

Automated detection techniques for off-limb solar coronal jets

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Abstract: This paper presents a unified framework for detecting and characterizing off-limb coronal jets in 304 Å solar observations by combining a semi-automated rule-based algorithm, a deep-learning segmentation model, and a morphology-driven machine-learning classifier. We propose the Semi-Automated Jet Identification Algorithm to construct a catalogue of 1215 off-limb jets (longer than 14 Mm) during Solar Cycle 24, from which power-law energy-frequency distributions, butterfly-diagram-like latitudinal migration, quasi-annual oscillations, hemispheric asymmetries, and indications of active longitudes are derived. To address the identification limits of the algorithm, we develop two machine-learning-based algorithms in parallel. The first, the Automated Jet Identification Algorithm, based on a U-Net convolutional neural network, is trained on labelled true and false jets, achieving pixel-level segmentations with precision, recall, and true-negative rates of order 0.8, while remaining robust to the long-term degradation of detectors. The second is a random-forest classifier, trained on mathematical morphology descriptors of nearly 900 000 off-limb structures, matched to those labelled by the algorithm, and then applied to the full morphology catalogue with a conservative probability threshold, yielding 3452 new jet candidates, of which 3268 are confirmed by visual inspection as genuine jets. Together, the three methodologies provide a more complete and accurate census of off-limb coronal jets than any single approach alone, revealing that jets share scale-free energetics with flares and coronal mass ejections, and demonstrate how modern image processing and machine learning can be integrated to support future high-resolution, high-cadence studies of small-scale solar eruptive phenomena.

Keywords: Astronomical techniques; Astronomical methods; Solar coronal transients; Plasma jets

1. INTRODUCTION

Coronal jets are ubiquitous, collimated plasma ejections that connect small-scale magnetic activity in the lower solar atmosphere with the overlying corona and solar wind. Observations over the past three decades, from a variety of instruments, have revealed a rich phenomenology of individual jet events^[1,2], including multi-thermal emission, recurrent activity, helical motions, shock signatures, and associations with flares, microflares, and coronal mass ejections (CMEs)^[3–7]. These case studies demonstrate that jets frequently originate at sites of flux emergence or cancellation^[8], are rooted in compact brightenings or mini-flaring regions, and that they can show complex kinematics involving both bulk flows and wave motions^[1].

In parallel, theoretical models and numerical simula-

tions have converged on magnetic reconnection as the primary driver of large-scale coronal jets^[9,10]. Early analytical and numerical work on emerging dipoles interacting with open or large-scale fields established the basic “standard” and “blowout” jet scenarios, in which reconnection at null points or quasi-separatrix layers launches hot and cool plasma along reconfigured open field lines^[11,12]. More sophisticated three-dimensional magnetohydrodynamic (MHD) simulations have since incorporated flux emergence, shearing and twisting motions, and flux cancellation, reproducing key observational signatures such as untwisting motions, recurrent jets, and multi-thermal outflows^[1,2]. These models highlight the role of magnetic topology, helicity injection, and instabilities in generating jets, with the intention of exploring their impact on the nascent solar wind and on the transport of energy and mass into the upper solar atmosphere.

Despite substantial progress in understanding individual jets, most work to date has focused on relatively small samples and on detailed analysis of isolated events or small event sets. Numerous studies have targeted a handful to a few tens of jets in specific environments, such as active-region jets, polar coronal-hole jets, quiet-Sun jets, or jets associated with mini-filament eruptions. These have been examined with multi-wavelength imaging, spectroscopy, and stereoscopy to infer temperatures, densities, velocities, and energetics on a case-by-case basis^[5,13]. These investigations have been invaluable for linking observational signatures to local magnetic configurations and to specific reconnection geometries, but by design, they do not address the global occurrence, long-term evolution, and statistical properties of jets over solar-cycle timescales^[7].

Large-scale statistical studies of jets remain comparatively rare, and those that exist are often constrained by manual identification or limited temporal coverage. Early efforts typically relied on visual inspection of X-ray or extreme ultraviolet (EUV) data over limited intervals, yielding tens to hundreds of jets and providing only coarse distributions of properties such as length, lifetime, or brightness^[13]. This imbalance between detailed knowledge of individual events and the paucity of large, homogeneous jet catalogues is now a significant limitation in connecting jet physics to broader questions in solar and stellar activity. Without statistically robust samples, it is difficult to assess whether jets, as a population, show scale-free energetics similar to flares and CMEs, how their occurrence and properties vary with the solar cycle and magnetic environment, or to what extent they contribute to coronal heating and solar-wind acceleration. Addressing these questions requires detection techniques that can systematically and reliably identify jets in long-duration image archives, with minimal human bias, and that can provide consistent measurements of jet properties across varying observing conditions. In this study, we develop and present such techniques for off-limb coronal jets, enabling a new generation of statistical studies that are directly comparable to existing observational, theoretical, and numerical results for individual events^[7,14,15].

To address this problem, we use a three-stage development of detection algorithms for off-limb coronal jets in Solar Dynamics Observatory/Atmospheric Imaging Assembly (SDO/AIA) 304 Å data. The first stage is a semi-automated procedure, the Semi-Automated Jet Identification Algorithm (SAJIA), which uses physically motivated image-processing and geometric filters to assemble a large, human-vetted catalogue of off-limb jets spanning nearly all of Solar Cycle 24^[7,16]. We further develop two algorithms using machine-learning techniques to address the limitations of SAJIA. The first is a deep-learning segmentation model, the Automated Jet Identification Algorithm (AJIA^[14]), which is based on a U-Net architecture trained on SAJIA-labelled jets and non-jets, and yields pixel-level probability maps for jet occurrence^[14]. The second one is a machine-learning classifier operating in the

space of Mathematical Morphology (MM) descriptors, which uses random-forest (RF) algorithms trained on SAJIA-labelled structures, to extend jet identification to a vastly larger catalogue of off-limb features^[15–17].

Together, these three approaches form a coherent detection framework that evolves from rule-based, semi-automated identification to fully automated deep-learning segmentation and feature-based classification. In this paper, Section 2 describes the observational data and the three detection methods, with emphasis on the U-Net architecture and training strategy. Then, Section 3 summarizes the main scientific outcomes, and Section 4 provides conclusions and outlines future directions.

2. DATA AND METHODS

2.1. Observational Data

All three algorithms are applied primarily to full-disk images from SDO/AIA, focusing on the 304 Å channel^[18]. This passband is dominated by He II emission at transition-region temperatures, but frequently contains contributions from hotter plasma, so that off-limb jets observed at 304 Å trace multi-thermal structures rooted in the chromosphere and extending into the corona. The key advantage of the 304 Å channel for jet detection is its relatively dark off-limb background compared with that of hotter EUV channels, which makes elongated brightenings stand out more clearly.

The SAJIA survey uses full-disk 304 Å images, recorded four times per day (at 00:00, 06:00, 12:00, and 18:00 UT) from June 1, 2010, to May 31, 2020^[7]. Each image has 4096×4096 pixels with a spatial sampling of approximately $0.6''$. This sparse cadence of 6 h was chosen because of the labor-intensive nature of SAJIA, and computational limitations. Further work increases temporal sampling to 3 h and 1 h over selected periods, to better capture jet evolution and test the performance of automated algorithms at higher cadence^[14,16]. For the deep-learning model, AJIA, 96×96 pixel patches are automatically extracted from the off-limb region around candidate jets, while for the MM-RF classifier, a separate segmentation of the off-limb corona into hundreds of thousands of individual structures is constructed using MM techniques^[15,17].

2.2. Semi-automated Detection with SAJIA

SAJIA is designed to isolate off-limb jets in 304 Å images, using a sequence of image-processing steps and geometric criteria, followed by manual validation^[7]. The solar disk is first excluded by masking from the disk center out to a radius slightly larger than the photosphere, typically around $1.02 R_{\odot}$, which suppresses on-disk emission and the dense population of spicules near the limb. This masking process makes the algorithm unsuitable for detecting coronal jets with a projected length less than 0.02 solar radii (i.e., 14 Mm). Consequently, in this paper,

when we consider coronal jets to be jets with lengths greater than 14 Mm. To remove static structures including static prominences and highlight transient off-limb brightenings, we use a background image for each day, created by averaging several 304 Å frames at different times. We then subtracting this background from each target frame, to highlight transient off-limb phenomena. The resulting off-limb image is downsampled from 4096×4096 to 512×512 pixels, to remove detailed small-scale features that affect the detection of jets, and to reduce computational cost while retaining sufficient spatial resolution for jet-scale structures^[7].

The downsampled off-limb region is normalized linearly to a fixed intensity range. We then apply a global threshold, to produce a binary map that separates relatively bright features from the diffuse background. This threshold is chosen empirically by testing multiple values on representative images spanning different phases of the solar cycle^[7]. The binary map typically contains many connected bright regions, including jets, prominences, small loop systems, and instrumental artifacts.

To extract jet-like candidates, we trace and approximate the boundaries of all bright regions with polygons, using the Douglas-Peucker algorithm, which iteratively simplifies each contour while preserving its overall shape^[7,19]. Because jets generally appear as narrow, elongated structures rooted at the limb, we only consider polygons with four vertices and bases that intersect the limb. In addition, the angle between the long axis of each polygon and the local radial direction must be smaller than a prescribed upper limit (around 60°) to exclude nearly horizontal structures such as quiescent filaments. We impose a minimum aspect-ratio condition, based on previous observations of coronal jets^[13], to favor slender shapes and further suppress compact or roughly circular brightenings.

For each candidate region that passes these geometric filters, SAJIA measures position angle (PA), projected length and width, cross-sectional area, and total 304 Å intensity, correcting intensities for the known sensitivity degradation of AIA over time^[20,21]. These candidates are then visually inspected^[7] using a short time series of 304 Å images. A candidate is retained as a jet if it shows a clear upward collimated ejection of plasma into the corona, whereas static or slowly evolving structures, downward-moving coronal rains, curved arcades, and prominence segments are discarded. Fig. 1 shows a flowchart summarizing the main processes of SAJIA, based on the description in Liu et al.^[7]. This semi-automated scheme yields approximately 3800 candidates at 6 h cadence from 2010 to 2020, of which 1215 are confirmed as jets^[7,15]. Fig. 2 presents a typical output of SAJIA.

We further estimate the incompleteness of the detection by manually searching for off-limb jets in a limited subset of the data and comparing with results from SAJIA. In two randomly chosen months, we manually identified at least 22 jets at low latitude, which were not detected by SAJIA, whereas 52 are successfully found by

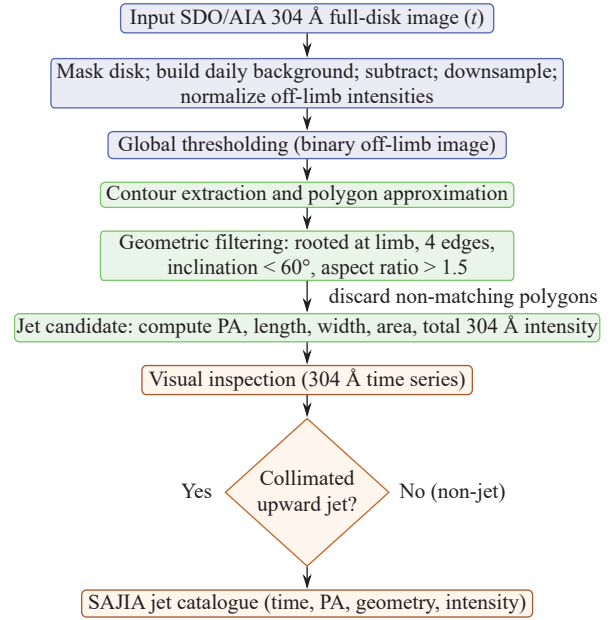


Fig. 1. Main processes of the SAJIA. Off-limb coronal jets are extracted from the input SDO/AIA 304 Å images. Detailed descriptions can be found in the main text in Section 2.2.

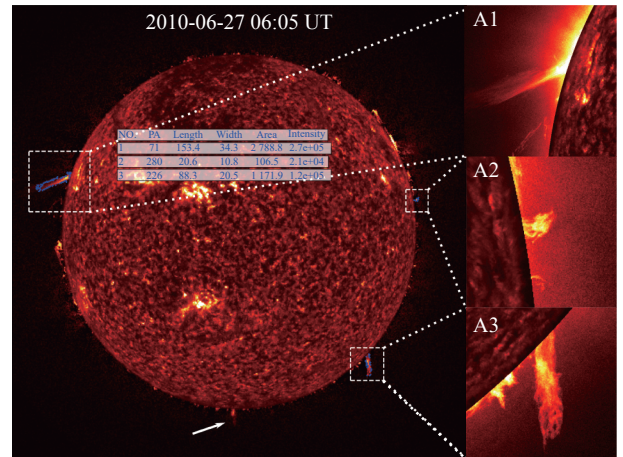


Fig. 2. An example of off-limb coronal jets detected by SAJIA in the SDO/AIA 304 Å passband, at 06:05 UT on June 27, 2010. Blue curves in panels A1 and A3 show jets successfully identified by SAJIA. The structure in panel A3 shows a false positive case, in which a static jet-like prominence is also identified as a jet but is later removed by manual check. The white arrow in panel a points to a polar jet missed by SAJIA because of its irregular shape. This figure is reproduced from Liu et al.^[7].

the algorithm, suggesting a non-polar missing fraction of approximately 30%. We expect the detection of faint polar jets to be even less complete, because their brightness relative to the background is often below the fixed threshold used by SAJIA. Another factor that affects the completeness of the SAJIA-detected coronal jets is the cadence of detection. In Liu et al.^[7], the cadence was chosen to be 6 h. Given that most coronal jets last for less than 1 h with a median lifetime of 10 to 20 min^[1,22], this 6-hour cadence can avoid multiple detections of a single jet appearing over different frames, but also leads to

many jets being missed. SAJIA is a computer-vision-based method that searches each frame for jet-like features using the same objective criteria, independent of the time of observation, and consequently, jets occurring at different times are treated uniformly. The reduced cadence primarily affects the total number of detected events, but not their distributions in the statistical analysis. A list of confirmed coronal jets and their properties is available at <https://space.ustc.edu.cn/dreams/sajia/index.php>.

Despite these limitations, SAJIA delivers a consistently selected, manually vetted sample of off-limb jets with well-defined properties, which can be used for direct statistical analysis. However, a key limitation of SAJIA is its relatively low identification accuracy, requiring additional human effort to remove false positives from those automatically identified. To address this limitation, we develop two further machine-learning-based algorithms to use the true and false identifications from SAJIA.

2.3. U-Net Segmentation: AJIA

The first machine-learning-based algorithm employs a convolutional U-Net neural network to perform pixel-level segmentation of jets in off-limb 304 Å patches^[14,23]. The key idea is to use labeled candidates from SAJIA as training data, in which true jets provide positive examples, and false candidates provide negative examples. This allows the model to learn jet morphology directly from the data, including cases that are difficult to characterize with simple geometric rules. U-Net is a type of convolutional neural network specifically designed for image segmentation tasks, consisting of an encoder-decoder architecture with skip connections that combine coarse, high-level features with fine, spatially detailed information. This makes it well suited to delineating narrow, elongated structures such as coronal jets in EUV images. We chose U-Net because it has proven effective in a wide range of scientific imaging problems, offers good performance with relatively limited training data, and naturally produces pixel-level segmentation maps. A limitation in our context is that the model operates on 2D snapshots and does not explicitly encode temporal evolution, so it may miss jets that are only weakly visible in single frames. Additionally, its performance can be sensitive to the representativeness and labeling quality of the training set.

The training set is constructed from SAJIA detections with a 3 h cadence over the period 2010–2021^[14,16]. In total, 7890 off-limb candidates are identified, of which 2704 are manually confirmed jets and 5186 are false detections. For each candidate, we extract a 96×96 pixel patch from the masked off-limb region, centered on the candidate's position. We choose this patch size so that even the largest jets occupy a single patch while minimizing unrelated off-limb emission. Each patch is normalized to a fixed intensity range by clipping at a threshold derived empirically from the full dataset^[14].

For each true jet, a corresponding binary label patch is created in which pixels belonging to the jet are

assigned the value 1 and all other pixels are assigned 0. For false candidates, the entire patch is given the value 0. The resulting dataset consists of paired input-label patches. Because the number of false candidates exceeds that of true jets by nearly a factor of two, the dataset is initially imbalanced. To address this, only true-jet patches are augmented using random rotations within a limited angular range and horizontal/vertical flips, generating additional, distinct examples without changing the underlying morphology^[14]. After augmentation, we compare the numbers of true and false patches, adopting an 80/20 split between training and validation sets.

The U-Net architecture used for AJIA resembles the standard design in biomedical image segmentation^[23,24]. The encoder section consists of repeated blocks of two 3×3 convolutions with rectified-linear-unit activation, followed by 2×2 maximum pooling that halves the spatial resolution while doubling the number of feature channels at each level. Starting from 64 channels at the input resolution of 96×96 pixels, the encoder reaches 1024 channels at the bottleneck layer with spatial size of 6×6 . The decoder reverses this process via up-convolutions (transpose convolutions), which double spatial resolution and halve the number of channels, and at each level, the upsampled feature maps are concatenated with the corresponding encoder maps via skip connections^[23]. This structure combines global context with local detail and is well suited to segmenting structured objects such as jets against a noisy background^[24]. Fig. 3 summarizes the architecture of the U-NET neural network used in Liu et al.^[14].

We carry out training with a batch size of 256, using the binary cross-entropy loss summed over pixels, exploring several learning rate schedules, including fixed and cosine-decay profiles, with a constant learning rate of 10^{-4} for the most stable convergence^[14]. Training and validation losses decrease steadily with epoch, and the model is selected at the epoch in which both losses are stable and close to their minima (i.e. less than 0.01). To convert the probabilistic output into discrete detections, we introduce a threshold on pixel probability, evaluating the model's performance on an independent test set by varying this threshold and computing standard classification metrics such as precision, recall, true-negative rate, and F1-score^[14]. At an optimal threshold, these metrics all reach values of around 0.8, indicating that four out of five jet labels are correctly assigned and that the false-positive fraction is strongly reduced, compared with that of SAJIA^[7,14]. Importantly, this performance remains stable across different years, even though the sensitivity of SDO/AIA has declined significantly during the course of the mission, whereas SAJIA's precision shows a decreasing trend over the same period^[14,21]. Fig. 4 presents a comparison of the jet identification between SAJIA and AJIA. It can be seen that compared with SAJIA, AJIA not only gives a smoother boundary of the jet, but also yields the possibility of a pixel in the image belonging to the jet.

As a further test of its potential for generalization,

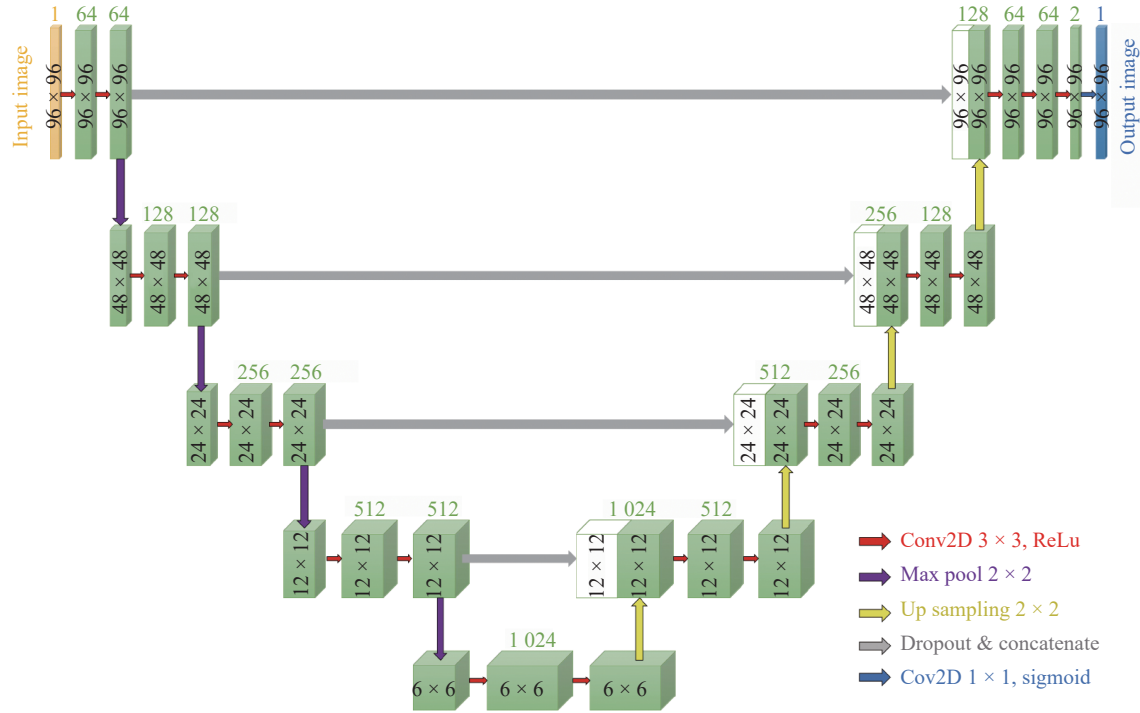


Fig. 3. Architecture of the U-Net neural network used for AJIA, showing the encoder-decoder structure with 3×3 Conv2DReLU blocks, 2×2 maxpooling for downsampling, 2×2 upsampling with skip connections for feature concatenation, and a final 1×1 Conv2Dsigmoid layer that maps the 96×96 input image to the 96×96 output image. This figure is reproduced from Liu et al.^[14].

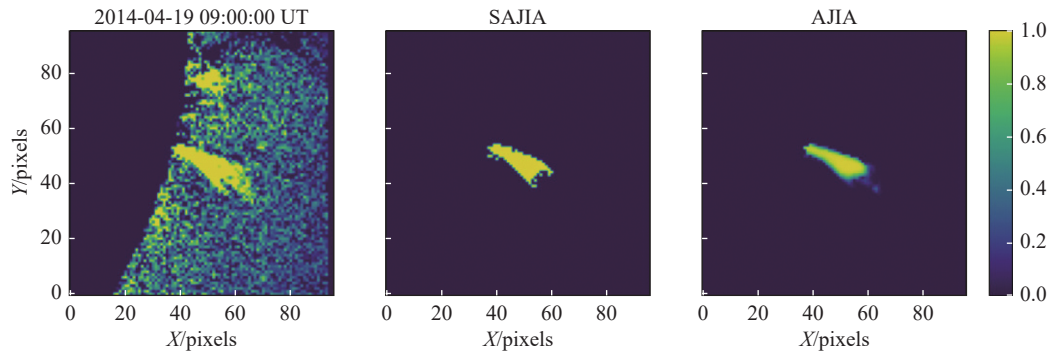


Fig. 4. The left panel shows a jet event observed in the SDO/AIA 304 Å passband at 09:00 UT on 2014 April 19. The middle panel shows the identification of the jet by SAJIA, and the right panel shows the identification of the jet by AJIA. This figure is reproduced from Liu et al.^[14].

AJIA is applied to an independently constructed set of 409 off-limb candidates detected at a 1 h cadence during a single month. Manual inspection identifies 235 of these as jets and 174 as non-jets. When evaluated on this set, AJIA reproduces precision, recall, and F1 metrics close to 0.8, demonstrating that it can be used to process higher-cadence data and detect previously unseen jets with similar reliability^[14,16]. AJIA therefore provides a robust, fully automated way to identify off-limb coronal jets and obtain pixel-level segmentations, offering a substantial improvement in precision over SAJIA and enabling high-cadence applications for kinematic and energetic studies.

2.4. Morphology-based Classification: Random Forests and MM Features

Another parallel approach to improve SAJIA using

machine-learning techniques takes a complementary approach by working in a space of morphological descriptors, derived from mathematical morphology applied to the off-limb corona^[15,17] (a flowchart summarizing the pipeline is presented in Fig. 5). MM uses operations such as dilation, erosion, opening, and closing with carefully designed structuring elements to identify and characterize shapes in binary and grayscale images. These techniques have been successfully applied to solar features such as sunspots, filaments, and prominences, and can be generalized to any segmented off-limb structure^[25].

In the MM-based study, we process full-disk SDO/AIA 304 Å images from 2010 to 2020 with an MM pipeline that segments all visible off-limb structures in each image^[15,17]. This yields a catalogue of 877843 distinct structures, each associated with a set of geometric

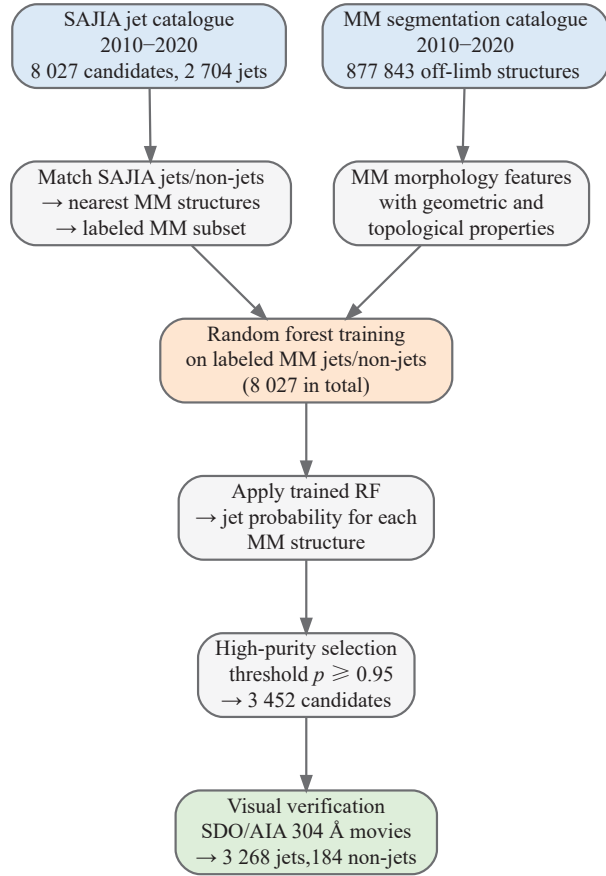


Fig. 5. Pipeline of the jet detection algorithm using random forests and MM features [15].

and intensity-based descriptors, computed using the DIPlib library^[17]. These descriptors include area, perimeter, intensity moments, elongation measures, curvature-related quantities, and position relative to the solar disk center. Independently, SAJIA applied at a 3 h cadence over

the same period, yields 8 027 jet candidates with manual verification carried out by Soós et al.^[16], with 2 704 classified as jets and 5 323 as non-jets^[15,16].

To construct a labelled training set for classification, we match each SAJIA candidate to its nearest MM structure in radial distance from the disk center (see Fig. 6), assigning the MM feature vector for that structure with the SAJIA jet or non-jet label. After selecting only structures close to the limb and removing cases too distant from the solar disk, the resulting dataset contains 2 667 jets and 5 028 non-jets with associated MM features. To reduce redundancy and improve learning efficiency, the initial feature set is pruned to remove highly correlated variables, leaving 17 features that together characterize shape, intensity distribution, and position in a non-degenerate way. Fig. 6 shows a comparison of the contouring results from SAJIA and the MM algorithm^[15].

We then train a RF classifier on this feature set. Random forests consist of an ensemble of decision trees, each constructed on a bootstrap-resampled subset of the training data. At each split we only consider a random subset of features, which helps to decorrelate the trees and improve generalization^[15,26]. Hyperparameters, such as the number of trees and their maximum depth, are tuned using tree-structured Parzen estimator optimization, combined with cross-validation^[15,27]. For each input feature vector, the classifier outputs an estimated probability that the structure is a jet, computed as the fraction of trees voting for the positive class^[15].

On a held-out test set, the RF achieves an overall accuracy of 0.76 and a receiver-operating-characteristic area under the curve of 0.81, along with balanced accuracy, precision, recall, and specificity values that indicate solid discrimination between jets and non-jets. When using a standard probability threshold of 0.5, the classifier has

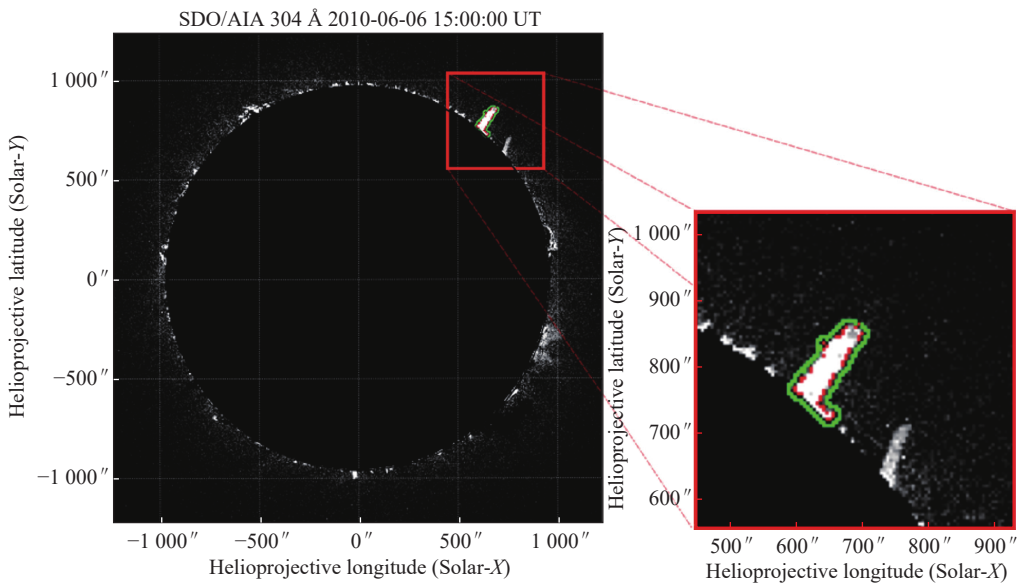


Fig. 6. Comparison of the contouring results from SAJIA (red contours) and the MM algorithm (green contours) on the SDO/AIA 304 Å image at 15:00:00 UT on June 6, 2010. This figure is reproduced from Chierichini et al.^[15].

roughly two-thirds precision and recall, suggesting that many jets can be automatically recovered from the MM catalogue. However, when the classifier is applied to the full $\sim 8.8 \times 10^5$ MM structures, the focus is on purity rather than completeness: The decision threshold is therefore raised to 0.95, so that only structures for which the vast majority of trees predict a jet label are retained as candidates. At this conservative threshold, the classifier identifies 3452 new jet candidates in the MM catalogue. Each candidate is then confirmed or rejected by visual inspection of 304 Å movies, covering a 2 h interval around the candidate time. During this manual verification we confirm 3268 candidates as genuine off-limb jets and reject 184, leading to a net gain of more than three thousand jets beyond those identified by SAJIA alone^[15].

3. RESULTS

3.1. Power-law Statistics and Self-organized Criticality

The SAJIA-based jet catalogue enables measurement of the energy-frequency distribution of off-limb coronal jets over nearly a full solar cycle. Because the 304 Å pass-band is optically thick and sensitive primarily to transition-region plasma, we use the total 304 Å intensity of the jet as a proxy for thermal energy, scaled so that the median jet has an energy of the order of 10^{28} erg, in line with earlier case studies^[7,13]. An analysis of the distribution of this proxy energy shows that the differential occurrence frequency follows a power-law over several orders of energy, with an index in the range of 1.4–1.6 (see Fig. 7), depending on the fitting method used^[7].

This index is very similar to power-law exponents found for solar flare energies, nanoflares, and CMEs, as well as for flare-like activity on solar-type stars (see Fig. 7, and Ref. [13, 30, 31]). For example, observational studies of flares report energy distributions with indices in the region of 1.5–2.0, while CME mass or width distributions also approximate power-laws with indices near 1.5–2.0 when fitted with maximum-likelihood techniques^[28,29]. Such power-laws are often interpreted as signatures of self-organized criticality in the coronal magnetic field, in which a slowly driven system releases stored energy through avalanches of reconnection events that lack a preferred scale^[31]. The similarity between the jet energy index and the power-law indices for flares and CMEs reinforces the view that jets are another manifestation of this scale-free process, spanning an intermediate regime between small-scale spicules and large-scale eruptions^[7].

3.2. Solar-cycle Modulation and Quasi-periodic Variability

The spatial and temporal distributions of off-limb jets show clear modulation by the solar cycle. When the positions of SAJIA-identified jets are plotted as a function of latitude and time (see Fig. 8), they form a pattern reminiscent of the classic butterfly diagram for sunspots: Jets at

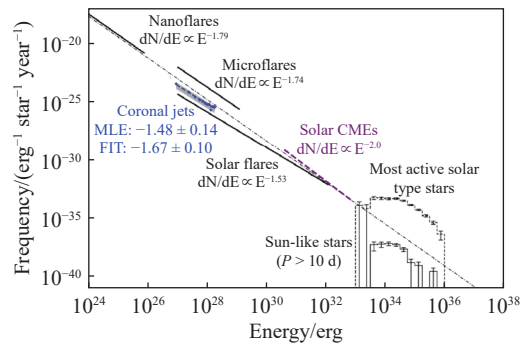


Fig. 7. Power-law distribution of coronal jets aligned with the power-law distributions of solar/stellar flares and CMEs. This figure is adapted from Liu et al.^[7]. Curves for flares are reproduced from Shibayama et al.^[28], and curves for coronal mass ejections are from Aschwanden^[29].

higher latitudes are more common early in the cycle, while jets at lower latitudes occur predominantly during the cycle’s maximum and declining phases^[7,16]. This resemblance is confirmed by a comparison with synoptic maps of the line-of-sight magnetic field and with the latitudinal evolution of sunspot activity. Jet counts at low latitudes correlate strongly with sunspot numbers, indicating that jets in active-region latitudes are closely tied to the evolution of the surface magnetic field^[7]. To the best of our knowledge, this study is among the first to present a butterfly-style latitude-time diagram specifically for coronal jets, as shown in Fig. 8.

Superposed on this long-term trend, jet properties display quasi-periodic variations on timescales of roughly one year. After removal of a smoothed background trend using a window longer than the suspected periods, wavelet analysis reveals enhanced power at periods between approximately 8 and 16 months in the monthly mean jet intensity, length, width, area, absolute latitude, and low-latitude counts^[7]. The dominant period is close to 11 months and reaches high significance levels when compared with red-noise backgrounds. Similar quasi-annual and Rieger-type periods have been reported in solar flares, CMEs, sunspot areas, and coronal brightness, and have been interpreted as manifestations of global Rossby-type waves in the solar interior interacting with the dynamo^[32]. The presence of such oscillations in jet statistics suggests that jets respond to the same global processes modulating other forms of solar activity, and that they could serve as an additional diagnostic of dynamical phenomena in the convection zone and tachocline.

The jet distribution also shows persistent hemispheric asymmetry and preferred longitudes. There are more polar jets in the Southern Hemisphere than in the Northern Hemisphere during the early part of Solar Cycle 24, in agreement with studies showing excess southern activity in sunspot areas and flare rates during that cycle^[7,16]. Furthermore, when jet occurrences are mapped into Carrington longitude, they tend to cluster into bands reminiscent of active longitudes previously identified using sunspots and flares^[33]. These patterns support the

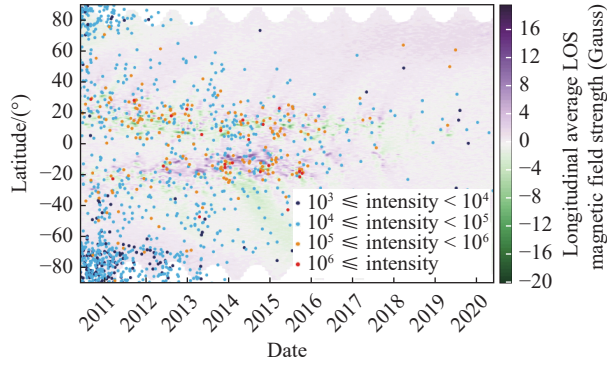


Fig. 8. Butterfly diagrams of solar magnetic field and off-limb coronal jets. The purple and green background shows the longitudinal monthly average line-of-sight magnetic field strength observed by SDO/HMI, with red and blue showing positive and negative polarities, respectively. Latitude and total intensity (in different colors) of all detected off-limb jets from June 1, 2010, to May 31, 2020, as detected by SAJIA, are shown as dots.

idea that small-scale eruptive phenomena, such as jets, are also organized by the same non-axisymmetric dynamo structures that shape larger-scale activity.

3.3. Improvements in Detection Quality and Catalogue Completeness

AJIA and the MM-RF classifier complement SAJIA's strengths and address its shortcomings in different ways. SAJIA's automated candidate selection, followed by manual vetting, provides a transparent and physically grounded sample, but its automated stage produces many false positives^[7]. AJIA's U-Net segmentation, trained on SAJIA's label set, learns the complex morphological patterns that characterize jets and their surroundings, achieving much higher precision without sacrificing recall. Consequently, AJIA substantially reduces the manual burden needed to obtain clean jet samples and can, in principle, be run continuously to provide near-real-time jet detection^[14].

The pixel-level probability maps produced by U-Net also offer richer information than SAJIA's polygon-based output. These maps can be thresholded at several levels to investigate jet core and halo regions, used to derive cross-sectional width distributions, and, when applied to time-series data, combined with tracking algorithms to measure velocities and accelerations^[14]. Such capabilities are crucial for connecting global statistics to detailed physics, for example, to understand the relative contributions of bulk flows, torsional motions, and waves to jet energetics^[1,34].

The MM-RF classifier, in turn, extends jet identification to a very large morphological catalogue, derived independently of SAJIA and AJIA^[15,17]. By representing each off-limb structure with a set of carefully designed shape and intensity descriptors, the classifier can identify jets that are morphologically similar to known jets but may not trigger geometric or intensity thresholds in SAJIA^[15]. The resulting set of more than 3000 newly confirmed jets significantly increases the statistical power of studies of

jet distributions in intensity, area, latitude, and time, and strengthens the evidence that the jet population is governed by scale-free processes and cycle modulation^[7,15].

The combination of the three methods yields a more complete and reliable census of off-limb coronal jets. SAJIA establishes a baseline catalogue with clear selection criteria, AJIA boosts the precision and enables high-cadence analysis, and the MM-RF classification expands the sample size using an independent representation of jet morphology^[7,14,15]. To date, most statistical studies and scientific findings have been made based on the SAJIA coronal jet catalogue, but new catalogues based on the AJIA and MM-RF algorithms are in progress.

4. CONCLUSIONS AND PERSPECTIVES

In this paper, we summarize techniques we have developed to detect off-limb coronal jets and highlight key scientific findings derived from the jet dataset constructed using these techniques. The development of SAJIA, AJIA, and the MM-RF classifier has transformed the way off-limb coronal jets can be studied statistically. SAJIA provides a decade-long, uniformly selected catalogue of off-limb jets in SDO/AIA 304 Å data, from which energy-frequency power-laws, solar-cycle modulation patterns, and quasi-periodic oscillations can be derived^[7]. AJIA, trained on SAJIA-labelled jets, uses a U-Net architecture to deliver pixel-level jet segmentation, with high precision and robustness to instrumental degradation, making it suitable for high-cadence, large-volume applications^[14]. The MM-RF classifier, trained on morphological descriptors of off-limb structures, uses a large segmentation catalogue to uncover thousands of additional jets, particularly at low intensities and small spatial scales, thereby improving the completeness of jet statistics^[15,17].

These advances open up several promising directions for future work. One is the integration of the three detection approaches into a unified pipeline, in which SAJIA, AJIA, and the MM-based classification provide complementary assessments of jet likelihood, possibly combined through ensemble or Bayesian methods to produce joint probability maps. Such a pipeline could be tuned for either high completeness or high purity, depending on the scientific application. Another direction is to apply AJIA and the MM-based methods to higher-resolution datasets from missions such as the Solar Orbiter and future high-cadence EUV imagers. These data reveal jets with widths as small as a few hundred kilometers, which pose new challenges in terms of signal-to-noise ratio and background confusion^[1,34]. Adapting U-Net architectures and MM descriptors to such observations, possibly in combination with multi-scale wavelet filtering and advanced denoising techniques, could extend the detection framework into the regime of small-scale explosive events such as spicules and nanojets.

Extending this pipeline to other EUV passbands, such as transition-region emission near 46.5 nm, will require

modifications to account for the different optical properties of these lines. The current algorithm relies critically on the relatively faint off-limb background in the 30.4 nm passband. Nonetheless, with appropriate data preparation and the continued development of machine-learning techniques, it should be feasible to design automated jet-detection schemes at additional wavelengths.

Finally, the expanded jet catalogues assembled with these methods can be combined with flare, CME, and sunspot statistics to provide stringent tests of models of self-organized criticality and global dynamo action^[30]. For example, joint analyses of power-law slopes, active longitudes, hemispheric asymmetries, and quasi-periodic signals in different types of eruptive phenomena may help to constrain the spectrum and spatial structure of Rossby waves in the solar interior and their coupling to the coronal magnetic field. In this sense, jets, once considered secondary features, become a powerful probe of the multi-scale, magnetically driven processes that shape the Sun's atmosphere and its influence on the heliosphere.

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AI DISCLOSURE STATEMENT

Perplexity was employed for language and grammar checks within the article. The authors carefully reviewed, edited, and revised the Perplexity-generated texts to their own preferences, assuming ultimate responsibility for the content of the publication.

AUTHOR CONTRIBUTIONS

Jiajia Liu conceived the ideas, implemented the study, and wrote the paper. Cheng Zhong, Chunyu Ji, and Yuming Wang contributed to revising the paper. All authors read and approved the final manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.

1. <https://sdo.gsfc.nasa.gov/data/>

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