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The Role of Machine Learning in Predicting Natural Disasters

Claire Niyonzima K.

Faculty of Engineering Kampala International University Uganda

ABSTRACT

Natural disasters such as earthquakes, floods, and storms have a profound impact on human life and infrastructure. Despite advancements in early warning systems and disaster preparedness, predicting these events with high accuracy remains a significant challenge. Machine learning (ML) offers promising solutions for enhancing prediction accuracy and mitigating the adverse effects of natural disasters. This paper explores the role of ML in predicting various natural disasters by analyzing large datasets, extracting relevant features, and applying advanced algorithms. The study also examines the challenges associated with data quality, model transferability, and the nonstationary nature of natural disasters. Case studies demonstrate the practical applications of ML in real-world scenarios, highlighting its potential to revolutionize disaster prediction and risk management. Finally, the paper discusses future directions for research in ML, focusing on improving model robustness, feature engineering, and the integration of synthetic data to better predict natural disasters.

Keywords: Machine Learning, Natural Disaster Prediction, Earthquakes, Floods, Tsunamis.

INTRODUCTION

The frequented occurrence of natural disasters such as floods, earthquakes, tsunamis, etc. has had a great impact on human life. Governments and institutions have tried to prevent these disasters, create warning systems, and protect lives and property, but there are still problems in these areas that need to be solved. This is why artificial intelligence and machine learning techniques have been applied to analyze and forecast natural disasters. With the careful selection of parameters and features, machine learning adds potential to many of the existing methods that have difficulties in predicting natural disasters [1] A growing number of natural hazards have a global impact on people's safety and their properties. Due to population growth, global warming, and climate change, the number of affected people, number of fatalities, and economic loss from natural hazards are increasing over time. For example, the number of reported natural hazards from 1900 to 2020 is about 33,088. Earthquakes, floods, and storms are the most common natural hazards causing the greatest number of fatalities [2]. Natural disasters can happen in an unexpected way and at any time, which makes prevention and preparedness difficult. As a result, machine learning has been applied to natural disasters, including analysis and identification, and is rapidly expanding. Natural disasters that can be early recognized include earthquakes (temporal, spatial, and magnitude), floods (river, coastal, and flash floods), global warming (temperature, positive snow cover, and PM10), and storms (cyclones and typhoons). In this research, the role of machine learning is focused on the forecasting of natural disasters [1]. In order to forecast natural disasters, feature extraction is paramount. However, although there are advances in analysis, not much research is focused on feature extraction. There are many problems with features such as inaccuracy, selection of noise, and over-parameterization. Feature extraction is done with wavelet analysis, autoregressive, and minimum description length. Wavelet analysis extracts geoelectric fields with wavelet transform. The autoregressive based on geoelectric anomalies extracts seismic precursors. The minimum description length extracts temperature variations as precursors of global warning. By applying machine learning to the extracted features, prediction can be obtained with good accuracy [3].

FUNDAMENTALS OF NATURAL DISASTERS

Natural disasters are extreme, sudden events caused by environmental factors, resulting in significant damages, casualties, and economic losses. These catastrophic events are mostly unforeseen and cannot be prevented, leading to a disaster when they hit populated areas. Natural disasters typically occur in specific geographic locations, making some areas more prone to disasters than others. According to the United Nations Office for Disaster Risk Reduction (UNDRR), 2284 natural hazard events were reported globally in 2021. From these, 824 were classified as disasters, affecting 112 million people, resulting in 30,000 deaths and over 270 billion U.S. dollars (USD) in economic losses. Despite being renowned as an event with dreadful consequences, terminology and definition remain diverse among people from different educational and cultural backgrounds. For example, Asian countries were mostly affected by floods and cyclones, while Western countries were affected mainly by drought and wildfires. Hence, it is crucial to understand the different types of natural disasters that can occur [4]. Natural disasters are classified into broad categories based on the underlying phenomena. Wowk pioneered the classification of natural disasters into nine categories. The first five are atmospheric hazards, including tropical cyclones, tornadoes, thunderstorms, and winter storms. The sixth category is hydrological hazards, such as floods from heavy rainfall or dam construction failure. The seventh category is seismic hazards, including earthquakes, tsunamis, and volcanic eruptions. The eighth category is electromagnetic hazards such as asteroids and meteorites. The final category, biological hazards, involves disease outbreaks of bacteria, fungi, and viruses. The most common natural disasters that occur are flooding, wind storms, droughts, heat waves, earthquakes, forest fires, volcanic eruptions, and displacement waves [5]. Natural disasters are a threat to communities globally, causing severe loss of life and property, distress to people, and disruption to the social system. It is essential to assess the possible consequences of such hazards, particularly in developing countries where existing networks might be inadequate. To avoid disasters, vulnerability assessments of urban and interurban areas are a sound approach to detect possible hazards. Risk assessment helps to depict the impact of natural disasters on widely used stakeholders and decision-makers. Natural disaster risk assessment aims to minimize adverse negative impacts and enhance resilience through risk mitigation [6].

MACHINE LEARNING TECHNIQUES FOR DISASTER PREDICTION

Machine learning (ML) techniques are being widely promoted for the prediction of natural disasters, such as earthquakes or tsunamis. A natural disaster is a catalyst for devastation due to human and economic casualties. Bayes' theorem has proven helpful, and computer science has contributed algorithms based on Markov chains for simulating the dataset, as well as algorithms like Latent Dirichlet Allocation to classify on the topic of disaster. Various techniques to obtain earth and ocean-based scientific measurements are proposed using ML techniques. Sean O, a research scholar, proved through literature that ML prediction rates are nearly 92% for natural disasters. Abu Abdalla, M et al. performed a comparative study on earthquake prediction, using eight machine learning classifiers finding Random Forest had the best performance for data between 2000 and 2011 predicting some days in advance [7]. Tsunami hazards pose considerable threats to coastal communities, especially in developing nations. Accurately predicting tsunami impact has been a central interest for scientists for decades, and the recent development of big data technology is expected to facilitate this goal. Pioneering machine learning approaches on tsunami hazard modeling considering both tsunami inundation fields and hydrodynamic forces are reviewed. Moreover, significant groundwork has been laid to pave the way for the large-scale application of a new era of tsunami hazard modeling. The oceanic disasters' database has been used in a long-term and time-varying basis for an algorithm of supervised and unsupervised learning. The widely used clustering algorithm in hydrology, ML, unsupervised learning, and Hierarchical Ascendant Clustering has been proposed to delineate regions in the Hawaiian Islands and introduced a new approach in the delineation of regions. The prediction of ITD had a significant gain in performance using ML algorithms with inputs based on local ocean conditions. Hurricane occurrence prediction products based on ML techniques were developed, and the high potential for this methodology to significantly improve the operational tsunami warning capabilities has been demonstrated [8].

CASE STUDIES AND APPLICATIONS

The global increase in the frequency and severity of natural disasters poses a serious threat to the stability of society. Natural disasters may lead to human casualties, economic losses, disruption in services, dispersion of chemicals, timings, and much more that may jeopardize the quality and safety of social life. Natural disasters induce long-term effects on local communities and infrastructure that makes recovery possible only with a long-term strategy [6].

It therefore becomes important to develop strategies for disaster risk mitigation and management so that losses due to disasters can be greatly reduced. The development of such strategies requires a comprehensive understanding of the social and economic costs and the technical and institutional requirements for reducing them. This task requires a wide range of information on the potential risks and vulnerability of natural disasters, which is often not available at an appropriate level or in a suitable form [9]. Machine learning (ML) is one of the important branches in artificial intelligence (AI) and computer science. Over the last two decades, ML has penetrated almost every aspect of day-to-day human life. In the recent decade, increasing computing power along with the creation of large datasets has brought a sudden spike in the popularity of ML applications. Building complex physical models to predict natural hazards is challenging due to difficulties in acquiring the required high-quality and large datasets, creation of numerical simulations, high dimensionality of the parameter space, etc. As an alternative, ML-based approaches demonstrated their applicability due to the ability to learn directly from existent datasets [10]. A brief overview of disaster-prone regions of the world and the data source of natural hazards is presented. Then, several nano- to mega-scale natural disasters are studied with convolutional and recurrent neural networks that take raw datasets with only the location and time as inputs to predict the future damage radius of the natural hazard. It is demonstrated that using the same modeling framework, these networks can also be utilized to forecast natural disasters like tsunamis, earthquakes, tornadoes, and typhoons. Unlike the past approaches of hazard modeling, with econometric equations based on extensive domain knowledge, ML approaches learn solely from past data, which essentially simplifies the modeling framework. In this regard, the challenges to be overcome by the ML approaches to be used as a rapid and accurate real-time hazard forecasting tool are also discussed [1].

CHALLENGES AND FUTURE DIRECTIONS

Despite its immense potential, machine learning applications in natural disaster prediction and mitigation are fraught with challenges. Data quality and availability often plague researchers, especially in developing nations, where the ramifications of underpreparedness are devastating. Machine learning's inherent "black box" nature further complicates things, obstructing cross-context knowledge transfer. This problem is amplified in natural disasters, which are often multifactorial and nonstationary. Consequently, a machine learning model tuned for the prediction of a particular event in a specific area may not yield accurate predictions for the same event in a different region, or even for a different event in the same area. The prevailing approach to modeling natural disasters often assumes that events are independent and stationary over time. This means that models developed for earlier events are generally not well suited to future events, prompting the need for consistently updated models [11]. Several research opportunities in machine learning could help address some of these challenges. Synthetic features could be engineered in order to aid prediction, considering the range of spatial scales in which natural disasters are observed. Ensemble methods may also aid in increasing robustness to space-time dependence and nonstationarity even within a single machine learning framework. Finally, the informative coherent structure of the language used could be utilized to analyze large-scale space-time observations of the events [12].

CONCLUSION

Machine learning has emerged as a critical tool in the prediction and management of natural disasters. Its ability to process vast amounts of data and identify patterns offers a significant advantage over traditional methods. However, challenges such as data quality, model interpretability, and the nonstationary nature of natural disasters must be addressed to fully realize the potential of ML in this field. Future research should focus on developing more robust models, enhancing feature extraction techniques, and exploring the use of synthetic data to overcome these challenges. By advancing ML methodologies, we can improve disaster preparedness, reduce economic losses, and save lives, ultimately making communities more resilient to the devastating effects of natural disasters

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