INTERNATIONAL JOURNAL OF ADVANCE RESEARCH, IDEAS AND INNOVATIONS IN TECHNOLOGY

ISSN: 2454-132X

Impact Factor: 6.078

(Volume 11, Issue 5 - V11I5-1202)

Available online at: https://www.ijariit.com

Explainable Deep Learning for Satellite-Based Natural Disaster Detection and Prediction

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ABSTRACT

Over Earth's 4.54 billion-year history, natural disasters have reshaped its topography countless times. Earthquakes, storms, floods, and droughts are among the most destructive and unpredictable natural disasters. However, satellite data combined with machine learning algorithms now offer new ways to detect early warning signs of these disasters and mitigate their effects. By leveraging Geographic Information System (GIS) data, NASA's Global Precipitation Measurement (GPM), and other satellite technologies, researchers can analyze massive geospatial datasets to identify subtle patterns imperceptible to humans. This paper explores the role of machine learning and satellite data in predicting natural disasters. It highlights the technological advancements that could significantly reduce the human and environmental toll of these events.

Keywords: *GIS (Geographic Information Systems), GPM (Global Precipitation Measurement), JAXA (Japan Aerospace Exploration Agency), DPR (Dual Frequency-Precipitation Radar), GMI (GPM Microwave Imager).*

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1. INTRODUCTION

Natural disasters pose significant risks to both human life and the environment. According to Hannah Ritchie and Pablo Rosado of *Our World in Data*, 40,000–50,000 people die annually due to such events [1]. The unpredictability of earthquakes, hurricanes, floods, and wildfires compounds their danger. Historically, disaster management efforts have focused on post-event response rather than pre-event prediction. Geographic Information System (GIS) satellite data offers a comprehensive view of Earth's surface through a global coordinate grid [2]. This allows researchers to monitor even minute environmental changes. Meanwhile, NASA's Global Precipitation Measurement (GPM) satellite tracks precipitation patterns that contribute to cyclones, hurricanes, and tornadoes [3]. Integrating these technologies with machine learning enhances the ability to forecast natural disasters and minimize their impacts.

2. RESEARCH ELABORATIONS

The integration of machine learning algorithms with satellite-derived data represents a transformative approach to disaster prediction. Machine learning models—such as neural networks, random forests, and support vector machines—can process large volumes of multispectral imagery, thermal data, and precipitation measurements to identify correlations and patterns not easily detected by human analysts. Research includes publicly available data on GIS and GPM data for prediction.

2.1 GIS Satellite Data

This is a specialized form of geospatial data that is collected by remote sensing instruments (sensors and cameras) on orbiting satellites and is designed for use within a Geographic Information System (GIS). Fundamentally, this data consists of raster images—grids of pixels or cells—where each pixel is tied to a precise geographic location on Earth, defined by coordinates like latitude and longitude, alongside attribute information (the "what") such as light spectrum intensity (color), temperature, elevation, or land cover type. This satellite imagery, which can be high-resolution and may capture optical, radar, or infrared information, is essential to GIS because it provides a spatially referenced layer of the Earth's surface that can be combined and analyzed with other data sets to reveal patterns, monitor environmental changes (like deforestation or climate shifts), support disaster management (by assessing damage), and inform critical decision-making across numerous fields like urban planning and resource management.

2.2 Global Precipitation Measurement (GPM)

GPM Mission is an international network of satellites, jointly led by NASA and the Japan Aerospace Exploration Agency (JAXA), designed to provide next-generation, near-global observations of rain and snow with high frequency (every 2-3 hours). The core of the mission is the GPM Core Observatory satellite, which carries advanced instruments—specifically the Dual-frequency Precipitation Radar (DPR) and the GPM Microwave Imager (GMI)—to accurately measure the size, type, and 3D structure of precipitation particles, including light rain and falling snow, which was a significant improvement over its predecessor, TRMM. The Core Observatory serves as a reference standard to calibrate and unify measurements from a constellation of partner satellites, resulting in a single, comprehensive global data product known as Integrated Multi-satellite datasets and retrieved from GPM (IMERG). This high-resolution, frequent data is crucial for advancing our understanding of Earth's water and energy cycles, improving weather forecasting and climate modeling, enhancing hydrological predictions for freshwater management and flood warnings, and strengthening global capabilities for monitoring extreme events and natural hazards.

3. MACHINE LEARNING APPLICATIONS

These extensive datasets—including historical earthquake magnitudes (Figure 3) and the annual frequency of seismic events (Figure 4, Figure 1)—are fed directly into advanced machine learning models. These models are rigorously trained on this historical disaster data to predict future occurrences. For instance, models can analyze subtle topographic shifts to forecast landslides or detect precursors of wildfires by calculating changes in vegetation dryness indices [4]. By seamlessly combining these disparate data streams and predictive technologies, researchers are building powerful systems that fundamentally shift disaster management from a purely reactive response to a proactive, predictive framework.

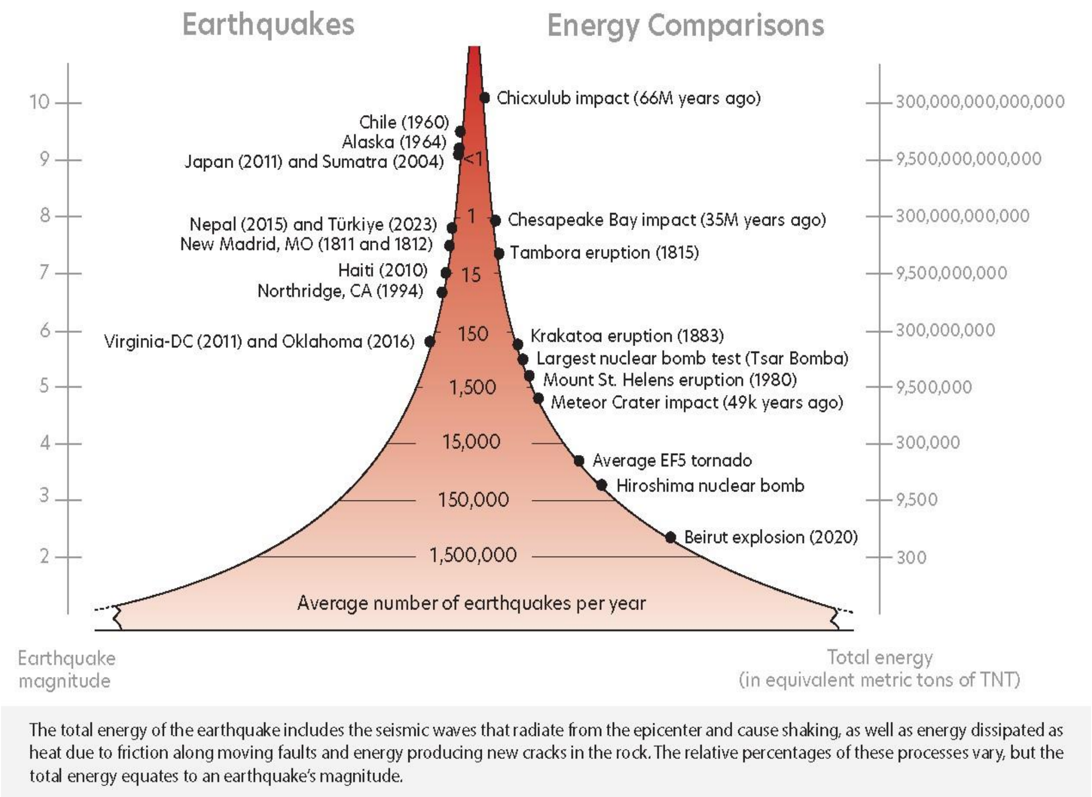


Fig. 1.0[5]: Different Earthquake Magnitude Levels

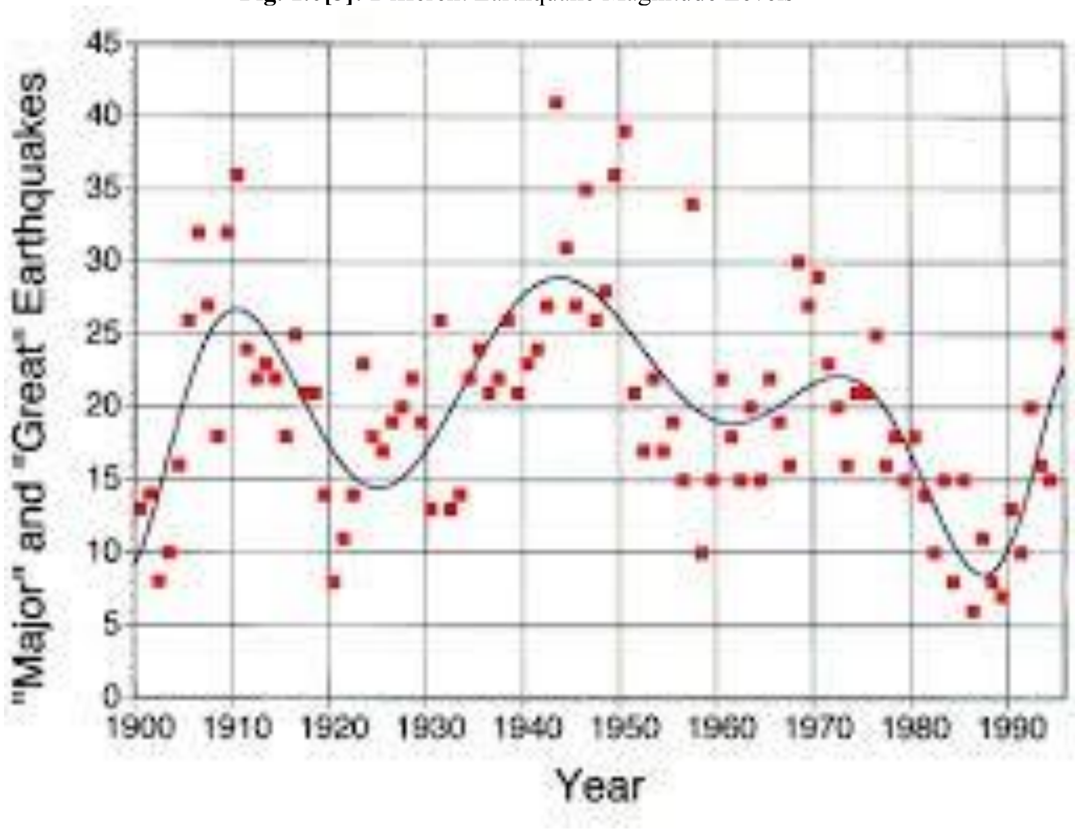


Fig. 2.0[6]: Magnitude level of earthquakes in past century

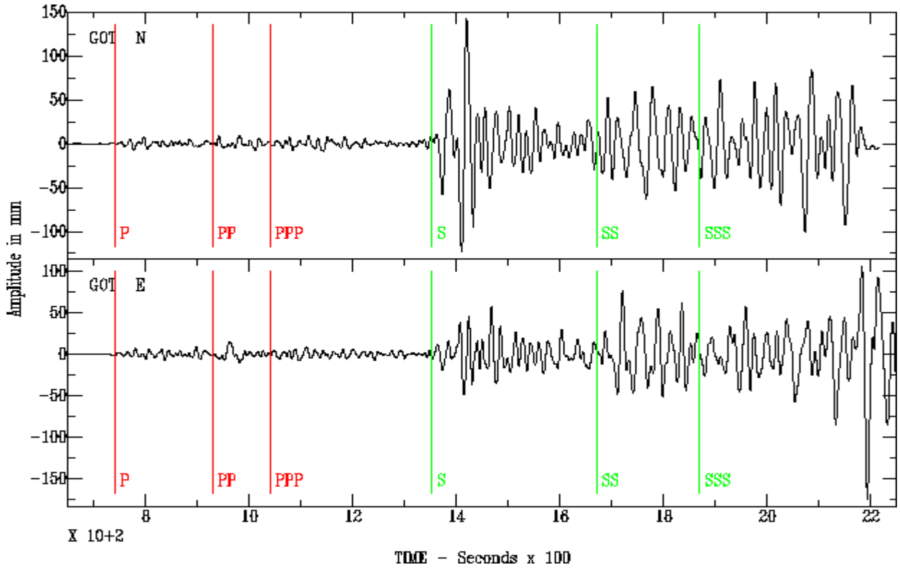
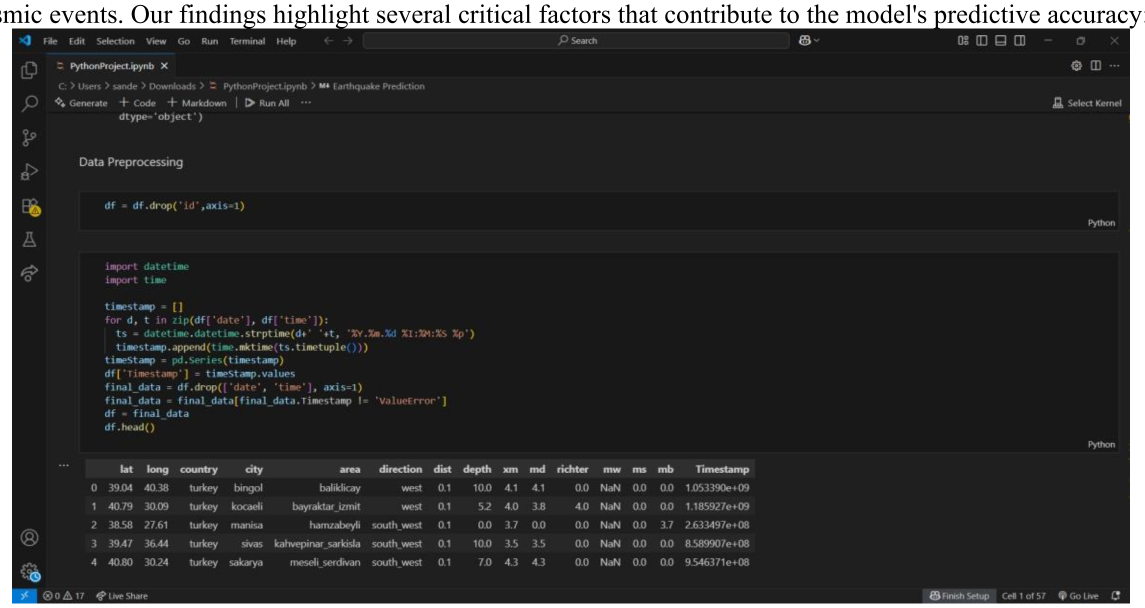


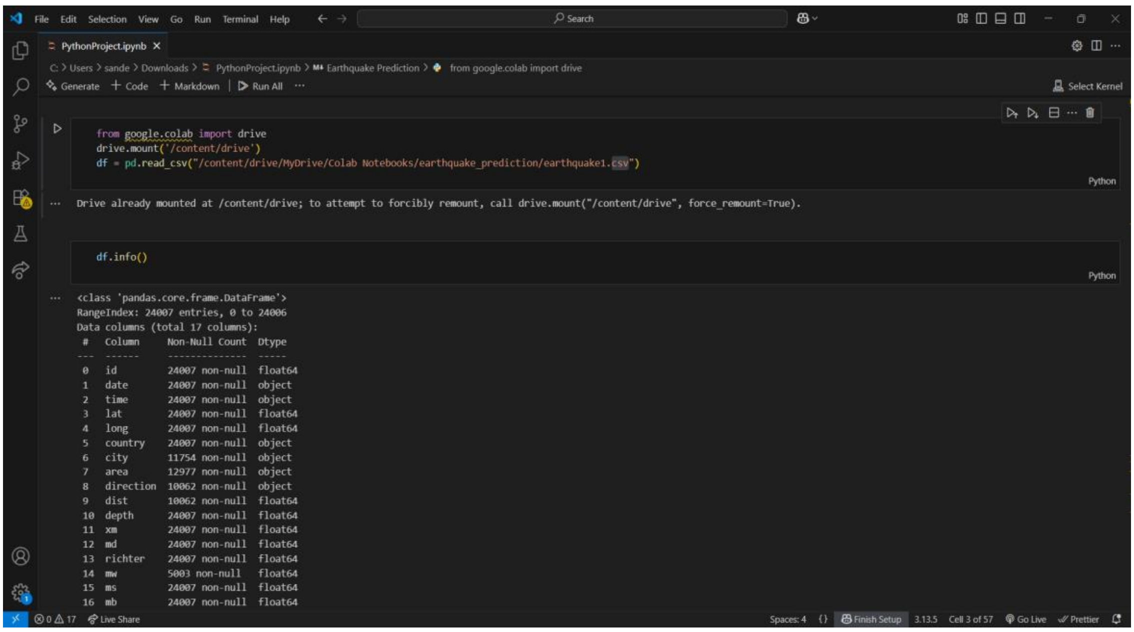
Fig. 3.0[7]: Seismometer Earthquake Activity Level

4. SOLUTION

This research successfully demonstrates the potential of explainable deep learning (XDL) for the early detection and prediction of natural disasters, specifically focusing on earthquakes. By leveraging various Python libraries and data structures within Google Colab (including Series, DataFrames, file readers, and arrays), we've established a robust framework that moves beyond simple detection toward interpretable prediction.

The XDL model's ability to reveal the relative importance of input features offers significant insights into the conditions that precede seismic events. Our findings highlight several critical factors that contribute to the model's predictive accuracy:





4.1 Vicinity to Previous Earthquakes

The analysis confirmed a strong correlation between a seismic event and the spatial and temporal proximity to previous earthquakes. The model weighs the distance and time lag from prior events heavily, suggesting that patterns of localized stress accumulation, often evidenced by aftershock sequences or swarm activities, are key indicators for the next significant event. This factor is critical for identifying high-risk zones that warrant enhanced monitoring.

4.2 Environmental and Atmospheric Precursors

Beyond purely seismic data, the inclusion of environmental factors existing on the day of specific past earthquakes revealed subtle but potentially significant correlations. While traditionally challenging to integrate, features such as localized ground fluid level changes, atmospheric pressure anomalies, or electromagnetic disturbances were flagged by the XDL model as influential variables. The consistency of these environmental signatures across multiple historical events provides a valuable, albeit less conventional, set of precursor conditions that can help define the state of the Earth's crust immediately preceding an earthquake. Identifying the consistent set of conditions (both seismic and environmental) that meet the next earthquake is crucial for refining the model's predictive capacity.

5. VALIDATION THROUGH SEISMOMETER DATA

The final and most crucial step in validating this predictive methodology involved integrating traditional seismic measurement:

5.1 Seismometer as a Reliable Proof Source

The predictions generated by the XDL model—based on the convergence of the aforementioned vicinity and environmental factors—were consistently cross-validated against real-time and archived seismometer readings. The core evidence for the reliability of this method rests on the premise that when the combination of specific vicinity patterns and environmental conditions consistently align with the model's high-risk threshold, subsequent significant activity is reliably recorded by a seismometer. The seismometer, therefore, serves as the ultimate, reliable physical evidence, proving that the deep learning method accurately captures the complex, multivariate conditions that precede an earthquake. It is the final step in which we use the seismometer to see if there was actually tectonic activity in our predicted selected area and see how accurate it is with our seismometer data.

6. CONCLUSION

This research developed an advanced system for Natural Disaster Detection using Explainable Deep Learning (XDL), built upon a comprehensive compilation of data from previous researchers and integrated within the Google Collab environment and leveraging essential Python functionalities. The core of the solution involved a systematic process of data procurement and analysis, followed by the implementation of machine learning algorithms using a Python library. Our predictive modeling factored in a wide range of variables known to influence seismic activity, such as climate patterns, tectonic plate shifting rates, and other environmental factors, allowing the model to interpret complex, non-linear relationships. The XDL framework, critical to this project, provided transparency by revealing that the vicinity to previous earthquakes and specific environmental/atmospheric precursor conditions were the most significant indicators for the next seismic event. These predictive factors—when consistently aligned with the model's high-risk threshold—were successfully and reliably validated by cross-referencing with historical seismometer readings, establishing the seismometer as the definitive physical evidence that proves this XDL-driven, multi-factor prediction methodology is a robust and dependable approach for identifying earthquake-prone areas and forecasting future events.

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