FLOOD PREDICTION BASED ON DEEP LEARNING NETWORKS WITH VARIATIONAL MODE DECOMPOSITION

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FLOOD PREDICTION BASED ON DEEP LEARNING NETWORKS WITH VARIATIONAL MODE DECOMPOSITION

by

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LIST OF SYMBOLS

K	Number of IMFs after SSA-VMD decomposition
α	The quadratic penalty factor of VMD
$\boldsymbol{u}_k$	The k-th mode after VMD decomposition
y_i	The value of the i-th sample in the test set
$\hat{y}_i$	The value of the i-th predicted sample
$\boldsymbol{x}_t$	The current time step t of the input vector

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
GIS	Geographic Information System
EMD	Empirical Mode Decomposition
Arima	Autoregressive integrated moving average
SVM	Support Vector Machine
VMD	Variational Mode Decomposition
IMFs	Intrinsic Mode Functions
BP	Back Propagation
MLP	Multilayer Perceptron
ANN	Artificial Neural Network
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory network
BiLSTM	Bidirectional Long Short-Term Memory network
SSA	Sparrow Search Algorithm
PSO	Particle Swarm Optimization
IPSO	Improved Particle Swarm Optimization
SVIBA	SSA-VMD-IPSO-BiLSTM-Attention
SABO	Subtraction-Average-Based Optimizer
GRU	Gated Recurrent Unit
TCN	Time Convolutional Network
KDE	Kernel Density Estimation

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RAMALAN BANJIR BERDASARKAN RANGKAIAN PEMBELAJARAN DALAM DENGAN PENGURAIAN MOD VARIANS

ABSTRAK

Perubahan iklim meningkatkan frekuensi kejadian cuaca ekstrem. Banjir dari limpahan sungai merupakan ancaman utama yang berpotensi membahayakan keselamatan manusia dan ekosistem. Naik turunnya paras air disebabkan oleh topografi dan curahan hujan menjadikan ramalan banjir semakin mencabar. Model ramalan banjir tradisional sering menghadapi kesukaran untuk menangani gangguan secara berkesan terhadap data hidrologi dan pembolehubah meteorologi yang mengakibatkan ramalan yang kurang tepat. Tesis ini bertujuan untuk meningkatkan ketepatan ramalan banjir dengan membangunkan dan menilai tiga model baharu pembelajaran mesin yang menggabungkan penguraian data, pemilihan ciri, dan mengoptimumkan parameter. Dua model pertama menggunakan data paras air bagi setiap jam. Model pertama menggunakan data hidrologi dengan menggabungkan kaedah Penguraian Mod Variasi (VMD) untuk mengurangkan gangguan, serta Rangkaian Memori Jangka Pendek Berarah Dua (BiLSTM) yang dioptimumkan dengan perhatian untuk tujuan peramalan. Model kedua meningkatkan keberkesanan ramalan dengan menggabungkan data meteorologi iaitu maklumat hujan, kelembapan, dan kelajuan angin. Model ini menekankan manfaat pengelasan komponen VMD dan pemilihan ciri dengan cara mempertimbangkan perubahan paras air untuk mengkategorikan Fungsi Modul Intrinsik (IMF) yang diperoleh dari kaedah VMD dan menggunakan pemilihan ciri melalui kaedah korelasi *Pearson*. Model ketiga menggunakan kaedah Unit Berulang Berpagar yang dioptimumkan dengan Rangkaian Konvolusi Temporal (GRU-TCN) untuk meramal data harian pada anggaran titik dan

dalam selang keyakinan. Model ini memperbaiki Anggaran Ketumpatan Inti (KDE) untuk menilai ketidakpastian ramalan secara lebih tepat dan meningkatkan kebolehpercayaan model. Ketiga-tiga model yang dicadangkan ini mampu mengatasi kelemahan kaedah tradisional dengan menggunakan data sebenar dari stesen Sungai Yangtze. Hasilnya, model-model yang diuji telah menunjukkan pengurangan ralat purata kuasa dua akar (RMSE) sebanyak lebih daripada 30%. Hasil analisis menunjukkan kaedah Penguraian Mod Varians (VMD) lebih berkesan untuk data set selang bagi setiap jam, manakala integrasi pembolehubah meteorologi meningkatkan ramalan jangka pendek terutamanya semasa musim tengkujuh. Model-model yang dicadangkan ini mempunyai potensi diaplikasikan dalam sistem pengurusan banjir bagi selang masa nyata dalam mengatur strategi respons bencana dan dapat memantau kejadian penyesuaian perubahan iklim dengan cara menyediakan ramalan dan simulasi yang tepat bagi kemungkinan berlakunya senario banjir di masa hadapan.

FLOOD PREDICTION BASED ON DEEP LEARNING NETWORKS WITH VARIATIONAL MODE DECOMPOSITION

ABSTRACT

Climate change increases the frequency of extreme weather events, causing river overflow floods that threaten human safety and ecosystems. Traditional flood prediction models face challenges due to fluctuations in water levels from topography and rainfall, leading to less accurate forecasts. This thesis aims to enhance flood prediction accuracy by developing and evaluating three new machine learning models that incorporate data decomposition, feature selection, and parameter optimization. The first two models use water level data for each hour. The first model utilizes hydrological data by integrating the Variational Mode Decomposition (VMD) method to reduce disturbances, along with Directional Bidirectional Long Short-Term Memory (BiLSTM) optimized with attention for forecasting purposes. The second model enhances prediction effectiveness by incorporating meteorological data specifically rainfall, humidity, and wind speed. This model emphasizes the benefits of VMD component classification and feature selection by considering water level changes to categorize Intrinsic Mode Functions (IMFs) obtained from the VMD method and using feature selection through the Pearson correlation method. The third model uses an optimized Gated Recurrent Unit - Temporal Convolutional Network (GRU-TCN) to forecast daily data at point estimates and confidence intervals. This model improves Kernel Density Estimate (KDE) predictions to assess forecast uncertainty more accurately and enhance model reliability. These three proposed models can overcome the weaknesses of traditional methods by utilizing real data from the Yangtze River station. As a result, the tested models have shown a reduction in the

Root Mean Square Error (RMSE) by more than 30%. The analysis indicates that the Variational Mode Decomposition (VMD) method is more effective for interval dataset for each hour, while integrating meteorological variables improves short-term forecasts, especially during the monsoon season. These proposed models have potential applications in real-time flood management systems for disaster response strategies and can monitor climate change adaptation events by providing accurate forecasts and simulations for potential future flood scenarios.

CHAPTER 1

INTRODUCTION

1.1 Research Background

With global climate change, the frequency and intensity of extreme weather events have increased. Floods, as one of the primary forms of disasters, have a significant negative impact on human society and the natural environment. Such impacts lead to many material losses and long-term socio-economic problems (Mobini *et al.*, 2022; Kou *et al.*, 2019). Floods not only directly threaten the safety of human life and property but can also lead to agricultural losses, the spread of disease, transportation disruptions, and long-term environmental degradation. Flood impacts are particularly severe in areas that lack effective forecasting and emergency preparedness. The percentage of personnel losses caused by natural disasters in Asia is approximately 90%, usually attributed to floods (Skevas *et al.*, 2023). As the planet faces the increasing disruptions of climate change, floods are becoming not only more frequent but also more destructive. The consequences of flooding are devastating, from the immediate destruction of infrastructure and homes to the long-term socioeconomic disruption that follows. Accurate flood forecasting has become a key focus for researchers and policymakers, it can help predict future floods and inform people to prevent and reduce loss of life and economic damage during floods (Jain *et al.*, 2018), enhance emergency response efficiency, and reduce human casualties and economic losses while supporting more informed decision-making and community resilience building.

Hydrologists and mathematical statisticians have been studying flood characteristics for a long time, trying to predict water level or volume changes by constructing statistical models of hydrological processes. The research on flood prediction is mainly divided into two categories. One is based on meteorological and hydrological characteristics through satellite observation data (Jain *et al.*, 2018), with the help of a geographic GIS system, combined with hydrology (Mondal *et al.*, 2023), dynamics (Mondal *et al.*, 2023), and other knowledge (Coelho *et al.*, 2022; Kou *et al.*, 2017), to establish a flood prediction system, simulate the process from rainfall to flood formation, and carry out water level prediction. The other is based on combining traditional statistical models and other algorithms, such as the combination of time series models (Hadhbi and Kacem, 2022; Yang and Chen, 2019; Hakim *et al.*, 2023), and deep learning (Kim and Han, 2020; Bentivoglio *et al.*, 2022; Ma *et al.*, 2024). With the development of Artificial Intelligence (AI), machine learning and deep learning have become the research hotspots of flood prediction. However, deep learning algorithms face challenges in parameter selection, model construction, and uncertainty assessment of predictions. Different research areas are suitable for different prediction models, and the oscillation of water levels during floods also increases the prediction difficulty.

As the longest river in China, the Yangtze River has a total length of about 6397 kilometers and flows through multiple provincial-level administrative regions. The total basin area is about 1.8 million square kilometers, accounting for about one-fifth of China's land area. Although the Yangtze River provides irrigation and drinking water for China, it has also experienced multiple floods, causing significant losses to the Chinese people and property. This thesis will study the methods of flood prediction and conduct novel prediction models based on data from the Yangtze River stations, develop deep learning models with better prediction accuracy, analyze the uncertainty and reliability of prediction models, and verify the stability of the constructed models.

Aiming to provide more competitive prediction methods for flood prediction and more advanced methods for flood control and disaster reduction along the Yangtze River.

1.2 Problem Statement

The water level fluctuates dramatically during floods, and various noises are introduced due to wind and dust, making prediction more challenging. Several studies have employed data decomposition techniques like Empirical Mode Decomposition (EMD) and Variational Mode Decomposition (VMD) to enhance prediction accuracy. Examples include EMD-Arima (Wang *et al.*, 2018), EMD- Artificial Neural Network (ANN)(Ahmad *et al.*, 2024), EMD- Long Short-Term Memory (LSTM) (Yuan *et al*., 2021), , and VMD based methods such as VMD-LSTM (Han *et al.*, 2019; Guo *et al*., 2023), VMD-Kernel Extreme Learning Machine (Liu *et al.*, 2023), VMD-Time Convolutional Network (TCN)(Wang and Liang, 2021). However, the EMD algorithm lacks a solid mathematical foundation and relies on local features and extreme points in the signal to decompose signals, making it sensitive to noise (Civera and Surace, 2021). If the signal contains rapidly changing frequencies, EMD decomposition is prone to misidentify the noise and cause modal overlap (Guo *et al.*, 2023). VMD improves the accuracy of frequency separation and reduces mode overlap by solving the variational problem, but VMD's performance heavily depends on the parameter settings, such as the number of modes and the penalty parameters that are challenging to select. Intelligent optimization algorithms will be explored in this thesis to assist in identifying suitable parameters for VMD, thereby enhancing its efficacy in flood prediction models.

Machine learning, deep learning, and LSTM have become popular methods in flood prediction analysis since 2019(as shown in Figure 2.1). Traditional linear models, such as ARIMA, require data to be stationary and tested, and assume that errors are independently and identically normally distributed, which limits their applicability to the real-world (Hadhbi and Kacem, 2022; Valipour, 2015; Garg *et al.*, 2023). Deep learning is a branch of machine learning, and LSTM is a widely used deep learning network It features gated memory units and the ability to model nonlinear data, particularly suitable for predicting random and complex signals like floods (Kim and Han,2020; Chen *et al.*, 2023; Bentivoglio *et al*., 2022; Sun *et al*., 2023), but LSTM has difficulty selecting hyperparameters. Improper choice of hyperparameters may result overfitting or underfitting, leading to learning the noise in the training data or failing to capture the complex patterns, and LSTMs only pass information from front to back, ignoring the backward information to the current state, which may be less than optimal for predicting continuous water flows. It is imperative to develop deep learning models with multidirectional learning ability and build more accurate models with excellent generalization capabilities.

The effectiveness of deep learning models heavily depends on the choice and configuration of parameters and their internal architecture. Incorrect parameter settings can lead to weakened performance, overfitting, underfitting, or even gradient vanishing, all of which negatively impact the model's predictive accuracy (Arora *et al.*, 2021; Ahmed *et al*., 2022). To overcome these challenges, this research will explore advanced parameter adjustment techniques and the construction of integrated networks to enhance the model's generalization ability and mitigate overfitting and underfitting.

Combined with the meteorological data, the model constructed by VMD combined with CNN and LSTM can enhance spatial information extraction and improve model effectiveness (Guo *et al.*, 2022; Wu *et al*., 2023), but the frequency of IMFs changes after the VMD decomposition, which makes it difficult to reasonably match with multiple input variables (Guo *et al.*, 2023). Addressing this issue requires developing classification methods for VMD and feature matching of VMD IMFs with input variables.

Most flood forecasting research focuses on point estimate forecasting, but it is difficult to estimate the uncertainty of flood forecasting, for it just provides a single predicted value, which inherently overlooks the variability and potential range of outcomes in complex flood systems, leading to potentially misleading predictions about flood risks and magnitudes (Beven and Freer, 2001; Khanesar and Branson, 2021). Interval forecasting helps to give a better understand of the scope and risks of the flood prediction (Khanesar and Branson, 2021; Wang and Li, 2023; Pan *et a*l., 2020). Xu *et al.* (2022) and Wu *et al.* (2023) utilized both point and interval prediction to further quantify the uncertainty of the prediction results, but they lacked an in-depth analysis of error distribution. Further analyzing the prediction error distribution can reflect the stability of the predicting models and improve their performance.

1.3 Research Questions

Based on the problem statement above, we summarize the following research questions:

(1) In the data pre-processing stage, how can flood forecasting accuracy be improved by selecting appropriate noise reduction techniques (EMD or VMD) and decision parameters?

(2) How can deep learning models with multi-directional learning ability and excellent generalization capabilities be constructed to achieve higher accuracy, especially during the flood-prone period?

(3) How to improve the performance and stability of the constructed deep learning models through parameter optimization and structural tuning?

(4) Given that varying parameter selections can result in different VMD IMFs, how can a hybrid model be constructed to extract spatiotemporal input information and classify these different frequency VMD IMFs to match the input variables better?

(5) How to interpret and evaluate the predictive models' uncertainty and further prove the prediction models' reliability?

1.4 Research Objectives

To address the research questions, the following research objectives are proposed:

(1) To remove noise using the decomposition technique VMD and apply intelligent optimization methods for VMD parameter selection.

(2) To develop optimized hybrid flood prediction models based on VMD for short-term prediction.

(3) To build neural networks with improved efficiency by avoiding gradient vanishing through adjustments in model structure, activation function, and optimizer.

(4) To construct hybrid models by extracting spatiotemporal information from hydrology and meteorology data, with feature selection on multi-variable inputs.

(5) To evaluate the uncertainty and reliability of flood prediction models using interval prediction through non-parametric kernel density estimation (KDE) and bootstrap sampling.

1.5 Scope of the Study

This study focuses on the Yangtze River hydrological stations in Hubei Province, combined with the information of the surrounding meteorological stations. Using hourly and daily data, a comprehensive prediction study, aiming to improve the prediction accuracy and assess the uncertainty of the prediction is carried out. Firstly, based on hourly data under the VMD decomposition technique, the performances of models constructed only by hydrological data are compared with models that use hydrological and meteorological information. Then, the improvement effect of parameter optimization and feature selection on model prediction is explored. Lastly, based on daily data from 2017 to 2021, a novel hybrid prediction model that can learn the long pattern of the flood is established, and the model's reliability is proved by analyzing the distribution of prediction errors. Point prediction and interval prediction is compared, and the flood prediction error is analyzed.

The research mainly involves five aspects: data decomposition techniques for noise reduction, model parameter optimization methods, hybrid deep learning model construction and structure adjustment, hybrid spatiotemporal model construction with feature selection, and model prediction comparison and error analysis.

1.6 Significance of the Study

The world is currently experiencing the impact of climate change, manifesting in ongoing floods that pose substantial threats to lives and property. Forecasts suggest that by 2050, both the frequency and intensity of floods will escalate, potentially leading to substantial financial losses estimated at 1 trillion dollars (Huang *et al.*, 2019), (Rahman *et al.*, 2021). Floods commonly arise from factors such as intense rainfall and increased water levels in rivers and reservoirs. Precise prediction of water levels is crucial for optimizing water resource utilization and enhancing water resource management, which is conducive to promoting sustainable resource management development.

During the flood period, water level fluctuations become more random, and frequency changes become more complex, introducing noise that complicates flood prediction. This study is crucial for advancing flood prediction methodologies, particularly as climate change heightens the frequency and severity of extreme weather events. By employing VMD for data preprocessing, the study effectively reduces noise and improves data feature interpretation, leading to more accurate predictions. The integration of hybrid models combining different approaches has demonstrated superior performance over traditional models, offering more reliable forecasts. Furthermore, optimal parameter selection enhances model stability and efficiency, while feature selection techniques ensure the use of the most relevant variables, significantly boosting predictive accuracy. Additionally, incorporating interval prediction provides a comprehensive evaluation of model uncertainty by offering a range of potential outcomes, thus aiding in better error estimation analysis, and assisting practical application.

Three novel models for flood prediction are proposed to improve the prediction accuracy of deep learning models. These models will enhance the applicability and effectiveness of hybrid models in complex environments, providing better support for the decision-making process in flood management. Specifically, their implementation holds significant importance for predicting floods in the Yangtze River and aiding decision-makers in effectively mitigating such disasters.

1.7 Thesis Organization and Contributions

This thesis consists of 7 chapters. Chapter 1 describes the study on flood prediction, the research problem, and the objectives. It also gives the study area and data sources. Chapter 2 presents the literature review, covering research trends, research methods, deep learning-based flood forecasting methods, data decomposition techniques, and forecast error analysis. Summarize the main methods and research directions of flood prediction.

Chapters 3 to 6 are the main contributions of this Ph.D. thesis. Chapter 3 is a preliminary analysis of the EMD and VMD decomposition predictions for the Yangtze River water level to identify more suitable data decomposition techniques for our study, and the logical and methodological connection of the research in chapters 4-6 is given. Chapters 4 and 5 introduce two innovative hybrid prediction methods based on hourly data. Chapter 4 (corresponding to the first paper in the list of publications) involves constructing hybrid deep-learning models based on hydrological data, focusing on VMD decomposition technique and parameter optimization, while Chapter 5 (corresponding to the second paper in the list of publications) takes meteorological data into account, using BiLSTM to extract long-time information and CNN to extract spatial information, focusing on feature selection and VMD IMFs' classification. To further explore the long-term variations in Yangtze River floods and evaluate the prediction model's uncertainty and reliability, Chapter 6 (corresponding to the third paper in the list of publications) progresses to daily data from hydrological and meteorological stations, where an advanced hybrid prediction model using GRU and

TCN is developed. This chapter conducts experimental simulations to assess the model's predictive performance across 2 station data and provides interval estimation results, a KDE nonparametric analysis is used to enhance the prediction model’s reliability.

Finally, Chapter 7 provides a conclusion and future work section that summarizes the research contributions and limitations, offers directions and recommendations for future research.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Floods are regional and seasonal, and flood prediction methods based on decomposition techniques and deep learning networks are widely researched and applied by scholars and decision-makers in various countries. Accurate flood prediction can improve the ability of human beings to cope with risks, which is conducive to managers making the correct assessment and decision-making. Hydrologists and statisticians have extensively studied flood characteristics to predict water level or flow changes by constructing hydrological statistical models. New data-mining techniques are providing better help in prompting researchers to obtain accurate flood prediction data. However, the water level fluctuates wildly and randomly during floods and often introduces a certain degree of noise, dramatically increasing the prediction difficulty. Data decomposition methods and feature selection can aid in reducing noise to smooth the data and enhance the accuracy of subsequent time-series predictions. This chapter aims to sort out the flood prediction methods based on deep learning networks and decomposition techniques, classify and analyze the research methods and the research trends, discuss the prediction uncertainty and reliability, summarize the research directions, advantages, and limitations, and give the research direction of this Ph.D. thesis.

2.2 Flood Prediction Research Trends

In this section, a comprehensive literature search is conducted for studies related to flood prediction methods using two well-known academic databases, Web of Science and China Knowledge Network. By carefully screening and comprehensively analyzing the searched papers, this study aims to depict the research dynamics in flood prediction, clarify current trends, and identify the mainstream prediction methods. During the data collection process, particular attention is paid to information such as the year of publication, research organization, and number of citations, which helped determine the influence and popularity of different methods. The search results are classified and organized through statistical analysis of highly cited papers to determine which methods are more widely accepted and used in academia and practice and what the leading research directions are.

2.2.1 Trends in Flood Prediction Methods

To understand the development trends of flood prediction methods, further research was conducted by combining searches for international literature in the CNKI (China Knowledge Network) database with the topic "flood prediction", selecting relevant literature from 2015 to 2024, totaling 1360 publications. A keyword analysis of the literature was performed, and Figure 2.1 presents the research trends of the main associated methods.

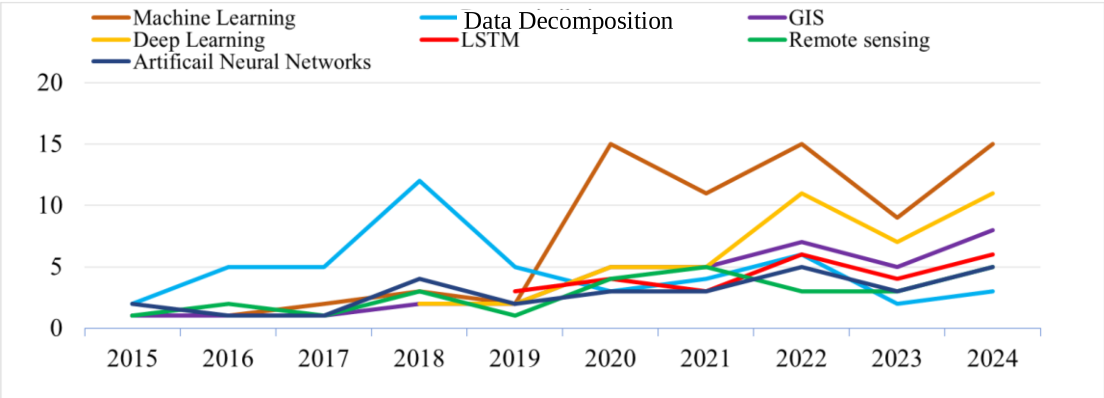

Figure 2.1 Trends in flood prediction methods

From Figure 2.1, it is evident that machine learning methods based on data decomposition combined with Artificial Neural Networks and Remote sensing are the mainstream approaches for prediction. Since 2019, research papers related to deep learning and LSTM have begun to increase, and papers on flood prediction related to machine learning have also shown significant growth. This is because Google released the TensorFlow and PyTorch deep learning frameworks in 2015 and 2017 (Steiner *et al.*, 2019, 2016), respectively, making building and deploying complex deep learning models more accessible and efficient. Deep learning algorithms excel at processing nonlinear data, yet they involve complex model structures and numerous parameters, making it challenging to configure the optimal model architecture and parameter settings for specific problems. These limitations underscore the crucial importance of parameter selection and model construction in enhancing the deep learning models' performance and applicability.

2.2.2 Research Methods Analysis

From the comprehensive literature analysis, approaches in flood forecasting include hydrological models, statistical methods, and data mining methods (Hakim *et al.*, 2023). Current research in flood prediction mainly includes topics such as the development of early warning systems (Habibi *et al.*, 2023; Syed *et al.*, 2021), relationship between climate change and floods (Nguyen *et al.*, 2023; Yan *et al.*, 2022), and the development of advanced flood prediction models (Schumann *et al.*, 2022; Mosavi *et al.*, 2018; Hu *et al.*, 2019a; Yan *et al.*, 2022; Chen *et al.*, 2022a; Zhang *et al.*, 2023).

River flood prediction is mainly for water level, runoff, water flow, flood level prediction, flood frequency prediction, and flood duration prediction, combined with other data from hydrological stations (Mondal *et al.*, 2023) and meteorological (Rahman *et al.*, 2021; Coelho *et al.*, 2022). Some researches also focus on the topographic characteristics of the research area (Syed *et al.*, 2021), with the help of

Geographic Information System (GIS) systems (Chou *et al.*, 2020a), to make a comprehensive prediction (Ahmed *et al.*, 2022; Ma *et al*., 2024).

Autoregressive integrated moving average (Arima), as a classic time series prediction method, is often used to extract statistical features of flood sequences (Elganiny and Eldwer, 2018; Yan *et al.*, 2022) and construct time series prediction models (Subha and Saudia, 2023; Ab *et a*l., 2016). Arima model is often combined with Seasonal Arima (Saleh and Tei, 2019; Valipour, 2015) and Garch models (Pandey *et al*., 2018; Wang *et al*., 2023) to achieve more accurate forecasts. However, they are good at handling linear features and lacks predictive ability for complex nonlinear data (Jain *et al*., 2018). Support Vector Machine (SVM) is suitable for nonlinear regression problems, to identify the global optimal solution in flood models(Mirkazemi *et al*., 2023; Tehrany *et al*., 2015). However, SVMs face challenges in flood forecasting due to their sensitivity to parameter selection, scalability issues with large datasets, and difficulty in capturing complex, non-linear relationships in hydrological data (Samantaray *et al*., 2023).

In response to the limitations of linear and nonlinear prediction methods like Arima and SVM, recent research has focused on joint prediction using spatio-temporal features (Noor *et al*., 2022; Chen *et al*., 2022a). By incorporating spatial and temporal data, models are better equipped to capture the complex interactions that influence flood events. Building hybrid models that combine machine learning and statistical approaches has become a popular trend (Samantaray *et al.*, 2023; Xu *et al*., 2021; Yang and Zhang, 2022; Ji *et al*., 2021). These hybrid models aim to leverage the strengths of different techniques, improving prediction accuracy and robustness in handling both linear and nonlinear patterns.

With the development of AI, research trends have turned to data-driven models facilitated by machine learning and deep learning prediction methods (Ma *et al*., 2024; Sankaranarayanan *et al*., 2019; Hu *et al*., 2019a). Machine learning and deep learning prediction methods surpass Arima models in efficiently handling large datasets, capturing complex nonlinear relationships, and exhibiting superior predictive accuracy and adaptability with high-dimensional data (Garg *et al*., 2023; Hakim *et al*., 2023). Combined with data preprocessing (Wang *et al*., 2018; Guo *et al*., 2023) and feature screening (Habibi *et al*., 2023; Garg *et al*., 2023), exploring the construction of deep learning networks to enhance the learning ability of spatiotemporal data becomes the direction of flood forecasting research. Based on the comprehensive literature review, the main research directions about deep learning methods on flood prediction are shown in Figure 2.2 (Hakim *et al*., 2023).

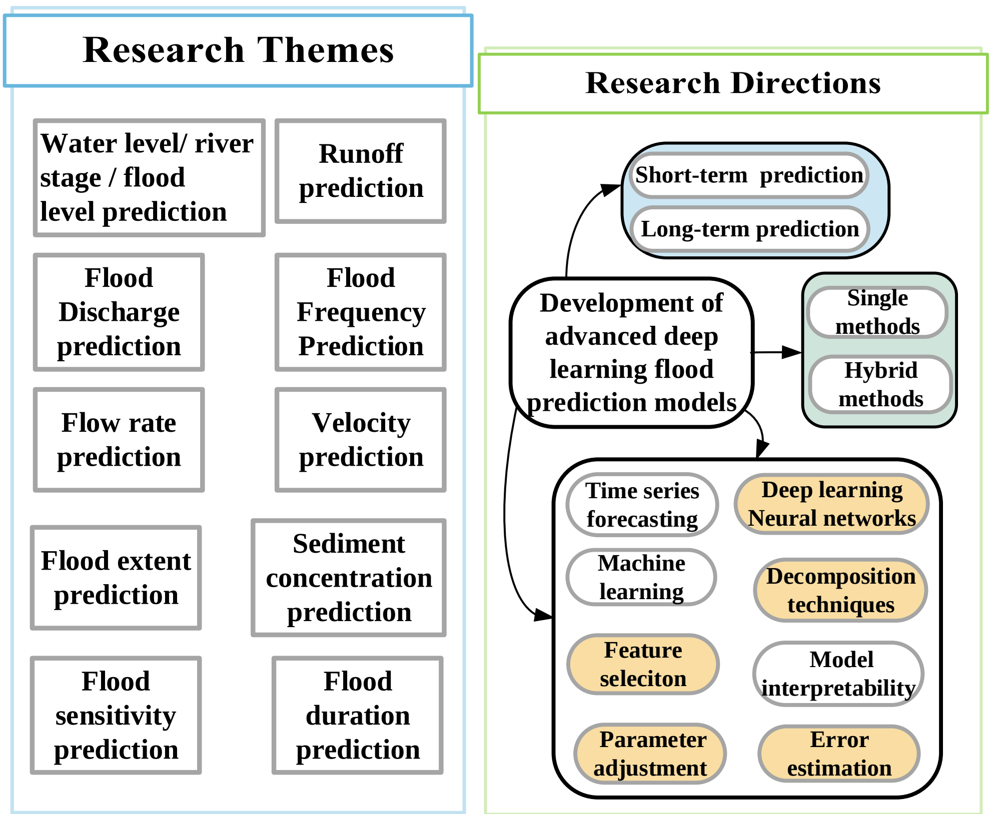

Figure 2.2 Current Research Themes and Directions

From Figure 2.2, flood prediction is categorized into long-term and short-term predictions. Long-term forecasts are typically made weekly, monthly, quarterly, or yearly. They are usually based on climate patterns, historical precipitation data, land use, and hydrologic and hydrodynamic models, focusing on seasonal or annual flood risk prediction. Short-term predictions have a forecast period of hours and days and are considered essential research challenges, particularly in highly urbanized areas, for timely warning of residences to reduce damage (Zhang *et al.*, 2018). It is of great practical value in technological innovation and emergency response strategies, especially in improving early warning systems' accuracy and response time. This research will focus on short-term prediction.

The predictive models are usually singular models and hybrid models. Hybrid models have been proven to enhance prediction accuracy and are currently a focal research point (Jain *et al.*, 2018; Hakim *et al.*, 2023). To improve flood forecasting accuracy, advanced models are constructed through data decomposition (Chen *et al.*, 2023; Liu *et al.*, 2023), feature extraction (Habibi *et al.*, 2023; Bui *et al.*, 2019), parameter optimization (Li *et al.*, 2021; Zhou *et al.*, 2023), and adjustments in model structure (Yang *et al.*, 2024; Wei *et al.*, 2023), and the models are evaluated and compared through prediction error estimation (Yang *et al.*, 2024). However, there are significant research gaps: more effective methods are needed for data decomposition and feature extraction to better capture flood data patterns; optimizing parameters and adjusting model structures are complex and require further development; and there is a need for more robust prediction error estimation techniques to accurately assess and compare model effectiveness.

2.3 Deep Learning Networks for Flood Prediction

Deep learning is a branch of machine learning that explores high-level features and patterns in data through deep neural networks. In contrast to traditional machine learning methods, which often rely on manually extracted features, deep learning models can automatically extract complex features from raw data, thus simplifying the model development process. Deep learning is particularly adept at working with high-dimensional data, such as images, sounds, and text. In addition, deep learning allows researchers to design a variety of network architectures based on application-specific requirements, enabling the training of stable and efficient models. Deep learning shows great potential for application, especially in prediction tasks.

Deep learning can effectively simulate the memory function of the human brain, it is a multilayer neural network. Classic neural network algorithms mainly include Multilayer Perceptron (MLP) (Haribabu *et al.*, 2021), Back Propagation (BP) (Zhao, 2015), ANN (Kumar *et al.*, 2021), CNN (Chou *et al.*, 2020b), LSTM (Hochreiter and Schmidhuber, 1997), Recurrent Neural Network (RNN) (Dyer *et al.*, 2016), GRU (Chung *et al.*, 2014), TCN (Wang and Liang, 2021; Xu *et al.*, 2021), and Transformer (Waswani *et al.*, 2017). This section presents the application of these models in flood forecasting and provides an analysis of their advantages and disadvantages.

2.3.1 Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs) are most commonly used Deep Learning (DL) method in flood prediction (Shamseldin, 2009; Tamiru and Dinka, 2021; Dtissibe *et al.*, 2020), inspired by biological neural networks, ANN aims to mimic the way the human brain processes information through interconnected "neurons". Compared to most traditional models, ANNs possess acceptable generalization capabilities and speed for flood prediction (Li *et al.*, 2021; Cai and Yu, 2022). However, a major drawback of ANNs is that they typically process inputs in a one-off manner, unable to maintain state or memory across different time steps (Tu, 1996; Ni *et al.*, 2024). This results in relatively lower accuracy, the need for repeated parameter tuning, and a slow response to the gradient-based learning process (Deo and Şahin, 2015; Mosavi *et al.*, 2018).

2.3.2 Multilayer Perceptron (MLP)

MLP refers to a network design with at least one hidden layer, while a feed-forward neural network describes any network where data moves in one direction, from input to output (Aljaaf *et al.*, 2021; V. Kumar *et al.*, 2023b). MLPs require an effective training algorithm to adjust their weights, enabling accurate mapping of inputs to outputs. In the mid-1980s, Back Propagation (BP) provided an efficient method for MLP training, allowing the network to learn from input-output data (Lippmann, 1989). In practice, employing the BP algorithm usually involves using BP within the MLP structure for network training. MLPs and BP networks have extensive applications in assessing flood sensitivity and forecasting (Haribabu *et al.*, 2021; Hong *et al.*, 2016; Wang and Tang, 2018; J. Wang *et al.*, 2017). Leveraging historical data and current meteorological conditions, MLPs can simulate and learn the complex nonlinear relationships within flood data, predicting the severity of flood events and significantly contributing to disaster risk management and emergency planning efforts. There remains a notable gap in the literature regarding the inability of MLPs to effectively learn the spatial and temporal structures of input data is a significant drawback for tasks involving images, video, and sequential data. Moreover, MLPs are prone to bias towards most classes when dealing with unbalanced data, which affects the prediction of flood peaks (Yang and Chen, 2019; Haribabu *et al.*, 2021). There is a need to improve the predictive ability and generalizability of MLPs by developing hybrid models, enhanced feature engineering and optimization algorithms.

2.3.3 Convolutional Neural Networks (CNNs)

CNNs use their convolutional operations to capture detailed features such as edges and corners within local regions and preserve the spatial relationships between them, demonstrating a strong learning capability for spatial data. CNNs were initially used to automatically and efficiently extract features from images using convolutional layers, which greatly improved the performance of image recognition tasks (LeCun *et al*., 2015). In 1998, LeCun *et al*. proposed LeNet-5, marking the early successful application of convolutional neural networks (LeCun *et al*., 1998). Recent studies have leveraged CNN for flood forecasting with promising outcomes. Sakpal *et al*. (2023) and Munawar *et al*. (2021) utilized satellite imagery, trained CNN models to distinguish between pre-flood and post-flood conditions, effectively identifying areas prone to flooding. These approaches demonstrated high accuracy in flood detection, underscoring its potential for real-time monitoring and disaster response. Furthermore, CNN models have been applied to data-driven flood forecasting, predicting river flood levels by analyzing historical data on river levels, rainfall, and other pertinent hydrological parameters (Yan *et al*., 2023; Guo *et al*., 2022; Wang *et al*., 2017). These models showcased the capability to forecast flood events days in advance with significant accuracy, highlighting the critical role of temporal data in prediction efforts.

Additionally, CNNs have been employed to predict urban flooding resulting from heavy rainfall by integrating urban terrain and drainage data with meteorological inputs (Liao *et al.*, 2023; Kumar *et al*., 2023a; Yuan *et al*., 2024). The findings revealed that CNNs could accurately predict the locations and extent of urban floods, offering valuable tools for city planning and infrastructure development (Liao *et al.*, 2023;

Kumar *et al*., 2023a; Yuan *et al*., 2024). A novel research trend involves enhancing accuracy by combining CNN with other deep learning models or techniques (Nie *et al*., 2021; Abid *et al*., 2023; Yang and Zhang, 2022). Studies have demonstrated that these hybrid approaches outperform single-method strategies and traditional hydrological models (Yan *et al*., 2021; Zhao *et al*., 2023). These advancements illustrate the enhanced predictive capabilities of CNNs have across various environments and scales, emphasizing the importance of integrating diverse data types (spatial and temporal) to improve flood prediction accuracy (Liao *et al*., 2023; Tang *et al*., 2020; Chou *et al.*, 2020b; Chen *et al*., 2022a). CNNs, while powerful in image recognition and fixed-size input processing, face limitations in time-dependent processing due to their inherent architectural design (Kratzert *et al*., 2018; Cai and Yu, 2022). Moreover, there is an inability to adequately capture complex spatio-temporal dynamic relationships and a lack of prediction accuracy for flood peaks in the presence of data imbalance (Shi *et al*., 2015). Hybrid models combining temporal models with CNNs can be explored to develop enhancement methods for spatiotemporal features and data imbalance handling techniques.

2.3.4 Recurrent Neural Networks (RNNs)

RNNs, on the other hand, have a unique "memory" function that excels in sequence data analysis by utilizing information input from the past to influence future outputs, making them particularly suitable for applications in time series analysis such as flood forecasting (Dyer *et al*., 2016). Although RNNs have advantages in handling variable-length series data and real-time prediction updates (Cai and Yu, 2022; Hayder *et al*., 2023), RNNs face challenges such as gradient vanishing when learning from long data sequences, and overfitting on smaller datasets, which makes it limited when dealing with data-scarce or highly variable data in hydrologic models. (Fang *et al*., 2021; Gude *et al*., 2020).

2.3.5 Long Short-Term Memory (LSTM) neural network

As RNN is prone to gradient descent and gradient explosion problems during the data training process, LSTM is designed to overcome the vanishing gradient problem common in traditional RNNs. LSTM is a special kind of RNN with "memory" capability (Hochreiter and Schmidhuber, 1997). This network improves the gradient disappearance problem that occurs over time in RNNs during backpropagation, which introduces an internal mechanism called "gating" and enhances the learning capability for long-time sequences (Hochreiter and Schmidhuber, 1997).

Recent studies have demonstrated LSTMs' superiority over traditional models in various flood prediction applications (Le *et al*., 2019; Li *et al*., 2021; Fang *et al*., 2021; Noor *et al*., 2022; Zhou *et al*., 2023; Xia and Chen, 2020a), from river flow prediction to urban flood modelling, indicating a trend towards integrating deep learning techniques in environmental science (Kim and Kim, 2020; Cho *et al.*, 2022a; Zhang *et al*., 2023). Parameter optimization (Sahadevan *et al*., 2022; Ruma *et al*., 2023) and data pre-decomposition techniques (Yuan *et al.*, 2021; Sun *et al*., 2023; Sun *et al.*, 2022; Guo *et al*., 2023; Wang *et al*., 2023) are innovative approaches to improve the predictive performance of LSTM hybrid models. In Hu *et al*. (2019b), an integrated LSTM and reduced order model framework combined with two data decomposition methods was developed to improved flood prediction performance. Noor *et al*. (2022) considered the rainfall and flow at different stations, combined with the latitude and longitude information of the target area, used a spatio-temporal attention model integrated with LSTM to improve flood prediction performance further. It is confirmed that further combining spatio-temporal features to construct a hybrid model is conducive to discovering the pattern of flood change and improving the performance of the prediction model (Hu *et al*., 2019a; Zhao *et al*., 2023). The water level prediction method based on LSTM improves the prediction accuracy, but the disadvantage of LSTM lies in its transmission of information only from front to back in one direction and its inability to encode information transmitted from back to front, and LSTM has many parameters that are prone to cause problems with hard training and overfitting.

2.3.6 Gated Recurrent Unit (GRU)

GRU (Chung *et al*., 2014) is a variant of LSTM, which has the advantage of a more straightforward structure and fewer parameters than LSTM. In the case of small samples, GRU is more accessible to train and tune to obtain good flood prediction ability (Ji *et al*., 2021).

With fewer parameters, the GRU efficiently addresses long-term dependency issues with less computational complexity, making it widely used in flood forecasting (Yan *et al*., 2023). Abid *et al*. (2023) proposed a multi-directional GRU with a CNN to improve the accuracy of load and energy forecasting. In the case of small samples, GRU is more accessible to train and tune to obtain good flood prediction ability (Ji *et al.*, 2021). However, the simplified structure of GRUs, while reducing the number of parameters and improving computational efficiency, may underperform on very complex sequence data, where the intricate gating mechanisms of LSTMs may provide superior performance (Cho *et al.*, 2022a). Specific models need to be chosen reasonably according to the data characteristics, and GRUs are often used to construct hybrid models, such as LSTM-GRU (Zhang *et al.*, 2023), GRU-CNN (Pan *et al.*, 2020), SVM-GRU (Dong *et al*., 2024) for more accurate flood forecasting and better efficiency.

2.3.7 Temporal Convolutional Networks (TCN)

Time Convolutional Network (TCN) is a CNN network that utilizes convolution layers to process time series data. Unlike CNNs, which excel in spatial data analysis but may struggle with sequential data over long periods, TCNs are specifically designed to handle long-range temporal dependencies with their unique architecture, including dilated convolutions (Bai *et al*., 2018). In 2018, Bai *et al*.(2018) showed that TCNs, which use a particular convolution, do better than other common networks like LSTM and GRU in many different tasks. Since then, TCNs have been used extensively in flood prediction (Xu *et al*., 2021; Zhang *et al*., 2023) proved that the TCN-based model outperformed the LSTM-based model in flood and water level prediction. Moreover, in Li *et al*. (2024), three deep learning models, TCN, LSTM, and GRU, were used to predict water levels at five stations. The results showed that the hybrid model of TCN, LSTM, and GRU synthesized by Bayesian model averaging improved the prediction accuracy. TCN and TCN-based hybrid models show good prediction performance and application value in flood prediction (Wang and Liang, 2021; Shao *et al.*, 2023; Sun *et al*., 2022; Yao *et al.*, 2023). However, TCNs need more in-depth research to optimize the model's generalization ability and real-time prediction performance in dealing with long-term dependence and multivariate time series, and also face the same problems of parameter selection and model interpretability.

2.3.8 Transformers

The Transformer is a neural network that was firstly introduced by Waswani *et al*. (2017) as a groundbreaking architecture for solving machine translation problems. They have been early adopted in other application domains involving the analysis of fairly long input sequences, such as time series forecasting and classification (Li *et al*., 2019). With the attention mechanisms, Transformers have shown promising results in various time series forecasting tasks, including hydrological processes such as flood prediction (Liu *et al*., 2022; Castangia *et al*., 2023; Xu *et al*., 2023). In comparison to traditional methods, Transformer models in flood forecasting offer the advantage of being able to handle large, multidimensional datasets and capture long-term dependencies, which are crucial for understanding complex hydrological phenomena, and can potentially offer better performance for multi-step prediction tasks compared to LSTMs (Xu *et al*., 2024). They are also generally faster to train due to their ability to process data in parallel, and the improved transformer-integrated model can outperform a CNN or LSTM-integrated model (Jin *et al.*, 2024; Wei *et al*., 2023). However, they may require extensive data for training, and their performance might decrease with the increase in forecast lead time or sequence length, require large amounts of training data, need high computational resources, and face the potential risk of overfitting (Bentivoglio *et al.*, 2022; Xu *et al*., 2023), in the case of limited data or limited computational resources, LSTM and TCN may achieve better prediction results.

2.3.9 Summary of Deep Learning Models

Table 2.1 shows the advantages and disadvantages of different deep learning algorithms and related literature in flood prediction.