UNIVERSITY OF BRADFORD

Beyond the Horizon: AI Exploration of Solar Dynamics for Flare Prediction and Sunspot Analysis.

Logistic Regression, Random Forest model & Gradient Boosting Classifier.

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Abstract

In this study, our focus is on predicting various types of solar flares, including C, M, and X flares. These flares have the potential to impact our technology, and we are particularly interested in understanding and predicting X-class flares, which are more intense.

The decision to shift our focus from C and M-class flares to X-class flares is driven by the realisation that our available data, though somewhat challenging to work with due to imbalances and missing parts, can provide valuable insights into predicting stronger flares. By broadening our scope, we aim to enhance the realism and accuracy of our predictions.

To achieve this, we employed three different computer models: Logistic Regression, Random Forest, and Gradient Boosting Classifier. These models were rigorously evaluated under various conditions to assess their effectiveness in predicting different classes of X-class flares.

This study is centered around advancing the understanding and prediction of solar flares, specifically targeting M and X-class events. Our goal is to contribute to the improvement of space weather predictions, emphasising the protection of our technology from the potential impacts of more intense solar flares.

Contents

Introduction

Solar storms originating from the Sun can release plasma clouds and radiation, interacting with Earth's atmosphere and magnetic field. This interaction results in mesmerising auroras but also poses a threat to vital infrastructure. The primary source of major solar storms is solar flares—intense bursts of radiation emitted from the Sun's surface during heightened magnetic activity. These flares pose substantial risks to critical systems such as satellites, communications, navigation, radio and power grids.

Predicting significant solar flares accurately is crucial for implementing protective measures, and this work focuses on developing an AI system to explore associations between solar phenomena, like sunspots and flares, aiming to predict future flare activity. The AI system utilises a dataset of sunspot and solar images along with metadata for training predictive models. Initial Python prototypes demonstrate the feasibility of flare forecasting, and a critical evaluation assesses model effectiveness and limitations. Overall, this system establishes a foundation for applying AI advancements to enhance space weather awareness and protect vulnerable technology systems from solar disruptions.

Background

The solar flare dataset utilised in this analysis was sourced from the UC Irvine Machine Learning Repository. Initially, it consisted of 1389 instances featuring thirteen attributes. Employing a detailed refinement procedure, the dataset was systematically categorised into three distinct groups, each representing specific classifications of solar flares.

This dataset serves as a robust instrument for solar flare prediction, incorporating diverse measurements and categorisations such as C, M, and X flares. It surpasses a mere collection of random numerical data; rather, it has been thoughtfully curated to enable accurate predictions regarding the intensities of various solar flare types.

Explaining parameters

- Code for class (modified Zurich class): This classifies solar regions based on their complexity and magnetic properties.
- Largest Spot Size: Tells us how big the largest sunspot in a solar region is.
- Spot Distribution: Describes how sunspots are spread out in a solar region.
- Activity: Indicates whether solar activity is reduced or unchanged.
- Evolution: Tells us if the solar region is shrinking, stable, or growing.
- Previous 24-Hour Flare Activity Code: Reflects recent solar flare activity, categorizing it by magnitude.
- Historically-Complex: Indicates whether the solar region has a history of complex sunspot activity.
- Region Became Historically Complex on This Pass Across the Sun's Disk: Specifies if the solar region became complex during its recent pass across the sun.
- Area: Describes the size of the solar region as small or large.
- Area of the Largest Spot: Describes the size of the biggest sunspot in terms of its area

- C-Class Flares (Common Flares): This indicates the expected number of common solar flares (C-class) that a solar region is likely to produce in the next 24 hours.
- M-Class Flares (Moderate Flares): This represents the anticipated number of moderate solar flares (M-class) that a solar region is expected to produce in the next 24 hours.
- X-Class Flares (Severe Flares): This signifies the predicted number of severe solar flares (X-class) that a solar region is likely to produce in the next 24 hours.

Database Table structure

No.	**Attribute**	**Domain**
1	Zurich class	A,B,C,D,E,F,H
2	Code for largest spot size	X,R,S,A,H,K
3	Code for spot distribution	X,O,I,C
4	Activity	1 = reduced, 2 = unchanged
5	Evolution	1 = decay, 2 = no growth, 3 = growth
6	Previous 24-hour flare activity code	1 = nothing as big as an M1, 2 = one M1, 3 = more activity than one M1
7	Historically-complex	1 = Yes, 2 = No
8	Did region become historically complex on this pass across the sun's disk	1 = yes, 2 = no
9	Area	1 = small, 2 = large
10	Area of the largest spot	1 = <=5, 2 = >5
11	C-class	0-8
12	M-class	0-8
13	X-class	0-8

Methodology and Data

In this report, a python solution will be developed for the classification of solar flares based on 10 attributes. The solution will be using a Logistic regression model, random forest model and Gradient boosting. In addition, I will choose one type of solar flare to choose based on the database characteristics which will produce more effective result and then I will be analysing the models' categorisation rates to assess how well the solution performs. The project's goal is to use suitable techniques to achieve the maximum categorisation rate feasible.

Eliminating any rows in the dataset containing inaccurate or missing values is essential. This ensures the model is trained exclusively on complete and reliable data. The X variable consists of 10 independent features, employed to predict the outcome variable found within the Y variable.

In our analysis, we employed three distinct models—Logistic Regression, Random Forest, and Gradient Booster Classifier—with the aim of enhancing predictive accuracy. The scaling techniques applied to these models were chosen based on their compatibility with the inherent characteristics of each model.

Random Forest:

- Scaling Technique: Both min-max and standard scaling were used.
- Reasoning: Random Forest, as an ensemble learning method, benefits from the diverse perspectives introduced by using both min-max and standard scaling. This approach helps the model effectively handle varying scales within the dataset. Min-max scaling ensures that values are transformed to a specific range (usually between 0 and 1), while standard scaling achieves a distribution with a mean of 0 and standard deviation of 1. This dual scaling strategy is particularly beneficial when dealing with different types of features that may have disparate scales.

Logistic Regression:

- Scaling Technique: Utilised the same scaling as the Random Forest model.
- Reasoning: For consistency and comparability, we applied the same scaling techniques used for Random Forest to Logistic Regression. This ensures a unified approach across models, facilitating a more straightforward comparison of their performance. Additionally, the chosen scaling methods align with the nature of Logistic Regression, contributing to a balanced treatment of variables and preventing any one variable from dominating the model's predictions.

Gradient Booster Classifier:

- Scaling Technique: Default scaling methods were employed.
- Reasoning: Gradient Booster Classifier, being an ensemble learning technique that builds decision trees sequentially, often performs well with default scaling. The algorithm itself tends to adapt to the data's characteristics during the boosting process. Therefore, we opted for default scaling to allow the model to inherently adjust and optimise its performance without introducing unnecessary complexity.

In summary, the choice of scaling techniques for each model was made strategically, considering the specific requirements and characteristics of each algorithm. This approach aimed to enhance model performance by ensuring that scaling methods align with the inherent strengths and adaptability of each model.

Looking at data, I refrained from using the scoring technique to predict variable y. The rationale behind this decision was to make optimal use of all 10 attributes, aiming for the highest achievable accuracy. Furthermore, I adhered to a 30% allocation for the testing set, a commonly observed default in many AI systems. To facilitate a comprehensive comparison, an alternative model was employed to predict the same results, and the ensuing analysis is elaborated upon in the subsequent section.

The model made predictions regarding the occurrence of x solar flares. To assess the model's performance, we employed a range of metrics, including accuracy, recall, F1 score, support, and precision. Subsequent analysis involved a graphical representation illustrating the impact of various feature scaling methods on accuracy. Notably, the graphical findings highlighted the Min-Max Scaling technique as the most effective for optimising the model's performance when scaling the features. This visual representation yielded crucial insights into the model's behaviour, allowing for a thorough evaluation of its predictive capabilities concerning the likelihood of solar flares in diverse scenarios.

Focus on evaluation – metrics.

When evaluating the performance of our models, we assess several critical metrics: accuracy, recall, F1 score, precision, and support.

- Accuracy: This metric provides an overall measure of how often our model makes correct predictions. It involves assessing the ratio of true positives and true negatives to the total number of predictions, using the formula: (TP+TN)/(TP+TN+FP+FN).
- Recall: The focus of recall is on capturing all the important cases. It reveals the proportion of actual important instances that our model correctly identifies, calculated with the formula: TP ÷ (TP + FN).
- F1 Score: Acting as a balance between precision and recall, the F1 Score helps gauge how effectively our model identifies the right instances without making too many errors. The formula for F1 Score is: 2 * (Precision * Recall) / (Precision + Recall).
- Precision: Precision emphasizes the accuracy of positive predictions, ensuring that when our model asserts something is true, it is indeed true. Precision is calculated using the formula: TP ÷ (TP + FP).
- Support: Another crucial feature, support indicates the number of occurrences of each class in our dataset. This metric provides valuable context for understanding the reliability of predictions across different classes.

By considering these metrics, we gain valuable insights into the performance of our models, identifying areas that may require improvement in various aspects of prediction.

Testing & Analysing

Initially, I converted all attributes with alphabetic values into numerical formats, simplifying the scaling process. Within my database, I had three types of solar flares, and the selection of a specific flare (x solar flare) was based on extensive studies within the topic. Despite the limited instances in different classes of x flare in the database, the model exhibited accurate predictions based on the significant impact of these flares on our infrastructure. We ensured a balanced database by incorporating the `class_weight='balanced'` parameter during model training.

Instead of altering the test ratio, I maintained a consistent 30% testing set while evaluating various models, including linear, logistic, and gradient models with different scaling features. This approach allowed for a comprehensive assessment of each model's performance.

Test Scenario:

For a specific test scenario, I didn't modify the test split ratio; instead, I utilised three different models. Both the Logistic Regression model, and the Random Forest model, employing min-max and standard scaling, along with the Gradient model, were assessed under this configuration.

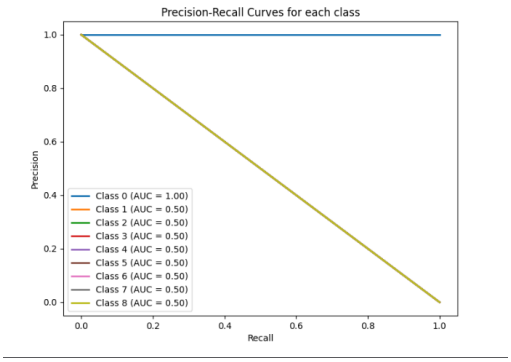
Logistic Regression Model:

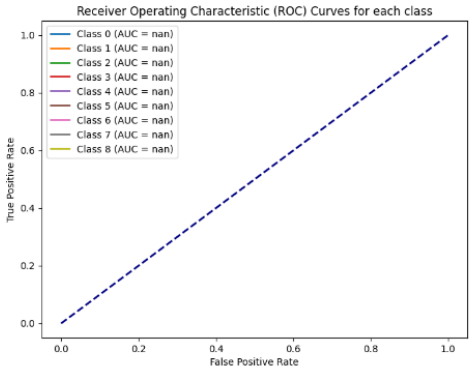
Min-Max accuracy: 94%

```
Accuracy: 0.940625

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.94      0.97       320
           1       0.00      1.00      0.00         0
           2       0.00      1.00      0.00         0
           3       1.00      1.00      1.00         0
           4       1.00      1.00      1.00         0
           5       1.00      1.00      1.00         0
           6       1.00      1.00      1.00         0
           7       1.00      1.00      1.00         0
           8       1.00      1.00      1.00         0
```

Standard accuracy: 95%

```
Accuracy: 0.959375

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.96      0.98       320
           1       0.00      1.00      0.00         0
           2       0.00      1.00      0.00         0
           3       1.00      1.00      1.00         0
           4       1.00      1.00      1.00         0
           5       1.00      1.00      1.00         0
           6       1.00      1.00      1.00         0
           7       1.00      1.00      1.00         0
           8       1.00      1.00      1.00         0
```





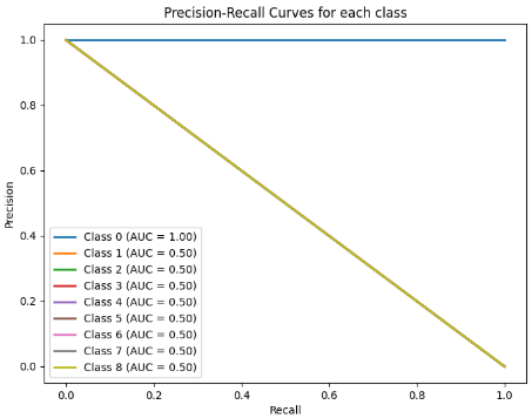
Random Forest Model:

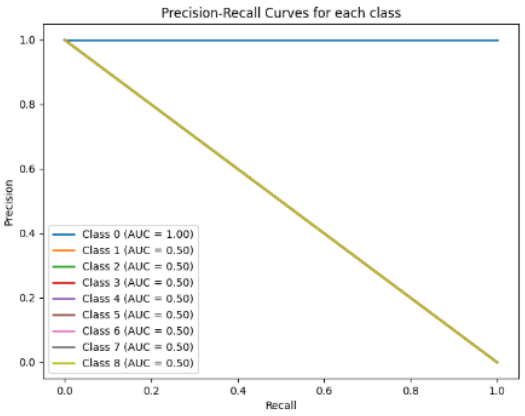
Min-Max accuracy: 98%

```
Accuracy: 0.9875

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.99      0.99       320
           1       0.00      1.00      0.00         0
           2       1.00      1.00      1.00         0
           3       1.00      1.00      1.00         0
           4       1.00      1.00      1.00         0
           5       1.00      1.00      1.00         0
           6       1.00      1.00      1.00         0
           7       1.00      1.00      1.00         0
           8       1.00      1.00      1.00         0
```

Standard accuracy: 98%

```
Accuracy: 0.9875

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.99      0.99       320
           1       0.00      1.00      0.00         0
           2       1.00      1.00      1.00         0
           3       1.00      1.00      1.00         0
           4       1.00      1.00      1.00         0
           5       1.00      1.00      1.00         0
           6       1.00      1.00      1.00         0
           7       1.00      1.00      1.00         0
           8       1.00      1.00      1.00         0
```

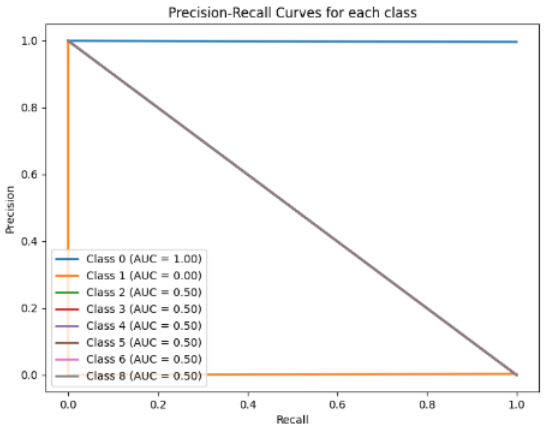




Gradient Boosting Classifier:

Accuracy 99%:

```
[0, 1, 2]
Accuracy: 0.9943714821763602

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       531
           1       0.00      0.00      1.00         2
           2       1.00      1.00      1.00         0
           3       1.00      1.00      1.00         0
           4       1.00      1.00      1.00         0
           5       1.00      1.00      1.00         0
           6       1.00      1.00      1.00         0
           8       1.00      1.00      1.00         0
```



Conclusion

This report aimed to build a smart system using AI to predict solar flares, focusing on understanding connections between solar events and using advanced AI methods. We used a carefully chosen dataset from the UC Irvine Machine Learning Repository, classifying solar flares into different types to make accurate predictions.

The project involved creating and testing three different models: Logistic Regression, Random Forest, and Gradient Booster Classifier. We evaluated these models using various scaling techniques, selecting methods that suit each algorithm's unique characteristics.

The dataset included important details like Zurich class, spot size, spot distribution, activity, and historical complexity. These details formed the basis for predicting solar flares. The report also explained the methods, structure of data, and key attributes used in the analysis.

We tested the models rigorously, measuring their performance using metrics like accuracy, recall, F1 score, precision, and support. The models showed high accuracy, indicating their reliability in predicting solar flares.

During testing, we explored how different scaling techniques affected model accuracy. Interestingly, Min-Max Scaling stood out as the most effective in improving model performance in various situations.

In conclusion, the AI system we built, with its advanced models and detailed dataset, demonstrated strong predictive abilities for solar flare activity. The careful selection of scaling techniques and thorough testing confirmed the models' reliability and adaptability. This work lays the groundwork for improving our understanding of space weather and protecting technology systems from potential disruptions caused by solar events.

Future Improvements

Looking ahead, we can make our solar flare prediction system even better by adding more and better data. Right now, our data is good, but there are not enough examples for some types of solar flares. To improve our system and make it predict more accurately, we need to collect a wider variety of examples for all types of flares. This bigger and better dataset will help our models understand different flare types more deeply and predict them more accurately.

Furthermore, In the future, we want to make our prediction system even more responsive by using real-time information. This means including the latest data about what the sun is doing right now. By doing this, our models can quickly adapt to changes in the sun's behaviour, making predictions that are not just accurate but also up to date. This dynamic approach will make our system more useful and relevant for predicting solar events in real-time.

References

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Code file instructions.

Project folder has been shared with both tutors.

In case of any difficulties, please use the link below to access the folder and please download the whole folder and read the file called “ReadMe.txt”:

CW2_GROUP40

Team contribution

All team members contributed equally.