

The Evolution of Backpropagation Neural Network Algorithms in the Development of Intelligent Flood Detection Systems

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Abstract: Flooding is a hydrometeorological disaster with widespread social, economic, and environmental impacts, requiring an accurate and adaptive early detection and warning system. This study aims to identify, analyze, and synthesize the evolution of the Backpropagation Neural Network (BPNN) algorithm in the development of intelligent flood detection systems and provide direction for future research. The research method used is qualitative with a Systematic Literature Review (SLR) approach, using literature sources from DOAJ, Scopus, and Google Scholar with a publication range of 2015–2025. The results of the study show that BPNN has undergone a significant transformation, from a simple feedforward model to an intelligent component capable of processing more complex non-linear patterns. This development is marked by the integration of optimization algorithms (such as Genetic Algorithm and Particle Swarm Optimization), the application of adaptive optimizers, regularization techniques, and integration with deep learning models. The implementation of BPNN has also been expanded through the integration of hydrological and spatial data, including rainfall, river discharge, topography, and satellite imagery, as well as the support of IoT and big data technologies to build adaptive early warning systems. Challenges remain in terms of the risk of overfitting, high computational requirements, data quality limitations, and low model interpretability. These findings confirm that the evolution of BPNN in flood detection systems reflects a shift towards more complex, adaptive, and integrated models, while also opening up future research opportunities in the development of hybrid models, ensemble methods, and the application of cloud-based computing to support more accurate, robust, and responsive flood detection systems.

Keywords: Backpropagation; Neural Network; Flood Detection; Disaster Mitigation.

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A. INTRODUCTION

Flooding is one of the most frequent natural disasters with significant social, economic, and environmental impacts, especially in areas with dense population growth and economic activity (Aldardasawi & Eren, 2021). Climate change, uncontrolled urbanization, and environmental degradation play a major role in increasing the frequency and intensity of floods in various countries (Beshir & Song, 2021). These conditions emphasize the importance of developing an early flood detection system to minimize losses and protect vulnerable communities. However, traditional systems that rely on conventional sensors and statistical methods have limitations in prediction accuracy, especially in the face of increasingly complex extreme weather patterns. This has created an urgent need to implement artificial intelligence (AI)-based smart technologies that are capable of providing faster, more adaptive, and more accurate flood detection.

The development of AI opens up great opportunities in disaster mitigation, particularly flooding, through the use of machine learning models that can improve prediction accuracy compared to traditional methods (Saravi et al., 2019). One of the most widely used algorithms is Neural Networks, especially Backpropagation Neural Network (BPNN), which is widely applied in environmental data analysis for hydrometeorological disaster prediction (Zhang et al., 2021). BPNN has advantages in handling complex non-linear relationships between various factors that cause flooding, including rainfall patterns, hydrological characteristics, and the topographical conditions of an area (Samantaray & Sahoo, 2020). The ability of this algorithm to recognize dynamic data patterns makes it relevant as the basis for developing a more accurate and adaptive flood detection system.

The backpropagation algorithm was initially developed with a simple structure, but over time it has undergone various developments to improve its performance in complex data processing (Fang et al., 2021). Various modifications have been made, such as optimizing convergence speed, reducing the risk of overfitting, and improving accuracy in data pattern recognition (Santos et al., 2022). One notable approach is the integration of BPNN with other optimization methods, including Genetic Algorithm, Particle Swarm Optimization, and more adaptive variants of Gradient Descent, resulting in more robust models (Zhang & Qu, 2021). The evolution of BPNN can also be seen from its initial application based on a simple feedforward model to a more complex architecture to support predictive analysis in various fields, including disaster management (Yan, 2024). The development of this algorithm is highly relevant to the growing need for environmental data analysis in the context of flood detection and mitigation.

Thankappan et al. (2023) developed the Adaptive Momentum-Backpropagation (AM-BP) algorithm, which demonstrated 96% accuracy and an F1-Measure of 96.4% in flood detection systems, outperforming traditional methods in terms of accuracy and processing efficiency. (Wang, & Feng, 2025) developed a flood change detection model with an algorithm that showed an improvement in accuracy of up to 95.52% and high stability during the training process, reflecting its adaptability to constantly changing data. Many recent studies combine BPNN with Internet of Things (IoT) sensor technology, satellite imagery, and hydrological big data to obtain a more comprehensive representation of environmental conditions (Miller et al., 2025). In addition, the adoption of BPNN is increasingly widespread in the development of early warning systems that aim to provide rapid information to affected communities (Fajrillah et al., 2024). The expansion of this application is not only limited to local studies in specific watersheds, but also reaches a global scale with cross-border integration in support of flood disaster mitigation (Surjono et al., 2022).

Although much research has been conducted, there are still limitations in systematically understanding the evolution of BPNN algorithms in the context of flood detection. Most existing studies tend to focus solely on technical applications without providing an in-depth review of the comprehensive methodological development of BPNN. To date, there has been no literature review that summarizes trend shifts, algorithmic innovations, and the integration of the latest technology in the application of BPNN for flood detection. This study aims to identify, analyze, and synthesize the evolution of the BPNN algorithm in the development of intelligent flood detection systems while providing direction for future research.

B. METHOD

The qualitative method with a Systematic Literature Review (SLR) approach was chosen because it provides a comprehensive understanding of the evolution of BPNN algorithms through a synthesis of various studies that have been conducted. This approach also allows researchers to identify trends, innovations, and relevant research gaps for the development of intelligent flood detection systems in the future. The stages of the research are shown in Figure 1.

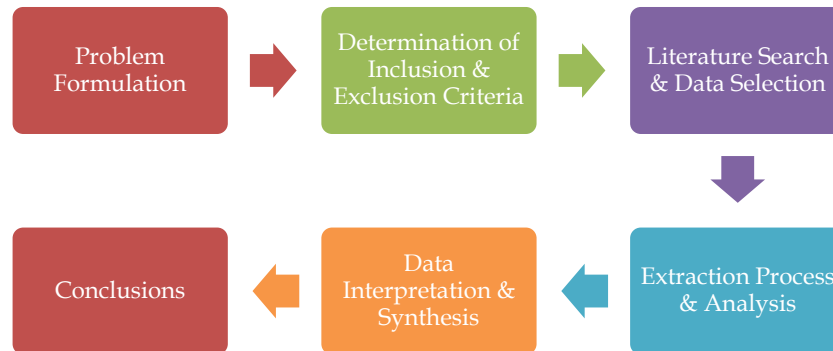


Figure 1. Research Implementation Flow

The first stage is Problem Formulation, which is formulating research problems related to the evolution of BPNN algorithms in the development of intelligent flood detection systems. Next, the Determination of Inclusion & Exclusion Criteria was carried out to set the boundaries of the articles to be reviewed, including peer-reviewed publications, proceedings, academic books, and research reports from 2015 to 2025, with the exclusion of non-peer-reviewed articles, publications before 2015, and research without relevance to BPNN in the context of flooding. The next stage was Literature Search & Data Selection, conducted through the Google Scholar, DOAJ, and Scopus databases using selected keywords relevant to the research topic. The process continued with Extraction Process & Analysis to collect important information from relevant studies, such as algorithmic innovations, technology integration, and the results of applying BPNN in flood detection. Next, Data Interpretation & Synthesis was carried out to identify research trends, map method developments, and highlight knowledge gaps. The final stage was Conclusions, which presented a synthesis of research findings and provided direction for the development of BPNN-based flood detection systems in the future.

C. RESULTS AND DISCUSSION

After conducting a search of 65 pieces of literature obtained from various academic databases, we identified 18 studies that met the inclusion criteria and were substantially relevant to the focus and objectives of this study. The selected studies made important contributions in describing the evolution of the BPNN algorithm in the development of intelligent flood detection systems, including improvements in prediction accuracy, convergence acceleration, and model stability. The review covers aspects of BPNN integration with optimization algorithms (such as GA and PSO), the application of adaptive optimizers, regularization, ensemble methods, hybridization with deep learning models, and integration with supporting technologies such as real-time sensors, IoT, satellite imagery, and big data processing. The details of each study's characteristics, including the type of BPNN algorithm used, the optimization or technology integration approach, and its implications for the effectiveness of the flood detection system, are presented systematically in Table 1.

Table 1. Research Variables Discussed in the Article

No	Focus	Authors	Insights / Research Variables Discussed
1	BPNN Optimization	Chen (2024)	Integration of BPNN with Genetic Algorithm (GA) to improve global solution search, reduce risk of getting stuck in local minima, and enhance prediction stability.
2	BPNN Optimization	Wu et al. (2015)	Combination of BPNN with Particle Swarm Optimization (PSO) accelerates convergence and improves prediction accuracy on non-linear data, including hydrology and rainfall.
3	BPNN Optimization	Li et al. (2015)	Use of Adaptive Gradient Descent for dynamic weight updates improves BPNN performance on big data and changing environmental conditions.
4	Performance and Prediction Accuracy	Kumar et al. (2023)	Optimization of training parameters and network architecture tailored to non-linear flood data patterns improves prediction accuracy.
5	Performance and Convergence	Haji & Abdulazeez (2021)	Development of derivative algorithms and adaptive learning rates accelerates training and reduces computational load.
6	Prediction Stability	Bian & Priyadarshi (2024)	Regularization techniques and modern optimization methods improve prediction consistency under dynamic environmental conditions.
7	Hydrological Modeling	Liao & Li (2024)	Rainfall modeling using BPNN captures non-linear patterns and extreme fluctuations.
8	Hydrological Modeling	Samantaray & Sahoo (2024)	River discharge estimation enhances accuracy of water flow predictions in watersheds (DAS), a key flood risk indicator.
9	Hydrology & Topography Modeling	Hasnaoui et al. (2025)	Integration of elevation and topographic parameters supports flood vulnerability mapping.
10	Integration with Supporting Technologies	Biazar et al. (2025)	Combining BPNN with IoT and real-time sensors enables adaptive predictions according to changing field conditions.
11	Integration with Supporting Technologies	Tanim et al. (2022)	Satellite imagery enriches spatial information, including rainfall distribution, soil moisture, and land cover changes.
12	Big Data & Complex Pattern Analysis	Sun & Scanlon (2019)	Environmental big data processing improves analysis of complex flood patterns.
13	Hybrid and Ensemble Models	Tosan et al. (2025)	Integration of BPNN with deep learning enhances extraction of non-linear patterns in large-scale hydrological data.
14	Hybrid and Ensemble Models	Mosavi et al. (2018)	Ensemble methods increase accuracy and robustness of predictions, particularly for extreme flood events.
15	Cloud-Based Systems	Karnam (2025)	Cloud-based flood monitoring enables real-time big data processing and cross-regional collaboration.
16	Limitations & Challenges	Bejani & Ghatee (2021)	Overfitting reduces model generalization ability.
17	Limitations & Challenges	García et al. (2023)	High computational requirements limit applications in regions with infrastructure constraints.
18	Limitations & Challenges	Yu et al. (2025)	Limited availability of high-quality data, due to incomplete, inconsistent, or hard-to-obtain real-time hydrological data.

flooding and spatial and environmental factors that contribute to disaster risk; (c) The green cluster focuses on systems and applications, with keywords such as technology, resilience, detection, attack, IoT, sensor, feature, and deep learning model. This cluster shows research on the implementation of technology, intelligent detection systems, and the integration of IoT and deep learning to support flood detection and mitigation systems; (d) The yellow cluster highlights keywords such as natural disaster, hazard, and aspect, which connect the topic of disaster risk in general with the context of flooding; and (e) The purple cluster is relatively small, marked by the keyword carbon emission, which links the issues of climate change and carbon emissions to the risk of flooding and other hydrometeorological disasters. This will be discussed in detail in the following three sub-discussions.

1. The Development of Backpropagation Neural Network (BPNN) Algorithms in The Context of Flood Detection

The evolution of BPNN from their basic model to more advanced versions is marked by the integration of optimization algorithms to improve performance in complex data processing. Integration with Genetic Algorithms (GA) helps improve global solution search capabilities while reducing the risk of getting stuck in local minima, resulting in more stable prediction models (Chen, 2024). The combination of BPNN with Particle Swarm Optimization (PSO) has been proven effective in accelerating convergence and improving prediction accuracy in systems involving non-linear data, including hydrology and rainfall (Wu et al., 2015). The application of Adaptive Gradient Descent enables more dynamic and efficient weight updates, thereby improving the performance of BPNN in the context of big data and changing environmental conditions (Li et al., 2015). The integration of these optimization algorithms shows the significant development of BPNN from a simple feedforward model to a more complex architecture that is adaptive to the needs of intelligent flood detection.

Improving the performance of BPNN is a major focus in various studies, particularly in relation to accuracy, convergence speed, and prediction stability when dealing with complex hydrological data. Higher accuracy is achieved through training parameter optimization and the use of network architectures tailored to the non-linear patterns in flood data (Kumar et al., 2023). In terms of convergence speed, the development of derivative algorithms such as adaptive learning rates has been proven to accelerate the training process while reducing the computational load (Haji & Abdulazeez, 2021). Prediction stability also increases with the application of regularization techniques and integration with modern optimization methods that prevent overfitting, resulting in more consistent predictions in dynamic environmental conditions (Bian & Priyadarshi, 2024). This confirms that BPNN continues to evolve to meet the needs of more reliable and intelligent flood detection systems.

The development of BPNN in flood detection systems shows that the main requirements are prediction accuracy and convergence speed. Integration with optimization algorithms helps avoid getting stuck in local solutions, while the use of adaptive optimizers maintains the stability of the learning process in fluctuating data. Regularization and ensemble techniques improve generalization capabilities so that predictions become more consistent in dynamic environmental conditions. The adoption of deep learning architecture marks the transformation of BPNN from a single model to a flexible component in a more complex system. However, the GA and PSO-based hybrid approach, while improving accuracy and stability, adds to the computational load, making it less efficient for early warning systems that require a quick response. Adaptive optimizers accelerate convergence, but parameter selection remains a challenge, while the use of regularization and ensemble, despite reducing overfitting, makes model interpretation more difficult. In addition, the quality and availability of hydrological data remain limiting factors, as model performance is highly dependent on adequate input data.

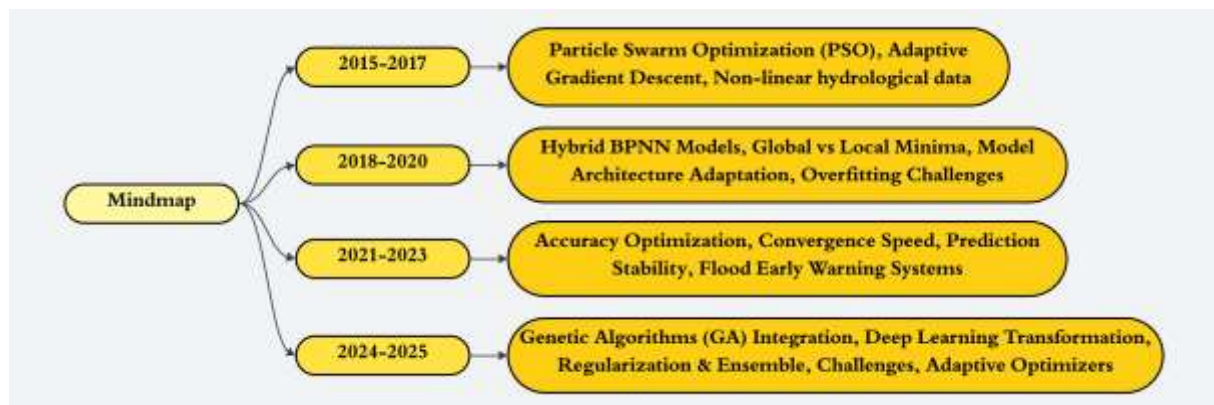


Figure 3. Development of research variables on BPNN Development in the Context of Flood Detection

Figure 3 illustrates the development of BPNN research variables in flood detection systems from 2015 to 2025. During the 2015–2017 period, research focused on accelerating convergence and improving accuracy through Particle Swarm Optimization (PSO), weight update efficiency with Adaptive Gradient Descent, and application to non-linear hydrological data. Furthermore, in the 2018–2020 period, the direction of development shifted to hybrid BPNN models with the integration of optimization algorithms such as GA and PSO to balance global vs. local solution searches, accompanied by adjustments to the network architecture according to flood data characteristics, as well as the emergence of overfitting challenges that required regulation strategies. In the 2021–2023 period, research will emphasize accuracy optimization with adaptive architecture design, increased convergence speed through adaptive learning rates, improved prediction stability through regularization, and the application of BPNN in flood early warning systems that demand efficiency and reliability. Entering the 2024–2025 period, the evolution of BPNN is becoming increasingly complex with the integration of Genetic Algorithms (GA) for global solutions, the transformation towards deep learning as part of a broader AI system, the use of regularization and ensemble to improve generalization, and the use of adaptive optimizers to accelerate convergence. However, major challenges remain, such as high computational load, data quality limitations, and reduced model interpretability.

2. The Main Implementation of BPNN in The Development of An Intelligent Flood Detection System

The BPNN application in flood prediction is widely used to model various hydrological parameters such as rainfall, river discharge, regional elevation, and other environmental factors that interact in complex ways. Modeling rainfall with BPNN has proven effective in identifying non-linear patterns and extreme fluctuations that are difficult to capture using conventional statistical methods (Liao & Li, 2024). On the other hand, the use of BPNN to estimate river discharge can improve the accuracy of water flow predictions in Watershed Areas (DAS), which are a key indicator of flood risk (Samantaray & Sahoo, 2024). In addition, the integration of regional elevation data and topographic parameters into the BPNN model assists in flood vulnerability mapping, as it can represent the influence of land morphology on surface runoff (Hasnaoui et al., 2025). The combination of these various hydrological parameters demonstrates the great potential of BPNN as an intelligent approach to supporting a more accurate and adaptive flood detection system.

The integration of BPNN with supporting technologies such as the Internet of Things (IoT), real-time sensors, satellite imagery, and environmental big data is an important strategy in developing a more effective flood early warning system. The use of IoT and real-time sensors

enables continuous collection of high-resolution hydrological data so that BPNN models can provide more adaptive predictions of changes in field conditions (Biazar et al., 2025). Satellite imagery is also used to enrich the model with spatial information such as regional rainfall, soil moisture, and land use changes that contribute to flood risk (Tanim et al., 2022). Meanwhile, environmental big data processing enables BPNN to utilize large volumes of data, allowing complex flood patterns to be analyzed with greater accuracy (Sun & Scanlon, 2019). This integration strengthens the position of BPNN as a core component in artificial intelligence-based flood detection and early warning systems.

The implementation of BPNN in flood detection systems shows that this model does not merely produce a single numerical output, but functions as a flexible pattern processing engine. For rainfall and discharge predictions, BPNN is able to extract non-linear relationships between hydrometeorological variables, enabling it to predict spikes more sensitively than linear statistical methods. By incorporating elevation, topography, and satellite imagery data, BPNN can capture the spatial influences that determine runoff patterns and inundation points, supporting more contextual vulnerability mapping. Integration with IoT and real-time sensors makes the model adaptive, updating predictions according to changing field conditions and approaching the needs of early warning systems. The strength of BPNN lies in its input flexibility, ability to extract complex non-linear patterns, and compatibility with real-time systems. However, this model also faces significant challenges, including the need for large volumes of high-quality data, high computational costs, especially for hybrid or ensemble models, low interpretability that complicates decision-making, and limited transferability between regions, requiring adaptation or recalibration.



Figure 4. Development of research variables in the Main Application of BPNN in the Development of Intelligent Flood Detection Systems

Figure 4 shows the development of research variables related to the application of BPNN in flood detection systems based on the research period. In the 2015–2017 period, the main focus was on environmental big data processing to analyze complex flood patterns, capture non-linear hydrometeorological patterns, and improve flood prediction accuracy through large-scale data modeling. Entering the 2018–2020 period, the direction of research developed with the use of IoT-based data collection and real-time sensors to support model adaptability, as well as the integration of remote sensing for mapping rainfall, soil moisture, and land use changes. In the 2021–2023 period, research will emphasize the integration of satellite imagery as a source of spatial information, the application of contextual vulnerability mapping based on elevation and topography, and the development of adaptive prediction systems that can be updated in real time to support early warning systems. The 2024–2025 period shows increasingly practical developments, with a focus on rainfall modeling for non-linear patterns and extreme fluctuations, river discharge prediction to improve the accuracy of flow

predictions in watersheds, and the use of topography and elevation data for flood vulnerability mapping. In addition, the integration of IoT and real-time sensors with BPNN confirms the strength of this model in terms of input flexibility, ability to recognize non-linear patterns, and compatibility with real-time systems, despite still facing challenges in the form of the need for large amounts of high-quality data, high computational costs, low interpretability, and limited transferability between regions.

3. Future Challenges and Opportunities in the Use of BPNN for Flood Detection Systems

Although BPNN is widely used in flood detection systems, there are a number of limitations that still need to be considered. One of the main obstacles is overfitting, where the model adapts too closely to the training data, thereby reducing its ability to generalize to new data (Bejani & Ghatee, 2021). In addition, BPNN requires high computational resources, especially for large and complex hydrological datasets, which can limit its application in areas with infrastructure limitations (García et al., 2023). Another challenge lies in the availability of high-quality data, given that hydrological data is often incomplete, inconsistent, or difficult to obtain in real-time, which impacts the accuracy of flood predictions (Yu et al., 2025). Identifying these limitations is an important basis for further development, whether through algorithm optimization, hybrid method integration, or the use of advanced computing technology.

Future research opportunities in the development of BPNN for flood detection systems emphasize hybrid models that combine BPNN with other artificial intelligence methods. The integration of BPNN with deep learning enables improved capabilities in extracting complex non-linear patterns from large-scale hydrological data (Tosan et al., 2025). Another approach is the application of ensemble methods, which can combine the advantages of several algorithms to improve the accuracy and robustness of predictions for extreme flood conditions (Mosavi et al., 2018). In addition, the development of cloud-based flood monitoring systems opens up great opportunities on a global scale, as it enables real-time processing of environmental big data and cross-regional collaboration to support more effective flood early warning systems (Karnam, 2025). This research direction provides an important foundation for the development of smarter, more adaptive, and integrated flood detection systems.

The limitations of BPNN confirm that although this model is powerful in recognizing non-linear patterns, additional innovations are still needed to make it more practical and reliable in real-world contexts. The problem of overfitting highlights the need for more sophisticated regularization strategies, while computational requirements emphasize the importance of algorithm efficiency and the use of supporting technologies such as cloud or edge computing. Data limitations underscore that algorithmic advances must be supported by improvements in data collection infrastructure. Opportunities for BPNN development arise through hybrid and ensemble integration, making it part of a larger, adaptive ecosystem, and the use of cloud computing and IoT for scalable, ready-to-use systems in cross-regional early warning operations. The strengths of this development direction include the ability of hybrid with deep learning to handle complex temporal and spatial patterns, increased prediction reliability through ensemble methods, and large-scale real-time processing through the cloud. However, remaining challenges include the complexity and increased computational requirements of hybrid/ensemble models, limitations in network infrastructure for cloud-based systems in flood-prone areas, limitations in data quality, and decreased model interpretability as architecture complexity increases, even though transparency is crucial for emergency decision-making.



Figure 5. Development of research variables in Challenges and Future Opportunities in the Use of BPNN-Based Artificial Neural Networks for Flood Detection Systems

Figure 5 illustrates the development of research variables related to the limitations and opportunities for developing BPNN in flood detection systems from 2015 to 2025. In the 2015–2017 period, research focused on the application of ensemble methods to improve the accuracy and resilience of predictions against extreme conditions, as well as the use of BPNN in hydrological pattern recognition to capture non-linear patterns. The 2018–2020 period began to address technical issues such as the need for regularization strategies to overcome overfitting, algorithm optimization for computational efficiency, and the importance of improving infrastructure and hydrological data quality. Furthermore, in 2021–2023, the research focus will be directed at improving computational efficiency, the early introduction of edge and cloud computing to support flood detection, and fundamental issues related to the quality and completeness of real-time data. The 2024–2025 period shows a more complex and integrated development direction, with efforts to overcome overfitting challenges through more sophisticated regulatory strategies, the application of hybrid models (BPNN + deep learning) to handle complex temporal and spatial patterns, and the development of cloud-based flood monitoring systems for real-time processing and cross-regional collaboration. The integration of IoT and big data further strengthens model adaptability, while prediction reliability is improved through a combination of hybrid and ensemble methods. However, new challenges arise in the form of interpretability issues, where the increasing complexity of models actually reduces the transparency of prediction results, which is very important in emergency decision-making.

D. CONCLUSIONS AND SUGGESTIONS

Based on the evaluation results of the use of BPNN in flood detection systems, it can be concluded that BPNN has evolved from a simple feedforward model into an intelligent component capable of processing non-linear patterns, integrating various data sources (rainfall, river discharge, topography, satellite imagery), and supporting adaptive early warning systems through IoT and big data. However, there are several important gaps that need attention. First, the risk of overfitting and high computational requirements remain obstacles to large-scale or real-time implementation, especially in areas with limited infrastructure. Second, the limited quality and availability of complete and consistent hydrological data limits the accuracy of the model, while the low interpretability of complex models makes evidence-based decision making difficult. Third, the transferability of models between regions is still limited, so model adaptation requires intensive recalibration. Based on these gaps, urgent research topics that need to be explored in the future include the

development of more computationally efficient hybrid and ensemble BPNN models, strategies for augmenting and improving the quality of real-time hydrological data, and interpretable AI approaches for flood prediction that remain accurate yet transparent to decision makers. Such research is crucial for creating flood detection systems that are more adaptive, robust, and ready for widespread implementation across various geographical conditions and infrastructure.

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