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Review

A Review of the Application of Artificial Intelligence in Climate Change-Induced Flooding—Susceptibility and Management Techniques

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Abstract: A fresh paradigm for classifying current studies on flood management systems is proposed in this review. The literature has examined methods for managing different flood management activities from a variety of fields, such as machine learning, image processing, data analysis, and remote sensing. Prediction, detection, mapping, evacuation, and relief efforts are all part of flood management. This can be improved by adopting state-of-the-art tools and technology. Preventing floods and ensuring a prompt response after floods is crucial to ensuring the lowest number of fatalities as well as minimizing environmental and financial damages. The following noteworthy research questions are addressed by the framework: (1) What are the main methods used in flood control? (2) Which stages of flood management are the majority of research currently in existence focused on? (3) Which systems are being suggested to address issues with flood control? (4) In the literature, what are the research gaps regarding the use of technology for flood management? To classify the many technologies that have been studied, a framework for classification has been provided for flood management. It was found that there were few hybrid models for flood control that combined machine learning and image processing. Furthermore, it was discovered that there was little use of machine learning-based techniques in the aftermath of a disaster. To provide efficient and comprehensive disaster management, future efforts must concentrate on integrating image processing methods, machine learning technologies, and the understanding of disaster management across all phases. The study has proposed the use of Generative Artificial Intelligence.

Keywords: climate change; flood management; spatial analysis; disaster

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1. Introduction

Modern cutting-edge technologies have fundamentally altered how the world works. The field of disaster management is, like all other fields, moving more and more toward the use of contemporary technologies. Flood threats are a persistent concern for both industrialized and developing nations [1]. According to predictive research of future flood risks, historical levels of flood-related damage are anticipated to occur due to the growing effects of the changing climate [2] and inadequate flood readiness in several global regions [3]. The increasing number of flood incidents worldwide [1] makes it necessary to find practical approaches to risk management during emergencies. Flooding disasters are linked to the global loss of life, agriculture, infrastructure, and financial resources [3]. According to Polina Lemenkova estimations [4], floods carry greater risks and losses than any other climate hazard, running into several millions of dollars. Climate change and population growth are associated with an increase in flood occurrences [5]. These two elements are considered essential to comprehending flood events. Communities have grown up in river basins and coastal areas as a result of the expansion of commercial and residential areas, which are among the areas that are naturally vulnerable to flooding [6]. The number of floods and their propagation are also significantly influenced by land use and vital infrastructure.

It is still unknown how much urbanization and climate change actually affect the frequency of floods. In many parts of the world, rising urbanization has created flood plains within residential neighborhoods, raising the danger of flooding [7]. Analyzing the dangers of flooding in a nation or area has been the subject of numerous research [8]. But as technology advances, data-driven model advancements, for their contributions to the field of flood risk management, deserve recognition.

Today, technologies such as remote sensing and satellite imaging are used to map the risk of floods globally [9]. Due to the very dynamic nature of floods and the incredibly slow rate at which satellite imagery is captured, such deployment at the local level has not yet proven successful. Relying solely on remotely sensed images to analyze, capture, and comprehend the entire scope of flood threats has its limitations [10]. Furthermore, it is well recognized that floods seriously harm vital infrastructure, like bridges, highways, and the communications system, making it challenging to get assistance to those stranded in flooded areas [11]. The world lost USD 40 billion in total as a result of a study titled "Organization for Economic Cooperation and Development's Financial Management of Flood Risk"; there were floods in a number of different parts of the world in 2016.

Floods will significantly affect the creation of flood maps, impeding rescue operations and risk management [12]. Local data on flood risks must be gathered in order to raise the degree of preparedness for disasters. Recent technological advancements have made it feasible to combine computer models and remote sensing, enabling the continuous simulation of dynamic events like floods in space and time [13–17]. Using machine learning and image processing is one of the methods that has become increasingly popular over time. Thus, the purpose of this review is to monitor the latest advancements in methods for disaster management based on machine learning and image processing. The literature's lack of focus on post-disaster management systems in relation to contemporary flood detection techniques is one important issue that must be addressed [18].

By reviewing and analyzing the most recent technologies, this study hopes to improve post-disaster management systems. To classify the research based on the technology domain and the disaster management phase they are working with, a classification system has been established. The framework will precisely determine which domain and for which phase the technology is intended. Following the identification of these variables, a thorough analysis of each technique's methodology, applications, results, and shortcomings is conducted. At the moment, maps that show the locations most vulnerable to disasters and flood predictions are the primary goals of flood risk management systems [19]. To get around many of the drawbacks of the conventional approaches, strategies including artificial intelligence (AI)-based algorithms, machine learning, and computer vision have been proposed [20,21]. Numerous studies on flood control methods have been carried out, leveraging machine learning for flood prediction [20], systematic literature studies on leveraging big data for disaster management [22], a review of flood forecasting technology [23], flood mapping, and systems of evaluation [24]. Nevertheless, it appears that these traditional review papers only focus on flood prediction, risk assessment, and forecasting technologies to map disaster-prone areas [19]. However, they do not examine the technology being employed to find impacted people, identify floodwater, or handle the aftermath of the incident. Furthermore, the majority of these do not use the most recent methods based on image processing and machine learning [25]. Previous research has concentrated on the conventional approaches to flood control, such as remote sensing, hyper-ion imaging, and satellite imaging [26].

The literature now in publication rarely discusses the image processing techniques currently in use. Additionally, there is a dearth of attention paid to the latter stages of the disaster management process, such as recovery and reaction, which are crucial because it is not always possible to predict natural disasters with precision [27]. The following key phrases will be covered in this study's evaluation of the literature: (i) disaster management in the pre- and post-disaster phases, with an emphasis on the application of cutting-edge technologies based on artificial intelligence, machine learning, and image processing; (ii) a comprehensive framework for categorizing the study. The following highlights the significance of studying image processing and machine learning methods in flood management: These methods have significantly changed since the invention of technology. They are partly connected since they employ comparable techniques and algorithms. There is much data in the field indicating that automating flood prediction, detection, and control is essential.

Studies that use more modern methods from domains including artificial intelligence (AI), machine learning, image processing, and computer vision are given special attention. Specifically, the research classification framework that is suggested addresses the following key questions:

What are the main methods used in flood control?

1. Which stages of flood management is the majority of research currently in existence focused on?
2. Which systems are being suggested to address issues with flood control?
3. In the literature, what are the research gaps regarding the use of technology for flood management?

A thorough procedure of searching for and analyzing literature was carried out to provide answers to these queries.

This study is organized as follows: The method for gathering research papers for the review and the plan for retrieving articles are covered in the section that follows. The classification scheme developed for this investigation is presented in Section 3. In Section 4, the review's findings are presented along with a comprehensive examination of the main research subjects. Section 5 examines the many gaps in the literature that this study found, taking into account the limitations of the technology and the technique's rare implementation in relation to the crisis management cycle. This review presents a novel approach to the application of Generative Artificial Intelligence (GAI) in Climate Change-Induced Flooding—Susceptibility and Management Techniques which considers the pre-disaster, disaster, and post-disaster phases in the following steps:

- Data Acquisition
- Data Preprocessing
- Feature Extraction
- Flood Risk Analysis and Mapping
- Evacuation Route Optimization
- Testing and Validation

Ref. [28] used GAI powered by GPT-4 (Large Language Model) to facilitate real-time flood forecasting for effective communication between the decision-makers, the general public, and flood modeling experts. An advanced flood imagery detection model has been developed to mitigate losses as a result of flooding incidences [29]. There is an urgent need for the use of GAI because most recent studies on urban flooding are mainly focused on the study of remote sensing and satellite imagery [1,30].

2. Materials and Methods

The literature review approach addresses the review issues posed above. This procedure consists of three basic steps: using internet search engines like Springer Nature, MDPI, Google Scholar, Scopus, Science Direct, and Taylor and Francis, pertinent material is initially gathered. In order to achieve this, certain keywords were chosen for the literature review search. The most relevant articles for these keywords were found using semantic searches. Second, after being evaluated for relevancy, the articles were filtered. To ascertain the research's applicability, this required reading and analyzing the abstracts. Third, two groups, methods based on machine learning (ML) and image processing, were created from the chosen research publications. Methods used in both developed and developing nations were taken into consideration in order to illustrate the methods that are now in use around the world for flood detection, prediction, and management. Global Positioning System (GPS) and Global Information System (GIS) flood control techniques, as well as sophisticated methods based on ML and image processing, were also examined. Third, as a substitute to enhance the detection and rescue operations, an integrative category was suggested. This category mixes machine learning algorithms with image processing techniques. A conceptual framework that combines machine learning and image processing methods will be the answer to better flood management.

Keywords such as strategies for managing flooding, climate change, flood management based on image processing, post-flood control, flood control through spatial analysis, and artificial intelligence-based flood detection were chosen. First, distinct keywords were chosen, which were subsequently merged utilizing catchphrases such as "flood management methodologies" The purpose of these well-crafted search terms and phrases was to search the entire database to locate the studies that have been utilized in reviews that are most relevant to the study [31–33]. The only kind of publications that were taken into consideration were peer-reviewed research papers.

Figure 1 shows the graphical abstract for proposed flood management developed in this review.

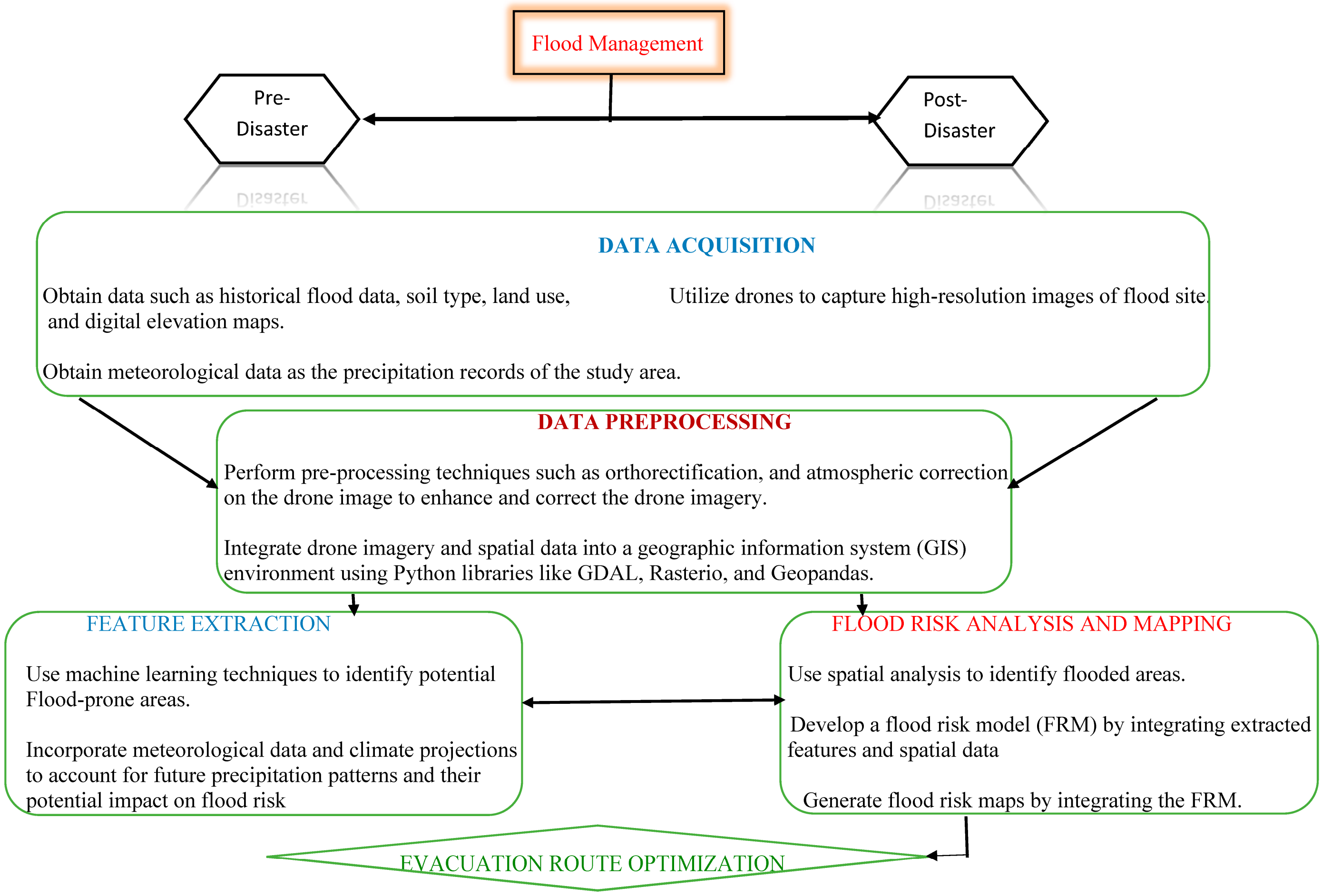

Figure 1. Graphical abstract of the proposed flood management.

Figure 2 shows the flow chart for the screening procedure used to filter the identified articles. Researchers devised and justified an assessment criterion that guided the implementation of a four-step screening method for mitigating bias related to the subjectivity of the retrieved articles, as suggested by Tranfield [34]. To begin with, only articles about "floods" and "flood management" are included in the search results. Second, the technical component of flood management is filtered out of the results. Third, while removing publications, significance to the fields of machine learning and image processing was taken into account. Fourth, restrictions were placed on the search results according to language, document category, time, and search result duplication. The "Categorization" block serves as a collective representation of these boundaries. The resulting articles decreased in quantity following each filtering procedure, as the figure illustrates. Ultimately, 100 articles in all were obtained. Out of these 100 studies, the distribution among various techniques is presented in Table 1, and just five studies looked at post-disaster management using machine learning and image processing. These five studies may increase if the scope of the search engine is increased.

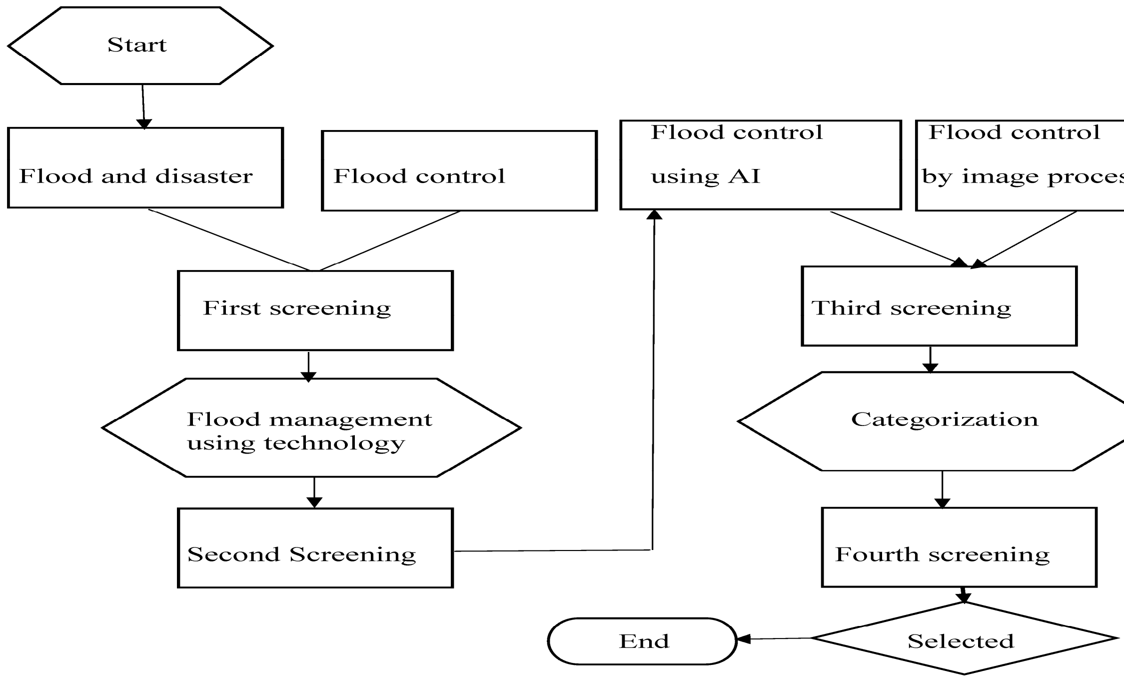

Figure 2. Articles screening process. Adapted with permission from [35].

Table 1. Distribution of techniques before and after the disaster.

Technique	Pre-Disaster	Post-Disaster
Image Processing	Edge detection, hyperion imaging, UAV imaging, remote sensing, and SAR imagery [3,5,11,15,26,28,33]	Edge Detection, SAR Imagery, UAV Imaging, and Hyperion Imaging [1,4,7,8,10,16,19,21,27,31]
Machine Learning	ANN, MLP, ANFIS, and WNN [5,9,12–14,20,24,25]	

3. Classification Guidelines

A grouping structure based on a list of recognized flood management study areas pertaining to pre- and post-disaster stages is put forward in this survey. The methods are further divided into categories according to the domains they fall under. Three technology domains have been identified: hybrid models, machine learning, and image processing. The several categories and subcategories that were employed to arrange the research papers that were retrieved are shown in Figure 3, along with the proposed classification system. This chart shows that the chosen studies are pre- or post-disaster in nature. These are the primary groups into which the approaches are thus divided. The chosen papers suggest a machine learning model, an image-processing technique, or a combination of the two. Consequently, machine learning, hybrid, and image processing are the subcategories. The primary image-processing techniques and technologies utilized in flood management are pixel analysis, edge detection, imaging from unmanned aerial vehicles (UAVs), remote sensing, and synthetic aperture radar (SAR). Artificial Neural Networks (ANN), Support Vector Machines (SVM), Wavelet Neural Networks (WNN), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), and Multilayer Perceptron (MLP) models were the machine learning models utilized in the pre- and post-disaster phases. Hybrid approaches include combining ANN and SVM models with pixel-based image categorization and machine learning methods like SVM with edge detection.

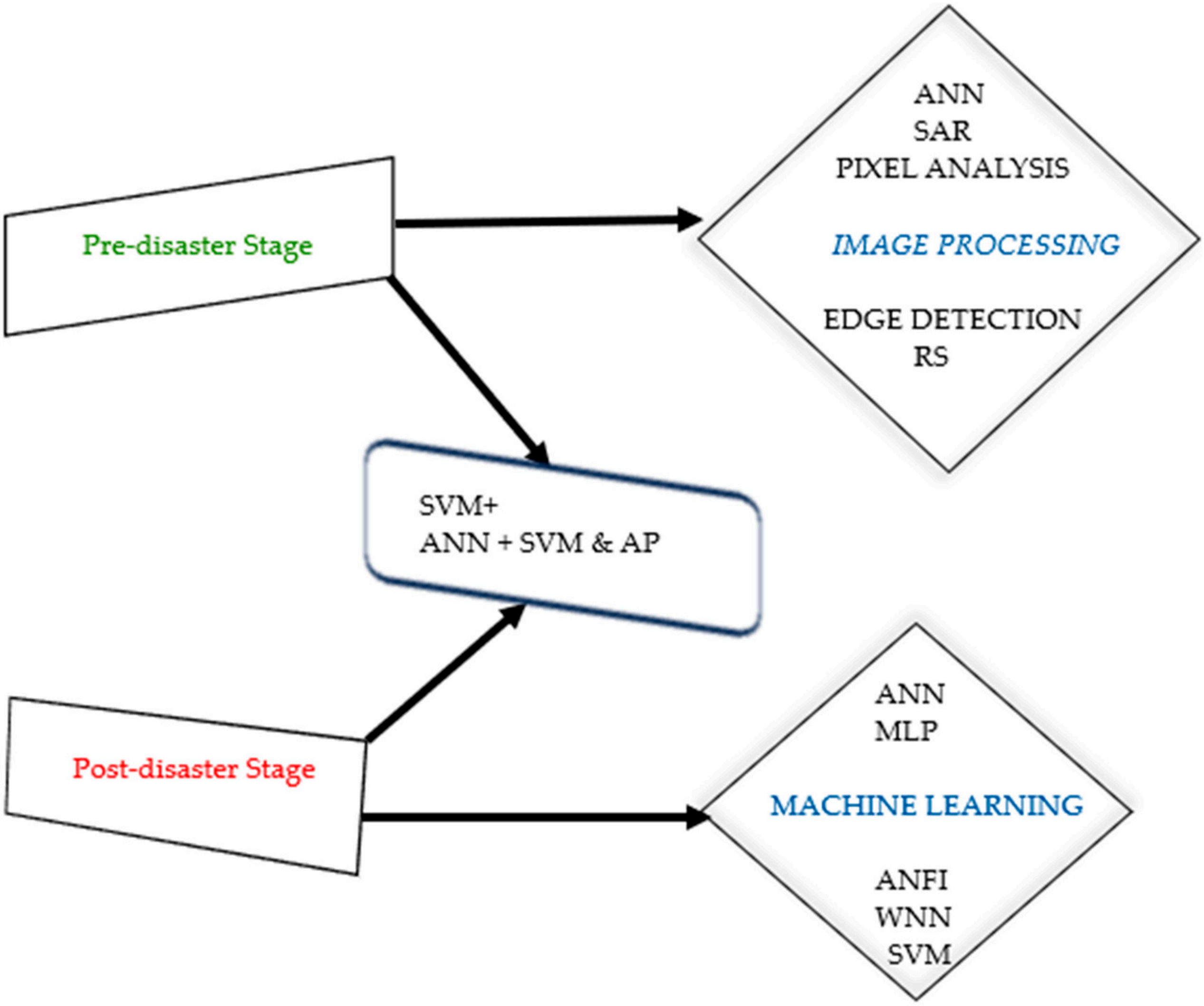

Figure 3. Technologies Classification Framework.

4. Results

1. Flood management major techniques

A number of tasks involved in flood control have been covered within the publications that have been reviewed. Four categories can be used to group these duties: Flood Hazard, Flood Mapping, Flood Detection, and Flood Prediction are the four main categories. The process of estimating the likelihood of flood events using rainfall data, river water level monitoring, storm-generated moisture information, and details regarding a river's drainage basin such as temperature, vegetation levels, and soil moisture is known as flood prediction. To provide information on the possible severity and dangers of any future flooding catastrophe, these variables are monitored throughout the region. These projects are classified in the pre-disaster phase. Important elements of the detection of flooding include tracking water levels and issuing alerts when a flood is thought to be occurring.

At the moment, satellite data and remote sensing are used to determine river flood levels instantly. The process of charting areas that are at risk of flooding or have already flooded is known as flood mapping. The produced maps can be utilized for flood risk assessment, mapping inundated areas, locating stranded individuals, and figuring out how to get to them. Flood risk assessment, also known as hazard assessment, is a process for mitigating floods that entails determining what actions should be made to mitigate flooding; one must consider the likelihood of flood instances from all sources of flooding.

Table 1 lists some appropriate analytic classes for each category. The gathered research articles were first categorized according to the phases of disaster management that they fall under. These phases are divided into four categories: risk assessment, flood hazard analysis, flood prediction, and flood mitigation, which occurs prior to a disaster. The second phase is preparedness for disasters. The post-disaster phase, which includes rescue and relief operations, is referred to as the third phase, or disaster response. The fourth and final stage focuses on restoring the damage and helping individuals recover from the impacts of the tragedy. Each of these phases' methodologies is categorized according to AI, and there is the usage of machine learning and image-processing methods. Due to the numerous overlaps between the various phases of disaster management that were found in the literature, the selected studies were primarily separated into two categories: pre-disaster and post-disaster.

Following phase identification, the study's methodologies were categorized into three groups: hybrid, image processing, and machine learning. Numerous research works that use remote sensing techniques such as GPS, GIS, and satellite imaging have combined image processing with machine learning, or both. These investigations were placed in the Hybrid category. The works in the image processing category include flood management strategies based on pixel analysis, object detection, and edge detection. Research utilizing trained statistical models to map and identify flooded areas, forecast future flood events or flood hazards, and evaluate flood damage are included in the machine learning category. The primary goals of this categorization were to classify the articles according to the domains that the corresponding, implemented, and suggested algorithm belonged to and to identify and assign each study to the proper phase of flood control. With the help of the suggested framework, tasks associated with each stage of the disaster management process might be completed utilizing image processing, machine learning, or both, depending on the most recent methods. Table 1 shows that while machine learning models were limited to handling flood risk assessments, prediction, and forecasting, they were primarily focused on the pre-disaster phase, while image processing techniques addressed both the pre- and post-disaster phases.

2. Which stages of flood management is the majority of research currently in existence focused on?

Whether the systems are used in advance of or during a disaster will determine which categories the literature study on flood control methods falls into. Pre-flood phase systems frequently focus on flood mitigation, planning, risk assessment, and hazard analysis tasks, whereas post-disaster flood management systems prioritize flood detection, mapping, damage assessment, and evacuation planning. Techniques for managing floods both before and during a crisis are suggested, including machine learning and image processing. It is also crucial in this situation to distinguish between machine learning and image-processing methods. It matters how an input image is handled using image-processing techniques, whether the goal is to extract information from it or just make it better or more appealing. For the purpose of flood management, these techniques are used to extract flood information from an input image of a flooded or flood-prone area. For instance, in order to send out warnings about possible flooding, edge detection techniques have been employed to estimate the water levels in various bodies of water [36]. Machine learning techniques automatically learn and make judgments by drawing on prior data and their own expertise. These systems use trained prediction models that can rapidly estimate the danger of flooding based on hydraulic data and meteorological parameters in order to manage floods [37].

3. Which systems are being suggested to address issues with flood control?

It is important to set up early warning signals along flood-prone areas with the aid of Internet of Things (IoT) and to follow urban planning strictly along already identified areas from historical flooding.

4.1. Cyber-Physical System

This comprises elements that combine various engineering disciplines and scientific theories, such as control theory, artificial intelligence, big data, embedded systems, cybernetics, IoT, distributed control, sensor networks, and systems engineering. These kinds of systems are autonomous and capable of making decisions. Modern technologies have aided in the anticipation, preparation, and reaction to floods. Examples include smartphones, blockchain, big data, social media, robots, artificial intelligence, and the internet of things.

A rising body of research is looking for ways to use technology for flood catastrophe management in the most efficient way possible [23]. The use of AI, IoT, and big data for flood management has increased dramatically in recent years [38–40]. These systems use available data from past catastrophes to create a well-informed appraisal of the hazards associated with flood disasters and public safety.

The IoT employs radio frequency identification, or RFID, technology to communicate with the outside world. Data gathering and storage become more efficient when sensor technology and IoT scanning characteristics are used. Sensor data collection creates data nodes, which are subsequently used to analyze flood patterns and dangers [41]. The management of information systems is improved by IoT, particularly when it comes to machine-to-machine communication. Profiting from weather forecasts and climate change science is made possible by artificial intelligence. In order to facilitate long-term planning for dealing with prospective flood disasters, remote sensors and drones can be used for meteorological purposes. This can help improve the data obtained by taking photographs of the damaged region that are difficult for relief workers to access [13]. When a region is prepared, for example, by creating efficient flood diversion strategies or planned routes for population evacuation, the assessment of prospective flood dangers may be helpful.

These resilience metrics directly result from the applications of cyber-physical systems. The incorporation of AI will result in a significant improvement in meteorological agencies' prediction power for forecasting and reporting disaster risks and creating mitigation plans. In a similar vein, big data offers enormous potential for developing strategies for preparedness, mitigation, and responses to flood disaster risk [42]. The idea of big data and the instruments used to organize, store, and analyze big data can be used to create frameworks that aid in determining the degree of catastrophe risk as well as in getting ready for post-disaster management [31].

4.2. System for Pre-Disaster Management

The methods discussed here are predicated on the forecasting, prediction, and evaluation of flood risk. In order to predict the occurrence of floods and assess the possible severity of flood occurrences, these techniques are used for mapping the areas that are prone to flooding, studying areas, tracking different meteorological conditions, and monitoring water levels in water bodies.

The pre-disaster flood management strategies are outlined in Table 2 and are discussed in the sections that follow.

Table 2. Techniques for Pre-Disaster Flood Management.

Technique	Method	Limitation
Image Processing	Using edge detection in order to ascertain an urban area's water surface levels [3]. Assessing flood risks through the use of UAVs to study morphological changes and coastal dynamics [31].	Manually selecting edge detection parameters; poor performance in areas of low contrast in photos The UAVs' short battery life
Machine Learning	The river's water flows are simulated at several points using an ANN model [35]. The technique for forecasting river water levels is based on fuzzy logic [43].	ANN algorithm's increased reliance on technology; parallel processing is necessary Extensive hardware testing is required to validate the fuzzy knowledge-based system.

4.3. Managing Floods When They Occur

During a flood occurrence, flood control is crucial, particularly in the first 72 h following a disaster when lives are at risk and rescue operations need to be finished as soon as possible [44]. The primary problem during a flood occurrence is the first responders' team's decreased effectiveness and breakdown in communication as a result of their lack of situational awareness of the crisis [45]. The most effective technique in analyzing the level of damage and tracking the disaster's evolution is to conduct an aerial assessment of the impacted area. Figure 4 shows a pictorial approach of monitoring and reporting flood occurrences in real time. Research on the establishment of a UAV network to support search and rescue efforts has produced promising results [46]. Unmanned aerial vehicles (UAVs) are a useful tool for identifying structures damaged by floods and for obtaining up-to-date information on the degree of damage to structures plus transportation systems. This will assist first responders in figuring out how many individuals are trapped and the safest route to get to safety [47]. The damage can be assessed using a variety of techniques, such as UAV-captured images, instruments for monitoring structure health, and UAV video inspection [47]. In order to prepare the authorities for any unanticipated eventualities, disaster preparedness can be implemented before the flood event through the use of cyber-physical systems, historical data, satellite imaging prior to and following the event, and big data analytics. One of the biggest challenges is getting relief to the impacted population when the safest path has been built to the target region. To increase the effectiveness of the relief effort, it is critical to fix technical problems and optimize the distribution of resources and vehicle routing. When addressing such a challenge, two main areas of research have been vehicle routing and resource allocation. Various models for delivering aid to victims after a disaster have been proposed in the past [48].

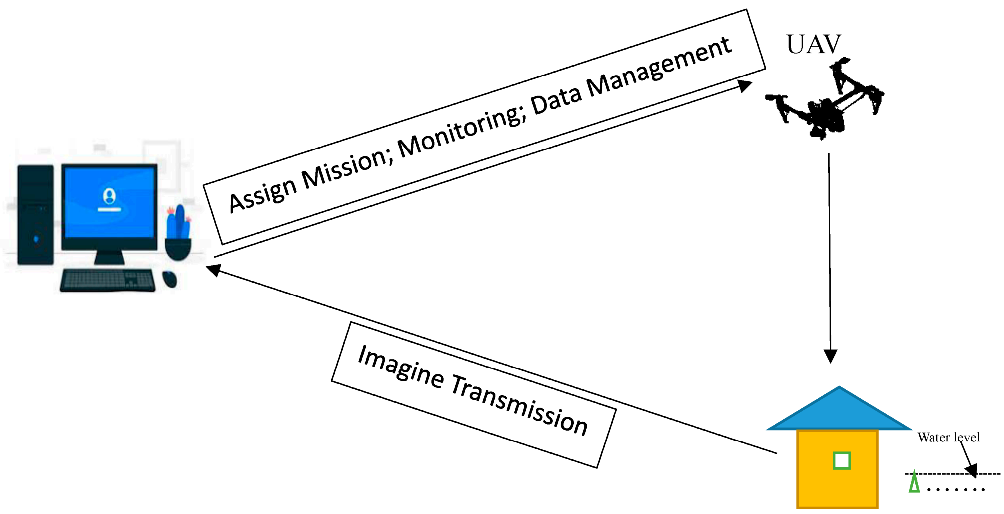

Figure 4. UAVs flood monitoring systems.

4.4. Flood Management Following a Disaster

The methods from the domains of image processing and machine learning that are meant to be applied in the aftermath of flood disasters are covered in this part. Events pertaining to disaster response and recovery are included in the post-disaster phase. As a result, the strategies covered here are based on the fast mapping of flooded areas, the estimation of water levels, and the coordination of evacuation activities.

By identifying the flooded areas and initiating rescue efforts by determining the best routes and transportation options in the area, these techniques help respond to flooding right away. The post-disaster flood management strategies covered in the following sections are compiled in Table 3.

Table 3. Techniques for Flood Management following Disasters.

Technique	Method	Limitation
Image Processing	Utilizing unmanned aerial vehicles (UAVs) to collect and send high-resolution spatial images to servers over intricate environments [3,31]. GPS flood risk management allows for guided rescue and evacuation operations [11].	Limited tracking duration due to battery-powered UAVs Lack of clarity when mapping the precise location and internet accessibility during the flood catastrophe.
Machine Learning	Using an SVM classifier and landmark detection on UAV photos, it is possible to identify photos of flooded areas [12,13].	Noise-induced enhancement in the landmark identification algorithm's sensitivity.

4.5. Flood Analysis Improvement Model

This is an attempt to overcome the limitations stated in Table 3; a Python (version 11) based software that overlaps pre-disaster and post-disaster phases is proposed. [49] used Gumbel Extreme Value to analyze data from 1972 to 1997 to study flood scenarios in the flood prone region of the lower Burhi Dehing River in Assam, while [50] used it for Timis River. The following steps are suggested:

1. The proposed model involves subjecting precipitation data to probability distribution functions such as Gumbel Extreme Value Type I, Normal, Log-Normal, Pearson Type 3, and Log-Pearson Type 3 distributions. The distribution with the best combination of the coefficient of determination (R^2) and Root Mean Square Error (RMSE) is then selected for modelling the data to obtain an extreme event return period.

Gumbel's Extreme Value Type I (GEVT-1) Distribution

Gumbel distribution is one commonly used probability distribution for obtaining the rainfall intensity values. The rainfall intensity values were obtained using Equation (1):

$$X_T = \overline{\overline{X}} + K_T S \tag{1}$$

where X_T = rainfall intensity values (magnitude of hydrologic event)

$$\overline{\overline{X}} = \text{mean}$$

K_T = Gumbel's frequency factor; S = standard deviation

The Gumbel's frequency factor is obtained using Equation (2).

$$K_T = -\frac{\sqrt{6}}{\pi}\{0.5772 + \ln\left[\ln\left(\frac{T}{T-1}\right)\right]\} \tag{2}$$

where T = return period (years)

2. Create a file for the flood record, soil type, and land use record of the affected area.

3. Use a drone to capture the topography of the flood-prone area and analyze the results to aid in flood pathway identification.

5. Discussion

The use of ML for the prediction of flood and post-flood management is currently lacking in studies. The use of ML techniques to develop a flood prediction model has not been extensively studied [13]. Machine learning techniques are highly beneficial for forecasting floods because of the resilience of these models and their capacity to learn fast for the analysis of hydrological data [51]. Some of the variables discovered in these data sources include the rainfall, precipitation, soil moisture, water levels, river inflow, run-off water, streamflow, river flood, frequency of floods, flash floods, peak flow, groundwater level, storm surge, and rainfall stages [20]. It is important to keep in mind that several causes, like elevated soil moisture or prolonged stream flow, can cause unique flood types, which makes it difficult to accurately generate long-term flood estimates [52]. There are technological gaps that need to be addressed when looking at the flood control technologies and approaches currently in use. The primary cause of these disparities is a lack of coordination in the post-disaster stage and the use of currently available methods and technologies. UAVs, machine learning, and image processing have all been used in flood risk control [35]. However, this is primarily useful for mapping floods and assessing flood hazards from the perspective of flood prediction.

Machine learning algorithms have undergone extensive testing in the last several years, leading to the conclusion that the method is quite effective in detecting floods. For the machine learning algorithms that have been evaluated thus far, an accuracy level of up to 90% has been recorded. The majority of algorithm testing has been carried out for binary classifications, in which classifying flooded vs. unflooded areas is the only option [20]. A dependable system that can support enhanced security, rescue, and public safety activities as well as enable prompt communication regarding flooded areas must be built in order to recover from a disaster. The utilization of machine learning methodologies holds promise for enhancing extant emergency management systems and generating novel ones. The goal of the suggested model is to guarantee that post-flood management scenarios may make use of contemporary technologies. Floods cannot be completely prevented or stopped, but by understanding flood hazards and flood-prone locations, a strategy that could support relief efforts both before and after a disaster could be developed. UAVs are able to take pictures of flood-prone locations in advance of a disaster. It is possible to gather information about important sites, dams, transportation infrastructure, bridges, etc. In the future, these data may be helpful for scanning and grouping. These regions can be easily located by UAVs using their internal navigation system (INS), and they can be designated to perform any relief operations during flood occurrences [48].

Finding the shortest path out of the disaster area may be aided by floor plan modeling and route optimization. The shortest path algorithm can be used to lead relief personnel and help create the best evacuation strategy. The established models and methods can be used to manage the disaster in many scenarios. As a result, these technologies may function in dynamic contexts and assist the authorities with planning, decision-making, and catastrophe preparedness. The emergency departments can expedite relief operations by gaining deeper comprehension and a more efficient use of these technology.

6. Conclusions

The application of modern technology in the field of flood management was examined in a systematic evaluation of the literature. For the purpose of classifying different research that was conducted for flood management in the fields of image processing, machine learning, or both, a classification framework was developed. The following noteworthy research questions are addressed by the framework: (1) What are the main methods used in flood control? (2) Which stages of flood management is the majority of research currently in existence focused on? (3) Which systems are being suggested to address issues with flood control? (4) In the literature, what are the research gaps regarding the use of technology for flood management? Through the examination of these issues, this review has brought to light the cutting-edge technology that has been applied at various stages of the disaster management lifecycle, as well as the shortcomings of each method.

The classification primarily focuses on the application of machine learning and image-processing techniques used for mapping flood hazards or risks, mapping floods, mapping floods, and mapping flood inundations. Systems that use machine learning models like ANN, SVM, MLP, and WNN, as well as systems that use image-processing techniques like edge detection, segmentation, and pixel analysis, are the main tools used to handle the challenges associated with flood control. The three most often utilized methods for acquiring images are remote sensing, SAR, and UAV imaging. The methods now in use in the realms of machine learning and image processing often concentrate on both the pre- and post-disaster stages. To classify the many flood management technologies that have been studied, a categorization framework has been presented. One of the research gaps that has been discovered is the underutilization of hybrid models for flood management, which integrate machine learning and image processing. Additionally, it has been discovered lately that using machine learning-based techniques to address post-disaster crises is uncommon. This necessitates using GAI for automation to improve the post-disaster management procedure. Future research on the application of AI-enabled big data for flood management is also quite promising.

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