

# Predicting CME Arrival Time Through Data Integration And Ensemble Learning

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## Purpose

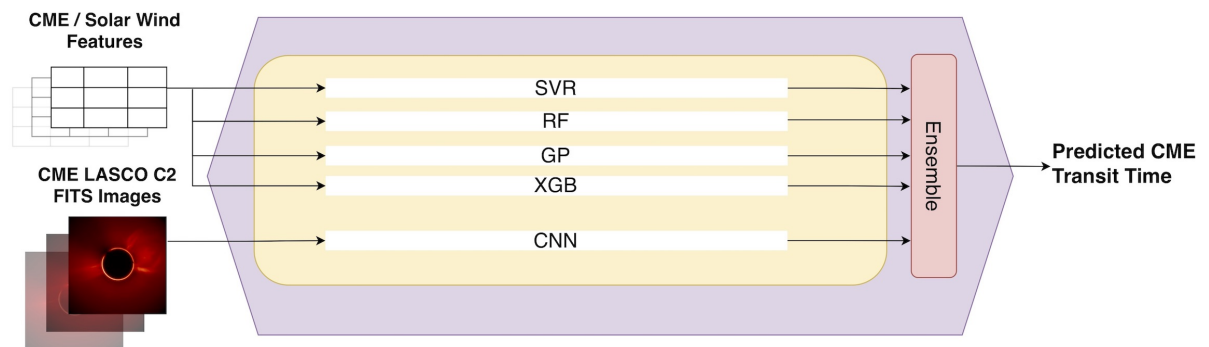
The Sun constantly releases radiation and plasma into the heliosphere. Sporadically, the Sun launches solar eruptions such as flares and coronal mass ejections (CMEs). CMEs carry away a huge amount of mass and magnetic flux with them. An Earth-directed CME can cause serious

consequences to the human system. It can destroy power grids/pipelines, satellites, and communications. Therefore, accurately monitoring and predicting CMEs is important to minimize damages to the human system. In this study we propose an ensemble learning approach, named CMETNet, for predicting the arrival time of CMEs from the Sun to the Earth.

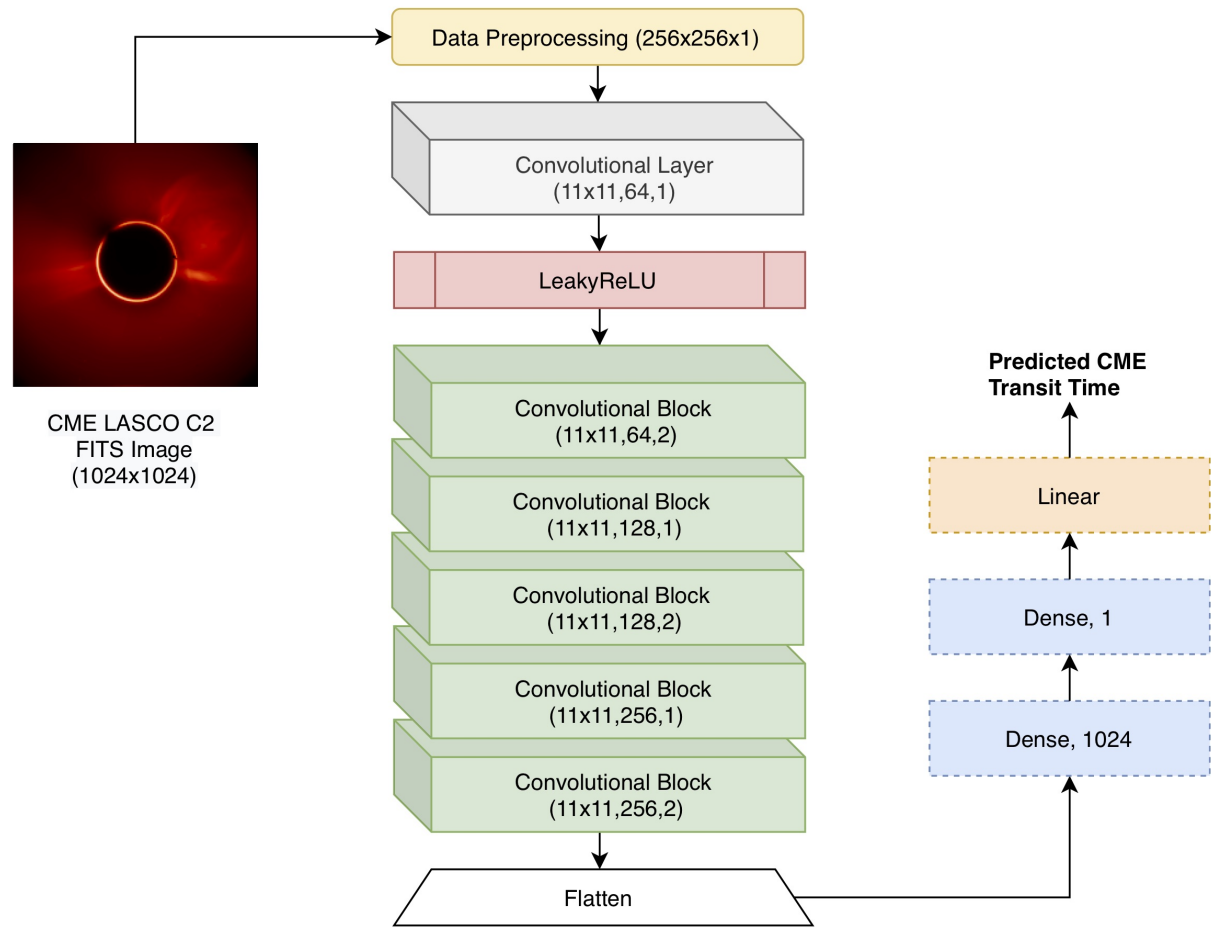
In this notebook we provide an overview of the CMETNet system to demonstrate how to predict the arrival time of CMEs using machine learning (ML) and data include CME features, solar wind parameters and CME images obtained from the SOHO/LASCO C2 coronagraph.

## Methodology

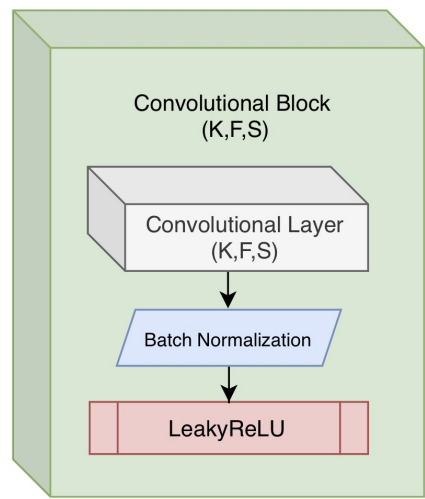
Our ensemble learning framework, named CMETNet and illustrated in Figure 1, comprises five base learners: (i) a support vector regression (SVR) algorithm , (ii) a random forest (RF) algorithm , (iii) a Gaussian process (GP) algorithm , (iv) an XGBoost (XGB) algorithm , and (v) a convolutional neural network (CNN) illustrated in Figure 2. The first four learners are regression algorithms used for analyzing the numeral/tabular data related to the CME features and solar wind parameters considered in the study. These four regression algorithms are commonly used in heliophysics and space weather research. The fifth learner is a CNN model used for CME image processing. More details can be found in the paper.



(Figure 1)



(a)



(b)

(Figure 2)

Funding

This work was supported by U.S. NSF grants AGS-1927578, AGS-1954737 and AGS-2149748.key

## Keywords

keywords=["heliophysics", "space weather", "coronal mass ejections", "interplanetary shocks", "machine learning"]

## Citation

To cite this notebook: Khalid A. Alobaid, Yasser Abdullah, Jason T. L. Wang, & Haimin Wang. Predicting CME Arrival Time through Data Integration and Ensemble Learning, available at: [https://github.com/ccsc-](https://github.com/ccsc-tools/CMETNet/blob/main/KA_01_PredictingCMEArrivalTimeThroughDataIntegrationAndEnsembleL)  
[tools/CMETNet/blob/main/KA\\_01\\_PredictingCMEArrivalTimeThroughDataIntegrationAndEnsembleL](https://github.com/ccsc-tools/CMETNet/blob/main/KA_01_PredictingCMEArrivalTimeThroughDataIntegrationAndEnsembleL)  
([https://github.com/ccsc-](https://github.com/ccsc-tools/CMETNet/blob/main/KA_01_PredictingCMEArrivalTimeThroughDataIntegrationAndEnsembleL)  
[tools/CMETNet/blob/main/KA\\_01\\_PredictingCMEArrivalTimeThroughDataIntegrationAndEnsembleL](https://github.com/ccsc-tools/CMETNet/blob/main/KA_01_PredictingCMEArrivalTimeThroughDataIntegrationAndEnsembleL)

## Acknowledgements

The solar wind data is provided by NASA's Goddard Space Physics Data Facility. The SOHO LASCO CME Catalog is created and maintained by NASA's CDAW Data Center and the Catholic University of America in cooperation with the Naval Research Laboratory. SOHO is a project of international cooperation between ESA and NASA.



## Setup

### Installation on Local Machine

To install the required packages, you may use Python package manager "pip" as follow:

1. Copy the text file "requirements.txt" into the working directory.
2. Execute the command:

Type:

```
pip install -r requirements.txt
```

Note: There is a requirements file already created for you to use that includes all packages with their versions. The files are located in the root directory of the CMETNet. Note: Python packages and libraries are sensitive to versions. Please make sure you are using the correct packages and libraries versions as specified above.

Cuda Installation Package: You may download and install Cuda v 10.1 from <https://developer.nvidia.com/cuda-10.1-download-archive-base> (<https://developer.nvidia.com/cuda-10.1-download-archive-base>)

## Data Processing and Analysis

We stored 351 LASCO C2 FITS data samples in the data folder of this repo. The "ICMEs\_C2\_fits\_list.csv" file represents a list of the LASCO C2 FITS images along with the transit time which is the label. The transit time is in hours. These labeled images are used to train/test the

CNN model. For the other models in CMETNet, "ICME\_list.csv" file represents the CME events considered in this study along with the CME and SW parameters. These events are used to train/test the COMB model (SVR, RF, GP, XGP) of CMETNet.

For this notebook, we use sample data sets for training and testing.

## Binder

This notebook is Binder enabled and can be run on [mybinder.org](https://mybinder.org/) (<https://mybinder.org/>) by using the image link below:

 [launch binder \(https://mybinder.org/v2/gh/ccsc-tools/CMETNet/HEAD?labpath=KA\\_01\\_PredictingCMEArrivalTimeThroughDataIntegrationAndEnsembleLearning.ipynb\)](https://mybinder.org/v2/gh/ccsc-tools/CMETNet/HEAD?labpath=KA_01_PredictingCMEArrivalTimeThroughDataIntegrationAndEnsembleLearning.ipynb)

Please note that starting Binder might take some time to create and start the image.

Please also note that the execution time in Binder varies based on the availability of resources. The average time to run the notebook is 10-15 minutes, but it could be more.

## Plotting the Pretrained Models Results

The prediction result can be plotted as shown in the following example. The result shows the performance metrics: PPMCC and MAE for each model.

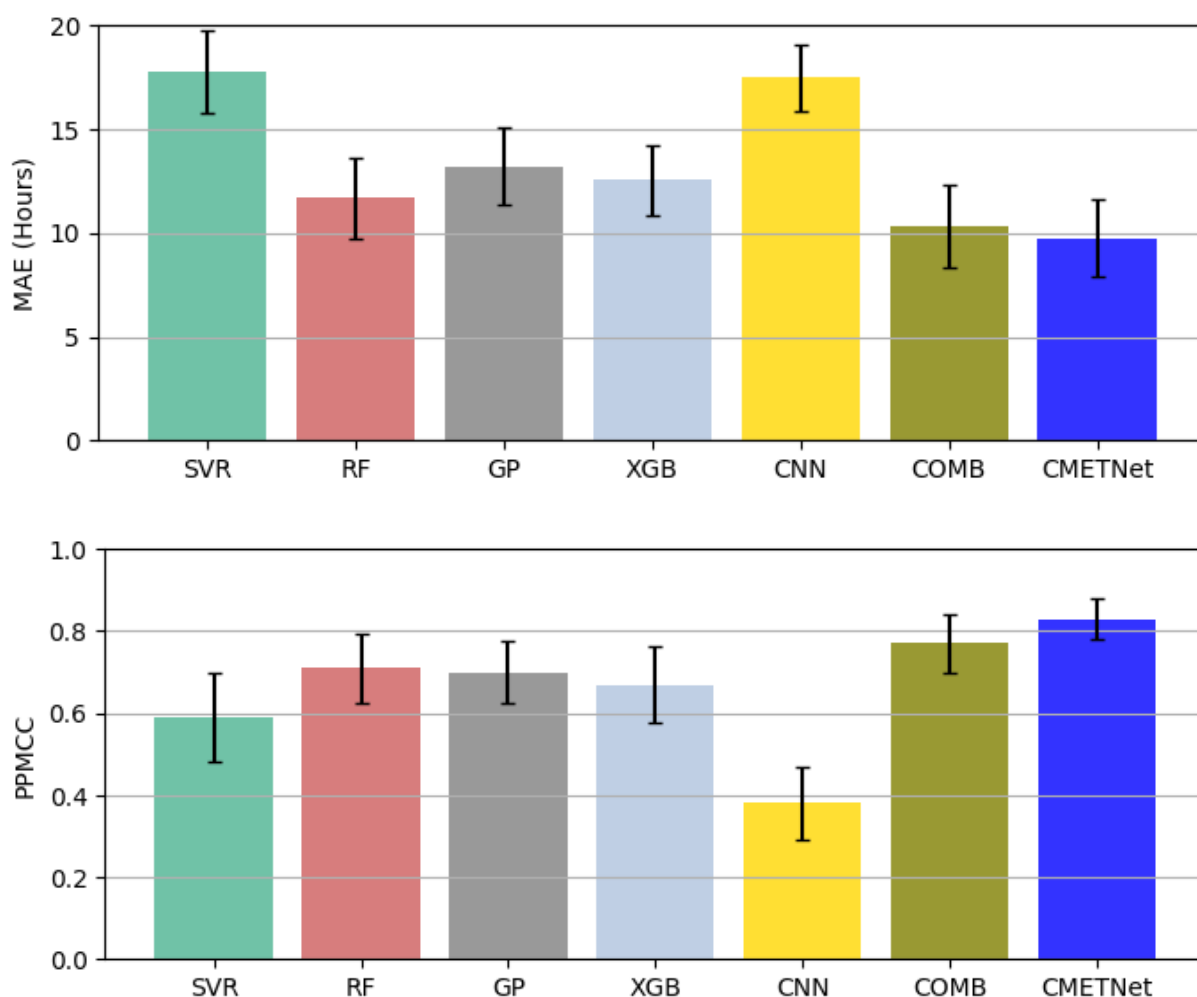
```

In [1]: 1 import warnings
        2 warnings.filterwarnings('ignore')
        3
        4 import os
        5 print('Packages imported')
        6 #make sure the scripts are executed in the correct package location.
        7 if os.path.exists('CMETNet_Package'):
        8     print('Changing working directory to CMETNet_Package..')
        9     os.chdir('CMETNet_Package')
       10 import sys
       11 sys.path.append('.')
       12
       13 from pretrained_models_results import plot_results
       14 #Plotting the results
       15 plot_results()

```

Packages imported

Changing working directory to CMETNet\_Package..



## CMETNet Training and Testing

### CNN Model Training and Testing

You may train the model with your own data or train the model with the default data.

Here, we show how to train the CMETNet model with default data. To train the model with your own data:

1. You should first upload your file to the data directory (in the left hand side file list).
2. Edit the "ICMEs\_C2\_fits\_list.csv" file in the data directory by adding the C2 FITS images file name and the transit time.

```
In [2]: 1 print('Running the CMETNet_CNN_train.py file...')
2 print('Starting with data preparation, then training the CNN model of CMETNe
3
4 %run CMETNet_CNN_train.py
```

Running the CMETNet\_CNN\_train.py file...

Starting with data preparation, then training the CNN model of CMETNet  
Model: "model"

Layer (type)	Output Shape	Param #
=====		
input_1 (InputLayer)	[(None, 256, 256, 1)]	0
conv2d (Conv2D)	(None, 256, 256, 64)	7808
leaky_re_lu (LeakyReLU)	(None, 256, 256, 64)	0
conv2d_1 (Conv2D)	(None, 128, 128, 64)	495680
batch_normalization (BatchNo	(None, 128, 128, 64)	256
leaky_re_lu_1 (LeakyReLU)	(None, 128, 128, 64)	0
conv2d_2 (Conv2D)	(None, 128, 128, 128)	991360
batch_normalization_1 (Batch	(None, 128, 128, 128)	512
leaky_re_lu_2 (LeakyReLU)	(None, 128, 128, 128)	0
conv2d_3 (Conv2D)	(None, 64, 64, 128)	1982592
batch_normalization_2 (Batch	(None, 64, 64, 128)	512
leaky_re_lu_3 (LeakyReLU)	(None, 64, 64, 128)	0
conv2d_4 (Conv2D)	(None, 64, 64, 256)	3965184
batch_normalization_3 (Batch	(None, 64, 64, 256)	1024
leaky_re_lu_4 (LeakyReLU)	(None, 64, 64, 256)	0
conv2d_5 (Conv2D)	(None, 32, 32, 256)	7930112
batch_normalization_4 (Batch	(None, 32, 32, 256)	1024
leaky_re_lu_5 (LeakyReLU)	(None, 32, 32, 256)	0
flatten (Flatten)	(None, 262144)	0
dense (Dense)	(None, 1024)	268436480
dense_1 (Dense)	(None, 1)	1025
activation (Activation)	(None, 1)	0
=====		
Total params: 283,813,569		



Trainable params: 283,811,905

Non-trainable params: 1,664

---

```
Epoch 1/10
4/4 [=====] - 240s 58s/step - loss: 656.5841 - val_loss: 5837.6143
Epoch 2/10
4/4 [=====] - 220s 53s/step - loss: 1313.6345 - val_loss: 1370.9991
Epoch 3/10
4/4 [=====] - 211s 51s/step - loss: 879.7335 - val_loss: 593.1344
Epoch 4/10
4/4 [=====] - 227s 57s/step - loss: 235.8077 - val_loss: 331.7867
Epoch 5/10
4/4 [=====] - 236s 56s/step - loss: 241.0799 - val_loss: 341.0512
Epoch 6/10
4/4 [=====] - 254s 66s/step - loss: 298.2330 - val_loss: 215.0477
Epoch 7/10
4/4 [=====] - 215s 51s/step - loss: 172.9196 - val_loss: 68.3227
Epoch 8/10
4/4 [=====] - 208s 51s/step - loss: 166.6405 - val_loss: 43.2754
Epoch 9/10
4/4 [=====] - 208s 51s/step - loss: 61.1987 - val_loss: 52.2627
Epoch 10/10
4/4 [=====] - 214s 53s/step - loss: 42.5132 - val_loss: 55.2612
Done -----
```

## COMB Model Training and Testing

In this step, the COMB models (SVR, RF, GP, XGP) will be trained with a sample data. The trained models then will be used to predict test data.

```
In [3]: 1 print('Running the CMETNet_COMB_train.py file...')
        2 print('Starting with data preparation, then training the COMB models of CMET
        3
        4 %run CMETNet_COMB_train.py
```

Running the CMETNet\_COMB\_train.py file...

Starting with data preparation, then training the COMB models of CMETNet

Epoch 01 /10

Epoch 02 /10

Epoch 03 /10

Epoch 04 /10

Epoch 05 /10

Epoch 06 /10

Epoch 07 /10

Epoch 08 /10

Epoch 09 /10

Epoch 10 /10

Done -----

## Testing the Ensemble Learning method

Combining CNN and COMB models to show CMETNet prediction results

```
In [4]: 1 print('Running the results_ensemble.py file...')
        2 print('Final results also will be stored in the results directory')
        3 %run results_ensemble.py
```

Running the results\_ensemble.py file...

Final results also will be stored in the results directory

Observed Data				Prediction	
CME Appearance Time	CME Arrival Time	CMETNet	Difference in Hours		
2014-01-04 21:25:00	2014-01-07 14:25:00	2014-01-07 09:53:48	4		
2014-01-07 18:24:00	2014-01-09 19:24:00	2014-01-09 21:14:24	-1		
2014-01-14 10:24:00	2014-01-18 17:24:00	2014-01-17 04:43:48	36		
2014-01-30 16:24:00	2014-02-02 22:24:00	2014-02-02 07:48:36	14		
2014-02-04 01:25:00	2014-02-07 15:25:00	2014-02-06 18:04:00	21		
2014-02-12 06:12:00	2014-02-15 13:12:00	2014-02-15 07:04:12	6		
2014-02-18 01:25:00	2014-02-20 02:25:00	2014-02-20 18:59:48	-16		
2014-02-19 16:00:00	2014-02-23 06:00:00	2014-02-22 16:53:24	13		
2014-02-25 01:25:00	2014-02-27 20:25:00	2014-02-27 06:01:36	14		
2014-03-23 03:48:05	2014-03-26 04:48:05	2014-03-25 19:05:29	9		
2014-04-01 17:00:00	2014-04-05 09:00:00	2014-04-05 00:10:12	8		
2014-04-02 14:00:00	2014-04-05 22:00:00	2014-04-05 03:55:48	18		
2014-04-08 23:12:00	2014-04-11 08:12:00	2014-04-12 01:49:12	-17		
2014-04-18 13:25:51	2014-04-21 06:25:51	2014-04-20 23:26:27	6		
2014-06-25 12:54:00	2014-06-29 17:54:00	2014-06-28 07:22:12	34		
2014-08-15 18:12:00	2014-08-19 06:12:00	2014-08-18 22:29:24	7		
2014-09-09 00:16:00	2014-09-12 09:46:00	2014-09-11 16:07:36	17		
2014-09-10 18:24:00	2014-09-12 15:24:00	2014-09-13 06:31:48	-15		
2014-11-01 05:12:00	2014-11-03 22:12:00	2014-11-03 11:34:12	10		
2014-11-07 18:08:00	2014-11-10 01:08:00	2014-11-10 08:46:24	-7		
2014-12-17 05:00:00	2014-12-21 11:30:00	2014-12-19 21:14:24	38		

CMENet PPMCC: 0.42

CMENet MAE: 15.33

Done -----

## Conclusions

In this work we presented an ensemble framework (CMETNet) for predicting the arrival time of CME events. Each event contains 5 CME features (angular width, main position angle, linear speed, 2nd-order speed at final height, and mass), 7 solar wind parameters (Bx, Bz, alpha to proton ratio, flow longitude, plasma pressure, flow speed, and proton temperature) and 0-17 CME images. The CMETNet framework is composed of five machine learning models including support vector regression (SVR), random forest (RF), Gaussian process (GP), XGBoost (XGB), and a convolutional neural network (CNN). Our experimental results demonstrated that using all the CME features, solar wind parameters and CME images together yields better performance than using part of them.

## CMETNet paper

Predicting CME arrival time through data integration and ensemble learning

Khalid A. Alobaid, Yasser Abduallah, Jason T. L. Wang, Haimin Wang, Haodi Jiang, Yan Xu, Vasyl Yurchyshyn, Hongyang Zhang, Huseyin Cavus and Ju Jing

<https://www.frontiersin.org/articles/10.3389/fspas.2022.1013345/full>

[.https://www.frontiersin.org/articles/10.3389/fspas.2022.1013345/full](https://www.frontiersin.org/articles/10.3389/fspas.2022.1013345/full)