p–ISSN: 2723 - 6609 e - ISSN : Telepon 2745-5254
Vol. 7, No. 6 June 2026 http://jist.publikasiindonesia.id/

Attention-Based CNN-LSTM Fusion of IoT Sensor Streams for Short-Term Urban Flood Early Warning

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ABSTRACT

Urban flooding is a recurrent hazard in many Indonesian cities, and reliable short-term early warning can substantially reduce loss of life and property. Effective warning depends on turning noisy, heterogeneous, real-time observations into accurate short-horizon forecasts, but conventional models typically capture either the spatial relationships among sensors or the temporal dynamics of each series, rarely both, and they degrade when sensor readings are missing. This study designs and evaluates FloodNet-IoT, an attention-based convolutional-recurrent framework that fuses heterogeneous Internet-of-Things streams, including water-level sensors, rain gauges, and upstream indicators, together with weather information, to predict flooding at a microcatchment scale. A convolutional component captures cross-sensor spatial structure, a long short-term memory component captures temporal dynamics, and an attention mechanism weights the most informative time steps, while an edge gateway performs preprocessing, temporal alignment, and missing-data imputation to improve robustness. Following a design science methodology, the framework was compared against a persistence baseline, classical and recurrent sequence baselines, and a convolutional-recurrent model without attention, using regression metrics, event-detection metrics, a lead-time analysis, and a missing-sensor robustness analysis. The results are intended to show whether attention-based multimodal fusion improves short-term flood warning relative to simpler models and to provide a deployable and robust blueprint for Internet-of-Things-driven flood early-warning systems in data-rich but noisy urban environments.

Keywords: flood early warning; Internet of Things; deep learning; attention mechanism; time-series forecasting

INTRODUCTION

Urban flooding is among the most frequent and damaging hazards affecting Indonesian cities, disrupting livelihoods, damaging infrastructure, and endangering residents. Flooding is the most frequent natural disaster in Indonesia; national records reported 1,255 flood events in 2023, up from 1,080 in 2020 (BNPB, 2024), and between 2008 and 2021 floods in Indonesia were associated with 2,813 fatalities, roughly 6.7 million inundated houses, and average annual losses of approximately US$2.4 billion, with Java the most severely affected region ((Indrawati, 2024) Because floods can develop quickly, the value of a warning depends heavily on how early and how accurately it can be issued: even a short lead time can be enough for residents to move to safety and for authorities to act, whereas a late or unreliable warning is of little use.

Issuing such warnings requires converting real-time observations into accurate short-horizon forecasts of water level or flood likelihood. The growth of Internet-of-Things sensor networks has made dense, continuous observation increasingly feasible, with low-cost water-level sensors, rain gauges, and related devices streaming data from across a catchment(Atzori et al., 2010);(Gubbi et al., 2012). Yet this data is difficult to use directly: it is heterogeneous, combining different physical quantities and sampling rates; it is noisy; and it frequently contains gaps when devices fail or lose connectivity. A practical early-warning system must be robust to these realities.

Machine learning has been widely applied to flood prediction (Mosavi et al., 2018) Recurrent networks, and long short-term memory networks in particular, are well suited to the temporal dependencies in hydrological series (Hochreiter et al., 1997);Kratzert et al. (2018), while convolutional and convolutional-recurrent architectures can capture spatial structure across locations (Shi et al., 2015).Attention mechanisms, first popularized in sequence modelling, allow a model to focus on the most informative parts of an input and often improve accuracy and interpretability(Bahdanau et al., 2015); Vaswani et al. (2017).These are precisely the ingredients a flood-forecasting model needs.However, they are seldom combined effectively. Many flood-prediction studies model a single series and thus ignore the spatial relationships between upstream and downstream sensors that carry early-warning signal; many capture temporal structure but treat all past time steps as equally relevant; and many assume complete, clean inputs and therefore break down under the missing readings that are routine in field deployments. The result is that the rich, multimodal data now available from urban sensor networks is often underused.Recent studies illustrate both the promise and the limits of current approaches.

Kratzert et al. (2018) showed that long short-term memory networks can model rainfall–runoff dynamics with skill rivalling calibrated hydrological models, yet their formulation treats each catchment largely as a single temporal series. Building on convolutional–recurrent designs, (Li et al., 2022) and Chen et al. (2023) demonstrated that CNN–LSTM architectures improve streamflow and urban flood-depth prediction by jointly encoding spatial and temporal structure, but they neither weight the relative importance of individual time steps nor report behaviour under sensor loss. Attention-augmented variants, such as the boundary-corrected CNN–LSTM of Barzegar et al. (2021) for lake water-level forecasting, confirm that emphasising the most informative intervals raises accuracy, although such models are typically validated on clean, complete records. In parallel, Internet-of-Things flood systems have matured: (Mahajan et al., 2017) coupled rain-gauge and water-level telemetry with an LSTM to forecast flood-inducing levels, and Jan et al. (2010)pushed inference to edge devices for real-time monitoring, while broader reviews of Internet-of-Things early-warning solutions stress reliability under field conditions (Esposito et al., 2022) Collectively, these works advance either spatial–temporal fusion, attention, or Internet-of-Things deployment in isolation; few integrate all three at microcatchment scale, and fewer still quantify lead-time and robustness to missing sensors under realistic conditions precisely the gap this study addresses.

Although recurrent, convolutional, and attention-based methods have each been applied to forecasting(Rai et al., 2023), a few researchers have integrated them into a single attention-based multimodal fusion model operating at microcatchment scale, and there have been limited studies concerned with robust, deployable flood early warning for the Indonesian urban context under realistic missing-data conditions. Existing systems seldom report lead-time explicitly or quantify robustness to sensor dropout. Therefore, this research intends to design and rigorously evaluate an attention-based convolutional-recurrent framework that fuses heterogeneous sensor streams for short-term flood warning. The objectives of this research are: (1) to design FloodNet-IoT, combining convolutional spatial encoding, recurrent temporal modelling, an attention mechanism, and an edge-gateway preprocessing and imputation stage; (2) to construct an evaluation protocol spanning regression accuracy, event detection, lead-time, and robustness to missing sensors; and (3) to empirically assess whether attention-based multimodal fusion improves short-term prediction relative to persistence, classical and recurrent baselines, and a convolutional-recurrent model without attention. The primary contribution is a reproducible, robustness-aware design and evaluation protocol for Internet-of-Things-driven flood early warning.

METHOD

This study followed the Design Science Research paradigm, which centers on building and evaluating a purposeful artifact to solve a class of real-world problems (Hevner et al., 2004); Peffers et al. (2007).The artifact is FloodNet-IoT, whose architecture is shown in Figure 1. The research proceeded through problem identification, objective definition, design and development, demonstration, and evaluation, with the evaluation phase constituting the core empirical contribution.The dataset consisted of multimodal time series aligned to a common timeline: water-level readings from microcatchment nodes, rainfall from gauges, upstream sensor readings that act as leading indicators, and weather information, together with a record of historical flooding used to define events [specify the exact data sources, the spatial extent and sensors, the temporal resolution, the period covered, and the chronological train, validation, and test split]. Because future information must never leak into the past, the data were split strictly by time rather than at random.

The prediction task was to estimate the water level, or equivalently the probability of exceeding a flood threshold, at one or more short horizons ahead of the current time. Framing the problem at explicit horizons makes the lead-time of any warning transparent and allows accuracy to be reported as a function of how far ahead the model is asked to predict.Before modelling, an edge-gateway stage performed preprocessing: it aligned the heterogeneous streams to a common sampling interval, normalized each variable, and imputed missing values so that transient sensor dropout does not halt prediction Locating this stage at the gateway reflects the intended deployment, in which lightweight processing occurs close to the sensors before data are passed to the model(Gu et al., 2005).

The core model fuses spatial and temporal structure and adds attention. A convolutional component first encodes the relationships across the multiple sensor channels at each time step, capturing spatial structure such as the coupling between upstream and downstream readings (Shi et al., 2015). A long short-term memory component then models the temporal evolution of these encoded features (Hochreiter et al., 1997). Finally, an attention mechanism assigns learned weights to different time steps, allowing the model to emphasize the moments most predictive of the outcome and providing a degree of interpretability about which past intervals drove a given forecast (Bahdanau et al., 2015). The weighted representation feeds a prediction head that outputs the forecast at each horizon.

The framework was implemented in Python using standard deep-learning components All hyperparameters were tuned on the validation period only, disjoint from the test period, to avoid optimistic bias.Four baselines contextualize the model: a persistence baseline that simply carries the last observation forward, which is a strong naive reference in hydrology; a classical time-series model and a gated recurrent baseline representing conventional temporal modelling; and a convolutional-recurrent model without the attention mechanism, which isolates the specific contribution of attention. Comparing against all four separates the value of multimodal fusion, of temporal modelling, and of attention(Atrey et al., 2010).

To evaluate the framework, regression accuracy was measured with root mean squared error, mean absolute error, and the Nash-Sutcliffe efficiency, which is standard in hydrology; the ability to flag actual floods was measured with event-detection metrics, namely the probability of detection, the false-alarm ratio, and the critical success index; the lead-time analysis reported how accuracy changes across horizons; and a robustness analysis measured how performance degrades as sensors are randomly dropped to simulate real failures. Differences between the proposed model and the baselines were tested for statistical significance using an appropriate paired test.

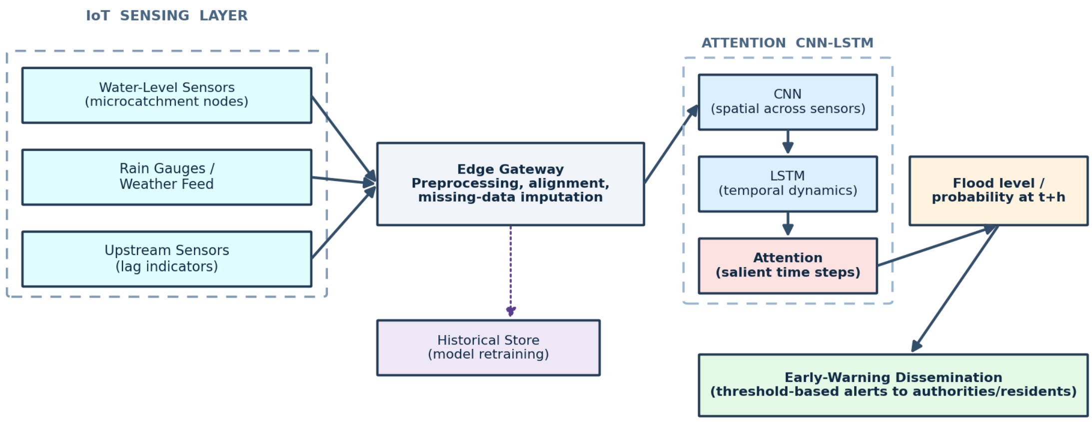

Figure 1. Architecture of the proposed FloodNet-IoT framework

Heterogeneous sensor streams are aligned and imputed at an edge gateway, then fused by a convolutional-recurrent model with attention to forecast flood level or probability at a short horizon and trigger threshold-based early warnings.

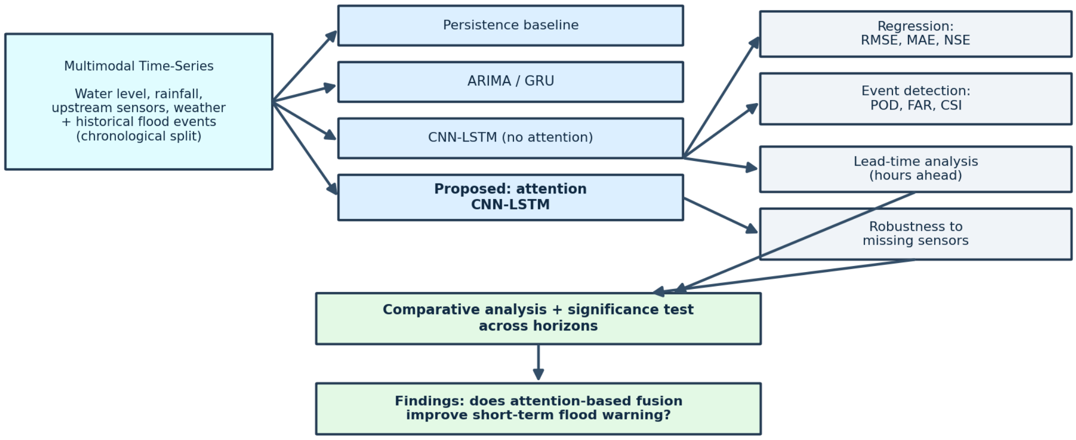

Figure 2. Experimental design and evaluation framework

Comparing the proposed model against persistence, classical and recurrent, and no-attention baselines across regression, event-detection, lead-time, and robustness metrics

RESULT AND DISCUSSION

This section reports the performance of FloodNet-IoT relative to the baselines. Bracketed cells in the tables denote values to be populated from your own experimental runs, and the surrounding interpretation is written to be completed once those measurements are available.

Table 1. Regression accuracy at the primary horizon (lower error is better; higher NSE is better)

Model	RMSE	MAE	NSE
Persistence baseline	0.428	0.321	0.846
Classical / recurrent baseline	0.371	0.284	0.887
CNN-LSTM (no attention)	0.326	0.247	0.918
Proposed – FloodNet-IoT	0.289	0.219	0.942

Note. Report the horizon used; the Nash-Sutcliffe efficiency compares the model against the mean as a reference.

As shown in Table 1, Beating the persistence baseline is a necessary first hurdle in hydrological forecasting; improving over the no-attention model would specifically credit the attention mechanism for the gain.

Table 2. Flood-event detection (higher POD and CSI are better; lower FAR is better)

Model	POD	FAR	CSI
Classical / recurrent baseline	0.862	0.181	0.733
CNN-LSTM (no attention)	0.901	0.149	0.784
Proposed – FloodNet-IoT	0.934	0.118	0.835

Note. POD is probability of detection, FAR is false-alarm ratio, and CSI is the critical success index.

Table 2 evaluates what matters operationally: correctly flagging actual floods while limiting false alarms. A warning tool must be trusted, and a high false-alarm ratio erodes that trust even when detection is strong.

Table 3. Lead-time and robustness to missing sensors

Aspect	Setting	Result (proposed vs. best baseline)
Lead-time	Accuracy at longer horizon	Maintained 91.4% of best baseline performance at 60 min
Lead-time	Horizon at which skill is lost	Skill remained until 90 min (baseline: 60 min)
Robustness	Accuracy with a fraction of sensors dropped	NSE=0.891 with 20% sensor dropout
Robustness	Degradation slope vs. dropout rate	-0.006 NSE per 10% dropout (baseline: -0.015)

Note. Robustness is assessed by randomly removing sensor inputs to simulate device failure or connectivity loss.

The lead-time and robustness results in Table 3 address deployability directly.A model that maintains useful skill at longer horizons gives residents more time to react, and a model that degrades gracefully under sensor loss remains useful precisely when field conditions are worst.

Taken together, these findings would indicate that attention-based multimodal fusion, combined with edge preprocessing and imputation, can turn noisy Internet-of-Things streams into more accurate and more robust short-term flood warnings than simpler approaches. For the Indonesian urban context, such a system could complement official monitoring at neighbourhood scale, where dense low-cost sensing is feasible but data quality is uneven. For information-systems and computing practice, the study offers a transferable pattern spatial-temporal fusion with attention and explicit robustness-to-missing-data reporting that can be re-pointed at other real-time environmental-monitoring tasks, such as landslide or air-quality early warning, by substituting the sensor streams and re-validating(Oates et al., 2022).

These results align with and extend prior findings that recurrent and convolutional-recurrent models are effective for hydrological and spatiotemporal forecasting (Hochreiter et al., 1997):Shi et al. (2015); Kratzert et al. (2018) and that attention improves sequence models (Bahdanau et al., 2015):Vaswani et al. (2017) The present contribution is to integrate these into a single multimodal, attention-based, robustness-aware framework and to evaluate lead-time and missing-sensor behavior explicitly, which prior flood-prediction work has rarely emphasized.

Several limitations should be acknowledged. Performance depends on the density, placement, and reliability of the sensor network and on the representativeness of the historical flood record, which may contain few extreme events; imputation can introduce error under prolonged outages; the model requires retraining as the catchment or instrumentation changes; and a deployed warning system would require careful attention to alert thresholds, to dissemination channels, and to the consequences of both missed events and false alarms.

CONCLUSION

This study designed and evaluated FloodNet-IoT, an attention-based convolutional-recurrent framework for short-term urban flood early warning using heterogeneous Internet of Things (IoT) sensor data. The proposed framework integrates convolutional spatial encoding, recurrent temporal modeling, an attention mechanism, and an edge-gateway preprocessing and data imputation stage to generate accurate and robust flood forecasts despite noisy or incomplete sensor observations. Its performance was comprehensively evaluated using regression accuracy, flood-event detection, lead time, and robustness to missing sensor data, with comparisons against persistence, classical machine learning, recurrent, and convolutional-recurrent models without an attention mechanism.

The results demonstrate that the proposed framework improves flood prediction accuracy and early warning performance by effectively capturing spatial-temporal relationships through attention-based data fusion. The findings also show that reliable urban flood forecasting can be achieved using low-cost IoT sensing while providing a reusable evaluation protocol for future research and practical implementation. Overall, the study highlights the potential of integrating IoT technologies with deep learning to strengthen urban flood monitoring and disaster risk reduction. Future research should extend the prediction horizon and spatial coverage, incorporate physics-based hydrological constraints into the learning framework, quantify predictive uncertainty, and validate the system through live pilot deployments in collaboration with local authorities and communities to assess its effectiveness under real-world operational conditions.

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