Deep learning towards Solar flare prediction

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Abstract

Solar flares are a natural phenomenon of brightening the local region of the Sun, thrusting away a large amount of energy and charged particles all around it. Before releasing, this extra energy is stored inside the magnetic flux loops originating from active solar regions. Any such major event on the line of sight from Earth can be disastrous. Moreover, such events can affect the overall space weather. With the advent of our understanding and observations in solar astronomy, our ability to study the Sun in minute details enables us to build a better model and consistently correlate them. However, existing models can still not portray the correct triggering mechanism and possible intensity of such flares.

Statistical analysis built upon different available observational data from Sun can bring new opportunities to look at this problem differently. Machine learning analysis, especially the deeper ones, has a tremendous capacity to exploit in such a direction. In this present report, we are looking to explore the same. We want to examine different deep neural networks in conjugation with available observational data to find their capability toward Solar flare prediction and further refine the same with theoretical inputs.

1. Introduction

As our nearest star, different aspects of the Sun are very closely observed. Among them, transpiring in a local area over the solar surface, succeeding flare can have significant consequences on Earth, satellites, space station and overall space weather around the solar system. Solar flares are associated with electromagnetic radiation and energetic charged particles, which can potentially endanger modern civilisation through significant solar eruption if that occurs on the line of Earth. Amidst all the historical records on September 1, 1859, the Carrington event [https://doi.org/10.1093/mnras/20.1.13] observed the strongest flare and accompanying CME. More recently, during 2012, another solar eruption is noticed of a similar class. Fortunately, Earth has avoided its trajectory narrowly. In the modern era of technology, such an occurrence would significantly disrupt communication systems, power grids, GPS, compromising the safety of satellites, space stations and astronauts both in space and on Earth. Therefore, it is of paramount importance to develop a predictive model for a solar flare and its impact, which is reliable in real-time.

We have a fair understanding of the solar flare mechanism and corresponding mathematical model. Due to differential rotation and convection, coronal magnetic fluxes form a loop-like structure containing hot plasma that extends over the photosphere, and such magnetic networks are dynamically changing. As a consequence of magnetic reconnection of such fields energises the eruptive phenomena that can be ranging from 10^{28} to 10^{32} erg. Based on their peak electromagnetic flux in the range between $1 - 8$ angstrom soft X-ray, measurement at the X-ray Sensor (XRS) stationed on the Geostationary Operational Environmental Satellite (GOES) classifies each solar flare as A, B, C, M, and X in a logarithmic scale. Each of these flare classes is further divided into subclasses scaled from 1 to 9. While micro-flares of class A and B are pretty abundant throughout the solar cycle, intense flares such as M and X causes occasionally. Outbursts are often followed by coronal mass ejections (CMEs) as an outcome of the common magnetically driven mechanism, where very energetic charged particles and plasma are thrown into the space.

We still lack a complete description of the flaring mechanism of an active region and how it gets triggered. Hence work is in progress to connect such phenomena accurately purely from a theoretical consideration. Over the last few decades, efforts are going on to relate solar flares statistically with the available solar observations, especially the sunspots and corresponding complex magnetic geometry and parameters [https://doi.org/10.1007/BF00712882, https://doi.org/10.1023/A:1020950221179]. In this direction, a significant step is realised with the first instrument to map the vector magnetic field continuously over the entire solar disk by the Helioseismic and Magnetic Imager (HMI) over Solar Dynamics Observatory's (SDO) [https://doi.org/10.1007/s11207-011-9842-2]. Moreover, continuous observations over different wavelengths of electromagnetic data are also available from SDO.

The present advent of deep Machine Learning (ML) as nonlinear classifiers got remarkable success in different domains. ML Algorithms intend to learn the features from the input data automatically. Supervised classifier gets trained by classified data, such as input data with corresponding class. The corresponding model is constructed internally by producing a nonlinear decision boundary among the different categories within the data. Different ML algorithms are recently built to forecast solar flares [https://doi.org/10.1086/377512, https://doi.org/10.1088/1009-9271/7/3/15, https://doi.org/10.1007/s11207-008-9288-3, https://doi.org/10.1088/1674-4527/10/8/008, https://doi.org/10.1007/s11207-011-9896-1, https://doi.org/10.1088/0004-637X/798/2/135, https://doi.org/10.3847/1538-4357/835/2/156, https://doi.org/10.1007/s11207-018-1250-4].

We intend to explore the effectiveness of different machine learning frameworks in the context of solar physics in the presence of available global observation data, including that of ISRO. While the primary objective being solar flare prediction, such capability would bring out the scope of formulating a hybrid framework relating to theoretical models and other phenomena.

2. Objective

Solar flares are generated from sudden explosion above the solar corona, where magnetic reconnection in coronal loops release excess magnetic energy in the form of optical, UV & accelerated plasma from the active region. Such violent events can affect the space weather and different installations on the ground and space. In this context, we aim to analyse the solar data collected through various satellite-based sensors for predictive model development using a deep neural network and test the effectiveness. Primary objectives are pointed as the following.

- Manage extensive solar mission data using AI and Big Data analysis techniques
- Explore Convolutional neural network (CNN) also hybrid framework combined with Recurrent Neural Network (RNN) based techniques to apply on solar flare data
- Find categories and patterns in solar flares
- Classify the data and detect other features indicating at the sub-category

3. Description

As indicated before, this is an area of active research. Fortunately, Physical Research Laboratory already has a dynamic group of solar physicists who have expertise in theoretical modelling and handling different solar data. We wish to develop an artificial intelligence framework based on such inputs. We follow the working principle as described below:

- Scrutinise the capability and limitation of the present theoretical understanding of the standard solar flare model.
- Find out different solar data globally available to us. We can use old archival data sets in the model building and testing phase. However, understanding the underlying structures of such data is crucial in model building.
- It is noteworthy that all types of input feature data may not be sensitive in solar flare prediction. Uncorrelated (or mildly correlated) attributes won’t provide any learning

information to the model but unnecessarily increase its complexity. Hence, prioritising the target features is crucial at the beginning of the project.

- Special attention needs to be given to suitably pre-processing the input data. Filtering is also necessary to reduce the noise in the input data.
- Based on our objectives, different supervised and unsupervised network architecture is planned for implementation. This process includes the selection of topology, input, output nodes and hidden layers. Optimisation of network parameters and initialising values has a significant role in determining the network's training process and performance.

Data Sources: Solar flares are traditionally categorised in soft X-ray data continuously collected through X-ray sensor (XRS) onboard Geostationary Operational Environmental Satellite (GOES) [https://www.goes-r.gov]. However, our present work objective is governed by directly analysing the solar surface's magnetic field information. Helioseismic and Magnetic Imager (HMI) onboard the Solar Dynamics Observatory (SDO) [https://sdo.gsfc.nasa.gov/data] observe the entire solar disk continuously in the Fe I absorption line at 6173Å with a resolution of 1 arc-second. HMI has the additional ability to measure the magnetic fields in all orientations beyond the polarity and 'line of sight' to the observer. This enables us to improve our comprehension of the three-dimensional structure of the evolving field.

Sample datasets from these two sources are used to train our model. Initially, flares information details are extracted from the National Geophysical Data Center (NGDC) as Data Catalogue [https://www.ngdc.noaa.gov/stp/solar/solar-features.html]. All detected solar flairs between the years 1975 to 2017 are available from XRS and also corresponding class mentioned. After selecting the NOAA_ARS active region codes indicating where and when the individual flares were originated, we feed such a catalogue to collect relevant active region magnetic field data from Joint Science Operations Center (JSOC) Science Data Processing Site [http://jsoc.stanford.edu/ajax/lookdata.html]. Line of sight magnetogram solar data is downloaded in FITS file format. To conduct a hands-on experience in data structure and related theoretical concepts, we had a day-long meeting with one of our mentors and students at Udaipur Solar Observatory, PRL.

4. Innovative Aspect

By identifying the active region at solar corona, conventional techniques look at different parameters encapsulating shapes, size, and complexity. However, they proved to have a limited scope in predicting the flare types. The primary obstacle in this problem is correctly identifying the feature space in light of the standard model of solar flares and practical use of different data sets available in solar observations. We believe that powerful machine learning frameworks such as CNN (along with the possible addition of RNN) can explore the internal design for accurate prediction.

Another significant challenge comes from the unequal sample size from different classes. For example, approximate available data size is in the order of 1000:100:10 for C, M, X classes, respectively.

5. Technologies Involved

This project involved exploring datasets from different experiments and manipulating the data structure for suitable input space. This data is further required to filter and pre-process to get any meaningful efficiency.

The second part of the development involves constructing different machine learning neural network algorithms suitable for this purpose. For this study, we explored different supervised and unsupervised network architectures.

Deep learning algorithms are developed in Python using Keras and TensorFlow library. Model building and training are done using workstation consist of 2 x Intel Xeon E5-2697v4, 2.3 GHz, 45 MB L3 cache with 18 cores. Also, during stages of development, such models are tested in the VIKRAM-100 is a High-Performance Computing (HPC) Cluster at Physical Research Laboratory, Ahmedabad.

6. Present Capabilities and Gap Areas

We identify although the electromagnetic radiation image from the Sun in different spectral bands is abundantly available, the origin of a solar flare is hidden in the magnetogram data from the solar disk. Differential rotation and convection on the Sun generate magnetic loops, and magnetic reconnection in coronal loops releases excess magnetic energy that powers solar flare. While magnetic reconnection and triggering mechanism is still unknown, present measurement of a complex magnetic field map can uncover such mechanism if deep machine learning is suitably applied.

7. Feasibility Studies

Lately, there is tremendous development in the field of computer vision supported by convolutional neural networks and their variants. Many real-life problems are solved, from face recognition to self-driving cars. Recently, we successfully established some of the exciting deep neural network strategies in the context of theoretical physics and tested the power of this network [https://doi.org/10.1140/epjc/s10052-020-08629-w]. We have shown that the unprocessed low-level data analysed with CNN can outperform all previous analyses and improve the existing upper bounds on the invisible-branching ratio of the Higgs by a factor of three. Similarly, the present study is also expected to provide a desirable efficiency if suitable training can be provided.

8. Implementation Plan

We went forward with two classes of models.

On the first setup, we consider the temporal evolution of the entire disc magnetogram map of Sun in light of CNN (Convolutional neural network) also combined with RNN (Recurrent Neural Network) looking for a correlation between the active magnetic pixels from the rest.

The second setup tries to correlate the local active region's (or sunspot) magnetic field map responsible for generating some particular flair of type C, M or X. We developed two different models to test the effectiveness of the unsupervised and supervised framework.

9. Milestones Achieved

It is evident from the previous discussion that the CNN/ CNN-RNN analysis consists of the full solar disc magnetogram map. An accurate prediction of the signal region of pixels is possible at the 85% level.

Models with local active region analysis have been tested with the unsupervised and supervised class of models. The unsupervised methodology has the advantage in the agnostic classification of data. However, we found a significantly improved accuracy in supervised analysis. Supervised models based on CNN gave an overall accuracy of 86% in a mixture of C, M and X classes of data. Individual test accuracies are 93%, 60% and 68%, respectively, considering C, M and X classes.

10. Interim Results and Discussions

As discussed before, we worked on two different setup. First setup is looking entire disc magnetogram map of Sun for a correlation between the active magnetic region pixels from the rest and thus effectively isolate the active region with a very high accuracy. Second setup actually testing the variability of local active region to build the capability for the flare prediction. Such predictions are further looked into with a purely unsupervised way and a powerful supervised network. In the following we describe our models in sequence.

A. Model looking for active region pixels :

From NGDC catalogue solar flare test data of the year 2015 is downloaded. Following are the examples for three classes (M, C and B class) of flair data from NGDC in the year 2015. Corresponding numbers indicate the event's unique id, starting, ending, and peak times of such flairs, solar location, flair class and category, energy intensity, and NOAA_ARS active region id respectively.

M-Class:

31777150103 0940 0950 0947 S04E17 M 11 G15 3.1E-03 12253 150104.6

C-Class:

31777150103 1028 1044 1039 S05E16 C 17 G15 1.1E-03 12253 150104.6

B-Class:

1777150102 0950 0955 0953 S05E33 B 93 G15 1.5E-04 12253 150104.8

We collect the corresponding magnetic field data from the Joint Science Operations Center (JSOC) Science Data Processing Site for these three flair class and category. This data format is in Flexible Image Transport System (FITS, since machine/deep learning model developed in Python, takes input data in generic BIL file format, so FITS solar files are converted to generic BIL files. Raw FITS data values are signed data ranged between -7 to +7 bits, which is later converted to unsigned 14 bits so that while processing in machine/deep learning model functions should not create a problem of saturation etc. After FITS files covered to generic BIL format, two subclasses within the solar flare area are built - the negative and positive areas. From both subclasses, training samples are created. Machine/deep learning algorithm is trained based on iterations if the conversion occurs, the error is within the acceptable range, and the training is terminated. Later, to validate the model, an unknown full disc data have been provided as input. We found pixels having membership close to one considered a favourable class for solar flare in the output. The pixels having membership values close to zero are considered background. This process has been demonstrated to all 'B', 'C' and 'M' class data. Once such deep learning model is established, an unknown magnetogram data can be analysed for solar flare producing active spots. This adopted methodology is explained in the attached flowchart. For example, magnetogram data in an M-class generates two outputs in the positive and negative side. They are shown in the attached Figure, also including the input from magnetogram data.

Model parameter optimisation and validation of results were done while evaluating outputs at test data sites. A separate set of unseen samples kept aside to test the machine/deep learning model's performance. The methodology adopted for temporal data has been shown as flow chart in Figure (1).

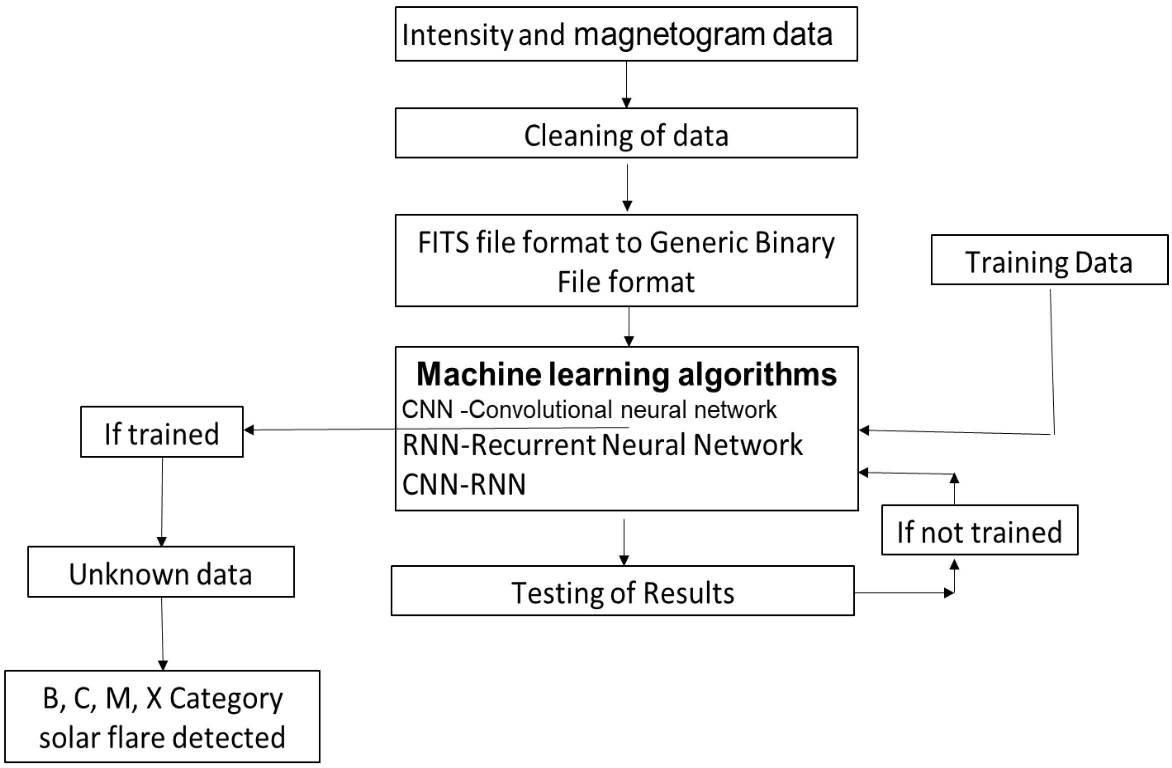
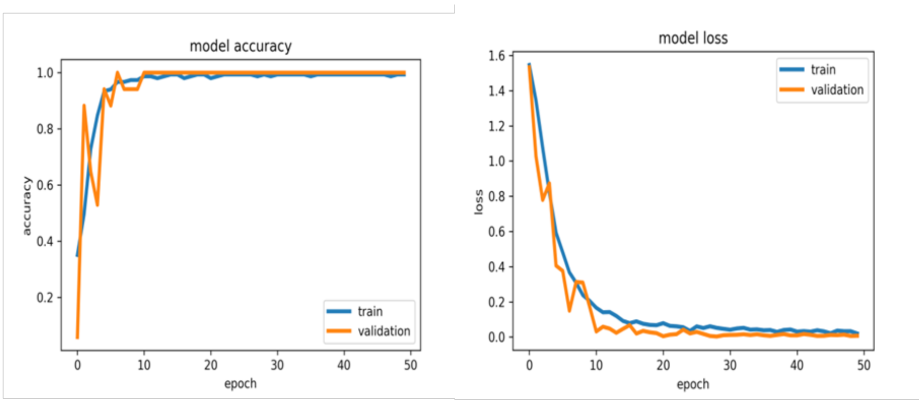


Figure 1: Flowchart: Adopted methodology

Trained CNN model parameters and the model structure are shown in Figure (2). Temporal data outputs generated as an example of 'M' class solar flare extracted with the positive and negative side together with the original 'M' class input have been shown in Figure (3). Table (1) shows the evaluation of outputs in the form of mean membership difference between within flare area as well as between flare and background areas.



CNN based model

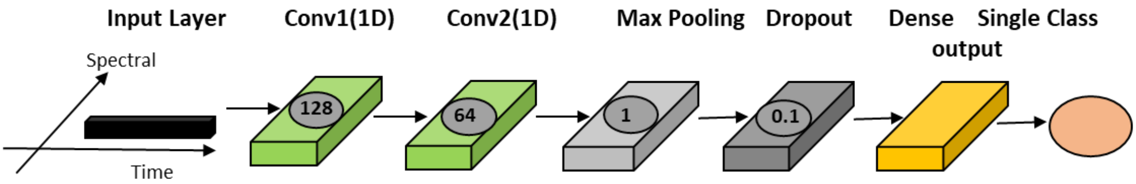
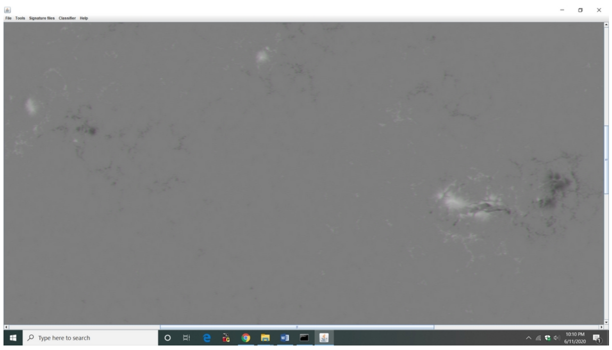
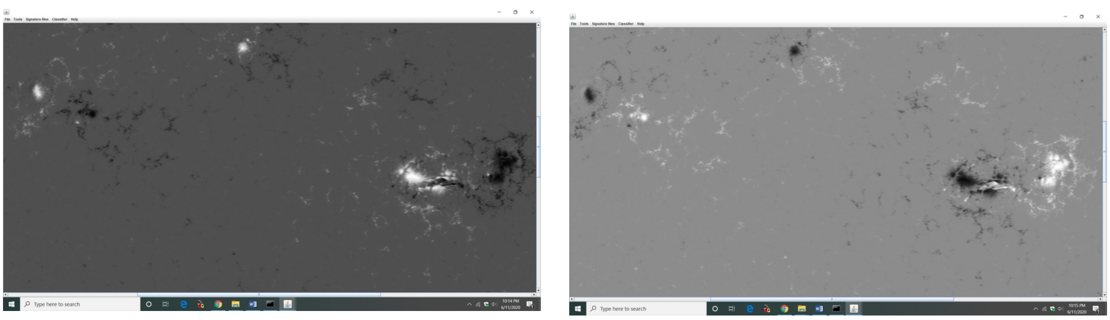


Figure 2: CNN model and trained parameters



(a)



(b,c)

Figure 3: Example 'M' Class (a) magnetogram input data and (b, c) positive side and negative side classified output

Table 1: Mean membership values difference

Within Negative flare side mean membership values difference 8bit (zero to one scale)	Within Positive flare side mean membership values difference 8bit (zero to one scale)	Negative flare and background side mean membership values difference 8bit (zero to one scale)	Positive flare and background side mean membership values difference 8bit (zero to one scale)
254-253=1 (0.003)	252-242=10(0.03)	254-142=112(0.43)	252-80=172(0.67)

B. Model for flare prediction with local active region analysis:

In this section, we describe the different unsupervised and supervised methods constructed for flare prediction based on the variability of local active regions. We first studied the available solar flare data and their type during the period between 2010 and 2017. We further refine our search where the associated active region is clearly identified, and corresponding magnetogram data is available on that spot. We accumulate all local active region magnetogram input data responsible for generating each flare and corresponding flare type. We assumed that the local magnetic regions change negligibly before the actual burst happens. Hence, all instances of magnetogram data available before the flare are considered for our analysis. We used this input data along with class definitions to find the corresponding class in different unsupervised and supervised methods. For both these methods, we use CNNs and provide a brief explanation in the following.

Convolutional Neural Networks are a class of deep learning algorithms inspired by the visual cortex of animals. In particular, the neurons in the visual cortex have a receptive field, which gets activated only in certain areas of the visual field. CNNs use this notion by reducing the connectivity of a node (artificial neuron) to a small subset of the output of its previous layer. The learnable parameters of such type, whose dimensions are lesser than the input dimension, are often referred to as filters. These filters are shared in a CNN architecture for the whole image input. Multiple filters are applied to a single image to learn different features of the data. CNNs also contain a downsampling layer, whose function is to combine the information in a larger image area (the pooling area) to a single neuron. This operation, known as pooling, reduces the size of the image and makes only the relevant information pass through for the next layer to handle. Some popular pooling methods are taking the average, sum, or maximum of the pooling area.

Autoencoders are a class of neural networks used for various unsupervised scenarios like clustering and anomaly detection. It consists of an encoder and a decoder. The first part encodes the data into compressed feature space, while the second part reproduces the original data correctly. The whole network is trained to reduce the reconstruction error of the input data by the decoder. Hence the network learns all the useful features by constructing a latent representation in the lower dimensional output of the encoder. Therefore, an autoencoder trained with a particular data class (say, C type flare) would identify other classes as an anomaly over the base feature by incurring a higher reconstruction error.

Note that input data is the local magnetogram plot in FITS format. A CNN based autoencoder is a powerful method to place a new type that we may not have observed yet. However, since corresponding classes and sub-categories are known to us, it may also be prudent to test a supervised framework of the combined categories. We tested both types and found better accuracy in the later framework. Since we have a highly unbalanced dataset, we used an oversimplified data augmentation procedure. Making multiple copies of the images in M and X classes to have the same number as the C class, we train the supervised CNN and find that it improves the M and X accuracies considerably. In the future, to have even better generalisation power for these two classes, we could use realistic data augmentation techniques with transformed images.

We consider solar flares between 2010 and 2017, where each flair can be identified with a corresponding active region. In such a way, we screened and accumulated more than 5000 magnetogram maps of active regions. In the process, we identified several instances where part of the input magnetogram maps are either incomplete or have null data. We replaced such redundant pixels with a randomly generated background in Gaussian distribution without rejecting such input maps. Since they have a varied pixel size, we transformed them into a uniform array of (128 X 128) pixel maps before converting them as the suitable input array.

Table 2 encapsulate the number of active region input data we accumulated year wise for this analysis. Note that a sizable amount of data remains unusable for the training process, hence discarded during the pre-processing. Although we finally could analyse a set of 5000 entries, one needs to note that the data classes are heavily skewed. Figure 4 describes the working principle of autoencoder to work as an unsupervised network. Corresponding model Parameters followed in the unsupervised CNN autoencoder network is shown in Table 3. Finally, Table 4 lists the construction and parameters followed in the supervised CNN supervised network.

YEAR	C-CLASS	M-CLASS	X-CLASS	TOTAL
2010	55 => 51	12 => 9	0 => 0	67 => 60
2011	1244 => 1028	180 => 145	13 => 10	1437 => 1183
2012	721 => 635	155 => 119	19 => 13	895 => 767
2013	744 => 691	91 => 85	9 => 9	844 => 785
2014	1170 => 1011	227 => 162	30 => 27	1427 => 1206
2015	1062 => 943	125 => 109	1 => 1	1188 => 1053
2016	204 => 193	14 => 13	0 => 0	215 => 206
2017	0 => 0	0 => 0	0 => 0	0 => 0
TOTAL IMAGE	**5200 => 4552**	**804 => 642**	**72 => 60**	**6073 => 5260**

Table 2, Year wise No. of images (initial and usable data) in each class

HYPERPARAMETER	VALUE
Activation function	ReLU
Padding	Same
Learning rate	0.01
Optimisation	Adam
Loss-function	Binary_crossentropy
No. of epoch	50
Batch_size	128
No.of filters(per layer)	128

Table 3: Model Parameters followed in the unsupervised CNN autoencoder network

Layer (Types)	Output Shapes	No. Of Parameters
Input_1 (InputLayer)	[(None, 128, 128, 1)]	0
conv2d (Conv2D)	(None, 128, 128, 32)	320
max_pooling2d(MaxPooling2D)	(None, 64, 64, 32)	0
conv2d_1 (Conv2D)	(None, 64, 64, 32)	9248
max_pooling2d_1 (MaxPooling2)	(None, 32, 32, 32)	0
conv2d_2 (Conv2D)	(None, 32, 32, 32)	9248
max_pooling2d_2 (MaxPooling2)	(None, 16, 16, 32)	0
conv2d_3 (Conv2D)	(None, 16, 16, 32)	9248
max_pooling2d_3 (MaxPooling2)	(None, 8, 8, 32)	0
conv2d_4 (Conv2D)	(None, 8, 8, 32)	9248
max_pooling2d_4 (MaxPooling2)	(None, 4, 4, 32)	0
flatten (Flatten)	(None, 512)	0
dense (Dense)	(None, 128)	65664
dense_1 (Dense)	(None, 64)	8256
dense_2 (Dense)	(None, 32)	2080
dense_3 (Dense)	(None, 3)	99
Total trainable parameters		**113,411**

Table 4: Parameters followed in the supervised CNN supervised network.

11. Technology Readiness Level (TRL)

The current project involves the development of a predictive machine learning network based on existing solar data. Provided benchmark matrix for payload development cannot be applicable for such purpose.

We are happy in learning an active research area in solar physics, and we could connect such problems and corresponding data in our newly acquired techniques of machine learning. We tried to build our models into two main streams with two different objectives. We also established new possible networks providing accuracy at the level of 85% or up.

12. Spin-off Technologies

In our current project, we implement the solar data in a predictive model. We find that the scope can be extended in different broad directions.

Recently, stat-of-the-art data-based numerical simulations of coronal transients like solar flares, coronal mass ejections (CMEs) and plasma jets have started to paint scenarios of magnetic reconnections beyond the standard flare model. Magnetic reconnection is the process which converts the magnetic energy stored in twisted field lines into heat and accelerates charged particles and is envisaged to be the physical cause in activating the transients. Such simulations are routinely carried out at PRL using the 100TF computing facility Vikram-100.

The simulations can also complement the AI-assisted flare prediction by enriching the physics to train the AI. Additionally, the present usage of the line of sight magnetogram employed as an input parameter will be replaced with the vector magnetogram also having transverse components and hence, the complete information of the photospheric magnetic field. Further advancement will be made by using extrapolated coronal magnetic fields as inputs to the AI. Using an extrapolated field is important because it is the corona where the reconnection takes place and not on the photosphere. We believe this combined approach of an extrapolated coronal magnetic field, simulation, and vector magnetogram will enhance the reliability of the AI-assisted flare forecasts by manifold.

The coronal heating problem is one of the challenging problems in astrophysics. Plenty of attention has been given to understand the solar corona. Multiple spacecraft are observing the solar corona in various wavelengths. However, the chromosphere - an interface between the photosphere and the corona was not understood well until recently. Nevertheless, this layer has an important role in heating the solar corona. A special instrument, the Solar Ultraviolet and Imaging Telescope (SUIT), is dedicated to observing the solar chromosphere in the upcoming Aditya-L1 mission. Therefore, we must strengthen our modeling effort of the solar chromosphere, which will eventually help us explain the observations from SUIT.

Solar chromosphere is highly dynamic in nature with multiple shocks, waves and magnetic reconnections. Unlike the corona, the chromosphere does not get a chance to be in local thermal equilibrium. This makes the modelling effort difficult. Simple magnetohydrodynamic simulations can not model the chromosphere properly. One needs to invoke chromospheric chemistry in the simulation to predict the observed spectral lines. However, such an effort is computationally expensive. Only recently simulations of radiative magnetohydrodynamic (MHD) systems have become possible, which can simulate the chromosphere more appropriately.

Without getting into complicated numerical simulations one can approximate the outcome using the neural network. Earlier efforts of chromospheric modelling have started with the 1D hydrodynamic simulations. Such 1D simulations are capable of simulating ionization non-equilibrium of the solar chromosphere. These models can simulate plasma variables and predict spectral lines for a 1D solar chromosphere. These models are computationally less expensive. Such a model can be run with various combinations of initial conditions. The simulated outputs can be used for the training purposes. The trained model then can be used on the output of the MHD simulations to predict the spectral lines.

13. Future Scope of Work

We have limited scope to increase the input data, especially for the higher classes of flair data, so further optimisation can be achievable for the network types and structure. One may look for parallel implementation of additional sub-leading features such as different components of magnetic field strength. Moreover, an important science goal can be to implement real-time and fully automated solar monitoring and forecasting mechanisms. Such a facility can provide us with important feedback onboard future Aditya-L1 type space missions provided suitable coronal magnetogram measurements can be made available.

Among the different spin-off projects, we are in discussion to implement a combined approach of an extrapolated coronal magnetic field, simulation, and vector magnetogram that can significantly enhance the reliability of the AI-assisted flare forecasts. Secondly, AI-based magnetohydrodynamic can provide us with a setup to study the coronal heating problem.

14. Summary and Conclusion

Two different models are developed and tested applying CNN, RNN, and its hybrid setup to detect the solar flare category. They are all based on the inputs directly from the active solar region, especially the magnetic field data. The critical science goal of such prediction is to foresee the possible situations in space weather, protect different installations on the ground and space.

Acknowledgement

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