Project 1 – Denoising a video sequence.

The presence of noise in videos affects subsequent image processing phases, such as three-dimensional reconstruction, registration, classification of objects, motion segmentation and analysis, tracking, identification and recognition of humans. Thus, denoising is an extremely important pre-processing phase that is used to improve the perceptual appearance of images; however, a trade-off between noise reduction and data preservation is important to enhance the characteristics of images that are relevant for high level algorithms

1) Implement the robust bilateral and temporal filter (RBLT) for denoising a video sequence. Spatial and temporal components are incorporated into the filter formulation, which increases the filter's ability to remove strong noise components. Consider the Geman-Mcclure or the Charbonnier as error norms for M-Estimators.

2) Consider the following evaluation metrics to assess the quality of your implementation:

- SIIM
- PNSR

The original image (distortion-free or reference), must be compared to the distorted image, using these two evaluation metrics. The distorted image is obtained by corrupting the original image with a distinct noise configuration (<u>Salt-Pepper</u> and <u>Gaussian Noise</u>) and then, the image sample is filtered by each filter, individually. The level of noise that should be added to each original image is 20 to 40 of standard deviation for Gaussian noise and 10 to 30% for the Salt-Pepper noise. Results must be provided graphically.

3) Discuss the results by taking into consideration the median and Gaussian filter. You can also consider the following paper: *Andry et al. (2013), Enhancing dynamic videos for surveillance and robotic applications: The robust bilateral and temporal filter, Signal Processing: Image Communication, Elsevier, 2014.*

4) Consider the image sequences for this project and estimate the optical flow using these two techniques. Produce two videos per image sequence showing the magnitude and orientation of the flow using the color scheme presented in the lectures. Discuss the results obtained.

Image sequences for this project:

- *mlky_6*
- *210329_06A_Bali_4k_004*
- *Saint_Barthelemy_2*

Project 2 – Captcha decoding.

A CAPTCHA (Completely Automated Public Touring test to Tell Computers and Humans Apart) is a commonly used feature in web applications to block non-human access. CAPTCHAs' purpose is to prevent spam on websites, such as promotion spam, registration spam, and data scraping, and bots are less likely to abuse websites with spamming if those websites use CAPTCHA. Many websites use CAPTCHA to prevent bot raiding, and it works effectively. CAPTCHA's design is that humans can complete CAPTCHAs, while most robots can't.

1) This project aims to develop a CNN with ability to decode CAPTCHA images considering 4 and 5 encoders. The model of the CNN needs to be designed, implemented and trained (no fine tuning approaches should be applied);

2) Consider the following metrics:
    a. Train and test accuracy;
    b. Confusion matrix;
    c. Others evaluation methodologies (e.g., confusion matrix, histograms).

3) Discuss the result of your approach, in particular, limitations;

4) Consider the CAPTCHA dataset provided which has 4 to 5 digits.
    a. Soft dataset is formed by CAPTCHAs that are more simple. Students <u>must</u> start the project with this dataset.
    b. Hard dataset is formed by CAPTCHAs with strange elements added, to make the identification more difficult to predict.

Project 3 – Thermal inspection (classifying the defects) of photovoltaic modules.

Thermal inspection of photovoltaic (PV) modules is a non-invasive technique used to assess the health and performance of solar panels. By capturing and analyzing the heat signatures emitted by PV modules, thermal inspections can detect anomalies such as hotspots, dust accumulation, or damaged cells. Hotspots, in particular, can indicate potential issues like cell degradation or electrical faults. This proactive approach to maintenance allows for the early identification of problems, reducing downtime and maximizing the overall efficiency and lifespan of solar installations. Thermal inspection plays a crucial role in ensuring the reliability and energy yield of PV systems, making it an essential tool in the field of solar energy management and maintenance.

1) Develop an AI-model that classifies the status of the PV module using thermal signatures. Consider the following 12 classes:

Class Name	Images	Description
Cell	1,877	Hot spot occurring with square geometry in single cell.
Cell-Multi	1,288	Hot spots occurring with square geometry in multiple cells.
Cracking	941	Module anomaly caused by cracking on module surface.
Hot-Spot	251	Hot spot on a thin film module.
Hot-Spot-Multi	247	Multiple hot spots on a thin film module.
Shadowing	1056	Sunlight obstructed by vegetation, man-made structures, or adjacent rows.
Diode	1,499	Activated bypass diode, typically 1/3 of module.
Diode-Multi	175	Multiple activated bypass diodes, typically affecting 2/3 of module.
Vegetation	1,639	Panels blocked by vegetation.
Soiling	205	Dirt, dust, or other debris on surface of module.
Offline-Module	828	Entire module is heated.
No-Anomaly	10,000	Nominal solar module.

Dataset: https://github.com/RaptorMaps/InfraredSolarModules

2) Describe data augmentation techniques that were used.
3) Compare the results of your AI-model with at least 2 existing models (e.g., ResNet, VGG, or other). These last models should be refined. Use the following metrics to assess the quality of your implementation:

- Accuracy (%) and F1-Score(%) of training and testing
- Confusion matrix
- AUC (%)
- Model complexity (# parameters).

4) Discuss the results, taking into consideration the following paper: *https://doi.org/10.1016/j.measurement.2023.113135*

Project 4 – Power loss estimation for photovoltaic modules.

Solar photovoltaic (PV) modules are integral to renewable energy systems, but their efficiency can be significantly compromised by environmental factors, particularly the accumulation of dust, dirt, or other forms of soiling on their surfaces. Accurately estimating power losses in PV modules due to soiling is essential for several reasons. Firstly, it allows solar plant operators and maintenance teams to proactively assess the impact of soiling on energy production. By quantifying the extent of power loss, they can plan and prioritize cleaning and maintenance schedules to maintain optimal performance.

Consider images from the following dataset: SolarPanelSoilingImageDataset.zip - Google Drive.

1) Develop an AI-model that predicts the power loss of a PV module.
2) Describe data augmentation techniques that were used.
3) Use the following metrics to assess the quality of your implementation:
- MSE (or MAE) of training and testing
- Model complexity (# parameters).

4) Discuss the results, taking into consideration the following paper: *https://ieeexplore.ieee.org/document/8354147*
5) Develop a CV pipeline to segment automatically the soiling of PV modules. Generate a new label for each image:
    i. Percentage (0 to 1.0) of the module covered with dust, bird drop or other.
    ii. Type of soiling (can be manually specified).
    iii. Power loss (from original label)
    iv. Irradiance level (from original label)
6) Re-design your AI-model to predict the power loss, type of soiling and percentage of soiling. Use appropriate metrics (e.g., Accuracy, F1-Score, MSE, etc) during the discussion of your results.

Project 5 – Estimate defective PV cells in electroluminescence imagery

Visual identification of defective solar cells in electroluminescence (EL) imagery is a critical process in the quality control and maintenance of photovoltaic (PV) modules. Electroluminescence imaging captures images of solar cells by measuring their light emission under an applied voltage.

Consider images from the following dataset: https://github.com/zae-bayern/elpv-dataset#a-benchmark-for-visual-identification-of-defective-solar-cells-in-electroluminescence-imagery

1) Develop an AI-model that predicts the defect probability (a floating point value between 0 and 1) and the type of the solar module (either mono- or polycrystalline).
2) Describe data augmentation techniques that were used.
3) Compare the results of your AI-model with at least 2 existing models (e.g., ResNet, VGG, or other). These last models should be refined. Use the following metrics to assess the quality of your implementation:

- MSE (or MAE) of training and testing
- Accuracy and F1-score of training and testing
- AUC
- Model complexity (# parameters).

4) Discuss the results, taking into consideration the following paper: *https://www.sciencedirect.com/science/article/pii/S0038092X19302014?via%3Dihub#s0025*

Project 6 – Segmentation of defective PV cells in electroluminescence imagery

Segmentation of defective photovoltaic (PV) cells in electroluminescence imagery is a crucial step in identifying and isolating areas of the PV module that exhibit anomalies or flaws. This process involves the precise delineation of defective regions from the overall electroluminescence image.

Consider images from the following dataset:
https://www.kaggle.com/datasets/yaozhang01182010/dataset-of-solar-cells-defect-segmentation

1) Enhance an AI-model that segments the defects in EL images.
2) Describe data augmentation techniques and the specific datasets that were used.
3) Compare the results of your AI-model with at least one existing model (e.g., U-Net with different encoders, ENet or other).
4) Use appropriate metrics to assess the quality of your implementation.
5) Discuss the results, taking into consideration the following paper: https://link.springer.com/article/10.1007/s00138-021-01191-9

Project 7 – Drone inspection images of wind turbine

Drone images offer a unique aerial perspective of wind turbines, allowing for a comprehensive view of the entire structure, including the blades, nacelle, and tower. This perspective is crucial for inspecting and evaluating the overall condition of the turbine. Routine drone inspections are an integral part of wind turbine maintenance. These images help maintenance teams identify issues like blade erosion, lightning strikes, or structural damage that may require immediate attention.

Consider images from the following dataset:
https://data.mendeley.com/datasets/hd96prn3nc/2

Annotations: https://github.com/imadgohar/DTU-annotations

1) Enhance an AI-model that detects the defects of wind turbines from visual images.
2) Describe data augmentation techniques that were used.
3) Compare the results of your AI-model with at least two existing model (e.g., YOLO's family, Faster R-CNN, DETR, etc).
4) Use appropriate metrics to assess the quality of your implementation.
5) Discuss the results, taking into consideration the following paper: https://www.sciencedirect.com/science/article/pii/S2352484721005102 or Machines | Free Full-Text | Slice-Aided Defect Detection in Ultra High-Resolution Wind Turbine Blade Images (mdpi.com)

Project 8 – Open Project.

Students can develop a project in CV that is related to their MSc Thesis. Therefore, the teams should send a project proposal containing the following topics:

- Motivation
- Objectives
- Problem statement (eg, classification, regression, etc)
- Dataset