A Review on Application of Machine Learning Techniques in Climate Change and Disaster Management

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Abstract

Climate change and its associated impacts have emerged as critical global challenges, posing significant threats to both natural ecosystems and human societies. Concurrently, the frequency and severity of natural disasters, such as hurricanes, floods, wildfires, and droughts, have increased in recent years, leading to devastating consequences for communities worldwide. To address these multifaceted challenges effectively, the integration of advanced technologies like Machine Learning (ML) has become essential. This paper presents a comprehensive review of the application of Machine Learning techniques in climate change and disaster management. The primary objective is to explore how ML models and algorithms can contribute to enhancing understanding, prediction, and mitigation efforts related to climate change and natural disasters. Firstly, the paper discusses the use of Machine Learning in climate change analysis. ML models are leveraged to analyze vast amounts of climatic data, including temperature records, precipitation patterns, and atmospheric compositions, enabling researchers to identify long-term trends, detect anomalies, and forecast future climate scenarios more accurately. Additionally, ML-based climate models help in assessing the impacts of various greenhouse gas emission scenarios, aiding policymakers in formulating effective mitigation and adaptation strategies. Secondly, the paper delves into the application of Machine Learning techniques in disaster prediction and early warning systems. By analyzing historical disaster data, satellite imagery, weather patterns, and other relevant variables, ML algorithms can forecast the occurrence and severity of disasters in specific regions. These early warning systems enable authorities to issue timely alerts, evacuate vulnerable populations, and allocate resources more efficiently, potentially reducing the loss of life and property. Furthermore, the paper examines how Machine Learning facilitates disaster response and recovery efforts. ML algorithms are utilized to process real-time data from remote sensors, social media, and other sources to assess the extent of damage after a disaster. This information aids disaster response teams in prioritizing rescue operations, allocating aid, and coordinating relief efforts promptly. The review also addresses the challenges and limitations associated with the application of Machine Learning in climate change and disaster management. These challenges include data quality and availability, model interpretability, and ethical considerations related to decision-making in critical situations.

Keywords

Machine learning, Neural Networks.

INTRODUCTION

The issues posed by natural catastrophes and the planet's shifting climate patterns are best addressed by combining the fields of disaster management and climate change. Long-term changes in temperature, precipitation, wind patterns, and other aspects of the Earth's climate system are referred to as "climate change," and they are mostly brought on by human activities such the burning of fossil fuels, deforestation, and industrial operations. These actions cause the atmosphere to be filled with heat-trapping greenhouse gases including carbon dioxide (CO2) and methane (CH4). As the world warms, a number of environmental effects are brought about, such as an increase in the frequency and severity of extreme weather events, increasing sea levels, the melting of the ice caps, altered rainfall patterns, and disruptions to ecosystems [1]. As the world warms, a number of environmental effects are brought about, such as an increase in the frequency and severity of extreme weather events, increasing sea levels, the melting of the ice caps, altered rainfall patterns, and disruptions to ecosystems. Climate change is a major worldwide issue that needs immediate attention and action since these changes have far-reaching effects on both human cultures and the natural world. On the other hand, disaster management includes all planning, preparation, response, and recovery activities intended to lessen the effects of disasters brought on by natural hazards. Natural hazards are unpredictable phenomena that can affect people, their property, and the environment. They are brought on by geological, meteorological, hydrological, or climatic variables. Examples include landslides, wildfires, tsunamis, hurricanes, floods, droughts, and earthquakes. The severity and frequency of natural catastrophes have increased recently as a result of climate change [2]. For instance, larger storms may result from warmer oceans, frequent and severe heatwaves may result from rising temperatures, and protracted droughts or periods of heavy rain and flooding may result from changing precipitation patterns.
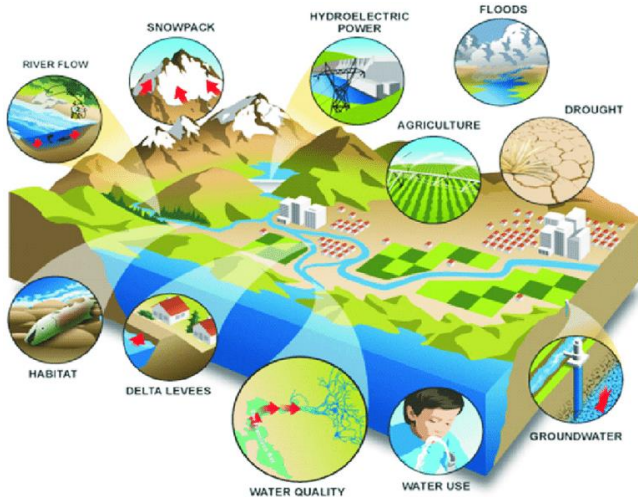
Figure 1. Implications of Climate change in environment and natural resources
Source: http://www.opengreenspace.com

Comprehensive plans and coordinated actions at the local, national and international levels are necessary for effective disaster management. Mitigation aims to lower the likelihood of disasters by putting in place laws and procedures to lessen exposure to dangers. In order to address the underlying causes of climate change, it involves initiatives to reduce greenhouse gas emissions and embrace sustainable practices. Planning and organizing resources, infrastructure and protocols in advance in order to respond to anticipated calamities is known as preparation. Raising public awareness and holding exercises to instruct people on what to do in an emergency are also parts of preparation. When a calamity strikes, response activities are put into action. This stage entails taking urgent measures to solve the issue, manage resources, and save lives [3]. Collaboration between numerous institutions, including emergency services, governmental entities, NGOs, and foreign assistance organizations, is common during this phase. Following the disaster, the emphasis is on moving forward with the impacted communities' reconstruction. Restoring infrastructure, sustaining livelihoods, and making the damaged communities more disaster-resistant are all part of this phase. Because climate change can exacerbate the effects of natural disasters, efficient disaster management is even more crucial. This is why climate change and disaster management are interwoven. A more resilient and sustainable future for the earth and its inhabitants depends on comprehensive programmes that address disaster risk reduction, adaptation, and mitigation of climate change.
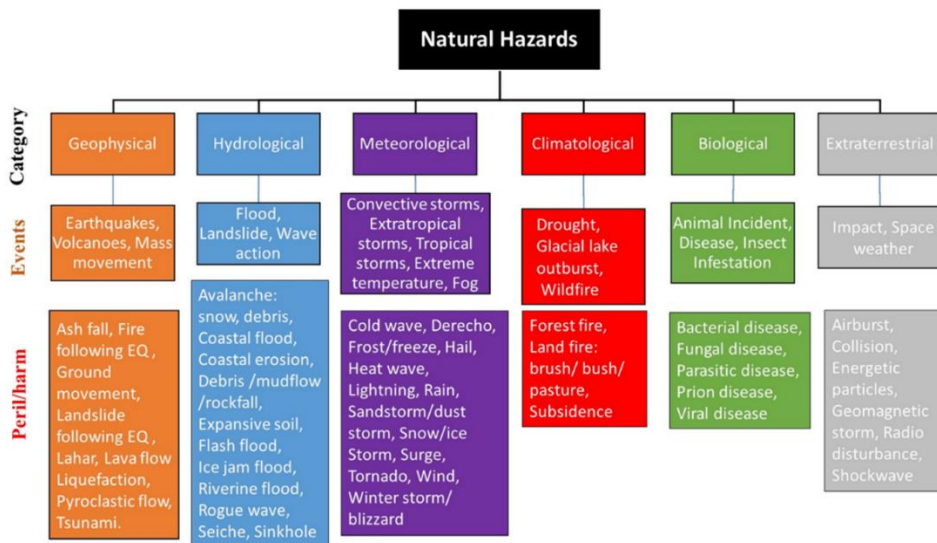
Figure 2. Classification of Natural Hazards
Source: https://www.mdpi.com/2673-8392/1/4/84

CLIMATE CHANGE

Long-term changes in Earth's climate patterns, such as fluctuations in temperature, precipitation, wind patterns, and other climatic elements, are referred to as climate change. The word "climate change" most often refers to the quick and dramatic changes seen during the Industrial Revolution, which are mostly ascribed to human activity. While climate naturally fluctuates across geological time scales, it is most generally used to describe these changes.

The quantity of greenhouse gases (GHGs) in the atmosphere, mainly carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and fluorinated gases, is the main cause of the present climate change [4]. The greenhouse effect is a result of these gases' ability to retain solar heat that would otherwise escape back into space. Global warming is the effect of the Earth's surface and lower atmosphere warming.

The emission of greenhouse gases into the atmosphere has greatly grown as a result of human activities such as the burning of fossil fuels (coal, oil, and natural gas), deforestation, industrial processes, agriculture, and waste management. The Earth's average temperature has risen throughout the past century and beyond as a result of these activities amplifying the natural greenhouse effect.

Effects of climate change

The impacts of climate change on the environment and human societies are extensive. Since the late 19th century, the Earth's average temperature has dramatically risen. Numerous repercussions of this warming trend include increasingly frequent and severe heatwaves, which can be harmful to ecosystems, agriculture, and human health. As a result of polar ice caps and glaciers melting due to global warming, sea levels are rising. As a result, there is a greater chance of floods, erosion, and the destruction of many plant and animal species' habitats in coastal areas and low-lying islands. Extreme weather phenomena, such as hurricanes, typhoons, droughts, torrential rains, and flooding, are becoming more common and severe due to climate change. These occurrences have the potential to seriously harm infrastructure, destabilise ecosystems, and lead to the destruction of lives and property. Increasing atmospheric CO2 concentrations cause ocean acidification in addition to global warming. The oceans' increased acidity from absorbing extra CO2 can affect marine life, especially corals and some shellfish and other animals with calcium carbonate shells or skeletons. As a result of climate change, plant and animal species' distribution patterns and behavioral patterns may change [5]. The inability of some species to move or adapt to new habitats may cause changes in biodiversity and even the extinction of some species. Changes in temperature and precipitation patterns can have an impact on agricultural output, which can result in crop failures and food shortages in sensitive areas. Extreme weather conditions can also harm crops and destabilise food supply lines. In particular for vulnerable people, climate change can make health issues worse. Heat waves can result in heat-related illnesses, and alterations in weather patterns can have an impact on the transmission of infectious diseases as well as the quality of the air and water. As a result of forced migration due to rising sea levels and an increase in the frequency of extreme weather events, populations may be displaced due to climate change and may face resource-related conflicts. Global collaboration, sustainable practices, and initiatives to minimize greenhouse gas emissions are all necessary for combating climate change and its repercussions [6].

Transitioning to renewable energy sources, increasing energy efficiency, preserving forests, and implementing sustainable land-use practices are all examples of mitigation techniques. Additionally, adaptation strategies work to increase communities' and ecosystems' capacity to withstand climate change's inevitable effects. There is hope for reducing the most severe effects of climate change and securing a more sustainable future for the world by acting collectively. Extreme weather phenomena, such as hurricanes, typhoons, droughts, torrential rains, and flooding, are becoming more common and severe due to climate change. These occurrences have the potential to seriously harm infrastructure, destabilise ecosystems, and lead to the destruction of lives and property. Increasing atmospheric CO2 concentrations cause ocean acidification in addition to global warming [7]. The oceans' increased acidity from absorbing extra CO2 can affect marine life, especially corals and some shellfish and other animals with calcium carbonate shells or skeletons. As a result of climate change, plant and animal species' distribution patterns and behavioral patterns may change. The inability of some species to move or adapt to new habitats may cause changes in biodiversity and even the extinction of some species. Changes in temperature and precipitation patterns can have an impact on agricultural output, which can result in crop failures and food shortages in sensitive areas. Extreme weather conditions can also harm crops and destabilise food supply lines. In particular for vulnerable people, climate change can make health issues worse. Heat waves can result in heat-related illnesses, and alterations in weather patterns can have an impact on the transmission of infectious diseases as well as the quality of the air and water. As a result of forced migration due to rising sea levels and an increase in the frequency of extreme weather events, populations may be displaced due to climate change and may face resource-related conflicts. Global collaboration, sustainable practises, and initiatives to minimise greenhouse gas emissions are all necessary for combating climate change and its repercussions.
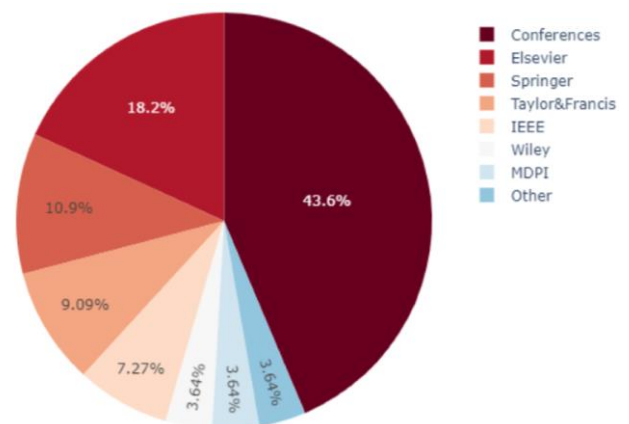
Figure 3. Literature Survey in different publications
Source: https://www.mdpi.com/2504-4990/4/2/20

The systematic planning, organization, coordination, and implementation of actions to mitigate, respond to, and recover from natural or man-made disasters is referred to as disaster management, sometimes known as emergency management. It entails a number of procedures and actions meant to lessen the effects of catastrophes on people's lives, property, and the environment. Disaster management aims to reduce fatalities, lessen property damage, and make it easier for impacted communities to recover and rebuild.

Disaster Management Key Elements

Risk assessment is the process of identifying potential risks and their weak points in order to assess the degree of risk that a community or region faces. Effective disaster management plans can be created by having a thorough understanding of the different sorts of catastrophes that may occur and their possible effects. Disaster risk reduction and

effect reduction are the main goals of mitigation strategies. To prevent construction in high-risk locations, this can entail a number of initiatives, including the implementation of building rules and standards, the construction of flood defenses, the establishment of early warning systems, and the promotion of sustainable land-use practises. Being ready to respond to calamities when they strike is being prepared [8]. It include creating emergency plans, establishing communication channels, planning training sessions and drills for emergency responders, and informing the public on what to do in the event of certain calamities. When a disaster occurs, the immediate actions phase entails saving lives and providing emergency aid. First responders, including police, fire departments, medical teams, and search and rescue professionals, are also sent to the impacted areas.

In order to meet the most pressing requirements, it also entails coordination of resources and efforts. Following the disaster, the restoration of normalcy to the impacted towns' infrastructure is the primary goal of the recovery phase. This include repairing the broken infrastructure, giving survivors medical attention and emotional assistance, and assisting the affected people and their families in finding new employment. Coordination and communication are essential for effective disaster management. These stakeholders include the public, commercial sector organisations, government agencies, non-governmental organisations (NGOs) and international assistance agencies [8]. It is easier to spread information, issue warnings, and coordinate relief operations when there are open lines of communication. International cooperation is frequently necessary for disaster relief because they frequently cross national borders. During major disasters, nations may ask for or provide assistance to help the afflicted areas. Continual improvement, taking lessons from the past, and adjusting to new situations and hazards are all part of disaster management. Building resilience and readiness for future disasters calls for the cooperation of numerous agencies and organisations at all levels of government as well as the active participation of communities. Strong disaster management methods are increasingly important to preserve lives and livelihoods as climate change increases the frequency and severity of some natural catastrophes.

NECESSITY OF MACHINE LEARNING (ML) IN DISASTER MANAGEMENT AND CLIMATE CHANGE

Due to its capacity to analyse massive volumes of data, identify insightful patterns, and generate precise forecasts, machine learning is essential to managing disasters and addressing climate change. To create complex climate models, machine learning algorithms can examine past climate data, satellite observations, and various environmental elements. These models aid researchers and decision-makers in comprehending climatic patterns, spotting trends, and forecasting potential climate scenarios. Making successful climate change mitigation and adaptation

methods requires accurate climatic predictions. Machine learning can examine weather data and spot trends that appear before catastrophic weather occurrences like hurricanes, floods, and heatwaves. Machine learning-powered early warning systems can send timely alerts to communities that are at risk, allowing them to take the required measures and evacuate as necessary. Following a natural catastrophe, machine learning algorithms may examine satellite pictures and data from drones to determine the degree to which infrastructure, agriculture, and ecosystems have been harmed. Authorities can more effectively priorities response efforts and allocate resources with the use of this information. By foreseeing the regions that will be most affected and the resources needed for relief operations, machine learning can help to optimize disaster response activities. As a result, the impact on the impacted populations is reduced and aid and support are delivered to the appropriate locations at the appropriate times. Machine learning can be used to analyse the effects of climate change on a variety of industries, including agriculture, water resources, and public health [9]. For policymakers to create policies for adaptation and resilience-building, they need this information. Machine learning can analyse enormous datasets, such temperature records, sea level measurements, and greenhouse gas emissions, to find patterns and trends in climate change that conventional statistical methods could overlook. To combat climate change, policies and actions can be informed by this better understanding. Machine learning can help to produce risk estimates that are more precise for both climatic and disaster-related events. Decision-makers can more efficiently deploy resources for mitigation and readiness by having a greater grasp of the risks. Machine learning may enhance energy efficiency, optimise energy systems, and promote the growth of renewable energy sources, all of which can help with the fight against climate change.

The vast amount of data relating to disasters and the climate can be too much to handle manually. Machine learning may automate data processing, freeing academics and practitioners to concentrate on analysing the findings and coming up with practical solutions.

The power of machine learning to handle enormous volumes of data, identify trends, and generate precise predictions makes it crucial for attempts to control disasters and climate change. We can improve catastrophe planning and response, better understand the causes of climate change, and take proactive measures to create a more resilient and sustainable future by utilizing the power of machine learning.
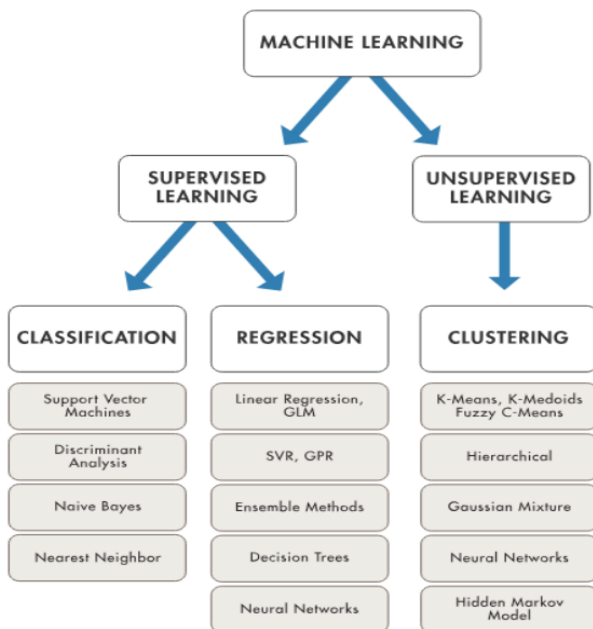
MACHINE LEARNING

Machine learning is a branch of artificial intelligence (AI) that focuses on creating statistical models and algorithms that let computers learn and get better at a given task without having to be explicitly programmed. Allowing computers to learn from data, recognize patterns, and make predictions or judgements based on that acquired knowledge is the main

premise of machine learning. Machine learning systems learn from examples and progressively improve their performance as opposed to traditional rule-based programming, which relies on explicit instructions being given to solve a problem. The algorithms alter their parameters to increase their accuracy or performance on the task at hand throughout this iterative learning process, which is driven by data.

A data analysis method known as machine learning trains computers to make decisions based on past experiences. Calculation techniques are used in this learning process to "learn." As the quantity of existing samples raises, algorithms become further efficient. Machine learning has emerged as a critical approach to problem solving with the growth of Big Data [10]. It uses two techniques: unsupervised learning, which unearths hidden patterns & intrinsic structures in the input data, as well as supervised learning, which utilizes a model using known input & output data to predict future outputs.

Table 1. ML Technique types

Learning type	Model building	Tasks
Supervised	Algorithms or models learn from labeled data (Task-Driven Approach)	Classification, Regression
Unsupervised	Algorithms or models learn from unlabeled data (Data-Driven Approach)	Clustering, Associations, Dimensionality Reduction
Semi-supervised	Models are built using combined data (Labeled + Unlabeled)	Classification, Clustering
Reinforcement	Models are based on reward or penalty (Environment-Driven Approach)	Classification, Control

Figure 4. Techniques in Machine Learning

MACHINE LEARNING TECHNIQUES

Based on the learning methodology and the availability of labelled training data, machine learning may be roughly divided into three basic types:

In supervised learning, each input data point is linked with the appropriate output or label, and the system is trained on a labelled dataset. Once the algorithm masters mapping input features to the desired output, it is capable of making predictions on previously unexplored data. Image classification, speech recognition, and regression challenges are examples of common supervised learning tasks.

In unsupervised learning, the algorithm is trained on a dataset that has no labels or specific outputs, in which the input data points are not linked with any particular labels or outputs [11]. The goal of the method is to automatically identify structures or patterns in the data, such as associations or clusters. Unsupervised learning is employed for tasks including dimensionality reduction, anomaly detection, and clustering comparable data points.

The algorithm learns to make judgements by interacting with the environment through reinforcement learning. Based on its activities, the algorithm receives feedback in the form of rewards or penalties. The algorithm's goal is to discover the best course of action to maximize long-term cumulative rewards. The use of reinforcement learning is widespread in fields including robotics, autonomous systems, and gaming.

Several machine learning techniques can be employed for climate change and sustainable environment applications. The choice of technique depends on the specific task and the nature of the data. Some commonly used techniques include:

1. Regression Analysis: Regression models are used to predict numerical values based on input features. In the context of climate change, regression can be applied to predict temperature changes, sea level rise, or greenhouse gas emissions based on historical data and environmental factors.

2. Time Series Analysis: Time series models are suitable for analyzing data collected over time. They are used to identify trends, seasonal patterns, and long-term variations in climate data. Time series analysis can help in understanding climate change trends and making forecasts.

3. Classification: Classification models are used to classify data into different categories or classes. For sustainable environment applications, classification can be used to identify land use types, classify species of plants or animals, or detect environmental pollutants.

4. Cluster Analysis: Cluster analysis is used to group similar data points together based on their characteristics. In the context of sustainable environment, cluster analysis can be applied to identify areas with similar environmental conditions or group species based on their ecological characteristics.

5. Deep Learning: Deep learning, specifically deep neural networks, is suitable for complex tasks such as image and speech recognition. In sustainable environment applications, deep learning can be used for image-based species identification, monitoring land cover changes through satellite imagery, and analyzing environmental sensor data.

6. Reinforcement Learning: Reinforcement learning can be applied to optimize resource allocation and management in sustainable environmental practices. For example, it can be used to design optimal strategies for water resource management or energy consumption in smart grids.

7. Anomaly Detection: Anomaly detection techniques can identify unusual patterns or outliers in environmental data. This can be useful for detecting environmental pollution incidents or monitoring unusual climate events.

8. Transfer Learning: Transfer learning can be employed to adapt pre-trained models to specific environmental tasks. For instance, models pretrained on image datasets can be fine-tuned for environmental monitoring using image data specific to the environment.

9. Support Vector Machines (SVM): SVM is a powerful classification technique that can be used for various environmental applications, including land cover classification, species distribution mapping, and pollution detection.

10. Natural Language Processing (NLP): NLP techniques can be used to analyze textual data related to climate change research, policy documents, and environmental reports, facilitating knowledge extraction and decision-making.

Machine learning offers great potential for addressing climate change and promoting sustainable practices by providing data-driven insights, automating complex tasks, and improving decision-making processes [12]. However, it's essential to use machine learning in conjunction with domain expertise and ethical considerations to ensure its effective and responsible application in environmental conservation and climate change mitigation.

These three primary kinds also have some of the following subclasses and combinations:

Unsupervised and supervised learning components are combined in semi-supervised learning. In order to increase performance, the algorithm is trained on a dataset that contains both labelled and unlabelled data.

Transfer Learning: Transfer learning is the process of applying knowledge from one task to a similar one in order to learn better. Transfer learning can be used to modify pretrained models, which are models trained on huge datasets for general tasks.

Deep Learning: Deep learning is a branch of machine learning that makes use of deep neural networks, which include several layers. In areas including image identification, natural language processing, and gaming, deep learning has made tremendous strides.

Machine learning is a potent tool with several uses in a variety of fields, and its ongoing growth has resulted in considerable improvements in AI technologies.
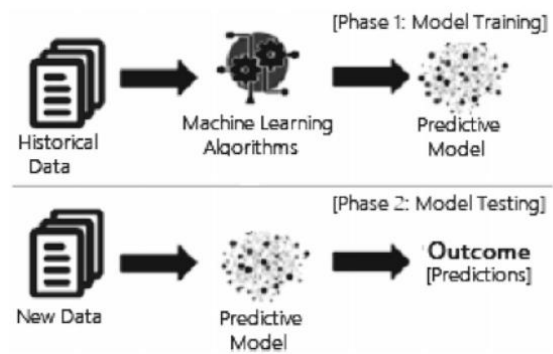
Figure 5. ML based predicted model

A comparison chart of the traits of the most popular machine learning algorithms is displayed.

The following factors for picking an algorithm are included in the table, which is based on articles

Precision (C1): The outcome need not always be as precise as is possible. Depending on the intended usage, an approximate may be adequate in some circumstances. Thus, embracing approximations can significantly shorten handling time. These techniques also have the advantage of preventing overadjustment.

Training time (C2): Depending on the algorithm, a model might take anything from a few minutes to many hours to train. Accuracy as well as training time frequently go hand in hand.

Many machine learning methods rely on linearity (C3): The expectations made by linear classification algorithms like logistic regression as well as SVM are that the data trails a straight line trend as well as that classes must be separated by a straight line (or its alike in complex dimension environments). These expectations may not be erroneous for some issues, but they can compromise accuracy.

Number of parameters (C4): Scientists initialise algorithms by pressing buttons that act for parameters. They are numerical values that have an effect on the algorithm's behaviour, such as the algorithm's error tolerance, even different behaviour variations, the number of iterations. The algorithm's accuracy as well as training time can be quite sensitive besides only the ideal configuration will work. Typically, acquiring a proper balance for algorithms with a lot of parameters occupies more testing as well as potential mistakes.

Frequency of usage (C5): This metric calculates how frequently a technique was used as the primary technique in publications advertised between 2010 as well as 2011 in databases comprising Science Direct, IEEE Digital Library, WoS, Scopus.

How many other machine learning approaches are combined? (C6): It is how frequently articles published between 2010 and 2011 in databases like Scopus, IEEE Digital Library, Science Direct, WoS relate machine learning techniques.

Reasonableness (C7): Sensitivity is the likelihood of organizing an element as fitting to the positive class when it actually does. Sensibility is regulated by the percentage of

positive situations that delivered accurate predictions.

Precision (C8): This variable exhibits the fraction of correctly categorized elements, or the rate of accurate expectations.

Table 2 presents a comparison based on rates of the prior abilities of each method. Since this assessment is qualitative, the results are categorized as "Excellent (E), Good (G), or Deficient (D)" for the precision criterion. The labels for the directing time criterion are "Brief (B)" or "Moderate (M)". It is suggested whether or not a linear behaviour is used for the linearity requisite [13]. The number of ideal variables for the method is specified by the parameters criterion. The subsequent qualitative labels are used for the "frequency of use criterion as main technique," "level of combination with other ML techniques," "Sensibility," & "Accuracy": "Very High," "High (H)," "Medium (M)," "Low (L)."

Finally, a pertinent & succinct point about the algorithm is endowed in the notes below.

Table 2. Comparative table of ML algorithms

Machine Learning Technique	C1	C2	C3	C4	C5	C6	C7	C8	Notes
Multi-class classification									
Decision Tree	E	M	NO	6	L	M	H	H	
Decision Jungle	E	M	NO	6	L	M	M	M	Low memory usage
Boosted Decision Tree	E	M	NO	6	L	M	M	M	Large memory usage
Neural Network	E	-	NO	9	L	M	M	L	Further customizations are possible
Support Vector Machines	-	M	SI	5	H	VH	M	M	Useful for large sets of characteristics
Targeted Local Support Vector Machines	B	-	NO	8	H	VH	M	M	Useful for large sets of characteristics
Bayes point machine	-	B	SI	3	M	H	L	M	
Regression									
Bayesian Linear Regression	-	M	SI	2	M	H	L	M	
Decision Forest	E	M	NO	6	L	M	H	H	
Boosted Decision Tree	E	M	NO	5	L	M	M	M	Large memory usage
Fast Forest Quantile	E	M	NO	9	-	M	M	M	Distributions instead of point-based predictions
Neural Network	E	-	NO	9	L	M	M	L	Further customizations are possible
Anomaly detection									
Support Vector Machines	B	M	NO	2	H	VH	M	M	Especially useful for large sets of characteristics
K-Means	-	B	SI	4	M	M	M	M	A cluster-based grouping algorithm

MACHINE LEARNING IN CLIMATE CHANGE AND DISASTER MANAGEMENT

Due to its ability to analyse big datasets, find patterns, and make predictions, machine learning is widely employed in disaster management and climate change research. Here are some examples of how machine learning is used in various fields specifically:

1. Climate Prediction and Modelling: To create climate models that replicate intricate interactions between the atmosphere, oceans, land, and ice, machine learning methods are used. These models aid in understanding regional climate trends, forecasting future climatic scenarios, and evaluating the effects of climate change.

2. Prediction of Extreme Weather occurrences: To anticipate extreme weather occurrences like hurricanes, cyclones, floods, and heatwaves, machine learning analyses past patterns and weather data. Machine learning-powered early warning systems can improve catastrophe preparedness by sending out timely alerts to susceptible communities.

3. Analysis of Climate Data: A large amount of climate data, such as temperature records, precipitation patterns, and greenhouse gas concentrations, are analysed using machine learning techniques. This study aids in the discovery of patterns, anomalies, and potential indications of climate change.

4. Assessment of the Damage Caused by Natural Disasters: Following a natural catastrophe, machine learning algorithms analyse satellite pictures, drone data, and other remote sensing data to determine the degree of ecosystem, agricultural, and infrastructure damage. Using this information, response efforts and resource allocation can be prioritised.

5. Risk Assessment and Vulnerability Mapping: Machine learning is used to determine the degree to which regions are vulnerable to various climate-related risks and disasters. Machine learning assists in identifying locations at higher risk by analysing a variety of factors, such as geographic data, population density, and infrastructure. This enables better resource allocation for risk reduction and preparedness.

6. Disaster Response Optimisation: By forecasting the regions that will be most affected and calculating the resources needed for relief operations, machine learning algorithms optimise disaster response efforts. As a result, catastrophe responses are more effective and focused.

7. Climate Change Impact Analysis: Machine learning is utilised to comprehend how climate change will affect numerous industries, including public health, agriculture, and water resources. Policymakers can use this information to create effective adaptation strategies.

8. Forest Fire Prediction and Monitoring: By examining satellite data, weather conditions, and past fire patterns, machine learning is used to predict and monitor forest fires. This facilitates early detection and prompt action to lessen the effects of fire.

9. Sea Level Rise Prediction: To analyse historical sea level data and forecast future sea level rise, which is crucial for coastal planning and adaptation measures, machine learning methods are applied.

10. Monitoring and Reduction of Carbon Emissions: Machine learning is used to track and analyse carbon emissions from a variety of sources, including transportation and industry. Using this knowledge, measures can be developed to cut greenhouse gas emissions and stop climate change.

11. Climate Change Mitigation Strategies: Machine learning is used to enhance energy efficiency,

optimise energy systems, and assist the growth of renewable energy sources, all of which help with the fight against climate change.

Machine learning is a flexible technology that considerably improves our comprehension of catastrophe management and climate change. Machine learning provides more precise predictions, better decision-making, and more effective ways to handle the issues posed by climate change and natural catastrophes by processing and analysing massive datasets.

ADVANTAGES

The benefits that machine learning techniques provide for managing disasters and addressing climate change make them ideal instruments for overcoming the difficulties faced by these intricate and dynamic sectors. Some major benefits include:

1. Data-Driven Insights: Machine learning analyses vast and varied datasets to provide data-driven insights. It can process enormous amounts of historical data, sensor measurements, and climate data to extract patterns and trends that can be difficult to spot using conventional statistical techniques.

2. Better Forecasting and Predictions: Machine learning algorithms are excellent at forecasting using past data. They can predict changes in the environment, severe weather, and future disasters, which helps with proactive preparation and readiness.

3. Early Warning Systems: Early warning systems for natural disasters like hurricanes, floods, and earthquakes can be powered by machine learning. These technologies can send timely notifications to vulnerable communities by analysing real-time data, enabling people to take the required preparations and evacuate if necessary.

4. Enhanced Climate Modelling: Climate models can be made more accurate and effective by using machine learning techniques. Researchers may simulate complicated climate interactions and evaluate the effects of various scenarios by applying machine learning into climate modelling.

5. Resource Allocation Optimisation: Machine learning can make disaster management resource allocation more effective. Authorities can more effectively distribute resources, such as emergency response teams and relief supplies, by anticipating the areas most likely to be affected by disasters.

6. Large datasets may be quickly analysed thanks to machine learning. Machine learning can analyse incoming data, assess the situation, and offer insights in real-time in catastrophe circumstances where quick judgements are essential.

7. Automation of Repetitive processes: Automating time-consuming and repetitive processes like data processing, pattern detection, and data classification is possible with machine learning. Experts may now concentrate on making more important decisions and activities.

8. Personalised Risk Assessments: Using historical data and regional variables, machine learning can evaluate personal or community-specific dangers. Individualised disaster preparedness and mitigation techniques are made possible by this personalisation.

9. Enhanced Environmental Monitoring: To track environmental changes and spot anomalies, machine learning may examine satellite pictures and sensor data. This skill is useful for monitoring ecosystem health, land use changes, and deforestation.

10. Supporting Climate Change Mitigation and adaption: Policymakers can concentrate on adaption measures and execute focused mitigation initiatives by using machine learning to identify regions where climate change impacts are most severe.

11. Interdisciplinary Collaboration: Climate scientists, environmental specialists, data analysts, and computer scientists may work together more effectively thanks to machine learning. A more comprehensive understanding of climate change and disaster management results from this collaboration.

Even though machine learning has many benefits, it's important to recognise its limitations and the necessity for domain knowledge when analysing results and coming to judgements. The application of machine learning techniques in disaster management and climate change should also take ethical considerations, data protection, and transparency into account. Machine learning may considerably aid in constructing sustainability and resilience in the face of environmental difficulties when applied ethically and in conjunction with human expertise.
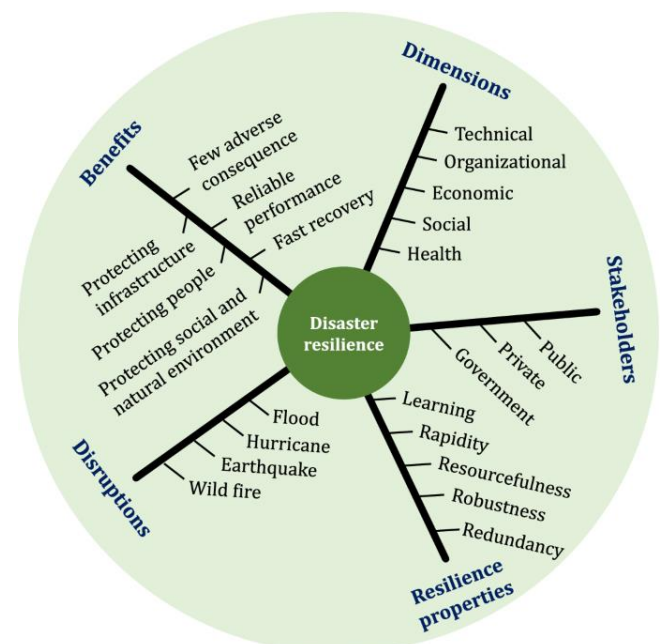
Figure 6. Disaster resilience
Source: https://link.springer.com/article/10.1007/s11069-020-04124-3

CONCLUSION

The management of natural disasters and climate change have emerged as major worldwide challenges, and the use of machine learning (ML) approaches to these problems promises promising results. These important inferences from the research allow us to state the following:

1. Better Prediction and Early Warning Systems: Machine learning algorithms are able to process enormous volumes of climate data, making it possible to predict catastrophic weather occurrences like hurricanes, floods, and wildfires with greater accuracy. Communities may now take timely and proactive actions to reduce risks and the effects of disasters because to this improved forecasting capability.

2. Enhanced Adaptation and Resilience: ML algorithms may examine previous disaster data and climate data to detect weaknesses in particular places. With the help of this knowledge, stakeholders and policymakers can create infrastructure and solid adaptation plans that can survive the effects of natural disasters and climate change.

3. Effective Resource Allocation: During catastrophe response and recovery activities, machine learning can optimise resource allocation. In order to ensure that help, relief, and emergency services are provided quickly and effectively, ML algorithms can identify the locations and communities who need them the most by analysing historical data and real-time data.

4. Environmental Monitoring and Conservation: ML-based systems can analyse information from sensors, satellites, and other sources to track environmental changes including deforestation, habitat loss, and air pollution. These revelations help us comprehend the implications of climate change better and direct conservation efforts to safeguard ecosystems and biodiversity.

5. Risk Assessment and Insurance: Machine learning can help insurance companies identify climate-related risks, determine suitable premiums, and build better risk assessment models. This makes it easier for vulnerable areas to obtain affordable insurance protection, promoting investments in climate resilience and catastrophe preparedness.

6. Policy Support and Decision-Making: ML algorithms can aid in the analysis of large data sets and the evaluation of the efficacy of various disaster and climate management strategies. As access to evidence-based decision-making increases, initiatives and international, national, and local partnerships become more significant.

7. Public Awareness and Education: Machine learning-driven visualisation tools can efficiently inform the general public about the effects of climate change and upcoming calamities. This encourages people to adopt sustainable practises and promotes increased awareness, comprehension, and engagement in climate action.

However, it is critical to recognise that machine learning is not a magic solution for preventing climate change and managing natural disasters. It ought to support established scientific methodologies, informed decisions, and community involvement. The creation and application of ML systems in this setting must properly take into account ethical considerations, data protection, and bias reduction. The use of machine learning to disaster management and climate change has the potential to fundamentally alter how we perceive, respond to, and lessen the effects of these issues. We can encourage a more resilient, sustainable, and prepared world for future generations by utilising technology and human inventiveness.

REFERENCES

[1] Tameem Adel, Isabel Valera, Zoubin Ghahramani, and Adrian Weller. One-network adversarial fairness. In 33rd AAAI Conference on Artificial Intelligence, 2019.

[2] Syed Mumtaz Ali and Samuel D Silvey. A general class of coefficients of divergence of one distribution from another. Journal of the Royal Statistical Society: Series B (Methodological), 28(1):131–142, 1966.

[3] Solon Barocas and Andrew D Selbst. Big data's disparate impact. Calif. L. Rev., 104:671, 2016.Solon Barocas, Moritz Hardt, and Arvind Narayanan. Fairness in machine learning. NIPS Tutorial,2017.

[4] Richard Berk, Hoda Heidari, Shahin Jabbari, Michael Kearns, and Aaron Roth. Fairness in criminal justice risk assessments: The state of the art. Sociological Methods & Research, page 0049124118782533, 2018.

[5] Alex Beutel, Jilin Chen, Zhe Zhao, and Ed H Chi. Data decisions and theoretical implications when adversarially learning fair representations. arXiv preprint arXiv:1707.00075, 2017.

[6] Avrim Blum and Kevin Stangl. Recovering from biased data: Can fairness constraints improve accuracy? In Symposium on Foundations of Responsible Computing (FORC), volume 1, 2020.

[7] Joy Buolamwini and Timnit Gebru. Gender shades: Intersectional accuracy disparities in commercial gender classification. In Conference on fairness, accountability and transparency, pages 77–91.PMLR, 2018.

[8] Toon Calders, Faisal Kamiran, and Mykola Pechenizkiy. Building classifiers with independency constraints. In 2009 IEEE International Conference on Data Mining Workshops, pages 13–18.IEEE, 2009.

[9] Jianfeng Chi, Yuan Tian, Geoffrey J Gordon, and Han Zhao. Understanding and mitigating accuracy disparity in regression. In International Conference on Machine Learning, 2021.

[10] Alexandra Chouldechova. Fair prediction with disparate impact: A study of bias in recidivism prediction instruments. Big data, 5(2):153–163, 2017.

[11] Evgenii Chzhen, Christophe Denis, Mohamed Hebiri, Luca Oneto, and Massimiliano Pontil. Fair regression with wasserstein barycenters. arXiv preprint arXiv:2006.07286, 2020.

[12] Sam Corbett-Davies, Emma Pierson, Avi Feller, Sharad Goel,

and Aziz Huq. Algorithmic decision making and the cost of fairness. In Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pages 797–806. ACM, 2017.

[13] Imre Csiszár. Eine informationstheoretische ungleichung und ihre anwendung auf beweis derergodizitaet von markoffschen ketten. Magyer Tud. Akad. Mat. Kutato Int. Koezl., 8:85–108, 1964.