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ARTIFICIAL INTELLIGENCE IN SOLAR FLARE PREDICTION: PROGRESS, CHALLENGES, AND FUTURE DIRECTIONS

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Abstract: Solar flare is the most crucial space weather phenomena where a sudden burst of radiation and charged elements can affect the working behavior of satellites, power grids and communication system on Earth adversely. The accurate and timely prediction of solar flares allows government and industries to take preventive actions. The complex and non-linear behavior of the solar magnetic fields make the forecasting of solar flare a challenging task. This study aims to review the evolution of artificial intelligence (AI) based data-driven approaches in flare prediction task. This endeavor covers different AI approaches ranging across machine learning (ML) and deep learning (DL) methods for flare prediction, categorizing approaches into classical ML, neural networks, and hybrid models. The study also provides insights into key challenges and outlines the future directions in the field of AI-based flare forecasting research.

IndexTerms - **Solar flare forecasting, space weather, machine learning; deep learning, predictive models**

1. Introduction

Solar flares are sudden and intense bursts of radiation and charged elements occurring in complex magnetic fields areas. Their collision with solar magnetized particles and coronal mass ejections (CMEs) affects space environment of Earth including satellites, power grids, communication networks adversely [1]. These geomagnetic storms may cause economic loss of up to 2.6 trillion dollars with long-term disruptions to communication system [2]. Significant accelerating orbital decay has been observed on satellites owing to severe geomagnetic disturbances [3][4]. X-class flares disrupt high-frequency communication over continental scales [5] and Ionospheric perturbations caused by strong solar events degrade Global Navigation Satellite System (GNSS) accuracy impacting aviation systems [6]. Solar particle events (SPEs) may cause an increase of 300-500% in radiation emission which may result in severe consequences for astronauts outside the magnetosphere [7].
These wide-range impacts of solar flares make it essential to forecast flares timely and accurately for operational readiness and space-weather mitigation [8]. Solar flares are classified into 1–8 Å (Angstrom) wavelength and measured by the GOES classes A, B, C, M, and X range based on their X-ray flux. Forecasting solar flare includes monitoring the Sun's magnetic activity and predicting the likelihood, timing, and intensity of upcoming flares. The effectiveness of predicting flares in technological sustainability has made it a global necessity. The conventional approaches for forecasting flares included rule-based employing physics-inspired indicators and simple statistical models. Owing to their dependence on heuristic features and limited dataset these traditional approaches struggle to model the complex and non-linear dynamics of the solar magnetic field. Meanwhile, high-resolution data from the Solar Dynamics Observatory (SDO), including Atmospheric Imaging Assembly (AIA) imagery and Helioseismic and Magnetic Imager (HMI) magnetograms, X-ray flux measurements and NOAA flare catalogs have enabled the emergence of artificial intelligence-based data-driven models [9]. These data-driven AI approaches have shown their potential in capturing non-linear dependencies in solar magnetic data [10]. In recent years, deep learning-based approaches, ranging from convolutional neural networks and recurrent architectures to hybrid systems, have shown significant potential in capturing pioneering characteristics associated with flare onset [11]-[13]. Despite advancement in technology, certain challenges persist pertaining to multimodal data fusion, class imbalance, limited temporal modeling capability and limited interpretability. These limitations motivate the development of more advanced architectures capable of learning the complex spatio-temporal dynamics of active regions. To address these gaps, this work proposes a novel deep learning framework to improve the accuracy, robustness, and interpretability of solar flare prediction.
This study aims to review the AI-based flare forecasting approaches from classical machine learning based methods to deep-learning based approaches. The AI -based flare-forecasting research is analyzed to provide a comprehensive status update in the field. In the manuscript, Section 2 describes the numerous AI approaches used in flare prediction. Section 3 covers different dataset available in the field. Section 4 discusses the challenges and outlines the open research directions. Finally, Section 5 presents conclusion.

2. AI Methodologies for Flare Prediction

AI techniques for flare prediction can be broadly classified based on inherent model type. These techniques range across feature-based classical machine learning models to hybrid deep learning-based model, as discussed below:

2.1 Feature-based Machine Learning based Approaches

Early AI approaches used manually extracted physical features of active regions (ARs) as input to classical classifiers. Bobra et al. [14] used 25 magnetic field parameters from SDO/HMI vector magnetograms with a Support Vector Machine (SVM) to forecast whether an AR would produce an M- or X-class flare within 24 hours. Asaly et al. [15] explored the effect of ionospheric Total Electron Content (TEC) on solar flare activity by training an SVM model on TEC-derived features. Their findings highlight an unconventional but promising data source for short-term flare forecasting. Bringewald et al. [16] employed 13 SHARP parameters as inputs to Random Forest (RF), k-Nearest Neighbors (kNN), and XGBoost models to classify flares into GOES classes B, C, M, X [16]. They evaluated both binary and multiclass schemes using principal component analysis (PCA) for dimensionality reduction. RF and XGBoost achieved the strongest performance with high-dimensional features. In feature-based ML approaches hyperparameter tuning and careful data partitioning plays important role for robust evaluation. Other classes of work have applied ensemble tree methods and regression to flare metrics. Chen et al. [17] used machine learning to predict the Flare Index (a continuous measure of flare productivity) from sunspot and magnetic parameters, employing regression and obtaining significant correlations. Bayesian and fuzzy classifiers have also been used for solar flare level prediction [18].

Feature-based ML methods rely on expert-chosen physical quantities (magnetic field gradients, shear, energy proxies, etc.) as inputs. The advantage is interpretability of features and lower data requirements. Their performance can be strong for binary classification (flare/no flare) tasks. However, feature selection remains a challenge, and hand-crafted features may not capture all relevant patterns.

2.2 Deep Convolutional Neural Networks (CNNs) based Approaches

Deep learning has enabled models to learn features directly from raw images or data matrices. CNNs have been applied to flare prediction through localized AR images like magnetograms or multi-wavelength intensity maps. Nishizuka et al. [19] introduced Deep Flare Net (DeFN), a deep feedforward network that uses 79 features including vector magnetic field components and coronal intensity measures to predict the probability of ≥M-class flares. Li et al. [20] developed four CNN models for complex ARs using only HMI magnetogram images as input. Jonas et al. [21] presented a hybrid CNN approach to process SDO images across multiple wavelengths and combined these with AR flare history in a classifier. The sophisticated feature-extraction followed by classification pipeline achieved high accuracy. Recently, Hu et al. [22] used multi-input CNNs and data augmentation mechanism by stratifying HMI AR observations at different altitudes and feeding them to various CNN backbones including AlexNet, ResNet-18, SqueezeNet.

CNNs can automatically extract spatial features from images, eliminating manual feature engineering. They are suited for utilizing full-disk images or AR patches from instruments like SDO's HMI (magnetograms) and AIA (EUV). CNNsbased approaches outperformed feature-based methods but their performance is dependent on availability of large labeled datasets and careful pre-processing.

2.3 Recurrent Neural Networks based Approaches

Solar flare forecasting inherently involves temporal dependencies because ARs evolve over hours to days. To extract temporal information, Recurrent Neural Networks (RNNs) and their variants (LSTM, GRU) have been employed to capture temporal patterns. Jiao et al. [23] developed an LSTM-based regression model to predict flare intensity. Authors fed sequences of SHARP parameters (24-hour history) into an LSTM and found that using the 24 hours of data before the prediction time yielded the best performance. Datla et al. [24] proposed an attention-based LSTM for short-term flare forecasts, incorporating an attention mechanism over SHARP time-series features. Embedded attention mechanism outperformed standard LSTM baselines in 24-hour flare (M-class) prediction.

LSTMs can leverage temporal evolution of AR features and have shown strong predictive skill for both flare intensity and occurrence when trained on time-series inputs. RNN based models can complement CNNs by feeding CNN-extracted features at each timestep into an RNN. However, long sequences increase computational cost, and the scarcity of long continuous flare data can limit training.

2.4 Hybrid and Ensemble Approaches

In hybrid approaches, multiple techniques are combined to boost robustness. Benvenuto et al. [25] proposed a hybrid supervised/unsupervised pipeline where AR feature data is clustered to handle imbalance followed by a boosted classifier for flare prediction. Deshmukh et al. [26] showed that ensembling CNNs and using balanced training can reduce false alarms in flare forecasts using HMI data. The pipeline presented by Jonas et al. [21] can also be viewed as a hybrid system as they fused image features with flare history and physics-based quantities.

Ensembles and hybrid networks aim to leverage the strengths of different models. They can improve overall performance and reliability. Boosting trees like XGBoost combined with deep features or multi-model voting can yield better predictions. However, hybrid models are more complex and require careful training to avoid overfitting.

2.5 Transformer-Based Approaches

Recent work has begun to explore transformer architectures for solar flare forecasting. Riggi et al. [27] evaluated foundation transformer models across image, video, and time-series modalities. They fine-tuned three pretrained models, an image transformer (SigLIP2), a video transformer (VideoMAE), and a time-series transformer (Moirai2), on a consistent flare forecasting dataset. The image/video models achieved moderate skill (True Skill Statistic (TSS) ≈0.60–0.65), but time-series transformer trained on irradiance history from GOES achieved higher skill (TSS ≈0.74). This indicates that transformers can capture complex temporal dependencies and can be pretrained on large datasets for improved performance. The authors highlight that multimodal learning, integrating visual and temporal data, is a promising direction for unified flare forecasting.

Transformer architectures can process spatio-temporal solar data effectively, offering state-of-the-art performance when properly pre-trained. Their self-attention mechanism can learn global correlations in data. The field is moving toward large pre-trained models that can be adapted for space weather forecasting.

2.6 Explainable and Knowledge-Informed AI based Approaches

As AI models become more powerful, there is growing interest in interpretability and physics integration. Some studies have applied explainable AI (XAI) techniques to flare prediction to identify which inputs drive model decisions. Attribution methods like grad-CAM and feature importance, have been used to highlight critical magnetogram regions or features. knowledge-informed models add physics-inspired constraints or features to neural nets. Li et al. [28] presented LSTM networks guided by physical constraints on energy. These efforts suggest future hybrid AI-physics models could improve reliability. Given the high stakes of space weather, understanding AI decisions is vital. Research is beginning to focus on visualizing neural network activations, using counterfactual examples and ranking features by importance. Physics-informed models ensure energy conservation and field topology consistency. The numerous AI-driven endeavors for solar flare prediction are compared based on their inherent model, input to model, dataset used and important remarks in Table 2.1.

Table 1.1: Comparative `Summary of Representative AI Models for Solar Flare Prediction

Study	Task performed	Model used	Input to the model	Dataset used	Evaluation metrics	Remarks
Yu et al. [18]	Short-term flare level prediction	Bayesian network	Time sequences of magnetic parameters	Sequences of photospheric magnetic field parameters	probability -based scores	Simple approach, explicitly models dependencies and uncertainty
Bobra et al. [14]	ARs classification that will produce M/X flares	Support Vector Machine (SVM)	25 vector-field derived SHARP parameters per AR	SDO/HMI vector magnetic field catalogue	TSS	First large-scale use of HMI vector data; good feature selection; high TSS, careful tuning required
Asaly et al. [15]	Predict solar flares using ionospheric Total Electron Content (TEC)	SVM	Ionospheric TEC time series features	GPS / ionospheric TEC records matched to flare events	Precision, recall, HSS, TSS	Employs near-Earth ionospheric predictors, performance depends on TEC-flare coupling and geophysical drivers
Florios et al. [9]	Binary forecasting of >M1 and >C1 flares within 24 h	Random Forest (RF), MLP, SVM	Magnetogram-based predictors	SDO/HMI SHARP	ACC, TSS, HSS, ROC metrics	RF performs robustly Model suffer with class imbalance
Bringewald et al. [16]	Multi-class classification (B/C/M/X)	Random Forest, k-NN, XGBoost	SHARP parameters, PCA components	SHARP-based parameter dataset	ACC, TSS, multiclass confusion metrics	Limited to tabular SHARP parameters as no image inputs; suffers with multiclass imbalance
Hu et al. [22]	Flare prediction	CNN	Magnetograms and derived field at different heights	SDO/HMI magnetograms	TSS, accuracy	evaluated effect of coronal field height on flare prediction Interpretation depends on extrapolation method and assumptions
Jonas et al. [21]	Flare prediction	CNN-like single-layer with linear classifier	Photospheric vector magnetograms + coronal images	SDO image archives)	TSS, accuracy, precision, recall	First attempt to combine photospheric and coronal image data

Nishizuka et al. [13]	Probabilistic 24-hour flare forecasts (≥M/≥C)	Deep Flare Net (DeFN)	Multi-wavelength features + 79 extracted features per AR	SDO (JSOC) multiwavelength products	TSS	Real-time and operational approach, employed strong multiwavelength feature set, Suffers with outliers
Li et al. [20]	Forecast flares in complex active regions	Multiple deep neural network architectures (CARFFM)	AR longitudinal/vector magnetograms; neutral-line flux metrics	SHARP / HMI AR samples selected for complex regions	TSS, accuracy, class metrics	Focus on complex ARs; multiple network variants for different input choices, suffers with generalization issues
Hassani et al. [8]	Flare occurrence Prediction	LSTM, Decomposition-LSTM (DLSTM)	Time series of peak fluxes and waiting times	GOES X-ray flare catalogue	TSS, recall, ROC-AUC	DLSTM + ensemble gives stronger large-flare detection and lower false alarms Long-term patterns limited by solar complexity
Riggi et al. [27]	Cross-modal flare forecasting	transformer	Magnetogram images, video sequences, irradiance time series	Public SDO/HMI magnetograms and GOES irradiance time series	TSS, AUC	Explores cross-modal pretraining; strong TSS, computationally expensive approach
Li et al. [13]	flares prediction	ResNet + SVM classifier	Magnetogram-based predictors	SDO/HMI SHARP	TSS, AUC, accuracy	reduced end-to-end CNN calibration issues Handles overfitting for small, labelled dataset
Jiao et al. [23]	maximum flare intensity	regression LSTM models	Time windows of HMI features	HMI/HARP time series	Regression metrics (RMSE), TSS for discretized thresholds	useful for magnitude estimation, suffers with skewed distribution and rare extremes
Datla et al. [24]	M/X flares prediction	Interpretable LSTM with attention	Time-series of SHARP parameters	GOES flare catalogue + SHARP parameters	TSS, AUC, interpretability diagnostics	Interpretability provided; modelled temporal information, suffers with class imbalance and dataset labelling choices
Benvenuto et al. [25]	Binary flare/no-flare classification	supervised regularization + unsupervised clustering for decision	Feature vectors derived from magnetograms	NOAA SWPC data	TSS, accuracy, clustered validation metrics	Combined pipeline offering interpretability and feature selection, Cluster decisions may be sensitive to pre-processing and priors
Deshmukh et al. [26]	flare prediction	Two-stage hybrid architecture - CNN followed by Extremely Randomized Trees (ERT)	Temporal stacks of magnetogram images	SDO/HMI magnetogram image stacks	Scaled TSS, precision, F1, false-alarm rate (FAR)	Substantial false-alarm reduction, complex fine-tuning
Li et al. [28]	Forecast ≥M-class flares	Knowledge-informed deep neural networks (KI-DNN)	SHARP parameters plus embedded physical constraints	SHARP parameters / SDO datasets	TSS, probabilistic skill scores	Blends physics knowledge with DNN, enhanced generalization and interpretability

The existing studies indicate that magnetic-field descriptors derived from magnetograms continue to be among the most influential predictors for flare forecasting across both classical and deep-learning strategies. Among machine learning based approaches, Random Forest models reliably handle SHARP-based magnetic parameters because they tolerate noise, correlations, and nonlinear feature interactions. Further, LSTM-based time-series models are effective at tracking long-range patterns in GOES X-ray flux compared traditional machine-learning techniques. Also, approaches that decompose solar time series during preprocessing tend to yield higher forecast skill by separating short-term fluctuations from broader trends. Emerging transformer architectures are showing promise as unified models capable of jointly analyzing images, video sequences, and temporal data. Further, flare datasets are heavily imbalanced, successful models must apply resampling, class weighting, or modified loss functions to prevent biased predictions. Studies confirm that forecasting M- and X-class flares remains far more challenging due to their infrequency and complex precursors. Over the past two decades, solar-flare forecasting has evolved from statistical feature engineering to classical ML, then to CNN/LSTM deep learning, and now toward multimodal transformer-based systems.

3. **Solar Flare Datasets**

The AI model curated for solar flare prediction require large-scale dataset for good accuracy. The various solar flare prediction related dataset, used in the literature. GOES X-ray Flare Catalog (NOAA/SWPC) dataset provides Geostationary Operational Environmental Satellites (GOES) captured continuous X-ray images of the Sun. The NOAA National Centers for Environmental Information archive GOES flare lists including class, time and location from the 1970s to present [30]. These catalogs contain labeled flare events, including peak flux, facilitating supervised learning. Another dataset labelled as SDO/HMI and SHARP contains NASA's Solar Dynamics Observatory Helioseismic and Magnetic Imager (SDO/HMI) generated full-disk vector magnetograms every 12 minutes. The *Space-weather HMI Active Region Patch (SHARP)* data product automatically identifies and tracks active regions and produces 20 magnetic parameters including flux, currents, helicity, etc. for each AR. SHARP dataset is widely used for existing studies [16][20][28] . For example, Liu et al. [31] created a public database of 6.5 years of SHARP data with flare labels. Dataset SDO/AIA EUV comprises atmospheric Imaging Assembly (AIA) on SDO based Sun's images in multiple EUV wavelengths. Several image datasets have been assembled for ML. *SDOBenchmark* dataset provides sequences of AIA and HMI magnetograms labeled for 24-hour peak. Each sample includes ten images, eight AIA channels + two HMI channels, at four-time steps before an event (up to 24h ahead)i4ds.github.io. This dataset is used for regression of peak flux [21]. In GONG and H-alpha Dataset, the Global Oscillation Network Group (GONG) provided ground-based solar images, including H-alpha. While GONG is often used for filaments and CMEs, it has been applied to flare studies. Ahmadzadeh et al. [29] proposed *MAGFiLO v1.0* dataset of annotated filaments from GONG H-alpha images [31]. The various dataset available in the field along with their description and data information are presented in Table 3.1.

3.1: Major Solar Flare Datasets

Dataset	**Description**	**Data Type**	**Time Span & Coverage**
GOES X-ray Catalog	Soft X-ray (0.1–0.8 nm) peak flux events (C, M, X class) recorded by NOAA/SWPC	Flare event list	1975–present (continuous)
SHARP (SDO/HMI)	Space-weather Active Region Patches (magnetic features): vector magnetogram parameters for each AR (NOAA AR)	Derived parameters (magnetogram) [33]	2010–present (12-min cadence)
HMI Magnetograms (SDO)	Full-disk vector and line-of-sight magnetograms (continuum and field maps)	Images	2010–present
AIA Images (SDO)	Full-disk EUV images (multiple wavelengths, 12-second cadence)	Images	2010–present
SDOBenchmark	Multi-wavelength image dataset (8 AIA + 2 HMI channels) for flare flux forecasting	Images + flux labels	2012–2018 (8,336 samples)
GONG (NSO)	Ground-based solar network images (Hα, magnetograms, etc.)	Images (Hα, magnetograms)	1995–present (daily synoptic)
MAGFiLO (GONG) [32]	Annotated solar filament dataset from GONG Hα images	Image annotations	2011–2022 (10,244 filaments)
NOAA SWPC Flare Lists	Flare event reports (dates, times, peak flux, location) from GOES and other instruments	Flare lists	1938–present
Flare Index (KSO)	Daily flare indices from Kandilli Solar Obs.	Index values	1976–2024 [30]

3.1: Major Solar Flare Datasets 1

4. Challenges and Future Directions

This section discusses the various challenges involved in the successful implementation of AI for processing solar data. It also outlines potential future directions and research opportunities to enhance the accuracy, reliability, and operational use of AI-driven solar data analysis.

4.1 Challenges and Considerations

Despite progress, AI-based flare prediction faces several challenges in the implementation of AI for flare prediction tasks, as discussed below:

- **Class Imbalance and Rareness of Flares:** Large flares (M/X class) are rare compared to non-flaring or B/C-class days. This imbalance can be biased learning. Addressing these issues increases the complexity of the model by involving pre=processing steps like oversampling, cost-sensitive losses, or hybrid framework. The flares-per-AR distribution and the 11-year solar cycle variability make datasets highly skewed.
- Temporal Non-stationarity: The Sun undergoes an 11-year cycle, meaning flare statistics and background conditions change over time. Models trained on one cycle may not generalize to others without adaptation. Instrument changes or calibration drifts like darkening of AIA detectors over years can also affect model input distributions.
- Data Quality and Labeling: While SDO/HMI provides high-quality magnetograms, ground-based data (Hα) suffer from seeing conditions. Defining "active region" boundaries and associating flares to the correct AR can be error prone. Event lists may have missing or duplicate records. The choice of forecasting window and class thresholds also complicates consistent labeling across studies.

- Evaluation Metrics: Metrics like TSS, Heidke Skill Score, and Area Under ROC are used, but domain specific tasks require different metrics and validation schemes. Cross-validation must avoid temporal leakage. Operational evaluation [13] may employ a chronological split or time-series cross-validation to mimic forecasting conditions.
- Model Interpretability: Deep models are often "black boxes." Work on explainable AI in this domain is growing but still limited. Identifying which magnetogram features or image regions drive predictions can help validate models against known physics.
- Computational Demands: Deep-learning based model requires high end computational systems. The large-scale dataset make training further costlier. Efficient pipelines are required to develop real-time forecasting architectures that need to run a model every 6 hours on new SDO data.
- Multimodal Fusion: Combining heterogeneous data like magnetograms, EUV, solar wind etc. can improve forecasts, but fusing different resolutions and formats is nontrivial. Riggi et al. [27] developed promising architecture with multimodal transformers, but this is an emerging area.
- Generalization and Overfitting: Many models show excellent performance on specific datasets but may not generalize across solar conditions. Ensuring robustness via augmented data, dropout, regularization, is important. Benchmarking on independent solar cycles is rarely done due to data limitations.

Addressing these challenges is critical for reliable space weather forecasting. Researchers continue to develop methods to mitigate imbalance and to incorporate domain knowledge to constrain models.

4.2 Future Directions

Several trends are likely to shape solar flare AI research:

- **Unified Multimodal Models:** Integrating diverse data (magnetic maps, multi-wavelength images, heliospheric conditions) into a single model that holds promise. The success of transformers for multimodal tasks suggests the development of "foundation models" trained on broad solar datasets. These could provide a common representation for flares, CMEs, and other phenomena.
- **Explainable and Physics-Guided AI:** There is a push toward AI systems whose decisions can be interpreted in terms of solar physics. For instance, incorporating conservation laws or topological constraints into network architectures can improve trust. Visualization tools, like saliency maps, will become standard to link model outputs to magnetogram features.
- **New Data Sources and Missions:** Upcoming solar observatories, like Solar Orbiter, Parker Solar Probe, DKIST, will provide novel measurements (off-Earth viewpoints, high-resolution fields). Employing these novel observations into forecasting models is an open challenge. The software infrastructure to handle exascale solar data may require AI-friendly databases.
- **Operational Implementation:** Some AI models, like DeFN [13], are already run in quasi-operational mode. Future work will refine pipelines for real-time flare watches, including uncertainty quantification. Integration with NOAA's Space Weather Prediction Center and CCMC could see AI forecasts combined with traditional analysis.
- **Cross-domain Transfer Learning:** Methods from terrestrial weather forecasting, medical imaging, or even finance could inspire new flare models. Conversely, successful solar flare models might inform stellar flare prediction for exoplanet studies.
- **Benchmarking and Open Science:** Continued creation of standardized benchmarks and open datasets will foster fair comparison and reproducibility. Community challenges like Kaggle-style competitions, on flare forecasting could accelerate progress.

In summary, solar flare prediction is moving toward larger-scale AI models that learn from increasingly rich data streams, while also demanding greater interpretability and operational readiness. The synergy of solar physics and machine learning promises to advance our predictive capabilities for space weather.

5. Conclusion

The presented study highlights the emergence of artificial intelligence in reshaping the research related to analysis of solar magnetic fields and solar flare forecasting. The amalgamation of AI in physics discipline offered tools that can interpret the intricate behavior of solar magnetic field with high accuracy compared to conventional rule-based methods and statistical approaches. AI techniques allow the modelling of complex and non-linear dependencies in solar observation. These techniques range from classical machine-learning models built on hand-crafted features to deep neural networks and emerging transformer architectures. The explainable AI concepts further enhance the interpretability of the AI framework. Each family of models including feature-driven, image-based, time-series oriented or hybrid, brings its own advantages and demonstrates the growing maturity of data-driven space-weather prediction.

At the same time, several challenges persist in this inter-disciplinary approach. Challenges such as skewed flare distributions, shifting solar-cycle conditions, inconsistent labelling practices, and the limited interpretability of complex models continue to affect reliability. These issues underscore the need for stronger dataset standards, better handling of temporal variability, and model designs that incorporate knowledge from solar physics rather than relying solely on statistical patterns.

Looking ahead, the field is clearly moving toward richer multimodal frameworks, greater emphasis on explainability, and improved integration with operational forecasting pipelines. As datasets expand and AI techniques evolve, the collaboration between solar physicists and machine-learning researchers will be essential for creating more dependable and practical flare prediction systems. Through this combined effort, AI-driven forecasting has the potential to significantly enhance our preparedness against space-weather hazards.

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