

Chapter 2

Transitioning From Legacy Systems to AI: A Holistic Approach to Disaster Detection

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ABSTRACT

Disaster detection has long been a challenge due to the complexity and dynamic nature of natural disasters. Traditional methods often lack real-time capabilities and struggle to account for these challenges. This chapter explores the transition from legacy systems to Artificial Intelligence (AI) and Machine Learning (ML) for a more holistic approach. AI and ML concepts, including supervised and unsupervised learning algorithms, can analyze vast amounts of data from various sources to identify patterns and anomalies indicative of impending disasters. The integration of plant science offers additional insights into ecosystem responses to environmental changes, further refining AI models. The chapter explores the business benefits of AI/ML in disaster detection, including cost savings, improved risk management, and enhanced resilience. It advocates for multidisciplinary collaboration among scientists, technologists, and business leaders to create a comprehensive, real-time disaster detection system.

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1. INTRODUCTION

1.1. Threat of Natural Disasters

The frequency and severity of natural catastrophes are escalating at an alarming rate, inflicting significant damage and devastating impacts on populations worldwide. (Caldera & Wirasinghe, 2022) According to the United Nations Office for Disaster Risk Reduction (UNDRR), the number of recorded natural disasters has seen a dramatic surge in recent years. Between 2000 and 2019, approximately 7,348 notable disaster events resulted in a staggering \$2.97 trillion in economic damages and affected over 4 billion individuals globally (UNDRR, 2020). These figures underscore the urgent need for effective systems of catastrophe identification and management.

Natural disasters have a profound economic impact, with the World Bank estimating an annual economic loss of over \$520 billion (World Bank, 2016). These events push nearly 26 million people into poverty each year. The financial implications are broad, encompassing direct costs such as damage to infrastructure, homes, and businesses, as well as indirect costs like lost productivity, disrupted trade, and long-term effects on livelihoods and economic stability.

From an environmental perspective, natural disasters have equally detrimental impacts. Floods, hurricanes, wildfires, and earthquakes have the potential to result in habitat destruction, loss of biodiversity, erosion of soil, and pollution of water. The 18.6 million hectares scorched by Australian wildfires from 2019 to 2020 had a significant and detrimental impact on ecosystems and the population of many species. The 2011 earthquake and tsunami in Japan led to substantial environmental destruction, including radioactive contamination caused by the Fukushima Daiichi nuclear crisis.

Urbanization, climate change, and environmental degradation are all contributing to the rising occurrence and severity of natural disasters. Among these factors, climate change stands out as a significant driver, altering weather patterns and increasing the likelihood of intense storms. The IPCC warns that climate change is not just likely but certain to exacerbate the occurrence and severity of heat waves, intense precipitation events, and the vulnerability to droughts and floods in many regions. This underscores the urgent need for climate action to mitigate these effects.

Despite these challenges, traditional methods of identifying disasters, which typically rely on human expertise and predetermined thresholds, need to be more effective. These methods need help managing the intricacy and ever-changing nature of modern disasters; hence, there is a critical need for the development of more advanced, real-time detection systems. The integration of artificial intelligence (AI)

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