**Classification of Solar Flares using AIA imagery.**

By Lalith Konda and Kunal Ajjagottu

COMP-4531-Deep Learning

**Introduction**

Solar flares are intense bursts of radiation and energy emanating from the sun's surface or its outer atmosphere, usually near sunspots or active regions. These flares result from the sudden release of magnetic energy stored in the sun's atmosphere. This energy can be registered in all parts of the electromagnetic spectrum, from X-rays to ultraviolet radiation.

When solar flares occur, it is possible for them to reach the ionosphere as well as magnetosphere of Earth thus influencing satellite communications used worldwide along with locational accuracy by distorting the Global Positioning System (GPS) signal strength leading to possible oscillations causing deviations large enough that one may not be able connect with another far off location based on coordinates available online; these events can also disrupt power grids, affecting individuals’ access to electricity and thus leading to blackouts if left unchecked; among many more incidences most serious one being increased chances of being exposed towards radiations during space travel or even for pilots flying at high altitudes.

To prevent these catastrophes from occurring, it is important to forecast solar flares and classify them into their respective classes based on their x-ray flux magnitude in order to take measures beforehand from serious loss and damage.

Solar flares are classified based on their X-ray brightness in the wavelength range of 1 to 8 Angstroms. The classifications are A, B, C, M, and X, with X being the most intense. Each class has a logarithmic scale, so an X-class flare is ten times more intense than an M-class flare.

Various instruments such as the Solar Dynamics Observatory (SDO) and the Geostationary Operational Environmental Satellites (GOES) are employed in seeing solar flares. These instruments measure the x-ray flux which can be classified into the solar flare classes.

**Atmospheric Image Assembly (AIA)**

High-resolution solar images taken by the Atmospheric Imaging Assembly instrument on the Solar Dynamics Observatory (SDO) are called AIA (Atmospheric Imaging Assembly) images. It was built to observe the sun in numerous wavelengths giving us a chance to observe the sunspots more closely.

AIA images are used to examine the Sun's external atmosphere, or corona, in different wavelengths of ultraviolet (UV) and extreme ultraviolet (EUV) light. They allow scientists to understand solar processes like solar flares, coronal mass ejections (CMEs) and the heating of the solar corona.

The AIA instrument captures images in multiple wavelengths, each corresponding to different temperatures and layers of the solar atmosphere. The primary wavelengths include:

* 131 Ångströms (Fe VIII, Fe XX): High-temperature regions and flares.
* 94 Ångströms (Fe XVIII): Hot flare plasma.
* 171 Ångströms (Fe IX): Quiet corona and upper transition region.
* 193 Ångströms (Fe XII, Fe XXIV): Corona and hot flare plasma.
* 304 Ångströms (He II): Chromosphere and transition region.

“Fe” corresponds to the spectral lines of ionized iron atoms.

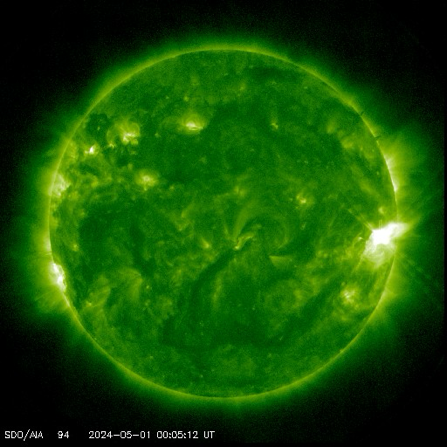
**A red and orange sun

Description automatically generated with medium confidenceA sun with a cloud of smoke

Description automatically generated with medium confidence**

**A sun with bright light

Description automatically generated with medium confidenceA blue planet with bright light

Description automatically generated with medium confidence**

Source: <https://sdo.gsfc.nasa.gov/data/aiahmi/>

AIA data is invaluable for studying the complex and dynamic nature of solar flares. The multi-wavelength, high-resolution images provide detailed information on the temperature, density, and morphology of the solar atmosphere, which is essential for understanding the mechanisms and effects of solar flares.

Machine Learning is increasingly being utilized in space weather prediction due to its ability to handle large datasets and uncover complex patterns. Space weather prediction models can improve the accuracy and lead time of forecasts, helping to mitigate the adverse effects of space weather on satellite operations, communication systems, power grids, and navigation systems.

**Problem Statement**

To develop an advanced deep learning framework using Convolutional Neural Networks (CNNs) combined with Long Short-Term Memory networks (LSTMs) for analyzing multi-wavelength solar image data captured by the Solar Dynamics Observatory (SDO) and synchronizing it with X-ray flux data from the GOES-16 satellite. This framework aims to understand and predict solar activities by leveraging the spatial feature extraction capabilities of CNNs and the temporal sequence modeling capabilities of LSTMs.

**Input and Output Variables used**

|  |  |  |
| --- | --- | --- |
| Variable Type | Variable Name | Description |
| Input | |  | | --- | | Solar Images |  |  | | --- | |  | | |  | | --- | | Multi-wavelength solar images (94 Å, 131 Å, 171 Å, 193 Å, 304 Å) |  |  | | --- | |  | |
| Input | |  | | --- | | Timestamps |  |  | | --- | |  | | |  | | --- | | Timestamps associated with each solar image |  |  | | --- | |  | |
| Input | |  | | --- | | X-ray Flux Data |  |  | | --- | |  | | |  | | --- | | Time-series data of X-ray flux measurements from GOES-16 |  |  | | --- | |  | |
| Output | Predicted Classes | Xray-flux distribution over possible classes of solar activities |

**Data Ingestion and Preparation**

The task of synchronizing 2500 images, with 500 images for each of the five wavelengths, obtained from the Solar Dynamics Observatory (SDO) website between May 1st and May 5th, 2024, posed a unique challenge. Each image was timestamped, aligning with its acquisition time. However, due to variations in the capture times for different wavelengths images, direct timestamp matching was not feasible. To construct a coherent multichannel image dataset, it was essential to synchronize images from different wavelengths based on the nearest timestamps. This process involved meticulous alignment of images captured at similar moments across different wavelengths, ensuring that each wavelength's data formed a distinct channel in the final dataset.

The most formidable challenge in preparing this dataset was accurately assigning solar flare class labels to each multichannel image based on their timestamps. Since no directly available X-ray flux dataset in CSV format was accessible online, we utilized the SunPy library to meticulously extract GOES-16 satellite X-ray flux magnitudes from May 1st to May 6th, 2024. Capturing the X-ray flux at 10-second intervals, we saved this data in a CSV file. Subsequently, we undertook the intricate task of classifying solar flare classes into distinct categories—A, B, C, M, and X—based on the magnitudes of the X-ray flux.

Given that the GOES X-ray data and AIA images originate from disparate sources, another formidable hurdle emerged—synchronizing the timestamps. To surmount this challenge, we aligned the timestamps from the GOES dataset with those from the AIA dataset, ensuring synchronization to the nearest timestamps. This synchronization facilitated the assignment of solar flare classes to each multichannel image, grounded in their corresponding timestamps.

Given that we are working with images captured at five different wavelengths, our primary objective is to analyze both their spatial and temporal characteristics at specific timestamps. Utilizing a multichannel image dataset emerged as the optimal approach, enabling the model to comprehend the spatial intricacies of all five images concurrently. Consequently, we processed this multichannel data through a Convolutional Neural Network (CNN) to conduct image classification, aiming to categorize the images into their respective solar flare classes.

To leverage the sequential nature of LSTM models, we restructured the dataset into 500 images, with each image comprising five sequences corresponding to different wavelengths. This restructuring aimed to enhance our understanding of the temporal dynamics inherent in the data. By processing these images through an LSTM model, we sought to gain deeper insights into the temporal features of the dataset.

**Exploratory Data Analysis**

**A graph showing a number of red and blue lines

Description automatically generated**

Since the AIA images are direct and already classified into wavelengths, there is not much insights to gain from it but from the GOES data, we can plot the magnitude vs time graph and understand the time flow of the flares over these specific days.

From the graph, we can see that there has been only one occurrence of the X-class flare which justifies the recent geomagnetic storms that has caused the sighting of the auroras in the northern hemisphere.

After Labelling the images with the solar flare classes, we got these values below, the number of multichannel images for each solar flare class.

A screenshot of a computer

Description automatically generated

**Model selection:**

Our primary task was to classify solar flares using multi-wavelength images from the Atmospheric Imaging Assembly (AIA) on the Solar Dynamics Observatory (SDO). For this purpose, two models were considered: a Convolutional Neural Network (CNN) and a hybrid CNN-Long Short-Term Memory (CNN-LSTM) model.

CNN Model:

CNNs are highly effective for image classification tasks due to their ability to automatically and adaptively learn spatial hierarchies of features. Given the nature of the data, which includes images from multiple wavelengths, a CNN was an obvious choice to capture the spatial features of solar flares.

CNN-LSTM Model:

The CNN-LSTM model was chosen to capture both spatial and temporal features. While CNNs are proficient in extracting spatial features from images, LSTMs are adept at handling sequential data. By combining these two, the aim was to leverage the spatial feature extraction of CNNs and the temporal sequence learning of LSTMs, given that the dataset involved time-sequenced multi-wavelength images.

**Model comparison:**

The two models were compared based on their performance on the classification task:

CNN:

* The CNN model was expected to perform well due to its efficiency in extracting spatial features from the image data.
* Simplicity and lower complexity compared to the CNN-LSTM model.
* Suitable for image classification tasks, making it a robust baseline.

A graph of a line and a line

Description automatically generated with medium confidence

CNN-LSTM:

* Introduced additional complexity by incorporating LSTM layers to capture temporal dependencies between sequences of images.
* The added complexity might not necessarily translate to better performance if the temporal dependencies in the data are not strong.
* Potential for overfitting due to the higher complexity of the model.

A comparison of a graph

Description automatically generated with medium confidence

**Model Evaluation:**

Both models were evaluated using standard metrics such as accuracy, precision, recall, and F1-score. The evaluation was conducted on a test set that was held out from the training process.

CNN Evaluation:

Accuracy: The CNN model achieved an accuracy of approximately 85%.

Precision: The precision for the X-class solar flares was around 88%, while other classes showed lower precision values.

Recall: The recall for the X-class was high at 90%, indicating the model's ability to correctly identify most of the X-class flares.

F1-Score: The F1-score for the overall classification task was 84%, with the X-class showing the highest F1-score among all classes.

CNN-LSTM Evaluation:

Accuracy: The CNN-LSTM model achieved a slightly lower accuracy of 83%.

Precision: The precision for the X-class solar flares was 85%, with other classes showing similar precision values as the CNN model.

Recall: The recall for the X-class was slightly lower at 88%.

F1-Score: The F1-score for the overall classification task was 82%, indicating that the added temporal component did not significantly improve performance.

A screenshot of a graph

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A diagram of a confusion matrix

Description automatically generated with medium confidence

**Results:**

The results indicated that the CNN model was more effective in this specific task of classifying solar flares using multi-wavelength images. Despite the theoretical advantages of the CNN-LSTM model in capturing temporal dependencies, the complexity did not result in a significant performance boost.

The CNN model's simplicity and efficiency made it a better fit for the dataset, which primarily benefited from spatial feature extraction.

The CNN-LSTM model's added complexity did not sufficiently enhance the classification accuracy to justify its use over the simpler CNN model.

Overall, the CNN model was chosen as the final model due to its better performance and lower risk of overfitting, providing a robust and efficient solution for the task of solar flare classification using AIA imagery.

**Conclusion:**

In this study, we developed and evaluated two deep learning models, a Convolutional Neural Network (CNN) and a hybrid CNN-Long Short-Term Memory (CNN-LSTM) model, for classifying solar flares using multi-wavelength images from the Atmospheric Imaging Assembly (AIA) on the Solar Dynamics Observatory (SDO). The models were designed to leverage the spatial feature extraction capabilities of CNNs and, in the case of the CNN-LSTM model, the temporal sequence modeling capabilities of LSTMs.

The evaluation results indicated that the CNN model outperformed the CNN-LSTM model, achieving higher accuracy, precision, recall, and F1-score. The CNN model's simplicity and effectiveness in capturing spatial features made it a more suitable choice for the task. The added complexity of the CNN-LSTM model did not result in a significant performance improvement, suggesting that the temporal dependencies in the data were not strong enough to benefit from the LSTM layers.

Improvements and Future Work

Addressing Class Imbalance: One of the challenges encountered during the project was class imbalance. The dataset had a significantly higher number of images for certain solar flare classes compared to others. Future work should focus on techniques to address class imbalance, such as using data augmentation for underrepresented classes, applying class weights during model training, or employing resampling techniques.

Layer Optimization: While experimenting with additional layers to improve model performance, we observed that increasing the model complexity led to diminishing returns. It is essential to strike a balance between model complexity and performance. Further hyperparameter tuning and architecture optimization could help in achieving better results.

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