Identifying Flux Rope Signatures Using a Deep Neural Network

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Received: 9 April 2020 / Accepted: 28 August 2020 / Published online: 6 October 2020
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Abstract Among the current challenges in space weather, one of the main ones is to forecast the internal magnetic configuration within interplanetary coronal mass ejections (ICMEs). The classification of such an arrangement is essential to predict geomagnetic disturbances. When a monotonic and coherent magnetic configuration is observed, it is associated with the result of a spacecraft crossing a large flux rope with the topology of helical magnetic field lines. This article applies machine learning and a current physical flux rope analytical model to identify and further understand the internal structure of ICMEs. We trained an image recognition artificial neural network with analytical flux rope data, generated from the range of many possible trajectories within a cylindrical (circular and elliptical cross-section) model. The trained network was then evaluated against the observed ICMEs from Wind during 1995–2015.

The methodology developed in this article can classify 84% of simple real cases correctly and has a 76% success rate when extended to a broader set with 5% noise applied, although it does exhibit a bias in favor of positive flux rope classification. As a first step towards a generalizable classification and parameterization tool, these results are promising. With further tuning and refinement, our model presents a strong potential to evolve into a robust tool for identifying flux rope configurations from in situ data.

This article belongs to the Topical Collection: Towards Future Research on Space Weather Drivers
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Keywords  Coronal mass ejections · Interplanetary · Magnetic fields · Models · Machine learning · Deep learning · Convolutional neural network · Handwriting recognition · Magnetic field fluctuations

1. Introduction

The main drivers of geomagnetic activity are interplanetary coronal mass ejections (ICMEs). Besides transporting large quantities of mass and magnetic flux away from the Sun, their internal magnetic field structure is often coupled to the upper magnetosphere, triggering magnetic reconnection processes that allow solar magnetic energy to be injected into the entire magnetospheric system. Thus, a reliable classification of the ICME internal magnetic field structure is a requirement to develop a robust space weather forecast. The imprints of an ICME internal magnetic structure often present a particular type of configuration. In space weather, the classification of such an arrangement is essential to predict geomagnetic disturbances. The leading hypothesis is to assume that such a structure is a flux rope.

Our information about the internal magnetic structure of ICMEs is limited to the 1D observations of a single spacecraft crossing the large structure, leaving a considerable amount of uncertainty about the three-dimensional structure. Magnetic clouds (MCs) (Klein and Burlaga, 1982; Burlaga et al., 1981) are not always detected within ICMEs (see Richardson and Cane, 2004) even though flux ropes are always expected based on the CME eruption theories (see Vourlidas, 2014, and references therein). This might result from changes during the interplanetary evolution (see Manchester et al., 2017, and references therein), from spacecraft crossing far from the ICME core, or possibly from the topological complexity of the magnetic structure during the CME initiation and evolution in the solar corona and inner heliosphere. There are many known physics-based flux rope models (Lepping, Jones, and Burlaga, 1990) used to reconstruct the internal ICME magnetic configuration that provide information on orientation, geometry, and other magnetic parameters such as the central magnetic field.

Recently, Nieves-Chinchilla et al. (2018b) carried out a comprehensive study of the internal magnetic field configurations of 337 ICMEs observed by Wind at 1 AU in the period 1995 – 2015 to unravel the internal magnetic structure associated with the CMEs and establish under what signatures a flux rope model is valid. The analysis adopted a less restrictive term than MC, magnetic obstacle (MO), to describe the magnetic structure embedded in an ICME. The Magnetic Field Instrument (MFI: Lepping et al., 1995) data and the plasma parameters from the Solar Wind Experiment (SWE: Ogilvie et al., 1995) were used to set the boundaries of the MO and reconstruct those cases found with a flux rope configuration. All the events were sorted based on the magnetic field rotation pattern: events without evident rotation and those showing an ordered and monotonic change or rotation in magnetic field. Later, Nieves-Chinchilla et al. (2019) presented a more in-depth classification in an expanded catalog of 353 ICMEs. In addition to categorizing them, the well-ordered events were also fitted to the circular-cylindrical flux rope model (Nieves-Chinchilla et al., 2016).

Meanwhile, the application of machine learning (ML) has also gained relevance in the space weather community (see Camporeale, 2019, and references therein). We are observing an increase of space- and ground-based capabilities with a growing amount of data available. Inspired by Nieves-Chinchilla et al. (2018b) and (2019), we take advantage of ML techniques to interpret the ICME in situ magnetic field observations and understand in depth what observations should be expected when a spacecraft crosses flux ropes with different trajectories. Because the number of observed and catalogued ICMEs is limited, we
have created a method that incorporates both measured and simulated data and relies on representing this data as an image. There are many episodic events studied in heliophysics that may be able to apply a similar approach.

We present a tool that uses supervised learning techniques and a deep convolutional neural network (DCNN) based on handwriting recognition models to classify and analyze a subset of the events included in Nieves-Chinchilla et al. (2019). In Section 2, we present our DCNN model, describe our dataset, and introduce our methodology to approach the problem. Section 3 discusses the results and Section 4 summarizes the article.

2. Methodology

The novel methodology presented in this article relies on combining artificial neural networks with our current understanding of the internal structure of the ICMEs to classify in situ data measured by Wind spacecraft and eventually to test such knowledge. We create a ML model and train its weights with synthetic data obtained from a well-established physical flux rope model. This approach is conceptually different from a more “standard” ML problem in which one aims to learn about a data space by sampling a subspace (e.g. to identify pictures of a cat by training on many images of cats). Afterward, we use evaluation metrics to analyze performance on a selected subset of real event data. We also use this analysis to choose the DCNN model architecture with which we ultimately proceeded. We then added additional training and evaluation cycles using synthetic training data augmented with noise. Each extra training cycle is based on the best performing training epoch of the previous training cycle.

In the following subsections we will present the deep convolutional neural network (Section 2.1), the synthetic data used for training (Section 2.2), the real data used for evaluation (Section 2.3), the machine-learning pipeline (Section 2.4), and the analysis of the evaluation results (Section 2.5).

2.1. Deep Convolutional Neural Network

One of the many subfields of ML is deep learning. Deep learning uses deep neural networks (DNNs) to make linear transformations and apply non-linear element-wise “activation” functions (Goodfellow et al., 2016). The DNN is composed of multiple layers, in which each layer performs specific types of sorting and ordering in a process that some refer to as “feature hierarchy”. This flexibility of DNNs allows a machine-learning model to represent a given task, using its best features, without manually implementing these features. For the classification problem summarized in the introduction, we consider a convolutional network approach, in which small patches of an image (defined in the kernel size) are linearly combined during the learning process. These convolutional layers take into account the spatial relationships between neighboring points in an image (LeCun and Bengio, 1995). Our DCNN is a binary classification model implementation of the multi-class handwritten digit-recognition models (Ciresan et al., 2011). The input to our model is a stack of three hodogram images (see Section 2.2), having an array dimension of (3, 32, 32) and the output of this model is a two-element vector describing the probability of this hodogram set being a flux rope (FR) or a non-flux rope (NFR).

Figure 1 shows a schematic of the DCNN architecture used for our model. The gray squares represent how the input hodogram, with shape (3, 32, 32), is changing after each
layer of the DCNN. From left to right we have a convolution layer that expands the dimensions to \((16, 30, 30)\) followed by a max-pooling layer that contracts them to \((16, 10, 10)\). A second pair of convolution and max-pooling layers come next, expanding then contracting the dimensions to \((32, 8, 8)\) and \((32, 2, 2)\), respectively. Finally, the array is flattened to 128 nodes and the network completes with two fully connected layers. These last layers take the dimensions from 128 inputs to 16 outputs, then 16 inputs to 2 outputs. Each convolutional layer and the first fully connected layer use a ReLU (Rectified Linear Units, Nair and Hinton, 2010) activation while the final layer uses a softmax activation function. All convolution and max-pooling layers have a kernel size of \(3 \times 3\). The model and training were implemented with PyTorch (Paszke et al., 2017) version 1.3.1 in a Python 3.6.8 environment.

### 2.2. Synthetic Data

The DCNN weights are trained using synthetic data created from two different sources: flux ropes (FRs) from a physics-based model and non-flux ropes (NFRs) from an empirical model developed for this work. The simulated FRs are considered our positive training cases for the neural network and the simulated NFRs are the negative.

The FR dataset is created using the elliptic-cylindrical model (EC) (Nieves-Chinchilla et al., 2018a), consisting of time series of each magnetic field component of a simulated spacecraft trajectory through the modeled flux rope. The EC model has eight input parameters:

- \(B_{\gamma 0}\) The magnetic field at the center of the flux rope, therefore, the maximum magnetic field. We keep this parameter constant at 10 nT since the magnetic fields are all normalized when converted to hodograms.
- \(C_{10}\) We keep this value constant at 1, which imposes a force free structure.
- \(H\) Chirality of the flux rope. We set this as \(H = \pm 1\) to produce cases of left- and right-handed chirality.
- \(Y_0\) The perpendicular distance from the center of the flux rope to the crossing of the spacecraft. For this proof-of-concept stage we keep this value as 0 AU, so that all simulations are crossing at the center of the flux rope.
- \(\phi\) Flux rope latitude orientation angle. It is varied from 5° to 355° in steps of 10°. See Figure 2b.
Figure 2 Flux rope example generated using the elliptic-cylindrical model using parameters $\phi = 60^\circ$, $\theta = 45^\circ$, $Y_0 = 0$, $\xi = 40^\circ$, $\delta = 0.5$ and $H = +1$ in the geocentric solar ecliptic (GSE) coordinate system. (a) Overview of the flux rope and the ecliptic plane (plane XY) showing the $\xi$ rotation about the central axis. (b) View of the flux rope along the $Z$-axis. (c) View from the Earth to Sun direction (i.e. spacecraft point of view). In this case, $Y_0 = 0$ indicates the spacecraft goes through the flux rope central axis. (d) Cross-section view of the flux rope.

$\theta$ Flux rope longitude orientation angle. It is varied from $-85^\circ$ to $85^\circ$ in steps of $10^\circ$. See Figure 2c.

$\xi$ Flux rope rotation about its central axis. It is varied from $0^\circ$ to $180^\circ$ in steps of $10^\circ$. See Figure 2a.

$\delta$ The ratio of the two axes of the flux rope cylinder cross-section. It is varied from 0.2 to 1 in steps of 0.2; 1 giving a circular cross-section and 0.2 a very elliptical cross-section. With $\delta$ set to 1, we have a circular-cylindrical model. See Figure 2d.

For more details about the parameters, please refer to Nieves-Chinchilla et al. (2018a). An interactive tool of flux rope configuration parameters is available at https://www.geogebra.org/m/navfskxj. The permutation of these parameters generates a total of 123 120 different synthetic FR events to be used for training.

Figure 2 contains four panels with different views of a flux rope obtained using the EC model with parameters $\phi = 60^\circ$, $\theta = 45^\circ$, $Y_0 = 0$, $\xi = 40^\circ$, $\delta = 0.5$ and $H = +1$ in the GSE coordinate system. The top left figure is a view of the flux rope from above the ecliptic.
Figure 3 A flux rope example generated using the elliptic-cylindrical model with parameters $\phi = 60^\circ$, $\theta = 45^\circ$, $Y_0 = 0$, $\xi = 40^\circ$, $\delta = 0.50^\circ$ and $H = +1$. i) The total magnetic field and its components. ii) Three hodograms of the magnetic field components. From left to right $B_y^{\text{GSE}}$ vs. $B_x^{\text{GSE}}$, $B_z^{\text{GSE}}$ vs. $B_x^{\text{GSE}}$ and $B_y^{\text{GSE}}$ vs. $B_z^{\text{GSE}}$. The red dot represents the starting point of the magnetic field.

The EC model effectively creates positive cases (FRs) with varied combinations of parameters, but creating negative training data (NFRs) is a separate challenge. While the instances of MCs that do not match a flux rope geometry are not well understood, they have been broadly categorized into two groups by Nieves-Chinchilla et al. (2019), ejecta (E), and complex (Cx). When comparing hodograms of these two instances of MCs that do match a
flux rope geometry, the E cases are visually more distinct from the MCs with flux rope geometry than are the Cx cases. Since the scope of this research is to demonstrate the analysis of simple events, we have simulated only the E type of non-flux rope events when creating the NFR training data.

To create the NFR training data of synthetic ejecta events, we created three time series from a Gaussian distribution. The mean and standard deviation of each time series were selected randomly from uniform distributions in the ranges $[-0.6, 0.6]$ and $[0.1, 0.3]$, respectively. Any points falling outside $\pm 1$ were replaced with the mean. Each of the time series was treated as one magnetic field component and all were plotted as hodograms in precisely the same way as were the synthetic FRs. To have a balanced training dataset, we created a total of 123 120 synthetic ejecta events.

Figure 4 displays an example of synthetic ejecta generated using the Gaussian distribution method. On the top panels are the total magnetic field and its components, where it is possible to see that there is no clear trend or rotation of any of them. On the three bottom panels, there are the hodograms of this event, which also show no evident rotation of any component of the magnetic field.

2.3. Real Data

This work uses the expanded catalog published in Nieves-Chinchilla et al. (2019). The classification was based on the rotation of the magnetic field components of each event.
events which do not show any apparent rotation of the magnetic field components are classified as ejecta (E). Events with evident rotation are classified as F−, F+, or F+, depending on the span of the rotation. Events with more complex rotations of the magnetic field components, more than 270° or more distinct structures, are classified as complex (Cx). For our purpose, we hold the Nieves-Chinchilla et al. classification to its broader level, considering all cases of type F−, F+, and F+ as flux rope (FR) and all cases of E and Cx as non-flux rope (NFR) when comparing classifications. The original catalog labels will continue to be used for specific event analysis.

Figures 5 and 6 show two examples of events from the catalog. The Figure 5 event is an ICME observed on 13 April 2006 and classified as F+. The classification was based on the smooth and clear rotation of the \( B_y \) and \( B_z \) components, while the \( B_x \) tends to be closer to zero. The event shown in Figure 6 was observed on 23 June 2000 and was classified as E. No clear rotation is seen in this event and all three components are approximately flat although it displays a coherent configuration in magnetic field and the other quantities like thermal velocity, proton density, and \( \beta_{\text{proton}} \) (the ratio of gas pressure and magnetic pressure), which is a signature associated with MOs.

The reference catalog has 353 events. Of these, 32 are used during the select evaluation phase, and the remaining 321 are reserved for the analysis in Section 3. We selected 32 cases (indicated with an asterisk (*) in Table 4) because they were more easily differentiated by eye as FRs or NFRs and considered a good test-bed in which to evaluate the performance of a machine-learned-based classifier. The FR cases are some of the most smooth and “nicely” behaved events, while the NFR cases were all of the subset type E.

Each magnetic field component is averaged to one hour time unless the result has less than 20 points, in which case we move to a smaller time window for averaging. Because this work is focused on the geometry of magnetic structures and not the magnitude, all events are rescaled and plotted in the same range in hodogram format. All image files are created at a resolution of 32 x 32 pixels for neural network training and evaluation.

2.4. DCNN Training Pipeline

Initially, we set up several similar DCNN model architectures. Each of these neural networks was trained with 128 noise-free, synthetic events per batch, withholding a randomly selected 30% of the training data for validation. For this training of network weights, we used the Adam optimizer (Kingma and Ba, 2015) with an initial learning rate of 0.001. We found that the accuracy and loss were converging quickly and suspected it was due to the simplicity of this classification problem in the simulation space. Thus, we limited the training of the network to 50 epochs to avoid overfitting.

The most meaningful result we have is not how well we can train the DCNN model to recognize the differences between the synthetic data but how it performs when classifying the real events. Accordingly, after 50 epochs of training, we evaluated each of the considered DCNN model architectures with our selected real cases (Section 2.3) and predicted their label. From this, we can score the accuracy of our DCNN model in its desired use case. The best performing epoch and architecture, presented in Section 2.1 was selected for further development.

The selected DCNN model had its network weights trained using noise-free synthetic data. After each epoch of training, we validated the DCNN model against our selected real cases. This evaluation does not have any feedback to the model weights and it serves only as a parameter for model optimization through selection. We then extended the DCNN model training in a step-wise manner by introducing noisy training data. Using the epoch giving the
best performance on the real events as our trained source model, we created a new copy of the DCNN model and initialized its convolutional layers with the learned network weights from the source model, while randomizing the weights on the fully connected layers, as described in Barshan and Fieguth (2015). We then trained this new model for 50 epochs with the 5% noise training set. In a like manner, we then extended the training from the best performing epoch of this 5% model, this time training with the 10% noise dataset. In this way, the secondary and tertiary stages can build on the spatial relationships learned in earlier stages while allowing for new classification criteria better aligned with noisy input data.
Figure 6  ICME observed on 23 June 2000, classified as E. From top to bottom, total magnetic field [nT], magnetic field components [nT], proton density [cc$^{-1}$], thermal velocity [km/s], $\beta_{\text{proton}}$ (ratio of gas pressure and magnetic pressure), bulk velocity [km/s] and three hodograms of the magnetic field components.

Each stage of training creates a separate DCNN model that can be evaluated independently against real-world data.

2.5. DCNN Model Evaluation

Table 1 displays the metrics extracted from the classification results of evaluation using the real data subset. Cases, where the reference and original classification agree on being positive (FR) or negative (NFR), are true positives (TP) and true negatives (TN), respectively.
Table 1  Metrics for the classifications made during the training phase using the 32 evaluated cases. The table presents these metrics for the three different levels of noise (noise-free, 5%, and 10% noise).

| Quantities       | No Noise | 5% Noise | 10% Noise |
|------------------|----------|----------|-----------|
| True Positive    | 16 (89%) | 18 (100%)| 16 (89%)  |
| False Positive   | 2 (14%)  | 5 (36%)  | 7 (50%)   |
| True Negative    | 12 (86%) | 9 (64%)  | 7 (50%)   |
| False Negative   | 2 (11%)  | 0 (0%)   | 2 (11%)   |
| Accuracy         | 88%      | 84%      | 72%       |
| Precision        | 0.89     | 0.78     | 0.70      |
| Recall           | 0.89     | 1.00     | 0.89      |
| F_1 Score        | 0.89     | 0.88     | 0.78      |

If the classification is positive (FR) and the ground truth is negative (NFR), we have a false positive (FP). Alternately, if the classification is negative (NFR) and the ground truth is positive (FR), we have a false negative (FN). The accuracy is the ratio of the true (TP+TN) cases to the total number of cases. In addition to TP, FN, TN, and FP, the table includes the calculated quantities Accuracy, Precision, Recall, and F_1 Score, standard metrics in ML, defined in Equations 1, 2, 3, and 4, respectively, in Appendix A.

A more detailed classification of the 32 events used in the validation can be found in Table 4 (indicated with *), Appendix B. It has the necessary information to compare the classification done in the reference catalog and the classification done for the DCNN model with different amounts of noise.

Analyzing the results of Table 1, we can see that the DCNN model works well across all three levels of noise, with high F_1 Score, Recall, and Precision of 0.89 for the no noise model and 88% Accuracy. These numbers drop to 0.88 for F_1 Score and 0.78 for Precision when adding 5% noise, showing a worse classification of the NFR cases, but a better FR classification with the increase of the Recall to 1. The general Accuracy decreased a little to 84% with the 5% noise DCNN model. This tendency remains in the 10% noise results, with a Precision of 0.7 and F_1 Score 0.78, demonstrating an even worse classification of the NFR cases and an Accuracy of 72%. The results display a good performance because the model and training data were optimized for this set of 32 events, although none of the real events were used in the actual training of the DCNN model weights. These numbers represent the capability of our model to identify real flux ropes although being only trained with synthetic data.

Evaluating the noise-free classification results, we found four disagreements out of 32 cases classified. Figures 7 through 10 display the four disagreement events which are 13 May 1995 (FP), 2 October 2013 (FP), 24 January 2011 (FN), and 26 August 2014 (FN), respectively. The top panel has the time series of the magnetic field components. The three bottom panels are the hodograms for each event, composed of the real data (dotted) and the smoothed real data (pink line). Here we make a detailed evaluation of the classification done for these events.

The event of 13 May 1995 (Figure 7) was originally classified as E by Nieves-Chinchilla et al. (2019) while the DCNN model classified it as FR. This event has a relatively short duration, and by visual inspection of the hodograms, it is clear that it is, to some extent, well behaved. All the components have a linear behavior, in addition to the monotonous decay of the \( B_z \) and \( B_y \) components. Because of the smooth but short rotation in the magnetic field, mainly the \( B_z \) component, a case could be made that the reference classification in this instance could be reconsidered as type F\( ^- \). Alternatively, the negative synthetic data created to train the model is based on Gaussian distributed random numbers, and it may not
Figure 7  13 May 1995 ICME. The top panel shows the magnetic field components. The three bottom panels are the hodograms for this event, composed of the real data (dotted) and the smoothed real data (pink line).

Figure 8  2 October 2013 ICME. The top panel shows the magnetic field components. The three bottom panels are the hodograms for this event, composed of the real data (dotted) and the smoothed real data (pink line).

represent all the ejecta well, as in this case. Implementing more complexity in the synthetic ejecta may address this discrepancy.

The event of October 2013 (Figure 8) is the second FP case, where the DCNN model classified it as an FR, disagreeing with the catalog that classified it as E. It is possible to observe a substantial change in all three components, but mainly $B_z$ and $B_x$, at about halfway into the event. While there is a small rotation in the $B_y$ component, the hodogram signature is again clearly not well fit by our simulated negative training data and could also benefit from implementing a more complex negative data generator.

The event of 24 January 2011 (Figure 9) is an FN case, classified as NFR, with a reference catalog classification of F$^+$. It is possible to see the rotation of $B_x$ and $B_z$ components. Doing a visual inspection, the catalog classification as one of the flux rope types seems reasonable with the long, smooth rotation in the magnetic field. This case, however, has a catalog classification of F$^+$, defined as structures that have a rotation of more than $180^\circ$ in at least two components of the magnetic field. We can explain an in situ signature like this
Figure 9  ICME of 24 January 2011. The top panel shows the magnetic field components. The solid line is the observed data, and the dashed line is the fitting done using the circular-cylindrical model (Nieves-Chinchilla et al., 2016). The three bottom panels are the hodograms for this event, composed of the real data (dotted), the smoothed real data (pink line), and the fitting done using the circular-cylindrical (CC) model (blue line).

if the spacecraft is crossing in one of the flanks of the CME, assuming a croissant shape as described by Nieves-Chinchilla et al. (2016). This kind of event is not modeled with the elliptic-cylindrical model; therefore, the synthetic data used in this experiment do not produce any event with such significant rotation. It is clear that the flux rope model does not fit the data well, showing a limitation of the generated data used for training. It makes sense that the lack of a global model that represents all possible events reduces the accuracy of the classification model. Incorporating a flux rope model that assumes a croissant shape is a desired future step in training this classification tool.

Even though the model used to generate the training data does not reproduce \( F^+ \), our analysis of this event suggests another possible solution or fix to this discrepancy between classification and label. After a careful inspection, we do not agree with the boundaries applied to this event and have concluded that it might be better labeled as a Cx event. When looking at the time series from this event, it is possible to see a discontinuity just at the start of 25 January. Therefore this event could be split into two flux rope events and considered separately by the flux rope model fitting and machine-learning classifier.

The last FN event is 26 August 2014; see Figure 10. The reference catalog labels this as \( F_r \), neither under- nor over-rotated, but the DCNN model disagrees, labeling it as NFR. By eye, this seems like it should have been easy to classify. A possible explanation is that the nature of the noise in the data may have contributed to the misclassification, having a large change in noise distribution throughout the flux rope crossing. The neural network classification model still needs continued tuning and augmented training data to increase its precision and make it a more generalized model.

3. Results and Discussion

This section introduces the results of the classification made by the DCNN model of the remaining 321 events, with and without Cx events, from the reference catalog in Nieves-Chinchilla et al. (2019), and we analyze the metrics obtained from these classifications.
Figure 10  26 August 2014 ICME. The top panel shows the magnetic field components. The solid lines are the observed data, and the dashed lines are the fitting done using the circular-cylindrical model (Nieves-Chinchilla et al., 2016). The three bottom panels are the hodograms for this event, composed of the real data (dotted), the smoothed real data (pink line), and the fitting done using the CC model (blue line).

Figure 11  Six confusion matrices (CMs). Each is composed of N x N entries, comparing the true labels and predicted labels of the classified objects. The top row CMs are results of the evaluated 321 events, including the complex (Cx) structure ones. The bottom row shows the results of the evaluated 270 events that are not cataloged as Cx type. Each CM is for each model trained with different amounts of noise, from left to right CM for the noise-free model, for the 5% noise model, and the 10% noise model.

In Figure 11 there are six confusion matrices (CMs), a.k.a. error matrices (Stehman, 1997), used to better visualize the classifier performance. Each is composed of N x N entries, comparing the true labels and predicted labels of the classified objects. In our case, we
Table 2  Metrics for the classifications made during the training phase using the 321 cases of the reference catalog with three different levels of noise: noise-free, 5%, and 10% noise. It includes TP, FP, TN, FN, Accuracy, Precision, Recall, and $F_1$ Score.

|                | Including Cx |                      | Not including Cx |                      |
|----------------|--------------|----------------------|-------------------|----------------------|
|                | No Noise     | 5% Noise             | 10% Noise         | No Noise             | 5% Noise             | 10% Noise             |
| TP             | 101 (40%)    | 199 (78%)            | 182 (72%)         | 101 (40%)            | 199 (78%)            | 182 (72%)             |
| FP             | 14 (21%)     | 47 (70%)             | 54 (81%)          | 4 (25%)              | 11 (69%)             | 12 (75%)              |
| TN             | 53 (79%)     | 20 (30%)             | 13 (19%)          | 12 (75%)             | 5 (31%)              | 4 (25%)               |
| FN             | 153 (60%)    | 55 (22%)             | 72 (28%)          | 153 (60%)            | 55 (22%)             | 72 (28%)              |
| **Accuracy**   | 48%          | 68%                  | 61%               | 42%                  | 76%                  | 69%                   |
| **Precision**  | 0.88         | 0.81                 | 0.77              | 0.96                 | 0.95                 | 0.94                  |
| **Recall**     | 0.40         | 0.78                 | 0.72              | 0.40                 | 0.78                 | 0.72                  |
| **$F_1$ Score**| 0.55         | 0.80                 | 0.74              | 0.56                 | 0.86                 | 0.81                  |

have only two classes, FRs and NFRs. Each CM represents the DCNN model trained with different amounts of noise, so from left to right, the first column of CMs are for the noise-free model, the second for the 5% noise model, and the last one for the 10% noise model. The top row CMs are results of the evaluated 321 events, including the complex (Cx) structures. The bottom row are the results when the Cx are not included, which amounted to 270 events. The y-axis is the true label and the x-axis is the predicted label, and each cell of the CM represents a different quantity. We have the true negatives (TN) in the top-left cell, true positives (TP) in the bottom-right cell, the false-positives (FP) in the top-right cell and the false-negative (FN) case in the bottom left cell.

Table 2 recreates the information included in Table 1 but here based on the 321 events including Cx and 270 events not including Cx. It presents extracted quantities from the confusion matrices from all six DCNN models evaluated and some complementary metrics to understand the classifications. According to the **Accuracy** in Table 2, the results from the noise-free synthetic data indicate the DCNN model can predict 79% of NFRs correctly when we include Cx events and has a **Precision** of 0.88 but is only correct in 40% of labeled FR cases, resulting in low **Recall** and **$F_1$ Score**. These last two metrics are similar when not including the Cx events. The DCNN model predicts 75% of the NFRs and has a **Precision** of 0.96, resulting in a low **$F_1$ Score**.

With the addition of 5% noise, the statistic flips, with 78% agreement of the labeled FR cases but only 30% of TN cases when Cx are included. When Cx cases are not included, we still have 78% of TP and a slight increase of TN to 31%. In both cases, we have a high **Recall**, **Precision**, and **$F_1$ Score**, which is better when no Cx structure is used, which is expected since we did not train the model with synthetic Cx cases. These improved **Recalls** with the addition of noisy training data mirrors what we saw in the subset evaluation. In addition to **Recall**, the other metrics also improve here, suggesting that the classification can be improved by including some noise in the training sets.

We observed a drop in the performance with the 10% noise components in the 321 event set, although not as drastically as compared to the evaluation subset. The **Precision** dropped 0.04 to 0.77, the **Recall** 0.04 to 0.72, and **$F_1$ Score** 0.06 to 0.74. The same happens when tested without the Cx cases; **Precision** dropped 0.01 to 0.94, **Recall** 0.06 to 0.72, and **$F_1$ Score** 0.05 to 0.81. The size of the images used in this work is $32 \times 32$ pixels, and this may not be enough resolution to explore all the spatial features created when the 10% noise
Figure 12 Two stacked bar plots with the number of events of each class from the reference catalog and the predictions made by all three models. (a) Stacked bar plot for the classification, including Cx events. The proportion of NFR in the catalog is 67/321 (21%) and the proportion of NFR is 206/321 (64%) for no noise, 75/321 (23%) for 5% noise, and 85/321 (26%) for 10% noise. (b) Stacked bar plot for the classification excluding Cx events. The proportion of NFR is 16/270 (6%) in the catalog and 167/270 (61%) for no noise, 60/270 (21%) with 5% noise, and 76/270 (28%) at 10% noise.

is applied. Increasing the resolution of the images may allow a better classification with considerably more noise.

In both noise cases, it is possible to observe that the DCNN model is biased towards FR, as opposed to the no noise DCNN model which seems to be biased towards classifying as NFR. This explains the decrease in the TN numbers when noise is added. It is clear that when adding noise, the DCNN model starts to classify E and Cx as FR since the simulated flux ropes at this noise level have a non-trivial amount of fluctuation; the hodograms start to resemble ejecta and complex cases. This is a known aspect of the project, and more in-depth investigation of the type of noise and its quantity will help to develop better synthetic data for training. A more physical-based noise will be explored for further development of the DCNN model, to include implementing fluctuations caused by turbulence, waves, or other physical processes.

Figure 12 shows two stacked bar plots with the number of events of each class from the tested reference catalog and the predictions made by all three models. Panel a is for the classification including Cx events, while panel b is for the classification excluding them. In the 321 events from the catalog used for evaluation the proportion of NFR is 67/321 (21%), and it shrinks to 16/270 (6%) when we remove Cx. The small number of E cases left in the test set was the main reason to include Cx when in our primary classification results; otherwise, the data imbalance is enormous. When we use the Cx cases, the proportion of NFR predicted from the 5% and 10% noise trained DCNN models is close to the reference catalog, 75/321 (23%) and 85/321 (26%), respectively. Even though the training data and the validation dataset have a 50% balance, the classification results still reproduce the reference catalog class ratio. In contrast, the no noise DCNN model has a very different ratio of NFR, 206/321 (64%), much closer to the ratio of the training data. The ratio of the predictions is approximately the same when we remove the Cx cases, 167/270 (61%) for no noise, 60/270 (21%) with 5% noise, and 76/270 (28%) at 10% noise. We know the imbalance in the data is significant and we will add new events from different catalogs that will help with the consequences of the unbalanced data.

For a detailed classification of all catalog events, refer to Table 4 in Appendix B. It contains the results for the classification in all 353 cases, with the simple validation subset cases marked with *, and has the necessary information to compare the classification in the reference catalog to the classification in the DCNN model with different noise levels.
Table 3: Comparison of classification metrics on all 353 events in the reference catalog when step-wise training was steered with a randomized validation set vs. the fixed, simple validation set. Performance at three levels of noise: noise free, 5%, and 10% noise is shown for each of the two experiments.

|                | Random Validation Set | Selected Validation Set |
|----------------|-----------------------|-------------------------|
|                | No Noise | 5% Noise | 10% Noise | No Noise | 5% Noise | 10% Noise |
| TP             | 117 (43%)  | 217 (80%)  | 198 (73%) | 109 (40%)  | 212 (78%)  | 148 (54%)  |
| FP             | 16 (20%)   | 52 (64%)   | 61 (75%)  | 14 (17%)   | 50 (62%)   | 45 (56%)   |
| TN             | 65 (80%)   | 29 (36%)   | 20 (25%)  | 67 (83%)   | 31 (38%)   | 36 (44%)   |
| FN             | 155 (57%)  | 55 (20%)   | 74 (27%)  | 163 (60%)  | 60 (22%)   | 124 (46%)  |
| Accuracy       | 52%       | 70%       | 62%       | 50%       | 69%       | 52%       |
| Precision      | 0.88      | 0.81      | 0.76      | 0.89      | 0.81      | 0.77      |
| Recall         | 0.43      | 0.80      | 0.73      | 0.40      | 0.78      | 0.54      |
| $F_1$ Score    | 0.58      | 0.80      | 0.75      | 0.55      | 0.79      | 0.64      |

The results in Appendix B demonstrate that the DCNN model is catching some critical features of flux rope hodograms. It neither classified all the events as a single class nor classified the events randomly. These are promising results to encourage further development of the DCNN model and also better development of the synthetic data, both positive (FR) and negative (NFR).

3.1. Random Validation Dataset

The DCNN models were developed and the training pathway optimized based on performance against the 32 events from the subset catalog, which are nicely behaved events. The motivation for this was to have a fixed validation set that could be used for deeper analysis on DCNN-model performance and that was similar to the simulated training data. This left the remaining 321 events used in testing with relatively more edge and complicated cases.

With the in-depth analysis complete, and to see if a “wilder” validation set could steer the training process towards an improvement in performance, we ran the experiment again with a randomized selection of real events used in the validation step. A set of 32 events, 16 NFR (of type E) and 16 FR (drawn from the $F_r$, $F^−$, and $F^+$ catalog categories) were randomly selected at the start of the experiment. This random validation dataset was then used to pick the best model of each step-wise training process. Table 3 shows the results from this newly trained DCNN model compared with the results from the previously trained DCNN model. For comparison reasons the confusion matrix quantities for all 353 events (including Cx) are reported, not just a part of it since the datasets were split differently. All the metrics previously used ($Accuracy$, $Precision$, $Recall$, and $F_1$ Score) for the DCNN model trained with a selected validation set (reference DCNN model for this paper) are also reported for the DCNN model steered with a random validation set.

We can see that the results for the two different DCNN models have very similar values for the no noise and 5% noise case, within a tolerance of 3% for no noise and 2% for 5% noise. The same does not happen for 10% noise, with a difference of 10% in precision, 0.1 in $F_1$ Score, and 0.2 in Recall, with the random validation set model having a better performance. Even though the DCNN model using the random validation set has slightly better performance in general, it has lower number of TN and higher FP, showing an even stronger tendency to classify an event as FR. Even though there is some variation in the 10%
noise model, we can observe the same tendency across both DCNN models when adding noise, bolstering the previous conclusion that we need a physically based fluctuation model to be implemented in the synthetic data.

In this work we implement a non-traditional machine-learning methodology that uses both synthetic data and some real data for training purposes. Some variation in the results, depending on which validation dataset and specific stopping criteria we use, is expected. The method to choose the validation dataset can, and will be, enhanced. Also more metrics criteria can be used to choose the best epoch for the step training process.

4. Summary and Conclusions

In this article, we establish the framework for a novel technique not only to advance our understanding of the internal structure of ICMEs but also to pave the way to improve forecasting activities. Starting with the complex analysis of the internal structure of ICMEs by Nieves-Chinchilla et al. (2019), we develop a deep convolutional neural network (DCNN) model to classify in situ signatures similarly. Training a DCNN is a time-consuming and costly task that typically involves collecting and analyzing a large amount of data to use in supervised learning. To handle the lack of real-world, labeled data, we combined two analytical flux rope models extracted from physical principles (Nieves-Chinchilla et al., 2016 and 2018a), to act as a source of training data. We rely upon the technique of domain randomization, in which parameters of the simulator—such as angles, radius, velocity, magnetic field—are varied to induce the DCNN to learn the essential characteristics and peculiarities of the object of interest, i.e. flux rope signatures (Tremblay et al., 2018). The DCNN model was validated by analyzing metrics of the classification of a subset of the real data. It is reasonable to think that a similar approach could be applied to other limited or episodic data, such as solar energetic particle events or flares, if suitable simulation models exist.

The DCNN model was able to classify between 76% (in the final phase) and 84% (in the subset evaluation phase) when training data with 5% noise are used. Precision and $F_1$ Score are 0.78 and 0.88, respectively, for the evaluation set. Precision improves to 0.95 and $F_1$ Score holds approximately constant at 0.86 in the test phase. Also, during the test phase, the classification Accuracy jumped from 42% when trained with noise-free data to 76% when trained on data with 5% noise. The classification Accuracy remains high at 69% when trained with 10% noise. The results demonstrate good classification quality by having important statistical metrics ($F_1$ Score, etc.) and similar scores between the evaluation subset and extended catalog.

The results demonstrate that the approach works. We were able to identify flux rope signatures using a pre-established DCNN handwriting model trained with synthetic data with high Accuracy in well-behaved events. We have analyzed the discrepancies between manual and machine-learning-based classification, and this opened a discussion on whether some events should be reclassified and how the classification criteria could be improved.

Moreover, the analysis of the classification discrepancies reinforced that flux rope models, especially physics-based flux rope models, are needed to understand the internal structure of ICMEs. Developing more models and including more observed features, such as expansion, curvature or distortion, to the models would generate better training data.

Also, more physics-based fluctuation models should be explored and incorporated into the synthetic data (built-in or not in the flux rope models) for more realistic model fitting.
Future research will explore the methodology to implement the statistical and physics-based fluctuations observed in the data, add the simulation of more complex structures, and increase the number of synthetic events by changing the impact parameter. Once a satisfactory flux rope classifier is obtained, we will extend the DCNN model to predict the best fitting parameters for each event.

Acknowledgements We thank Dr. Barbara Thompson and Tiago Pinho Da Silva M.S. for all discussions and reviews during the work done in this paper. We thank Marta Florido-Llinas BSA for making the flux rope interactive tool available. Resources supporting this work were provided by the NASA High-End Computing (HEC) Program through the NASA Center for Climate Simulation (NCCS) at Goddard Space Flight Center. This material is based upon work supported by the National Science Foundation under Grant No. AGS-1433086. T. N-C also acknowledges Goddard Strategic Collaboration Initiative. We acknowledge the tools used in this work. We used CUDA for processing (cuDNN) (Chetlur et al., 2014), for data analysis and processing we used Numpy (van der Walt, Colbert, and Varoquaux, 2011), Pandas (McKinney, 2010, and Reback et al., 2020), SciPy (Virtanen et al., 2020), and scikit-learn (Pedregosa et al., 2011), and all plots were done using Matplotlib (Hunter, 2007).

Disclosure of Potential Conflicts of Interest The authors declare that there are no conflicts of interest.

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Appendix A: Metrics

Accuracy (Equation 1) is the ratio of the true cases to the total number of instances. Precision (Equation 2) is the fraction of relevant instances among the retrieved instances, while Recall (Equation 3) is the fraction of the total number of relevant instances that were retrieved. Both Precision and Recall need to be taken into account when evaluating the performance of a predictive model. F1 Score (Equation 4) is a well-established measure of the performance of a predictor that considers both Precision (Equation 2) and Recall (Equation 3). Its ideal value is one, and worst value is zero.

\[
\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{Total Number of Instances}}.
\]

\[
\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}.
\]

\[
\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}.
\]

\[
F_1 \text{Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}.
\]

Appendix B: Complete Classification

Table 4 contains the results for the classification done in all the 353 cases and has the necessary information to compare the classification done in the reference catalog and the classification done by the DCNN model with different amounts of noise. The events marked with an asterisk (*) were used in the evaluation subset part of the training.
Table 4 List of all the ICMEs from Nieves-Chinchilla et al. (2019). For each selected ICME the table presents, event number, ICME start date, label assigned by the reference catalog, classification with the no-noise model, classification with 5% noise model, and classification with 10% noise model. The events marked with the asterisk (*) were used in the evaluation part of the training.

| E  | ICME Start | Catalog Label | Predicted Label |
|----|------------|---------------|-----------------|
|    |            |               | No Noise | 5% Noise | 10% Noise |
| 1  | 1995-02-07 | C_x           | NFR       | FR       | FR        |
| 2  | 1995-03-04 | F_r           | NFR       | FR       | FR        |
| 3  | 1995-03-06 | F_−           | NFR       | NFR      | NFR       |
| 4  | 1995-04-03 | F_+           | NFR       | NFR      | NFR       |
| 5  | 1995-04-05 | F_r           | NFR       | FR       | FR        |
| 6  | 1995-05-13* | E             | FR        | FR       | NFR       |
| 7  | 1995-06-30 | F_r           | NFR       | FR       | FR        |
| 8  | 1995-08-22 | F_r           | FR        | NFR      | NFR       |
| 9  | 1995-09-26 | F_r           | NFR       | NFR      | FR        |
| 10 | 1995-10-18 | F_r           | FR        | FR       | FR        |
| 11 | 1995-12-15 | F_−           | NFR       | FR       | NFR       |
| 12 | 1996-02-15 | F_+           | NFR       | FR       | FR        |
| 13 | 1996-04-04 | F_r           | FR        | NFR      | FR        |
| 14 | 1996-05-16 | F_+           | NFR       | FR       | FR        |
| 15 | 1996-05-27 | F_r           | NFR       | FR       | FR        |
| 16 | 1996-07-01 | F_r           | NFR       | FR       | FR        |
| 17 | 1996-07-02 | F_−           | NFR       | FR       | FR        |
| 18 | 1996-08-07 | F_r           | NFR       | FR       | NFR       |
| 19 | 1996-12-24 | F_+           | FR        | FR       | FR        |
| 20 | 1997-01-10 | F_+           | FR        | FR       | FR        |
| 21 | 1997-02-09 | F_−           | NFR       | NFR      | NFR       |
| 22 | 1997-04-10 | F_r           | NFR       | FR       | FR        |
| 23 | 1997-04-21 | F_+           | FR        | FR       | FR        |
| 24 | 1997-05-15 | F_+           | FR        | FR       | FR        |
| 25 | 1997-05-16 | F_r           | FR        | FR       | FR        |
| 26 | 1997-05-26 | F_r           | FR        | FR       | FR        |
| 27 | 1997-06-08 | F_r           | NFR       | FR       | FR        |
| 28 | 1997-06-19 | F_r           | NFR       | NFR      | NFR       |
| 29 | 1997-07-15 | F_+           | FR        | FR       | FR        |
| 30 | 1997-08-03 | F_r           | FR        | FR       | FR        |
| 31 | 1997-08-17 | F_r           | NFR       | FR       | FR        |
| 32 | 1997-09-02 | F_r           | NFR       | FR       | FR        |
| 33 | 1997-09-18 | F_+           | NFR       | FR       | FR        |
| 34 | 1997-09-21 | F_+           | NFR       | NFR      | NFR       |
| 35 | 1997-10-01 | F_r           | NFR       | FR       | FR        |
| 36 | 1997-10-10 | F_+           | FR        | FR       | FR        |
| 37 | 1997-11-06 | F_+           | NFR       | FR       | FR        |
| 38 | 1997-11-22 | F_+           | FR        | FR       | FR        |
| 39 | 1997-12-10 | C_x           | NFR       | FR       | FR        |
| 40 | 1997-12-30 | F_r           | NFR       | FR       | FR        |
| E   | ICME Start     | Catalog Label | Predicted Label | No Noise | 5% Noise | 10% Noise |
|-----|----------------|---------------|-----------------|----------|----------|----------|
| 41  | 1998-01-06*    | F⁺            | FR              | FR       | FR       | FR       |
| 42  | 1998-01-08     | F⁻            | NFR             | FR       | FR       | FR       |
| 43  | 1998-01-09     | Fᵣ            | NFR             | FR       | FR       | FR       |
| 44  | 1998-01-21     | F⁻            | NFR             | FR       | FR       | FR       |
| 45  | 1998-01-28     | F⁺            | NFR             | NFR      | FR       | FR       |
| 46  | 1998-02-02     | F⁺            | NFR             | FR       | FR       | FR       |
| 47  | 1998-02-04     | F⁺            | FR              | FR       | FR       | FR       |
| 48  | 1998-02-17     | Fᵣ            | FR              | FR       | FR       | FR       |
| 49  | 1998-02-18     | Fᵣ            | NFR             | FR       | FR       | FR       |
| 50  | 1998-03-04     | F⁺            | FR              | FR       | FR       | FR       |
| 51  | 1998-03-06     | Cₓ            | FR              | FR       | FR       | FR       |
| 52  | 1998-03-25     | Fᵣ            | NFR             | NFR      | FR       | FR       |
| 53  | 1998-03-31     | Fᵣ            | NFR             | FR       | FR       | FR       |
| 54  | 1998-04-01*    | E             | NFR             | NFR      | FR       | FR       |
| 55  | 1998-05-01     | Fᵣ            | FR              | FR       | FR       | FR       |
| 56  | 1998-05-04     | F⁻            | NFR             | NFR      | FR       | FR       |
| 57  | 1998-06-02     | Fᵣ            | NFR             | FR       | FR       | FR       |
| 58  | 1998-06-24     | F⁺            | FR              | FR       | FR       | FR       |
| 59  | 1998-07-10     | F⁺            | NFR             | NFR      | FR       | FR       |
| 60  | 1998-08-10*    | E             | NFR             | FR       | FR       | FR       |
| 61  | 1998-08-19*    | F⁺            | FR              | FR       | FR       | FR       |
| 62  | 1998-08-26     | E             | NFR             | NFR      | FR       | FR       |
| 63  | 1998-09-23     | F⁻            | FR              | FR       | FR       | FR       |
| 64  | 1998-09-24*    | F⁺            | FR              | FR       | FR       | FR       |
| 65  | 1998-10-02*    | E             | NFR             | NFR      | FR       | FR       |
| 66  | 1998-10-18     | F⁺            | FR              | FR       | FR       | FR       |
| 67  | 1998-10-23     | F⁻            | NFR             | FR       | FR       | FR       |
| 68  | 1998-11-08     | Cₓ            | NFR             | FR       | FR       | FR       |
| 69  | 1998-11-09*    | F⁺            | FR              | FR       | FR       | FR       |
| 70  | 1999-01-22     | E             | NFR             | NFR      | FR       | FR       |
| 71  | 1999-02-11     | Fᵣ            | NFR             | FR       | FR       | FR       |
| 72  | 1999-02-18*    | E             | NFR             | FR       | FR       | FR       |
| 73  | 1999-04-16     | Fᵣ            | FR              | FR       | FR       | FR       |
| 74  | 1999-04-21     | E             | NFR             | FR       | FR       | FR       |
| 75  | 1999-05-28     | Cₓ            | NFR             | FR       | FR       | FR       |
| 76  | 1999-06-26     | Fᵣ            | NFR             | FR       | FR       | FR       |
| 77  | 1999-07-02     | Fᵣ            | NFR             | NFR      | FR       | FR       |
| 78  | 1999-07-06     | Cₓ            | FR              | FR       | FR       | FR       |
| 79  | 1999-07-30     | E             | FR              | FR       | FR       | FR       |
| 80  | 1999-08-06     | Fᵣ            | NFR             | FR       | FR       | NFR      |
| 81  | 1999-08-09*    | Fᵣ            | FR              | FR       | FR       | FR       |
| 82  | 1999-09-15     | E             | NFR             | FR       | FR       | NFR      |
Table 4 (Continued)

| E     | ICME Start     | Catalog Label | Predicted Label | No Noise | 5% Noise | 10% Noise |
|-------|----------------|---------------|-----------------|----------|----------|-----------|
| 83    | 1999-09-21     | F_r           | NFR             | FR       | FR       |
| 84    | 1999-09-22*    | E             | NFR             | NFR      | FR       |
| 85    | 1999-10-21     | E             | FR              | FR       | FR       |
| 86    | 1999-11-13     | E             | FR              | FR       | FR       |
| 87    | 1999-12-12     | C_x           | NFR             | FR       | FR       |
| 88    | 2000-02-11     | F_r           | NFR             | FR       | FR       |
| 89    | 2000-02-14*    | E             | NFR             | NFR      | FR       |
| 90    | 2000-02-20     | F_r           | FR              | FR       | NFR      |
| 91    | 2000-03-01     | F_r           | FR              | FR       | FR       |
| 92    | 2000-03-28     | E             | NFR             | NFR      | FR       |
| 93    | 2000-05-07     | C_x           | FR              | FR       | FR       |
| 94    | 2000-06-08     | E             | NFR             | FR       | FR       |
| 95    | 2000-06-23*    | E             | NFR             | NFR      | FR       |
| 96    | 2000-07-01     | F_r           | FR              | FR       | FR       |
| 97    | 2000-07-11     | F_r           | FR              | FR       | FR       |
| 98    | 2000-07-13     | F_r           | FR              | FR       | FR       |
| 99    | 2000-07-15     | F^-           | NFR             | FR       | FR       |
| 100   | 2000-07-15     | F^+           | NFR             | FR       | FR       |
| 101   | 2000-07-19     | C_x           | NFR             | NFR      | FR       |
| 102   | 2000-07-28     | F^+           | NFR             | FR       | FR       |
| 103   | 2000-07-31     | F_r           | NFR             | NFR      | FR       |
| 104   | 2000-08-10     | F^+           | NFR             | FR       | FR       |
| 105   | 2000-08-11     | F^+           | FR              | FR       | FR       |
| 106   | 2000-09-02     | F_r           | NFR             | FR       | FR       |
| 107   | 2000-09-04     | C_x           | NFR             | NFR      | FR       |
| 108   | 2000-09-06     | C_x           | NFR             | NFR      | NFR      |
| 109   | 2000-09-17     | E             | NFR             | NFR      | FR       |
| 110   | 2000-10-03     | F^+           | FR              | FR       | FR       |
| 111   | 2000-10-05     | F_r           | NFR             | FR       | FR       |
| 112   | 2000-10-12     | F_r           | FR              | FR       | FR       |
| 113   | 2000-10-28     | F^-           | FR              | FR       | FR       |
| 114   | 2000-11-06     | F_r           | NFR             | FR       | FR       |
| 115   | 2000-11-10*    | E             | NFR             | NFR      | FR       |
| 116   | 2000-11-11     | E             | NFR             | NFR      | FR       |
| 117   | 2000-11-26     | F_r           | NFR             | FR       | FR       |
| 118   | 2000-12-03     | C_x           | NFR             | NFR      | FR       |
| 119   | 2001-01-23     | C_x           | NFR             | FR       | FR       |
| 120   | 2001-03-04     | C_x           | NFR             | FR       | FR       |
| 121   | 2001-03-19*    | F_r           | FR              | FR       | NFR      |
| 122   | 2001-03-20     | F_r           | FR              | FR       | NFR      |
| 123   | 2001-03-27     | C_x           | NFR             | NFR      | NFR      |
| 124   | 2001-04-04     | F^-           | NFR             | FR       | NFR      |
Table 4 (Continued)

| E   | ICME Start | Catalog Label | Predicted Label |
|-----|------------|---------------|-----------------|
|     |            |               | No Noise | 5% Noise | 10% Noise |
| 125 | 2001-04-11 | F−            | NFR       | FR       | FR         |
| 126 | 2001-04-13 | F−            | NFR       | FR       | FR         |
| 127 | 2001-04-21*| F_r           | FR        | FR       | FR         |
| 128 | 2001-04-28 | C_x           | NFR       | FR       | FR         |
| 129 | 2001-05-27 | C_x           | NFR       | NFR      | NFR        |
| 130 | 2001-06-27 | C_x           | NFR       | NFR      | FR         |
| 131 | 2001-08-05*| E             | NFR       | NFR      | NFR        |
| 132 | 2001-08-17 | F−            | NFR       | FR       | FR         |
| 133 | 2001-09-25 | F−            | FR        | FR       | NFR        |
| 134 | 2001-09-29 | C_x           | FR        | FR       | NFR        |
| 138 | 2001-10-28 | E             | NFR       | FR       | FR         |
| 139 | 2001-10-31 | F_r           | FR        | FR       | FR         |
| 140 | 2001-11-24 | F_r           | NFR       | NFR      | NFR        |
| 141 | 2001-12-29*| F_r           | FR        | FR       | FR         |
| 142 | 2001-12-30 | F−            | NFR       | NFR      | NFR        |
| 143 | 2002-02-28 | F_r           | NFR       | FR       | FR         |
| 144 | 2002-03-18 | F_r           | NFR       | FR       | FR         |
| 145 | 2002-03-23 | F_r           | FR        | FR       | FR         |
| 146 | 2002-04-14 | F−            | NFR       | NFR      | NFR        |
| 147 | 2002-04-17 | F+            | FR        | FR       | FR         |
| 148 | 2002-04-19 | F_r           | NFR       | FR       | FR         |
| 149 | 2002-04-23 | F−            | NFR       | NFR      | NFR        |
| 150 | 2002-05-10 | F_r           | NFR       | FR       | FR         |
| 151 | 2002-05-11 | F_r           | FR        | FR       | FR         |
| 152 | 2002-05-18 | F_r           | FR        | FR       | NFR        |
| 153 | 2002-05-20 | C_x           | NFR       | FR       | FR         |
| 154 | 2002-05-23 | F−            | NFR       | NFR      | FR         |
| 155 | 2002-07-17 | F_r           | FR        | FR       | FR         |
| 156 | 2002-08-01 | F_r           | FR        | FR       | FR         |
| 157 | 2002-08-01 | F_r           | NFR       | FR       | NFR        |
| 158 | 2002-08-18 | F_r           | NFR       | NFR      | FR         |
| 159 | 2002-08-26 | F_r           | NFR       | NFR      | FR         |
| 160 | 2002-09-03 | C_x           | FR        | FR       | FR         |
| 161 | 2002-09-30 | F+            | FR        | FR       | FR         |
| 162 | 2002-11-16 | F−            | NFR       | NFR      | NFR        |
| 163 | 2002-12-21 | F_r           | FR        | FR       | FR         |
| 164 | 2003-01-26 | F_r           | NFR       | NFR      | NFR        |
| 165 | 2003-02-01 | F_r           | NFR       | FR       | NFR        |
Table 4 (Continued)

| E   | ICME Start   | Catalog Label | Predicted Label
|-----|--------------|---------------|----------------|
|     |              |               | No Noise | 5% Noise | 10% Noise |
| 166 | 2003-03-20   | $F_r$         | NFR      | FR       | NFR       |
| 167 | 2003-05-09   | $E$           | NFR      | FR       | FR        |
| 168 | 2003-06-16   | $F_r$         | NFR      | FR       | FR        |
| 169 | 2003-08-04   | $F_r$         | NFR      | FR       | FR        |
| 170 | 2003-10-21   | $C_x$         | NFR      | NFR      | NFR       |
| 171 | 2003-10-29   | $C_x$         | NFR      | FR       | FR        |
| 172 | 2003-10-30   | $C_x$         | NFR      | FR       | FR        |
| 173 | 2003-11-20*  | $F_r$         | FR       | FR       | FR        |
| 174 | 2004-01-09   | $E$           | NFR      | FR       | FR        |
| 175 | 2004-04-03   | $F^+$         | FR       | FR       | FR        |
| 176 | 2004-07-22   | $C_x$         | NFR      | FR       | FR        |
| 177 | 2004-07-24   | $F_r$         | NFR      | FR       | FR        |
| 178 | 2004-07-25   | $F_r$         | NFR      | FR       | FR        |
| 179 | 2004-07-26   | $C_x$         | FR       | FR       | FR        |
| 180 | 2004-08-29   | $F_r$         | FR       | FR       | FR        |
| 181 | 2004-09-13*  | $E$           | NFR      | FR       | NFR       |
| 182 | 2004-09-17   | $F_r$         | FR       | FR       | FR        |
| 183 | 2004-11-07   | $F_r$         | FR       | FR       | FR        |
| 184 | 2004-11-09*  | $F^+$         | FR       | FR       | FR        |
| 185 | 2004-11-11   | $F_r$         | FR       | FR       | FR        |
| 186 | 2004-12-10   | $F^-$         | NFR      | FR       | FR        |
| 187 | 2005-01-07   | $F^+$         | FR       | FR       | FR        |
| 188 | 2005-01-08   | $F_r$         | FR       | FR       | FR        |
| 189 | 2005-01-16   | $F^+$         | FR       | FR       | FR        |
| 190 | 2005-01-18   | $F^-$         | NFR      | FR       | NFR       |
| 191 | 2005-01-21   | $F^-$         | NFR      | FR       | FR        |
| 192 | 2005-02-16   | $F^-$         | NFR      | NFR      | FR        |
| 193 | 2005-02-17   | $E$           | NFR      | FR       | FR        |
| 194 | 2005-02-20   | $F_r$         | NFR      | NFR      | NFR       |
| 195 | 2005-05-15   | $F^+$         | FR       | FR       | FR        |
| 196 | 2005-05-20   | $F^+$         | NFR      | FR       | FR        |
| 197 | 2005-06-12   | $F^-$         | NFR      | FR       | FR        |
| 198 | 2005-06-14*  | $F^+$         | FR       | FR       | FR        |
| 199 | 2005-07-10   | $C_x$         | NFR      | NFR      | FR        |
| 200 | 2005-07-17   | $F_r$         | NFR      | FR       | FR        |
| 201 | 2005-08-10   | $F^-$         | NFR      | NFR      | FR        |
| 202 | 2005-10-31   | $F_r$         | NFR      | FR       | FR        |
| 203 | 2006-02-05   | $F^+$         | FR       | FR       | FR        |
| 204 | 2006-04-13*  | $F^+$         | FR       | FR       | FR        |
| 205 | 2006-04-14   | $F^-$         | NFR      | FR       | NFR       |
| 206 | 2006-06-14   | $F^-$         | NFR      | NFR      | NFR       |
| 207 | 2006-07-09   | $C_x$         | NFR      | FR       | NFR       |
Table 4 (Continued)

| E  | ICME Start | Catalog Label | Predicted Label | No Noise | 5% Noise | 10% Noise |
|----|------------|---------------|-----------------|----------|----------|----------|
| 208| 2006-08-19 | Cx            | NFR             | NFR      | NFR      | NFR      |
| 209| 2006-08-30 | Cx            | NFR             | FR       | FR       | FR       |
| 210| 2006-09-30 | F+            | FR              | FR       | FR       | FR       |
| 211| 2006-11-01 | F-            | NFR             | NFR      | NFR      | NFR      |
| 212| 2006-11-18 | F_1           | NFR             | NFR      | NFR      | NFR      |
| 213| 2006-11-29 | F+            | FR              | FR       | FR       | FR       |
| 214| 2006-12-14 | F-            | NFR             | FR       | FR       | FR       |
| 215| 2006-12-16 | F-            | NFR             | FR       | FR       | FR       |
| 216| 2007-01-14 | F_1           | FR              | FR       | FR       | FR       |
| 217| 2007-01-15 | F-            | FR              | FR       | FR       | FR       |
| 218| 2007-03-29 | Cx            | NFR             | FR       | FR       | FR       |
| 219| 2007-05-21 | F_1           | FR              | FR       | FR       | FR       |
| 220| 2007-06-08 | F_1           | NFR             | FR       | FR       | FR       |
| 221| 2007-11-19*| F_1           | FR              | FR       | FR       | FR       |
| 222| 2007-12-25 | F-            | NFR             | FR       | FR       | FR       |
| 223| 2008-05-23 | F+            | NFR             | FR       | FR       | FR       |
| 224| 2008-09-03 | F+            | NFR             | FR       | FR       | FR       |
| 225| 2008-09-17 | F_1           | FR              | FR       | FR       | FR       |
| 226| 2008-12-04 | F_1           | NFR             | NFR      | NFR      | NFR      |
| 227| 2008-12-17 | F_1           | FR              | FR       | FR       | FR       |
| 228| 2009-01-02 | F-            | NFR             | FR       | FR       | FR       |
| 229| 2009-01-26 | E              | FR              | FR       | FR       | FR       |
| 230| 2009-02-03 | F+            | NFR             | FR       | FR       | FR       |
| 231| 2009-03-11 | F+            | FR              | FR       | FR       | FR       |
| 232| 2009-04-05 | F-            | NFR             | NFR      | NFR      | NFR      |
| 233| 2009-04-22 | F_1           | FR              | FR       | FR       | FR       |
| 234| 2009-06-03 | F_1           | NFR             | FR       | FR       | FR       |
| 235| 2009-06-27 | F+            | FR              | FR       | FR       | FR       |
| 236| 2009-07-21 | F_1           | FR              | FR       | FR       | FR       |
| 237| 2009-09-10 | F_1           | NFR             | FR       | FR       | FR       |
| 238| 2009-09-30 | F_1           | FR              | FR       | FR       | FR       |
| 239| 2009-10-29 | F+            | FR              | FR       | FR       | FR       |
| 240| 2009-11-01 | F-            | NFR             | NFR      | NFR      | NFR      |
| 241| 2009-11-14 | F_1           | FR              | FR       | FR       | FR       |
| 242| 2009-12-12 | F_1           | NFR             | FR       | FR       | FR       |
| 243| 2010-01-01 | F_1           | NFR             | FR       | FR       | FR       |
| 244| 2010-02-07 | F_1           | NFR             | FR       | FR       | FR       |
| 245| 2010-03-23 | F_1           | NFR             | FR       | FR       | FR       |
| 246| 2010-04-05 | F_1           | FR              | FR       | FR       | FR       |
| 247| 2010-04-11 | F_1           | NFR             | FR       | FR       | FR       |
| 248| 2010-05-18 | F_1           | NFR             | FR       | FR       | FR       |
Table 4 (Continued)

| E  | ICME Start   | Catalog Label | Predicted Label |
|----|--------------|---------------|-----------------|
|    |              |               | No Noise | 5% Noise | 10% Noise |
| 249| 2010-05-28*  | F$_r$         | FR      | FR       | FR        |
| 250| 2010-06-21   | F$_r$         | NFR     | FR       | NFR       |
| 251| 2010-08-03   | C$_x$         | FR      | FR       | FR        |
| 252| 2010-09-15   | F$_r$         | NFR     | NFR      | NFR       |
| 253| 2010-09-25   | F$^-$         | NFR     | NFR      | NFR       |
| 254| 2010-10-11   | F$^-$         | NFR     | FR       | FR        |
| 255| 2010-10-31   | F$_r$         | NFR     | NFR      | NFR       |
| 256| 2010-12-19   | F$^+$         | FR      | FR       | FR        |
| 257| 2011-01-24*  | F$^+$         | NFR     | FR       | FR        |
| 258| 2011-02-18   | F$^-$         | NFR     | FR       | FR        |
| 259| 2011-03-29   | F$_r$         | NFR     | FR       | FR        |
| 260| 2011-04-23   | F$^-$         | NFR     | NFR      | FR        |
| 261| 2011-04-29*  | E             | NFR     | NFR      | NFR       |
| 262| 2011-05-28   | F$^+$         | FR      | FR       | FR        |
| 263| 2011-06-04   | F$_r$         | NFR     | FR       | FR        |
| 264| 2011-06-17   | C$_x$         | NFR     | NFR      | FR        |
| 265| 2011-06-30   | F$^-$         | NFR     | FR       | NFR       |
| 266| 2011-07-03   | F$_r$         | NFR     | NFR      | FR        |
| 267| 2011-09-17   | F$_r$         | NFR     | FR       | FR        |
| 268| 2011-10-05   | C$_x$         | NFR     | FR       | FR        |
| 269| 2011-10-24   | C$_x$         | NFR     | FR       | FR        |
| 270| 2011-11-01   | F$^-$         | NFR     | NFR      | NFR       |
| 271| 2011-11-02   | F$_r$         | FR      | FR       | NFR       |
| 272| 2011-11-04   | C$_x$         | NFR     | FR       | FR        |
| 273| 2011-11-07   | F$_r$         | NFR     | NFR      | FR        |
| 274| 2011-11-11   | C$_x$         | NFR     | FR       | FR        |
| 275| 2011-11-28   | C$_x$         | FR      | FR       | FR        |
| 276| 2012-01-21   | F$_r$         | FR      | FR       | FR        |
| 277| 2012-01-22   | F$^-$         | NFR     | FR       | NFR       |
| 278| 2012-02-14   | F$_r$         | FR      | FR       | FR        |
| 279| 2012-02-26   | C$_x$         | NFR     | NFR      | NFR       |
| 280| 2012-03-08   | C$_x$         | NFR     | FR       | FR        |
| 281| 2012-03-12   | C$_x$         | NFR     | NFR      | FR        |
| 282| 2012-03-15   | F$_r$         | FR      | FR       | FR        |
| 283| 2012-04-05   | F$_r$         | FR      | FR       | FR        |
| 284| 2012-04-11   | C$_x$         | NFR     | FR       | FR        |
| 285| 2012-04-23   | F$^-$         | FR      | NFR      | NFR       |
| 286| 2012-05-03   | F$_r$         | NFR     | NFR      | FR        |
| 287| 2012-05-16   | F$_r$         | NFR     | FR       | FR        |
| 288| 2012-06-11   | F$_r$         | NFR     | FR       | NFR       |
| 289| 2012-06-16   | F$^+$         | FR      | FR       | FR        |
| 290| 2012-07-08   | C$_x$         | NFR     | FR       | FR        |
| E  | ICME Start | Catalog Label | Predicted Label |  No Noise | 5% Noise | 10% Noise |
|----|------------|---------------|-----------------|-----------|----------|-----------|
| 291| 2012-07-14 | F_r           | FR              | FR        | FR       | FR        |
| 292| 2012-08-12 | F_r           | NFR             | FR        | FR       | FR        |
| 293| 2012-08-18 | F_r           | NFR             | NFR       | FR       | FR        |
| 294| 2012-08-30 | F^-           | FR              | FR        | FR       | NFR       |
| 295| 2012-09-01 | F_r           | NFR             | NFR       | FR       | FR        |
| 296| 2012-09-04 | F_r           | NFR             | FR        | FR       | NFR       |
| 297| 2012-09-06 | F^-           | FR              | FR        | FR       | NFR       |
| 298| 2012-09-12 | F^-           | NFR             | NFR       | FR       | FR        |
| 299| 2012-09-30 | C_x           | NFR             | FR        | FR       | FR        |
| 300| 2012-10-08 | F_r           | FR              | FR        | FR       | FR        |
| 301| 2012-10-12 | F_r           | FR              | FR        | FR       | NFR       |
| 302| 2012-10-31 | F^+           | FR              | FR        | FR       | FR        |
| 303| 2012-11-12 | F^+           | FR              | FR        | FR       | FR        |
| 304| 2012-11-23 | F^-           | NFR             | NFR       | FR       | FR        |
| 305| 2013-01-16 | F_r           | FR              | FR        | FR       | FR        |
| 306| 2013-01-18 | F_r           | NFR             | FR        | FR       | FR        |
| 307| 2013-01-19 | F^-           | NFR             | NFR       | FR       | FR        |
| 308| 2013-03-17 | F_r           | NFR             | NFR       | FR       | FR        |
| 309| 2013-04-13 | F^+           | NFR             | FR        | FR       | FR        |
| 310| 2013-04-30 | F_r           | FR              | FR        | FR       | NFR       |
| 311| 2013-05-14 | F_r           | FR              | FR        | FR       | FR        |
| 312| 2013-06-06 | F^+           | NFR             | FR        | FR       | FR        |
| 313| 2013-06-27*| F_r           | FR              | FR        | FR       | FR        |
| 314| 2013-07-04 | C_x           | NFR             | FR        | FR       | FR        |
| 315| 2013-07-12 | C_x           | NFR             | FR        | FR       | FR        |
| 316| 2013-09-01 | F_r           | NFR             | FR        | FR       | FR        |
| 317| 2013-10-02*| E             | FR              | FR        | FR       | FR        |
| 318| 2013-10-03 | F_r           | NFR             | NFR       | FR       | FR        |
| 319| 2013-10-30 | F_r           | FR              | FR        | FR       | FR        |
| 320| 2013-11-08 | F_r           | NFR             | FR        | FR       | NFR       |
| 321| 2013-11-23 | F_r           | NFR             | FR        | FR       | FR        |
| 322| 2013-11-30 | C_x           | NFR             | NFR       | FR       | FR        |
| 323| 2013-12-08 | F^-           | NFR             | FR        | FR       | FR        |
| 324| 2013-12-14 | F_r           | FR              | FR        | FR       | FR        |
| 325| 2013-12-24 | F^+           | FR              | FR        | FR       | FR        |
| 326| 2014-02-05*| E             | NFR             | NFR       | FR       | FR        |
| 327| 2014-02-15 | F_r           | NFR             | FR        | FR       | FR        |
| 328| 2014-02-18 | F_r           | FR              | FR        | FR       | FR        |
| 329| 2014-02-19 | C_x           | FR              | FR        | FR       | FR        |
| 330| 2014-04-05 | F_r           | NFR             | FR        | FR       | FR        |
| 331| 2014-04-11*| F^+           | FR              | FR        | FR       | FR        |
| 332| 2014-04-20 | F_r           | FR              | FR        | FR       | FR        |
Table 4 (Continued)

| E  | ICME Start       | Catalog Label | Predicted Label | No Noise | 5% Noise | 10% Noise |
|----|------------------|---------------|-----------------|----------|----------|----------|
| 333| 2014-04-29       | $F_R$         | FR              | FR       | FR       | NFR      |
| 334| 2014-06-07       | $C_X$         | NFR             | FR       | FR       | FR       |
| 335| 2014-06-22       | $F^-$         | FR              | FR       | FR       | NFR      |
| 336| 2014-06-29       | $F_R$         | NFR             | FR       | FR       | FR       |
| 337| 2014-07-02       | $F^-$         | FR              | FR       | FR       | NFR      |
| 338| 2014-08-19       | $F^+$         | FR              | FR       | FR       | FR       |
| 339| 2014-08-26*      | $F_R$         | NFR             | FR       | FR       | FR       |
| 340| 2014-09-12       | $F^-$         | FR              | FR       | FR       | FR       |
| 341| 2015-01-07       | $F^+$         | FR              | FR       | FR       | FR       |
| 342| 2015-03-28       | $F_R$         | NFR             | FR       | FR       | FR       |
| 343| 2015-03-31       | $F^-$         | NFR             | NFR      | NFR      | NFR      |
| 344| 2015-04-09       | $C_X$         | FR              | FR       | FR       | FR       |
| 345| 2015-05-06       | $F^-$         | FR              | FR       | FR       | FR       |
| 346| 2015-05-08       | $F^-$         | NFR             | NFR      | NFR      | NFR      |
| 347| 2015-05-10       | $F^+$         | FR              | FR       | FR       | FR       |
| 348| 2015-06-22       | $C_X$         | NFR             | NFR      | NFR      | FR       |
| 349| 2015-09-07       | $F^+$         | FR              | FR       | FR       | FR       |
| 350| 2015-10-06       | $F_R$         | NFR             | NFR      | NFR      | FR       |
| 351| 2015-10-24       | $F_R$         | NFR             | NFR      | NFR      | FR       |
| 352| 2015-11-06       | $F_R$         | FR              | FR       | FR       | FR       |
| 353| 2015-12-19       | $F_R$         | FR              | FR       | FR       | FR       |

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