Detection and localization of solar sigmoids using deep learning

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Abstract

S or inverse S-shaped features appear in solar, coronal soft X-ray (SXR) images are termed as sigmoids. They are complex magnetic structures in the solar atmosphere with a high magnetic twist. Sigmoids are usually associated with solar flares and solar eruptive phenomenons. Despite their usual high activity, several sigmoids survive from days to weeks. The association of sigmoids to coronal mass ejections (CMEs) made them essential to study from a space weather perspective. Further, despite being an apparent unstable structure, their stability made them very interesting for study to solar physicists. The statistical analysis of sigmoids can provide valuable information about their properties, which can shed light on their formation and stability. It is crucial to identify sigmoids in solar images, in the first point, to do a statistical study of them, or predict solar eruptive phenomenons associated with them. In this work, we apply modern object detection and localization techniques using deep learning, in particular YOLO (you only look once) algorithm with classical object classification techniques. We have used XRT telescope data onboard the HINODE satellite for our study. A total of 1527 daily XRT images, spanning from 2011 to 2014, are used for our work. Among these images, we use 80% for training and 10% for validation and 10% for testing. Our model has achieved 85% precision with a 0.5 confidence score followed by 74% accuracy for the classification of the sigmoid. The model is ready for deployment in real-time use for detecting the sigmoids.

Introduction

IN YOKOH mission for the first time identification of S-shaped features in Solar soft X-ray images were reported [1] Determining precursor of solar Coronal Mass Ejections (CMEs) is of paramount importance in space weather research. Since sigmoids are highly twisted magnetic structure, they are prone to eruptions often producing CMEs. Thus sigmoids are one of the main precursor of CME. So identifying sigmoids is important and modern deep neural techniques can be very useful for it.

Data Collection and pre-processing

In this work, we have used the data from X-Ray telescope. As we require massive amount of data for training the deep learning model. To avoid the manual data collecting method, we developed the web scraping code for downloading the data on huge scale. We have used beautiful soup library in python for scarping the data from the official site of the X-Ray telescope (Add info about beautiful soup and site). Here we have considered the data from first of January 2011 to 31st of December of 2014. The data available on this web site is in 512 and 1024 dimensions with three filters : Al-mesh, Ti-poly, thin-Be. We have scraped the data with 1024 dimensions with Ti-poly filter. From the downloaded images, we have considered only the images in which, sun is aligned in the dead centre of the image. Images with missing data or corrupted data are eliminated using manual visual observation to streamline the dataset.

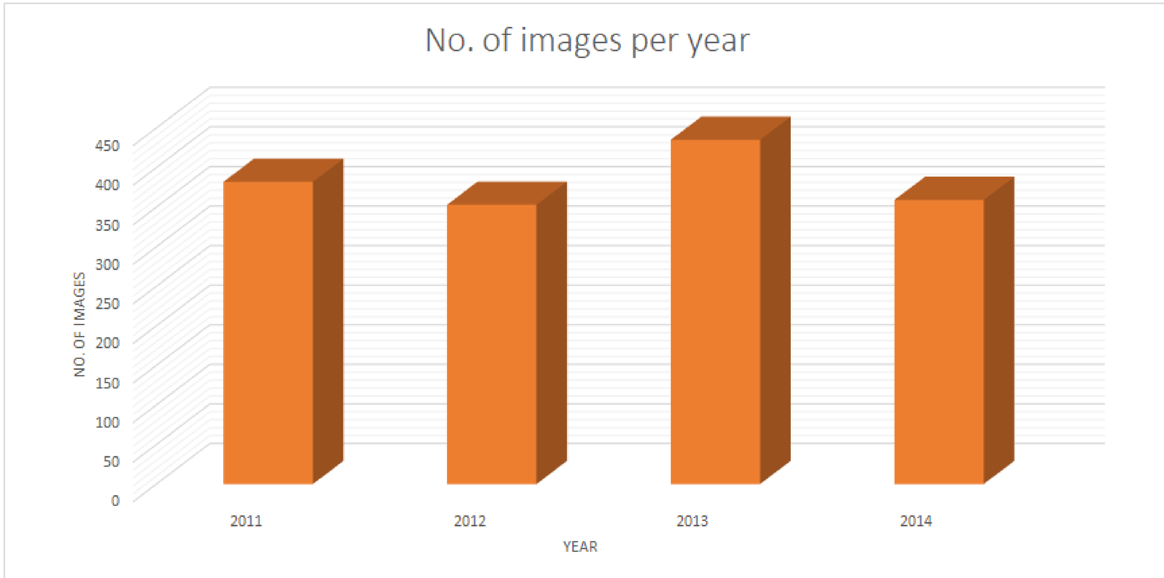

Figure 1: Distribution of number of images used for this study.

Methodoogy

With a research published in 2015 by Joseph Redmon et al. [2], YOLO entered the computer vision landscape. "You Only Look Once: Unified, Real-Time Object Detection" drew a lot of interest from other computer vision experts right away. The YOLO algorithm was improved to five versions over the following five years (including the original), with many of the inventive ideas. Joseph Redmon, the creator of the YOLO algorithm, studied and produced the first three iterations. After the release of YOLOv3, he declared that he will stop working in the computer vision sector. Alexey Bochkovskiy, the Russian developer who constructed the previous three versions of YOLO based on Joseph Redmon's Darknet architecture, launched the YOLO update version 4, YOLOv4, on the official YOLO Github account in early 2020. A month after the release of YOLOv4, Glenn Jocher and his Ultralytics LLC research group, which developed the YOLO algorithms using the Pytorch framework, released YOLOv5 with a few changes and enhancements. The YOLO algorithm divides the images involved in detection into SS grids, among which each grid has different detection tasks. The whole network structure is composed of two full connection layers and 24 convolution layers. After the full connection layer, the tensor of S S (B 5 + C) is output, in which B represents the number of predicted targets in each grid, and C denotes the number of categories. The final detection result can be obtained by regressing the detection box position and judging the category probability of the tensor data. The YOLO algorithm can achieve rapid detection of targets, but it cannot achieve the detection of small targets or its detection effect is not good. The specific reason is that without detailed grid division, there tends to be several targets in the same grid. Therefore, the YOLO-v5 algorithm is adopted to make up for this shortcoming. The YOLO-v5 algorithm transmits each batch of training data through the data loader, and meanwhile enhances the training data. The data loader can perform three kinds of data enhancements, i.e., scaling, color space adjustment, and mosaic enhancement. Moreover, the anchor mechanism of Faster R-CNN is utilized to strengthen the ability of the YOLO-v5 algorithm to small target detection in the image through a multi-scale mechanism in the process of image detection. In addition, it provides the YOLO-v5 algorithm with high adaptability to different sizes of images. To obtain the distribution characteristics of each target in remote sensing images more accurately, a YOLO-v5 + R-FCN fast small target detection system is designed based on YOLOv5 algorithm combined with FCN. This system can realize the rapid detection and recognition of small targets in remote sensing images with high accuracy.

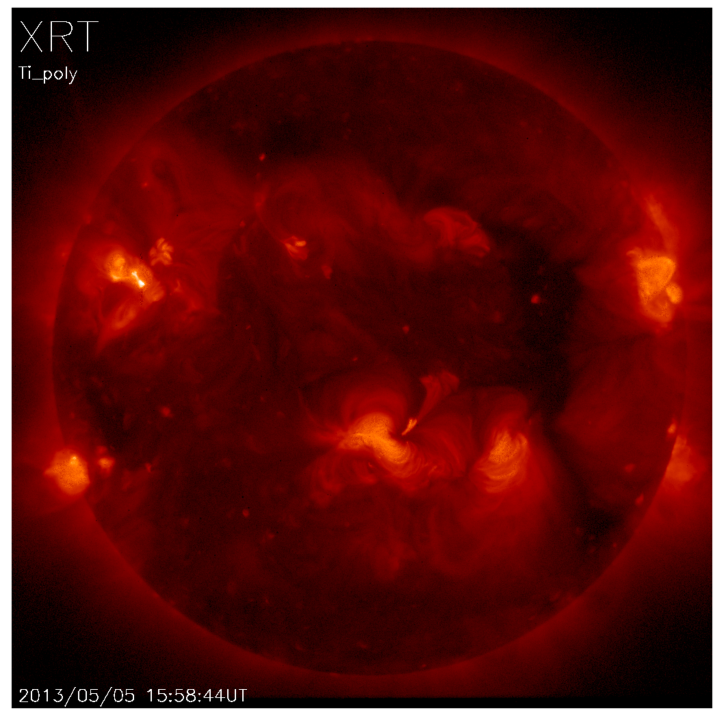

Figure 2: A sample XRT/Hinode X-ray Ti Poly image of the solar corona.

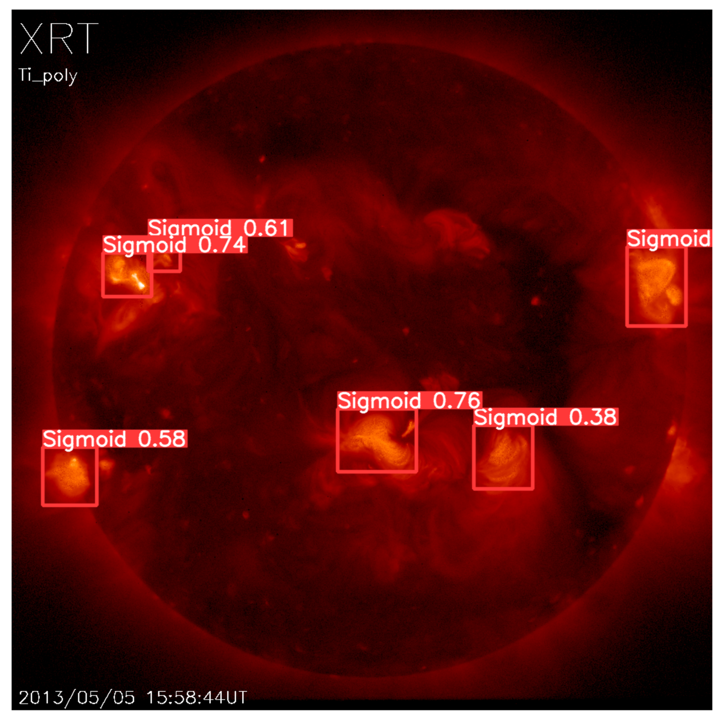

Figure 3: A sample XRT/Hinode X-ray Ti Poly image of the solar corona, labelled with detected sigmoids (using our model) in it.

Results and Discussions

In this work, we build a neural network model to detect sigmoids from X-Ray Telescope (XRT) on-board Hinode [3]. In particular we use you only look once (YOLO) algorithm [2]. Here we have considered the data from 1st January 2011 to 31st of December 2014 (see the histogram in 3).The data available on this web site is in 512 and 1024 dimensions with three filters : Al-mesh, Ti-poly, thin-Be. We have scraped the data with 1024 dimensions with Ti-poly filter. From the downloaded images, we have considered only the images in which, sun is aligned in the dead centre of the image. Images with missing data or corrupted data are eliminated using manual visual observation to streamline the dataset. A total of 1527 daily XRT images, spanning from 2011 to 2014, are used for our work. Among these images, we use 80% for training and 10% for validation and 10% for testing. Our model has achieved 85% precision with a 0.5 confidence score followed by 74% accuracy for the classification of the sigmoid. The model is ready for deployment in real-time use for detecting the sigmoids.

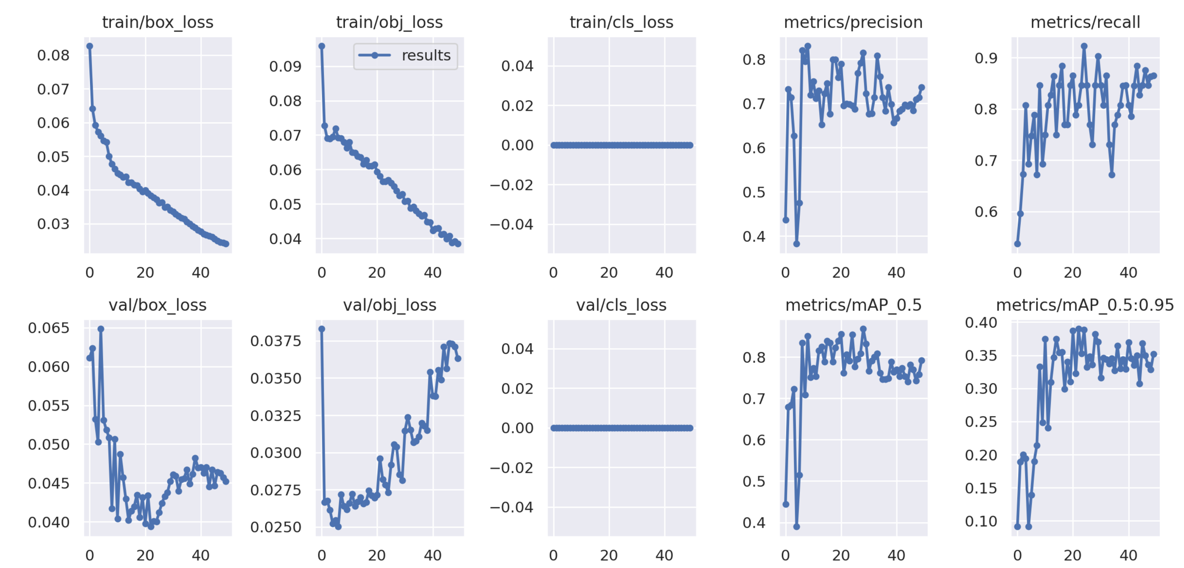

Figure 4: Loss and precision curves for training, validation and testing of model.

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