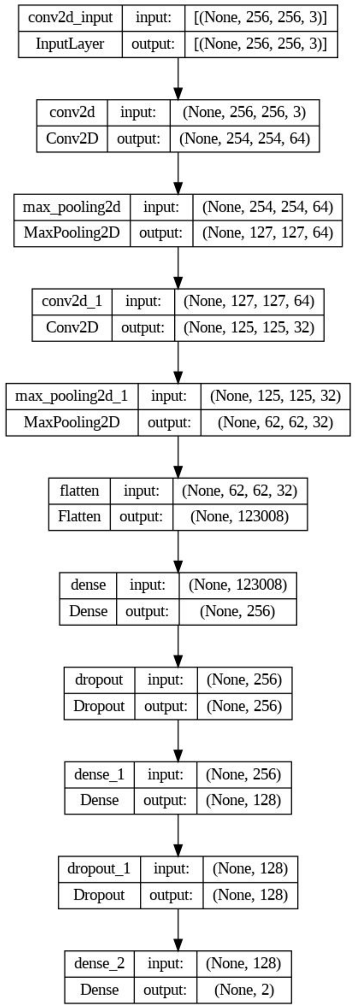
- Strengths:
  - Ability to automatically and adaptively learn spatial hierarchies of features, ideal for processing Sentinel-1 images.
  - Robust to minor variations in the images, such as shifts, rotations, and other distortions.
- Limitations:
  - High computational intensity, especially for large datasets.
  - Requires a large amount of labeled data for effective training.
- Suitability for Project:
  - Ideal for image data due to their unique property of keeping spatial information intact.
  - Especially useful for our Sentinel-1 images as they capture intricate spatial wind patterns.

Convolutional Neural Networks (CNNs)

- The choice of this specific architecture serves the purpose of the task effectively. It strikes a balance between complexity (to capture intricate patterns in the data) and simplicity (to prevent overfitting). The use of dropout layers, the ReLU activation function, and a linear output activation function complements the regression task and assists in achieving good predictive performance.

- **Advantages:**
  - Ability to extract hierarchical features from images, tolerance to minor changes in the image.
- **Disadvantages:**
  - May require large amounts of data, complex model interpretability, requires careful hyperparameter tuning.

CNN Architecture



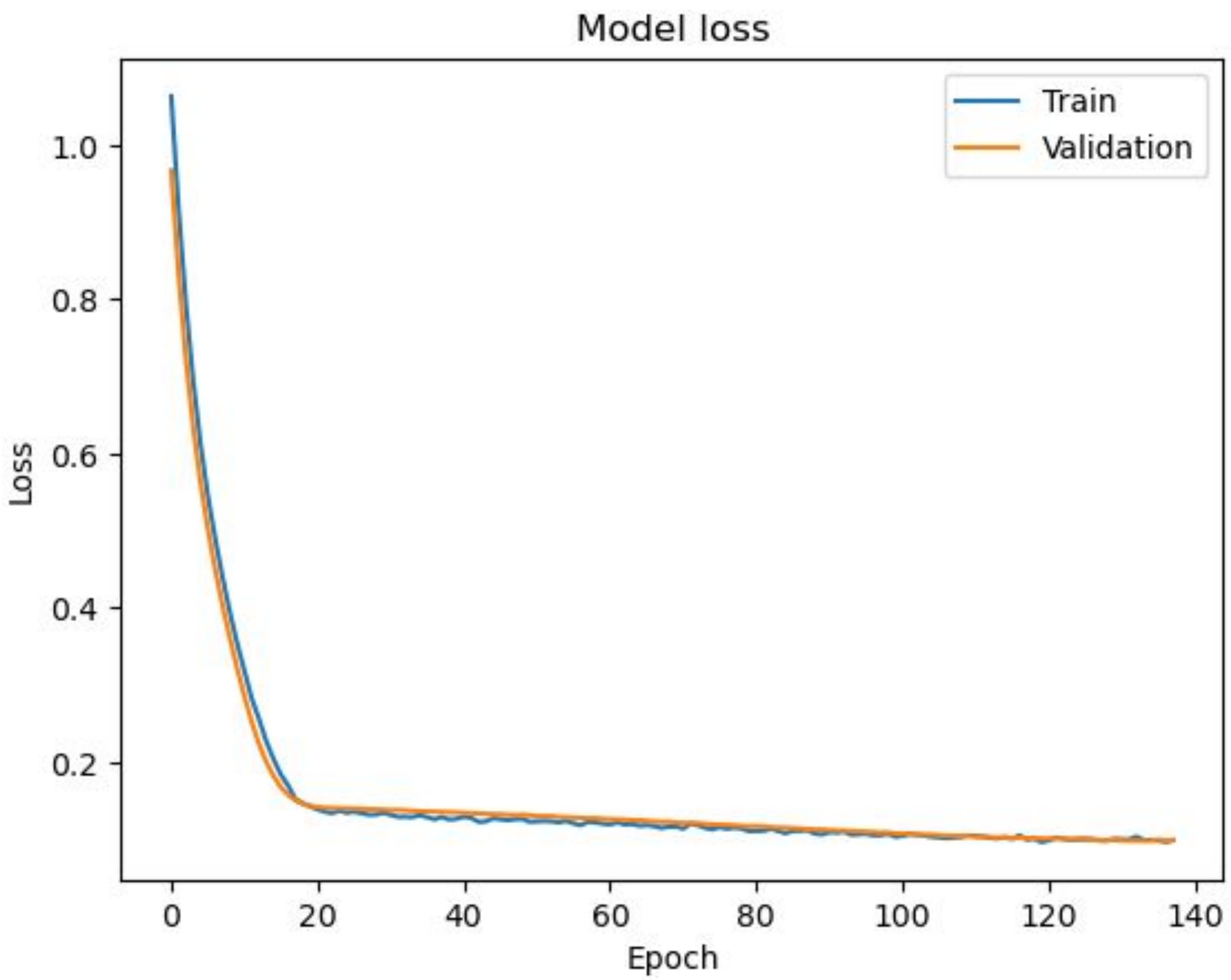
- The first layer is a Conv2D layer with 64 filters of size 3x3 and a ReLU activation function. The input shape of each image is defined by the input_shape variable.
- The second layer is a MaxPooling2D layer with a pool size of 2x2.
- The third layer is another Conv2D layer with 32 filters of size 3x3 and a ReLU activation function.
- The fourth layer is another MaxPooling2D layer with a pool size of 2x2.
- The fifth layer is a Flatten layer that flattens the output of the previous layer into a 1D array.
- The sixth layer is a Dense layer with 256 units and a ReLU activation function. A regularization term is added to the weights to prevent overfitting.
- The seventh layer is a Dropout layer that randomly drops out 25% of the units to prevent overfitting.
- The eighth layer is another Dense layer with 128 units and a ReLU activation function.
- The ninth layer is another Dropout layer that randomly drops out 25% of the units to prevent overfitting.
- The tenth and final layer is a Dense layer with 2 units and a linear activation function, which outputs the predicted class probabilities for the input image.

CNN : actual and predicted wind speed

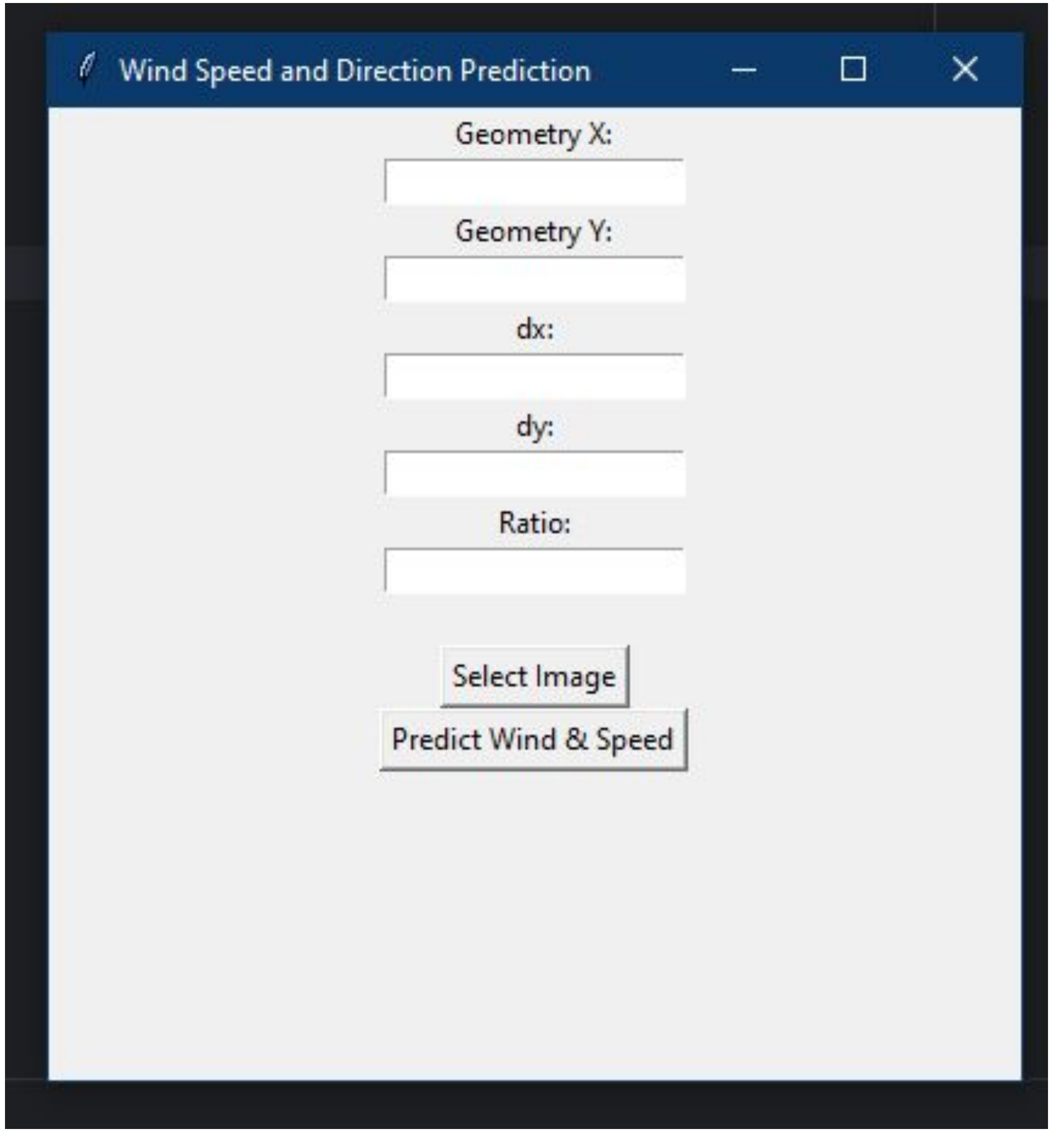
Accuracy	MAE	MSE
91.3%	0.104	0.026

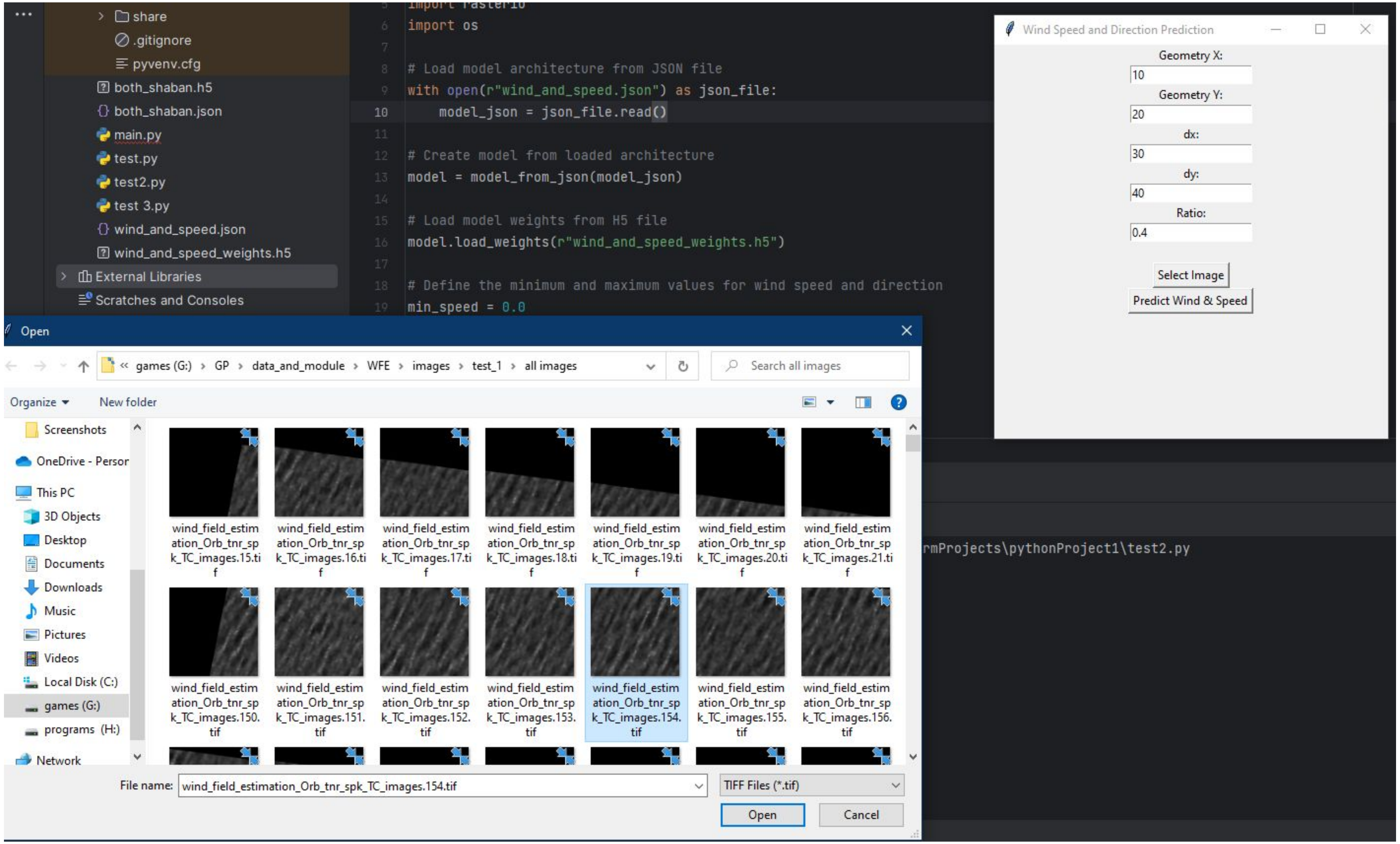
record	Actual	Predicted
1	10.7	12.01
2	16.7	14.4
3	15.8	12.91
4	15.2	14.23
5	10.9	11.93
6	179.59	161.2

Train and validation loss curve



Final Product


Wind Speed and Direction Prediction
Geometry X:
Geometry Y:
dx:
dy:
Ratio:
Select Image
Predict Wind & Speed


share
.gitignore
pyvenv.cfg
both_shaban.h5
both_shaban.json
main.py
test.py
test2.py
test 3.py
wind_and_speed.json
wind_and_speed_weights.h5
External Libraries
Scratches and Consoles
import os
# Load model architecture from JSON file
with open(r"wind_and_speed.json") as json_file:
model_json = json_file.read()
# Create model from loaded architecture
model = model_from_json(model_json)
# Load model weights from H5 file
model.load_weights(r"wind_and_speed_weights.h5")
# Define the minimum and maximum values for wind speed and direction
min_speed = 0.0
Wind Speed and Direction Prediction
Geometry X:
10
Geometry Y:
20
dx:
30
dy:
40
Ratio:
0.4
Select Image
Predict Wind & Speed
Open
games (G:) › GP › data_and_module › WFE › images › test_1 › all images
Search all images
Organize
New folder
Screenshots
OneDrive - Persor
This PC
3D Objects
Desktop
Documents
Downloads
Music
Pictures
Videos
Local Disk (C:)
games (G:)
programs (H:)
Network
wind_field_estimation_Orb_tnr_spk_TC_images.15.tif
wind_field_estimation_Orb_tnr_spk_TC_images.16.tif
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wind_field_estimation_Orb_tnr_spk_TC_images.18.tif
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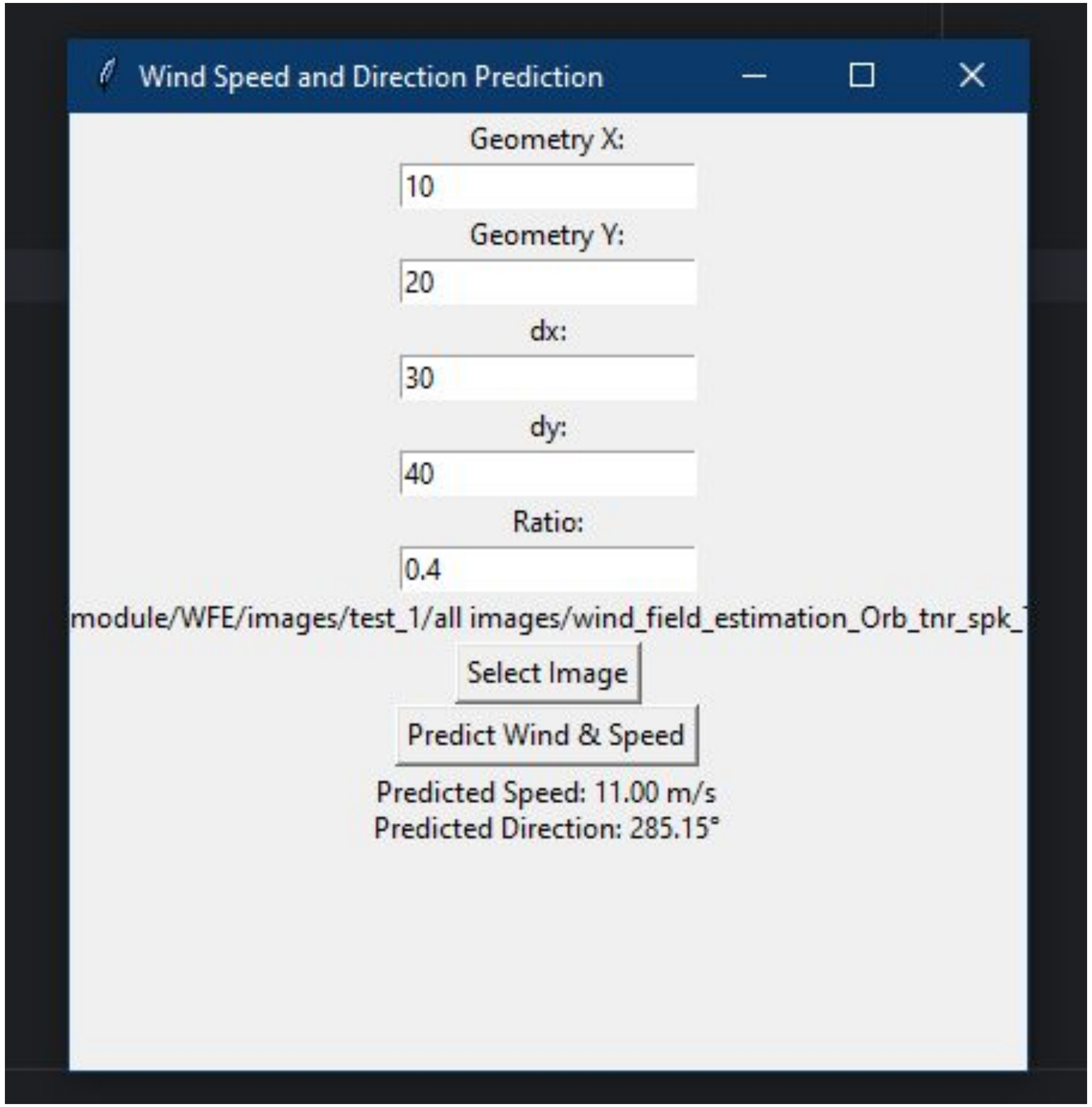
wind_field_estimation_Orb_tnr_spk_TC_images.21.tif
wind_field_estimation_Orb_tnr_spk_TC_images.150.tif
wind_field_estimation_Orb_tnr_spk_TC_images.151.tif
wind_field_estimation_Orb_tnr_spk_TC_images.152.tif
wind_field_estimation_Orb_tnr_spk_TC_images.153.tif
wind_field_estimation_Orb_tnr_spk_TC_images.154.tif
wind_field_estimation_Orb_tnr_spk_TC_images.155.tif
wind_field_estimation_Orb_tnr_spk_TC_images.156.tif
rmProjects\pythonProject1\test2.py
File name:
wind_field_estimation_Orb_tnr_spk_TC_images.154.tif
TIFF Files (*.tif)
Open
Cancel


Wind Speed and Direction Prediction
Geometry X:
10
Geometry Y:
20
dx:
30
dy:
40
Ratio:
0.4
module/WFE/images/test_1/all images/wind_field_estimation_Orb_tnr_spk_
Select Image
Predict Wind & Speed
Predicted Speed: 11.00 m/s
Predicted Direction: 285.15°

Conclusion

CONCLUSION

- ❑ Project Highlights
- ❑ Impact of our project in Wind Estimation
- ❑ Future of deep-learning-based Wind Estimation

Unleashing the Power of DL: Project Highlights

- Our application of Deep Learning (DL) techniques, such as Convolutional Neural Networks (CNN) and Feedforward Neural Networks (FNN), resulted in a robust wind estimation model using Sentinel-1 images.
- Comparative studies revealed that Sentinel-1 SAR data offers higher accuracy than other wind estimation methods.
- Our model effectively handled the complexities of Sentinel-1 images, overcoming key limitations in image-based wind speed prediction.
- We developed advanced pre-processing techniques for effective image analysis, optimizing DL hyperparameters for improved performance.

Transforming Wind Estimation: Impact & Lessons

- Our project has the potential to revolutionize the field of wind estimation, contributing to various sectors such as meteorology, renewable energy, and marine navigation.
- The research opened new avenues in the use of Sentinel-1 SAR data, unlocking its potential for interpretable wind field estimation.
- Throughout this project, we learned the importance of choosing the right DL technique and how to effectively handle and preprocess complex data for DL-based image analysis.

Charting the Future: Next Steps in Wind Estimation

- Future research will focus on refining the DL model, improving its performance and accuracy, and addressing remaining challenges in image-based wind speed prediction.
- Further exploration of other DL techniques and algorithms may lead to more sophisticated and efficient models.
- As technology advances, there are opportunities for more extensive and diverse applications of Sentinel-1 data in the field of wind estimation.

THANK YOU

Any questions ?