Solar Radio Burst Detection Method Combining Intensity Spectra and Polarization Spectra*

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Abstract

Solar radio burst data are crucial for understanding solar activity and forecasting space weather. Current deep learning-based burst detection methods mainly rely on dynamic spectra that characterize radio radiation intensity, considering relatively limited dimensions. A solar radio burst detection method that combines intensity spectra and polarization spectra can more fully exploit the physical information in spectral data. This method first preprocesses raw spectral data from the DAocheng Radio Telescope (DART) to directly generate high-quality image samples; then uses a traditional object detection model to automatically identify the locations of burst events and preliminarily distinguish the main bodies of four major classes of radio bursts; and, on this basis, further extends the approach by using ResNet (Residual Network) 18 to construct a polarization feature classification model supporting multi-channel input, which can simultaneously process intensity and polarization spectral information and ultimately output the type, time-frequency interval, and circular polarization features of burst events. Experimental results show that the model can effectively identify four common types of radio bursts, and that the multi-channel model (intensity channel and polarization channel) comprehensively outperforms the 3-channel pseudo-color model that directly uses polarization spectra as input in classifying polarization features, confirming the value of polarization data as an additional feature dimension and providing an effective technical approach for automatically extracting more physical information about burst events from massive solar radio data.

Full Text

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Solar Radio Burst Detection Method Combining Intensity Spectra and Polarization Spectra*

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Abstract Solar radio burst data are of vital importance for understanding solar activity and forecasting space weather. Current burst detection methods based on deep learning mainly rely on dynamic spectra representing radio radiation intensity, and the dimensions considered are relatively limited. A solar radio burst detection method combining intensity spectra and polarization spectra can more fully mine the physical information in spectral data. This method first preprocesses the raw spectral data from the Daocheng Radio Telescope (DART) to directly generate high-quality image samples; then uses a traditional object detection model to automatically identify the locations of burst events and preliminarily distinguish the main bodies of four major categories of radio bursts; on this basis, it is expanded by using ResNet (Residual Network) 18 to construct a polarization-feature classification model supporting multi-channel input, which can simultaneously process information from intensity and polarization spectra and ultimately output the type of burst event, its time–frequency interval, and circular-polarization features. Experimental results show that this model can effectively identify four common types of radio bursts, and that the multi-channel (intensity channel and polarization channel) model provides a classification performance for polarization features that is comprehensively superior to a three-channel pseudo-color image model that directly uses the polarization spectrum as input. This verifies the value of polarization data as an additional feature dimension, and provides an effective technical pathway for automatically extracting more physical information about burst events from massive solar radio data.

Keywords Sun: radio radiation; methods: deep learning; techniques: image processing, polarization

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1 Introduction

The Sun is the star at the center of the Solar System and is the Earth' s most important source of energy. The radio waves naturally generated by the Sun are called solar radio radiation, and can be received by observational equipment such as radio telescopes. Some material and energy released by intense solar activity often cause strong disturbances, on a global scale, to the Sun and to the near-Earth space environment, and are a major driving source of space-weather disaster events[1]. Therefore, it is necessary to carry out in-depth research on the physical mechanisms of solar atmospheric activity and their accompanying processes, so as to achieve timely and accurate forecasting and warning of space-weather effects and disaster events, thereby reducing their impact on human society.

Solar radio bursts are an important manifestation of solar activity in the radio-wave band. Among them, type I–V bursts in the meter-wave band are the most typical. They exhibit different morphological characteristics in dynamic spectra, corresponding to different electron-acceleration processes and radiation mechanisms, and are important probes for exploring coronal physical processes. They are introduced respectively as follows:

(1) Type I meter-wave bursts are usually composed of clusters of discrete point-like bursts (noise storms) and a background continuum spectrum. The former have very short durations (0.1–1 s), very narrow bandwidths

(relative bandwidth about 3%-5%), and brightness temperatures up to 10^{11} K; the latter are broadband continua with relatively low brightness temperatures (10^{7}-10^{10} K)

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radiation (relative bandwidth close to 1). The overall duration of type I bursts can sometimes reach several days. They usually show a discrete random distribution; except for type I burst chains, there is generally no obvious frequency-drift feature. In addition, the polarization level of type I bursts is usually relatively high, and the relationship between the sense of polarization and the magnetic-field direction conforms to the characteristics of the O mode; this supports the radiation mechanism of plasma emission by isotropic ions[^2]4.

(2) Microwave type II bursts appear in spectra as narrowband radiation that drifts slowly from high to low frequencies. The instantaneous bandwidth ranges from several MHz to several tens of MHz (the relative bandwidth is about 10%-70%[^3-^4]), the frequency-drift rate is no higher than 1 MHz/s, the radiation intensity is generally high, and the duration ranges from several minutes to more than ten minutes. In addition, type II bursts may contain harmonic-frequency structures, and their polarization level is usually weak. It is generally believed that type II bursts are plasma radiation excited by high-energy electrons accelerated by solar flare shock waves, and their frequency-drift data also help estimate the propagation speed of the corresponding shock waves[^2]5.

(3) Type III bursts are a common burst event closely related to flares. Their brightness temperature can vary from 10^{8} K to 10^{12} K, while the frequency can reach as high as several GHz and, at the low end, can extend into the frequency band of interplanetary radio bursts. In the high-frequency part, type III bursts are usually characterized mainly by high frequency-drift rates (from several tens of MHz/s to hundreds of MHz/s), decreasing as the frequency decreases. Some type III bursts also have harmonic-frequency structures, with polarization usually below 15%. In addition, type III storm groups composed of multiple continuously occurring type III bursts are also a common burst phenomenon, usually lasting from several seconds to several minutes. It is generally believed that type III bursts are plasma radiation excited by beam electrons moving outward along open magnetic field lines.

(4) Type IV bursts are generally broadband continuum-spectrum radiation. They can appear in frequency bands wider than the microwave band, may last as long as several tens of minutes, the maximum brightness tempera-

ture of the source region can reach 10^8–10^9 K, and the intensity variation is generally relatively gradual. During the eruption of type IV bursts, the sense of polarization is generally fixed, with no obvious tendency toward left- or right-handedness[^5]. However, because the properties of individual type IV burst events differ, a unified conclusion still requires support from more observations and theoretical studies. The radiation mechanism of type IV bursts remains controversial, but it is generally believed that they are excited by high-energy electrons confined in magnetic structures.

(5) Type V bursts usually occur immediately after type III bursts or type III storm groups. Their spectral morphology resembles a flag attached to the lower-frequency range of a type III burst, and they generally appear below 200 MHz. The duration of a type V burst is generally 1–3 min. Sometimes it shows broadband continuum-spectrum features, and its brightness temperature is usually close to or lower than that of the associated type III burst. The polarization degree of type V bursts is generally low, and the sense of rotation is often opposite to that of the associated type III burst[^6]. There is considerable debate about the generation mechanism of type V bursts, and further study is still needed.

(6) In addition, many eruptive events usually display more complex time–frequency characteristics in dynamic spectra. Some of these complex structures arise because the radiation process is more complicated, while others arise from the temporal and spatial superposition effects of radiation features from multiple source regions; they are usually difficult to distinguish using simple classifications.

In summary, classified observations and studies of solar radio bursts help us understand the physical nature of solar activity. Dynamic spectra play an important role in the above processes: they record changes in radio-radiation flux with time and frequency, and constitute the main data form for studying radio bursts. Among them, in addition to the commonly used intensity spectrum that characterizes radiation intensity, polarization spectra record the direction of circular/elliptical polarization of the radiation (left-handed/right-handed) and the variation of the circular/elliptical polarization rate with time and frequency; they are a key dimension for interpreting the deep physical processes of burst events. This mainly originates from the multiple radiation mechanisms involved in solar radio bursts. Among them, coherent radiation mechanisms include plasma radiation (in which the latter is converted into electromagnetic waves after electron beams excite Langmuir waves) and electron-cyclotron maser radiation (in which electrons directly generate electromagnetic waves through maser amplification near the cyclotron frequency). These two mechanisms make important contributions to fine structures and high-brightness-temperature bursts in spectra. In addition, incoherent gyrosynchrotron radiation—which forms the broadband continuum spectral background in type IV bursts—as well as gyrosynchrotron acceleration radiation, which likewise contributes to the formation of type I bursts, are also involved. Therefore, radio spectra alone are still insufficient to mine the rich physical information contained in solar radio bursts.

By combining polarization observations with features such as burst-event spectral morphology (e.g., fundamental–harmonic structures) and frequency-drift rate, further constraints related to the radiation mechanism and the magnetic field in the radiation source region can be provided. The O mode and X mode are two wave modes by which electromagnetic waves propagate in a magnetized plasma, and they are also the two manifestations of celestial radio radiation that we observe in space and on the ground. After the dispersion relation for a specific mode is solved, the relative strengths of the electric-field components of that mode under specified frequency, propagation angle, and given parameter conditions, as well as the polarization degree and polarization direction, can be obtained by combining the ratios and phase relationships of the perturbation amplitudes of the electric-field components. In this way, links can be established between cold-plasma wave modes and the relevant physical parameters and polarization-observation results. For example, in parallel propagation, the O mode and X mode correspond respectively to left-handed and right-handed circular polarization. As the propagation angle increases, the vertical electric-field components still respectively maintain left-handed and right-handed rotation directions, but become elliptically polarized[^2]97. Theory and observations indicate that plasma radiation mainly produces O-mode radiation, whereas electron-cyclotron maser radiation strongly tends to produce X-mode radiation.

emission[^7]. Therefore, the observed dominant polarization direction can provide key evidence for judging the coherent radiation mechanism of a burst event. For bursts with a fundamental–harmonic structure, the polarization characteristics of the fundamental and harmonic branches are also different: the former has a higher degree of polarization, whereas the latter is lower[^8]. The polarization direction can also be used to trace the magnetic-field direction and propagation path of the radiation source region. For example, in the study by Morosan et al.[^9], the polarization direction of a type-J burst (propagating along a closed magnetic loop) was opposite to that of other type-III bursts (propagating along open magnetic-field lines).

Therefore, multilevel classification of burst-event types and their polarization characteristics helps distinguish, from a physical perspective, radiation modes or fundamental/harmonic emission, and helps infer the magnetic-field direction and propagation path in the source region. From the practical perspective of data management, automatic classification of burst data is also important for handling massive observational data. Most of the massive data generated by high-performance equipment are low-value data that do not contain clear burst events. To save storage space, low-value data need to be compressed and stored as images, while burst data should be retained. Against this background, automated classification and detection technologies can play a key role. First, for efficient data management: by automatically screening historical data, low-value data can be efficiently removed, greatly saving storage space and the cost of manual review. At the same time, a "observation–classification–compression–

storage" pipeline can be gradually built for newly accumulated data, enabling near-real-time data refinement. Second, for efficient data retrieval: on the basis of multi-category detection technology, an automated indexing mechanism for burst data can be established and improved, building an efficient preliminary screening tool that helps researchers quickly locate subsets of bursts with specific physical significance and improves data sharing and research efficiency.

To realize automated analysis, high-resolution original spectra are often down-sampled into images, thereby allowing mature and advanced image-processing techniques to be used. Various deep-learning models in the field of computer vision have now been widely applied to spectral-image classification tasks. Some studies use classic classification models such as convolutional neural networks (CNNs)[^10-^11]; other studies regard spectral images as time sequences, use LSTM (Long Short-Term Memory) as the basic model, improve it, and capture temporal features[^12-^15]. In addition, Refs. [16] and [17] identify whether spectra contain burst events based on the ViT (Vision Transformer) and SWIN Transformer (Vision Transformer using Shifted Windows) models, respectively.

However, classification tasks take an entire image as the judgment unit, making it difficult to handle cases in which multiple events are contained in the same image. A target-detection model can not only determine the categories of events in an image, but also output their locations in the image, corresponding time intervals, and frequency bands, providing a technical foundation for higher-quality intelligent retrieval schemes. Early studies used the Radon transform[^18], Hough transform[^19], and statistical methods[^20] to detect specific types of solar radio bursts or determine whether bursts existed. Later, deep-learning models gradually demonstrated their advantages. Hou et al.[^21] identified and extracted solar radio spike bursts based on Faster R-CNN (Region-CNN). Scully et al.[^22] generated high-quality type-III burst samples through GAN (Generative Adversarial Network) adversarial training, and then used YOLO (You Only Look Once) v2 for detection. Zhang et al.[^23] used spectra from the Learmonth observatory to train YOLOv7 to detect type-II and type-III bursts, applied the model to spectra from the Murchison Widefield Array solar radio observation station, and provided valuable insights into related burst events through statistical burst parameters. He et al.[^24] used burst information and data provided by e-CALLISTO (Compact Astronomical Low-cost Low Frequency Instrument for Spectroscopy and Transportable Observatory) to further refine the detection categories, and combined MobileViT with SSDLite (Single Shot MultiBox Detector) to form a lightweight detection network. Deng et al.[^25] used a multi-scale feature-fusion network to replace the neck structure of YOLOv8, further improving detection accuracy. Wang et al.[^26] used MobileViTv2 as the backbone network and combined task alignment, channel-attention enhancement, and other methods to improve the model' s recall rate. Wang et al.[^27] continued to focus on improving the model' s recall rate and detection accuracy; on the basis of deformable DETR (DEtection TRansformer), they added a scale-sensitive attention module and used CHAT (Collaborative Hybrid Auxiliary Training) to alleviate the problem of imbalance between positive and negative samples.

Although automated analysis techniques for solar radio bursts have made significant progress, current research still has the following shortcomings: existing technologies focus on locating and classifying burst events in intensity spectra, while important information contained in polarization spectra has not been fully utilized; because of constraints such as the difficulty of obtaining high-resolution original data, most studies use public spectral images that have been processed or contain redundant information, which may lead to a loss in the correlation between images and original data. To address the above problems, this paper makes the following main contributions: it designs a pipeline dedicated to the generation of solar radio spectral images, realizing direct conversion from first-hand spectral data to high-quality image samples,

ensure a high degree of agreement in position and numerical values between the image and the original data, without requiring secondary processing; then construct a basic framework that can automatically identify the locations of burst events and preliminarily distinguish the four major types of radio-burst subjects. On this basis, a polarization-feature classification module is introduced, enabling the model to output richer physical information, including the type, time interval, frequency band, and polarization features of the burst event. A multichannel image-fusion mechanism incorporating intensity information is proposed to improve the classification performance of the model.

2 Dynamic spectra

The observational data used in this study come from the Daocheng Radio Telescope (DAocheng Radio Telescope, DART) located in Daocheng County, Sichuan Province, China. DART is a landmark instrument of the second phase of the Chinese Meridian Project[^28]. It can conduct full-disk and continuous monitoring of solar radio bursts and provide inputs for space-weather research and numerical forecasting models. DART is a circular array with a diameter of 1 km, including 313 antenna units with an aperture of 6 m and a central calibration tower located at the center of the array. The operating frequency of DART is approximately 150–450 MHz[^29], and the frequency resolution of the spectra can reach 7.6 kHz.

The DART digital subsystem is responsible for the high-speed synchronous acquisition, spectral analysis, sub-band filtering, and cross-correlation processing of 626 analog-band signals. Amplitude–phase consistency errors exist among the different receiving channels of the whole system. The receiving-channel errors can be obtained, and amplitude–phase correction factors derived, using calibration signals with different characteristics generated by the digital calibration-source network. After amplitude–phase correction, the digital correlator is responsible for signal preprocessing, including spectral analysis and cross-correlation calculation. In this paper, the spectral-analysis processing results packaged by an FPGA (Field Programmable Gate Array) are used as the

Fig. 1 Spectrum data processing flow

Figure 1: Fig. 1 Spectrum data processing flow

input raw data, and the above process ensures the accuracy and reliability of the data used.

After parsing, the raw spectral data are stored in the form of two-dimensional arrays, and the data type is double-precision floating point. By jointly using self-spectrum and mutual-spectrum data, Stokes parameters can be constructed. Among them, parameters I and V characterize the total intensity and circular-polarization intensity of the radio radiation, respectively. Further calculation yields the logarithmic Stokes I data (hereinafter referred to as I data) and the data characterizing the circular-polarization rate (Circular Polarization; hereinafter referred to as P data). The former compresses the dynamic range of the raw data, facilitating subsequent processing; the latter, through normalization, converts the variation range of the data to between -1 and 1, where positive and negative values represent right- and left-handed circular polarization, respectively. The two present solar radio radiation information from the two perspectives of radiation intensity and polarization characteristics, and can describe radio-burst phenomena more comprehensively.

Because spectral data occupy large space and have high resolution, they usually need to be processed into images first. During conversion, it is necessary to maintain consistency between the output image and the raw data. Limited by the difficulty of obtaining raw data or by other factors, most spectral classification and detection tasks use existing spectral images as their direct data source, and sometimes secondary processing of these images is required, which may not guarantee the rigor of the conversion process. Benefiting from the raw spectral data from DART, this paper briefly describes the processing flow from data to images, as shown in Fig. 1.

Fig. 1 Spectrum data processing flow

After logarithmic transformation, the I data and P data are sequentially converted into images of fixed size through three processing modules. Among them, "RFI mitigation" uses methods such as median filtering along the frequency direction to process RFI (Radio Frequency Interference) data whose values clearly deviate from the normal range, thereby suppressing horizontal stripe-like RFI; "Limit analysis" calculates the colormap based on the smoothed data.

(colormap), in order to determine the color-mapping range of the image pixel values; finally, the high-resolution data are converted, through steps such as downsampling, normalization, and color mapping, into a series of clean images without any additional information required for constructing the dataset, including intensity images (hereinafter referred to as image I) and polarization images (hereinafter referred to as image P). In addition, when conducting detailed analysis of a specific burst event, the analysis object should be the original

Fig. 2: A pair of solar radio intensity and polarization spectrum images containing a type IV burst (right-handed polarization).

Figure 2: Fig. 2: A pair of solar radio intensity and polarization spectrum images containing a type IV burst (right-handed polarization).

spectral data rather than images obtained after processing, because the former will not be affected by operations such as median filtering that may lead to a narrowing of the bandwidth burst (e.g., type II burst) range. Figure 2 shows one pair of such images. The left panel is a 3-channel intensity spectrum image, reflecting the distribution of radio radiation flux with time and frequency. The closer the color is to dark red or dark blue, the higher or lower the radiation intensity in that region; yellow-green indicates moderate intensity. If a single-channel grayscale image is used to represent the intensity spectrum, then colors closer to white or black respectively indicate higher or lower radiation intensity in that region. From the left panel, one type IV burst can be identified, and the radiation intensity of the main burst region is significantly higher than the background level. The right panel is a polarization spectrum image, reflecting the changes with time and frequency in the degree of circular polarization and the handedness of the radio radiation within the same time-frequency interval. Red or blue colors respectively indicate that the polarization handedness of the radio radiation in that region is right-handed or left-handed, and the darker the color, the relatively higher the degree of polarization; the closer the color is to gray-white, the relatively lower the degree of circular polarization. In the right panel, the main region of this type IV burst is red, indicating that its polarization handedness is right-handed.

(a) (b)

Fig. 2 A pair of solar radio intensity and polarization spectrum images containing a type IV burst (right-handed polarization) (time (UT): 2024-07-26 09:12:48–09:25:04). In the intensity spectrum (left panel), a type IV burst is present, where the radiation intensity of the main burst region (in red) is significantly higher than the background level (in blue). The polarization spectrum (right panel) shows the degree of circular polarization of the radio radiation in the same time-frequency interval, and the main burst region is in red, indicating that this type IV burst is right-handed polarized.

In this process, the conversion from data to images is concise and direct, helping to maintain consistency between images and data and avoiding data distortion that may be caused by multiple rounds of processing. In addition, the filenames of all images strictly follow the naming format shown in the figure during the processing workflow, including the specific date, image sequence number, start and end times, and image type. In subsequent tasks, by parsing the filenames, it is possible to match any pixel in an image with the data block at the same position, as well as to pair image I with image P. In this way, the information learned by the object-detection model from the images can be traced back to

Fig. 3 Overall detection and classification process

Figure 3: Fig. 3 Overall detection and classification process

the data, thereby enabling data classification and organization.

3 Detection of Radio Bursts and Classification of Polarization Features

Figure 3 shows the complete workflow for radio-burst detection and polarization classification: "SRB (Solar Radio Burst) detection" is used to detect image I and output the type of burst event and its location in the image; then, based on the location information, image I and image P are cropped to obtain paired image blocks corresponding to each burst event; subsequently, "Image processing" is used to comprehensively process the information in the image blocks and output the classification of polarization features.

the multi-channel fused image as input to "Polarization classification," so as to obtain classification results for polarization features; finally, the position information is converted into the relevant parameters, integrating the outputs of the two stages.

Compared with the traditional object-detection task (the part within the dashed box), this workflow is extended, so that the output information contains richer physical information related to the burst event: burst category, frequency band, time range, and polarization features. The implementation details of each part are introduced below.

图 3 检测与分类的整体流程

Fig. 3 Overall detection and classification process

3.1 Radio-burst detection based on intensity spectra

3.1.1 Dataset

Based on the images I and P output by the workflow shown in Fig. 3, labeling is used to manually annotate the categories and positions of burst events in the images, thereby obtaining the original dataset. During annotation, enhanced structures whose radiation intensity is clearly above the background level and that exhibit typical burst morphology are taken as the basic criterion for the presence of a radio-burst event (burst criterion). The division of burst types (type criterion) strictly follows visual judgment based on morphological features. To ensure the accuracy, rigor, and consistency of the annotations, the related work is carried out by researchers familiar with burst morphology. The dataset does not include samples whose morphology is difficult to identify, whose types are ambiguous, or whose features are atypical; what is mainly retained are samples with clear features, unambiguous samples that can be unambiguously classified, and some weak burst events in which the features in a quiet background are not very obvious. This processing approach is intended to provide the model with clear learning targets. Thereafter, the original dataset is divided into a training set and a validation set in a 4:1 ratio. It should be noted that conventional dataset-splitting methods consider only the numbers of images in the training and validation sets. However, in a detection task, images and annotations do not correspond one-to-one, and this splitting method cannot guarantee that the numbers of annotations in the two sets also satisfy the preset ratio. Therefore, the splitting method is improved here: random stratified sampling is used to obtain datasets with more balanced proportions, ensuring that the ratios of the numbers of both annotations and images in the two sets are close to the preset ratio. The specific information is summarized in Table 1.

表 1 目标检测数据集

Table 1 Dataset for object detection

Set	Type I	Type II	Type III	Type IV	Instances	Images
Total	678	149	1320	135	2282	1559
Training set	540	118	1061	108	1827	1249
Validation set	138	31	259	27	455	310
Training set (augmented)	594	472	1316	135	2517	1504

3.1.2 Data augmentation

It is noted that sample imbalance exists in the original dataset, which may adversely affect the training results. Data augmentation can increase the number of samples of certain categories in the training set, thereby improving its

during training, indirectly enhancing the model' s learning ability for such samples. However, for categories with relatively simple features, such data augmentation may lead to overfitting. Therefore, here only the Type III bursts, whose features are the most complex and whose sample size is relatively small, are augmented in quantity. First, the original image is rotated clockwise to generate three copies, corresponding respectively to the three rotation angles of 90°, 180°, and 270°. Then small-range brightness, contrast, and blur enhancements are applied to the copied images to further enrich their features. Finally, the set of copies is merged with the original training set to form an augmented training set. The sample size of the new training set is shown in the last row of Table 1.

The above augmentation is completed before formal training and targets samples of individual categories. Mosaic augmentation is also used during training. Its core idea is to stitch and combine four different training images into a new composite image according to random positions, proportions, and arrangements (for example, a 2-row by 2-column grid). This method significantly increases the density and diversity of targets in the image, forces the model to learn more complex scale and contextual information, and reduces the model' s dependence on relatively large batches of image samples. However, excessive mosaic augmentation may also make optimization difficult or cause performance oscillation. Therefore, mosaic augmentation is disabled in the late stage of training to promote convergence of model performance.

3.1.3 Detection model YOLO was first proposed by Joseph Redmon in 2016[^30]. It is a classic object detection model with CNN as its main structure. As a single-stage detection model, YOLO simplifies the entire detection process into a single regression problem, achieving a balance between efficiency and accuracy, and quickly occupying an important position in the field of object detection. YOLOv3[^31] first used "head-neck-backbone" as the overall structure, laying the structural foundation for subsequent versions of the model. Thereafter, Ultralytics developed classic models such as YOLOv5 and YOLOv8, enabling this series to be widely applied across various industries and further consolidating its status. This paper uses the relatively general YOLOv8s model to complete the detection task for radio bursts.

3.2 Polarization feature classification

3.2.1 Dataset According to the position of the burst event in the image, image I and image P are cropped simultaneously, so that the samples required for the polarization classification task can be obtained. Each sample consists of a pair of two image blocks of the same size. Then, according to the polarization features in image P, the samples are divided into three categories: left-hand circular polarization (Left-Hand Circular Polarization, LHCP), right-hand circular polarization (Right-Hand Circular Polarization, RHCP), and unpolarized (Unpolarized, Un), thereby forming a new dataset. Specifically, the burst events in the intensity spectrum and polarization spectrum are first compared: (1) if the polarization rotation-direction feature in the region where the burst body is located in the polarization image is clear, and its degree of polarization is significantly higher than the polarization measurement precision and noise level of the observation system (1%), it is assigned to the corresponding category (LHCP/RHCP); (2) if the region where the burst body is located in the polarization image does not have polarization rotation-direction features or the features are extremely weak, and its degree of polarization is close to or lower than the polarization measurement precision and noise level of the observation system (1%), it is classified as unpolarized; (3) if the corresponding region of the polarization image is composed of background noise and no burst-body structure exists, it is also classified as unpolarized. Then, the dataset is randomly divided into a training set and a validation set at a ratio of 4:1. The specific information is shown in Table 2.

Table 2 Dataset for classification

Fig. 4 The process of generating multi-channel images

Figure 4: Fig. 4 The process of generating multi-channel images

Set	LHCP	RHCP	Un	Images
Total	700	554	617	1871
Training set	558	442	492	1492
Validation set	142	112	125	379

3.2.2 Multichannel image fusion incorporating burst intensity information To train a classification model capable of distinguishing polarization image types, the most direct and simple method is to train using the polarization image itself. However, a rectangular polarization image is composed of burst pixels and background pixels, and the polarization features of the latter may interfere with the features of the former. To address this problem, this paper proposes a multichannel image fusion mechanism that incorporates burst intensity information, fusing the information in image I and image P, thereby guiding the model to focus on the polarization features of the burst region. At the same time, this design is also consistent with the actual physical relationship between burst events and their polarization properties.

Figure 4 shows in detail the content of "Image processing" in Figure 3. "Resizing" refers to scaling the image proportionally to a fixed size according to the length of the long side of the rectangular image block, while "padding" refers to filling the outer part of the resized image with a fixed pixel value, so that it becomes a square image of uniform size, satisfying the input-size requirements of the classification model while maintaining the proportional features of the burst event. Finally, image I and image P are concatenated along the channel direction to obtain a multichannel fusion image as the input for the subsequent classification task.

Figure 4 The process of generating multi-channel images

3.2.3 Classification model

The more convolutional layers and pooling layers a deep-learning model has, the more comprehensive the feature information it extracts. However, as the number of layers increases, traditional CNN structures face problems such as gradient vanishing and performance degradation, and cannot fully exploit the advantages of deep networks. The residual network (Residual Network, ResNet) effectively solves this problem. It is a deep convolutional neural network architecture proposed by He et al. [32], whose core innovation is the residual block. Each residual block directly adds the input to the output after passing through the convolutional layers via a shortcut connection, enabling the network to learn the difference between the output and the input, i.e., the residual. This structure allows the network to learn identity mappings more easily; when learning in certain layers becomes difficult, these layers can be skipped directly, effectively solving problems such as gradient vanishing.

Because the dataset size for the polarization classification task is not large, ResNet18 is selected as the base model, and the number of input channels in its first layer is modified to adapt to multi-channel fused images.

4 Experimental results and analysis

4.1 Experimental environment

All experiments were run in a hardware environment consisting of an Intel-i9 14900HX and an NVIDIA GeForce RTX 4060 Laptop GPU (8 GB RAM). The software environment was built on pytorch version 1.11.0 and cuda version 11.3. For YOLO training, the optimizer was SGD (Stochastic Gradient Descent), with momentum of 0.937, weight decay of 0.0005, an initial learning rate of 0.01, batch size of 32, and 300 training epochs; mosaic data augmentation was disabled in the last 30 epochs. For ResNet training, the optimizer was SGD, with momentum of 0.9, weight decay of 0.0001, an initial learning rate of 0.001, a stepLR scheduler with step size 20 and gamma 0.1, batch size of 32, and 70 training epochs.

4.2 Evaluation metrics

A confusion matrix can formally present experimental results in a classification task. It consists of four basic items: the true positive class of positive samples (True Positive, TP), the false negative class (False Negative, FN), and the false positive class of negative samples (False Positive, FP), and the true negative class (True Negative, TN), as shown in Table 3.

Table 3 Definition of confusion matrix

Confusion matrix	Confusion matrix	True value	True value
Confusion matrix	Confusion matrix	Positive	Negative
Predictive value	Positive	TP	FP
Predictive value	Negative	FN	TN

Compared with a classification task, an object detection task is more complex. It contains three subtasks: detecting all objects in the image, giving the positions and sizes of the predicted boxes, and correctly determining the category to which each object belongs. Therefore, the statistics of TP, FP, and FN must consider not only the category, but also IoU (Intersection over Union), which can characterize the degree of matching between the predicted box and the ground-truth box. The numbers of TP, FP, and FN ⋯

It is necessary to judge and count according to the relationship between the IoU of each predicted box and the IoU threshold. The IoU threshold is generally set to 0.5. At this time, TP refers to the number of predicted boxes with IoU $\geq$ 0.5; FP is the number of predicted boxes with IoU less than 0.5; and FN is the number of missed true boxes. In terms of quantity, the sum of TP and FP is the same as the number of predicted boxes, and the sum of TP and FN is the same as the number of true boxes. It should be noted that the matching between predicted boxes and true boxes is one-to-one. When one-to-many or many-to-one situations occur, the pair with the largest IoU is taken as the final matching result.

Furthermore, Precision and Recall are two ratios, respectively representing the accuracy and completeness of object detection under a certain category, and they are also key evaluation indicators for classification tasks. They are calculated by the following two formulas:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \qquad (1)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}. \qquad (2)$$

During prediction, each predicted box output by the model also contains category confidence information. After all predicted boxes of a certain category have been counted, they are sorted in descending order according to category confidence. Then, confidence thresholds are set from high to low, and Precision and Recall under different thresholds are calculated, thereby obtaining the Precision-Recall curve.

Finally, AP (Average Precision) and mAP (mean Average Precision) are used as core indicators for comprehensive evaluation of detection performance. AP measures the detection performance of the model on a single category and is obtained by calculating the area under the Precision-Recall curve of that category. mAP is a more comprehensive indicator; it measures the model' s multi-category detection performance. After calculating the AP of all categories, their average value is taken as the mAP.

4.3 Experimental Results

4.3.1 Solar Radio Burst Detection Based on Intensity Spectra

With mosaic data augmentation enabled, YOLOv8s was trained on the augmented grayscale-image training set with a size of 640. The model' s Precision-Recall curve is shown in Fig. 5. Table 4 compares the detection performance of the model under different conditions using AP50 as the metric. Here, "Jet" refers to the three-channel RGB image in which image I in the dataset uses

Precision-Recall curve of the detection model

Figure 5: Precision-Recall curve of the detection model

Jet color mapping, while "Gray" refers to the single-channel grayscale image in which image I in the dataset does not use color mapping.

Data augmentation on Type II burst samples in the training set can significantly improve the detection performance for this category. This indicates that increasing the number of difficult samples and their spatial features helps improve the sample imbalance phenomenon that is relatively common in radio-burst datasets.

Figure 5 Precision-Recall curve of the detection model

Fig. 5 Precision-Recall curve of the detection model

Table 4 The detection performance of the model on different datasets

Dataset	Type I	Type II	Type III	Type IV	mAP50
Jet	0.991	0.446	0.732	**0.809**	0.744
Gray	0.982	0.519	**0.784**	0.729	0.754
Gray (augmented)	**0.991**	**0.624**	0.768	0.794	**0.794**

In terms of color mapping, the commonly used three-channel RGB spectrum does not show an advantage. By contrast, the single-channel grayscale spectrum can not only preserve the physical meaning of pixel values, but also requires less storage space and video memory, and is therefore more suitable for constructing datasets for object-detection tasks.

From the training results, Type I bursts are relatively numerous, have obvious features, and usually appear as continuous structures with a wide frequency range and long time span, so they are relatively easy to detect. The detection performance for Type II bursts is relatively poor because the number of real samples is small and the spectral features are complex. Type III bursts are the most numerous, but the aspect ratios of many annotation boxes are seriously imbalanced, so the model has certain difficulty in learning this special feature. Although the number of Type IV burst samples is small, their features are simple and ⋯

usually occupy a relatively large region in the spectrum, so the detection effect is still acceptable.

4.3.2 Polarization-feature classification

Table 5 shows the classification results of two classification models for polarization images. For the model obtained by training using only polarization images,

Fig. 6 Normalized confusion matrix of the classification model

Figure 6: Fig. 6 Normalized confusion matrix of the classification model

the recall rates of the LHCP and RHCP classes are markedly low, while the precision of the Un class is also significantly low; that is, the model incorrectly classifies a large number of samples with polarization information as non-polarized. The multi-channel image fusion mechanism comprehensively considers the information in the intensity image and the polarization image, using the former to guide the model in learning the features of key regions in the latter; therefore, the classification results are comprehensively superior.

Table 5 Classification performance of the model before and after using multi-channel images

	LHCP Precision	LHCP Recall	RHCP Precision	RHCP Recall	Un Precision	Un Recall	Accuracy
Before	94.53%	85.21%	91.00%	81.25%	73.51%	88.80%	85.22%
After	**94.96%**	**92.96%**	**93.94%**	**83.04%**	**80.14%**	**90.40%**	**89.18%**

Figure 6 shows the normalized confusion matrix of this model on the validation set. The precision rates of the LHCP and RHCP classes are relatively high, and there is almost no confusion between the two. The main source of classification error is that the model tends to assign some samples with polarization features to the non-polarized class. Figures 7–9 show three validation-set samples that were correctly classified, along with their corresponding intensity images. In Example 1, although there is obvious stripe RFI near the burst, the model can still correctly identify the polarization feature. In Example 3, the polarization direction of the type-III burst is left-handed, but the background in which it is located is right-handedly polarized; at this time, the model can still make a correct judgment.

Fig. 6 Normalized confusion matrix of the classification model

For Example 3, Grad-CAM (Gradient-weighted Class Activation Mapping) can be used to further verify the role of the fusion mechanism. Grad-CAM is a gradient-based class activation mapping technique that can visualize the image regions attended to by a deep neural network during classification decision-making. It generates a heat map by calculating the gradients of the target class with respect to the feature map of the last convolutional layer, so as to intuitively show which regions in the image play a key role in the model's decision for a specific class. Figure 10 compares the Grad-CAM results of the model for Example 3 before and after introducing the multi-channel fusion mechanism. The significantly improved model can focus more accurately on the radio-burst region. Table 6 compares the class confidences output by the model under the two conditions. In the absence of intensity-information guidance, the model naturally tends toward the right-handed polarization feature with the larger area, thereby leading to misclassification.

Figure 11 shows a sample that was misclassified: when the burst event is partially polarized, the features in the intensity image and the polarization image may not match completely, thereby leading to class confusion.

4.4 Detection of weak-burst events

The model' s detection performance for weak-burst events can reflect its robustness, generalization ability, and application potential. To achieve quantitative evaluation, it is first necessary to define and extract a weak-burst subset from the validation set as objectively as possible. We selected two complementary evaluation dimensions: relative contrast and absolute intensity level. The relative contrast is obtained by calculating the difference between the median of the pixel values inside the annotated box of the burst event and the median of the pixel values in the surrounding background region, and then dividing by the standard deviation of the background pixel values; it can reflect the significance of the annotated-region data relative to the local noise. The absolute intensity level is the 75th percentile of the pixel values inside the burst box, reflecting the typical intensity of the burst region itself.

type intensity. The two indicators of all labeled events in the validation set are first normalized separately, and then a weighted sum is computed according to preset weights (such as $[0.5, 0.5]$) to obtain a comprehensive strength–weakness score for each event. All events are then ranked by the comprehensive score, and the events in the lowest 25% of scores are defined as weak bursts. After obtaining the weak-burst subset, the trained YOLOv8s model is used to perform inference on it, and the detection performance is evaluated using multiple metrics, including weak-burst recall, mean IoU, mean confidence, precision, and F1 score.

Figure 7 Example 1 of correctly classified spectrum image (time (UT): 2024-06-11 07:20:24–07:32:40; a type II burst without obvious polarization; left panel: intensity spectrum; right panel: polarization spectrum)

Fig. 7 Example 1 of correctly classified spectrum image (time (UT): 2024-06-11 07:20:24–07:32:40; a type II burst without obvious polarization; left panel: intensity spectrum; right panel: polarization spectrum)

Figure 8 Example 2 of correctly classified spectrum image (time (UT): 2024-07-26 09:12:48–09:25:04; a type IV burst of right-handed polarization; left panel: intensity spectrum; right panel: polarization spectrum)

Fig. 8 Example 2 of correctly classified spectrum image (time (UT): 2024-07-26 09:12:48–09:25:04; a type IV burst of right-handed polarization; left panel: intensity spectrum; right panel: polarization spectrum)

Fig. 9

Figure 7: Fig. 9

Fig. 10

Figure 8: Fig. 10

According to the above criteria, 125 weak bursts can be extracted from the validation set. After statistically analyzing the inference results, the following values are obtained: recall is 0.576; mean IoU is 0.781; mean confidence is 0.682; precision is 0.75; and the F1 score is 0.6516. This result is not ideal, but it can objectively reveal the limitations of the current model in detecting weak targets.

To illustrate this more intuitively, we selected two cases for visualization analysis, as shown in Figure 12. The green solid-line box indicates the annotation box, and the information in the green label represents, respectively, the burst type, the normalized score of the relative contrast, the normalized score of the absolute intensity level, and the strength–weakness mark. The red solid-line box in the figure indicates the prediction box, and the information in the red label represents, respectively, the predicted burst type, confidence, the property of this prediction in the confusion matrix, and IoU (if false detection ⋯

then that class would be absent. When the background is relatively quiet, even weak bursts can be detected accurately; moreover, the model also detected one event resembling a type III burst that had been ignored during annotation, although its intensity was extremely weak. When interference (an RFI similar in morphology to a type III burst) exists near a weak burst, the model' s detection performance may be affected, but high-intensity bursts can still be detected accurately.

Figure 9 Example 3 of a correctly classified spectrum image (time (UT): 2024-05-20 07:52:49–08:05:05; a type III burst with left-handed polarization; left panel: intensity spectrum; right panel: polarization spectrum)

Fig. 9 Example 3 of correctly classified spectrum image (time (UT): 2024-05-20 07:52:49–08:05:05; a type III burst of right-handed polarization; left panel: intensity spectrum; right panel: polarization spectrum)

Figure 10 Comparison of Grad-CAM results before (left panel) and after (right panel) model improvement

Fig. 10 Comparison of Grad-CAM results before (left panel) and after (right panel) model improvement

Table 6 The confidence and classification results output by the model before and after using multi-channel images

Fig. 11

Figure 9: Fig. 11

Fig. 12

Figure 10: Fig. 12

	LHCP	RHCP	Un	Results
Before	0.005	**0.905**	0.090	RHCP
After	**0.724**	0.031	0.245	LHCP

4.5 Practical application

To verify the effectiveness of this method in actual observational data, we first processed the dynamic spectrum data produced by DART from November 12, 2025 to January 12, 2026 to obtain spectrum images. After preliminary screening by the automatic detection workflow and supplementary manual verification, during this period we identified a total of 440 type III bursts (including type III burst groups), 11 type II bursts, and a large number of type I bursts. It should be noted that type I bursts often appeared frequently in the form of continua during this period. Their continuous

The continuous and scattered spectral characteristics make it relatively difficult to count the "number of events," and therefore they are not included for the time being.

To more intuitively demonstrate the model' s performance under complex conditions, we selected a scenario containing both type I and type III burst events for testing, and annotated the results on the original images, as shown in Fig. 13. In this scenario, the model accurately located two burst events with high confidence.

Figure 11. Example of a misclassified spectrogram image (time (UT): 2025-01-16 01:37:56–01:48:50; right-hand circularly polarized type III burst; left panel: intensity spectrum; right panel: polarization spectrum)

Fig. 11 An example of misclassified spectrum image (time (UT): 2025-01-16 01:37:56–01:48:50; a type III burst of right-handed polarization; left panel: intensity spectrum; right panel: polarization spectrum)

Figure 12. Detection results of weak bursts in a quiet spectrum (left panel: time (UT): 2024-05-28 07:15:16–07:27:32) and an RFI-containing spectrum (right panel: time (UT): 2024-06-16 08:46:22–08:58:38)

Fig. 12 Detection results of weak bursts in the quiet spectrum (left panel: time (UT): 2024-05-28 07:15:16–07:27:32) and the RFI-containing spectrum (right panel: time (UT): 2024-06-16 08:46:22–08:58:38)

Fig. 13 detection results of the model in complex scenes

Figure 11: Fig. 13 detection results of the model in complex scenes

The above statistical data and complex-scenario tests provide references for the model' s practical application effect and performance, and further verify the effectiveness of the method proposed in this paper in massive-data processing and automatic detection of radio bursts.

5 Conclusions

The solar radio spectra provided by DART are an important data resource for studying solar activity. To fully explore their scientific value, this paper constructs a dedicated spectrogram image generation workflow, which can directly generate high-quality image samples from the raw data and ensure consistency between the data and the images. A polarization-feature classification function is then introduced into the traditional detection framework, promoting the automatic analysis of radio-burst information from "event detection" toward "physical-parameter extraction." The experimental results show that appropriate data-augmentation strategies can alleviate the problems in spectrogram image datasets.

common sample-imbalance phenomenon; combined with a multi-channel image-fusion mechanism for burst-intensity information, it effectively uses the characteristics of intensity images and polarization images, improving the performance of the polarization-classification model. This feasible pathway is expected to provide more comprehensive data support for space-weather warnings and solar-physics research.

Figure 13 Detection results of the model in complex scenes (time (UT): 2025-11-29 01:25:17–01:37:34; a type III burst of right-handed polarization and a type I burst of left-handed polarization; left panel: intensity spectrum; right panel: polarization spectrum)

Fig. 13 Detection results of the model in complex scenes (time (UT): 2025-11-29 01:25:17–01:37:34; a type III burst of right-handed polarization and a type I burst of left-handed polarization; left panel: intensity spectrum; right panel: polarization spectrum)

This study still has some limitations. Although rigorous and conservative classification criteria for burst events can provide clear learning targets for the model, they also exclude samples with complex structures, hard-to-identify morphologies, or atypical features. Although these samples are difficult to define by category, they generally still contain the main structures of bursts and likewise have value for exploration and mining. Therefore, the current dataset still needs to expand its categories and increase sample richness, so that the burst-detection model will have the ability to cope with atypical burst events, thereby providing retrieval pathways for these special data that are consistent with those for regular bursts.

At the present stage, our judgment of polarization features still relies on manual annotation, and the conclusions obtained are qualitative. However, a polarization spectrum is a rectangular image containing pixels from the burst region and background pixels, and the polarization characteristics of different regions are often different. Therefore, quantitative and automated analysis of the polarization level in burst regions is still needed. This improvement will make the physical information output by automatic-detection technology more objective and richer.

In addition, the experimental results show that the model' s ability to detect weak burst events still needs improvement. To optimize the model' s recall rate for difficult samples, it is still necessary to explore more advanced detection frameworks, data-augmentation strategies, and training mechanisms for special samples.

It should also be pointed out that the present study focuses on locating and classifying the main structures of four types of typical burst events, and uses rectangular boxes to define the overall time–frequency intervals of bursts, facilitating efficient data retrieval by researchers; however, it has not yet achieved further analysis of the fine internal structures of various radio bursts (such as spikes, zebra patterns, fibers, etc.). In the future, we will develop algorithms capable of recognizing and segmenting these fine structures, so as to achieve more detailed and accurate extraction of physical parameters and structural analysis of burst events.

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A Method for Detecting Solar Radio Bursts by Combining Intensity Spectra and Polarization Spectra

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Abstract Solar radio burst data are crucial for understanding solar activity and forecasting space weather. Current deep learning-based detection methods primarily rely on dynamic spectra, which represent radio intensity, offering a limited dimensionality of information. To fully explore the physical information contained in spectral data, a detection method for solar radio bursts combining intensity spectra and polarization spectra is proposed. The approach begins with preprocessing raw data from the Daocheng Radio Telescope (DART) to directly generate high-quality image samples. And it utilizes a traditional object detection model to automatically identify the location of burst events and preliminarily distinguish the main bodies of four major types of radio bursts. Then, based on this, it is extended by constructing a polarization classification model utilizing ResNet18 that supports multi-channel input. This model can simultaneously process both intensity and polarization spectral information, ultimately outputting the event's type, time-frequency range, and circular polarization characteristics. The experiment results demonstrate that the model can effectively identify four common types of solar radio bursts. Furthermore, the multi-channel model (intensity channel and polarization channel) achieves comprehensively superior classification performance on polarization features compared to the three-channel pseudo-color image model that directly takes the polarization spectrum as input, confirming the value of polarization data as an additional feature dimension. This work provides an effective technical pathway for automatically extracting more physical information about burst events from massive volumes of solar radio data.

Key words Sun: radio radiation, methods: deep learning, techniques: image processing, polarization

Note: Figure translations are in progress. See original paper for figures.