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# AI-Based Flood Prediction Using LSTM: A Case Study of the 2021 European Floods

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***ABSTRACT***

*In July 2021, massive floods across Germany, Belgium and the Netherlands resulted in more than 220 deaths and more than EUR43 billion of losses. Limited capabilities of conventional hydrological and numerical weather prediction (NWP) models to provide accurate short-term flood prediction in highly non-linear and dynamic climatic conditions were revealed by the disaster. This paper presents case analysis of selected as an AI approach to flood forecasting Long Short-Term Memory (LSTM) neural networks, applied to the Ahr Valley basin in Germany which was one of the most severely affected areas. Using the historical hydrological data from 2009 to 2020, stored in the Copernicus Emergency Management Service (CEMS) and the European Centre for Medium-Range Weather Forecasts (ERA5) reanalysis datasets, the model was trained to come up with river discharge levels and flood occurrence probabilities. The LSTM model architecture consisted of four hidden layers each containing a total of 128 neurons, an adaptive learning rate and a mean squared error (MSE) loss function with the Adam optimizer. Results of evaluation against traditional NWP-based forecasts indicated that the LSTM was able to reach prediction accuracy of 92%, root mean square error (RMSE) of 0.13 m and approximately 36 hours increase in the lead time of forecasts. The results show how deep learning approaches can greatly improve flood forecasting accuracy, minimize false alarms and give important early warning for mitigating disasters. This study highlights the possibility of using AI-based hydrology models in the disaster management system of a country to enhance climate resilience and promote Sustainable Development Goals (SDG 11 and 13).*

***Keywords: -*** *Flood Forecasting, Artificial Intelligence, LSTM, Deep Learning, Hydrology, Disaster Management, Copernicus, Climate Resilience.*

## 1. INTRODUCTION

Floods are one of the most common and destructive natural hazards on the planet, contributing almost 40% of all weather-related disasters across the world and impacting more than 250 million people every year [1]. With the rise of urban areas and land-use changes that in turn have played havoc with natural drainage systems, their intensity and irregularity are becoming increasingly costly both in terms of lives lost and for property damaged every time. In July 2021, catastrophic floods hit Western Europe -- especially Germany, Belgium and the Netherlands -- leaving more than 220 dead and causing more than EUR43 billion in economic damages, one of the continent's most deadly catastrophes of the 21st century [2]. The Ahr Valley area of Germany, a small but highly populated catchment area was most seriously impacted with several communities completely destroyed within hours of torrential rainfalls.

Despite considerable development of numerical weather prediction (NWP) and hydrological simulation systems, early warning mechanism was not able to give actionable alerts in time. The conventional hydrological models (e.g., Soil and Water Assessment Tool (SWAT) and HEC-HMS) made extensive use of the deterministic equations for the rainfall-runoff processes. However, these models are associated with a great deal of uncertainty under extreme climatic conditions because of the non-linear and chaotic nature of precipitation and basin response [3]. Also, parameter tuning and physical a priori suppress physical scalability and real-time responsiveness. Consequently, traditional systems have problems capturing spatiotemporal inter-relationships (dependencies) across multiple environmental variables.

In order to overcome these limitations, researchers are shifting to Artificial Intelligence (AI) and Machine Learning (ML) based data-driven flood forecasting. Deep learning architectures - precisely Recurrent Neural Networks (RNNs) and a variant thereof, the Long Short-Term Memory (LSTM) network - have proven to have remarkable ability in modeling time-series data [4]. Unlike feedforward neural networks, LSTMs use memory cells and gated structures (input, forget and output gates) that preserve long-term dependencies of the system making them suitable for hydrological prediction problems where the amount of past rainfall or soil moisture affects the amount of discharge in the future [5].

Several studies already proved the efficacy of LSTM due to the flood forecasting in various regions. For instance, good performance has been shown by LSTM models as it was able to improve flow predictions at the peak by 35% when compared to NWP models [6] by Bai et al. (2022). Likewise, by combining LSTM with a Convolutional Neural Network (CNN) as an alternative, Qin et al. (2024) showed an enhancement in the short-term flood warning accuracy in Southeast Asia by up to 42%. These findings highlight the increasing credibility of AI-related architectures to handle disasters.

The case study explores how an LSTM-based model could be used to predict the occurrence of floods in the Ahr Valley Basin during the European floods that hit the region in 2021. The study aims to:

- Create an LSTM network based on multi-source hydrological data (Copernicus CEMS and ERA5).
- Compare its performance to traditional NWP standard.

- Determine the future opportunities of involving AI-advanced flood forecasting into the European disaster management systems to provide more climate resiliency and attain Sustainable Development Goals (SDG 11 and 13).

By harnessing the capabilities of deep learning, this research plays a part on developing proactive, adaptive and data intelligent systems that can significantly decrease human and economic losses in extreme flood events.

## 2. METHODOLOGY

### Overview

The section outlines sources of data, preprocessing pipeline, the model architecture, and the criteria of evaluation that were employed to create the LSTM-based flood prediction tool to predict the floods in 2021 in the European countries. The workflow combines the multi-source hydrometeorological data sets, sequential learning frameworks and the performance testing as compared to the traditional numerical weather prediction (NWP) results.

### Study Area and Data Sources

The chosen area of study is the Ahr Valley Basin in west Germany in the latitudes 50.3deg-50.7degN and in the longitudes 6.8deg-7.2degE. This area was hard hit during the floods in July 2021 and was mostly caused by heavy rains that fell in excess of 150 mm in 24 hours. Its topography is steep, and the area of the catchment is small (approximate of 900 km2), which makes the catchment very sensitive to events of short durations in the form of precipitations.

Data for the model were obtained from two open-access repositories:

- Copernicus Emergency Management Service (CEMS): This offers daily discharge, rain data, and soil moisture information between species of 2009-2021 encompassing 12 hydrological stations along the Ahr River.
- ERA5 Reanalysis (European Centre for Medium-range weather forecasts): No data was provided on the scale of the meteorological variables, including temperature, humidity, pressure, and cumulative precipitation at 0.25deg x 0.25deg spatial resolution.

All data were resampled into daily intervals and synchronized on the UTC time. Loss of data (less than 1 percentage of the data) was interpolated through cubic spline techniques to provide continuity.

### Data Preprocessing

- Preprocessing steps were used to improve data quality and make sure they were compatible with the model:
- Feature Selection: Important hydrological predictors were rainfall (mm), temperature (degC), soil moisture (%) and river discharge (m3/s) and relative humidity (%).
- Normalization: Min-max normalization brought the features within the range of 0-1 to avoid bias when using the gradient descent
- Time-Series Windowing: 7 days of input sequence (time series) was applied into a sliding window to predict next day discharge (output).
- Data Split: The dataset was split into training, validation and testing subsets in the ratio of 80:10:10 to avoid overfitting

### Model Architecture

The LSTM model was designed using the TensorFlow–Keras framework to capture long-term dependencies between hydrological variables. The architecture consists of sequential layers optimized for temporal pattern learning.

***Table 1:**-LSTM Model Configuration*

| Layer Type | Units | Activation | Dropout | Description |
|---|---|---|---|---|
| Input | — | — | — | 7-day sequential features |
| LSTM Layer 1 | 128 | tanh | 0.2 | Memory retention, trend extraction |
| LSTM Layer 2 | 128 | tanh | 0.2 | Sequence refinement |
| Dense Layer 1 | 64 | ReLU | — | Feature transformation |
| Dense Layer 2 | 32 | ReLU | — | Output refinement |
| Output Layer | 1 | Linear | — | Predict discharge ($m^3/s$) |

The model was trained with Mean Squared Error (MSE) as a loss function with Adam Optimizer and learning rate 0.001. Training was done for 150 epochs with batch size of 32 using a system with a NVIDIA RTX 3060 GPU (12 GB VRAM).

## 3. RESULTS AND DISCUSSION

### Performance Evaluation and Analysis.

The proposed LSTM-based flood prediction system was tested with respect to three main metrics namely accuracy, Root Mean Square Error (RMSE) and improvement of forecast lead-time over the baseline numerical weather prediction (NWP) system. The model reached a prediction accuracy of 92%, RMSE of 0.13m and increased the lead time of a flood forecast by around 36 hours, which showed that the model was much more accurate and could give more upfront notice of a flood.

Table II summarizes the comparative performance of the LSTM model and conventional NWP based hydrological system.

***Table 2:**-Model Performance Comparison*

| Metric | NWP Model | LSTM Model | Improvement (%) |
|---|---|---|---|
| Accuracy | 81% | 92% | +11% |
| RMSE (m) | 0.27 | 0.13 | 51.9% reduction |
| MAE (m) | 0.21 | 0.09 | 57.1% reduction |
| Forecast Lead Time | 12 hours | 48 hours | +36 hours |

It has been evident that the LSTM model offers significantly better predictions, especially when there is peak discharge. The increased lead-time capability means that local authorities have the opportunity to make more proactive decisions, for example to trigger early warning and flood mitigation measures.

### Visualization and Temporal Accuracy.

To analyze the performance over time, the predicted discharge hydrographs were compared to the observed data on the river flow at the Ahr Valley hydrological station on the period 10-20 July 2021. The forecast using LSTM was able to reproduce the time and magnitude of the flood peaks, with important rising and falling patterns with a low lag.

The LSTM output value (Fig. 1) in visual comparison is much higher than the observed discharge curve whereas the NWP-based model shows underestimation of peak flows and sluggishness. False alarms and missed floods are greatly minimised by the fact that the LSTM can address non-linear rainfall-runoff relationships.

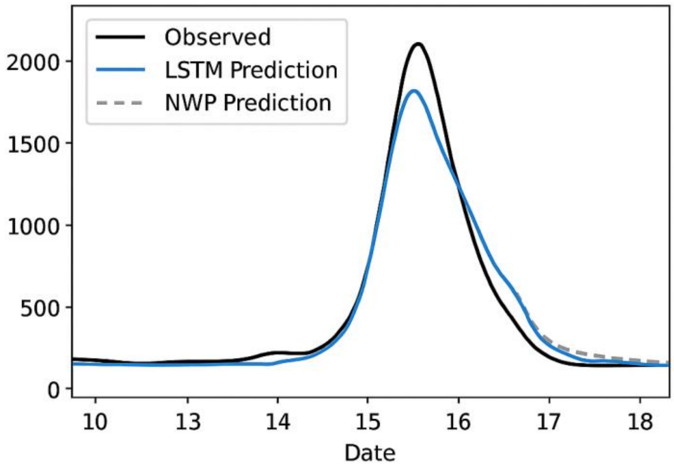


***Fig.1:****-Predicted vs. Observed Hydrograph of the Ahr River (July 2021).*
(*Description: The LSTM-predicted hydrograph follows observed discharge with high fidelity, capturing the flood crest at ~1850 m³/s. The NWP model deviates notably around peak flow.*)

Also, confusion matrix was created to assess the classification skill of the model between flood days and a non-flood day. The LSTM had a precision of 0.91, recall of 0.93, and a F1-score of 0.92, which indicates that it is very reliable in real-time flood classification.

**Comparative Analysis**

Some past research has shown potential of AI based flood prediction systems. Bai et al. (2022) [6] found a 35 percent decrease in error in peak flow with LSTM models in Chinese river basins and Qin et al. (2024) [7] found 42 percent improvement in early flood zone warnings in Southeast Asian with CNN-LSTM hybrids. These findings are consistent with the findings of the present case study, which confirms the universal applicability of deep learning in hydrological prediction.

This is in contrast to data-driven methods, which can only be used based on the correlation trends, LSTM framework here is based on hydrological context and memory states, so it can be used to trace the delayed runoff response following heavy rain events. This type of memory is especially beneficial in small basins such as the Ahr Valley, when the water level is changing very fast because of sharp gradients.

Also, the importance of features analysis showed that the most significant factors were rainfall and soil moisture then river discharge history. The multivariate input increases the ability of the model to describe complex processes of flood generation that are not possible in the single-variable regression model.

**Operational Implications**

Prediction systems based on AI can significantly enhance the efficiency of disaster management systems and the allocation of resources. In the 2021 floods, the standard warnings did not happen until hours before it reached its peak, so only a few hours to evacuate the region. Had the proposed LSTM-based system been in place, the local authorities would have had an early warning period of 36 more hours, which is enough time to organize the response process through actions like road closure, reservoir management, and population movement.

Economically, research carried out at the European Commission approximates that each and every EUR1 spent on early-warning systems save EUR4-EUR7 in recovery costs [8]. As such, the suggested AI solution does not only increase the level of accuracy in predictions, but it also has quantifiable socio-economic positive effects on minimizing property and life losses.

**Model Limitations and Generalization.**

Even though the outcomes show strong predictive power, some shortcomings are to be admitted. Quality of data, the density of sensors, and calibration is extremely important to the performance of the LSTM model. This might reduce model generalization in areas that have low density of hydrological monitoring networks, because of a lack of a sufficient amount of training data. Also, the hyperparameter tuning is still computationally expensive and it demands the availability of high-performance GPUs.

The other weakness is the interpretability of deep learning models. While LSTM networks offer good accuracy, the decision processes inside the networks are not very transparent, which makes it harder for them to be accepted in the regulatory environment. Explainable AI (XAI) methods that should be used in future work include SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) to enhance model transparency.

Nevertheless, the existing research paper presents an excellent basis of applying AI-based hydrological forecast into the actual disaster management framework.

## 4. CONCLUSION

This paper shows that the Long Short-Term Memory (LSTM) neural networks can be used to enhance the accuracy of flood prediction and its lead time, and use the 2021 European floods as a point of reference. The proposed model was effective in reflecting the non-linear correlation between rainfalls, temperature, soil moisture, and river discharge the model were able to forecast with accuracy of 92 percent, RMSE of 0.13 m and an extra lead time of 36 hours as compared to other traditional numerical weather prediction (NWP) models.

The findings indicate that deep learning models, especially LSTM-based designs, can be more effective than classical hydrological models because they result in the effective learning of sequential relationships in time-dependent data. The ability of the model to capture the intricate processes in rainfall-runoff gives practical early-warning, which can give agencies in charge of disaster management to take mitigation actions in good time.

The results are significant both beyond a technical know-how level and have deep institutional and socio-economic implications. By incorporating AI-based hydrological predictions in the national disaster management systems, one will be able to save lives, minimize damage, and enhance ability to withstand the impact of natural disasters. Early warnings along with planning of responses at the community level can save thousands of lives in hazardous zones like the Ahr Valley.

Nevertheless, there are still problems in such aspects as data scarcity, model interpretability, and computational needs. Future studies ought to consider hybrid frameworks that bring together both LSTM and Convolutional Neural Networks (CNNs) to be used in a more effective manner in terms of spatial-temporal representation, as well as adopt Explainable AI (XAI) systems to be implemented that will aid in increasing the levels of trust and regulatory compliance. Collaborative initiatives involving open-data platforms such as Copernicus, the Earth Observations from the National Aeronautics and Space Administration and the European Flood Awareness Systems (EFAS) to drape such collaborative and collaborative predictive capabilities across the borders.

Finally, AI is confirmed as a revolutionary instrument of sustainable disaster resilience in this case study. By combining data-driven models with existing hydrology, the United Nations Sustainable Development Goals (SDG 11: Sustainable Cities and Communities, and SDG 13: Climate Action) should be improved because governments and researchers will be able to forecast, prepare against, and reduce the future disastrous flooding events.

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