Machine Learning Predictions of Solar Flare Intensity and Occurrence

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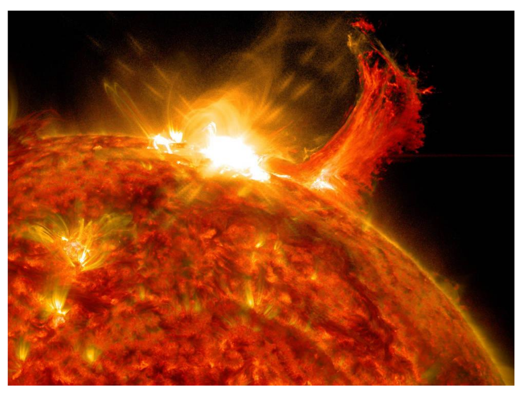
What is a Solar Flare?

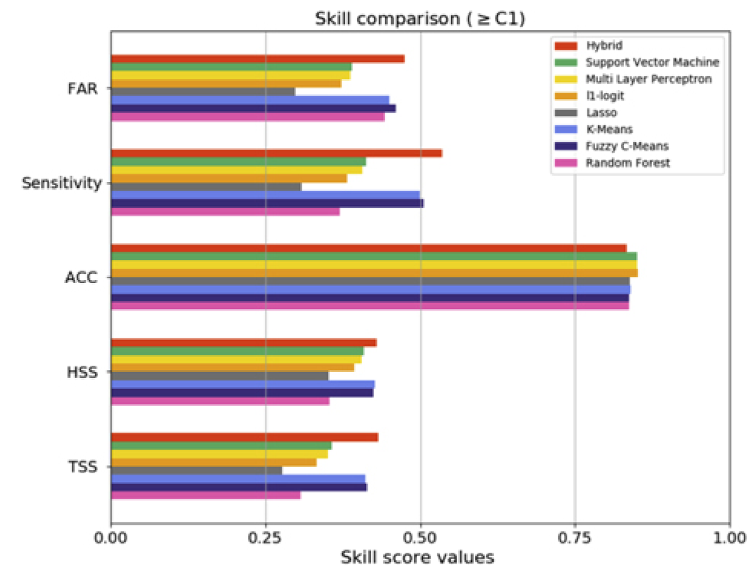
- **Origin:** Triggered by tangled magnetic fields in the sun's atmosphere.
- **Frequency:** Varies with the 11-year solar cycle, from multiple daily to less than weekly.
- **Effects:** Disrupts Earth's electronic systems but doesn't harm humans directly.
- **Classes:** Four strength classes (B, C, M, X); significant impacts from M and X. Class A is quiet, no solar flare.



Credits: NASA/SDO - Captured Oct.2, 2014

Introduction

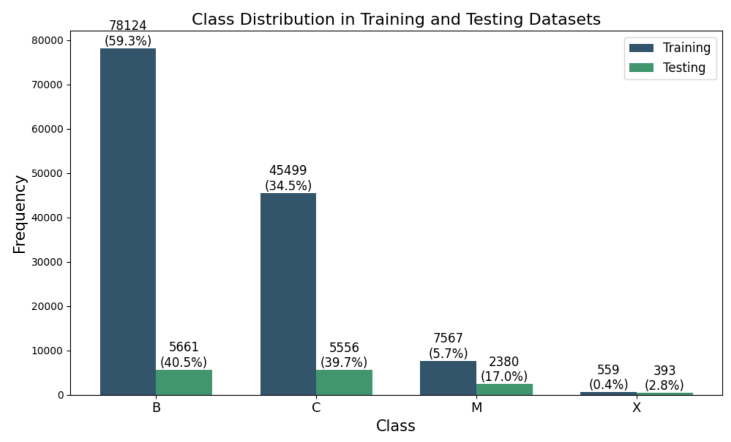
- **Challenge Addressed:**
  - Match previously documented TSS scores (see figure to the right) in predicting solar flares using various types of machine learning models
  - Explore and validate these advanced models to improve the prediction of different classes of solar flares
  - Contribute to the development of enhanced forecasting methods and more reliable space weather predictions, ultimately leading to better solar activity monitoring systems.
- **Significance:**
  - Accurate predictions of solar flares are crucial for reducing negative impacts on Earth's technological systems, making them an essential factor for improving space weather preparedness.

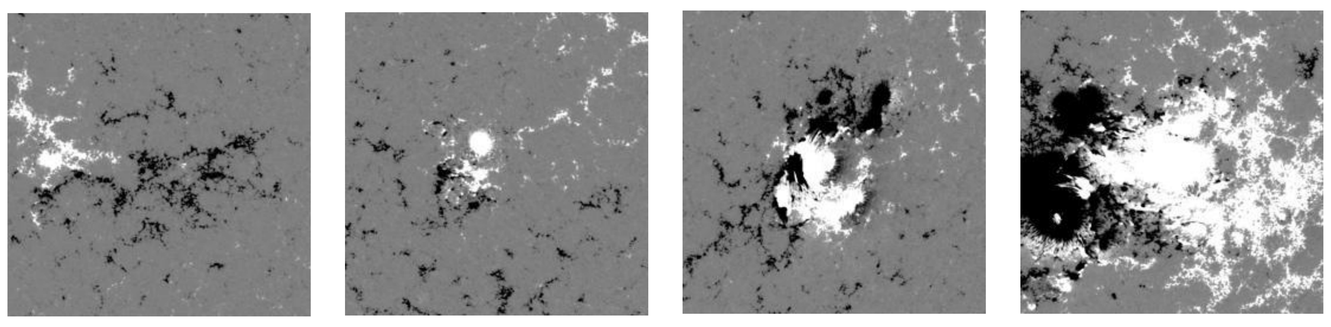


Credits: doi - 10.3847/1538-4357/aaa23c

Methodology

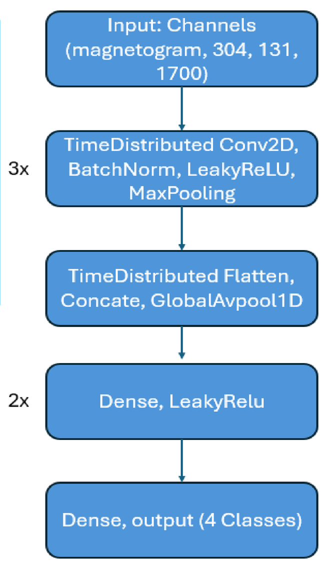
- **Dataset:**
  - ~375,000 images
  - 12 hours before the prediction period
  - Metadata with event details – solar flare intensity and time intervals
  - Imbalance between classes



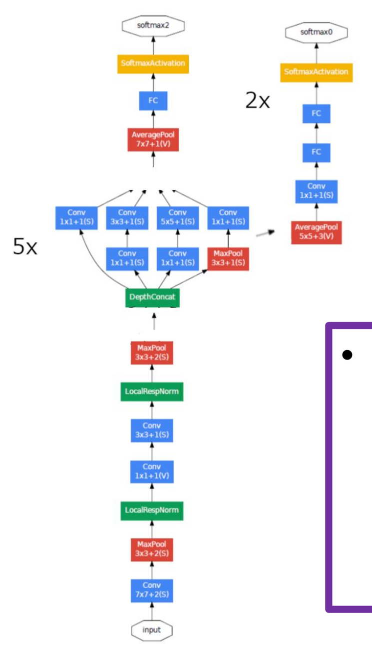


B >= 1e-7 C >= 1e-6 M >= 1e-5 X >= 1e-4

- **Multichannel CNN:**
  - Images of different wavelengths and time steps.
  - Using 3 time-distributed layers of convolutional layers.
  - Multi-class classification.



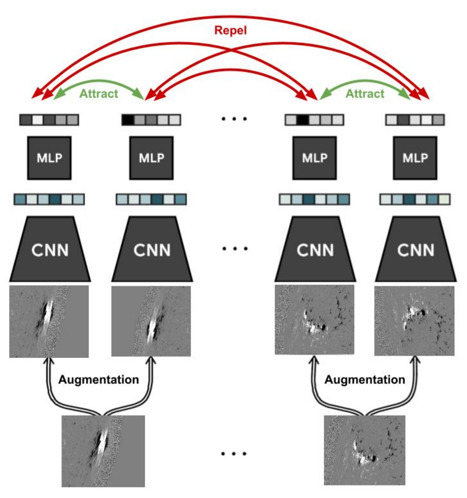
Multichannel CNN



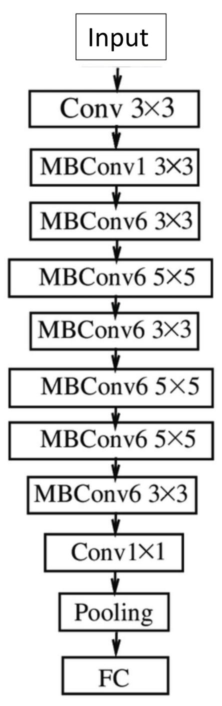
GoogLeNet

- **GoogLeNet:**
  - A pretrained model available through Torch
  - Made up by 22 layers – optimized for image recognition
  - Used for both multi-class and binary classification

- **Contrastive Self-supervised model with CNN:**
  - CNN is used for embeddings
  - Contrastive loss is designed to learn the embeddings that pull together positive pairs and push apart negative pairs without use of labels.
  - KNN is used to measure the model performance



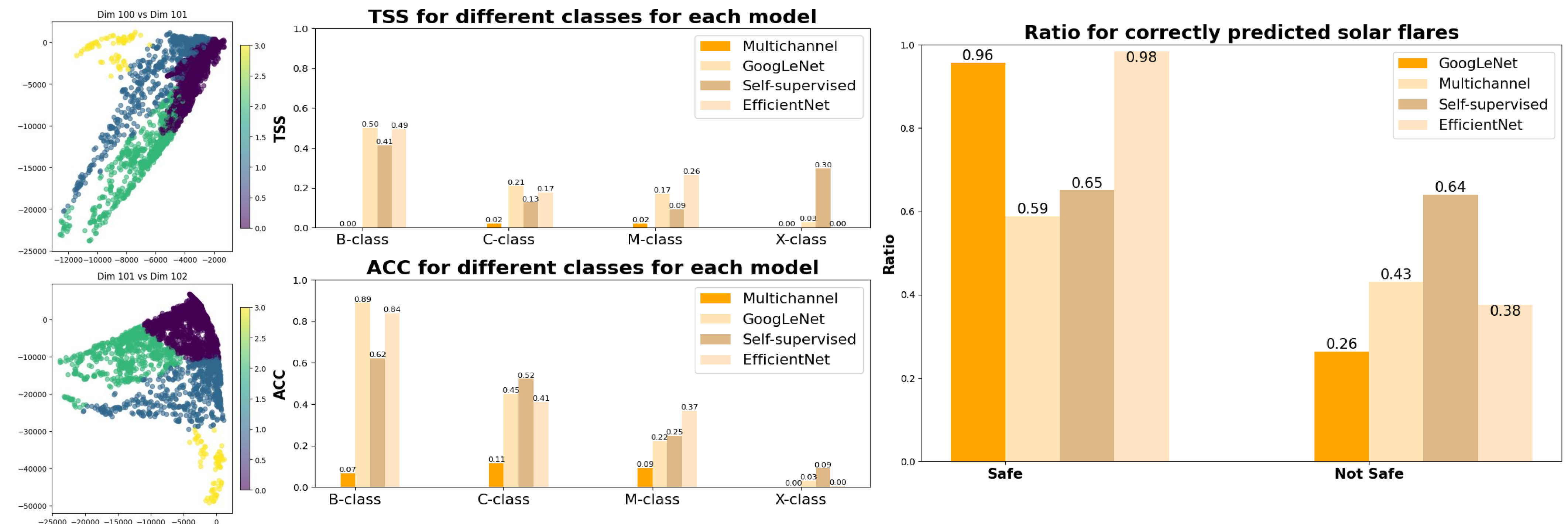
Self-supervised model with CNN



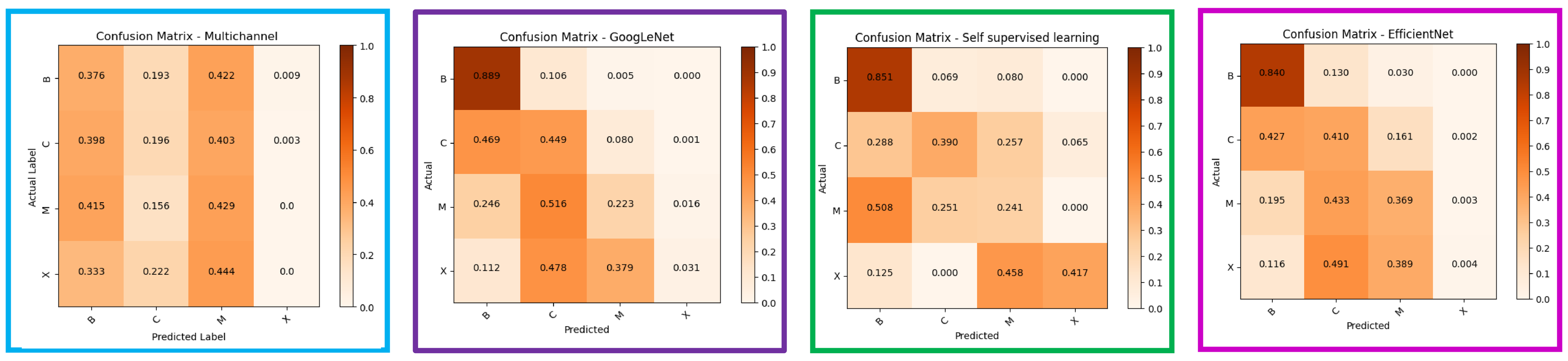
- **EfficientNet:**
  - Uses a unique compound scaling method - uniformly scales network's depth, width, and resolution, leading to a more balanced and efficient model
  - Available in various sizes (EfficientNet-B0 to B7), enabling selection based on computational resources and accuracy needs
  - Mobile inverted bottleneck convolution (MBConv) layers, which are optimized for both accuracy and efficiency.

Results

- Below are illustrations of KNN clustering for multi-class classification (left), graphs showing the TSS score and accuracy for the multi-class classifiers (middle) and ratio of correctly classified Safe/Unsafe flares for the binary approach (right)



- Confusion matrices showing the results of multi-class classification for the models, values normalized for comparison



- Table for TSS and accuracy for the four different models

Metric	Multichannel CNN	GoogleNet	EfficientNet	Self-supervised
TSS	0.0195	0.219	0.234	0.291
ACC	0.550	0.819	0.563	0.645

Conclusion

- Judging from the results, self-supervised learning seem to be the most promising approach with its fairly high prediction ratio
- Can not effectively predict X class with the current imbalanced dataset, augmentation or synthesized data would likely improve on this

Future Work

- **Modify Contrastive Self-Supervised Model:** Modify the self-supervised with Transformer instead of CNN for encoding the image.
- **Explore and Utilize Different Datasets:** Investigate and incorporate various datasets to enhance the training and validation processes, aiming to improve model robustness and accuracy.
- **Synthesize Data for X-Class Flares:** Explore generating synthetic data for X-class solar flares to improve True Skill Statistics (TSS) scores for this specific class, enhancing prediction reliability.

Acknowledgements

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