

# Processing Solar Images to Forecast Coronal Mass Ejections using Artificial Intelligence

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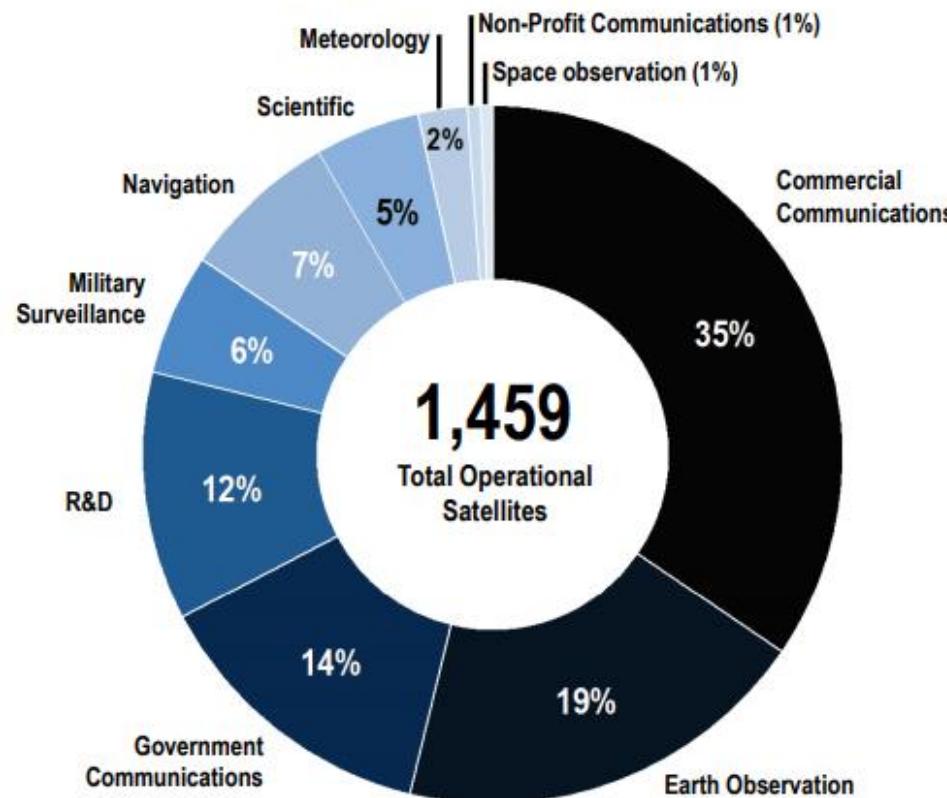
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# Preventing a disaster

## Operational Satellites by Function

(as of December 31, 2016)



## If Satellites Stop:

- No Telecommunications
- No Military surveillance
- No Weather forecast
- No GPS

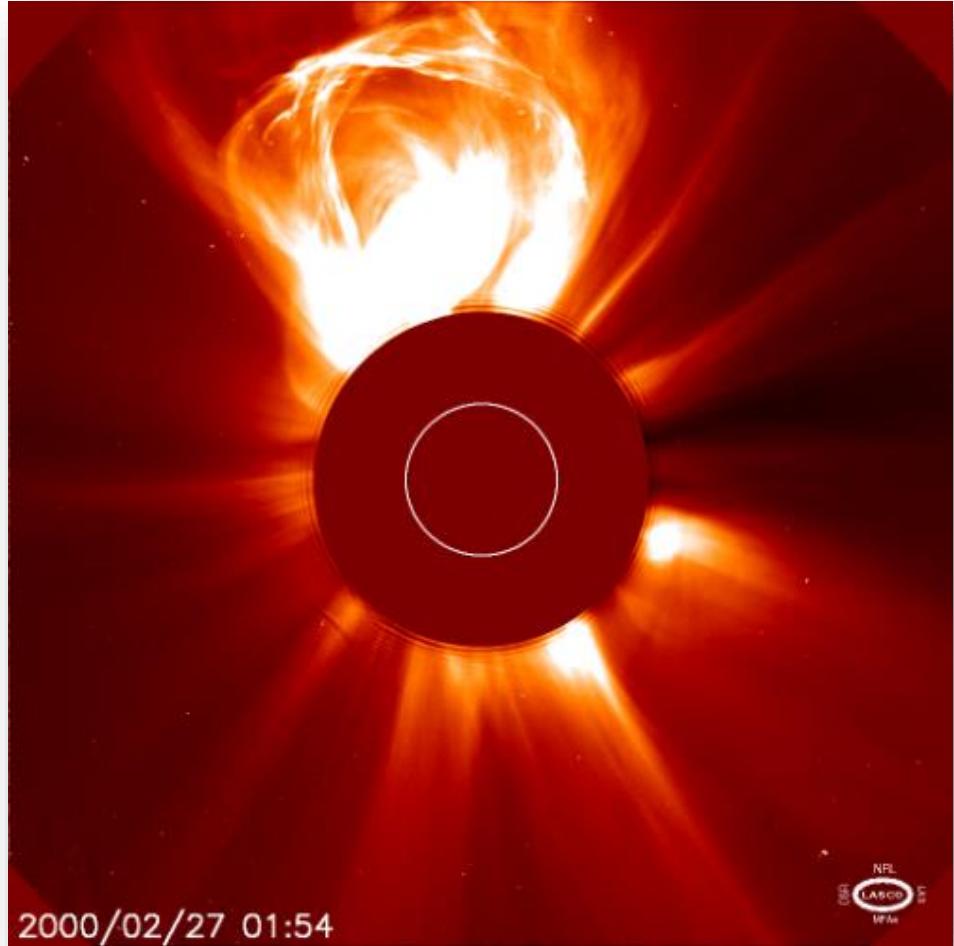
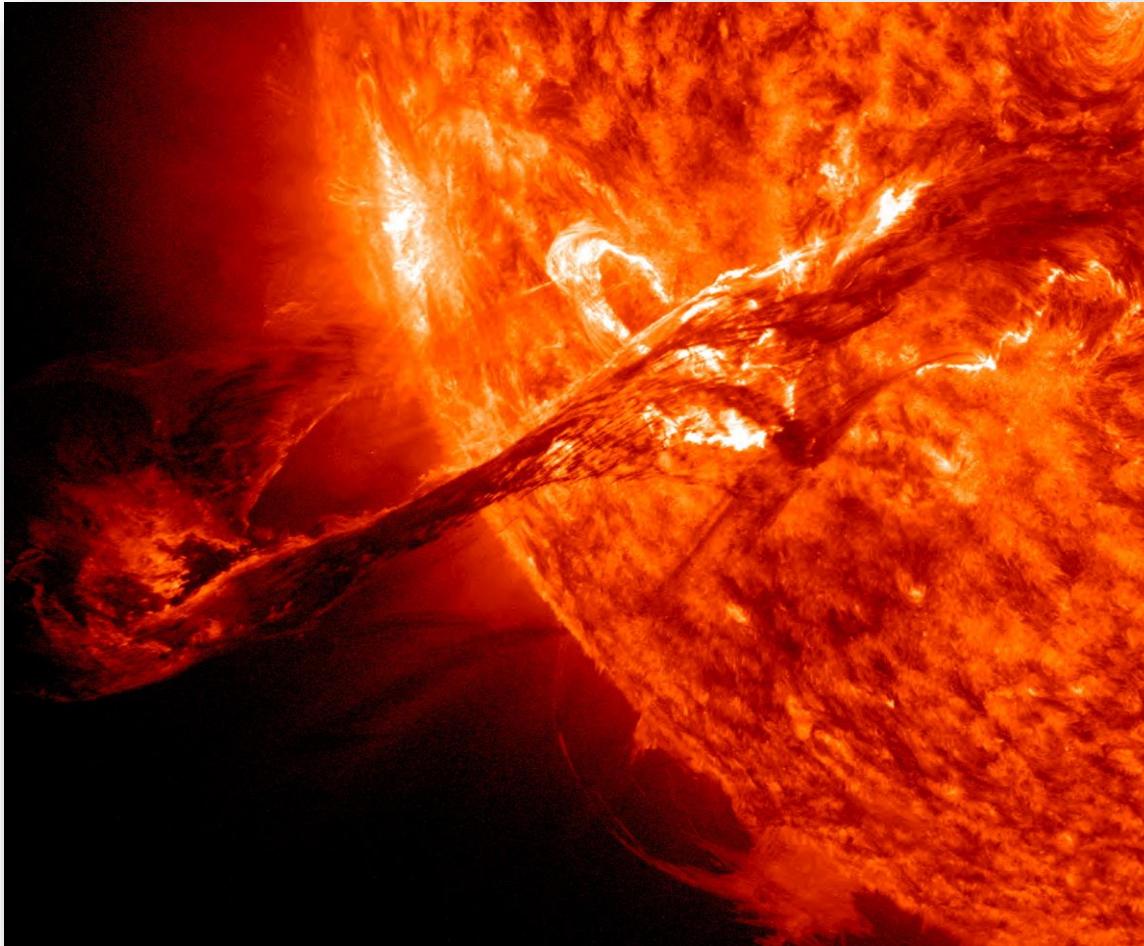
| DEPARTURES |             |        |      |           |
|------------|-------------|--------|------|-----------|
| TIME       | DESTINATION | FLIGHT | GATE | REMARKS   |
| 12:39      | LONDON      | BA 903 | 31   | CANCELLED |
| 12:57      | SYDNEY      | QF5723 | 27   | CANCELLED |
| 13:08      | TORONTO     | AC5984 | 22   | CANCELLED |
| 13:21      | TOKYO       | JL 608 | 41   | DELAYED   |
| 13:37      | HONG KONG   | CX5471 | 29   | CANCELLED |
| 13:48      | MADRID      | IB3941 | 30   | DELAYED   |
| 14:19      | BERLIN      | LH5021 | 28   | CANCELLED |
| 14:35      | NEW YORK    | AA 997 | 11   | CANCELLED |
| 14:54      | PARIS       | AF5870 | 23   | DELAYED   |
| 15:10      | ROME        | AZ5324 | 43   | CANCELLED |



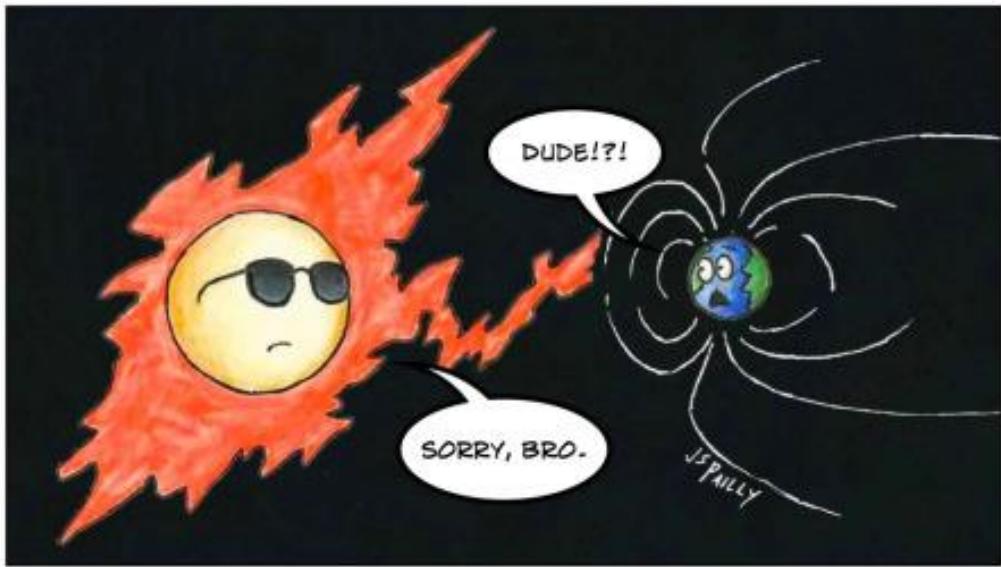
\*Figure Courtesy: SIA (Satellite Industry Association)

# What can cause this disaster?

Coronal Mass Ejections (CMEs)



\*Figure Courtesy: NASA/ESA, SDO and SOHO satellites



## Theory

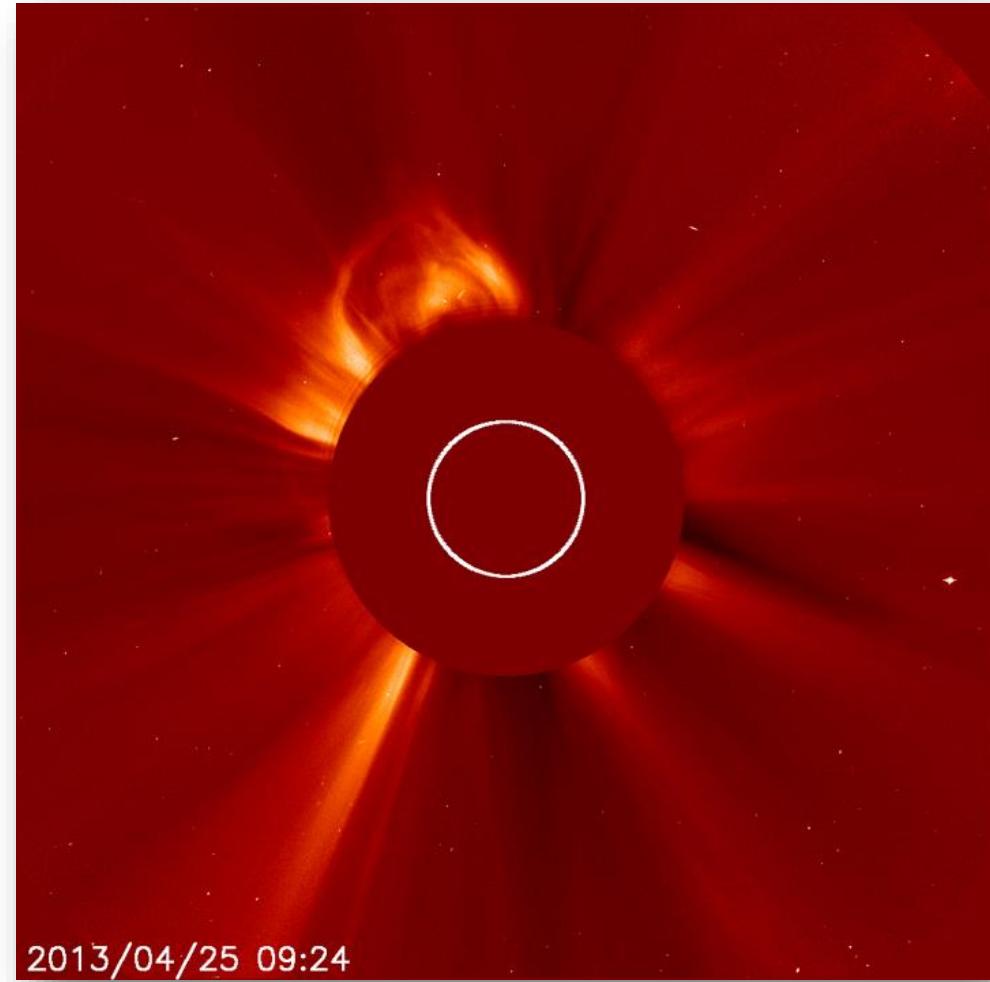
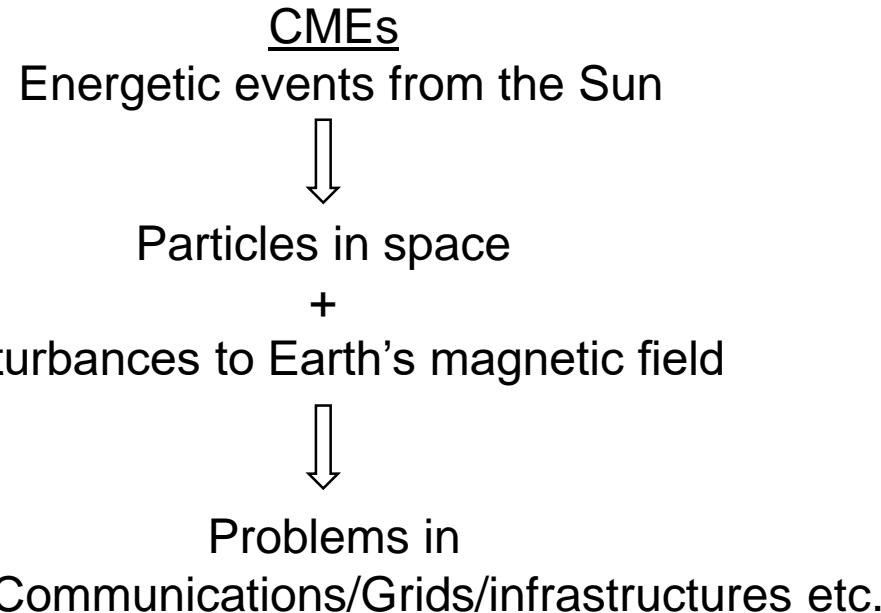
≡ Sections    BBC NEWS    AA    ⌂

TECHNOLOGY

AI will not kill us, says Microsoft

\*Figure Courtesy: <https://planetpailly.com/>

# Coronal Mass Ejections – CMEs



\*Figure Courtesy: NASA/ESA, SOHO satellite

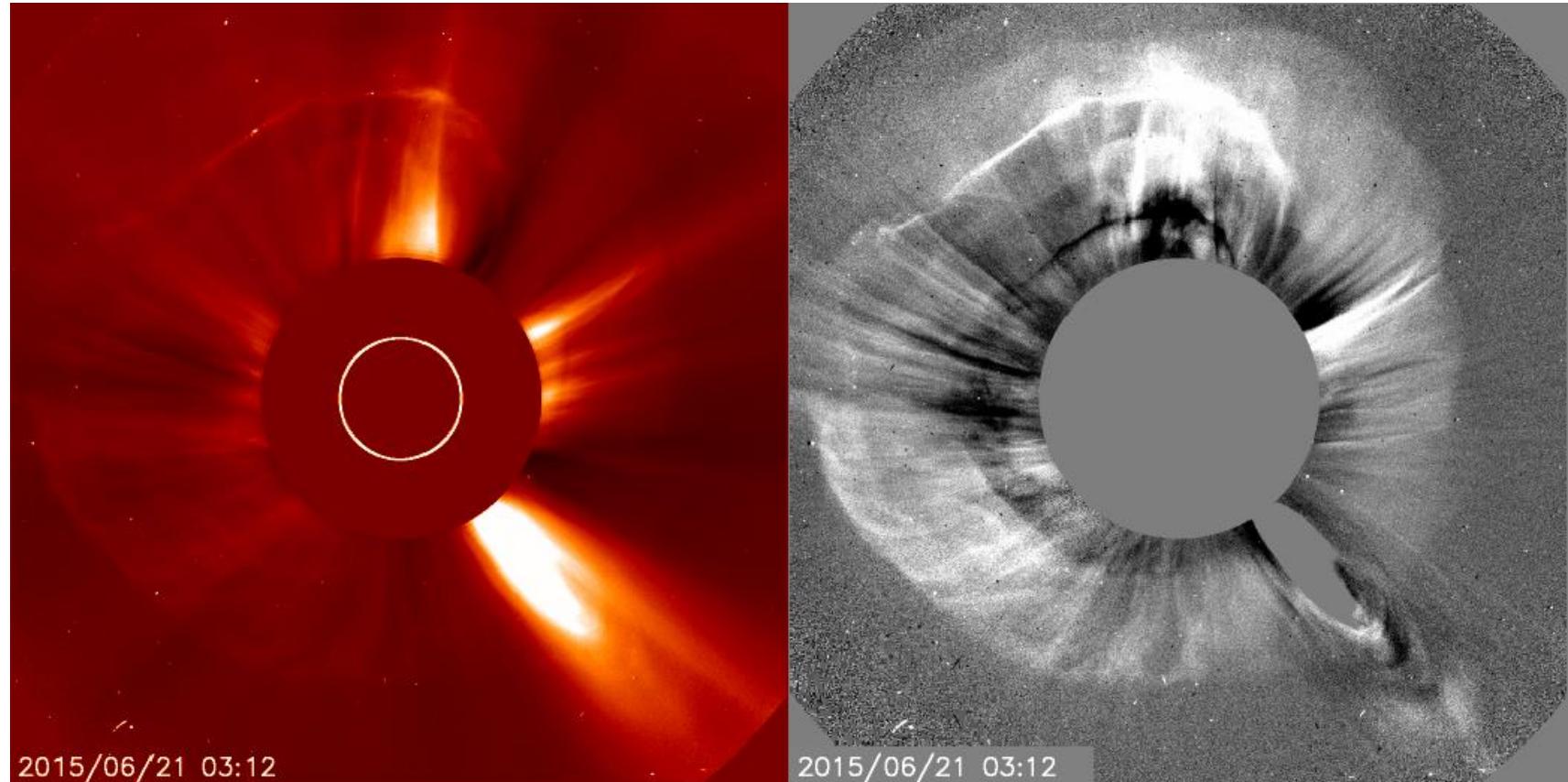
# Halo CMEs

Halo CMEs  
Earth-directed CMEs. Can be seen from coronagraph.

Why important?  
Going to Earth



More effects on mankind

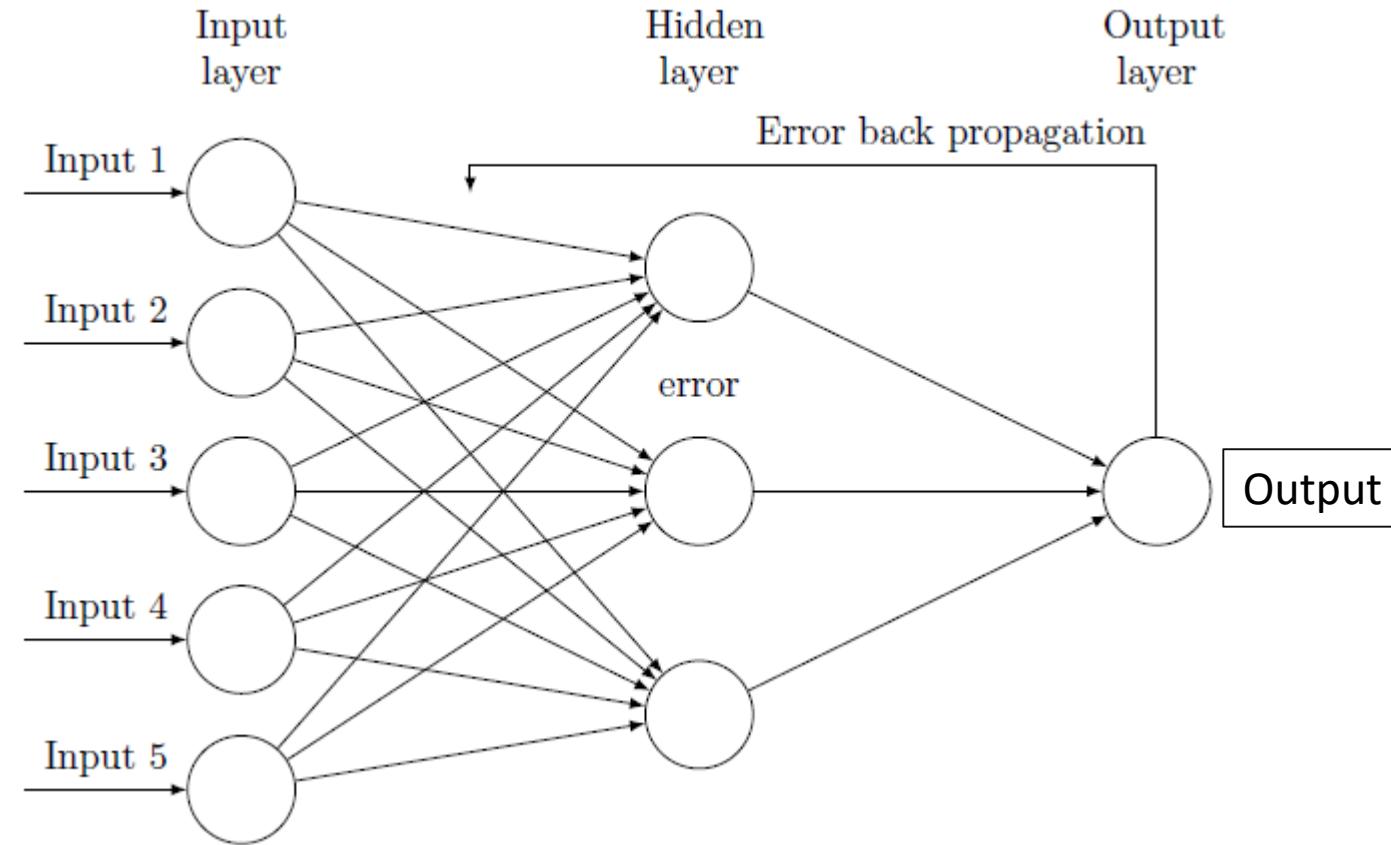


\*Figure Courtesy: NASA/ESA, SOHO satellite

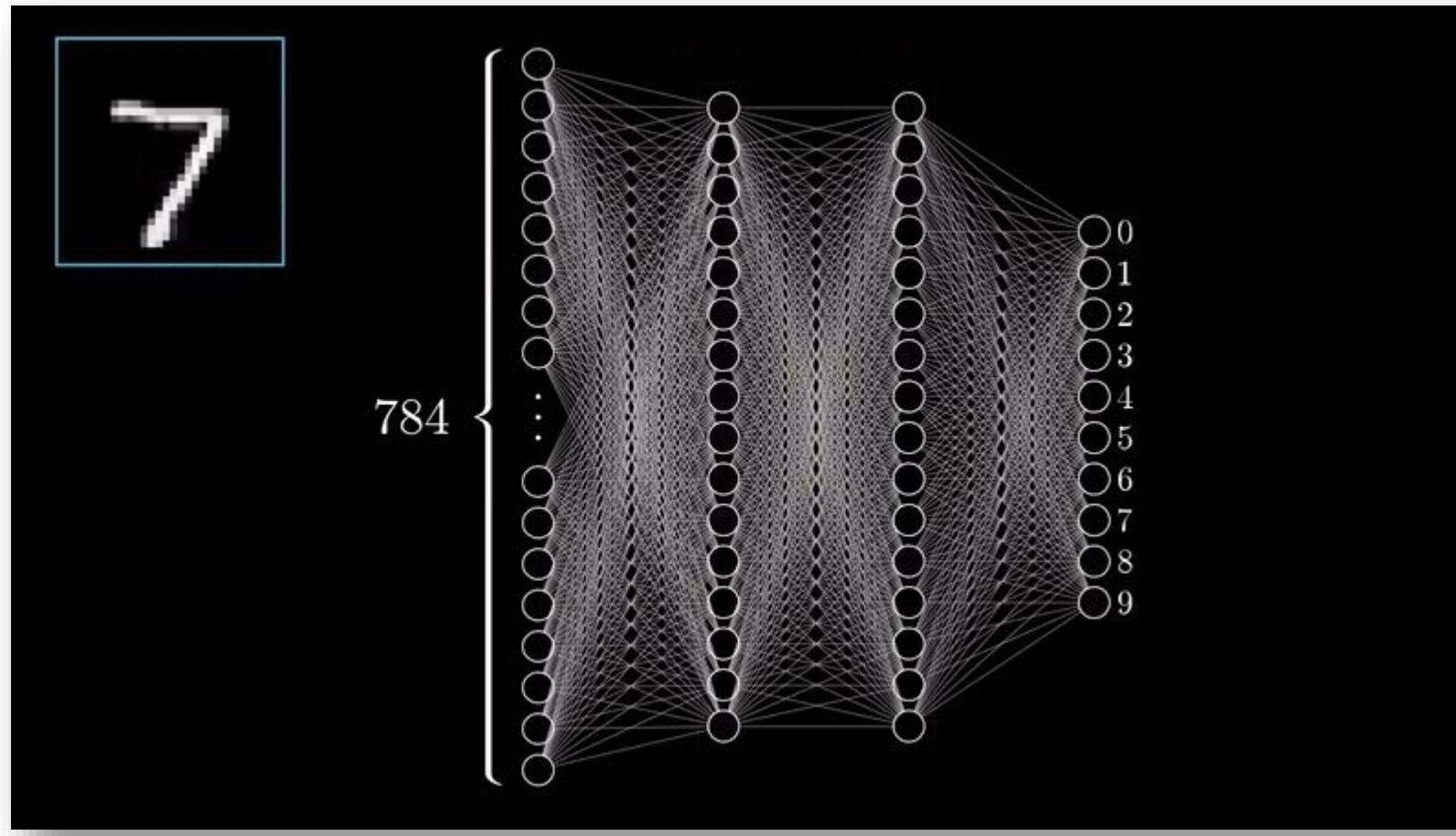
# What is machine learning & A.I. ?

*Making the computer “**learn**” from **data** without being explicitly programmed*

# Neural Networks & Backpropagation



# Visualization of Neural Network



\*Video Courtesy: **3Blue1Brown** (Check him on YouTube!)

# Convolution Neural Network (CNN) Layers

## Convolution

Extract features & Keep spatial relationship

|         |         |         |   |   |
|---------|---------|---------|---|---|
| 1<br>x1 | 1<br>x0 | 1<br>x1 | 0 | 0 |
| 0<br>x0 | 1<br>x1 | 1<br>x0 | 1 | 0 |
| 0<br>x1 | 0<br>x0 | 1<br>x1 | 1 | 1 |
| 0       | 0       | 1       | 1 | 0 |
| 0       | 1       | 1       | 0 | 0 |

Image

|   |  |  |
|---|--|--|
| 4 |  |  |
|   |  |  |
|   |  |  |
|   |  |  |
|   |  |  |

Convolved Feature

## Pooling/Subsampling

Reduce dimensionality & retain information

|     |     |    |    |
|-----|-----|----|----|
| 12  | 20  | 30 | 0  |
| 8   | 12  | 2  | 0  |
| 34  | 70  | 37 | 4  |
| 112 | 100 | 25 | 12 |

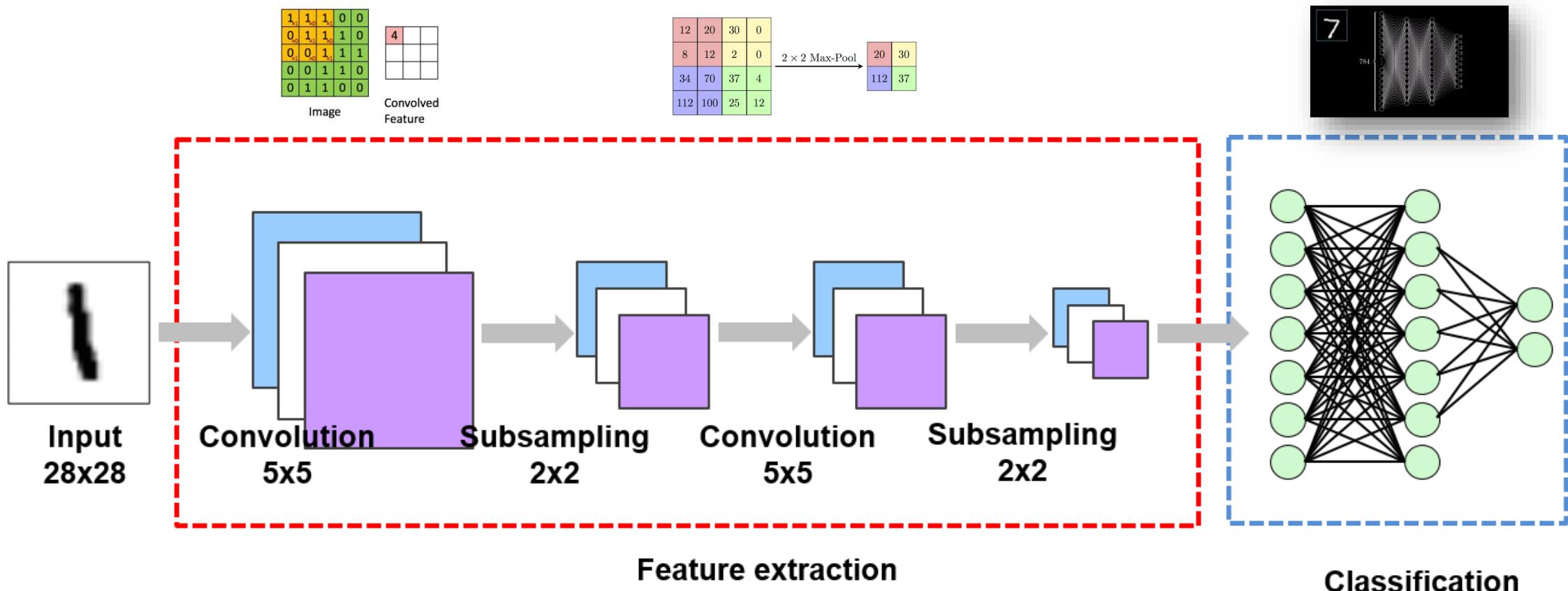
$2 \times 2$  Max-Pool

|     |    |
|-----|----|
| 20  | 30 |
| 112 | 37 |

\*Figure Courtesy: Erik Reppel

\*Figure Courtesy: Cambridge Spark Ltd

# Example of CNN



\*Figure Courtesy: Suhyun Kim iSystems Design Labs

# Analysis

# Main Goal

*Forecast the emerged CMEs using solar images taken from SDO and CNN*

| <u>Input</u><br>SDO Images during 2014 |                 | <u>Output</u><br>LASCO/CACTUS Catalogs |      |      |     |     |  |  |
|--|-----------------|--|------|------|-----|-----|--|--|
| Date                                   | Characteristics |  |      |      |     |     |  |  |
| 2014/01/02 13:48:06                    | 184             | 57                                     | 894  | 959  | 825 | 711 |  |  |
| 2014/01/03 00:24:05                    | 264             | 18                                     | 225  | 272  | 169 | 0   |  |  |
| 2014/01/03 02:24:06                    | 51              | 24                                     | 657  | 637  | 674 | 720 |  |  |
| 2014/01/03 03:47:08                    | 61              | 44                                     | 1132 | 1303 | 961 | 965 |  |  |
| 2014/01/03 07:36:05                    | 62              | 17                                     | 250  | 193  | 306 | 615 |  |  |
| 2014/01/03 10:36:05                    | 65              | 21                                     | 316  | 273  | 358 | 627 |  |  |
| 2014/01/03 12:36:05                    | 265             | 25                                     | 277  | 287  | 267 | 34  |  |  |
| 2014/01/03 18:00:06                    | 154             | 60                                     | 208  | 114  | 295 | 430 |  |  |
| 2014/01/03 18:48:05                    | 90              | 31                                     | 89   | 179  | 0   | 0   |  |  |
| 2014/01/03 19:36:05                    | 222             | 112                                    | 286  | 331  | 237 | 0   |  |  |

# Machine Learning Project

1<sup>st</sup> Part      Data Enhancement

2<sup>nd</sup> Part      CNN implementation

Improving Input Project

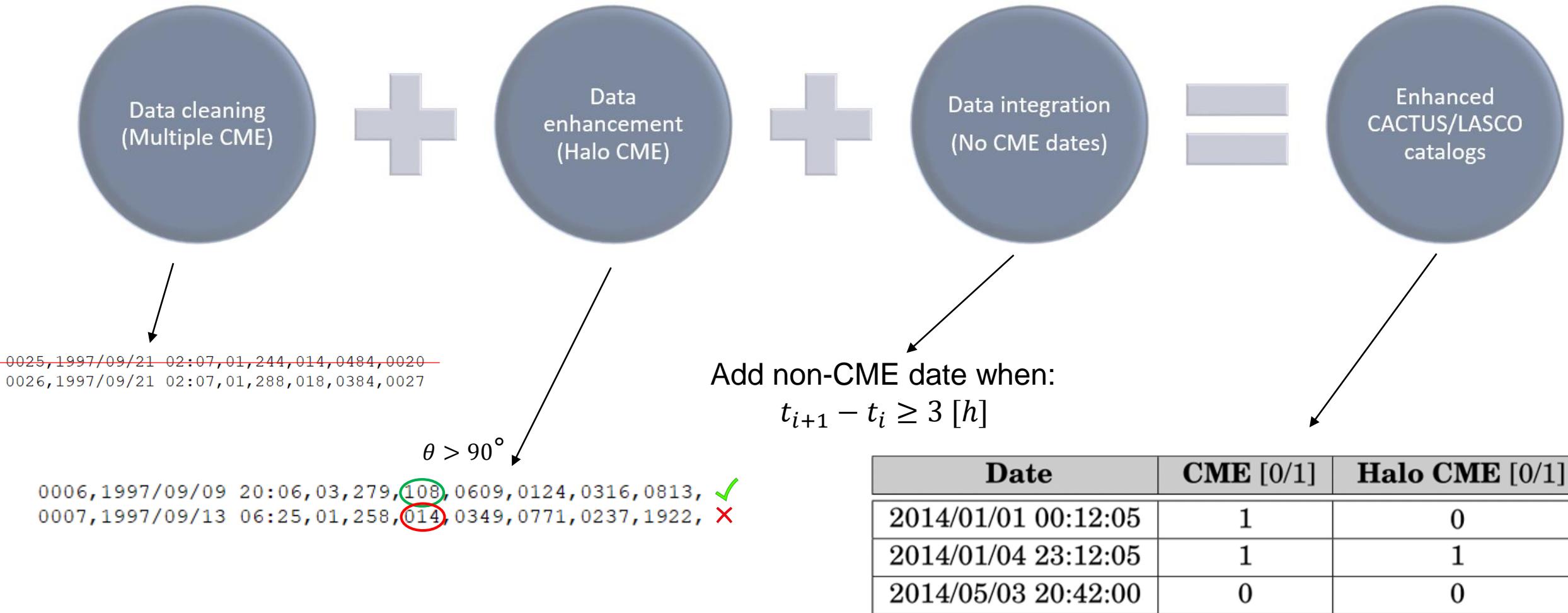
3<sup>rd</sup> Part      Pre-processing Tool & History Maps

**1<sup>st</sup> Part      Data Enhancement**

**2<sup>nd</sup> Part      CNN implementation**

**3<sup>rd</sup> Part      Pre-processing Tool & History Maps**

# The Data Enhancement Project



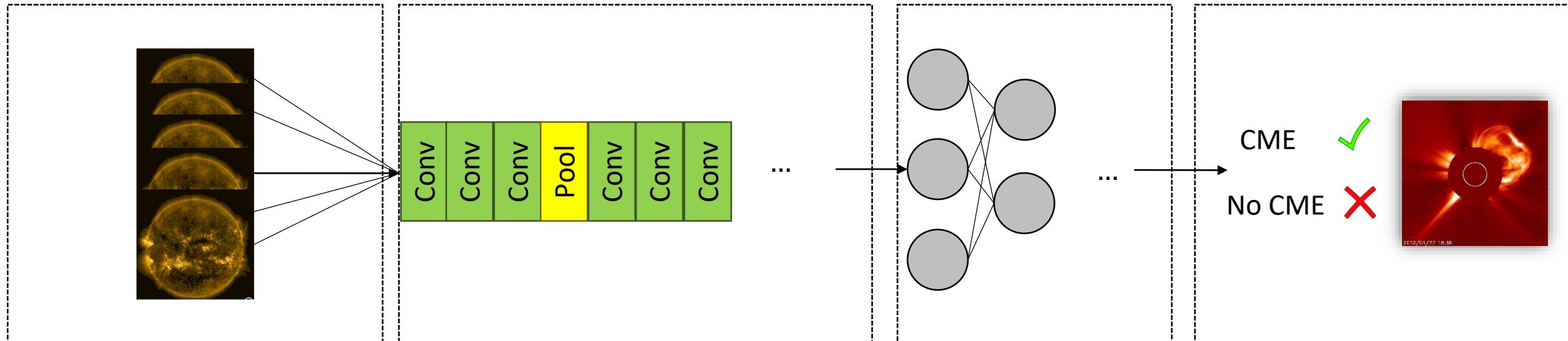
**1<sup>st</sup> Part      Data Enhancement**

**2<sup>nd</sup> Part      CNN implementation**

**3<sup>rd</sup> Part      Pre-processing Tool & History Maps**

# The Machine Learning Project

Input [13,512,512]      Convolution Neural Network      Dense Neural Network      Output  
Feature Extraction      Classification      CME / No CME

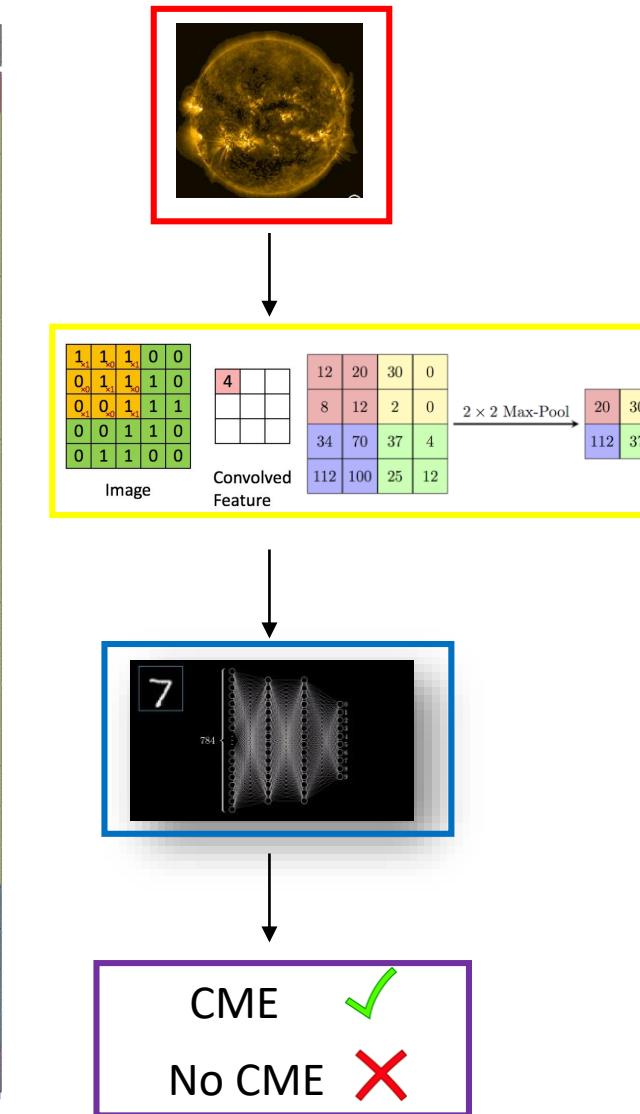


**Input** = 13 SDO images, 2 [h] history before the event.

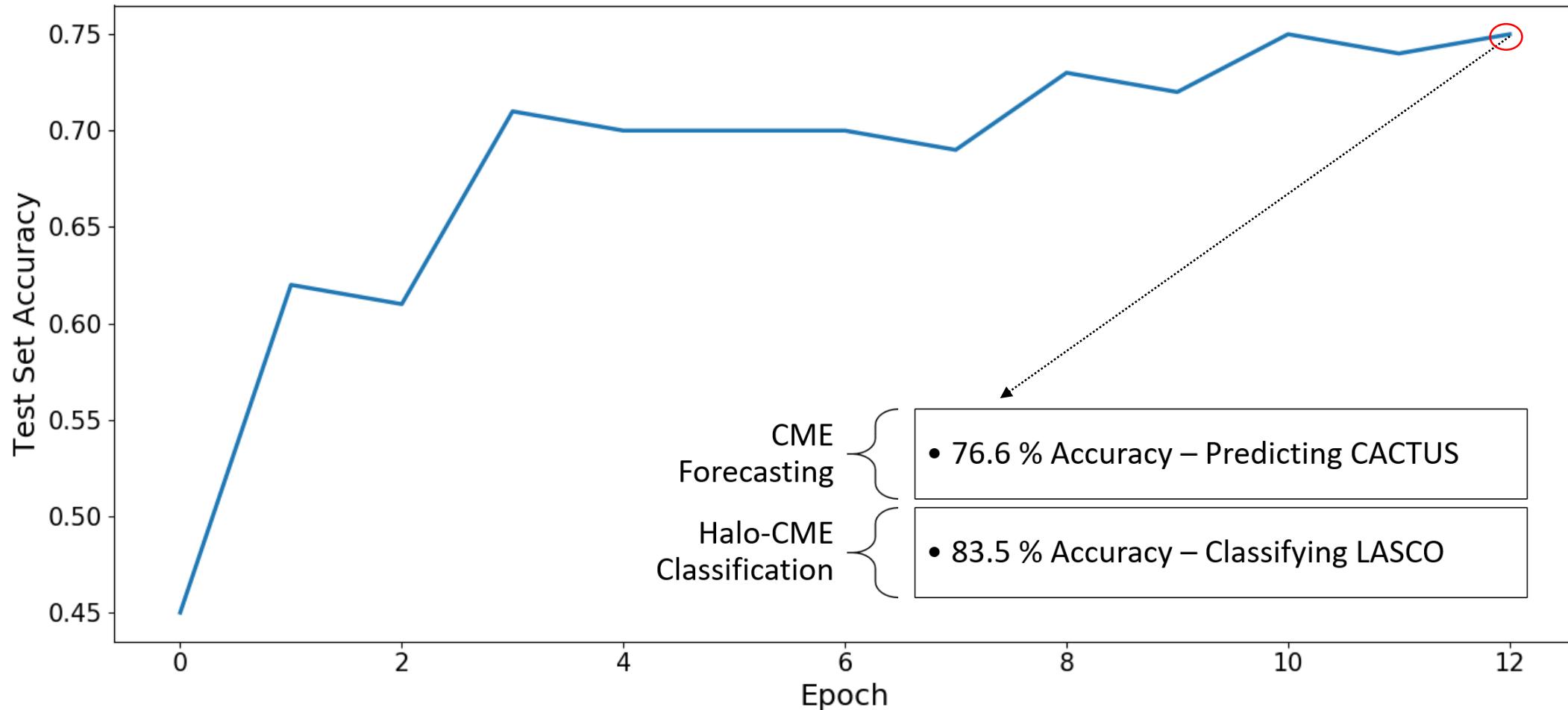
**Output** = 1/0

# Final CNN architecture

| Layer           | Details & Operations              | Output shape |
|-----------------|-----------------------------------|--------------|
| Input           | -                                 | [512,512,13] |
| Convolution     | Convolution [14] & 3x3 Kernel     | [510,510,14] |
| Convolution     | Convolution [16] & 3x3 Kernel     | [508,508,16] |
| Convolution     | Convolution [18] & 3x3 Kernel     | [506,506,18] |
| Max Pooling     | Max Pooling with 2x2 Kernel       | [253,253,18] |
| Dropout         | 20 % Dropout                      | [253,253,18] |
| Convolution     | Convolution [20] & 3x3 Kernel     | [251,251,20] |
| Convolution     | Convolution [28] & 3x3 Kernel     | [249,249,28] |
| Convolution     | Convolution [36] & 3x3 Kernel     | [247,247,36] |
| Max Pooling     | Max Pooling with 2x2 Kernel       | [247,247,36] |
| Dropout         | 20 % Dropout                      | [123,123,36] |
| Convolution     | Convolution [40] & 3x3 Kernel     | [121,121,40] |
| Convolution     | Convolution [56] & 3x3 Kernel     | [119,119,56] |
| Convolution     | Convolution [72] & 3x3 Kernel     | [117,117,72] |
| Max Pooling     | Max Pooling with 2x2 Kernel       | [58,58,72]   |
| Dropout         | 40 % Dropout                      | [253,253,18] |
| Convolution     | Convolution [80] & 3x3 Kernel     | [56,56,80]   |
| Convolution     | Convolution [112] & 3x3 Kernel    | [54,54,112]  |
| Convolution     | Convolution [144] & 3x3 Kernel    | [52,52,144]  |
| Max Pooling     | Max Pooling with 2x2 Kernel       | [26,26,144]  |
| Flatten         | Flattening of the input           | 97344        |
| Fully Connected | 400 Neuron - Dense layer          | 400          |
| Fully Connected | 200 Neuron - Dense layer          | 200          |
| Fully Connected | 2 Neuron - Dense layer            | 2            |
| Output          | Classifier, 0.5 Threshold Sigmoid | 2            |



# Result of CNN



**1<sup>st</sup> Part      Data Enhancement**

**2<sup>nd</sup> Part      CNN implementation**

**3<sup>rd</sup> Part      Pre-processing Tool & History Maps**

# Pre-processing Tool – Motivation

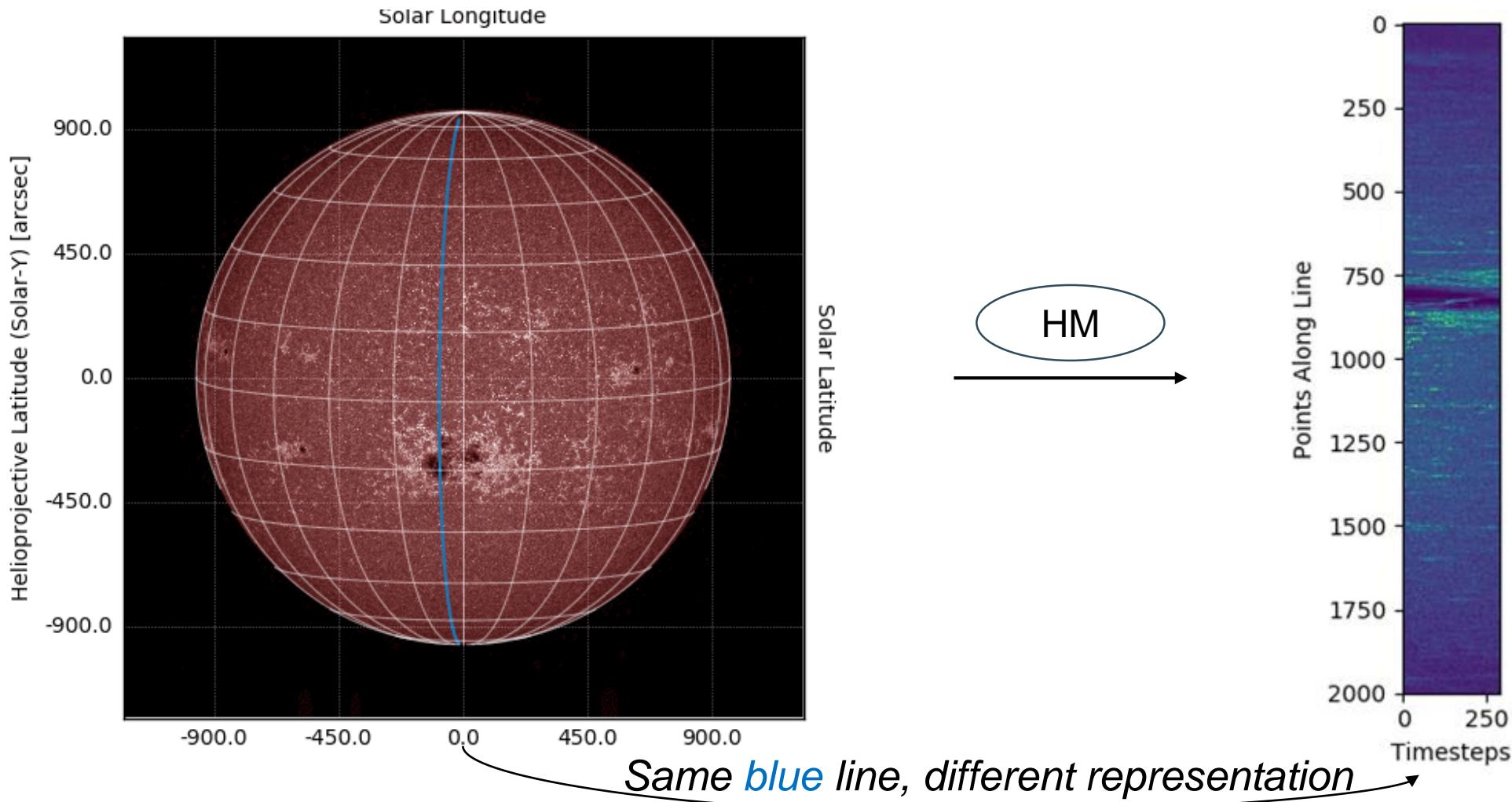
## Previous input

- (+) Promising results.
- (-) Expensive computationally and memory wise.

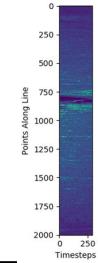
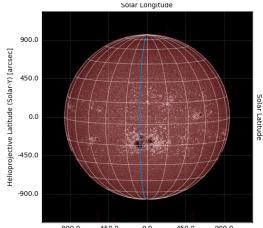
## Using the pre-processing tool

- (+) **New input** → less computational time & memory consumption.
- (?) Better results.

# History Map (HM) – Single Line Example



# Pre-processing Tool – Procedure & Output



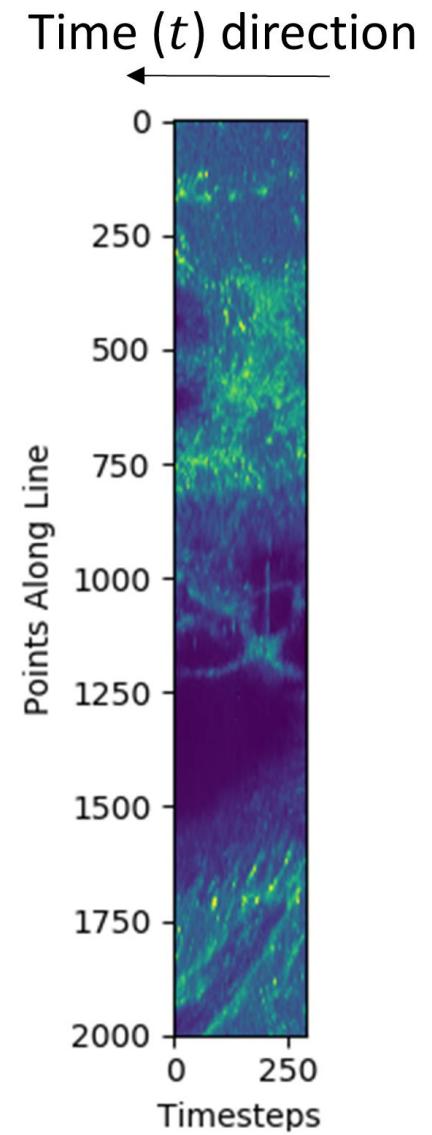
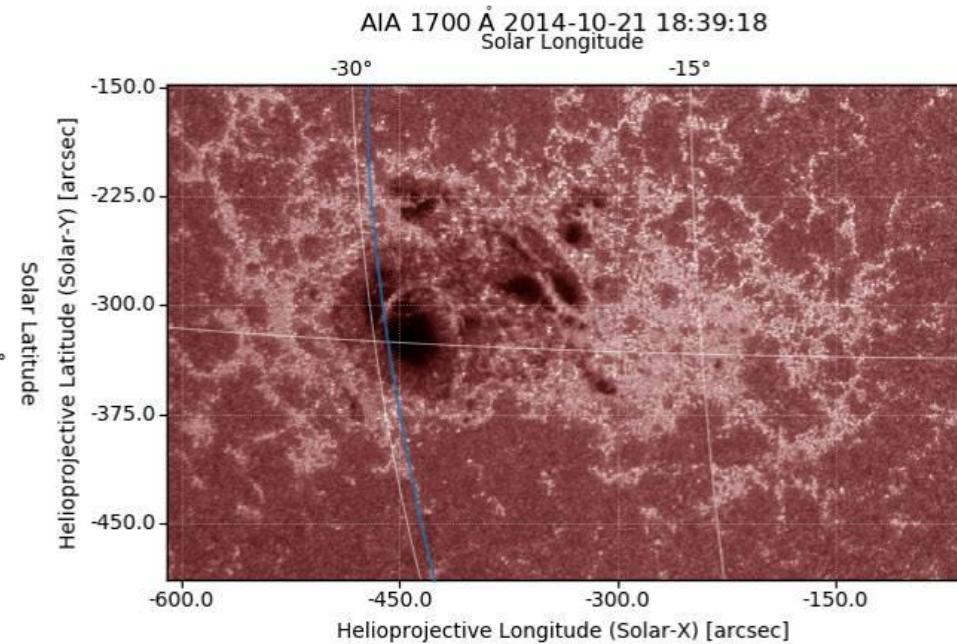
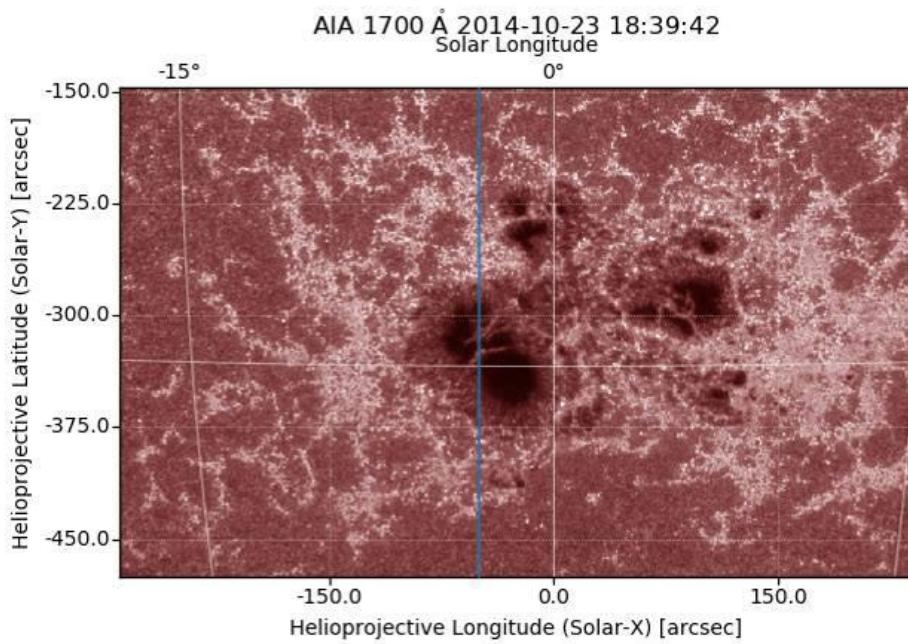
## Procedure

- Download data
- Track Sun's differential rotation for every longitude line
- Go to next date on Catalog
- Repeat

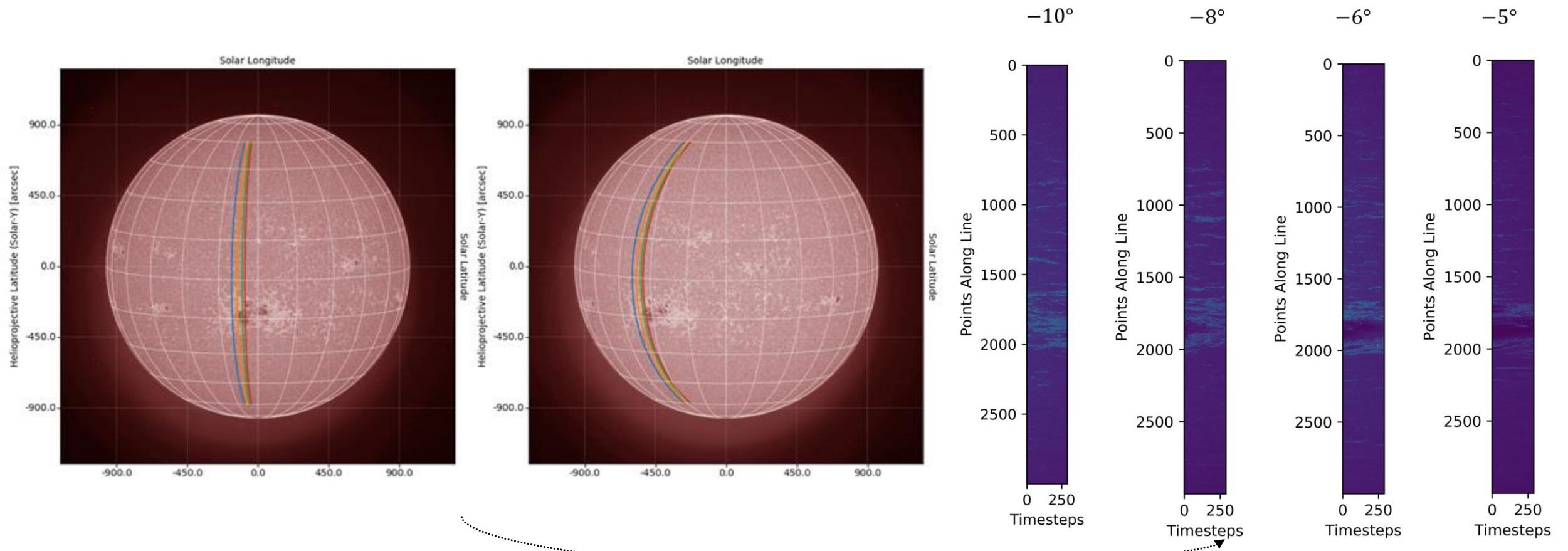
## Output

- 1) Database file (.sql)
- 2) Scientific images (.FITS)
- 3) History maps (.png)
- 4) NN input (.npy)
- 5) Animation (.gif)

# Pre-processing Tool – Sunspot



# History Map – Multi Line Example



# Why History Maps ?

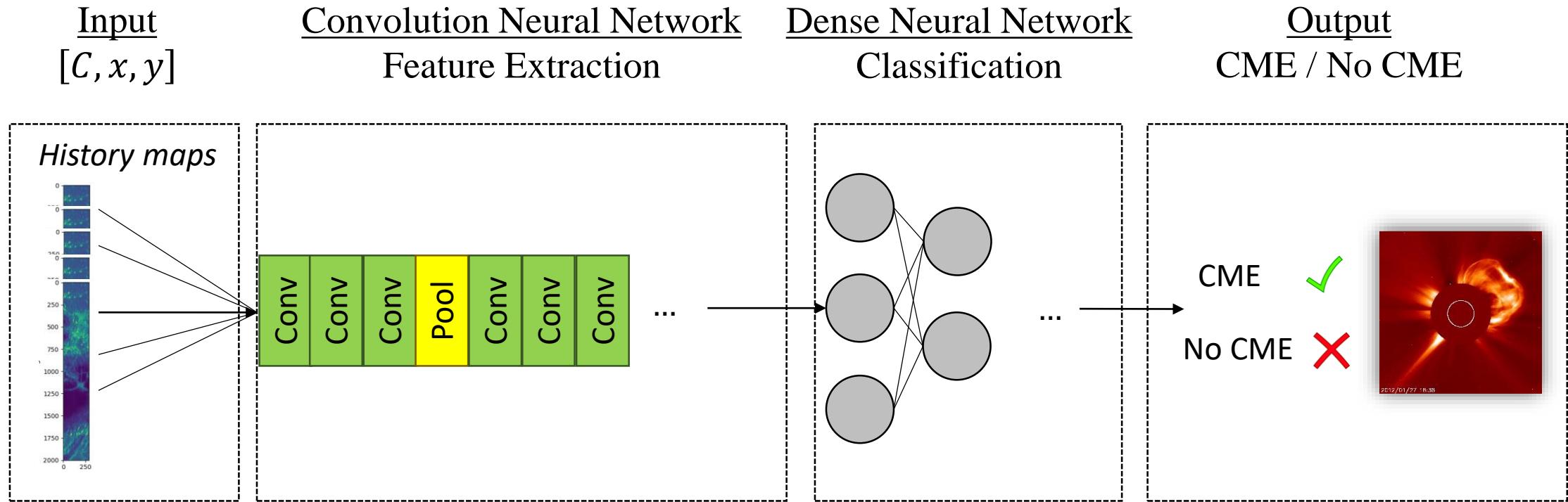
- Substantial decrease of data and computational time (order of magnitude).  
E.g. Originally: [512,512,13], now [x,y,13]. In practice,  $y \approx 10 \ll 512$
- Structures are shown in a frame that is co-moving → **time evolution is shown**.
- Possibly **useful** for **forecasting other phenomena** such as Solar flares or Sunspots.

# Conclusion

# Summary

1. Enhanced, clean and **processed SDO** data and **CACTUS/LASCO** catalogs
2. Created multiple CNN models, with the best obtaining **76.6% prediction** on CMEs and **83.5% classification** between CME and halo-CME.
3. Created a **pre-processing tool** that derives “**History Maps**” (HM). Possibly useful in future Machine learning research and Solar data analysis.

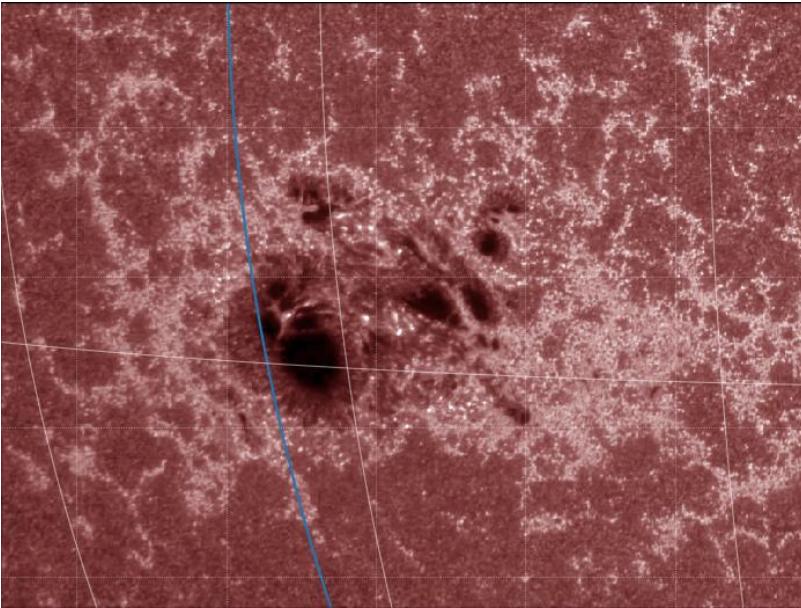
# Future Proposal



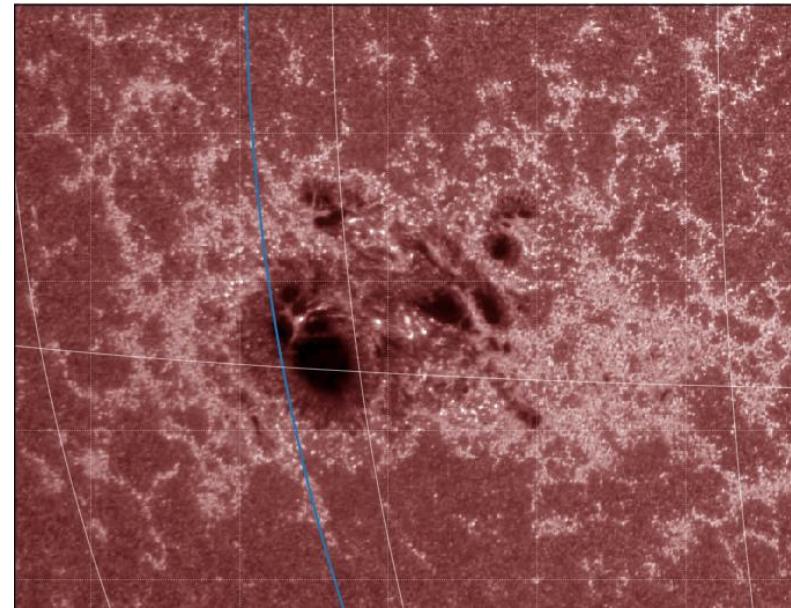
# Extras

# Differential Rotation Models

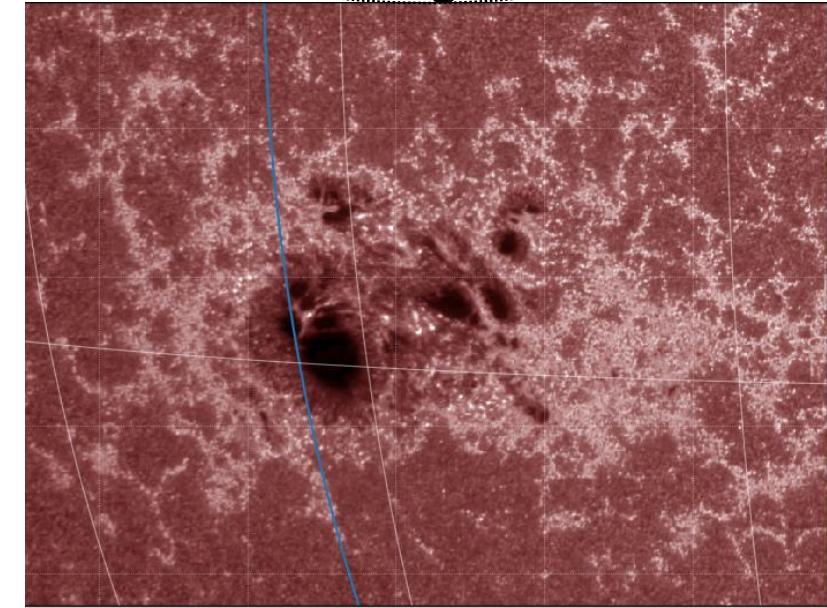
Allen



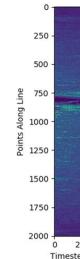
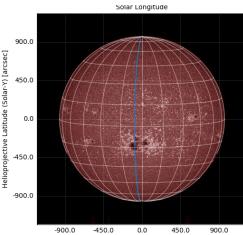
Howard



Snodgrass



# Pre-processing Tool – Design



## Input

- 1) Date – Date of event
- 2) x – Points on line
- 3) y – Longitude lines
- 4) dt – Time-step
- 5) T – Total time
- 6)  $\lambda$  – Wavelength
- 7) C – Catalog

## Procedure

- Download data for  $T$  [h] before event
- Track Sun's differential rotation for every line ( $y$ ) using  $dt$  step
- Go to next *date* on Catalog ( $C$ )
- Repeat

## Output

- 1) Database file (.sql)
- 2) Scientific images (.FITS)
- 3) History maps (.png)
- 4) NN input (.npy)
- 5) Animation (.gif)