DELPHFI

DEep Learning Prediction and Hindsight of Flare Initiation

Contract - B2/202/P1/DELPHI

1. CONTEXT: THE SPACE WEATHER CHALLENGE

The Sun has a direct and profound impact on modern life and infrastructure. Solar flares—sudden releases of energy from "active regions" in the solar corona—emit radiation across the entire electromagnetic spectrum and are often associated with other eruptive phenomena such as coronal mass ejections (CMEs) and solar energetic particle (SEP) events. These events can trigger space weather disturbances that disrupt GNSS signals, satellite electronics, radio communications, terrestrial power grids and increase radiation exposure for astronauts and high-altitude aviation routes within hours of the initial eruption.

Despite decades of research, the precise physical mechanisms that lead to the buildup of magnetic energy and its sudden release via reconnection remain a long-standing problem in solar physics. Historically, flare forecasting has relied heavily on human interpretation of sunspot complexity. The **DELPHFI project** was established to transition from these empirical, human-in-the-loop methods to automated, high-precision systems leveraging **Machine Learning (ML)** and **Deep Learning (DL)**.

2. PROJECT OBJECTIVES

The DELPHFI project, a collaborative effort between the **Royal Observatory of Belgium (ROB)** and **KU Leuven**, pursued three primary strategic goals:

1. **Scientific Understanding:** To improve the fundamental understanding of flare-triggering mechanisms by utilizing "interpretable" ML techniques to identify critical physical signatures in solar data.
2. **Operational Demonstration:** To prove that automated feature extraction from high-definition satellite imagery can consistently outperform traditional human forecasts and existing automated tools.
3. **Technical Capacity Building:** To establish a robust DL expertise at the ROB, laying the groundwork for a new generation of operational space weather services and autonomous monitoring tools.

3. RESEARCH METHODOLOGY

The project utilized over a decade of high-cadence data (2010–2021) from the Solar Dynamics Observatory (SDO), focusing on magnetograms (SDO/HMI) and Extreme Ultraviolet (EUV) images (SDO/AIA). It also used the Geostationary Operational Environmental Satellites (GOES) soft X-ray data.

3.1 Prediction of active regions flaring capacity with CNNs

A core technical contribution was the comparison of two Convolutional Neural Network (CNN) approaches:

- **Trad-CNN:** A traditional architecture requiring fixed-size inputs. This requires images to be resized, which often distorts or removes small-scale physical features critical for prediction.

- **SPP-CNN:** The implementation of a **Spatial Pyramid Pooling (SPP)** layer. This innovation allows the network to accept images of any size, preserving the original physical scale and integrity of magnetic structures.

3.2 Variational Autoencoders (β-VAE) for Parametrization

The project employed β-VAEs—probabilistic encoder-decoder networks—to learn compact, information-rich "latent" representations of solar active regions.

- **Latent Space:** Unlike deterministic models, VAEs map inputs to a distribution, capturing the inherent uncertainty of magnetic morphologies.
- **Disentanglement:** By weighting the β hyperparameter, the model "disentangles" latent features, allowing researchers to track individual physical attributes (e.g., compactness, flux concentration) in a human-interpretable way.

3.3 Self-Supervised Pretraining and Segmentation

- **Generative Model:** The team used self-supervised pretraining, where the model learns to reconstruct artificially deformed solar images. This "pre-initialization" improved data efficiency by 65% and accelerated training convergence.
- **Segmentation Frameworks:** High-precision U-Net architectures were used for coronal structure segmentation, alongside lightweight frameworks designed for resource-constrained onboard spacecraft hardware.

4. KEY SCIENTIFIC RESULTS

The DELPHFI project yielded several breakthrough findings:

- **Superiority of SPP-CNN:** The SPP-CNN architecture achieved strong predictive performance within a 24-hour window, particularly for high-intensity flare events. It significantly outperformed traditional models by avoiding the negative impacts of image scaling.
- **XAI Validation:** Using **Grad-CAM heatmaps**, a concrete proof is provided that the AI's "attention" is correctly focused on **Polarity Inversion Lines (PILs)**—the same regions solar physicists prioritize. This validates that the model is learning physics, not just noise.
- **Scaling Impact:** The study quantified that standard resizing/stretching (common in computer vision) drastically degrades flare prediction performance by distorting the very features (like PIL length) that signal an imminent eruption.
- **Prediction of the evolution of active region morphology:** a Long Short-Term Memory (LSTM) time-series model with two LSTM cells/layers predicted the time evolution of the VAE latent dimensions, which encode key aspects of active region morphology. This approach provides a data-driven way to track and forecast changes in active region structure, and to explore potential flare precursors reflected in evolving morphology.
- **Onboard Feasibility:** The project demonstrated that models trained on ground data retain high performance on raw satellite data (Level-0), proving that AI-powered autonomous operations are viable for future solar missions.

5. MAIN CONCLUSIONS

The project successfully demonstrated that Deep Learning, when tailored to respect the physical constraints of solar data (as seen with SPP and VAE architectures), offers a transformative path for space weather services.

Interdisciplinary collaboration proved that ML models are not merely "black boxes"; they can be rendered interpretable, aligning automated results with established solar physics. Furthermore, the development of lightweight, robust segmentation pipelines confirms that these high-level AI tools can be deployed on the limited hardware found in space environments, ensuring future mission autonomy.

6. RECOMMENDATIONS

Based on the project's findings, the following steps are recommended to move toward a fully operational system:

1. **Incorporate Temporal Dynamics:** Future models should transition from static image analysis to LSTM (Long Short-Term Memory) networks to capture the time-evolution and energy buildup of active regions.
2. **Transition to Regression:** Instead of binary "flare/no-flare" classification, models should predict the specific soft X-ray flux intensity, allowing for more granular and useful alert levels.
3. **Expanded Data Integration:** Incorporate vector magnetograms and multi-wavelength EUV data to provide the models with deeper 3D magnetic topology information.
4. **Hardware Optimization:** Finalize the deployment of lightweight segmentation frameworks on FPGA/CPU hardware typical of deep-space missions to enable real-time, onboard autonomous forecasting.
5. **Operational implementation:** the most successful models should be further developed into operational forecasting systems capable of supporting real-time space weather monitoring and early warning services.

Keywords

Solar Eruptions; magnetograms; Extreme Ultraviolet; Machine Learning; Deep learning