A

Project Report

on

Deep Learning Based Solar-Flare Forecasting Model

Developed at

Physical Research Laboratory, Ahmedabad.

Developed by

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Guided by

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CANDIDATE'S DECLARATION

I declare that final semester report entitled "**Deep Learning Based Solar-Flare Forecasting Model** "is my own work conducted under the supervision of the external guide **Prof. Partha Konar** from **Physical research laboratory, Ahmedabad, Gujarat, 380009.**

I further declare that to the best of my knowledge the report for B.Tech. final semester does not contain part of the work which has been submitted for the award of B.Tech. Degree either in this or any other university without proper citation. Also I declare that following students also worked in this project :

Pratik b. domadiya- Department of IT,DD University.

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CERTIFICATE

This is to certify that the project entitled "**Deep Learning Based Solar-Flare Forecasting Model**" is a bonafied report of the work carried out by **Mr. Pratik B. Domadiya**, **Student ID No:16ITUES067** of Department of Information Technology, semester VIII, under the guidance and supervision for the award of the degree of Bachelor of Technology at Dharmsinh Desai University, Nadiad. (Gujarat). He was involved in Project training during academic year 2019-2020.

Following student was also involved in this project:

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Ms. Akanksha Bhardwaj , Senior Research Fellow, Theoretical Physics , PRL, Ahmedabad.

With regards,

Pratik b domadiya

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ABSTRACT

Solar flare is happening on the surface of the solar because of magnetic reconnection. There are so many computer science application are already developed to analysis of this event.In the current work, the deep learning method is applied to set up the solar flare forecasting model, in which forecasting patterns can be learned from line-of-sight magnetograms of solar active regions. In order to obtain a large amount of observational data to train the forecasting model and test its performance, a data set is created from line-of-sight magnetograms of active regions observed by SDO/HMI from 2010 April to 2017 October and corresponding soft X-ray solar flares observed by GOES. These samples are categorized into three classes (C, M, and X). Then after we are training, validating, and testing our models .The main results are summarized as follows. We are train our model on c-class flares and validate on c-class flares data image . Then after we are testing the M-class flares as well as X-class flares on trained model. And check how much difference between this three classes.

Key words: methods: data analysis – Sun: activity – Sun: flares – techniques: image processing

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ABBREVIATION

- AR : Active Region
- SDO : Solar Dynamic Observatory
- SOHO : Solar and Heliospheric Observatory
- HMI : Helioseismic and Magnetic Imager
- MDI : Michelson Doppler Imager
- CNN : Convolution Neural Network
- GOES : geostationary operational environmental satellite
- SHARP : Spaceweather HMI Active Region Patch
- NASA : National Aeronautics and Space Administration
- ESA : European Space Agency
- AI : Artificial intelligence
- ML : Machine Learning
- IDL : Interactive Data Language
- MHD : magnetohydrodynamics
- CME : Coronal Mass Ejection
- GPS : Global Positioning System
- SVM : Support Vector Machine
- UFCORIN : A fully automated predictor of solar flares in GOES X-ray flux
- JSOC: Joint Special Operations Command
- NOAA: National Oceanic and Atmospheric Administration
- HARP : HMI Active Region Patch
- SAE : Sparse Auto-Encoder
- ReLU : Rectified Linear Units
- DAE : Denoising Auto-Encoder
- CAE : Contractive Auto-Encoder
- VAE : Variational Auto-Encoder
- PCA : Principal Component Analysis
- MSE : Mean Squared Error

1. INTRODUCTION

1.1 INTRODUCTION OF RESERCH PROBLEM

Solar flare refers to the sudden and large-scale energy release process occurring in a local area of the solar surface. This large sudden explosion from the sun is very dangerous effect for the earth as well. There is no specific time period on which they occurs , it occurs on any time when strong magnetic field is going to developed on the surface of the sun. these solar flares affects very badly to our satellite communication , power grids on earth and GPS system .so our first goal is to prevent all of them to cause damage. NASA has already launched the satellite named SDO to observe the activity on the sun.The Solar Dynamics Observatory's (SDO) Helioseismic and Magnetic Imager (HMI) is the first instrument to continuously map the full-disk photospheric vector magnetic field .Since 2010 May, HMI has mapped the vector magnetic field every 12 minutes 98.44% of the time .Many flare prediction studies involve using photospheric magnetic field data to parameterize active regions (ARs) such that they can be described by a few numbers.So, it is very significant to develop a high-accuracy and real-time predictive model for solar flare.

Therefore , there are so many different techniques are still available to understand the solar flare data. Also , some people were developed, how machine learning based application are useful in analysis of astronomical data. But , in recent year artificial intelligence are become more famous in different era such that defense , automobile, space technology etc. A branch of AI , which called deep learning , is quite become more popular into drive large-scale learning problems in astronomy and other branches of sciences. Deep learning architecture such as CNN(convolution neural network) , Auto-encoder , Hybrid CNN etc. are very useful in image processing , anomaly detection , as well as computer vision and robot automation. These architecture of DNN contains sequence of convolution layers which extract the features from the data and train model itself by using that data.

In this work, we attempt to propose an autoencoder with hybrid CNN model to predict solar flare occurrence with the outputs of four classes (i.e.C, M, and X). we used line-of-sight magnetogram data from GOES(Geostationary Operational Environment Satellite).The 720s line-of-sight magnetograms are constructed using filtergrams from the HMI vector magnetic field series. Filtergrams are obtained with the 4096x4096 vector field camera that has 0.5 arc second pixels. These data are publicly available at the Joint Science Operations Center, and the LOS magnetograms of ARs can be obtained from SHARP (Spaceweather HMI Active Region Patch)(hmi. sharp_cea_720s). The LOS magnetograms as the input data of our models from SHARP, from 2010 May 1 to 2018 September 13, and these data are taken continuously and averaged to a cadence of 12 minutes. A continuous stream of magnetograms provides more information about the photospheric magnetic field topology and thus is expected to lead to better predictive capabilities.

In this work , we systematically use HMI (Helioseismic and Magnetic Imager) magnetograms with a deep learning based model such as autoencoder with CNN to attempt to predict solar flares. This is the first time such a large data set of line-of-sight magnetograms has been used to forecast multiclass solar flares using autoencoder model.

1.2 MOTIVATION FOR THE RESEARCH WORK

We all know that classifying the solar flare based on the limited data is quite difficult for us. There are plenty of organization such as NASA, Europian Space Agency, Spacex etc. are working on finding the actual reason which are required for solar events. They all are applying different methods and approaches to solve that natural myth. Furthermore , different scientists from various countries are also developed the techniques for identifying that events.

Therefore, many methods of solar flare prediction based on statistical and machine learning algorithms have been developed and studied. From there we got motivation to develop our project from different DNN architecture.

Here some them are available…..

- Statistical methods have been applied in many solar flare prediction studies (Song et al. 2009; Mason & Hoeksema 2010; Bloomfield et al. 2012; Barnes et al. 2016).
- classic machine learning algorithms have become an increasingly popular approach for solar flare forecasts, such as the support vector machine (Yuan et al. 2010; Bobra & Couvidat 2015; Nishizuka et al. 2017; Sadykov & Kosovichev 2017).
- the artificial neural network (Qahwaji & Colak 2007; Ahmed et al. 2013; Li & Zhu 2013; Nishizuka et al. 2018).
- The Bayesian network approach (Yu et al. 2010).
- The random forest algorithm (Liu et al. 2017; Florios et al. 2018).
- and the ensemble learning (Colak & Qahwaji 2009; Huang et al. 2010; Guerra et al. 2015).
- All of the above studies have done binary class prediction, and Liu et al. (2017), Bloomfield et al. (2012), and Colak & Qahwaji (2009) have done multiclass prediction.
  They all are used traditional machine learning algorithm such as support vector machine , the Bayesian network approach, the random forest algorithm etc. and also some of them used convolution neural network , artificial neural network . By reading and analyze their work I think that there may be grate use of autoencoder architecture of neural network will be helpful to do this research work. Also we get the some basic idea from pre-existing deep learning model which will be quite useful in our work .

1.3 OBJECTIVE AND SCOPE

Objectives

In our research project “deep learning based solar flare forecasting model “ we implemented Auto-encoder with hybrid convolution neural network to predict the solar flare of class C,M and X. we used the data from Spaceweather HMI Active Region Patch(hmi. sharp_cea_720s) for this work.

The purpose of the research is to discover answer to question through the application of computer science procedures. The main aim of this work is to identify the solar flares which are coming towards the earth and prevent the earth from damage. Though each research study has it’s own specific purpose , we may think of research objectives as falling into a number of following broad groupings:

- To gain the familiarity with the phenomenon of solar flare forecasting methods.
- To accurately identify the solar events which are happening on solar surface as well as predict the solar flare.

Scope:

In future may be some countries are sending satellite to the sun orbit to understand some unknown events which are occurring on surface of the sun. That time if we are already prepared with some techniques , so it is very helpful to speed-up the work in that field.

Apart from that , there are many space agency also looking for an appropriate method or technique which can identify the solar flare within minimum time. Therefore , this work may become quite efficient for them.

1.4 TECHNOLOGY USED

- **Deep learning :** Deep Learning is core part of the machine learning. It contains several layers which called convolution layers , are responsible to extract important features from the data so that model can learn data properly and based on that it will give the best result in particular task.

- **Autoencoder:** Auto-encoder is one of the architecture of deep learning architecture. It's have a basically two part encoder and decoder. This is basically useful in dimensionality reduction , anomaly detection etc.

- **Convolution neural network:** convolution neural network is a part of the deep neural network. Convolution neural network is specifically used for image processing, classification and segmentation.

- **Keras –python machine learning library:** Keras is open-source library used in writing deep learning algorithm effectively . it is written in python.

1.5 HARDWARE AND SOFTWARE REQUIREMENTS

1. Idl 8.7.2: interactive data language
   It is a programming language used for the data large analysis. Popular in particular area of science such as astronomy , atmospheric physics and medical imaging and also used in image processing.

2. Google colab

   Google Colab is a free cloud service and now it supports free GPU! Which can improve your Python programming language coding skills. develop deep learning applications using popular libraries such as Keras, TensorFlow, PyTorch, and OpenCV.

3. Jupyter notebook:

   Project Jupyter is a nonprofit organization created to "develop open-source software, open-standards, and services for interactive computing across dozens of programming languages".

4. Windows 10(8 gb RAM)

5. Gpu : GeForce MX130(nvidia)

2. BACKGROUND THEORY

2.1 WHAT IS SOLAR FLARE?

A solar flare is very interesting phenomenon in the world of astrology science. Solar flares occurs on the surface of the sun because of some high magnetic field produced there. There is vast numbers of electromagnetic reconnection between the charge particles on the surface of the sun , which are responsible to produce high magnetic fields leads to solar flares. Energy released from the solar flares is equal to millions of megaton hydrogen bomb explosions. Two scientist named Richard C. Carrington and Richard Hodgson recorded first flare in 1st September , 1859.

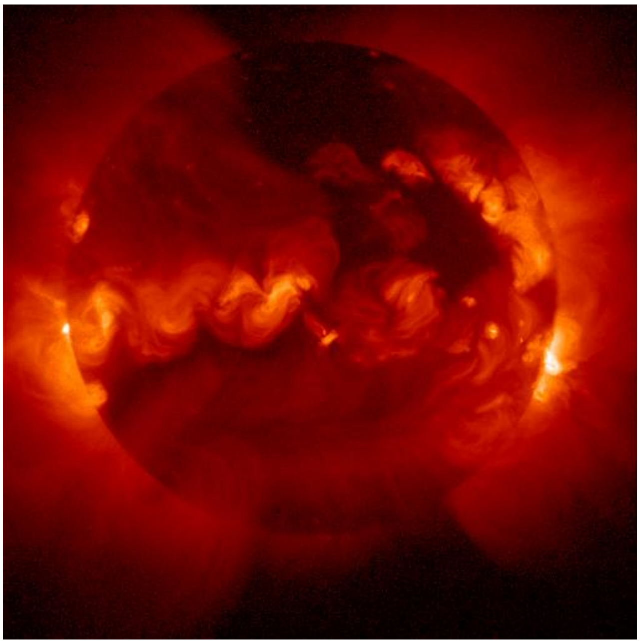


Fig 2.1 Solar Flare Image

When energy released from the solar flares , there is large numbers of particles including proton , electron and heavy nuclei released from the flares. It's about 10^27 ergs to 10^32 ergs per second energy released by the flares.
There are three stages to solar flares.

1. Precursor stage:
   - Released magnetic energy is triggered
   - Soft X-ray emission is detected

2. Impulsive stage:
   - Proton and electron are accelerated to 1MeV energy
   - Radio , x-rays and gamma rays are emitted.

3. Decay stage:
   - Detect decay of soft x-rays

Solar flares have a high temperature. It's about 10 to 20 million degrees Kelvin. From where solar flares are happen , it is a connected area on surface of the solar is called Active Region(AR). Sunspots are located in Active Region. Frequency of the solar flares are coincide with the 11 year solar cycle. When the cycle is min., there are few and small flares were occurs and when the cycle is max. there are more and large solar flares are occur. Last time in year 2010 it became high.

2.2 CAUSE

Solar flares are generally erupt from the Active Region (AR) from the surface of the sun where actually high magnetic fields is presented. Generally, what happened when the solar flares are occurs , charged particles on the surface of the solar such that electron, proton and heavy nuclei are interact with the plasma medium of the sun. so that , sudden burst of the energy is produces, which increase the speed of the particles that creates coronal mass ejection. This interaction transform the magnetic energy to kinetic energy.

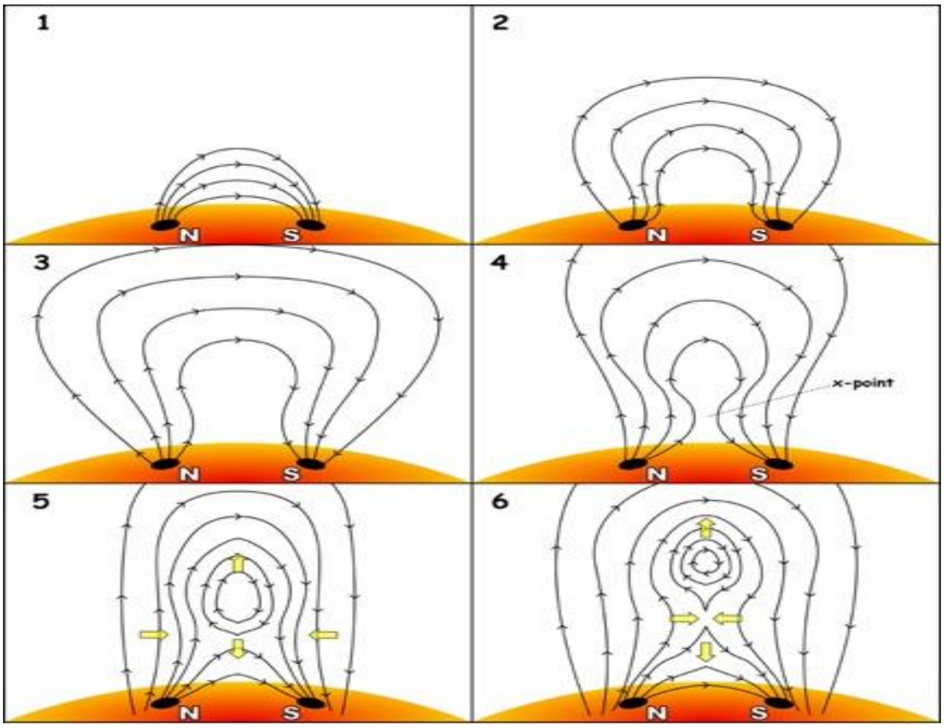


Fig 2.2 Solar Flare Cause Image

As we see in the above image, there is Active region which have two charged parts N (+ve) and S (-ve). Between these two parts magnetic reconnection is happening. As we know that the Sun is more or less hot plasma with internal convective motion that generates a magnetic field via a dynamo process. During the dynamo process, the fast moving charged particles of the plasma medium in the solar atmosphere interact each other which causes a sudden burst of energy which increase the speed of particles that creates coronal mass discharge. So that, it creates the series of closely occurring loops following magnetic lines of force . these lines of force quickly reconnect into lower arcade of loops. So that , it leaves the helix of the magnetic field unconnected to the rest of the arcade. The sudden energy released from the reconnection is the origins the particle acceleration. This unconnected magnetic helical fields leads to the solar flares.

2.3 CLASSIFICATION OF SOLAR FLARES

Solar flares are released from the surface of the sun because of magnetic reconnection between the charged particles.

Scientist classify the solar flares into five categories A,B,C,M and X. Among them they classify strong solar flares into C,M and X. A and B is very weak and negligible effect.

There is tenfold increase in the power from the one class to the next class. X class is 10 times much stronger than M class , and 100 times stronger than C class.

There is also fine gradation within each class from 1 to 9 in the case of the C , M and X class.

1. A: <10-7 [(in watts per square metre, W/m2) of 1 to 8 Angstroms X-rays near Earth] It is lowest intensity solar flare.
2. B: ≥10-7 <10-6 [(in watts per square metre, W/m2) of 1 to 8 Angstroms X-rays near Earth] It is lowest intensity solar flare.
3. C: ≥10-6 <10-5 [(in watts per square metre, W/m2) of 1 to 8 Angstroms X-rays near Earth] It is minor solar flare and have no effect on the Earth because coronal mass ejections are slow, weak and rare.
4. M: ≥10-5 <10-4 [(in watts per square metre, W/m2) of 1 to 8 Angstroms X-rays near Earth] It is medium large solar flare which causes solar radiation storms that can be experience aurora on the middle latitudes.
5. X: ≥10-4 [(in watts per square metre, W/m2) of 1 to 8 Angstroms X-rays near Earth] It is biggest and strongest solar flare that can cause severe (G4) to extreme (G5) geomagnetic storming at Earth.

2.4 DAMAGE CAUSED BY SOLAR FLARES

As we know that , scientist distribute the solar flares into five categories called A,B,C,M and X. In which, A and B have no or negligible effect on the earth. C class have almost no and rare bad effect on the earth.

M-class erupts a brief radio communication blackouts and minor or less radiation storms. Also , it may affect the orbiting astronauts. X class erupts radio blackouts and long lasting radiation storms.

When coronal mass ejection's charge particles interact with the earth's magnetic fields , they generates the geomagnetic storms. It can damage the GPS signals , radio communication and power grids.

In march 1989, coronal mass ejection caused a power blackouts in quebec, Canada. It leaves a millions of people into dark during the cold weather for 8 hours. Also it caused about $2 billion damage.

In 1859, during the carrigton event , the largest solar storm occurs in Honolulu and Cuba. It caused telegraph machine to shoot spark and fires.

Another one solar flares occurs in 1967, almost triggered nuclear war , as U.S military thought that radio communication signal jammed by the soviet union.

2.5 CAN SOLAR FLARES BE SEEN FROM EARTH?

NO.
Solar flares eruption contains the full energy in the form of radio waves , gamma rays and several others , which can't be seen from the earth with naked eyes. There are some equipments are available to see and observe the solar flares from the earth. Without them we can not seen it from the earth.

3. REVIEW OF LITERATURE

3.1 ANALYSIS OF DIFFERENT RESEARCH WORK

1.
Auther: Xin Huang

Year:2018

Title: Deep Learning Based Solar Flare Forecasting Model. I. Results for Line-of-sight
Magnetograms.

Aims: In the current work, the deep learning method is applied to set up the solar flare forecasting model, in which forecasting patterns can be learned from line-of-sight magnetograms of solar active regions.

Method: feed forward neural network

Data and samples: In order to obtain a large amount of observational data to train the forecasting model and test its performance, a data set is created from line-of-sight magnetogarms of active regions observed by SOHO/MDI and SDO/HMI from 1996 April to 2015 October and corresponding soft X-ray solar flares observed by GOES.

Conclusion :

- some stable forecasting patterns can be learned from the MDI data by using the convolutional neural network, and these forecasting patterns can be applied to the HMI data.
- the deep learning based solar flare forecasting model works stationarily for the given forecasting periods (6, 12, 24, or 48 hr)
- model pays attention to the area with the magnetic polarity-inversion line or the strong magnetic field in magnetograms of active regions.

2.

Author: T. Colak and R. Qahwaji

Year:2009

Title: Automated Solar Activity Prediction: A hybrid computer platform using machine learning and solar imaging for automated prediction of solar flares.

Aims: an automated hybrid computer platform for the shortterm prediction of significant solar flares using SOHO/Michelson Doppler Imager images.

Methods: machine learning , neural networks.

Data and samples : SOHO/MDI reported flares and sunspots for the periods from 1 January 1982 till 31 December 2006, which includes 36,736 solar flares (32,151 C class, 4258 M class, and 337 X class) and 186,324 sunspot groups.

Conclusion: the first time, a fully automated hybrid system called ASAP that integrates advanced machine learning and image processing techniques with solar physics to predict automatically whether a sunspot group is going to produce a solar flare and whether the predicted flare is going to be a C, M, or X class flare.

3.

Author: Yanfang Zheng

Year:2019

Title: Solar Flare Prediction with the Hybrid Deep Convolutional Neural Network.

Aims: propose a hybrid Convolutional Neural Network (CNN) model and modify a popular CNN model to predict multiclass solar flare occurrence within 24 hr.

Methods: convolution neural network

Data and samples: These data are publicly available at the Joint Science Operations Center, and the LOS magnetograms of Ars can be obtained from SHARP (hmi. Sharp_cea_720s). The LOS magnetograms as the input data of our models from SHARP, from 2010 May 1 to 2018 September 13, covering the main peak of solar cycle 24 are included, and these data are taken continuously and averaged to a cadence of 12 minutes.

Conclusion:

- this is the first time that the CNN models are used to predict multiclass solar flares, without manually engineered features extracted from the observational data, and our models adopt the very popular CNN method among deep learning methods.
- Experiment results show that our proposed model achieves an unprecedented performance in flare prediction. Therefore, we speculate that there may be some previously undiscovered features that could reveal the flare eruption mechanism, which are automatically extracted by the convolution filters of our model.

4.

Author: M. G. Bobra and S. Couvidat

Year: 2015

Title: solar flare prediction using sdo/hmi vector magnetic field data with a machine-learning algorithm.

Aims: forecast M- and X-class solar flares using a machine-learning algorithm.

Methods: machine learning , support vector machine.

Data and samples: To build this data set, we only consider flares with a Geostationary Operational Environmental Satellite (GOES) X-ray flux peak magnitude above the M1.0 level, i.e., only major flares. We reject C-class flares because a significant number of C-class flares in the GOES data are not associated with NOAA AR numbers, which makes it difficult to pinpoint their location. It is not clear what the impact of including or rejecting C-class flares from the catalog is on the performance of the forecasting algorithm. We build a catalog of flaring and non-flaring active regions sampled from a database of 2071 active regions, comprised of 1.5 million active region patches of vector magnetic field data, and characterize each active region by 25 parameters.

Conclusion: they surmise that this is partly due to fine-tuning the SVM for this purpose and also to an advantageous set of features that can only be calculated from vector magnetic field data. They also apply a feature selection algorithm to determine which of their 25 features are useful for discriminating between flaring and non-flaring active regions and conclude that only a handful are needed for good predictive abilities.

5.

Author: Takayuki Muranushi

Year: 2015

Title: UFCORIN- A fully automated predictor of solar flares in GOES X-ray flux

Aims: they have developed UFCORIN, a platform for studying and automating space weather prediction.

Method: machine learning , regression , image processing

Data and samples : Using this system they have tested 6160 different combinations of Solar Dynamic Observatory/ Helioseismic and Magnetic Imager data as input data, and simulated the prediction of GOES X-ray flux for 2 years (2011–2012) with 1 h cadence.

Conclusion: they have found that direct comparison of the true skill statistic (TSS) from small cross-validation sets is ill posed and used the standard scores (z) of the TSS to compare the performance of the various prediction strategies. UFCORIN's robustness against time noise may provide a solution for missing data. Yet another important use of UFCORIN is to search for the ways to shrink the input data, without worsening the TSS. It is easy to configure UFCORIN to predict quantities other than solar X-ray flux, such as mass and speed of coronal mass ejections, total flux and power indices of the solar energetic particles, or even the Dst index. UFCORIN has wide application in the space weather.

4. ANALYSIS AND FINDINGS

4.1 DATA

In order to collect the consistent and appropriate data for our project work , we employ the observational data from SDO/HMI.

SDO/HMI DATA:

SDO stands for "solar dynamic obsevatory" and HMI stands for "helioseismic magnetic images". When solar flares occurs there is some parts on the solar surface which is active during this period , but not whole surface of the sun have this effect. So the area which have this effect called Active Region(AR).

SDO is the first satellite under the Living with a Star program at NASA. However, since satellites go through a lot of testing and re-testing, they often keep working long past their initial mission life. It was launched in 2010 , to take a closer look at the Sun, the source of all Space Weather. All the data of SDO mission are publicly available on "Joint Science Operations Center (JSOC)" and it's website http://jsoc.stanford.edu/. In our project we used only HMI – line –of –sight magnetogram of active region which can be obtained from the HMI Active Region Patch (hmi.sharp_cea_720s). It contains only 8 year data from launch time May 10 , 2010 to December 01 , 2017 . Also , SDO generate the data from the interval of 12 minutes. Every 12 minutes , it generate the single set of the data.

To train a flare forecasting algorithm, we need only a catalog of flaring Ars, examples. To build this data set, we only consider flares with a Geostationary Operational Environmental Satellite (GOES) X-ray flux peak magnitude above the C1.0 level, i.e., only major flares. We reject A-class flares and B-class flares because a significant number of A-class flares as well as B-class flares in the GOES data are not associated with NOAA AR numbers, which makes it difficult to pinpoint their location. Furthermore, A-class flares and B-class flares caused minor or no bad effect on earth. That's why we are not considering A-class flares as well as B-class flares in our research work. It is not clear what the impact of including or rejecting A-class flares and B-class flares from the catalog is on the performance of the forecasting algorithm.

For flaring Ars, the sample time is defined to prior to the GOES X-ray flux peak time by construction. For flare-quiet times, the sample time is chosen randomly. Our catalog includes the 5254 examples mentioned (4552 C-class flares ,642 M-class flares and 60 X-class ones). The number of flaring Ars is relatively small, especially compared to other studies based on data from the Solar and Heliospheric Observatory's Michelson Doppler Imager.

4.1.1 Data Collection

- first of all go to the NOVA(national oceanic and atmospheric administration) website https://www.ngdc.noaa.gov/

- then go to the "data by discipline " column -> select the tab which name "space weather and solar events"

- And under the "solar data services"

  ➔ Select the "solar features "
  ➔ Then select the " X-ray"
  ➔ Then select "goes/" and then "xrs/"

- Then you find year wise data of solar flares which you want (here , basically we will select data from year 2010 to 2017 . Because
  In 2010 , NOAA satellite was just launched and there were an error in measuring the flare, but up to 2012 , it was corrected and fully worked.)
  Download all the files from year 2010 to 2017 data.

- now understand the contents of the text file which is previously downloaded.

  [31777120127 1737 1856 1837 N27W71 X 17 G15 3.2E-01 11402 120122.2]
  [no start end max location class - - NOAA_ARS -]

  No – 31777120127 -> **year-2012** **month-01(jan)** **date-27**
  start – 1737 -> 17:37:00 (time)
  location – N27W71 – north 27 west 71degree
  NOAA_ARS – 11402 – unique number associated with the AR.

  Use NOAA to HARP list : NOAA_ARS → HARP
  [The HARP number will be required to download files from the HMI SHARP CEA series]

  11402 => 1321

  http://jsoc.stanford.edu/ajax/lookdata.html
  select [hmi.sharp_cea_720s]
  format : hmi.sharp_cea_720s[11402][date and times; same as HMI 45s cadence files]

  # date and time taken from xrs data [31777120127 1737 1856 1837] => 27 Jan 2012 18:37
  This is considering peak time given for corresponding solar flair.

Final format generated from above information for data for the given date and time : hmi.sharp_cea_720s [1321][2012.01.27_18:37:00_TAI]

Then click on "export data" button -> then click on "export " -> and you will be redirected to "jsoc data export form " -> click on "check params for export" -> then click on " submit export request " -> then click on "submit status request"

Following files – url will be display ..

File	Record	Filename
1	hmi.sharp_cea_720s[1321][2012.01.27_18:36:00_TAI]	hmi.sharp_cea_720s.1321.20120127_183600_TAI.magnetogram.fits
2	hmi.sharp_cea_720s[1321][2012.01.27_18:36:00_TAI]	hmi.sharp_cea_720s.1321.20120127_183600_TAI.bitmap.fits
3	hmi.sharp_cea_720s[1321][2012.01.27_18:36:00_TAI]	hmi.sharp_cea_720s.1321.20120127_183600_TAI.Dopplergram.fits
4	hmi.sharp_cea_720s[1321][2012.01.27_18:36:00_TAI]	hmi.sharp_cea_720s.1321.20120127_183600_TAI.continuum.fits
5	hmi.sharp_cea_720s[1321][2012.01.27_18:36:00_TAI]	hmi.sharp_cea_720s.1321.20120127_183600_TAI.Bp.fits
6	hmi.sharp_cea_720s[1321][2012.01.27_18:36:00_TAI]	hmi.sharp_cea_720s.1321.20120127_183600_TAI.Bt.fits
7	hmi.sharp_cea_720s[1321][2012.01.27_18:36:00_TAI]	hmi.sharp_cea_720s.1321.20120127_183600_TAI.Br.fits
8	hmi.sharp_cea_720s[1321][2012.01.27_18:36:00_TAI]	hmi.sharp_cea_720s.1321.20120127_183600_TAI.Bp_err.fits
9	hmi.sharp_cea_720s[1321][2012.01.27_18:36:00_TAI]	hmi.sharp_cea_720s.1321.20120127_183600_TAI.Bt_err.fits
10	hmi.sharp_cea_720s[1321][2012.01.27_18:36:00_TAI]	hmi.sharp_cea_720s.1321.20120127_183600_TAI.Br_err.fits
11	hmi.sharp_cea_720s[1321][2012.01.27_18:36:00_TAI]	hmi.sharp_cea_720s.1321.20120127_183600_TAI.conf_disambig.fits

Fig 4.1.1 All Data Records Including Magnetogram Data

Click on file 1 - .magnetograms.fits file -> file will be download.

- now , it is very tedious task to manually download all the data from year 2010 to 2017 . it takes a lot of time . Therefore , I created an auto download python code which can automatically generate the format such as (hmi.sharp_cea_720s [1321][2012.01.27_18:37:00_TAI]) and download the data from *http://jsoc.stanford.edu/ajax/lookdata.html* website automatically. it takes less time as compare to manually download the data. Now , within 8 hour we can download all the data from year 2010 to 2017.
- Table 4.1 Total downloaded data(before removing unnecessary data)

	No. of images			
YEAR	C-CLASS	M-CLASS	X-CLASS	TOTAL
2010	55	12	0	67
2011	1244	180	13	1437
2012	721	155	19	895
2013	744	91	9	844
2014	1170	227	30	1427
2015	1062	125	1	1188
2016	204	14	0	215
2017	0	0	0	0
TOTAL IMAGE	5200	804	72	6073

- **Size of the images in dataset:** here we are used only active region of the solar flare event. So all the images have a different size , because every active region have a different size. All the images in dataset are between following range.
  Min . image size : 245 X 690
  Max. image size : 490 X 1120

4.1.2 Data Analysis

- Data visualization – open the .fits file in python
- Sample data looks like.

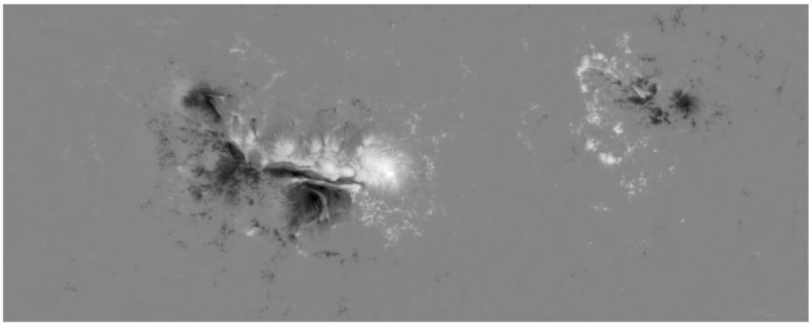


Fig 4.2 Sample Data Image (C-Class Image.(378X870)

4.1.3 Data Extraction

- We downloaded enough data for our model , but still there are some unnecessary data exist in the downloaded data sets.
- These unusual data can degrade the performance of the deep learning model , so it is very important to extract that data.
- Unnecessary data looks like..

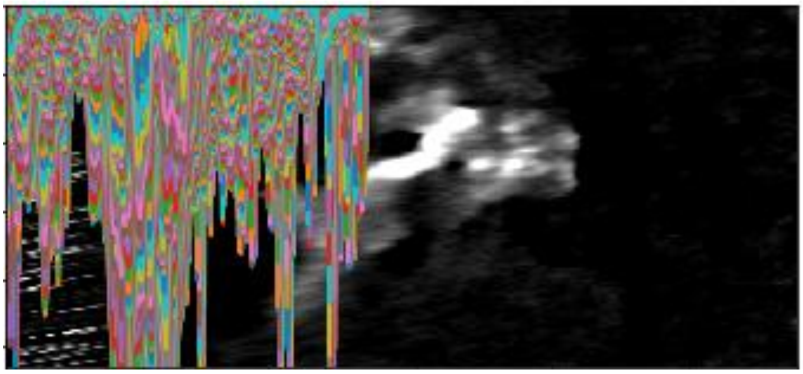


Fig 4.3 Unnecessary/Fake Data Image

4.1.4 Datasets

Table 4.2 Final Dataset (After removing unnecessary data)

Size : 3.36 GB

No. of images (per class)

YEAR	C-CLASS	M-CLASS	X-CLASS	TOTAL
2010	51	09	0	60
2011	1028	145	10	1183
2012	635	119	13	767
2013	691	85	9	785
2014	1011	162	27	1206
2015	943	109	1	1053
2016	193	13	0	206
2017	0	0	0	0
TOTAL IMAGES	4552	642	60	5260

4.2 EXPERIMENT SETUP

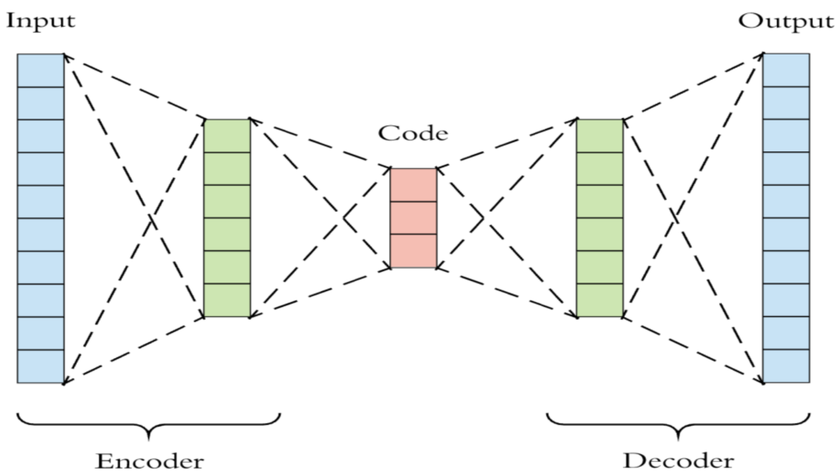
4.2.1 Model Architecture

- Many physical parameters have been proposed to characterize the complexity and nonpotentiality of active regions, and they play a role such as hand-craft parameters in the standard feed-forward neural network .The hand-craft parameters of the standard feed-forward neural network only contain part of the information artificially extracted from magnetograms. Instead of manually extracting the physical parameters, the auto-encoder with convolutional neural network, which is widely used to process image data, can automatically extract flaring patterns from a large number of magnetograms image.

- There are four main types of layers in a convolutional neural network:

  1. Convolutional layer : The convolutional layer performs the convolution between the input image and the filter defined by the convolutional layer. The convolutional layer is used to extract forecasting patterns from input images.
  2. Nonlinear layer : The nonlinear layer provides the nonlinear transform after the convolutional layer. The rectified linear unit (f (x) = max (0, x)) is applied in the layer. The nonlinearity is added into the neural network by this layer.
  3. Pooling layer : The pooling layer works on statistics concerning the mean or maximum value within a sliding region. The pooling layer reduces the dimensionality of parameters in the network and keeps their important information.
  4. UpSampling : UpSampling2D is just a simple scaling up of the image by using nearest neighbour or bilinear upsampling, so nothing smart. Advantage is it's cheap.

- **Auto-encoder**
  Fig 4.4 Autoencoder Architecture



- **Model Architecture**

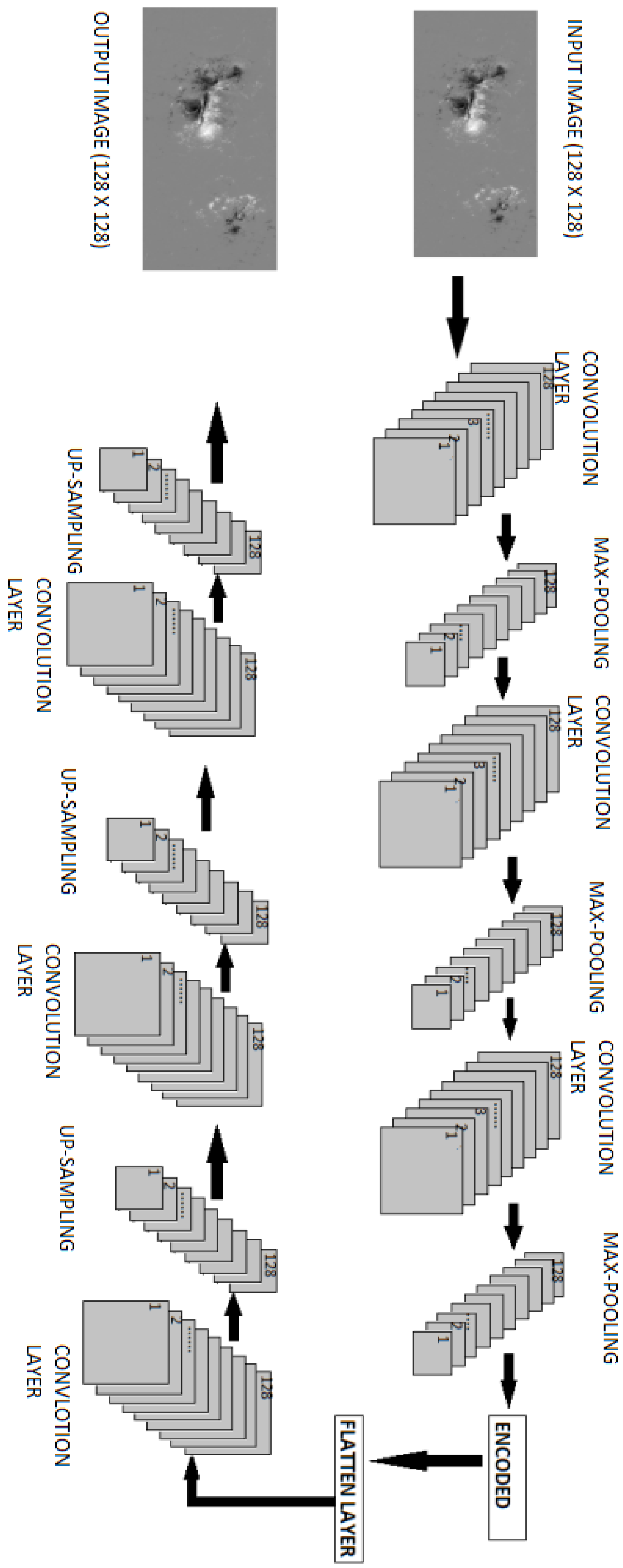


Fig 4.5 Model Architecture

4.2.2 Process Flow Diagram

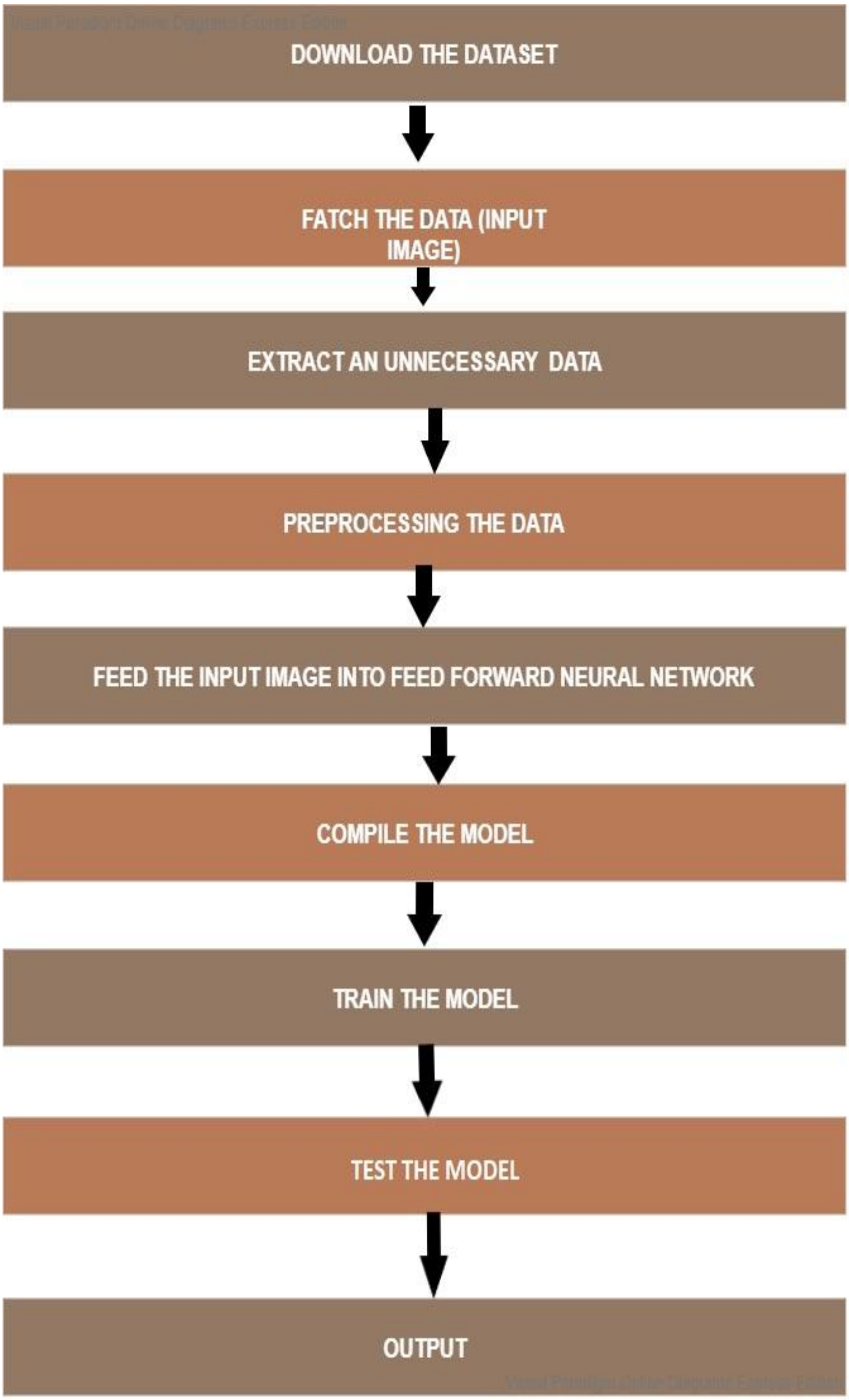


Fig 4.6 Process Flow Diagram

4.2.3 Preparing For The Training Data

We used only c-class flares for the training our auto-encoder model. The c-flare data as per following.

Total data:

c-flare = 4552
m-flare = 642
x-flare = 60
total = 5254

we used c-class as our training the model and for testing we used the c-class , m-class and x-class data . and finding for the difference between input image and generated image.

Total of c-class data : 4552
Data used for training : 4000 (87.87% of total data)
Data used for validation : 452 (9.92% of total data)
Data used for test : 260 (100 C-class , 100 M-class and 60
X-class, 2.19% of total data).

Table 4.3 C-CLASS data distribution for train the model

Size: 2.91 GB

No. of images

YEAR	TRAIN SAMPLES	VALIDATE SAMPLES	TEST SAMPLES
2010	45	5	1
2011	903	102	23
2012	558	63	14
2013	607	69	15
2014	888	101	22
2015	829	93	21
2016	170	19	4
2017	0	0	0
Total Image	4000	452	100

4.2.4 Preprocess The Images

Input image (490 x 890)

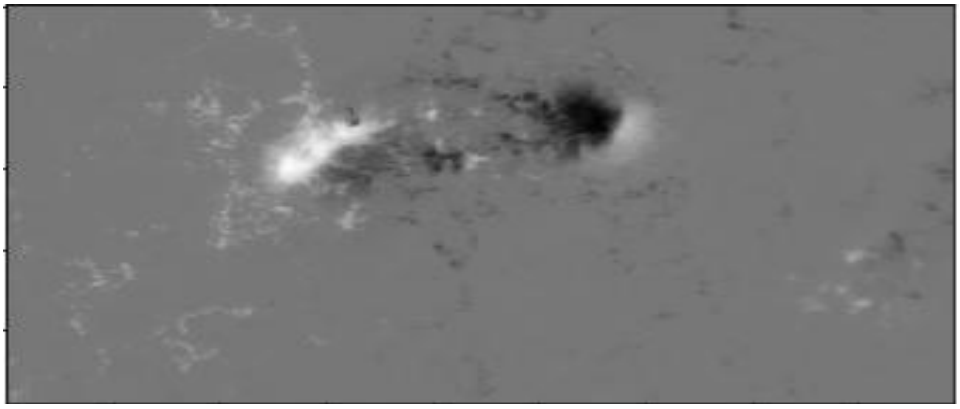
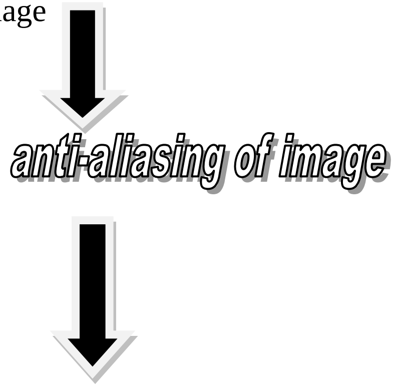


Fig 4.7 Sample Data Image



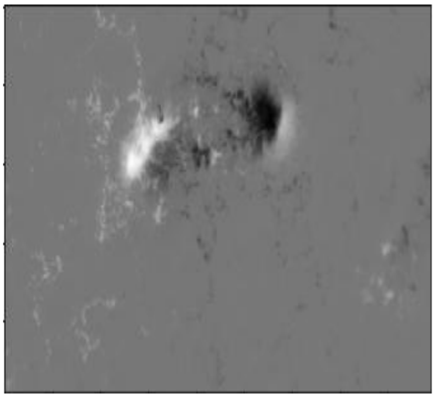


Fig 4.8 Output Image (128 X128)

Antialiasing : Antialiasing is a technique used in digital imaging to reduce the visual defects that occur when high-resolution images are presented in a lower resolution. Aliasing manifests itself as jagged or stair-stepped lines (otherwise known as jaggies) on edges and objects that should otherwise be smooth.Images are represented by discrete pixels, either on the screen or in an image file. When data that makes up the image has a different resolution than its representation on the screen we will see aliasing effects.
At this point we have the data which have a similar size 128X128 and ready to feed into model.

4.2.5 Compile And Train The Model

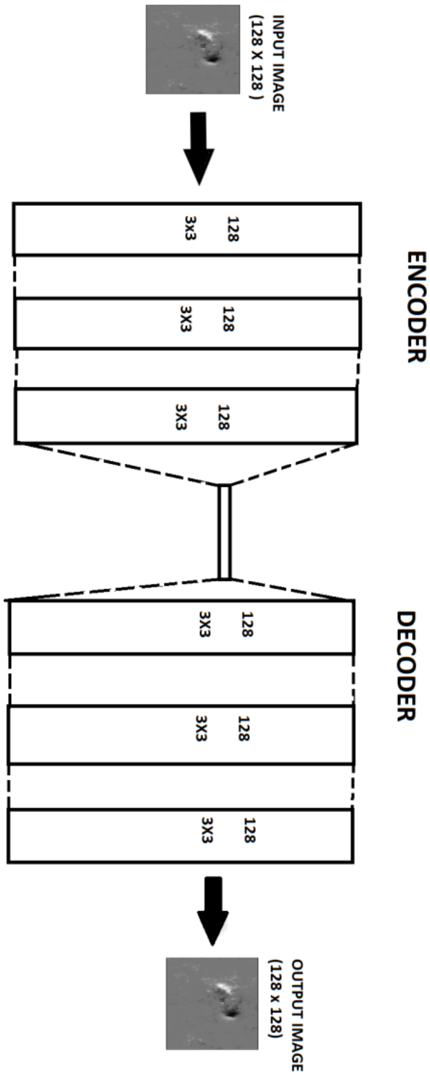


Fig 4.9 Model Architecture

Comprising these basic layers, we set up the neural network for the solar flare forecasting .Parameters of the convolutional neural network can be learned from the data set by using the iterative adam optimization. However, some hyperparameters should be set before the optimization process .Usually, hyperparameters are set by experience. There are two types of hyperparameters: model hyperparameters, which specify the structure of the neural network, and training hyperparameters, which determine how the neural network is trained.

The main model <u>HYPERPARAMETERS</u> include the following:

- **Table 4.4 Hyperparameter:**

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

4.2.6 Test the data

During the testing we test c-class data , m-class data and x-class data and we find the difference between the input image and output image and here we are used mean squared error for find the difference.

The **mean-square error (MSE)** are used to compare image compression quality. The MSE represents the cumulative squared error between the compressed and the original image. The lower the value of MSE, the lower the error.

Table 4.5 Test Dataset Samples:

FLARE NAME	NO. OF IMAGES
C-FLARE	100
M-FLARE	100
X-FLARE	60
TOTAL	**260**

4.2.7 Result

- we used auto-encoder to predict the solar flares of type C, M and X . we also use a deep convolution neural network for our approach, In which each of 6 layers contains 128 filter with the size 3X3 and followed by rectified linear unit (RELu) layer.

- Here we want to find difference between input image and generated image and based on the difference range we can predict the input solar flare image belongs to which class.

- We tested 100 C-class image , 100 M-class image and 60 X-class image. And , we got the following result.

Table 4.6 Result Table (Error Range Of Three Classes)

FLARE TYPE	MIN-VALUE OF ERROR	MAX-VALUE OF ERROR
C-CLASS	9.46e-05	3.9e-04
M-CLASS	1.15e-04	4.8e-04
X-CLASS	1.17e-04	6.01-04

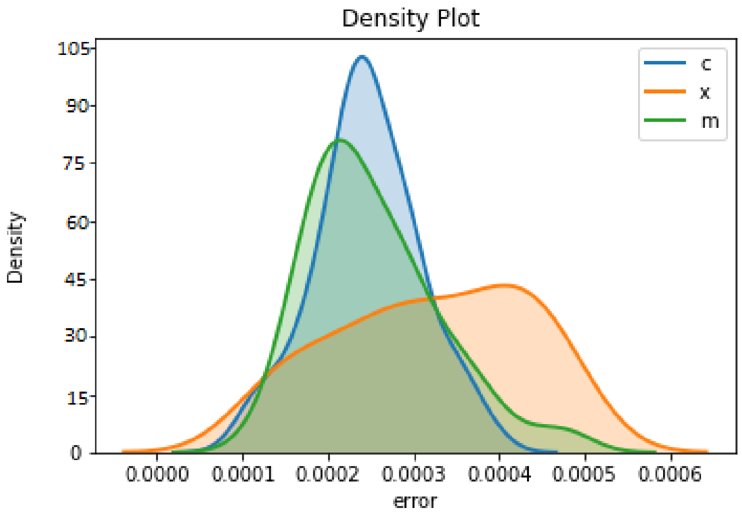


Fig 4.10 Error Density Plot

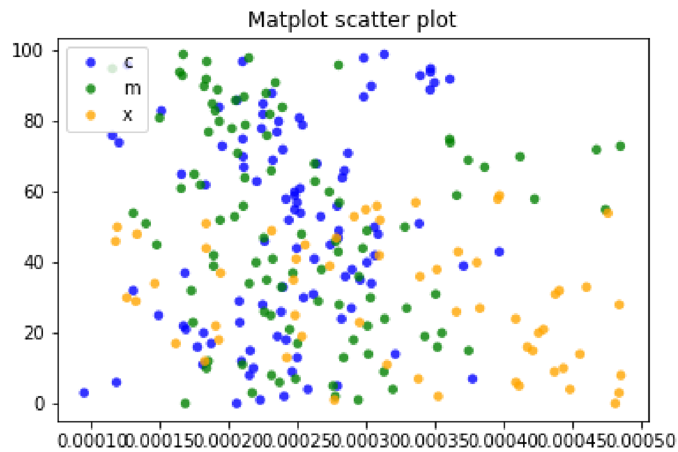


Fig 4.11 Scattered Plot Of The Error Value Of 3 Class

4.2.8 Issues And Difficulties

- Major problem we faced here is all about dataset for the project. The dataset was not exist before . All the data as we want for our work is available on NOAA website, but not in appropriate manner.

- The data is available on https://jsoc.stanford.edu/ and reference for this data (such as nova_ar number, time info , date info, harp_number and so on.) is available on https://www.ngdc.noaa.gov/ , so that we have to match that info and then we can download the data from above website . it takes too muck time for small amount of data. It takes about 5 minutes per one image data to download manually. So that we developed a python code using selenium api which can automatically download data from above website very fast .

- Another , major difficulty was preprocessing the dataset . the dataset we downloaded contains magnetogram.fits files . these files contains two parts 1. Header – contains header info such as time , date , size , and so on. 2. Data part – contains image array of pixels(2D) . we want only data part from there . we want to extract data part from all the data. Moreover , every image have a different size . we need to resize all of them into same size , because we want to feed the data into deep neural network architecture – Auto-encoder , which accept the input in uniform size and dimension .

- So , here we used a python function for resized the data into size we want. First of all we extracted the data part from the .fits files , then converted it into image object , then resize it using Resize() function and finally save to .png format .

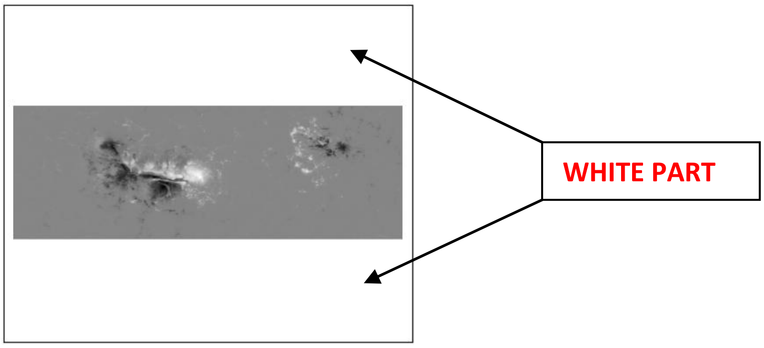


Fig 4.12 C-Flare Image Resized Using Resize() Function(128X128)

- But , here most of the part is white which has a pixel value 255 . when we feed the data as an input in auto-encoder architecture , it may be consider this white part as a most important feature . so that the model will focus on only white region , which is not necessary data. That's why we can not identify solar flare correctly . so that we changed our preprocessing method for an image to "Anti-aliasing ". then we got better result than resize() function.

5. PROPOSED SOLUTION

In our work , what we have done? We made a deep learning model such as autoencoder to test or predict the data. For that we had required the dataset for our model. For which , we download the dataset from the SHARP/ hmi active region solar flare data. We collected total 3 class (C,M and X) out of 5 class (A,B,C,M, and X). here we have not large dataset but enough for our work. Then , we trained our model with only one class of data such as c class data and find the error range for 3 classes.

Here we used only magnetogram image data for forecasting the solar flare. we collected around 5000 magnetogram image of sun from year 2010 to 2017. And we are done forecasting of solar flare by using that data.

But , still we didn't get satisfied result from magnetogram image data. Here basically , what we want to find ? we are finding some relationship of solar event happening on the surface of the solar. We don't know what is happening over there which is responsible for occurring the solar flare. So, finding that relationship of that event may be very helpful for human community. But we used only magnetogram image of solar for our finding . There is no any specific purpose for using only magnetogram data for this project , but this is initiative step for finding the result which we want. But , by using that data we couldn't get enough information about prediction of solar flare .

Each and every set of data contains some other files also except magnetogram image data. here it is.

File	Record	Filename
1	hmi.sharp_cea_720s[1321][2012.01.27_18:36:00_TAI]	hmi.sharp_cea_720s.1321.20120127_183600_TAI.magnetogram.fits
2	hmi.sharp_cea_720s[1321][2012.01.27_18:36:00_TAI]	hmi.sharp_cea_720s.1321.20120127_183600_TAI.bitmap.fits
3	hmi.sharp_cea_720s[1321][2012.01.27_18:36:00_TAI]	hmi.sharp_cea_720s.1321.20120127_183600_TAI.Dopplergram.fits
4	hmi.sharp_cea_720s[1321][2012.01.27_18:36:00_TAI]	hmi.sharp_cea_720s.1321.20120127_183600_TAI.continuum.fits
5	hmi.sharp_cea_720s[1321][2012.01.27_18:36:00_TAI]	hmi.sharp_cea_720s.1321.20120127_183600_TAI.Bp.fits
6	hmi.sharp_cea_720s[1321][2012.01.27_18:36:00_TAI]	hmi.sharp_cea_720s.1321.20120127_183600_TAI.Bt.fits
7	hmi.sharp_cea_720s[1321][2012.01.27_18:36:00_TAI]	hmi.sharp_cea_720s.1321.20120127_183600_TAI.Br.fits
8	hmi.sharp_cea_720s[1321][2012.01.27_18:36:00_TAI]	hmi.sharp_cea_720s.1321.20120127_183600_TAI.Bp_err.fits
9	hmi.sharp_cea_720s[1321][2012.01.27_18:36:00_TAI]	hmi.sharp_cea_720s.1321.20120127_183600_TAI.Bt_err.fits
10	hmi.sharp_cea_720s[1321][2012.01.27_18:36:00_TAI]	hmi.sharp_cea_720s.1321.20120127_183600_TAI.Br_err.fits
11	hmi.sharp_cea_720s[1321][2012.01.27_18:36:00_TAI]	hmi.sharp_cea_720s.1321.20120127_183600_TAI.conf_disambig.fits

Fig 5.1 Other Data Files Including Magnetogram Image

Here also some other data files are available with this data such as disambigues.fits , bp_err.fits ,bt_err.fits , continuum.fits, dopplergram.fits and so on.

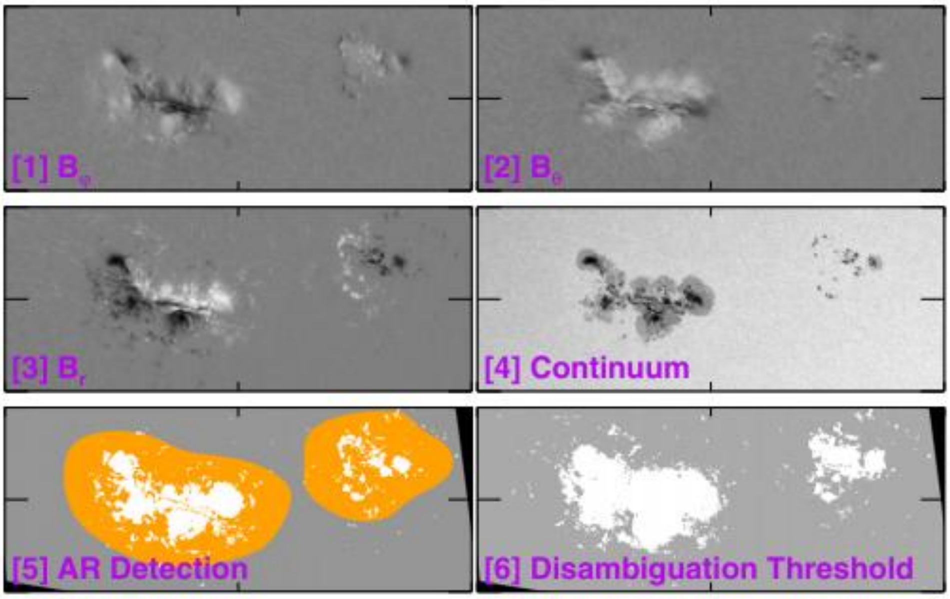


Fig 5.2 First four panels show each of the components of the vector magnetic field data, Bφ, Bθ , and Br, and the continuum intensity data for NOAA active region 11429 on 2012 March 7 at 00:24 TAI.

We don't know these other data have what kind of effect exist for accurate forecasting the solar flares. It may be possible that this data have a significant relationship with the solar flare occurring on surface of the sun.

In future we are analyze the data apart from magnetogram image and find some useful result for predicting the solar flare. We hope that we can find some better result than this.

We will use some other machine learning algorithm such like , support vector machine , k-nearest neighbor , and so on , to test the data other than magnetogram images . Also we will be try other deep learning architecture to identify the correct measurement between three solar flare class. So we can get more accurate result from there.

6. CONCLUSION

We are finding the actual relationship of the solar event which is happening on the solar surface. There are several other work were done to relate with this work. In our project we first prepared for the dataset . for that we downloaded Line-of-sight magnetograms of active regions can be obtained from the tracked active region patch data product on the Joint Science Operations Center (JSOC) database (http:// jsoc.stanford.edu/ajax/lookdata.html). For HMI data, line-of-sight magnetograms of active regions can be obtained from the HMI Active Region Patch (hmi.Mharp_720s). The HMI active region data from 2010 May 01 to 2017 december 01 are included. The cadence of the HMI Active Region Patch is 12 minutes. The magnetogram of an active region shows the magnetic flux distribution on the photosphere in this area.

Then we preprocess the data using some image processing technique such as image anti-aliasing and so on. Preprocessing is must required for the getting well performance of the model . During preprocessing we extract some unnecessary data which is not useful for training the deep-learning model . it may be possible that , these data might degraded the performance of the model which lead to poor forecasting result.

After that we feed the final dataset to the model and try to find error between the input image and output image .so by the end of the training we are testing the test data with trained model. And we got following result:

we find here difference range of error of three class C,M and X class solar flare as per following:

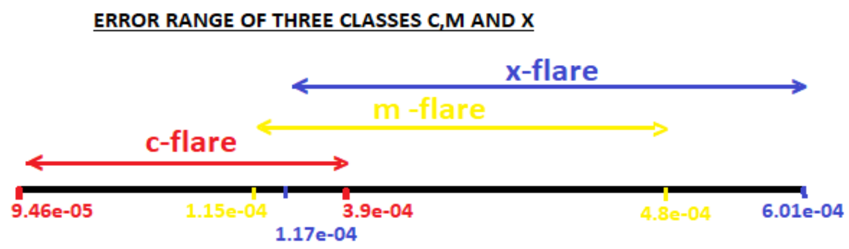


Fig 6.1 Error Range

c-class -> min : 9.46e-05 to max: 3.9e-04
m-class -> min : 1.15e-04to max: 4.8e-04
x-class -> min : 1.17e-04 to max: 6.01e-04

we can say that if any image which we will use for the testing our model have an error value between range defined above and we can forecasting the solar flare class.

But , unfortunately we could not got accurate result as we want. As per above fig. there is an overlapping section we got here . this shows that , if any error value fall within the overlapping part , that time we can not sure that this flare belongs to which class . that overlapped part create confusion in forecasting result.

In the near future, we shall work on several topics to try to improve the forecasting performances: we plan to combine the SVM with other algorithms, like the k-nearest neighbors and we plan to use multi-class classifiers to not only forecast a flare occurrence, but also to attempt to predict whether it will be an C-, M- or X-class flare. The AR parameters are fairly sensitive to which pixels contribute to their calculation. Therefore, we would also like to test different masks to yield the strongest pre-flare signature per AR parameter.

Reason for not getting best result:

Major reason for not getting the best result is , we have limited data only. We used the data from SHARP from 2010 to 2017. But it contains only 5200 correct data images , in which we used 4552 images for the train the model. It was a very small amount of data images to train any deep learning model. Also, the images are very difficult to analyze . All the images are very common to each other , it is very difficult to identify any correct measure which can make difference between them.

The data used here is courtesy of NASA/SDO and the SOHO/HMI science team, as well as the GOES team. SOHO is a project of international cooperation between ESA and NASA. This work is supported by the Physical Research Laboratory , Ahmedabad, Gujarat .

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RESEARCH PUBLICATION

- Solar Flare Prediction with the Hybrid Deep Convolutional Neural Network Yanfang Zheng1 , Xuebao Li1 , and Xinshuo Wang.

- SOLAR FLARE PREDICTION USING SDO/HMI VECTOR MAGNETIC FIELD DATA WITH A MACHINE-LEARNING ALGORITHM M. G. Bobra and S. Couvidat W. W. Hansen Experimental Physics Laboratory, Stanford University, Stanford, CA 94305, USA.

- Automated Solar Activity Prediction: A hybrid computer platform using machine learning and solar imaging for automated prediction of solar flares T. Colak1 and R. Qahwaji1 Received 1 April 2008; revised 22 December 2008; accepted 8 January 2009; published 4 June 2009.

- Deep Learning Based Solar Flare Forecasting Model. I. Results for Line-of-sight Magnetograms Xin Huang1 , Huaning Wang1,2 , Long Xu1 , Jinfu Liu3 , Rong Li4 , and Xinghua Dai1 1 Key Laboratory of Solar Activity, National Astronomical Observatories of Chinese Academy of Sciences Beijing, People's Republic of China; xhuang@bao.ac.cn 2 School of Astronomy and Space Science University of Chinese Academy of Sciences Beijing.

- UFCORIN: A fully automated predictor of solar flares in GOES X-ray flux Takayuki Muranushi1, Takuya Shibayama2, Yuko Hada Muranushi3, Hiroaki Isobe4,5, Shigeru Nemoto5,6, Kenji Komazaki6, and Kazunari Shibata3,5 1Advanced Institute for Computational Science, RIKEN, Kobe, Japan.

- Flare forecasting at the Met Office Space Weather Operations Centre S. A. Murray1 , S. Bingham2, M. Sharpe2, and D. R. Jackson2 1School of Physics, Trinity College Dublin, Dublin, Ireland, 2Met Office, Exeter, UK.

EXPERIENCE

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job title : project trainee (machine learning)

company name : Physical Research Laboratory, Ahmedabad, Gujarat, India.

Duration : jan(2020)- April(2020)

Physical Research Laboratory

Known as the cradle of Space Sciences in India, the Physical Research Laboratory (PRL) was founded in 1947 by Dr. Vikram Sarabhai. As a unit of Department of Space, Government of India, PRL carries out fundamental research in selected areas of Physics, Space & Atmospheric Sciences, Astronomy, Astrophysics & Solar Physics, and Planetary & Geo-Sciences.

First of all I would like to thanks our HOD sir ,DR.Vipul K Dabhi and my external project guide Prof. Partha Konar(Associate professor At PRL), who give me an opportunity to work in real world environment and contribute myself to the government research project named " Deep Learning Based Solar Flare Forecasting Model " at Physical research Laboratory.

I was assigned as a project trainee in PRL. In the beginning , I was felt a quite bit of difficult to understand and learn the totally new concept such as deep learning , but continues dedication and contribution of my external guide Prof. Partha Konar as well as my internal guide Prof. Dr. Vipul K Dabhi , I learn some basics of machine learning concept within a short period of time. After that , I was became more eager to learn a new things everyday , that's why my interest towards the project was continuously increased.

Company's environment is quite good . People of this organization very helpful and friendly. I learn lot of other skill such as good communication , team work , discussion about solving problem and so on. My project guide at PRL, Prof. Partha Konar sir is very hardworking person . he had an everyday meeting with me ,and during that time we discussed proposed solution for the project work . whenever I got confused ,he always ready to help me and provide well advice for the project . that's why I stayed motivated towards my work. And I really enjoyed such a kind of work.

So , within a short period of time I learned a lot of things apart from academic era.

Thanks once again………