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Review

The State of the Art in Deep Learning Applications, Challenges, and Future Prospects: A Comprehensive Review of Flood Forecasting and Management

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Abstract: Floods are a devastating natural calamity that may seriously harm both infrastructure and people. Accurate flood forecasts and control are essential to lessen these effects and safeguard populations. By utilizing its capacity to handle massive amounts of data and provide accurate forecasts, deep learning has emerged as a potent tool for improving flood prediction and control. The current state of deep learning applications in flood forecasting and management is thoroughly reviewed in this work. The review discusses a variety of subjects, such as the data sources utilized, the deep learning models used, and the assessment measures adopted to judge their efficacy. It assesses current approaches critically and points out their advantages and disadvantages. The article also examines challenges with data accessibility, the interpretability of deep learning models, and ethical considerations in flood prediction. The report also describes potential directions for deep-learning research to enhance flood predictions and control. Incorporating uncertainty estimates into forecasts, integrating many data sources, developing hybrid models that mix deep learning with other methodologies, and enhancing the interpretability of deep learning models are a few of these. These research goals can help deep learning models become more precise and effective, which will result in better flood control plans and forecasts. Overall, this review is a useful resource for academics and professionals working on the topic of flood forecasting and management. By reviewing the current state of the art, emphasizing difficulties, and outlining potential areas for future study, it lays a solid basis. Communities may better prepare for and lessen the destructive effects of floods by implementing cutting-edge deep learning algorithms, thereby protecting people and infrastructure.

Keywords: deep learning; flood forecasting; flood management; recurrent neural networks; convolutional neural networks

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1. Introduction

Flooding is a serious problem that affects many areas of the world. An area becomes submerged by water, usually as a result of heavy rain, melting snow, or rising sea levels [1]. Floods may cause serious harm to homes, businesses, infrastructure, and crops in addition to fatalities [2]. Along with its immediate impacts, flooding may also have long-term implications. Floodwaters may contaminate water supplies and spread illness [3]. Floods frequently disrupt transportation infrastructure, making it difficult to escape and receive essential goods and services. Flooding is a complex problem that requires a multidisciplinary approach to solve [4]. This includes programs to improve land use and urban growth, as well as the implementation of early warning systems and flood control measures [5]. Additionally, it is critical to spread knowledge about floods and teach people how to prevent and respond to these events [6]. There are several strategies to lower the risk of flooding and lessen flood damage. Here are some of the most well-liked methods. Building flood control structures like dams, levees, and dikes may hold back or redirect floodwaters [7]. These structures, which also aid in water flow regulation, reduce the risk of flooding in areas downstream. One part of managing floodplains is limiting development in areas that are prone to flooding. By doing so, flood damage is reduced, and both people and property are protected [8].

Several flood modeling approaches are used to forecast and simulate flood occurrences, each with its benefits and drawbacks. Listed below are a few of the most popular methods. To forecast how much water will be accessible during a flood event and how it will move over the landscape, a procedure known as "hydrologic modeling" simulates the flow of water in a watershed [9]. The benefit of hydrologic modeling is that it can simulate the consequences of changes in land use and human activity as well as take into consideration the intricate interactions between water, soil, and plants. Its disadvantages include the reliance on potentially incomplete or inaccurate data, as well as how difficult it may be to use on a large scale due to its computational complexity [10]. In hydraulic modeling, the flow of water in a river or canal is simulated to forecast the depth and speed of water during a flood event [11]. Hydraulic modeling has the benefit of being able to precisely forecast water levels and velocities while also taking into account the impacts of infrastructure like bridges and dams. Some of its disadvantages are its dependence on accurate information about the river or channel geometry, which can be difficult to obtain, and its complexity, which can make it difficult to apply to large-scale applications [12]. The movement of water may be simulated using physical equations and boundary conditions to predict water levels, velocities, and depth in a river or canal during a flood [13]. These models can be created numerically or analytically using fluid mechanics equations or finite element methods [14].

Applying statistical techniques to estimate the probability that a flood event will occur under different circumstances is known as probabilistic modeling [15]. The advantages of probabilistic modeling include its ability to account for the ambiguity and unpredictable nature of flood periods and its capacity to provide a quantitative evaluation of risk. Its drawbacks include its reliance on potentially incomplete or erroneous data as well as its sensitivity to the analysis's assumptions and techniques. Utilizing satellite and aerial data, remote sensing and geographic information system (GIS)-based modeling comprises mapping and assessing flood events [16]. The benefit of this method is that it may mix data from many sources and provides precise information on the nature and impact of floods. Its drawbacks include the fact that it depends on high-quality data, which could be scarce or unavailable, as well as the computational complexity that makes it challenging to apply to large-scale applications [17].

Machine learning (ML), a branch of artificial intelligence (AI), is concerned with creating models and algorithms that can learn from and forecast data [18]. The goal of ML is to automatically improve a model's performance on a task without having been specifically trained to do so. ML algorithms are divided into four categories: reinforcement learning, semi-supervised learning, unsupervised learning, and supervised learning [19]. In supervised learning, predictions are made on fresh, unforeseen data using an algorithm that has been trained on a labeled dataset [20]. Unsupervised learning uses an algorithm that is trained on an unlabeled dataset to find trends and correlations in the data [21]. Image recognition, natural language processing, recommendation systems, and predictive modeling are just a few of the many applications that make use of machine learning methods [22].

ML, which has several advantages over traditional approaches, is being used more and more in flood prediction and management [23]. Here are some examples of how ML is being applied to stop flooding: Predicting flooding to forecast future flood occurrences [24], ML models may be trained on past data including rainfall, river flow, and satellite images. These models can aid in early flood warning, enabling more efficient preparation and response [25]. ML models can assess real-time data from sensors and satellite imagery to monitor floods in near real-time [26]. This makes it possible to identify floods early and thus speed up responses. By examining data on variables like land use, geography, and infrastructure, ML models may be used to evaluate flood risk [27]. This can assist in locating flood-prone locations and providing information to guide management decisions. ML models are used to evaluate flood damage by using satellite images and other data sources. This speeds up the damage assessment process and provides information for decision-making on relief and recovery activities [28].

Deep learning (DL) is a subfield of ML that uses algorithms inspired by the structure and function of the brain, known as artificial neural networks, to model and solve complex problems [29]. Although traditional statistical methods and hydrological models have been utilized extensively for flood forecasting, they frequently fail to represent the intricate and nonlinear interactions present in flood dynamics. Researchers have looked at different strategies in response to this constraint, and DL has demonstrated remarkable possibilities. Convolutional neural networks (CNNs) [30], recurrent neural networks (RNNs) [31], and their variants are examples of deep learning models that can handle enormous amounts of data, recognize complex patterns, and generate precise predictions. Given the numerous factors involved, such as rainfall, river levels, soil moisture, and topographic characteristics, these models excel at managing high-dimensional and spatiotemporal data, which are crucial for flood forecasting. Figure 1 depicts the hierarchical representation of AI, ML, and DL in a simplified representation of how these terms are related. AI refers to the broader concept of machines or algorithms that can mimic human intelligence. As illustrated in Figure 1 deep learning is a subset of machine learning that falls under the larger AI umbrella. DL algorithms have demonstrated exceptional performance in a variety of applications, including computer vision, natural language processing, speech recognition, and gaming [32]. The depth of the model, which refers to the number of hidden layers in the neural network, is the key difference between traditional machine learning algorithms and deep learning algorithms.

1.1. Literature Review

DL models contain many hidden layers; they may learn at many levels of abstraction and complete challenging tasks. They are therefore suitable for problems like image classification, where the model needs to identify objects in an image despite variations in illumination, background, and perspective [33]. A lot of times, the stochastic gradient descent method is used to train DL algorithms on huge volumes of data. The parameters of the model are changed during training to reduce the discrepancy between the model's predictions and the actual labels in the training data [34]. Because of their ability to learn complex relationships and patterns in data, DL models are increasingly being used for flood forecasting. The prediction accuracy of these models is higher than that of conventional models, and they can be trained on a lot more data [35].

Applications for DL algorithms include the following: Predicting future flood occurrences—DL algorithms may be trained on significant historical flood data sets, such as rainfall data, river flow data, and satellite images. These algorithms contribute to the delivery of more precise and fast flood warnings, enabling greater preparedness and response [36]. Flood monitoring—near-real-time analysis of satellite images and other remote sensing data using DL algorithms can be used to monitor floods. These algorithms help identify flood-prone locations by detecting changes in water levels [37]. Assessment of flood risk—DL algorithms are capable of conducting extensive analyses of data on terrain, infrastructure, and land use. This assists in locating flood-prone locations and provides information for managing flood risk [38]. Flood damage assessment—DL algorithms may be used to examine satellite images and other data sources to determine the degree of flood damage. This helps assess the scope of a flood and informs decisions about relief and recovery activities [39].

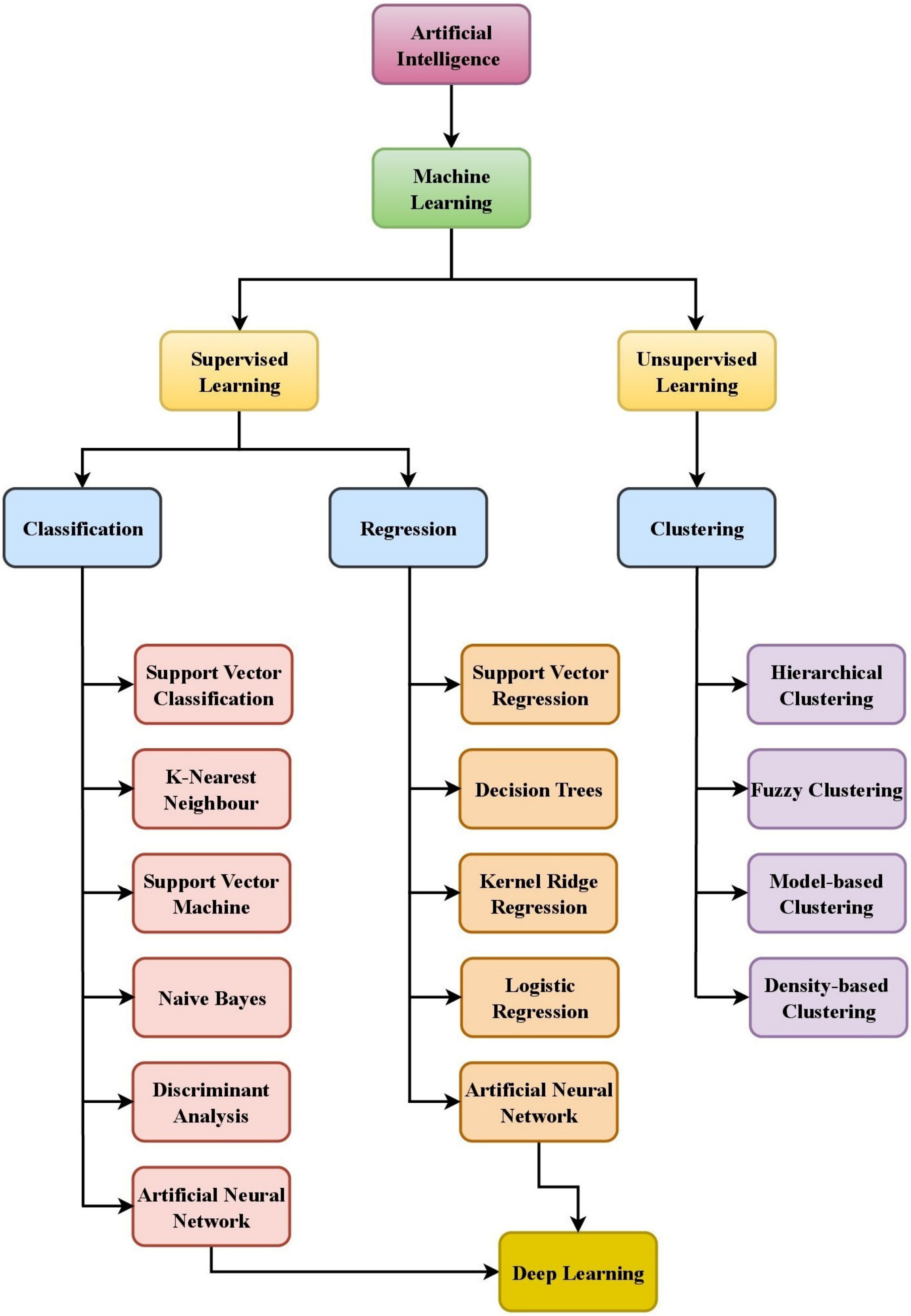

Figure 1. The hierarchical representation of artificial intelligence, machine, and deep learning.

In comparison to conventional models, ref. [40] investigated the construction of a DL-based flood prediction model that accurately anticipates flood features in both the temporal and spatial dimensions. The model showed exceptional performance and possible application in emergency planning and real-time flood management. Ref. [41] used DL approaches to reliably estimate flood gauge height with the increased temporal resolution, exceeding conventional models and providing enhanced flood forecasting for numerous applications. To forecast floods by capturing the spatiotemporal aspects of hydrological data, ref. [42] suggested a ConvLSTM model that integrates CNN with long short-term memory networks (LSTM). The model outperforms other models in its ability to anticipate the timing of the flood and its peak discharge. Ref. [43] introduced the spatio-temporal attention long short-term memory model (STA-LSTM), an interpretable flood forecasting model that integrates LSTM and attention processes. The model performs better than several already-used methods and offers attention weights that are both visually appealing and easily comprehensible. Ref. [44] assessed the precision of four data-driven approaches (linear regression (LR), multilayer perceptron (MLP), support vector machine (SVM), and LSTM) for daily streamflow forecasting in the Kentucky River basin. In hydrological modeling applications, the LSTM network performs better than alternative models, illustrating its reliability and efficiency. Other applications of DL in floods include flood forecasting [45,46], flood monitoring [47,48], and flood hazard mapping [49].

Some of the current shortcomings in the use of DL may be filled by future research. For instance, DL models may overfit certain datasets and fail to generalize to new data. More research is required to develop DL models that successfully generalize to various situations and data. Since deep learning models can be difficult to read and comprehend, their practical applications are rather limited. There is a need for more research on the interpretability and transparency of DL models, as well as the development of methods for expressing and elucidating the decision-making processes of these models. DL models require a significant amount of data and processing power and are computationally expensive. Further study on the scalability and computational efficiency of DL models is required, as well as the development of methods for boosting their efficiency on certain hardware platforms. To build DL models that can effectively manage this kind of data, more research is required. Missing or noisy data may render DL models vulnerable. Since DL models are vulnerable to adversarial attacks, further research is needed to ascertain how robust these models are and to develop defenses against them.

1.2. Contribution of the Paper

This paper aims to make a significant contribution to the field of flood forecasting and management by providing a comprehensive review and summary of recent advancements in deep learning (DL) applications. The key objectives of this review article are as follows:

1. Identifying the main challenges that DL approaches can solve in flood forecasting and management.
2. Conducting a comprehensive review on the use of DL for managing and forecasting floods.
3. Identifying current trends in the area and potential paths for future study, including chances for advancement and innovation in DL applications for flood forecasting and management.

1.3. Structure of the Paper

The structure of this review paper is as follows: The methodology for the article is described in Section 2. An in-depth discussion of DL, its methods, and its applications is presented in Section 3. The use of DL techniques, including the use of several DL models, in flood forecasting and management is covered in Section 4. In Section 5, problems with and possible solutions for employing DL in flood forecasting and management are identified. Future directions are covered in detail in Section 6. Section 7 concludes by summarizing the main ideas and highlighting the value of DL in flood predictions and management.

2. Methodology

Machine learning (ML) and deep learning (DL) are two subfields within the wider area of artificial intelligence (AI). The earliest AI algorithms and symbolic AI systems were created in the 1950s, marking the beginnings of AI [50]. The development of AI, however, was gradual until the 1980s, when ML made it possible for AI systems to continuously improve their performance by learning from data [51]. Among the early ML techniques were decision trees (DT) [52], neural networks (NN) [53], and support vector machines (SVM) [54]. These methods opened the way for the development of AI systems that can identify patterns in speech, text, and picture data [55].

DL is a branch of ML that uses multiple-layer artificial neural networks (ANN) to learn complicated data representations [56]. The early development of backpropagation, a technique for training neural networks, in the 1980s, gave rise to DL [57]. However, DL did not become a major force in AI research until the 2010s, when large datasets and potent GPUs were available [58]. AI, ML, and DL are now used in a variety of uses, including image, speech recognition, natural language processing, self-driving cars, and medical diagnosis [59]. Today, the development of AI, ML, and DL is a fast-expanding and changing field, with continuing research and innovation leading to new developments and applications across sectors and disciplines. The primary distinction between ML and DL is in how features are extracted and processed from input data (see Figure 2). ML relies on handcrafted features, whereas DL learns and extracts features automatically through multiple layers of non-linear transformations [60]. DL has proven to be extremely effective in a wide range of applications, particularly those involving complex and high-dimensional data. However, it necessitates a large amount of training data as well as computational resources [61].

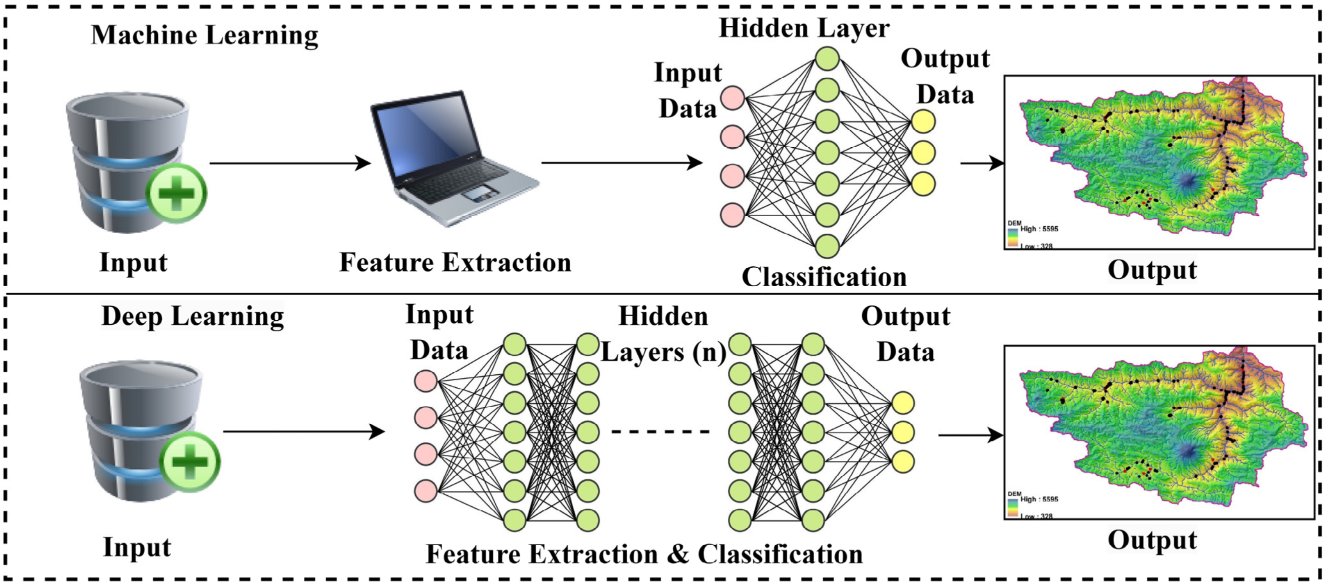

Figure 2. Difference between machine learning and deep learning.

The feed-forward neural network is the most frequently used neural network architecture in ML [62]. This network is made up of three levels: an input layer, one or more hidden layers, and an output layer. Each layer is made up of a group of neurons, and each neuron receives its input from the previous layer and generates an output that is passed on to the next layer. The weights of the connections between neurons are adjusted during training to minimize the difference between predicted and actual outputs [63]. A basic feed-forward network with an input layer, one hidden layer, and an output layer is depicted in Figure 3. The deep feed-forward neural network, also known as a deep neural network, is the most frequently used neural network architecture in DL [64]. This network is made up of several layers of interconnected neurons, each of which performs a non-linear transformation on the incoming data. The network may have tens or hundreds of layers and may include extra components such as convolutional layers, pooling layers, and recurrent layers [65]. Backpropagation, a gradient-based optimization method, is used during training to adjust the weights of the connections between neurons. Figure 4 depicts an example of a deep feed-forward neural network.

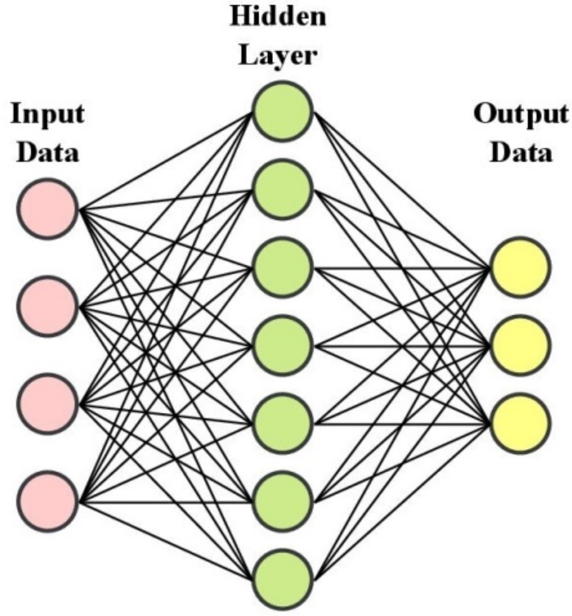

Figure 3. Simple feed-forward network.

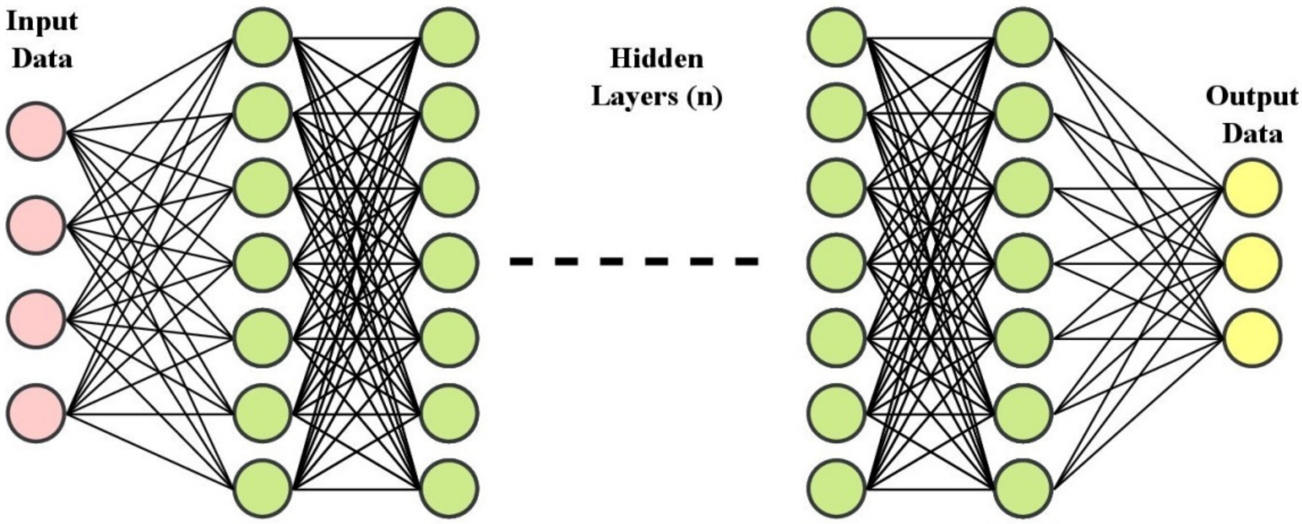

Figure 4. A deep feed-forward neural network.

Figure 5 shows the working methodology of the DL algorithm for flood forecasting. There are several stages involved in the operation of DL algorithms for flood forecasting. To begin, historical data on river flows, rainfall, temperature, and other pertinent variables are gathered from a variety of sources, including weather stations, satellite data, and ground-based sensors. To remove any outliers or missing values, the data are preprocessed and cleaned. Following that, the data are split into training, validation, and testing groups. The training set is used to train the DL model. The validation set is used to adjust the hyper-parameters of the DL model and prevent overfitting. The model's efficacy is evaluated using the testing set. These models, which were developed using historical data, can comprehend the complex relationships between the input variables and the river flow. The model may be used to predict future water flow conditions based on the input data once it has been trained. The effectiveness of the model's predictions may be evaluated using a variety of performance metrics, including mean absolute error, root mean squared error, and correlation coefficient. The precision of the model's predictions can be increased by using ensemble techniques like stacking and bagging. To decrease prediction errors and increase accuracy, these strategies combine the predictions of many models. Figure 6 shows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) method to demonstrate how the paper selection process is organized.

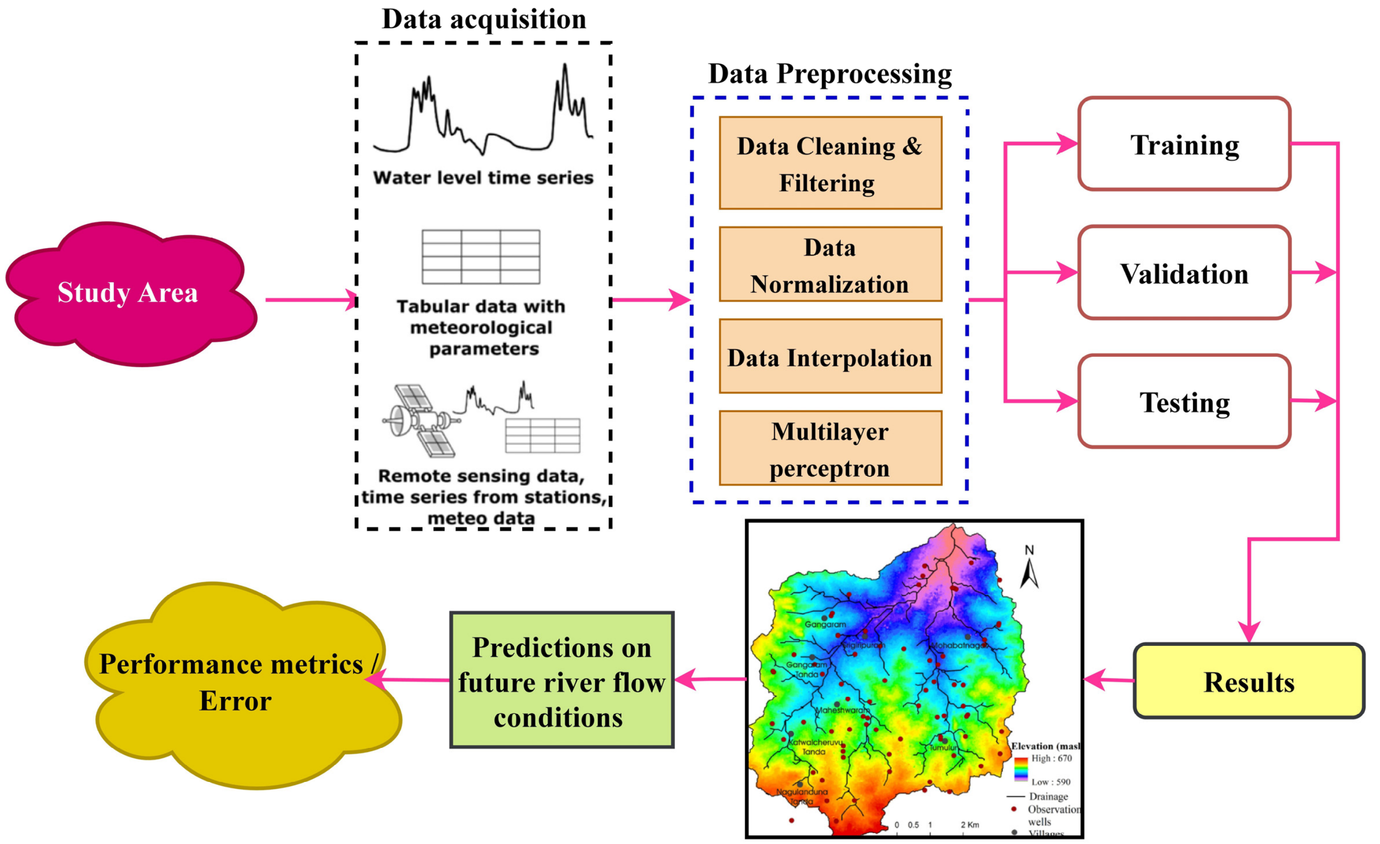

Figure 5. Flowchart of the deep learning algorithm's methodology for flood forecasting.

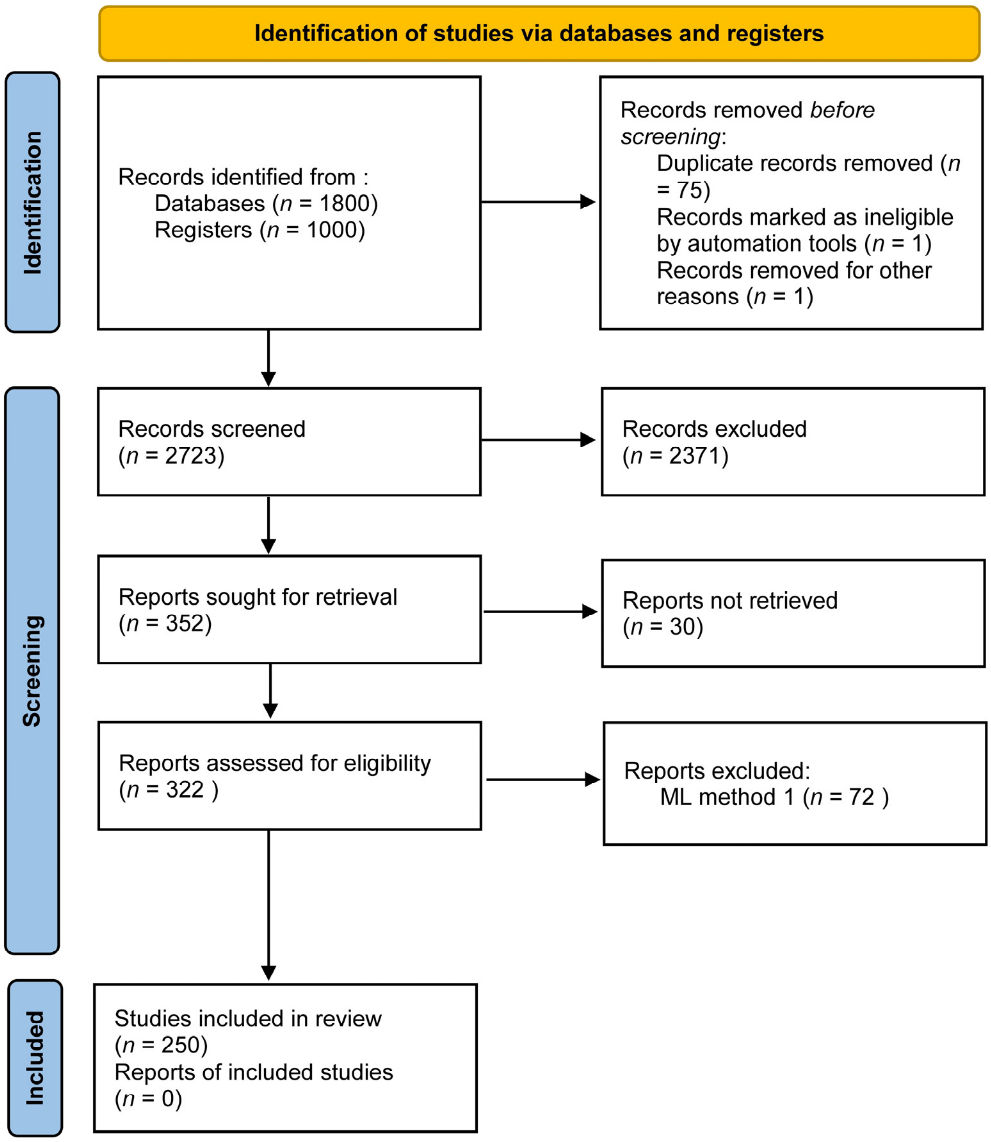

Figure 6. The PRISMA model.

3. Deep Learning Overview, Techniques, and Applications

3.1. Deep Learning Overview

The goal of DL algorithms is to automatically learn from huge amounts of data without the use of specialized programming or feature engineering [66]. The artificial neuron, which accepts inputs, carries out calculations, and generates output, is the essential building block of a DL algorithm [67]. The outputs of one layer serve as inputs to the following layer in this tier-based arrangement of neurons. To find complex links and patterns in data, DL techniques are utilized [68]. DL techniques fall into three categories: supervised learning, unsupervised learning, and reinforcement learning. In terms of flood forecasting and management, each of these approaches offers a unique set of applications. A model is trained on labeled data with known input and output pairings as part of supervised learning. In the case of floods, supervised learning can be used to forecast the water level or flood extent based on past data [69]. Unsupervised learning comprises training a model with data that have not been labeled with output values, or "unlabeled" data. In the case of floods, unsupervised learning can be used to spot patterns or abnormalities in the data that can be a sign of emerging flood-related events [70]. The process of teaching a model to make decisions based on the maximizing of a reward signal is known as reinforcement learning [71]. Comparing the costs and advantages of various activities, flood control systems may be improved through reinforcement learning. One illustration is the use of reinforcement learning to improve flood control dam performance [72]. The classification of DL algorithms into different categories is shown in Figure 7.

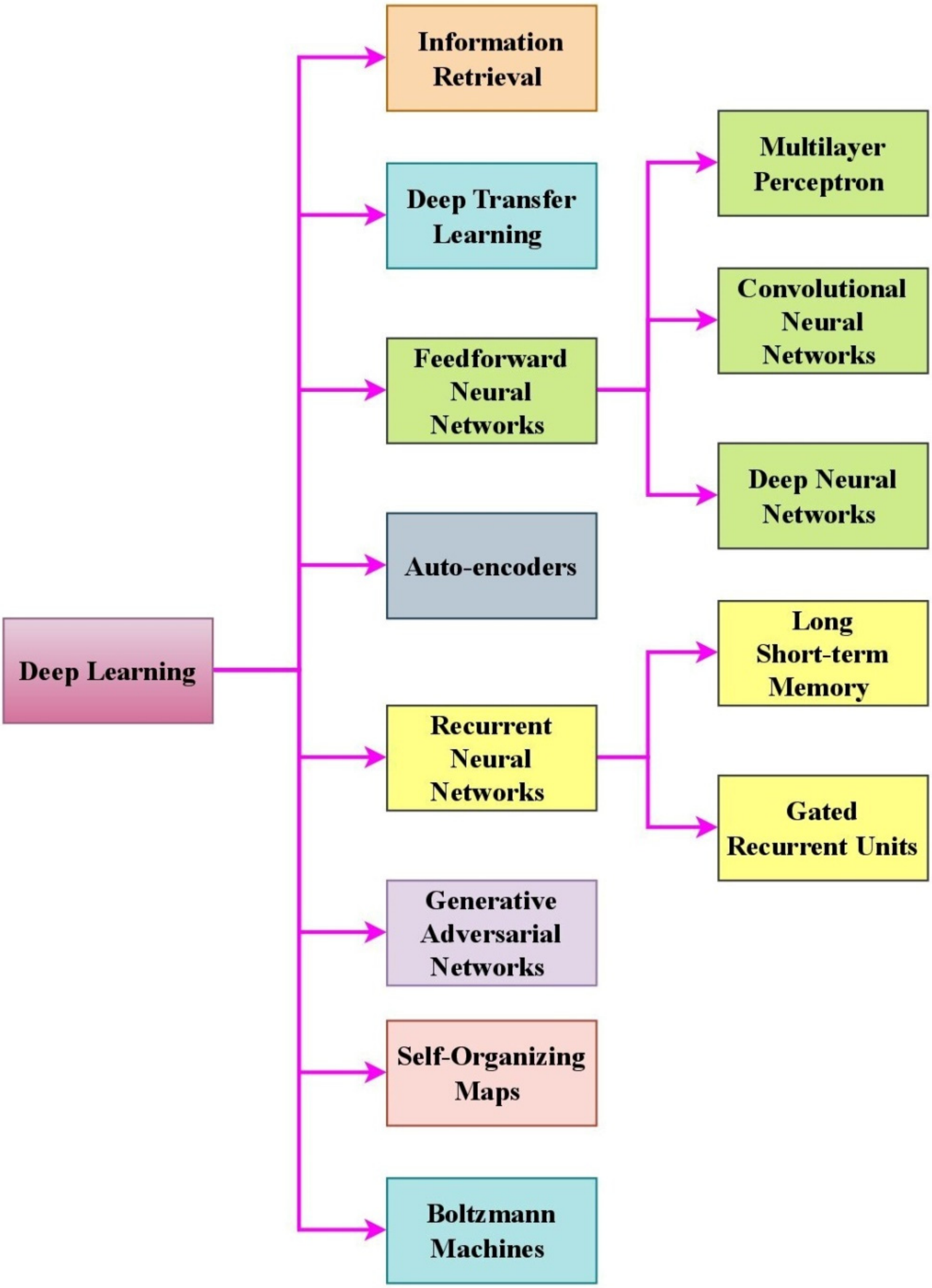

Figure 7. Different classifications of deep learning.

These categories include deep feed-forward neural networks (DFNN), multilayer perceptron (MLP), convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory (LSTM), gated recurrent units (GRUs), generative adversarial networks (GANs), self-organizing maps (SOMs), auto-encoders, deep neural networks (DNNs) deep transfer learning (DTL), Boltzmann machines (BM), information retrieval (IR). The method used depends on both the nature of the problem being addressed and the nature of the data being used. In recent years, DL has produced cutting-edge outcomes on a variety of tasks and has been extensively embraced in industry, academia, and government [73]. DL algorithms have a limited range of applications due to their computational complexity and data requirements [74]. Furthermore, because of their tendency for overfitting, DL may perform excellently on training data but poorly on new or untested data [75].

3.2. Application and Classification of Deep Learning Techniques

DL approaches are divided into a variety of classes based on their design and the types of problems they are intended to solve. Some of the most popular DL methods are outlined in the following subsections.

3.2.1. Deep Feed Forward Neural Network (DFNN)

DFNNs, which are the most fundamental kind of DL algorithms, are used for supervised learning tasks including image classification and regression analysis [76]. They consist of several layers of neurons, with the input from one layer acting as the output of the following layer [77]. DFNNs can be utilized for a variety of purposes, such as flood mapping [78], forecasting [79,80], and risk assessment [81]. DFNN can forecast flood levels based on historical data and meteorological variables like rainfall and river discharge [82]. These data may be used to train a neural network so that it can make precise predictions depending on the present situation. Ref. [83] used DFNN for the downscaling of rainfall for the Vietnamese Mekong Delta.

3.2.2. Multilayer Perceptron (MLP)

The first neural network of this kind was created in the 1960s, making it the most traditional [84]. An MLP is a particular kind of feed-forward neural network made up of several layers of artificial neurons called feed-forward perceptron [85]. MLP refers to a network design having at least one hidden layer [86], while a feed-forward neural network can refer to any network architecture in which data travel in only one way, from input to output [87]. This is the difference between MLP and a general feed-forward neural network. The development of effective training methods like back-propagation, which sparked a resurgence in interest in neural networks, did not occur until the 1980s [88]. During the 1990s, MLPs were widely employed in applications including speech recognition and picture classification [89]. MLPs can forecast the intensity of a flood occurrence based on past data and current weather conditions [90]. This can aid local governments and emergency services in better preparing for and responding to flood occurrences. Based on elements including elevation, geography, land use, and soil type, MLPs can be trained to recognize locations that are vulnerable to flooding [91]. Local governments may use maps of the flood risk created using these data to help them plan for and lessen the effects of floods. MLPs are also used in the evaluations of flood risk [92].

3.2.3. Convolutional Neural Networks (CNNs)

CNNs are a sort of feed-forward neural network (FNN) created in the 1990s by Yann LeCun and his associates for image identification [93]. Contrarily, the fundamental idea behind CNNs was developed in the 1970s [94]. Convolutional layers and pooling layers, which lower the dimensionality of the input, are used in CNNs, which are particularly created for image identification and computer vision applications, to extract features from pictures [95]. CNNs have fundamentally altered computer vision and are being used in a wide range of applications. The detection and mapping of flood-affected areas using remote sensing data, such as satellite and aerial images, is one such application [96]. By learning the patterns and characteristics of flooded areas, CNNs can automatically recognize and categorize flooded locations in real time, enhancing the ability of local governments and emergency services to respond to flooding incidents [97]. CNNs can be utilized for a variety of other flood applications, such as flood susceptibility mapping [98] and flood forecasting and flood warnings [99].

3.2.4. Recurrent Neural Networks (RNNs)

RNNs have been known since the 1980s, but they were not generally employed in ML until the 2000s when they were effectively applied to speech recognition and language modeling [100]. However, the approach had problems with training, which limited its use. These difficulties were addressed by the long short-term memory (LSTM) architecture, which was introduced in 2014 and led to a renewed interest in RNNs [101]. RNNs are useful, especially for sequential data like time series, audio signals, and text. They are excellent at tasks like speech recognition and natural language processing because they contain a memory system that enables them to remember information from previous time steps [102]. To anticipate future flood levels, RNNs may analyze sequential data, such as time series data, and use knowledge from prior observations and predictions. This approach may result in improved flood management and more accurate flood forecasts [103].

Long Short-Term Memory (LSTM): To address the vanishing gradient problem that regular RNNs face, LSTMs were developed in the 2000s [104]. Since they are particularly suited to handling sequential data, such as time series data, they may be used to forecast future flood levels by merging data from prior observations and forecasts. The main benefit of LSTMs is their capacity to grasp long-term dependencies in data [105]. Memory cells are used to do this, enabling the model to remember prior inputs that may be updated or forgotten dependent on the current input and the previous memory state. To anticipate future flood events, LSTMs may be used in flood control to examine time series data, such as river water levels [106]. By combining information from earlier observations and projections, the model may produce precise predictions and help emergency responders and policymakers better prepare for impending floods [107]. LSTM can be utilized for a variety of other flood applications, such as flood prediction [108] and flood forecasting [109].

Gated Recurrent Unit (GRUs): A GRU is a specific type of RNN architecture that was initially introduced by [110]. The vanishing gradient problem that can arise during the training of conventional recurrent neural networks is something that GRUs and LSTM networks are designed to address [111]. GRUs contain fewer parameters than LSTMs, which makes training them faster and with a lower risk of over-fitting possible [112]. This is one of the key benefits of LSTMs. GRUs are used in flood control for time series analysis and prediction, such as forecasting river levels and spotting possible flood occurrences [113]. GRUs can analyze historical data and use data from earlier time steps to create precise forecasts and help emergency responders and policymakers better prepare for impending floods [109].

3.2.5. Generative Adversarial Networks (GANs)

GANs are a class of generative models made up of two neural networks: a generator and a discriminator developed in the 2010s [114]. The generator is in charge of creating new data samples, whereas the discriminator is in charge of distinguishing between genuine and fake data samples [115]. This procedure is repeated until the generator is able to generate data that are indistinguishable from real data. GANs can have several different applications in flood management. Some of these applications include flood damage assessment, flood forecasting, flood early warning systems, and flood risk assessment [116]. GANs can be used to create synthetic flood data for model training and testing in the context of flood management [117]. The model can learn to handle a broad variety of flood conditions and increase its prediction accuracy by creating a diverse set of synthetic data [118]. This is especially helpful when data are scarce or when the data available do not cover all possible flood scenarios.

3.2.6. Self-Organizing Maps (SOMs)

In the 1980s, SOMs were presented as a neural network architecture that can be used for unsupervised learning, such as dimensionality reduction and clustering [119]. Despite being overshadowed in recent years by other neural network architectures, they are still extensively used in a variety of uses such as clustering, anomaly detection, and visualizing high-dimensional data [120]. SOMs are used to find patterns and relationships in flood-related data, such as topographic and hydrological data. SOMs help in spotting areas at high risk of flooding by visualizing the data and assisting in decision-making and resource allocation during flood events [121].

3.2.7. Auto-Encoders

Auto-encoders were first used to acquire efficient data representations in the 1980s [122]. Although they were less popular than other methods at the time, their successful applications in tasks like image de-noising and anomaly detection in the 2000s sparked renewed interest [123]. Auto-encoders are primarily used for unsupervised learning, such as dimensionality reduction and feature extraction. They are made up of two parts: an encoder that compresses the incoming data and a decoder that maps the compressed representation back to the original data [124]. To produce a more concise depiction of flood-related data, auto-encoders can extract features from topographic, hydrological, and meteorological data [125]. This representation can then be used to train a flood-predicting supervised learning model. To spot flood-prone regions and map the extent of flooding, auto-encoders extract features from satellite imagery or remote sensing data [126]. To better anticipate floods, auto-encoders are also used to obtain features from hydrological and meteorological data [127]. This process enables the identification of patterns and relationships in the data. Auto-encoders have the ability to improve the precision and effectiveness of flood-related applications by extracting important characteristics from big and complicated datasets [128].

3.2.8. Deep Neural Networks (DNNs)

DNNs are a type of FNN with several hidden layers that simulate complex non-linear interactions between inputs and outputs [129]. Applications for flood control using DNNs include flood forecasting, mapping, and risk assessment [130]. DNNs can forecast probable flood levels based on previous data and meteorological factors like rainfall and river discharge. The model's several hidden layers enable feature extraction from the data and learning from it, increasing prediction precision. Based on several inputs, including precipitation data, topography data, and river flow data, DNNs are utilized in flood forecasting to anticipate probable flood levels [35]. These models can offer helpful data for early warning systems, emergency response planning, and resource allocation during flood occurrences [131]. To map flood hazards, which requires locating flood-prone locations, DNNs can be utilized. To identify flood extent and indicate flood-prone locations, DNNs are used to evaluate satellite or aerial images [132]. Additionally, DNNs are used to assess flood risk, which comprises determining the possibility and possible consequences of a flood event [38]. It aids in the prioritization of areas for flood mitigation and preparedness by decision-makers.

3.2.9. Deep Transfer Learning (DTL)

Although DTL has been around for a while, deep learning did not really start to take advantage of it until the early 2010s [133]. Transfer learning was powerfully shown by the Image Net competition in 2012, and it has since evolved into a mainstream technique for training DNNs [134]. Transfer learning, which involves optimizing a previously trained DL algorithm for a new task, can drastically minimize the amount of data and computational resources required to train a model for a new activity. In the context of flood forecasting and management, DTL can be used to adapt pre-trained models to new tasks [135]. Flood-related photos, such as satellite photographs of inundated areas or images taken during flood occurrences, may be recognized and categorized using a pre-trained DL model for image classification. To increase the precision of flood forecasts, transfer learning may be used to adapt models that have already been trained for similar tasks like weather forecasting [136].

3.2.10. Boltzmann Machines (BM)

Initially, training BMs was difficult, but with contrastive divergence research in the 2000s, they became an effective tool for generative tasks and unsupervised learning [137]. They generate new data that are comparable to the training data by learning a probability distribution over the input data [138]. BMs can be used to create synthetic flood data for model training and testing in the context of flood management. It is useful when data are scarce or when the data provided does not cover all possible flood scenarios [139]. Furthermore, BMs are used to identify anomalies in flood-related data. By learning the normal data probability distribution, they can spot data points that deviate from it, suggesting potential anomalies or unusual events. During flood events, this will be useful for early warning systems and decision-making [140]. BMs are also used for forecasting floods. They learn to forecast future flood conditions with high accuracy by training on historical flood data and meteorological parameters. During flood events, this aids in emergency response planning and resource allocation.

3.2.11. Information Retrieval (IR)

IR has a long past that dates back to the dawn of computing. In the late 1990s and early 2000s, the development of search engines such as Google greatly popularized the field, leading to the development of new methods such as latent semantic indexing and word embedding [141]. Natural language processing and text analysis now make extensive use of these methods. IR approaches may be used to mine large flood datasets, including social media posts, news articles, and government reports, for relevant data [142]. This information may be used to support decision-making procedures including locating areas at high risk of flooding and crisis management in certain situations [143]. Additionally, to develop more precise flood forecasting models, IR approaches may be utilized to evaluate and simulate hydrological data, such as rainfall patterns and river flow rates.

This section included advanced methods including DFNN, MLP, CNN, RNN, LSTM, GRU, GAN, SOM, auto-encoders, DNN, DTL, BM, and IR, as well as their uses in flood forecasting and management. In general, applying deep learning techniques to flood forecasting and management can significantly increase the precision and dependability of flood predictions, facilitate decision-making during flood occurrences, and eventually help with flood mitigation. Table 1 shows the detailed comparison of DL models in terms of their performance, computational requirements, and suitability for different flooding scenarios. Table 2 shows the detailed comparison with respect to the accuracy, RMSE, advantages, and disadvantages. Please take note that the accuracy and RMSE values given in the table are only guidelines and may change based on the precise application, dataset, and implementation. A rapid comparison of the algorithms' accuracy and RMSE performance is made possible by the table, which provides a high-level summary of the results of several methods.

Table 1. A detailed comparison of DL models.

Deep Learning Model	Performance	Computational Requirements	Suitability for Flooding Scenarios
FNN	Good performance in capturing complex patterns and relationships	Moderate computational requirements	Suitable for both short-term and long-term flood forecasting
MLP	Effective in handling non-linear relationships	Moderate computational requirements	Suitable for general flood forecasting and management tasks
CNN	Excellent in capturing spatial information and patterns	High computational requirements due to convolutional operations	Suitable for analyzing flood-related imagery and spatial data
RNN	Suitable for time-series data analysis	Moderate computational requirements	Suitable for short-term flood forecasting and temporal analysis
LSTM	Superior in capturing long-term dependencies and handling sequence data	Moderate computational requirements	Suitable for both short-term and long-term flood forecasting
GRU	Similar to LSTM, effective in capturing long-term dependencies	Lower computational requirements compared to LSTM	Suitable for real-time flood forecasting and analyzing time-series data
GAN	Suitable for data generation and augmentation	High computational requirements, especially for training	Suitable for enhancing data availability and training robust flood prediction models
SOM	Effective in clustering and visualizing data patterns	Moderate computational requirements	Suitable for exploratory analysis and data visualization in flood management
Auto-encoders	Useful for feature extraction and dimensionality reduction	Moderate computational requirements	Suitable for preprocessing and extracting relevant features from flood-related data
DNN	Versatile and can be applied to various flood forecasting tasks	Computational requirements depend on the model complexity	Suitable for different flood scenarios based on problem-specific adaptation
DTL	Utilizes pre-trained models for transfer learning	Computational requirements depend on the pre-trained model size	Suitable for scenarios with limited labeled flood data and knowledge transfer
BM	Effective in unsupervised learning and pattern recognition	High computational requirements for training complex models	Suitable for unsupervised feature learning and anomaly detection in flood events
IR	Primarily used for data retrieval and analysis	Low computational requirements	Suitable for retrieving and analyzing flood-related information from textual and unstructured data

Table 2. A detailed comparison with respect to accuracy, RMSE, advantages, and disadvantages.

Algorithm	Accuracy	RMSE	Advantages	Disadvantages
FNN	High	Low	Effective in capturing complex relationships	Limited in handling sequential or spatial data
MLP	High	Low	Suitable for numerical inputs and large datasets	Limited in handling spatial or sequential data
CNN	Moderate	Moderate	Effective in capturing spatial features	Limited in handling non-image data
RNN	Moderate	Moderate	Captures temporal dependencies and long-term dependencies	Vulnerable to vanishing/exploding gradient problems
LSTM	High	Low	Effective in capturing long-term dependencies	Higher computational complexity than traditional RNNs
GRU	High	Low	Balances memory capacity and computational efficiency	May struggle with capturing very long-term dependencies
GAN	Variable	Variable	Can generate synthetic flood scenarios or augment datasets	Training can be challenging and require large datasets
SOM	Moderate	Moderate	Useful for feature extraction and dimensionality reduction	Require manual tuning of hyper-parameters
Auto-encoders	Moderate	Moderate	Effective for pre-processing data and extracting features	Sensitive to noisy or incomplete data
DNN	High	Low	Powerful for modeling complex relationships	Prone to over fitting if not properly regularized
DTL	High	Low	Improves performance in scenarios with limited training data	Requires access to pre-trained models and large datasets
BM	Moderate	Moderate	Useful for unsupervised learning and feature extraction	Computationally expensive and difficult to train
IR	Moderate	Moderate	Useful for specific tasks like flood data retrieval	Limited in terms of direct application in flood forecasting

4. Application of Deep Learning Methods in Flood Forecasting and Management

DL methods are increasingly being used in flood forecasting and management because they have several benefits over conventional machine learning methods. DL is commonly used in the following domains.

4.1. Time Series Forecasting

Based on historical data and climatic factors, DL algorithms are utilized to predict probable flood levels [144]. Better prediction accuracy is achieved by using these models which can describe non-linear correlations and temporal dependencies in data. Time series forecasting with DL is crucial for the control and prediction of flooding [145]. Using time series forecasts for flood prediction, DL may be utilized in the following situations.

4.1.1. River Flow Forecasting

The ability to make informed decisions regarding resource allocation, evacuation plans, and other flood protection measures is a benefit of accurate river flow forecasts for officials and emergency responders [146]. To create models for predicting river flow, DL techniques including DFNN, MLP, CNN, RNN, LSTM, GRU, GAN, SOM, auto-encoders, DNN, DTL, BM, and IR can be utilized. To forecast future river flow conditions, these methods extract relevant features from historical river flow data, meteorological data, and other relevant data sources [147]. Using historical data, the models can be trained to understand the relationships between various variables and how they affect river flow. Once trained, the model can be used to forecast future river flow based on current and expected weather conditions [148]. These projections are employed to assess flood risk and inform choices about the deployment of flood protection and evacuation of vulnerable areas.

Historical river flow data are gathered and preprocessed before using DL models for river flow forecasting [149]. River flow can be influenced by a variety of factors, including precipitation, snowmelt, and water demands. The data are usually divided into three sets—training, validation, and testing—and used to train the DL model. RNNs and LSTMs are especially well-suited for river flow forecasting because they can handle time series data with temporal dependencies [150]. In other words, they use information from earlier time steps to forecast later time steps. A supervised learning approach is usually used to train the model, with the target output being the river flow value at a future time step. Once trained, the model is used to forecast future river flow based on present and historical data [151]. These forecasts can be used to assess the likelihood of flooding and inform flood management choices such as the deployment of flood protection measures and the evacuation of vulnerable populations. Prediction accuracy can be measured using measures such as root mean square error (RMSE) and mean absolute error (MAE) [152,153].

4.1.2. Rainfall Forecasting

DL models can be used to analyze past rainfall data and forecast future rainfall. These forecasts can be used to assess flood risk and guide flood management choices, such as the deployment of flood protection measures and the evacuation of at-risk populations [154]. It is necessary to collect and prepare historical rainfall data before employing DL models to predict rainfall. Several factors, including humidity, temperature, and wind speed, have an impact on rainfall [155]. Three sets of data—training, validation, and testing—are frequently created and used to train the DL model. DL models like CNNs, RNNs, and LSTMs may be used to predict rainfall. CNNs can extract spatial features from weather imagery or satellite images, while RNNs and LSTMs can handle time series data with temporal dependencies [156]. The model is usually trained using supervised learning, with the output being the quantity of rainfall at a future time step [157]. With the use of these estimates, one may assess the likelihood of flooding and decide how to respond to it, such as by putting in place flood protection measures and evacuating vulnerable people. Metrics like RMSE and MAE are used to assess the forecasts' accuracy [158]. DL models are a helpful tool for forecasting rainfall and floods. Through the prompt and precise delivery of rainfall information, these models can aid in reducing the impact of floods on infrastructure and communities. It is important to keep in mind, however, that DL models may need domain knowledge to comprehend the findings and significant quantities of data and computer power to train properly [61]. Furthermore, terrain and other factors like river flow must be taken into account in addition to precise rainfall forecasts, which is only one component of flood prediction and management.

4.1.3. Flood Forecasting and Warning Systems

To create real-time flood forecasting and warning systems, DL models can combine a variety of data sources, such as river flow, rainfall, and meteorological data [36]. These technologies can assist in lessening the effects of floods by giving local authorities and rescue services a head start. Before DL models can be employed for flood forecasting and warning systems, many data sources must be gathered and preprocessed [27]. This data collection might include information such as historical flood data, river flow data, and rainfall data, among other things. The data are often combined and processed using several methods, including feature engineering and data fusion, to produce a single dataset. CNNs, RNNs, and LSTMs are employed in flood forecasting and warning systems [159]. These models may learn complicated correlations between data from numerous sources with varied temporal and spatial dimensions. The model is often trained using a supervised learning technique to predict flood risk or severity as the output [160]. When the model is complete, it will be possible to use it to generate real-time forecasts about the likelihood and severity of flooding based on recent and past data [161]. The local government, emergency services, and flood warning systems may all be informed using these forecasts. The accuracy of predictions may be evaluated using measures including accuracy, precision, recall, and F1 score [162].

4.2. Hydrological-Modeling-Based Forecasting

A collection of meteorological and topographical data, as well as flood levels, is gathered to apply DL algorithms for hydrological modeling. This dataset is often preprocessed to cope with missing or imperfect data as well as to normalize and standardize the data [163]. CNNs and RNNs may be used in a range of hydrological modeling applications. The relationship between topographical information (elevation and slope) and flood levels is frequently modeled using CNNs [164]. These models can recognize spatial patterns in data, such as how a river's bend or constriction affects flood levels. Conversely, RNNs are frequently used to predict the temporal link between meteorological data, such as rainfall, temperature, and flood levels [165]. Using these models, it is possible to see how flood levels are impacted over time by variations in the weather. The DL model is typically trained using a supervised learning technique, and the intended output is a prediction of flood levels based on the input data [144]. The model may be trained to incorporate a variety of inputs and outputs, including a variety of meteorological data sources and a variety of sites where flood levels are predicted. It improves prediction accuracy by taking into account the complex relationships between multiple variables that contribute to flood levels. Once trained, the model is used to forecast flood levels in real-time using current and historical data [166]. These data can be used to guide flood management choices like the deployment of emergency response teams and the implementation of flood prevention measures [167]. Prediction accuracy can be measured using measures such as mean absolute error and mean squared error.

4.3. Image-Based Flood Detection

Another use of DL in flood is image-based flood detection. To find flooded areas, CNNs can be used to analyze satellite or drone imagery [168]. Real-time flood monitoring and emergency response can both benefit from this information. Satellite or drone imagery must first be gathered and preprocessed before CNNs can be used for image-based flood detection [169]. The images could be red-green-blue (RGB) or multispectral and could have elements like the texture and reflectance of the water's surface. The images are used to train the DL model and are typically labeled as either flooded or non-flooded areas [170]. CNNs are particularly well-suited for image-based flood detection because they can learn relevant features from images automatically, eliminating the need for manual feature engineering [171]. The model is typically trained using a supervised learning approach, where the target output is a binary classification of flooded or non-flooded areas. After training, the model can be used to analyze new satellite or drone imagery in real time to detect flooded areas [70]. These data can be used to track flood conditions and inform emergency response efforts, such as the deployment of rescue and relief teams. Metrics such as precision, recall, and F1 score (combining both precision and recall) are used to assess the accuracy of flood detection [172].

Several DL techniques are available for image classification in flood applications. Some examples are as follows: CNNs, as previously stated, are frequently used for image classification in flood applications [173]. These models are intended to learn and extract features from raw images automatically, making them well-suited for jobs such as flood detection in remote sensing imagery [174]. DTL is a technique that entails using a previously trained CNN as a starting point for a new image classification assignment. This method is especially helpful when the labeled data are limited. For example, a pre-trained CNN that was trained on a large dataset of general images can be fine-tuned for a particular flood detection task using a smaller dataset of labeled flood images [128]. Deep convolutional neural networks (DCNNs) are CNN variants with extra layers that enable them to learn more complex features from input images [175]. These models have been demonstrated to be especially successful for image classification in applications with significant variability, such as flood detection in remote sensing imagery [176]. RNNs are intended to handle sequential data, such as time series or video data. RNNs are used to classify images from a sequence of remote sensing images in flood applications, enabling more accurate and robust flood detection [177]. GANs generate new, realistic images based on a training dataset. In the context of flood applications, GANs are used to generate synthetic flood pictures that are utilized to supplement the labeled dataset and increase the accuracy of image classification models [178].

4.4. Information Retrieval

DL information retrieval in flood forecasting comprises utilizing DL models to extract relevant information from multiple flood-related sources, such as social media postings, news articles, and government data [179]. This information is utilized to aid in flood predictions and decision-making during floods. DL techniques such as CNN and RNN are utilized for text categorization and information retrieval [180]. These models may be taught to extract relevant information from unstructured text data, such as tweets or news reports, and classify it as flood warnings, flood impacts, or flood recovery activities [181]. From several types of flood-related data, such as topographic, hydrological, and meteorological data, auto-encoders can extract characteristics and then compress the information. Then, using this summarized representation, a supervised learning model for flood forecasting can be trained. As a result of their capacity to develop a probability distribution across the input data, BMs are an efficient tool for processing and evaluating flood-related data [117] such as satellite photos or flood data, as well as for creating precise and trustworthy predictions about the likelihood of future floods [182].

4.5. Predictive Maintenance

The ability to maintain and repair infrastructure proactively before a flood occurrence makes predictive maintenance a key component of flood management [183]. Decision-makers can take action before a flood occurs by using DL algorithms to estimate the risk of flooding at specific sites based on historical data and present observations. Predictive models that foresee flood risk are developed utilizing DL approaches employing a number of inputs, including historical river levels, precipitation data, and soil moisture content [184]. Using methods like CNNs and RNNs, these models can analyze massive datasets to uncover patterns and trends that conventional approaches would overlook. Based on past data and current observations, DL algorithms can predict the likelihood of a dam failing [185]. The danger of catastrophic flooding in the event of a dam failure can be reduced by using these data to prioritize maintenance and repair work [186]. The likelihood of a levee failing may also be predicted using DL algorithms based on historical data and current observations [187]. This information may be used to identify regions where levees are vulnerable to failure and to set priorities for maintenance and repair work to lower the danger of flooding. Table 3 shows the different articles used in flood applications.

Table 3. The different articles used in flood application.

Paper	Network Type	Deep Learning Task	Water Field	Location
[188]	LSTM	Forecasting	River flow forecasting	Tunxi, China
[189]	DNN	Prediction	River flow prediction	Yangtze River, China
[190]	LSTM	Forecasting	River flow forecasting	Chao Phraya River Basin Thailand

Table 3. *Cont.*

Paper	Network Type	Deep Learning Task	Water Field	Location
[191]	GRU, MLP, LSTM	Forecasting	River flow forecasting	Awash River Basin/Ethiopia
[192]	CNN	Forecasting	River flow forecasting	Huanren Reservoir and Xiangjiaba Hydropower Station, China
[193]	SOM	Forecasting	River flow forecasting	Selangor, Malaysia
[155]	CNN, LSTM	Forecasting	Rainfall forecasting	Northwestern Pacific Ocean
[157]	LSTM, CNN	Forecasting	Rainfall forecasting	Niavaran station, Tehran, Iran
[194]	MLP	Forecasting	Rainfall forecasting	Meteorology Sites in China
[195]	LSTM	Forecasting	Rainfall forecasting	Indian summer monsoon
[196]	LSTM	Forecasting	Rainfall forecasting	Indonesia
[197]	GAN	Forecasting	Rainfall forecasting	Korea
[198]	MLR	Prediction	Flood forecasting and warning systems	Indonesia
[199]	LSTM	Forecasting	Flood forecasting and warning systems	Dorim River Basin, Seoul
[200]	CNN	Prediction	Flood forecasting and warning systems	Southwest Japan
[201]	GRU, LSTM	Prediction	Flood forecasting and warning systems	Southeast China
[202]	MLP	Forecasting	Flood forecasting and warning systems	Republic of Korea
[203]	LSTM	Forecasting	Flood forecasting and warning systems	Seoul metropolitan city
[204]	GRU, CNN, LSTM	Simulation	Hydrological-modeling-based prediction	Southeast China
[205]	GAN	Prediction	Hydrological-modeling-based prediction	Hunan Province
[206]	LSTM, RNN	Forecasting	Hydrological-modeling-based prediction	Nedon River, Greece
[207]	LSTM	Calibration	Hydrological-modeling-based prediction	Brazilian Cerrado biome
[208]	RNN	Forecasting	Hydrological-modeling-based prediction	Southern China
[209]	LSTM	Calibration	Hydrological-modeling-based prediction	USA
[210]	DNN	Prediction	Image-based flood detection	Brisbane River, Australia
[131]	DNN	Prediction	Image-based flood detection	Bangladesh
[211]	MLP	Susceptibility	Image-based flood detection	Vietnam
[212]	CNN	Prediction	Image-based flood detection	Indus River in Pakistan

5. Challenges and the Way Forward

Although there is a lot of potential for using DL in flood forecasting and management, there are several difficulties that must be solved. The following are some of the difficulties and potential solutions.

Complex Model Selection and Optimization: When selecting and enhancing complex models, DL faces significant challenges. It might be challenging to choose the appropriate DL model for a specific task when there are so many models available [213]. Hyper-parameter tuning of these models can also be expensive and computationally time-consuming [214]. One remedy for this problem is the employment of automated machine learning (AutoML) techniques. The selection and optimization of DL models, hyper-parameters, and even raw data pre-processing are all automated using auto-ML algorithms [215,216]. As a result, building an accurate and effective deep-learning model may take much less time and effort. Another choice is transfer learning. Transfer learning is the process of optimizing a DL model that has already been trained for a specific task [217]. By using information from an existing model to complete a new task, this approach can reduce processing time and resources. Numerous deep learning models can be combined using ensemble methods to boost overall prediction accuracy. Individual model shortcomings can be solved using ensemble approaches, which integrate many models to obtain predictions that are more reliable and precise [218].

Data Availability and Quality: One of the primary obstacles to the implementation of DL in flood forecasting and management is the availability and quality of data [219]. To properly train DL models, a substantial amount of high-quality data must be available, which might be challenging in some regions. For instance, a lack of sensors, poor infrastructure, or political considerations may result in restricted data. Furthermore, due to differences in data quality and format, comparing and merging datasets may be difficult. To solve this issue, efforts should be made to gather and exchange data from various sources as well as to develop quality control procedures to guarantee data consistency and correctness [220]. Crowdsourcing approaches might be used to replenish scarce data, and partnerships between researchers, governments, and private sector companies could be developed to enhance data gathering and sharing.

Model Interpretability: One of the main issues with DL models is that they are difficult to interpret, which makes it challenging to understand why the model predicts certain outcomes. In areas like flood forecasting and prediction [221], where decision-makers need to understand the reasoning behind a model's predictions to take the right action, this lack of interpretability is especially troublesome [222]. To address this problem, efforts should be made to develop more interpretable models, such as rule-based or decision-tree systems that offer transparent and comprehensible explanations of the models' prediction processes. Researchers might also focus on developing visualization methods that facilitate the comprehension and justification of the DL model results [223].

Model Generalization: Since DL models are often trained on historical data, they struggle to generalize to new and unexplored data [224]. Because new and unforeseen events might occur, this can be challenging in the forecasting and control of floods. To solve this problem, models should be trained on a range of data sets to increase their adaptability to novel scenarios [225]. Researchers might also focus on developing models that can learn from comments supplied by human experts or through crowdsourcing approaches and that are better at adjusting to new data [226].

Computational Resources: To train and operate DL models, a lot of processing power is required because of their computational demands [61]. In places with few computational resources, this may be challenging. To solve this problem, efforts should be made to develop deep learning algorithms that are more effective and to make use of cloud computing resources to lessen the burden on local infrastructure [227]. Researchers can also focus on developing models that can be taught and used on mobile or low-power edge computing devices [228].

Ethical Considerations: Applications of DL for flood prediction and management raise ethical issues including algorithmic bias and data privacy [229]. DL algorithms may produce biased results because of the biases present in the training data. Researchers should carefully choose and preprocess training data to ensure representativeness and fairness across various demographics to reduce algorithmic bias. Regular model testing and assessment for bias can help find and fix any possible problems. Data protection laws and ethical guidelines must be followed while gathering and using data for flood forecasting.

While still allowing for data interchange, anonymization techniques like differential privacy can be used to safeguard individual privacy. In addition to explicitly communicating data usage rules and putting in place effective data security measures, researchers should obtain informed consent from people whose data will be utilized. Efforts should be taken to guarantee that data collection and usage are ethical and transparent and that models be created and evaluated to lessen algorithmic bias to reduce these concerns [230]. For instance, differential privacy may be used to secure individual data privacy while yet allowing for data exchange. DL models are frequently regarded as "black boxes," which makes it difficult to comprehend how they make decisions. To address ethical issues, improving model openness and explainability is essential. Model-agnostic interpretability approaches and attention mechanisms are two techniques that can shed light on the characteristics affecting the model's predictions. Additionally, researchers might concentrate on developing models that are impartial and fair as well as those that take into account social and cultural elements that could affect decision-making [231].

Limited Adoption: Despite the potential benefits of DL, adoption will likely be limited due to a lack of understanding, competence, and information [232]. To address this, attempts can be made to raise awareness of the potential benefits of deep learning, as well as to provide practitioners with training and support. Collaborations between researchers, businesses, and governments can also aid in driving adoption and accelerating progress in the field [233]. These collaborations can promote the exchange of knowledge and expertise, assisting in the development of effective solutions that address local requirements and challenges. The difficulties of using DL for floods can be overcome through collaboration and innovation. DL can help to improve flood forecasting and management efforts and reduce the impact of floods on communities around the world by collecting and sharing data, developing more interpretable models, training models on diverse data, utilizing efficient computing resources, and addressing ethical concerns [234].

6. Discussion and Future Directions

DL applications for flood forecasting and management heavily depend on choosing the right algorithm. Several important algorithms have been widely used in this sector, each having unique advantages and adaptability for various input sources. The DFNN and MLP methods, which are often utilized, are good at detecting complicated correlations and patterns in the data. They are capable of handling huge datasets and are ideally suited for numerical inputs. CNNs are particularly good at processing spatial data, such as satellite images or maps, since they can extract spatial information through convolutional layers. Since they can analyze the spatial distribution of floods, they are useful for jobs involving that. RNNs, such as long short-term memory (LSTM) and gated recurrent units (GRUs), are used often for sequential data, such as time series data, and are meant to capture temporal relationships. They work well for capturing long-term relationships in the data and representing the dynamic character of floods. GANs are utilized for creating artificial flood situations or enhancing existing datasets. They can understand the underlying data distribution and produce accurate flood events. Feature extraction and dimensionality reduction may be accomplished using the SOM unsupervised learning method and auto-encoders. They help in preparing data for analysis and removing relevant representations from high-dimensional inputs. DTL uses pre-trained models from big datasets to enhance DT model performance in situations with little training data. In areas with limited data availability, this method is very helpful for applying DT to flood predictions and control. In some situations, BM and IR approaches can be used to solve certain problems or improve particular facets of flood forecasting and management.

DL in floods has the potential to revolutionize flood forecasting and management, but much work remains to be done to completely realize this potential. Some potential future directions and study areas for the field include the following:

Developing hybrid models*:* Combining DL and statistical models, flood forecasts and management can be improved in terms of accuracy and interpretability [235]. The strengths of both methods can be combined in hybrid models, such as using DL models to extract features from data, which can then be used as inputs to statistical models. The constraints of DL models, such as their inability to handle small datasets or high-dimensional data, can also be solved with the use of this technique [236].

Uncertainty estimation*:* DL models that include uncertainty estimates can improve the stability and accuracy of flood simulations [237]. Particularly when the models are unclear or do not have enough data, uncertainty estimates help to provide a more accurate and useful understanding of the projected outcomes [238].

Integrating multiple data sources*:* Integrating data from several sources can give a more comprehensive picture of flood occurrences and increase the accuracy of forecasts [239]. Examples of these sources include remote sensing, social media, and informal research. However, due to problems such as data inconsistency, missing data, and the requirement for data pre-processing, data integration is typically challenging [240].

Improving the interpretability of deep learning models*:* It is essential for boosting decision-makers' trust and fostering better communication with them [241]. Using methods like feature visualization, attention mechanisms, and rule extraction, deep learning models can be made more visible and understandable.

Addressing ethical concerns*:* When using deep learning to predict floods, there are ethical issues to be addressed, including those with data collection and usage, privacy, and algorithmic bias [242]. To reduce algorithmic bias, it is essential to design and test models and to gather and use data transparently and ethically.

Scaling models*:* Model scaling is a crucial challenge since deep learning models must be expanded to cover greater areas and longer periods due to problems with data quality and processing resources [243]. Researchers might look at methods like transfer learning, ensemble learning, and distributed computing to address these problems.

Transfer Learning*:* Transfer learning, which enables pre-trained models to be adapted to specific contexts and regions with limited data, can be especially helpful in flood forecasting [40]. For instance, a DL model that has been calibrated to predict flood events in a place with similar environmental and meteorological parameters can be trained on flood events in that region [244]. Future research could concentrate on the development of transfer learning methods that effectively utilize pre-trained models for downstream flood forecasting and management tasks.

Real-time data processing*:* The ability to handle large amounts of data in real time is essential for timely and accurate flood forecasting and control [219]. With the growing availability of data from various sources, such as satellite data, sensor networks, and social media, future research could concentrate on developing distributed computing and streaming data processing methods that allow real-time data processing [245]. This could include the creation of new algorithms and architectures capable of processing and analyzing data on the run, as well as the use of cloud-based solutions capable of scaling to meet the demands of real-time data processing [246].

Integration with other technologies*:* Integrating deep learning with other technologies, such as GIS, UAVs, and IoT devices, could provide a more complete view of flood events and enhance decision-making [247]. Deep learning models, for example, could be combined with GIS to evaluate and visualize flood risk maps, whereas UAVs and IoT devices could provide real-time data on flood events [248]. Future studies could concentrate on creating new techniques and frameworks for integrating deep learning with these technologies, as well as investigating new applications of these technologies in flood forecasting and management [249].

Open data sharing*:* Open data sharing is essential for the creation and training of DL models. Researchers can enhance the accuracy and generalizability of their models by sharing big and diverse datasets [250]. Future efforts could concentrate on encouraging open data sharing and cooperation among researchers, industry, and government agencies in order to improve flood forecasting and management [251].

To summarize, there is considerable potential for using DL in floods. To improve the accuracy and efficacy of deep learning models and reduce the impact of floods on communities around the world by addressing the challenges and pursuing future research directions.

7. Conclusions

The use of deep learning in flood forecasting and management has the potential to revolutionize the field by increasing the accuracy and timeliness of flood predictions. However, several issues must be addressed, including data availability, model interpretability, and ethical considerations. Future research directions could include creating hybrid models, incorporating uncertainty, integrating multiple data sources, improving interpretability, addressing ethical and social concerns, and scaling up models to cover larger areas and longer time periods. Transfer learning, real-time data processing, integration with other technologies, and open data sharing will all help deep learning models improve their accuracy and effectiveness in flood forecasting and management. We can reduce the impact of floods on communities around the world and improve their resilience to natural disasters by addressing these challenges and pursuing future research directions. Researchers, practitioners, and decision-makers interested in adopting DL approaches for flood-related activities will find this paper useful. It provides an overview of the present state of the art in the topic, as well as a discussion of the obstacles and potential solutions. The paper underlines the need for multidisciplinary collaboration and data exchange in tackling these challenges.

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