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GMAG: A Spatiotemporal Feature Fusion Enhanced Model for Water Level Prediction

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Abstract

Water level prediction plays a critical role in drainage network systems. An accurate prediction algorithm can not only effectively prevent flooding disasters but also provide timely decision-making support when anomalies arise in water management environments. To address this challenge, this study proposes an innovative model architecture (GMAG) designed to extract spatiotemporal features. By employing graph convolutional networks, the model captures spatial dependencies between hydrological nodes, while utilizing a gated recurrent mechanism to efficiently model temporal dynamics. Furthermore, attention mechanisms are incorporated to highlight key features at critical moments, leading to improved prediction accuracy. Experimental results show that the GMAG model outperforms other baseline models in terms of predictive accuracy, offering valuable scientific support for intelligent management and emergency response in urban drainage systems. This demonstrates its significant application potential and broad prospects for adoption.

Method

We propose **GMAG**, a novel and unified framework for water level prediction that synergistically integrates **Graph Convolutional Networks (GCN)**, **Gated Recurrent Units (GRU)**, and **Multi-Head Attention mechanisms**. GMAG is designed to comprehensively model both the **spatial dependencies** among hydrological monitoring stations and the **temporal dynamics** inherent in water level sequences, while also adaptively focusing on **informative features and time steps** to enhance prediction accuracy.

Key Components:

- ✓ **Feature-wise Self-Attention:** Identifies and emphasizes important input feature dimensions before spatial modeling.
- ✓ **Graph Convolutional Network (GCN):** Learns spatial dependencies between monitoring stations based on the hydrological graph structure.
- ✓ **Temporal Attention Module:** Assigns dynamic weights to different time steps to highlight key temporal patterns.
- ✓ **Gated Recurrent Unit (GRU):** Captures sequential temporal dependencies and dynamic trends in water level changes.
- ✓ **Prediction Layer:** Integrates multi-source features to produce accurate and robust water level forecasts.

Conclusion

GMAG is a spatiotemporal water level prediction model that captures complex spatial dependencies and temporal dynamics using graph-based topology and attention mechanisms. It achieves an accuracy of **0.8259**, showing **notable improvements** over baseline models. Its modular architecture allows flexible adaptation to various hydrological network structures.

Acknowledgement

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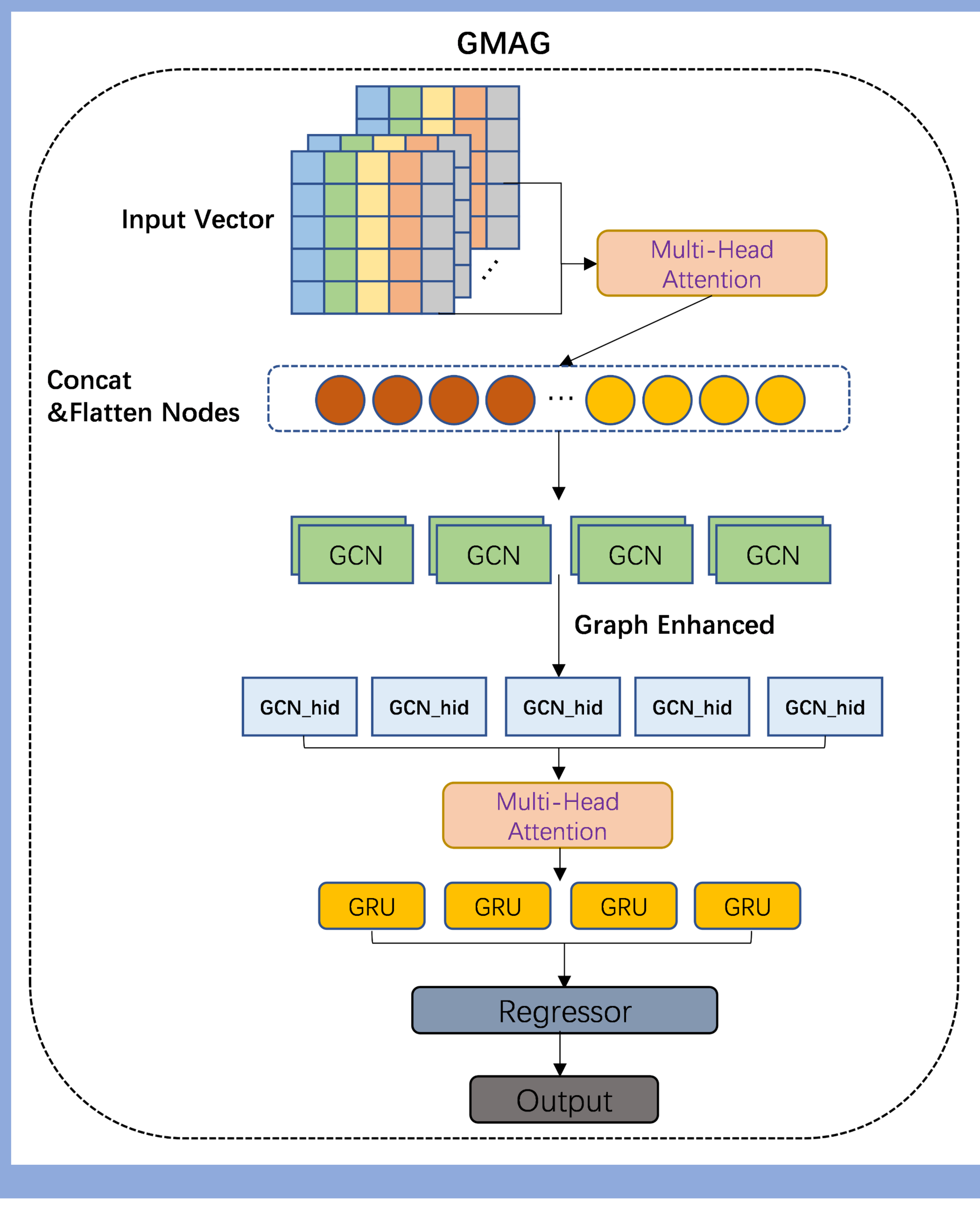
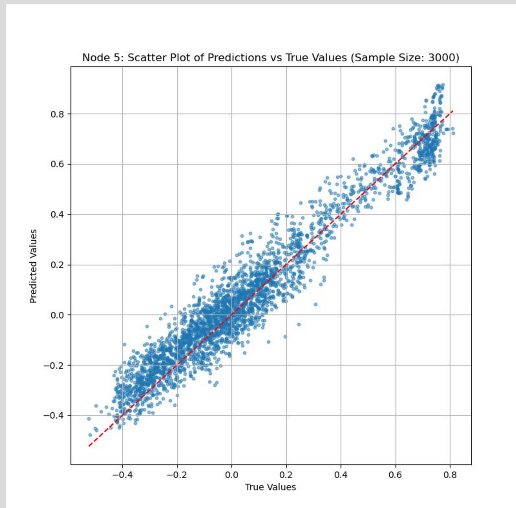
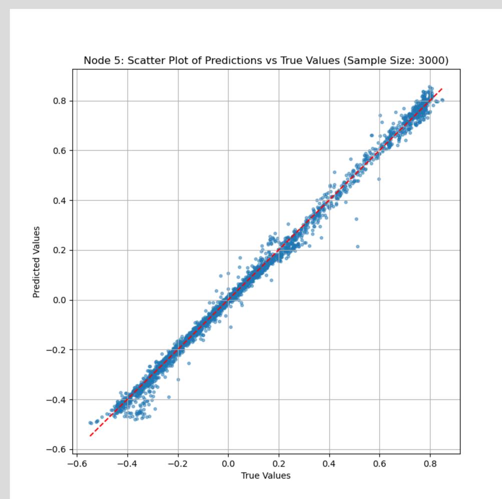
Model Structure

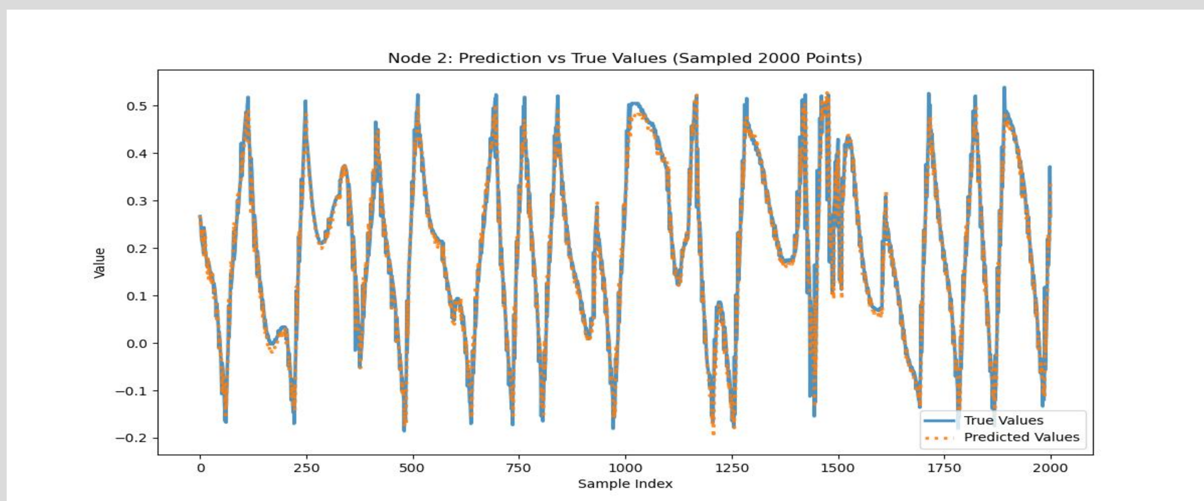


Experimental Results

We present a comparison scatter plot of predicted vs. true values for the GMAG and GCN models at the same hydrological site. The GMAG predictions align closely with the true values, showing minimal deviation along the ideal diagonal, while GCN shows more dispersion. This demonstrates our model's superior performance at a specific node. As shown in the figure and table below, the GMAG model significantly outperforms baseline models in accuracy and robustness for water level prediction.







Model	MAE	R^2	RMSE	Accuracy
GCN	0.2884	0.8469	0.3955	0.6256
GRU	0.1493	0.9467	0.2344	0.7817
GCN_GRU	0.1150	0.9619	0.1982	0.8155
GMAG	**0.1020**	**0.9660**	**0.1871**	**0.8259**
LSTM	0.1802	0.9322	0.2645	0.7537