# Predicting Solar Flares Using CNN and LSTM on Two Solar Cycles of Active Region Data

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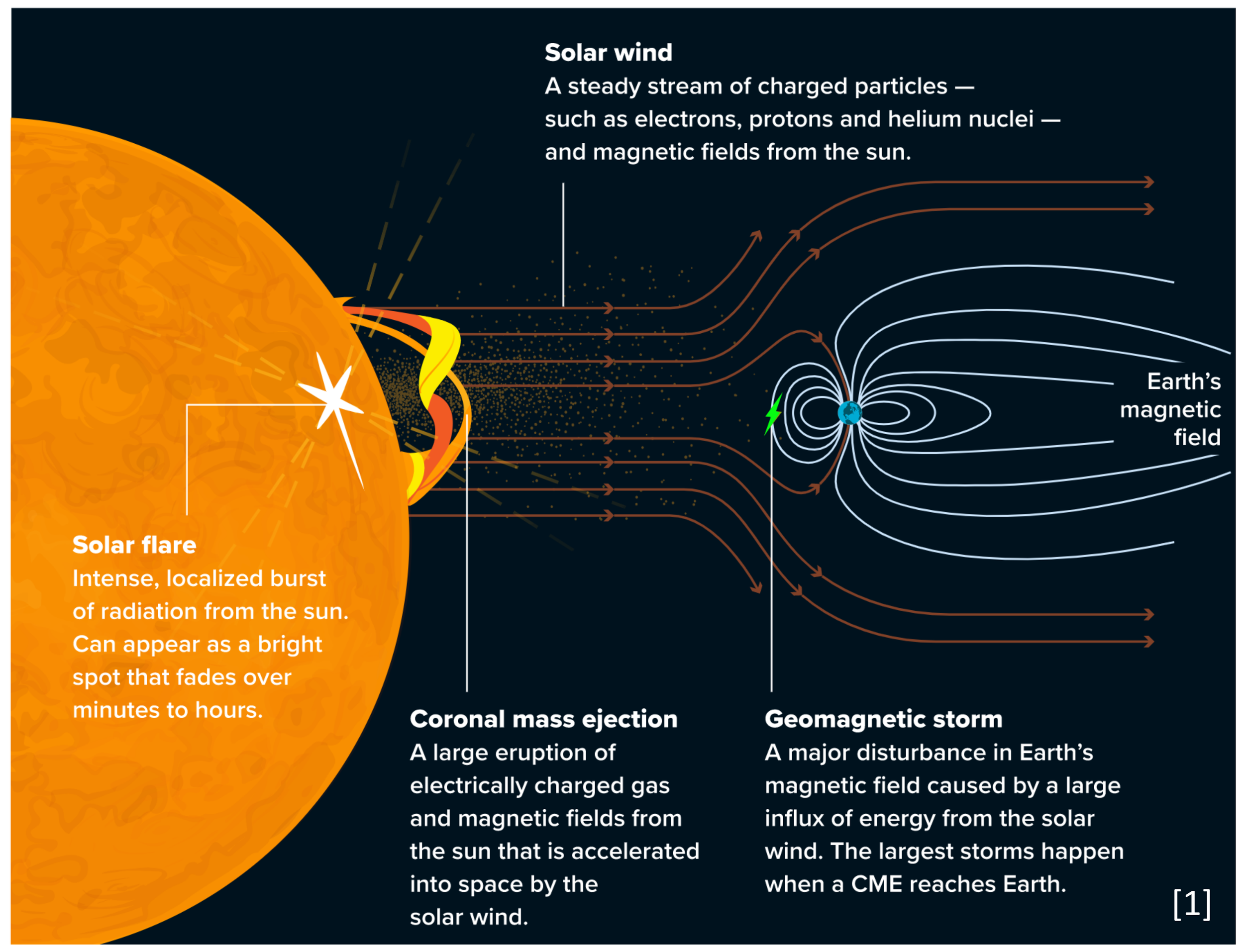
## Introduction




**Task**

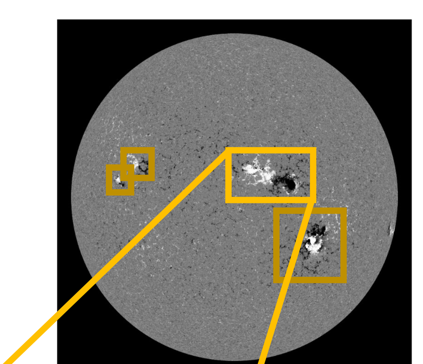
Sequence of AR image/parameters → Strong flares in next 24 hr?

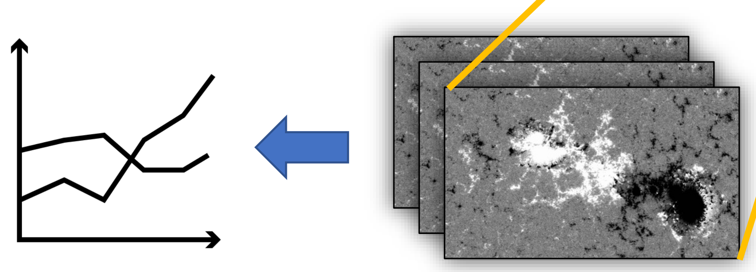
**Challenges**

- Short time span: SDO was launched in 2010
- Rare events: Positive class takes up 4%

**Data Source**

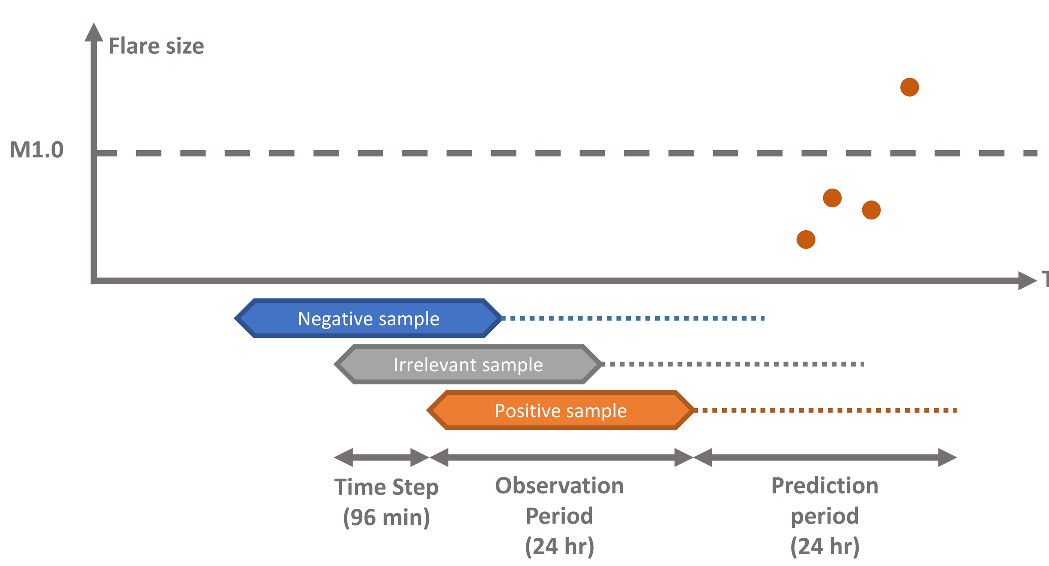
- Magnetic field of active regions as they travel across the solar disk.
- Summary parameters of the images
  - USFLUXL $\Phi = \sum |B| dA$
  - MEANGBL $\overline{|\nabla B|} = \frac{1}{N}\sqrt{\left(\frac{\partial B}{\partial x}\right)^2 + \left(\frac{\partial B}{\partial y}\right)^2}$
  - RVALUE $R = \Phi_{\text{strong field}}$
  - AREA $A = \sum dA$



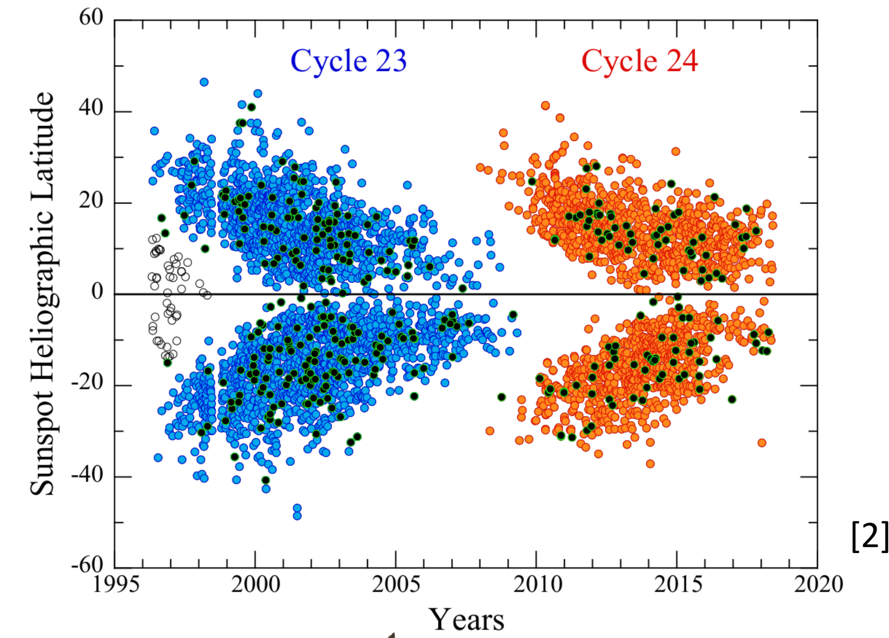


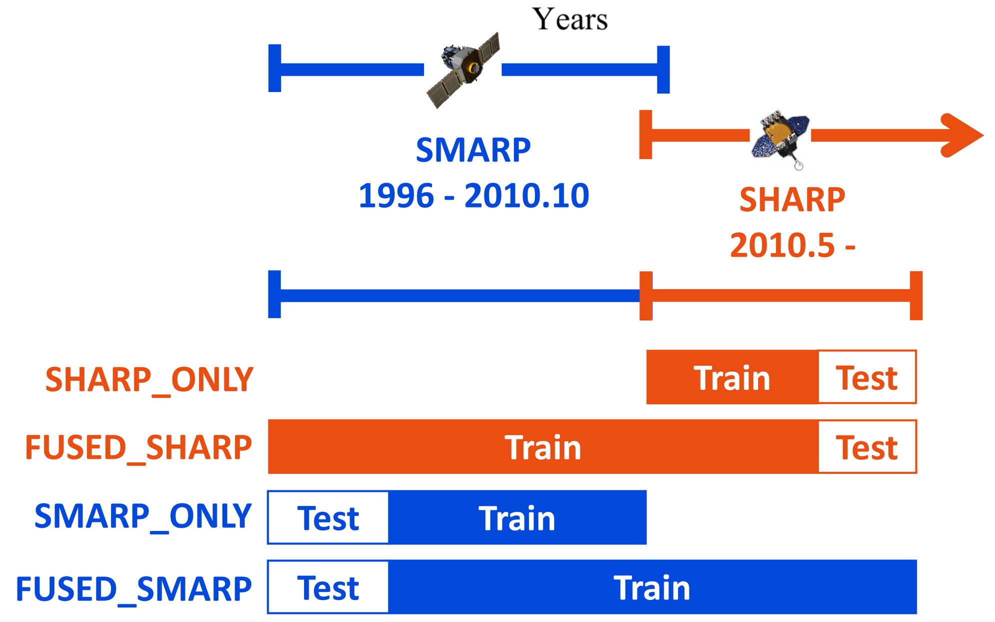
**Sample selection & labeling**

active region observation $x \to P[y=1|x]$



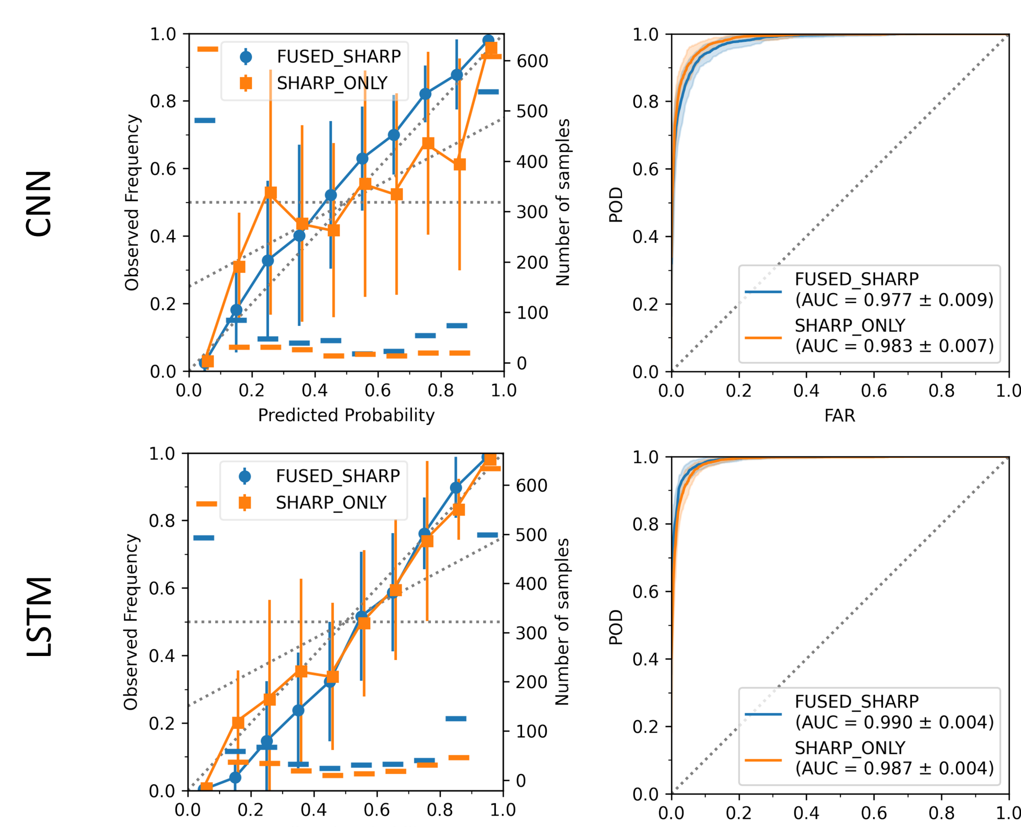

## Question 1: Does more data help?



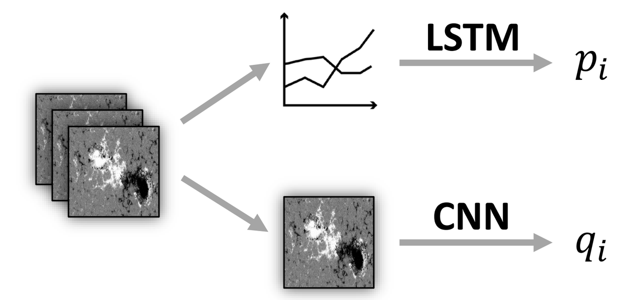

Outperform *_ONLY with $p \le 0.05$

| | Dataset / Model | Group 1 FUSED_SHARP | Group 1 SHARP_ONLY | Group 2 FUSED_SMARP | Group 2 SMARP_ONLY |
|---|---|---|---|---|---|
| ACC | CNN | 0.916+/-0.026 | 0.924+/-0.013 | $\boxed{\mathbf{0.900+/-0.023}}$ | 0.887+/-0.030 |
| | LSTM | $\boxed{\mathbf{0.952+/-0.014}}$ | 0.939+/-0.021 | **0.900+/-0.025** | 0.899+/-0.025 |
| AUC | CNN | 0.977+/-0.010 | 0.983+/-0.007 | $\boxed{\mathbf{0.964+/-0.016}}$ | 0.954+/-0.022 |
| | LSTM | $\boxed{\mathbf{0.990+/-0.004}}$ | 0.987+/-0.005 | 0.965+/-0.015 | 0.965+/-0.015 |
| BSS | CNN | 0.661+/-0.111 | 0.731+/-0.048 | $\boxed{\mathbf{0.621+/-0.096}}$ | 0.560+/-0.128 |
| | LSTM | $\boxed{\mathbf{0.806+/-0.043}}$ | 0.772+/-0.065 | **0.603+/-0.109** | 0.581+/-0.099 |




## Question 2: Does combining model help?

**Stacking ensemble** [3]




$$p_i, \quad q_i \xrightarrow{\text{Stacking}} r_i = \alpha p_i + (1-\alpha) q_i \quad (0 \le \alpha \le 1)$$

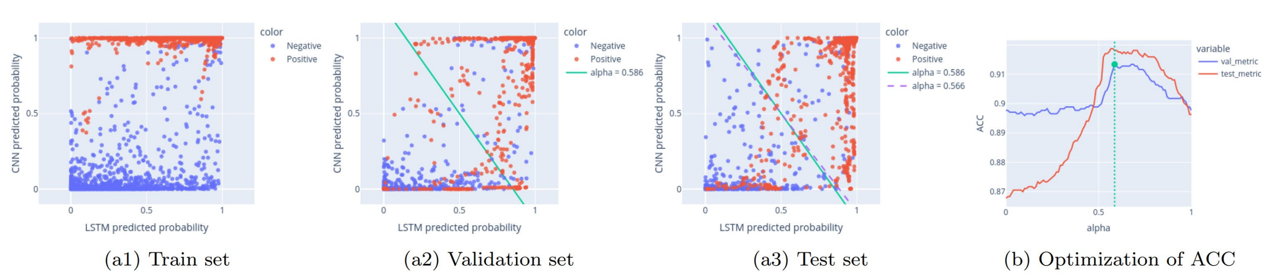
The combination weight $\alpha$ should be fitted the on the **validation sets.**
The criteria to train $\alpha$ can be:

- Nonconvex metrics: ACC, TSS (True Skill Statistics), …
- Convex loss functions: Cross-entropy loss, BSS (Brier Skill Score), …

We also consider baseline models:

- Base learners: CNN, LSTM
- Meta learners: AVG (Averaging), BEST (Best member on the val set)

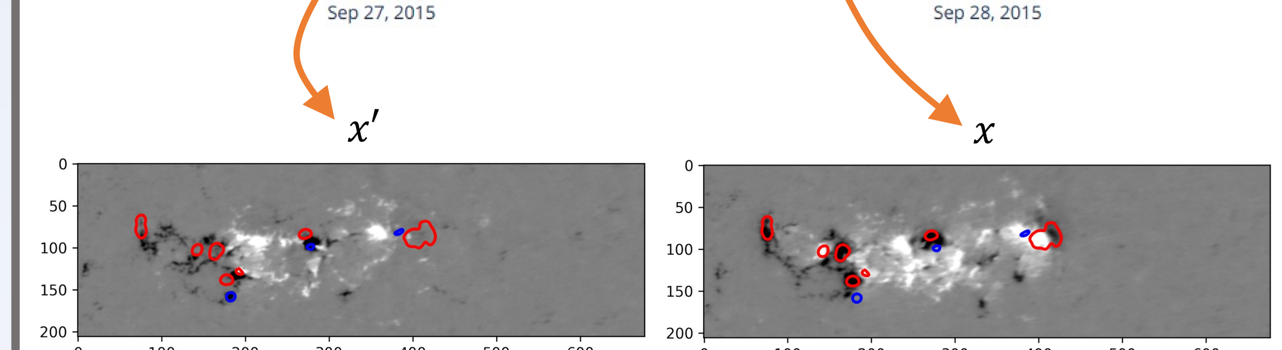
Outperform BEST with $p \le 0.05$


## Question 3: How does CNN predict?

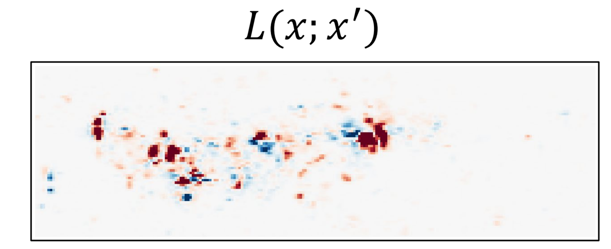
Visual attribution method: **Integrated Gradients** [4]

$$L(x; x') = (x - x') \odot \int_0^1 \nabla_x F_c(x' + \alpha(x - x'))\, d\alpha$$


Animation

$L(x; x')$



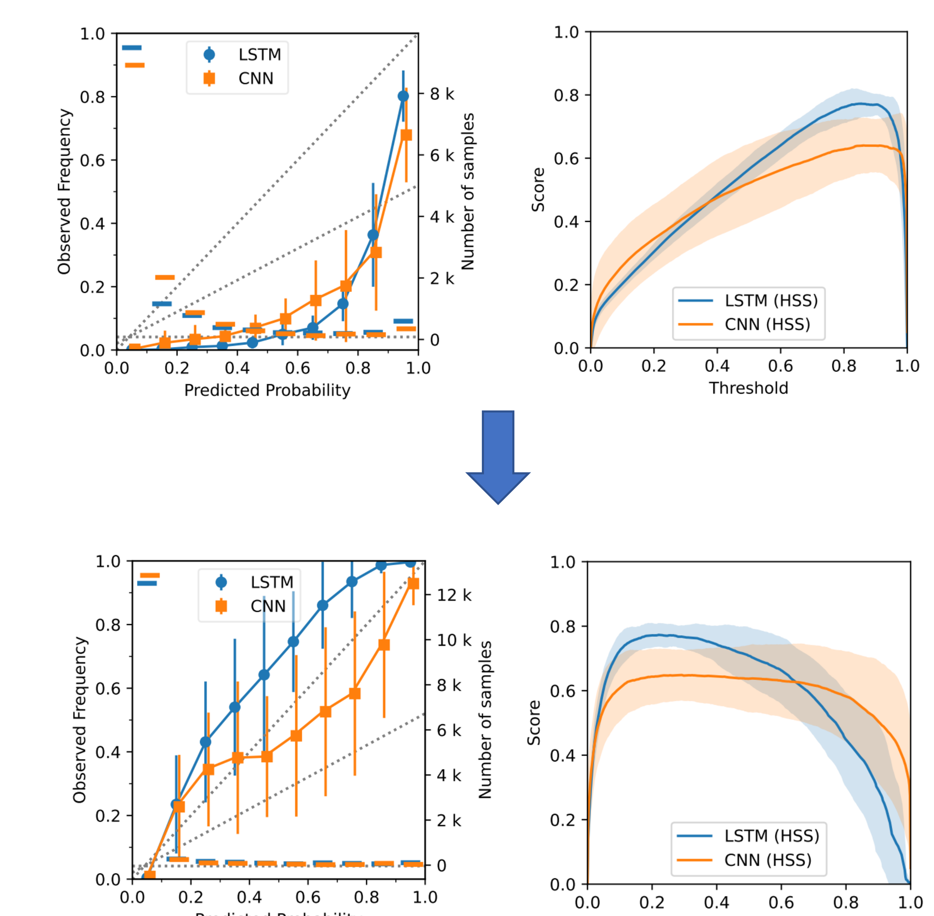
## Conclusions

1. Combining data two solar cycles of data generally improves predictions performance.
2. Stacking LSTM and CNN can improve flare prediction in certain cases.
3. CNN identifies the preflare features, e.g., emerging polarity inversion lines (PILs).

## Future work

- Evaluation under realistic event rate.
  Class priors: $\pi_k$ on train set, $\pi_k'$ on the test set.
  Suppose the class conditional prob doesn't change.
  Then the posterior can be corrected using Bayes rule [5]:

$$p'(y=1|x) = \frac{\frac{\pi_1'}{\pi_1} p(y=1|x)}{\frac{\pi_0'}{\pi_0} p(y=0|x) + \frac{\pi_1'}{\pi_1} p(y=1|x)}$$




- Improve operational utility by including:
  - weak flares
  - samples that indicates a decay in flare activity

## Reference

[1] https://knowablemagazine.org/article/physical-world/2021/understanding-just-how-big-solar-flares-can-get
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[5] Elkan, Charles. "The foundations of cost-sensitive learning." International joint conference on artificial intelligence. Vol. 17. No. 1. Lawrence Erlbaum Associates Ltd, 2001.