Convolutional neural network model for rapid prediction of urban flash flood: a case study in Matera, Italy

Muhammad Asif[1*], Roberto Bentivoglio[2], Raffaele Albano[3]

[1] *Department of Engineering, University of Basilicata, Potenza, Italy*

[2] *Department of Water Management, Faculty of Civil Engineering and Geosciences, Delft University of Technology, Delft, the Netherlands*

[3] *Department of Health Science, University of Basilicata, Potenza, Italy*

**e-mail: muhammadasif@unibas.it*

Abstract

The combination of fast urbanization and rainfall intensity increase due to climate change is posing significant threats to lives, economies, and infrastructures. Particularly, the extreme rainfall events in Mediterranean regions have led to devastating urban flash floods, resulting in destruction of homes, loss of life, and disruption of transportation networks (Albano, 2025). Therefore, fast prediction methods of urban flash floods are required to effectively manage the flood risk under climate change scenarios. One of the major issues for rapid urban flash flood prediction is the long computational time required by physically-based models especially for large simulation areas with small grid size (Guo et al., 2021). Despite there exist faster approaches that simplify the underlying physical equations, they tend to not be suitable for urban areas (Costabile et al., 2017). Recently, machine learning (ML) methods have emerged as an alternative approach that balances accuracy and computational efficiency (Asif et al., 2025; Bentivoglio et al., 2022). Among the several ML models, convolutional neural networks (CNNs) have become a popular choice due to their ability to process spatial patterns in the data and their easiness in use (Löwe et al., 2021).

In this work, we employ a CNN for the prediction of maximum water depths in the context of urban flash floods. We selected as a case study the city centre of Matera, Italy, because of its extensive urbanization and presence of severe pluvial flooding in the past years. The CNN model is trained using the outputs obtained from the physically-based model (LISFLOOD-FP) (Bates et al., 2013), to predict the water depths. As model architecture, we selected the U-Net structure developed by Guo et al., 2021 for pluvial flooding (Figure 1). This is an encoder-decoder CNN that includes a fully connected layer in its bottleneck to include the rainfall forcing as an input.

The model utilized as inputs seven spatially-distributed variables such as aspect, curvature, flow accumulation, slope, digital terrain model (DTM), topographic wetness index (TWI), and manning coefficient that capture the most relevant topographical and roughness characteristics of the catchment. We also selected a time-varying rainfall hyetograph as main input that changes throughout the simulations.

As dataset, we considered a total of 20 rainstorm events, nine based on real past events and eleven based on different rainfall return periods, ranging from two to 100 years. These were split into 14 events for training and validation, and six for testing. All dataset splits included both synthetic and real events. The input features were normalized with a minmax scaler, based on the training data, to homogenized wide ranges of values across the different inputs.

We trained the model using Adam optimization for 150 epochs, using a fixed learning rate of 0.001 and early stopping. We also trained the model for different combinations of training and validation simulations, both in terms of number of simulations and randomness seed, to ensure robustness for different rainfall events. As expected, the higher the number of training samples, the better the testing accuracy, measured in terms of critical success index (CSI) and root mean squared error (RMSE). In the best setting, the model tends to better predict high return period events while overpredicting low return period ones. In terms of speed, the model produces reasonable results in few seconds, offering a valuable tool for rapid flash flood predictions.

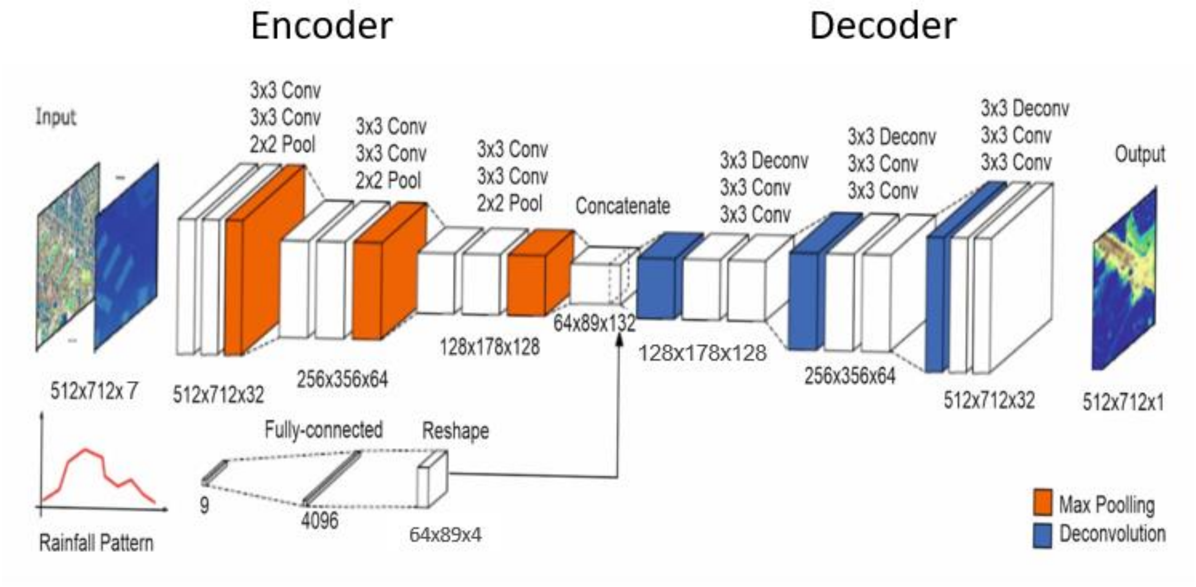

Figure 1. CNN model employed in this study (taken from Guo et al., 2021)

References

Albano, R., 2025. Using citizens recorded videos to estimate water surface velocity and dischargefor urban flash flood monitoring.

Asif, M., Kuglitsch, M.M., Pelivan, I., Albano, R., 2025. Review and Intercomparison of Machine Learning Applications for Short-term Flood Forecasting. Water Resour. Manag. 1–21.

Bates, P., Trigg, M., Neal, J., Dabrowa, A., 2013. LISFLOOD-FP user manual. Code release 5.

Bentivoglio, R., Isufi, E., Jonkman, S.N., Taormina, R., 2022. Deep learning methods for flood mapping: a review of existing applications and future research directions. Hydrol. Earth Syst. Sci. 26, 4345–4378.

Costabile, P., Costanzo, C., Macchione, F., 2017. Performances and limitations of the diffusive approximation of the 2-d shallow water equations for flood simulation in urban and rural areas. Appl. Numer. Math. 116, 141–156.

Guo, Z., Leitao, J.P., Simões, N.E., Moosavi, V., 2021. Data-driven flood emulation: Speeding up urban flood predictions by deep convolutional neural networks. J. Flood Risk Manag. 14, e12684.

Löwe, R., Böhm, J., Jensen, D.G., Leandro, J., Rasmussen, S.H., 2021. U-FLOOD–Topographic deep learning for predicting urban pluvial flood water depth. J. Hydrol. 603, 126898.