# SOLAR FLARE PREDICTION

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# ABSTRACT


Solar flares are sudden eruptions of electromagnetic radiation from the Sun's surface.

They can disrupt satellites, power grids, and communication systems.

This project aims to predict solar flares using a hybrid deep learning model (CNN + LSTM).


# INTRODUCTION

- Solar flares are classified based on intensity and can impact Earth's technological infrastructure.
- Current predictive methods rely on physics-based simulations, which are computationally expensive.
- Deep learning offers an efficient alternative by analyzing large datasets.
- Problem Statement: Can a hybrid CNN + LSTM model predict solar flare timing?

Research Questions:

- Can CNNs extract meaningful spatial features from solar images?
- How well does an LSTM model capture temporal dependencies in solar activity?
- Can combining CNNs with LSTMs improve predictive accuracy compared to standalone models?

# PROJECT OBJECTIVES

- Develop a hybrid CNN + LSTM model to predict the timing of solar flares.
- Preprocess and analyze solar images and historical flare data for model training.
- Compare the performance of the hybrid model with standalone CNN and LSTM models.
- Deploy the model as a real-time prediction tool for space weather forecasting

# METHODOLOGY

1.

***Neural Network Model & Architecture:***

- CNN Component: Extracts spatial features (e.g., sunspots, coronal loops) from solar images.
- LSTM Component: Models sequential dependencies using past solar activity data.
- Fully Connected Layer: Merges CNN and LSTM outputs for final prediction.

2.

***Data Collection & Preprocessing:***

- Solar Images: NASA SDO/Helioviewer API for solar images.
- Time-Series Data: NOAA SWPC Solar Flare Reports for historical solar flare occurrences.
- Preprocessing: Image resizing, normalization, and feature extraction; time-series normalization and sequence generation.

3.

**Data Visualization:**

- Heatmaps of sunspots and active regions.
- Temporal trends of solar activity indicators (X-ray flux, sunspot numbers).

4.

**Training & Testing Procedures:**

- Splitting dataset into training (80%) and testing (20%) sets.
- Using categorical cross-entropy loss and Adam optimizer.
- Training with various hyperparameters (learning rate, batch size, epochs).

5.

**Tools & Libraries:**

- Frameworks: TensorFlow, Keras, OpenCV, Pandas, NumPy.
- Visualization: Matplotlib, Seaborn.
- Deployment: Flask/FastAPI for API-based inference, Google Cloud Run.

# PROJECT PLAN

- **Phase 1: Data Collection & Preprocessing**
  - Collect solar images (NASA SDO/Helioviewer API) and historical flare data (NOAA SWPC).
  - Preprocess data: resizing, normalization, feature extraction.
  - Milestone: Cleaned dataset ready for training.

**Phase 2: Model Development**

- Design CNN for spatial features and LSTM for temporal dependencies.
- Combine CNN + LSTM into a hybrid model.
- Milestone: Hybrid model architecture finalized

**Phase 3: Model Training & Evaluation**

- Train hybrid model on preprocessed data.
- Evaluate using accuracy, precision, recall, F1-score, and MAE.
- Compare hybrid model with standalone CNN and LSTM.

- **Phase 4: Deployment & Testing**
  - Develop API using Flask/FastAPI.
  - Deploy model on Google Cloud Run.
  - Test real-time predictions.
  - Milestone: Real-time prediction tool deployed.

- **Phase 5: Documentation & Final Review**
  - Prepare project report and presentation.
  - Present findings and demonstrate deployed model.
  - Milestone: Final deliverables submitted.

# EXPECTED OUTCOMES

1. A trained CNN + LSTM model capable of predicting the occurrence of solar flares.

2. Comparative analysis of CNN-only, LSTM-only, and CNN + LSTM hybrid models.

3. Deployment of a real-time predictive tool for solar flare forecasting and insights into solar flare prediction for space agencies and researchers.

# EVALUATION METRICS

**Accuracy:** Percentage of correct predictions.

**Precision & Recall:** Evaluates model's performance in identifying flares

**F1-Score:** Balances precision and recall for imbalanced datasets.

**Mean Absolute Error (MAE):** Measures deviation in flare timing predictions.

**Confusion Matrix Analysis:** Visualizes classification errors.

# CONCLUSION

This project aims to develop a deep learning-based solar flare forecasting system using a hybrid CNN + LSTM model.

By leveraging both spatial and temporal features, the model is expected to provide accurate flare predictions, offering an early warning system for space weather monitoring.

The results of this project could contribute significantly to satellite protection, communication systems, and space exploration research.

# THANK YOU!