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Review

A Critical Review of Emerging Technologies for Flash Flood Prediction: Examining Artificial Intelligence, Machine Learning, Internet of Things, Cloud Computing, and Robotics Techniques

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Abstract: There has been growing interest in the application of smart technologies for hazard management. However, very limited studies have reviewed the trends of such technologies in the context of flash floods. This study reviews innovative technologies such as artificial intelligence (AI)/machine learning (ML), the Internet of Things (IoT), cloud computing, and robotics used for flash flood early warnings and susceptibility predictions. Articles published between 2010 and 2023 were manually collected from scientific databases such as Google Scholar, Scopus, and Web of Science. Based on the review, AI/ML has been applied to flash flood susceptibility and early warning prediction in 64% of the published papers, followed by the IoT (19%), cloud computing (6%), and robotics (2%). Among the most common AI/ML methods used in susceptibility and early warning predictions are random forests and support vector machines. However, further optimization and emerging technologies, such as computer vision, are required to improve these technologies. AI/ML algorithms have demonstrated very accurate prediction performance, with receiver operating characteristics (ROC) and areas under the curve (AUC) greater than 0.90. However, there is a need to improve on these current models with large test datasets. Through AI/ML, IoT, and cloud computing technologies, early warnings can be disseminated to targeted communities in real time via electronic media, such as SMS and social media platforms. In spite of this, these systems have issues with internet connectivity, as well as data loss. Additionally, Al/ML used a number of topographical variables (such as slope), geological variables (such as lithology), and hydrological variables (such as stream density) to predict susceptibility, but the selection of these variables lacks a clear theoretical basis and has inconsistencies. To generate more reliable flood risk assessment maps, future studies should also consider sociodemographic, health, and housing data. Considering future climate change impacts, susceptibility or early warning studies may be projected under different climate change scenarios to help design long-term adaptation strategies.

Keywords: flash floods; artificial intelligence/machine learning; Internet of Things; cloud computing; susceptibility predictions; early warnings

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1. Introduction

The World Economic Forum (WEF) reports that flash floods are climate-driven disasters capable of destroying infrastructure and properties, especially in arid desert environments [1]. The impact of floods, including flash floods, is felt in 761 locations around the world, resulting in more than 47 million deaths. Furthermore, more than 11 million and 4.7 million of these deaths are linked to cardiovascular and respiratory diseases, respectively [2]. According to estimates, 204 flash floods between 2010 and 2016 reduced the gross domestic product (GDP) by about 0.04%. In addition, they have a long-term impact on socioeconomics, the environment (e.g., waste generation, water pollution, and the spread of communicable diseases), and the mental well-being of receiving communities [3–5].

However, given these catastrophic impacts, it is imperative for communities/governments to have highly effective early warning forecasting and hazard assessment strategies to help reduce the damages caused by flash floods [6]. Traditional flash flood warning systems rely mainly on physically based modeling approaches (e.g., rainfall–runoff models, hydrological, hydrodynamic, and 1D/2D/3D numerical models).

Nevertheless, these approaches face challenges related to data resolution and mapping a highly complex mountainous topographical area. The inability of these traditional approaches to predict flow depth, flow velocity, and recurrence levels may also limit their effectiveness in mitigating future flash flood disasters [7]. This study shows that 1D hydrodynamic flood models may not accurately predict flash floods in urban areas because the model considers topographic and urban flow features as having one dimension. Also, these models are highly computationally and resource intensive (high data requirement), making it difficult to perform uncertainty analysis [8,9]. In order to optimize the efficiency of these traditional approaches, emerging technologies such as artificial intelligence (AI), machine learning (ML), and the Internet of Things (IoT) can be integrated.

There are several studies that analyze the role of these emerging technologies in predicting hydrological events, including flood management [10–12]. A study evaluated the effectiveness of machine learning ensemble techniques for flood monitoring and concluded that these techniques are rapidly increasing in hydrological disasters due to their high performance [13]. Based on a systematic literature review, it was found that the integration of machine learning and image processing techniques with flood management has not been extensively investigated [7]. A review study also assessed emerging technologies' contributions to flood-resilient built environments (e.g., artificial intelligence). According to some of the findings of the study, it is necessary for future studies to include comprehensive flood variables in order for emerging technologies to provide accurate flood prediction performance [14]. Several other emerging studies have investigated the use of these technologies in the prediction of flood events (e.g., river floods, coastal floods, urban floods, etc.) using time series data mining [11].

Flash floods are disastrous due to their short residence times, especially in highly impervious or impermeable landscapes. In this regard, early warning systems must be very efficient, and susceptibility maps must be accurate [15]. However, very few comprehensive reviews have examined the use of emerging technological tools to enhance the efficiency of flash flood management. The main objective of this study is to critically review the current innovative technologies used in flash flood management. To overcome this objective, the review will address the following research questions:

(1) What are the trends and characteristics of studies on smart technologies such as artificial intelligence (AI), machine learning (ML), the Internet of Things (IoT), cloud computing, and robotics that have been applied in flash flood early warning predictions?
(2) What are the performance levels of AI/ML algorithms in flash flood susceptibility predictions?
(3) What are the common indicators and influential factors in flash flood susceptibility assessment?
(4) What are the strengths and limitations of current studies that could improve future flash flood early warning and susceptibility predictions?

As a result of this review, technologically based flash flood early warning systems could be improved. These findings can be applied to future flash flood projects by policy-makers, engineers, and scientists.

This current review intends to improve the existing literature review studies in terms of coverage and focus. The major contributions of this study are as follows:

(1) Focusing exclusively on current evidence of these emerging technological tools applied in flash flood early warning and susceptibility predictions.

(2) Comprehensive coverage of several emerging technologies used in flash flood management: artificial intelligence (AI)/machine learning (ML), the Internet of Things (IoT), cloud computing, and robotics.
(3) Covering several artificial intelligence (AI)/machine learning (ML) internet algorithms utilized for flash flood warnings and susceptibility predictions.
(4) Including a detailed review of studies that have applied machine learning for flash flood susceptibility assessment supported by model performance evaluation levels.
(5) Including the temporal trends (from old to most recent papers) of flash flood-related technological studies.
(6) Synthesizing the findings of the studies and suggesting future research priorities and strengths.

The current study is organized into five main sections. Section 2 provides an overview of the study methodology, including the design, search strategies, and eligibility criteria. Section 3 presents the search results and general bibliographic analysis. Section 4 offers a comprehensive review of artificial intelligence (AI), machine learning (ML), the Internet of Things (IoT), cloud computing, and robotics. Section 5 provides a critical analysis of the findings, and Section 6 summarizes the strengths, limitations, and suggestions for future research directions. Finally, Section 7 concludes this study.

2. Methods

Through a gray literature search approach, we manually collected articles on flash flood technologies from different scientific databases, including Google Scholar, Scopus, and Web of Science. To retrieve the articles from these databases, different search terms were used ("flash flood" OR "flood technologies" OR "artificial intelligence" OR "machine learning" OR "internet of things" OR "deep learning" OR "robotics" OR "cloud computing"). Several studies were retrieved from Google Scholar and by a manual search. As a whole, the literature search commenced on 15 Sptember 2023 and ended on 10 December 2023 for research articles published between 2010 and 2023. As the purpose of this study is to review various emerging technologies used in flash floods, the search results were filtered to exclude studies that did not focus on flash floods (e.g., river floods, coastal floods, and urban floods). Studies on flash flood susceptibility or prediction without transparent methodologies for training and validating the test datasets were excluded. This current study included published papers that evaluated the performance of the models (e.g., artificial intelligence (AI)/machine learning (ML), etc.). Neither the publication year nor the country of origin was considered when searching for publications. Among the articles included in this study were only those published in English. Studies published in languages other than English were not translated and were excluded. The citations of all the eligible articles were exported into EndNote 20 Software, and their full-length articles were uploaded for data extraction and bibliographic analysis. Detailed search strings used in the electronic databases is shown in Table S1, Supplementary Material.

3. Results

3.1. Bibliographic Analysis of Flash Flood Publications and AI/ML Algorithms

3.1.1. Analysis by Year of Publications and Type of Technology

The current study began by conducting a bibliographic analysis to determine how many publications used AI/ML for flash flood susceptibility analysis and early warning predictions. Figure 1 shows that flash flood publications over the past decade have been distributed by year and technology type. Among 50 papers published between 2010 and 2023, 13 (26%) were published in 2021, but the number declined in 2022–2023, partly because of COVID-19. As can be seen, publication rates were stagnant between 2010 and 2017 but increased dramatically from 2018 to 2023. As a result of the analysis of flash flood technologies by type, 64% of the papers addressed the application of AI/ML to predict flash flood susceptibility and early warnings. Other technologies included storm cell identification, video-based surveillance, interactive voice response, and digital image analysis, which accounted for 9% of the publications, followed by the Internet of Things (19%), cloud computing (6%), robotics (2%), and other papers from different types of technologies.

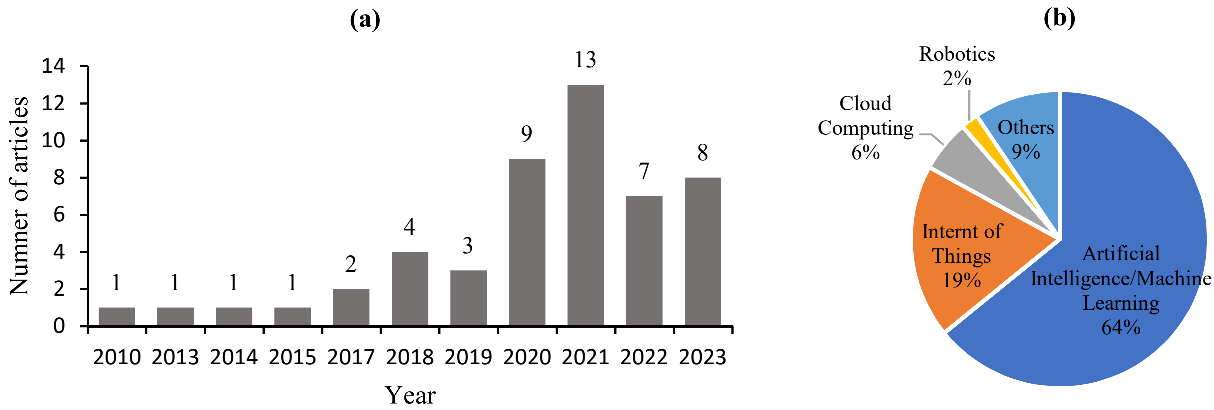

Figure 1. Distribution of articles (50) published in 2010–2023 according to (**a**) the number of papers and by year of publication and (**b**) categories of technologies such as artificial intelligence/machine learning (AI/ML), the Internet of Things (IoT), cloud computing, robotics, and other technologies (e.g., storm cell identification, video-based surveillance, interactive voice response, digital image analysis).

3.1.2. Analysis of Flash Flood Publications by Country

This analysis focused on the distribution of countries that applied AI/ML, the IoT, cloud computing, and robotics technologies for flash flood susceptibility and early warning predictions in 2010–2023, as shown in Figure 2. Quite a large number of the publications came from China, Iran, the United States, and India. In contrast, relatively lower publication rates were found among some Middle East and North African countries (e.g., United Arab Emirates, Tunisia, Egypt, etc.).

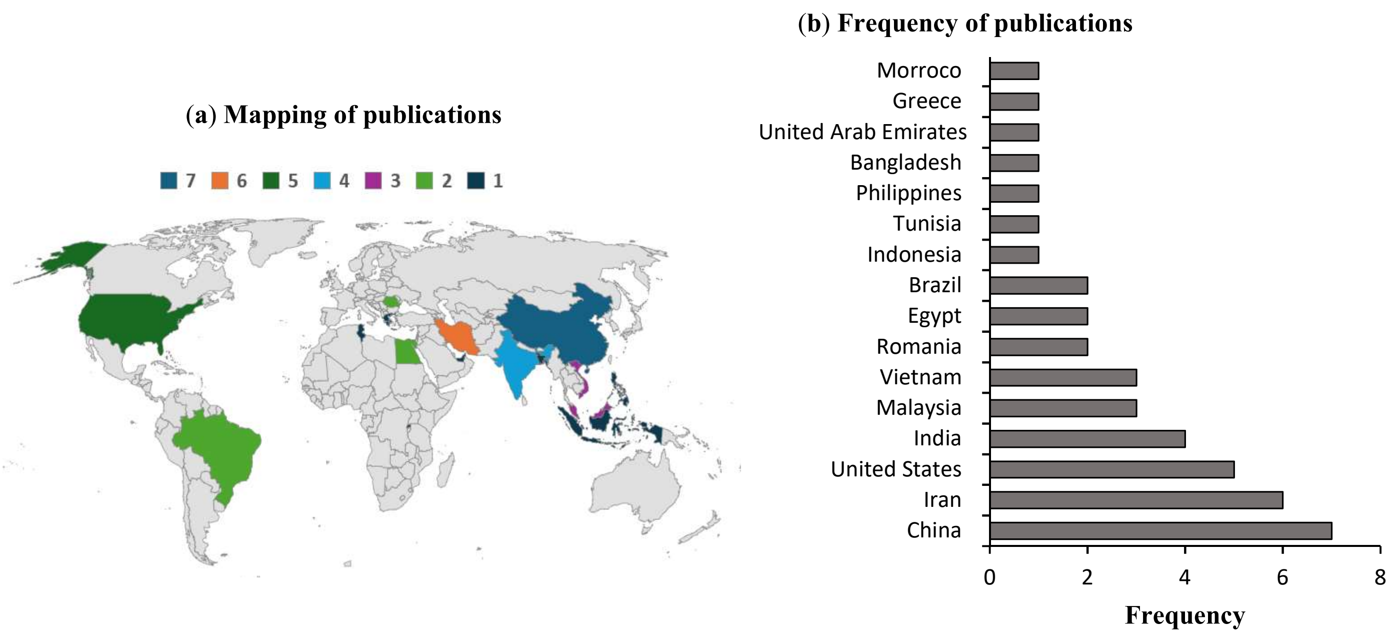

Figure 2. Geographical distribution (**a**) and frequencies (**b**) of published papers (2010–2023) on flash flood susceptibility and early warnings using AI/ML, the IoT, cloud computing, robotics, and other technologies (e.g., storm cell identification, video-based surveillance, interactive voice response, digital image analysis).

3.1.3. Analysis by Flash Flood AI/ML Algorithm Type

This study explored different AI/ML algorithms used for the flash flood susceptibility analysis and early warning, as shown in Figure 3. The analysis suggests that a total of 51 AI/ML algorithms were used for flash flood susceptibility and warning predictions between 2010 and 2023. Out of this, the most common methods used in the literature were random forest (8.05%) and support vector machine (8.05%), followed by artificial neural networks (6.9%) and logistic regression (6.9%). The majority of the algorithms presented in Figure 3 increased sharply from 2018 to 2021 and started to decline in 2022, as shown in Figure 4.

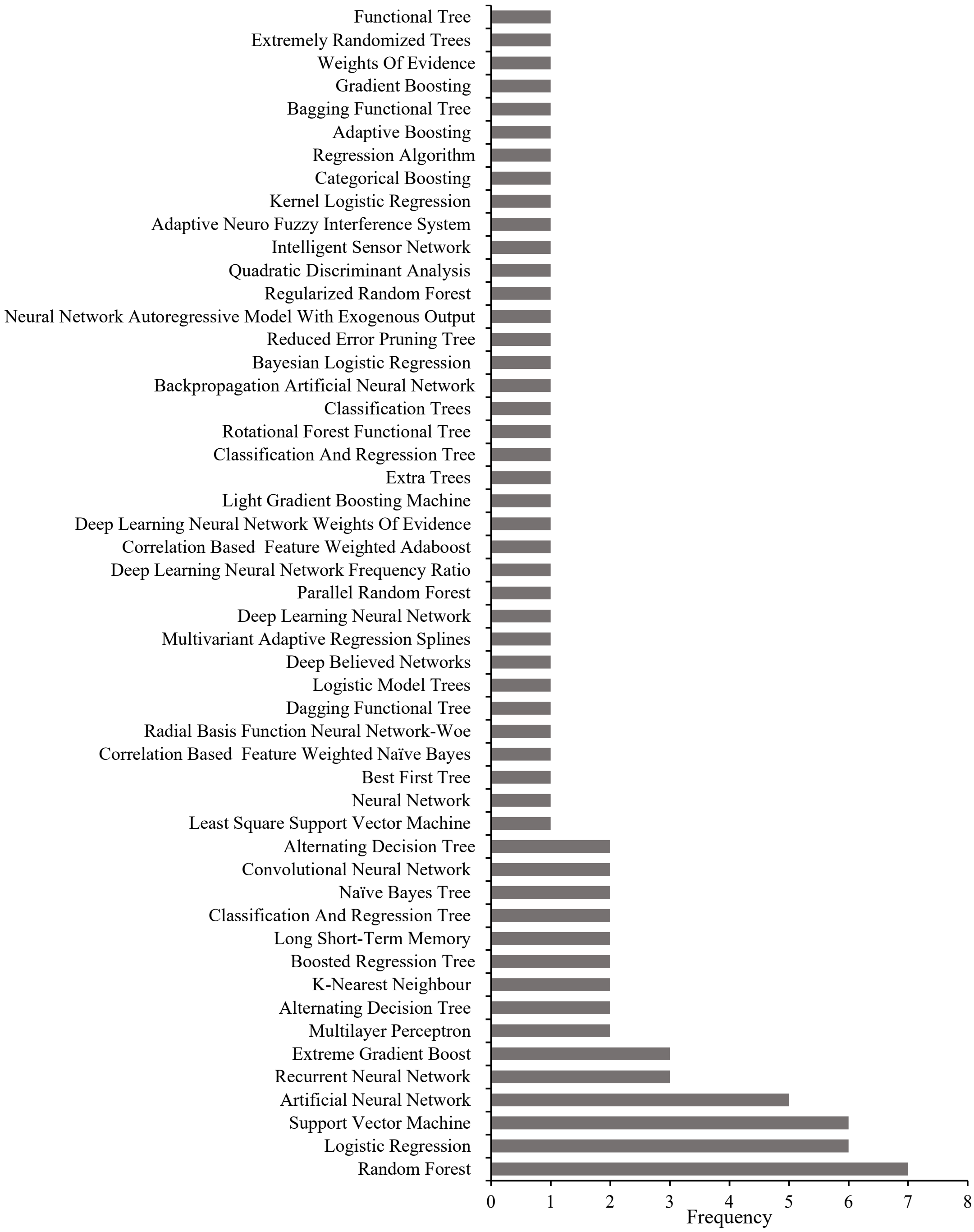

Figure 3. The number of different AI/ML algorithms (N = 51) used for flash flood susceptibility and early warning predictions (2010–2023).

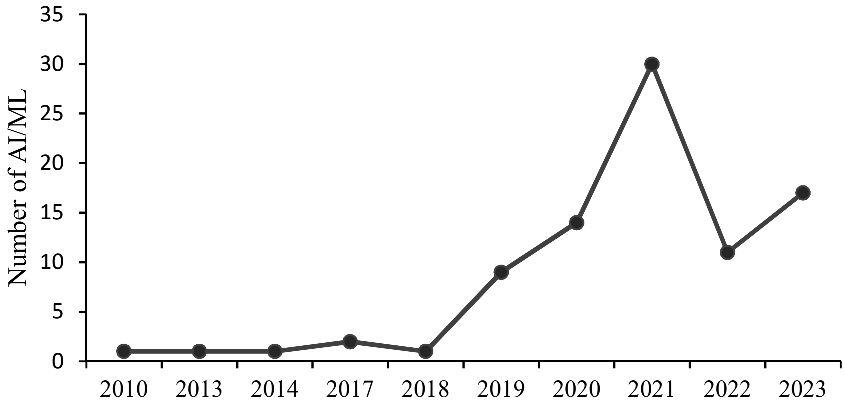

Figure 4. The number of AI/ML algorithms per year (2010–2023) applied in flash flood susceptibility and warning predictions.

4. Application of Emerging Technologies for Flash Flood Warnings and Susceptibility

4.1. Artificial Intelligence (AI)/Machine Learning (ML)

As the traditional hydrological models are not capable of accurately predicting flash flood early warnings, the integration of AI/ML into future early susceptibility assessments is essential [16]. In general, AI is the ability of computer systems to perform cognitive tasks or functions that are commonly associated with the intelligence of human beings. ML, which is a subset of AI, utilizes algorithms (e.g., random forest) to make predictions by training and validating data [17].

For flash flood assessment, AI/ML can employ a variety of algorithms (e.g., random forest, logistic regression) with historical flood datasets to predict/validate flood events [8]. A detailed description of various AI/ML algorithms for flash flood forecasting can be found in Table 1, divided into (A) traditional AI/ML algorithms for flash flood early warning predictions and (B) AI/ML algorithms for flash flood susceptibility predictions, including full model performance levels.

4.1.1. AI/ML Algorithms Used for Early Warning Predictions

In a study conducted in Khosf (Iran), three AI/ML algorithms were used to predict early warnings: support vector machines (SVMs), artificial neural networks (ANNs), and nearest neighbor classification (NNC), as shown in Table 1. SVM's coefficient of determination (r) was 0.88, ANN's was 0.79, and NNC's was 0.89. It was suggested that computer vision can help improve flash flood warning prediction [18].

Another study conducted in Amman city in Jordan evaluated the effectiveness of the ML-based artificial neural network (ANN) model in predicting flash flood early warning of street drainage water levels. The results suggested that ANN's forecasting accuracy was 93.5%, which was better when compared to the conventional forecasting model [19]. To support this, a study found that the application of a support vector machine (SVM) can accurately forecast flash flood events (2.5 milliseconds) better than the traditional numerical models (25 h). This study was conducted in urban areas surrounding the Jindong River basin located in Hangzhou, China [20]. An artificial neural network (ANN) could forecast flash flood events by a 2 h lead time. The application could transmit warning information through the telemetry system/short message services (SMSs) within 10 min for the Garang River located at Semarang (Indonesia). In Leyte Island in the Philippines, it was found that a regression algorithm driven by ML could send flash flood warnings, such as water level and water speed, via SMSs when the flood reached its threshold level [21]. The only issue identified was that the warning messages sometimes exceed the memory capacity of the SMS [22].

The application of the regression algorithm, a neural network autoregressive model with an exogenous output (NNARX), was able to improve prediction of flash flood water level, velocity, and ocean bottom pressure with a high accuracy of >80%. However, false alarm rates and communication challenges were the main issues faced by the study [23]. Forecasting of a one-hour lead time of the water level of a watershed located in Campos do Jordão, Brazil, was performed with a neural network (NN) using 3-year rainfall/water level data collected from 11 hydrometeorological stations. The study found 100% correctness in the classification of true positives for training and test sets, indicating that the NN can reliably be integrated to improve the accuracy of early warning systems. However, false positives were detected, indicating improvement in the NN algorithm [24].

Another study based on the long short-term memory (LSTM) approach predicted accurate one-day flash flood warnings with a false alarm rate of 0.09 and two-day warnings with a false alarm rate of 0.21. The LSTM approach gave the best predictions and had a critical success index of 0.75 [25]. The issue of false alarms can be addressed using an intelligent sensor network (ISN), as evidence shows that the ISN can reduce false alarms for flash flood events and can diagnose the health data of affected populations through alerts [26]. In Uttarakhand, India, gradient boosting (GBT) and recurrent neural network (RNN)-simulated warnings were based on varying degrees of alerts (e.g., danger, warnings, no alert). The accuracy of flash flood predictions according to the coefficient of regression value (R^2) for the RNN and GBT was 0.98 and 0.92, respectively. This study concluded that these methods have challenges in predicting water discharge levels due to frequent changes in the hydrogeological features of the area [27]. A study employed the LSTM method in Daqin (China) and found improved flash flood prediction levels with a reduced flood peak flow and volume error within a range of 3.02–57.4% and 6.3–39.3%, respectively, when coupled with hydrological models (Table 1) [28].

4.1.2. Application of AI/ML Algorithms for Flash Flood Susceptibility Predictions

Despite AI/ML's ability to predict flood susceptibility of an area, the performance of the algorithms must be evaluated with test data in order to understand their reliability/accuracy [29]. It is common practice to use receiver operating characteristics (ROC) in flood prediction. In order to assess the performance of different ML algorithms, the area under the curve (AUC) of the ROC is calculated by plotting the true positive rate against the false positive rate. The AUC is a measure of model performance that ranges from 0 to 1, with a high AUC value indicating high model accuracy [30,31].

Table 1 summarizes the flash flood susceptibility prediction performance measures for the various AL/ML methods. A study based on historical flash flood data across 226 locations in Gabes (Tunisia) suggested that the artificial neural network (ANN) technique could reliably predict 14% of the locations as very high flash flood susceptibility/prone areas. The ROC predicted an AUC value for the ANN of 0.86, indicating the reliability of the ANN. It should be noted that this approach could not determine the frequency of occurrence and timing of the flash flood events [32]. A comparative analysis between the convolutional neural network (CNN) and the recurrent neural network (RNN) was performed for flash flood historical data from Golestan, Iran. Evidence suggested that the CNN (RMSE = 0.83) slightly performed better than the RNN (RMSE = 0.81) in predicting flash flood susceptibility. In conclusion, both methods successfully captured spatial heterogeneities of flash flood vulnerabilities in the area [33]. In Tafresh, Iran, several AI/ML methods, including alternating decision tree (ADT), functional tree (FT), kernel logistic regression (KLR), MLP, and quadratic discriminant analysis (QDA), were used. Flash flood susceptibility predictions were very high for ADT (AUC = 0.97) compared to FT, KLR, MLP, and QDA, whose AUC values were >0.95. More than 80% of the area shows very high susceptibility to flash floods. It was recommended that computational highly efficient data mining methods could be employed to improve future studies [34]. Similar to Gorgan (Iran), the application of the bagging functional tree (BFT), dagging functional tree (DFT), and rotational forest functional tree (RFT) methods yielded AUC values of BFT (0.95), followed by RFT (0.94), with DFT (0.93) being the worst performing AL/ML model. About 1.99% and 5.41% of flash flood susceptibility areas were classified as very high and high, respectively, according to the BFT model. The study suggested the need to include hybrid models to reduce the uncertainties and improve prediction accuracy [35].

When the light gradient boosting machine (Light GBM) and categorical boosting (Catboost) were assessed using data from 445 flash flood locations in Hurghada (Egypt), AUC values showed that both the Light GBM (0.98) and Catboost (0.97) methods predicted the flood risk zones of the area with high accuracy. In addition, the two models predicted 42% and 44% of the areas as very high flash flood-susceptible zones [36]. In the same region (Central Eastern region, Egypt), extreme gradient boost (XGBoost) exhibited higher prediction accuracy (AUC = 90.2%) than the k-nearest neighbor (KNN), with an AUC value of 80.7% [37]. Least square support vector machine (LSSVM) and logistic regression (LR) were both evaluated to understand the warning predictive performance levels in Yunnan province, China. The prediction accuracy of LSSVM (0.79) was higher than LR (0.75). About 32% of the areas were classified as having a high flash flood risk. The AUC for LSSVM and LR were 0.8 and 0.78, respectively. However, the approach was considered data driven [38]. Another study in the same region (Yunnan) also found that extreme gradient boost (XGBoost) can reliably predict flash flood vulnerability areas with an AUC accuracy of 0.84. This time, larger areas (40.3%) were considered the high and highest susceptibility zones [39].

In Longnan County (China), multilayer perceptron (MLP), logistic regression (LR), a support vector machine (SVM), and random forest (RF) were used to identify flash flood vulnerability areas in the county. It was found that the order of AUC performance levels was the same for MLP (AUC = 0.97) and FR (AUC = 0.97) but higher than the SVM (AUC = 0.96) and LR (AUC = 0.88). The study concluded that the differences in prediction performance may be due to the differences in the weights of the input variables [40]. The support vector machine (SVM), k-nearest neighbor (KNN), random forest (RF), and logistic regression (LR) were also used in Jiangxi, China. The prediction accuracy was higher in RF (84.1%) than in the SVM (73.1%), KNN (72.8), and LR (70.3%). AUC values were found to be 0.89, 0.78, 0.78, and 0.76, respectively. High-risk zones of the areas based on RF predictions were 55.1%. However, there was an issue with the lack of high-resolution spatiotemporal data, as the study relied heavily on low-resolution satellite data [41]. Several types of ML methods, such as the naïve Bayes tree (NBT), reduced error pruning tree (REPT), logistic model tree (LMT), Bayesian logistic regression (BLR), and alternating decision tree (ADT), were used in watershed areas in Haraz, Iran. It was revealed that the prediction accuracy according to the AUC was higher in DBN (0.98) than in LR (0.88), NBT (0.97), REPT (0.81), LMT (0.93), BLR (0.93), and ADT (0.97) [42]. In the Islands of Rhodes (Greece) when the random forest (RF) and artificial neural network (ANN) methods were compared, flash flood susceptibility accuracy and the AUC were found to be 84% and 0.87 for RF and 81% and 0.77 for the ANN [43].

In Middle Eastern regions, such as the northern region of the United Arab Emirates (UAE), the boosted regression tree (BRT), classification and regression tree (CART), and naïve Bayes tree (NBT) methods were assessed. The AUC values show that BRT (0.92) achieved higher flash flood prediction accuracy than CART (0.90) and NBT (0.79). About 19.3% of the areas were considered very high flood-prone areas, and it was recommended that high-resolution remote sensing data could improve future prediction with better accuracy [44]. A study determined susceptibility with 860 flash flood events data and 421 non-flash flood events data in Tetouan city (Morroco) using an artificial neural network (ANN), a support vector machine (SVM), and random forest (RF). The flash flood susceptibility was accurately predicted in the order of RF (AUC = 0.99) > ANN (AUC = 0.98) > SVM > (AUC = 0.97) using 30% of test data [45]. Another study in Markazi (Iran) also applied boosted regression tree (BRT), parallel random forest (PRF), random forest (RF), regularized random forest (RRF), and extremely randomized tree (ERT) and found that the AUC values were higher in ERT (0.82) compared to RRF (0.8), PRF (0.79), RF (0.78), and BRT (0.75). The model found that 28.3% of the area is highly susceptible to flash floods [46].

Two different catchment-based studies in Romania showed similar prediction accuracies. The first study in Basca Chiojdului, Romania, used the deep learning neural network frequency ratio (DLNN-FR), the deep learning neural network weights of evidence (DLNN-WOE), alternating decision tree (ADT-FR), and alternating decision tree (ADT-WOE). The study reported the order of increasing prediction accuracy (AUC) as DLNN-WOE (0.92) > DLNN-FR (0.90) > ADT-WOE (0.89) > ADT-FR (0.87). Nearly 59.4% of the areas were classified as having a very high flash flood susceptibility [47]. The second study in Zabala, Romania, applied weights of evidence (WOEs), logistic regression (LR), classification and regression tree (CART), and radial basis function neural network–WOE (RBFN-WOE) algorithms. LR predictions were the most accurate (AUC = 0.92), whereas all the remaining models equally performed well, with an AUC > 0.85. About 55% of the areas were also found within high–very high susceptibility zones [48].

Two studies have conducted a nationwide flash flood susceptibility assessment in the United States. The first study focused on watershed areas in the United States' Southeast region using random forest (RF) methods. The study identified areas with a higher risk of flash flood events with high accuracy (AUC = 0.87) [49]. The second study in Alabama instead compared different methods. They include random forest (RF), extreme gradient boost (XGBoost), adaptive boosting (AdaBoost), and extra tree (ET), which identified 9.35% of the area as having high risk. The overall prediction precision was similar for all the methods: RF (0.975), XGBoost (0.976), Adaboost (0.974), and ET (0.975), whereas the AUC values were 0.845, 0.842, 0.790, and 0.834, respectively [50].

A study applied a deep learning neural network (DL), correlation-based feature weighted naïve Bayes (CFWNB), and correlation-based feature-weighted Adaboost (CFWNB-AB) for susceptibility analysis in Hanoi (Vietnam). It was revealed that DL (AUC = 0.97) predicted hilly terrain flash flood susceptibility better than CFWNB and CFWNB-AB, both with an AUC > 0.8. About 38.1% of the areas were classified as highly susceptible zones. According to the researchers, there was a lack of rainfall data time series for the analysis, which was the main limitation of the study. They also recommended that new ensemble ML models could help enhance model performance in the future [51]. In Bac Ha, Bao Yen, Vietnam, multivariant adaptive regression splines (MARSs), support vector machines (SVMs), back-propagation artificial neural networks (BPANNs), and classification trees (CTrees) found flash flood susceptivity performance levels (AUC) to be 0.96, 0.92, and 0.9, respectively, indicating relatively equal performance levels of all the three models [52]. Similar to Tran Yen (Vietnam), the support vector machine (SVM), classification and regression tree (CART), logistic regression (LR), and best first tree (BFTree) were applied for the susceptivity analysis. The performance of these AI/ML methods according to AUC values were SVM = 0.93, CART = 0.81, LR = 0.90, and BFTree = 0.88. The susceptibility areas were classified as very high (5%) and high (5%) [53].

Table 1. Summary of studies on artificial intelligence (AI)/machine learning (ML) and specific methods used for the prediction of flash flood warnings and susceptibility categorized according to (A) the traditional LM methods applied in flash flood warnings, without model evaluation, and (B) the ML methods used in flash flood susceptibility assessment with full model evaluation performance levels.

Location	AI/ML Method	Performance Levels	Conclusions	Reference
(A) Early Warning Prediction Studies				
Khosf, Iran	Support vector machine (SVM), artificial neural network (ANN), Nearest neighbor classification (NNC)	Flash flood risk was predicted by the three AI methods. The model performance through the coefficient of determination (r) for the three AI methods was SVM = 0.88, ANN = 0.79, and NNC = 0.89	An alternate application of computer vision can help improve the prediction of flash floods	[18]

Table 1. *Cont.*

Location	AI/ML Method	Performance Levels	Conclusions	Reference
Amman, Jordan	Artificial neural networks (ANNs)	The ANN improved flash flood warning forecasting by 93.5% when compared with the conventional forecasting model	High computation cost	[19]
Leyte Island, Philippines	Regression algorithm	Able to send flash flood warnings (water level and water speed) via SMS upon reaching the threshold	Warning messages sometimes exceed the memory capacity of the SMS	[22]
-	Adaptive neuro fuzzy interference system (ANFIS), meural metwork autoregressive model with exogenous output (NNARX)	It was found that NNARX accurately predicted flash flood water level, velocity, and ocean bottom pressure with >80% accuracy	-	[23]
Campos do Jordão, Brazil	Neural network (NN)	There is 100% correctness in the classification of true positives for training and test sets, indicating that the NN is reliably integrated to improve the accuracy of early warning systems	False positives were detected, indicating improvement in the NN	[24]
Golestan, Iran	Convolutional neural network (CNN), recurrent neural network (RNN)	The CNN (RMSE = 0.83) performed slightly better than the RNN (RMSE = 0.81) in predicting flash flood events. Both technologies successfully captured spatial heterogeneities of flash flood probabilities in the area	Hyper-parameter tunning could improve the accuracy of these DL networks	[33]
Hangzhou, China	Support vector machine (SVM)	The SVM (2.5 milliseconds) accurately forecasted flash flood events compared to traditional numerical models (25 h)	-	[20]
Semarang, Indonesia	Artificial neural network (ANN)	The ANN could forecast flash flood events by a 2 h lead time. The application could transmit information to the telemetry system/SMS in 10 min	-	[21]
-	Intelligent sensor network (ISN)	The system is fully automated. Reduces false alarms for flash flood events and can diagnose the health data of the affected population to issue alerts	-	[26]
China	Long short-term memory (LSTM)	The LSTM approach predicted accurate one-day flash flood warnings with a false alarm rate of 0.09 and two-day warnings with a false alarm rate of 0.21. The LSTM approach gave the best predictions with a critical success index of 0.75	The lack of a high resolution made predicting flash flood early warnings in complex geographies, such as mountainous areas, difficult	[25]
Uttarakhand, India	Gradient boosting (GBT), recurrent neural network (RNN)	The flash prediction accuracy according to the coefficient of the regression value (R2) for the RNN and GBT were 0.98 and 0.92, respectively	Using high-resolution remote sensing data may improve future predictions	[27]

Table 1. *Cont.*

Location	AI/ML Method	Performance Levels	Conclusions	Reference
Daqin, China	Long short-term memory (LSTM)	LSTM improved flash flood prediction by reducing flood peak flow and volume error by 3.02–57.4% and 6.3–39.3%, respectively, when coupled with hydrological models (e.g., WRF/WRF–hydro models)	-	[28]
(B) Susceptibility Assessment-Based ML Studies				
Gabes, Tunisia	Artificial neural network (ANN)	The ANN technique could reliably reveal 14% very high flash flood susceptibility/prone areas. The receiver operating characteristics (ROCs) predicted an area under the curve (AUC) value for the ANN of 0.86, indicating the reliability of the ANN risk predictions	The approach could not determine the frequency of occurrence and timing of the flash flood events	[32]
Golestan, Iran	The convolutional neural network (CNN) and recurrent neural network (RNN)	The deep learning neural network technique was able to predict heterogeneities in spatial patterns of flash flood risks. The area under the curve (AUC) values for the CNN (0.83) were slightly better than the RNN (0.81). About 40% of the area was considered to have very high susceptibility	There is a need to optimize the CNN and RNN algorithms	[33]
Tafresh, Iran	Alternating decision tree (ADT), functional tree (FT), kernel logistic regression (KLR), multilayer perceptron (MLP), quadratic discriminant analysis (QDA)	Flash flood susceptibility predictions were very high in ADT (AUC = 0.97) compared to FT, KLR, MLP, and QDA, whose AUC values were >0.95. More than 80% of the area is highly susceptible to flash floods	Computational, highly efficient data mining methods could be employed to improve future studies	[34]
Gorgan, Iran	Bagging functional tree (BFT), dagging functional tree (DFT), and rotational forest functional tree (RFT)	The three AI methods predicted flash flood susceptibility. The AUC values were BFT = 0.95, DFT = 0.93, and RFT = 0.94. About 1.99% and 5.41% of flood susceptibility areas were classified as very high and high, respectively, according to the BFT model	Introducing hybrid models to reduce uncertainties and improve prediction accuracy is important This approach could be used for flash flood vulnerability assessment	[35]
Hurghada, Egypt	Light gradient boosting machine (Light GBM) and categorical boosting (Catboost)	AUC values showed that both the Light GBM (0.98) and Catboost (0.97) methods accurately predicted flood-risk zones. The above models predicted 42% and 44% of the areas as very high flash flood-susceptible zones, respectively	-	[36]
Central Eastern region, Egypt	Extreme gradient boost (XGBoost) and k-nearest neighbor (KNN)	XGBoost (AUC = 90.2%) exhibited higher prediction accuracy than KNN (AUC = 80.7%)	Applying different optimization techniques can improve model performance	[37]

Table 1. *Cont.*

Location	AI/ML Method	Performance Levels	Conclusions	Reference
Yunnan, China	Least square support vector machine (LSSVM) and logistic regression (LR)	The prediction accuracy of LSSVM (0.79) was higher than and LR (0.75). A total of 32% of the areas were classified as high flash flood-risk areas. The AUC for LSSVM = 0.8 and LR = 0.78	These methods are data driven and lack the mechanisms causing the flash flood risk in the area	[38]
Yunnan, China	Extreme gradient boost (XGBoost)	Flash flood risk predictions were conducted. The prediction accuracy was 0.84. The high- and highest-risk areas were 40.3%	Long-term flash flood data should be considered in future studies	[39]
Longnan County, China	Multilayer perceptron (MLP), logistic regression (LR), support vector machine (SVM, and random forest (RF)	The MLP (AUC = 0.97) and FR (AUC = 0.97) techniques accurately predicted flash flood vulnerability areas compared to the SVM (AUC = 0.96) and LR (AUC = 0.88)	Differences in prediction performance may be due to the differences in the weights of the input variables	[40]
Jiangxi, China	Support vector machine (SVM), k-nearest neighbor (KNN), random forest (RF), and logistic Regression (LR)	The prediction accuracy was higher in RF (84.1%) than the SVM (73.1%), KNN (72.8), and LR (70.3%). AUC values were 0.89, 0.78, 0.78, and 0.76, respectively. High-risk zones were 55.1%	Lack of high-resolution spatiotemporal data could affect the reliability of the results	[41]
Haraz, Iran	Deep believed network (DBN), logistic regression (LR), naïve Bayes tree (NBT), reduced error pruning tree (REPT), logistic model tree (LMT), Bayesian logistic regression (BLR), alternating decision tree (ADT)	The prediction accuracy according to the AUC was higher in DBN (0.98) than LR (0.88), NBT (0.97), REPT (0.81), LMT (0.93), BLR (0.93), and ADT (0.97)	-	[42]
Islands of Rhodes, Greece	Random forest (RF), artificial neural network (ANN)	The flash flood prediction accuracy and the AUC was 84% and 0.87 for RF and 81% and 0.77 for the ANN	-	[43]
Northern regions, UAE	Boosted regression tree (BRT), classification and regression tree (CART), and naïve Bayes tree (NBT)	The AUC shows that BRT (0.92) achieved a higher flash flood prediction accuracy than CART (0.90) and NBT (0.79). About 19.3% of the areas were considered very high flood-prone areas	High-resolution remote sensing data could improve future flash flood risk predictions	[44]
Tetouan, Morroco	Artificial neural network (ANN), support vector machine (SVM), and random forest (RF)	Flash flood susceptibility was accurately predicted by RF (AUC = 0.99), the ANN (AUC = 0.98), and the SVM (AUC = 0.97)	-	[45]
Markazi, Iran	Boosted regression tree (BRT), parallel random forest (PRF), random Forest (RF), regularized random forest (RRF), extremely randomized tree (ERT)	AUC values were higher in ERT (0.82) compared to RRF (0.8), PRF (0.79), RF (0.78), and BRT (0.75). The model found 28.3% of the area to be highly susceptible to flash floods	-	[46]

Table 1. *Cont.*

Location	AI/ML Method	Performance Levels	Conclusions	Reference
Basca Chiojdului, Romania	Deep learning neural network frequency ratio (DLNN-FR), deep learning neural network weights of evidence (DLNN-WOE), alternating decision tree (ADT-FR), and alternating decision tree (ADT-WOE)	The prediction accuracy based on AUC values was higher in DLNN-WOE (0.92) than in DLNN-FR (0.90), ADT-WOE (0.89), and ADT-FR (0.87). Nearly 59.4% of the areas were classified as having a very high flash flood susceptibility	-	[47]
Zabala, Romania	Weights of evidence (WOEs), logistic regression (LR), classification and regression tree (CART), and radial basis function neural network–WOE (RBFN-WOE)	LR predictions were the most accurate (AUC = 0.92), whereas all the remaining models performed equally well, with an AUC > 0.85. A total of 55% of the areas fall within the high–very high susceptible zones	-	[48]
Southeast region, United States	Random forest (RF)	The RF approach accurately predicted damaged regions due to flash floods with 81% accuracy. The AUC = 0.87	Additional watershed predictor variables could improve future predictions	[49]
Alabama, United States	Random forest (RF), extreme gradient boost (XGBoost), adaptive boosting (Adaboost), extra tree (ET)	About 9.35% of the area was classified as high risk. The overall prediction precision was RF = 0.975, XGBoost = 0.976, Adaboost = 0.974, and ET = 0.975. Also, AUC values were RF = 0.845, XGBoost = 0.842, Adaboost = 0.790, and ET = 0.834	-	[50]
Hanoi, Vietnam	Deep learning neural network (DL), correlation-based feature weighted naïve Bayes (CFWNB), and correlation based feature weighted Adaboost (CFWNB-AB)	DL (AUC = 0.97) better predicted hilly terrain flash flood susceptibility than CFWNB and CFWNB-AB, which both had an AUC > 0.8. About 38.1% of the areas were classified as very highly susceptible zones	There was a lack of time series rainfall data for the analysis, and new ensemble ML models could enhance model performance in the future	[51]
Bac Ha, Bao Yen, Vietnam	Support vector machine (SVM), backpropagation artificial neural network (BPANN), classification tree (CTree)	Performance for flash flood susceptivity according to the AUC value was 0.96. A total of 10% of the areas were described as very high and high risk according to the MARS-PSO model	-	[52]
Tran Yen, Vietnam	Support vector machine (SVM), classification and regression tree (CART), logistic regression (LR), best first tree (BFTree)	The performance of these AI methods according to AUC values are SVM = 0.93, CART = 0.81, LR = 0.90, and BFTree = 0.88. The susceptibility areas were classified as very high (5%) and high (5%)	-	[53]

4.1.3. Flash Flood Susceptibility Indicators and Influential Factors

In order for AI/ML to reliably predict flash flood susceptibility, it will need a wide range of indicators/variables such as topographical (e.g., slope), geological (e.g., lithology), hydrological (e.g., rainfall), environmental (e.g., land use/cover features), and demographic (e.g., population) indicators [41,42]. It is important to note that the choice of indicators heavily depends on the features and characteristics of the area (e.g., watershed area). Based on AI/ML, Table 2 depicts a group of the most important variables that drive/control flood susceptibility.

For example, a study used a combination of different indicators (such as the topographic wetness index, altitude, plan curvature, proximity to roads, slope aspect, elevation, slope, land use, lithology, and rainfall) to conduct susceptibility mapping in the Golestan Province of Iran. Thus, the study focused on an urbanized area characterized by mountains, forests, industrial and residential facilities. It was concluded that low elevations and gentle slopes were the main predictors of flash flood events in the area [33]. Another study also used elevation slope, drainage density, land use, soil type, lithology, and rainfall and reported that increasing land use/cover, such as urbanization and drainage systems, increased the risk of flash floods [32]. Others have also identified elevation, distance to streams, and greenery, such as the normalized difference vegetation index (NDVI), as the main predictors of flash floods [35]. A study also found that flat terrain, low elevations, mountainous streams, and population are the main risk factors for flood susceptibility [39]. As indicated in Table 2, several other studies have also applied different susceptibility indicators and identified the most influential factors driving susceptibility, depending on the geographical characteristics of each area [34,36,37,40–53].

Table 2. Most common indicators/variables used by AI/ML for flash flood susceptibility predictions and influential factors causing susceptibility.

Location	Susceptibility Variables	Influential Factors	Reference
Tunisia	Elevation slope, drainage density, land use, soil type, lithology, rainfall	Land use, such as increasing urbanization, affects drainage systems	[32]
Iran	The topographic wetness index, altitude, plan curvature, proximity to roads, slope aspect, elevation, slope, land use, lithology, rainfall	Low elevation and gentle slopes have a strong association with flood events	[33]
Iran	Elevation, soil type, distance from rivers, slope aspect, slope, land use, lithology, rainfall	Land use features (residential areas, orchards) strongly influence flood occurrence	[34]
Iran	The topographic wetness index, the topography position index, the terrain ruggedness index, the convergence index, drainage density, the NDVI, soil type, distance to streams, altitude, plan curvature, land use, elevation, slope, land use, lithology, rainfall	Elevation, distance to streams, and greenery (NDVI) have a stronger impact on floods	[35]
Egypt	The topographic wetness index, flow accumulation, the sediment transport index, the NDVI, vertical flow distance, aspect, altitude, plan curvature, land use, elevation, slope, land use, lithology, rainfall	Land use, such as coastal areas, is prone to floods	[36]
Egypt	The topographic wetness index, distance from stream, stream density, plan curvature, elevation, slope aspect, slope, lithology	Elevation, slope, and stream density are the most influential floods to flood events	[37]
China	The topographic wetness index, rainfall, digital elevation model, slope, river density, vegetation coverage, curve number, soil moisture, population, gross domestic product, flash flood prevention efforts	Flat terrain, low elevation, mountainous streams, and population are risk factors for flood susceptibility	[39]
China	Elevation, slope, aspect, lithology, the NDVI, plan curvature, profile curvature, the topographic wetness index, surface radiation, gully density, rainfall, highway density, population density, the MNDWI	Elevation, gully density, and population density are the main contributors to floods	[40]

Table 2. *Cont.*

Location	Susceptibility Variables	Influential Factors	Reference
China	Slope, elevation, shape factor, concentration gradient, the topographic wetness index, the NDVI, distance to rivers, rainfall, peak discharge per unit area, and time of concentration	River distribution is associated with flood occurrence	[41]
Iran	Slope angle, elevation, curvature, rainfall, the topographic wetness index, distance to rivers, the NDVI, land use, river density, lithology, the sediment power index	Distance to rivers and river density are the major contributors to flood occurrence	[42]
Greece	Slope angle, elevation, aspect, curvature, land use, soil type, plan curvature, profile curvature, rainfall, the topographic wetness index, distance to rivers, the sediment transport index, sediment power index, lithology	Lithology, land use, slope, elevation, and the topographic wetness index were the main predictors of floods	[43]
UAE	Slope, altitude, land use, plan curvature, relief, distance to streams, stream density, lithology	Land use, such as mountainous areas and wider plains, has an elevated risk of floods	[44]
Morrocco	Elevation, aspect, slope, land use, the stream power index, plan curvature, profile curvature, the topographic power index, the topographic wetness index	Not given	[45]
Iran	Altitude, slope, aspect, plan curvature, profile curvature, distance to rivers, distance from roads, land use, lithology, soil type, rainfall, the topographic power index, the topographic wetness index	Altitude, rainfall, and distance to the river are the main predictors of flood occurrence	[46]
Romania	Slope, the topographic power index, the topographic wetness index, land use, profile curvature, lithology, the aspect, convergence index, the sediment power index, hydrological soil group	Slope angle and land use are the predictors of flood occurrence	[47]
Romania	Slope, rainfall, land use, hydrological soil group, lithology, plan curvature, profile curvature, the convergence index, aspect, the topographic wetness index, the modified Fournier index	Not given	[48]
United States	Population, home value, household composition and disability, intensity, slope, duration, latitude, longitude, onset time, month	Not given	[49]
United States	Elevation, slope, aspect, plan curvature, profile curvature, drainage density, distance to streams, curve number, rainfall, the NDVI, the sediment transport index, the topographic roughness index, the topographic wetness index, the stream power index	Curve number, the NDVI, slope, and drainage are the main factors influencing flood occurrence	[50]
Vietnam	Elevation, elevation difference, slope, aspect, curvature, the topographic wetness index, the sediment power index, drainage density, land use, geomorphology, structural zone, lithology, weathering crust, rainfall	Hilly areas are at an elevated risk of floods	[51]
Vietnam	Elevation, slope, curvature, toposhade, the topographic wetness index, the stream power index, stream density, the NDVI, soil type, lithology, and rainfall	Not given	[52]
Vietnam	Slope, aspect, curvature, elevation, the topographic wetness index, land use, river density, soil type, lithology, rainfall	Slope, land use, curvature, the and topographic wetness index are the most influential factors of flood occurrence	[53]

Note: MNDWI: modified normalized difference water index.

4.2. Internet of Things (IoT)

The Internet of Things (IoT) has led to rapid advances in flash flood management. Essentially, the IoT is a network of technology (e.g., electronic devices) connected to the internet that provides services based on sensor-based data [54]. In brief, the IoT is defined as a network of devices consisting of sensors, software, and computing systems that function together by gathering, processing, and transmitting data in real time to help improve the quality of human life. For example, the IoT can be used to provide early warnings for real-time flash floods in communities [55].

Through the integration of the IoT into flash flood management systems, the public can easily monitor flood-related early warnings in villages and cities in real time [56]. In spite of the fact that IoT integration into flash flood warning/monitoring systems is still in its infancy, several recent studies demonstrate the importance of these new emerging smart applications. Table 3 provides a summary of studies applying the IoT to monitoring flash floods and predicting early warnings.

A study developed an intelligent flash flood IoT system through a network of water sensor flows, rain gauge sensors, long-range radios (LoRas), subscriber identity modules (SIMs), warning systems, monitoring systems, and mobile applications (apps). This system helped communities living in flood-prone mountainous areas to receive continuous flash flood early warning notifications through short message service (SMS). The only challenge identified was fluctuations in steeper slopes and water levels in the area, making it difficult for the IoT system to read and transmit warning information effectively. A study assessed fault tolerance by applying a SENDI (System for dEtecting and Forecasting Natural Disasters based on the IoT) system and an ns-3 simulator. It was found that the overall accuracy of flash flood alerts for the system exceeded 65%, with 80% for red and 61% for yellow alerts. A high degree of accuracy was achieved, even under unfavorable conditions [57]. It recommended that this technology needs to be tested under system failure [58].

An innovative flash food IoT system (Gen1 On-Prem IoT: 3G Network protocol, flood level sensor, Linux, Apache, my structured query language (MySQL), Hypertext Preprocessor (PHP), Just Another Virtual Processor (JAVA), and email trigger) demonstrated high reliability in issuing flash flood warnings to the targeted communities. The early warning system was successful despite internet problems, except for some issues relating to performance and support for multiple users [59]. With an IoT-integrated early warning system (including Arduino microcontrollers, Raspberry Pis, a database server, a web server, and a smartphone), users were able to receive real-time flood status and alerts [60].

An IoT consisting of a network of distance measurement ultrasonic sensors, rain sensors, message queuing telemetry transport (MQTT), Arduino microcontrollers, ThingsSpeak, and WiFi was developed to enhance the effectiveness of flash flood early warnings. Although the system can effectively transmit flash flood alert messages (i.e., type of flash flood alert) to users, it was recommended that integration cameras and drones could improve system monitoring capabilities [61]. Others have also suggested the need to couple the IoT system (network of sensors, drainage data, flood data) with Al/ML to optimize its operation [62]. The current IoT system (Arduino microcontroller, mobile phone, cloud, water flow sensor, distance measurement ultrasonic sensor) can effectively transmit real-time flash flood alert messages but can be combined with remote sensing and geographical information systems (GISs) to improve its spatial–temporal performance levels [27]. However, it was concluded that the system successfully communicated flash flood alerts every 5 min [63].

A more sophisticated IoT system (TensorFlow, Raspberry Pi, Telegram Channel, camera, and a soft design document [SDD]) was developed and was able to successfully disseminate flash flood alerts via a Telegram Channel [64]. Another system (Raspberry Pi, Synology Network Access Storage, modem, web server, Android mobile phone, web browser (e.g., Google Chrome)) was able to perform multiple functions. This includes the ability to effectively provide useful information, such as lighting locations, rainfall levels, and locations of flash floods, as well as generate flash flood alert messages to the residents through mobile phone applications [65].

Table 3. Summary of Internet of Things (IoT) studies to predict early flash flood warning systems.

Location	Activity	Composition	The Study Outcome	Challenges	Reference
-	Early Warning Alert	Water Senser Flows, Rain Gauge Senser, Long-Range Radio (LoRa), Subscriber Identity Module (SIM), Warning System, Monitoring System, App	Communities living within mountain areas were able to receive continuous flash flood early warning notifications via short message service (SMS) through long-range (LoRa) systems due to internet issues in mountainous areas	Fluctuations in steeper slopes and water levels make it challenging for the IoT system to read and provide outputs	[57]
São Carlos, Brazil	Fault Tolerance Predictions	SENDI (System for dEtecting and Forecasting Natural Disasters Based on the IoT), ns-3 Simulator	The overall accuracy of flash flood alerts of the system exceeded 65%, with 80% for red and 61% for yellow alerts. A high degree of accuracy was achieved, even under unfavorable conditions	The performance of the technology needs to be tested under system failure and ensure readings from several nodes	[58]
Maryland, United States	Flood Prediction	Gen1 On-Prem IoT: 3G Network Protocol, Flood Level Sensor. Linus, Apache, MySQL, Hypertext Preprocessor (PHP), Just Another Virtual Processor (JAVA), Email Trigger	The system had high reliability and availability. However, it showed low performance. It successfully deployed information despite internet problems	There were challenges in supporting multiple users	[59]
Johor Bahru, Malaysia	Early Warning Alert	Arduino Microcontroller, Raspberry Pi, Database Server, Web Server, Smartphone	The system enabled users to receive real-time flash flood status (whether it will occur or not) and alerts	-	[60]
Kigali, Rwanda	Early Warning Alert	Distance Measurement Ultrasonic Sensor, Rain Sensor, Message Queuing Telemetry Transport (MQTT), Arduino Microcontroller, ThingsSpeak, WiFi	The system was able to effectively transmit flash flood alert messages (containing flash flood alert type and the state of the flash flood) to users	Future studies could integrate cameras and drones to improve monitoring	[61]
India	Early Warning Alert	IoT Sensors, Drainage Data, Flood Data	The system offered real-time information to users. The process was able to continue until the flash flood came under control	The current system can be coupled with ML in the future	[62]

Table 3. *Cont.*

Location	Activity	Composition	The Study Outcome	Challenges	Reference
Uttarakhand, India	Early Warning Alert	Arduino Microcontroller, Mobile Phone, IoT Cloud, Water Flow Sensor, Distance Measurement Ultrasonic Sensor	The system was able to effectively transmit real-time flash flood alert messages	The current system can be integrated with remote sensing and geographical information systems to improve its performance	[27]
Uttarakhand, India	Early Warning Alert	Arduino Microcontroller, Mobile phone, Android App, Google Cloud, Water Flow Sensor, Distance Measurement Ultrasonic Sensor	Users were able to effectively receive real-time flash flood alert messages through mobile applications and updated alerts every 5 min	The current system can be integrated with remote sensing and geographical information systems	[63]
Kuala Lumpur, Malaysia	Early Warning Alert	TensorFlow, Raspberry Pi, Telegram Channel, Camera, SDDMobileNetV1	The system successfully provided flash flood alerts on flash flood levels and normal levels via the Telegram Channel	-	[64]
Melaka, Malaysia	Flood Prediction, Early Warning Alert	Raspberry Pi, Synology Network Access Storage, Modem, Web Server, Android Mobile Phone, Web Browser (e.g., Google Chrome)	The system effectively predicts (e.g., lighting locations, rainfall levels, and locations of flash floods) and generates flash flood alert messages to the residents through mobile phone applications	-	[65]

4.3. Cloud Computing

The application of cloud computing technology for flood disaster management has gained a great deal of attention [66]. Cloud computing, or simply "Cloud", is interconnected computer grids or networks of sensors that can store, access, manage, secure, and organize data [67]. Because cloud computing offers unlimited data storage capacity, the ability to share data safely and integrate them into emerging computer technologies, such as high-performance computing (HPC) systems, is indispensable for flash flood management [68]. Despite being highly effective, flash flood warning systems have not yet widely used this technology. In contrast, few studies have shown that it can improve flood-related communications, as shown in Table 4. Thus, cloud computing does not operate on its own; rather, it combines with other networks, such as the Internet of Things, in order to enhance the operation of flash flood management [69].

A study conducted in Maryland, United States, developed integrated cloud-based systems (i.e., consisting of cloud, 3G, Central Processing Unit (CPU), water level ultrasonic sensors, solar panels, and the application programming interphase (API) for early warning alert forecasting. Interestingly, the system efficiently transmits flash flood status and visualizations into social media platforms, like Twitter. Some of the main changes faced during the operation were data loss issues and poor cloud connectivity, and it was suggested that integrating these systems into computer vision could help in future warnings [59].

Another study in Texas, United States, found that a hydrological-based cloud computing system (i.e., made up of a network of a Research Distributed Hydrological Model [RDHM], cloud, geographical JavaScript object notation [GeoJSON], GIS, Google Maps) was able to process data and show flash flood status online to the local emergency response managers and issued alerts through mobile apps [70]. However, another study from Bangladesh has pointed out that this current cloud-based system has difficulties reading water levels due to environmental-related issues, such as high water sediment levels. There is also a report about limited cloud centers across the country, making it difficult to employ this technology in rural areas or less developed countries [71]. However, the system was able to issue flash flood early warnings by mimicking water levels of river banks during rainfall [71].

Table 4. Summary of cloud computing studies used in flash flood warning systems.

Location	Activity	Composition	The Study Outcome	Challenges	Reference
Maryland, United States	Early Warning Alert	Cloud, 3G, Central Processing Unit (CPU), Water Level Ultrasonic Sensors, Solar Panels, Application Programming Interphase (API)	The system could transmit flash flood status, including images, through social media platforms, such as Twitter	Data loss issues and poor cloud connectivity. Integration of computer vision could help in the future	[59]
Texas, United States	Flash Flood Prediction	Research Distributed Hydrological Model (RDHM), Cloud, GeoJSON, GIS, and Google Maps	The RDHM in the cloud computer system could show flash flood status online to local emergency response managers and issue alerts through mobile apps	-	[70]
Bangladesh	Early Warning Alert	Cloud Servers (e.g., CloudSim), Gradient Servers Communications, Water Level, Ultrasonic Sensors	The system was able to issue flash flood early warnings by mimicking water levels of river banks during rainfall	The system was unable to read water levels due to sediments. A lack of cloud centers across the country was a major concern	[71]

4.4. Robotics

Robotics technologies are gaining attention in natural disaster management, especially for earthquakes, wildfires, landslides, etc., and for operations like searching for flood victims [72,73]. Furthermore, several studies have focused exclusively on the use of aerial robots to rescue flood victims [74–77]. From the aforementioned evidence, it is evident that robotic technologies have not been well documented in the literature when it comes to flash flood management, specifically for early warnings and communications. One study has utilized robotics in the Philippines' early warning systems for flash floods [78]. In this study, a robot was able to transmit accurate flash flood data to receivers when water levels reached critical levels. Additionally, a robot can display warnings on a liquid crystal display (LCD) and issue alarms via Global System Mobile Communication (GSM) to regulatory officials. The study's main limitations were deployment issues and the robots' electrical shielding [78].

4.5. Other Innovative Flash Flood Warning Technologies (Storm Cell Identification, Video-Based Surveillance, Interactive Voice Response, Digital Image Analysis)

In addition to the technologies (AI/ML, the IoT, could computing, and robotics) reviewed earlier in this study, many other innovative technologies such as storm cell identification, video-based surveillance, interactive voice response, and digital image analysis have been applied in flash flood warning systems, as shown in Table 5. A study in Catalonia (Spain) employed a storm cell identification and tracking algorithm (SCIT). It revealed that SCIT technology improved the flash flood forecasting systems by including different precipitation thresholds and identified topography as a triggering factor for storms occurring outside the convective periods [79].

The video-based surveillance system (VSS) was able to monitor water levels and potentially activate warnings on social media networks for public consumption [80]. Other systems, including SMS, interactive voice response (IVR), and cell broadcasting service (CBS), are easy to integrate with flash flood warning systems because they aid dissemination and are easily accessible to a majority of people [81]. There is also evidence that flash flood data, such as water levels generated through digital image analysis, can successfully be integrated into computer servers and shared via Android phones for public consumption. It should be noted that this application requires high-speed internet to be able to function effectively [82]. In addition, it has been found that international River Interface Cooperative (iRIC Version2.X) software can estimate flash flood events for both gauged and ungauged basins. It was concluded this software requires accurate digital elevation model (DEM) data to ensure successful early warning forecasting [83].

Table 5. Summary of emerging innovative technologies (storm cell identification, video-based surveillance, interactive voice response, digital image analysis) used in flash flood warning systems.

Location	Technology	Performance Levels	Challenges	Reference
Catalonia, Spain	Storm Cell Identification and Tracking Algorithm (SCIT)	Improved the current flash flood forecasting systems by including different precipitation thresholds. Was able to identify topography as a triggering factor	It can be enhanced by including the role of the ocean (e.g., melting of ice particles in the rain)	[79]
Manado, Indonesia	Video-Based Surveillance System (VSS)	The system can provide surveillance on water levels and has the potential to activate social media networks for public consumption	-	[80]
Sunamganj, Bangladesh	SMS, Interactive Voice Response (IVR), Cell Broadcasting Service (CBS)	SMS and IVR were suitable for the dissemination of flash flood forecasting due to ease of understanding and accessibility	The system can be enhanced by incorporating mixing push- and pull-based telecommunication services	[81]
Indonesia	Digital Image Analysis	Data on water levels were successfully integrated with a computer server and shared via Android phones for public consumption	The application was interrupted by an internet disconnection issue, especially during data transfer	[82]
Laos, Thailand	International River Cooperative (iRIC) Software	The iRIC showed satisfactory performance in estimating flash flood disasters for both gauged and ungauged basins	Requires an accurate digital elevation model (DEM) to ensure successful forecasting	[83]

5. Discussion

This review study has identified some strengths and limitations associated with applying AI/ML for flash flood early warning and susceptibility prediction (Figure 5). However, previous studies have exhibited high prediction performance levels based on a wide range of topographical, geological, and demographic indicators/variables. These indicators include slope, altitude, plan curvature, proximity to roads, slope aspect, elevation, land use, lithology, land cover, and population levels [41,42]. However, the basis for the selection of these indicators is lacking. For example, each indicator used in flash flood prediction should be evaluated to show it can reliably contribute to flash floods. This will lead to using a few reliable indicators for flash flood warnings and susceptibility prediction and help reduce the complexities in terms of the interpretation or application of the susceptibility maps.

To achieve a few indicators, multicollinearity must be conducted to help better identify variables that are not correlated and can independently contribute to flash flood vulnerability or early warning predictions [84]. Hydrological variables such as slope, elevation, and gully density usually show multicollinearity and should be excluded to reduce the data dimensions and complexities of the analysis [8].

It should be acknowledged that the main purpose of warnings or susceptibility mapping is to help develop interventions to reduce the catastrophic effects of flash floods or prevent their occurrence. Unfortunately, the majority of the indicators used for the predictions are natural features (e.g., elevation, slope, lithology, population levels). They are difficult to control, making it difficult to develop interventions. This implies that future flash flood predictive studies should focus on anthropogenic-driven or man-made indicators since they can be easily controlled or managed.

For example, using variables derived from urbanization, urban sewer systems, road networks, etc., for flash flood early warning and susceptibility prediction makes it possible to develop effective interventions compared to elevation or slope because the former can be managed. There is evidence that the common factors attributed to flash flood-related deaths are the inundation of buildings and a closer proximity of communities/neighborhoods to rivers [85]. Also, a study using an artificial neural network (ANN) algorithm was able to predict flash flood early warnings using urban drainage water level data with a forecasting accuracy level of 93.5%, suggesting the need to use man-made variables, such as drainage data [19].

This review has proven that despite operational and technical challenges, such as false alarms, internet connectivity issues, and data loss problems, including difficulties in reading and transmitting alerts, these modern smart technologies, A/ML, the Internet of Things, cloud computing, and robotics, can successfully predict flood-prone areas and issue early warnings for given reasonable lead times about imminent flood events for the planning of potential mitigation measures. However, there is no empirical evidence showing these innovative technologies' effectiveness in reducing flood-related deaths, disease, and property damages following their implementation. Studies suggest that among the different flood types (e.g., coastal flood, riverine), flash floods account for the highest number of fatalities per every event because of sudden occurrence and limited lead times [86].

Therefore, with the emergence of these smart technologies in terms of the efficient dissemination of early warnings, these tools must be evaluated to assess their effectiveness in reducing fatalities before and after implementation. New deep learning methods, such as transfer learning models [87] and hybrid ML models (based on predictions obtained from the methods) [88], may be utilized to improve the flash flood predictions since they reduce data complexities compared to the current algorithms. Considering the scope of this review study and the emergence of diverse smart technologies, it is evident that flood disaster management sectors will continue these new tools while improving their effectiveness in reducing flood-related burdens in the future.

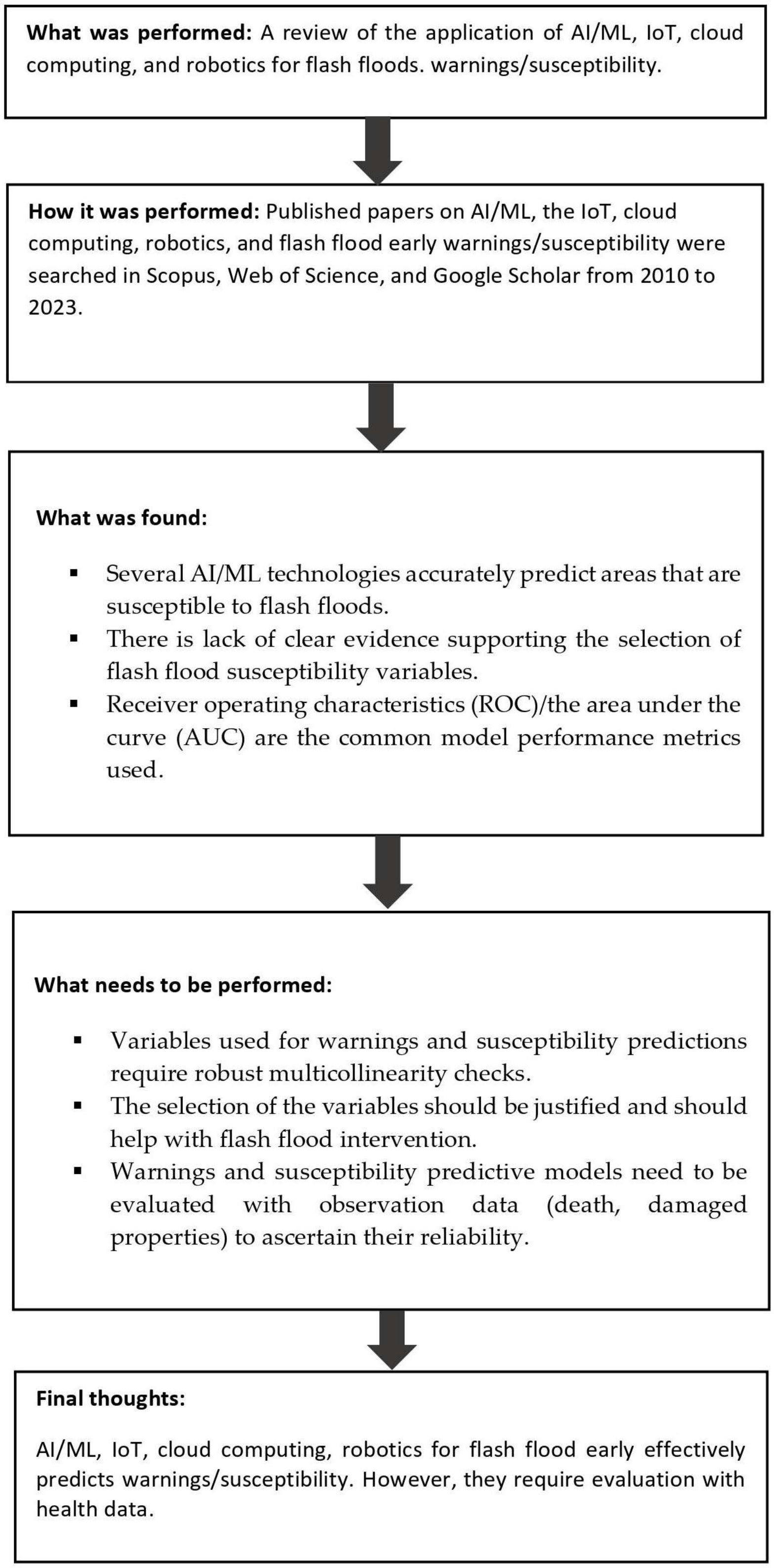

Figure 5. Study design, main findings, limitations, and future perspectives.

Regarding the main challenges that still exist in current flash flood predictions, the main problems are model reliability/accuracy and data quality issues. Several models make predictions based on the assumption that there is a linear relationship between input variables (predictors) and the likelihood of flash flood events/susceptibility/hazards, which may not be applicable to non-linear dynamics. The reliance on interdependent variables such as slope, altitude, slope aspect, and elevation could lead to the construction of biased flood susceptibility maps. Limited high-quality datasets have been a major challenge facing most developing countries. While open-access satellite data are the most common data sources in these countries, the issue of up-to-date data, data loss, and coarse resolution data are the important potential issues that could lead to inaccurate flood susceptibility maps in these countries [89]. Studies suggest that flash floods are driven by human-induced climate change impacts [90,91]. However, the current flash flood predictions using AL/ML technologies have not been projected under different climate change scenarios. It is imperative that flash flood predictions are projected under various greenhouse gas emissions Representative Concentration Pathways (RCPs), such as RCP 2.6 (low emissions), RCP 4.5 (medium emissions), and RCP 8.5 (high emissions), are used to help develop long-term adaptation strategies among vulnerable communities. These projections also help to track whether a particular country's climate change mitigation policies are contributing to reducing or increasing flash flood events.

Regarding future directions, flash flood predictions/early warning studies should involve several disciplines (epidemiology, urban forestry, economics, etc.) to help provide evidence-based study outcomes that can translate into policy. Future susceptibility studies may account for potential flash flood-associated deaths, hospital admissions, and ambulance call-out areas, including their attributable healthcare costs in highly/least susceptible areas. Studies show that vegetation cover/land cover are important predictors of flash flood events [92,93]. Future intervention studies may explore the role of urban forests, particularly vegetation density and species diversity on flash flood susceptibility. Finally, our review has highlighted several well-known variables (slope, altitude, plan curvature, proximity to roads, slope aspect, elevation, land use, lithology, and land cover) that cause the occurrence of flash floods. Future research may explore other unmeasured variables (known as confounding variables) that may influence flash flood susceptibilities or human health outcomes [94].

6. Summary of the Main Findings, Limitations, and Future Perspectives

The advancement of traditional models for flash flood prediction has proven valuable. However, it has been hindered by several inherent technological challenges, necessitating the integration of emerging smart technologies such as AI/ML, the IoT, cloud computing, and robotics for more accurate flash flood assessments and early warning systems. The traditional models, such as hydrological and hydrodynamic models, have been helpful in mitigating these impacts through early warning predictions. However, they face inherent challenges, such as issuing warnings in complex terrains, high computational costs, and less accurate predictions [7]. Therefore, it is crucial to employ emerging and innovative technological tools such as AI/ML, the IoT, cloud computing, and robotics to comprehensibly assess flash flood susceptibilities and develop more reliable early warning systems to help protect communities and properties. The findings of this critical review study suggest the following:

(I) Current technologies, especially AI/ML, the IoT, and cloud computing, can successfully issue flash flood early warnings in real time. However, this approach has challenges with false alarms, internet connectivity issues, and data loss problems. Therefore, future research should include aerial robotics and computer vision to improve their performance.
(II) The current AI/ML methods require optimization techniques to improve their current prediction performance.
(III) Random forest and the support vector machine were the most accurate AI/ML methods. However, these algorithms could be integrated with other technologies, such as computer vision, to help enhance their capabilities.
(IV) The current AI/ML utilizes a wide range of topographical, geological, and hydrological variables. Future studies should include sociodemographic, health, and housing data variables to help generate more realistic flood susceptibility maps.

(V) There are inconsistencies and limited information regarding the rationale for selecting the susceptibility variables, and there is potential multicollinearity among the variables.
(VI) The current flash flood susceptibility prediction models have not been evaluated with health data (flash flood-related death cases) to test their reliability in predicting vulnerable flood-prone areas.
(VII) Future AL/ML-based flash flood prediction studies should project susceptibility maps or early warnings under different climate change scenarios.
(VIII) Quantifying flash flood-associated deaths, morbidity, and healthcare costs among susceptible communities could improve future research.

7. Conclusions

The flash flood warnings and susceptibility predictions provide guidelines for emergency response planning, adaptability, and policy implementation for future flash flood events. This study aims to critically review current innovative technologies, such as AI/ML, the IoT, cloud computing, and robotics, for early flood warning predictions and susceptibility assessments. AI/ML, the IoT, and cloud computing technologies can disseminate early warnings to targeted communities through electronic media, such as SMS and social media platforms, in real time. However, these systems suffer from internet connectivity problems and data loss problems. Random forest and support vector machines are the most common AI/ML methods used in warnings and susceptibility predictions, but these technologies require optimization and other emerging technologies, such as computer vision, to perform well. Current Al/ML methods use several topographical, geometric, and hydrological variables to predict susceptibility, but there are inconsistencies and no clear theoretical bases for selecting the variables. Therefore, future flood risk assessment maps must incorporate factors such as sociodemographic, health, and housing data.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/w16142069/s1, Table S1. Detailed search strings used in the electronic databases.

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