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Application of Artificial Intelligence in Rainfall Nowcasting and Flash Floods Forecast in an urban catchment: First results from Research Project KIWaSuS in Germany

Application de l'intelligence artificielle dans la prévision à court terme des précipitations et de crues torrentielles dans une zone du réseau d'assainissement urbain : Les premiers résultats du projet de recherche KIWaSuS en Allemagne

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RÉSUMÉ

L'augmentation de la fréquence et de l'intensité des phénomènes météorologiques extrêmes est déjà une réalité en raison du réchauffement climatique. Afin de mieux informer les équipes de gestion des catastrophes sur la situation d'inondation à venir dans une zone du réseau d'assainissement, le projet de recherche KIWaSuS (système d'alerte basé sur l'intelligence artificielle pour les fortes pluies et les crues torrentielles en zone urbaine) va développer trois modèles avec intelligence artificielle (IA) pour la prévision à court terme des précipitations, la prévision des débordements du réseau d'assainissement et la prévision des zones inondées. Par rapport à un modèle habituel de prévision à court terme des précipitations pour un événement spécifique de fortes précipitations, le premier modèle de prévision des précipitations développé par IA peut fournir de meilleurs résultats pour des horizons de prévision compris entre 20 et 60 minutes. Il peut maintenir ses performances constantes jusqu'à un délai de 35 minutes. Dans les premières études pour le modèle de prévision des zones inondées, il a été analysé si l'inclusion d'autres entrants, en plus des informations sur les précipitations, pouvait améliorer les performances du modèle d'IA. Il est démontré que l'ajout des informations sur les débordements du réseau d'assainissement améliore la performance du dernier modèle, ce qui corrobore la connexion prévue de ces trois modèles d'IA pour atteindre les objectifs du projet de recherche KIWaSuS.

ABSTRACT

The increase in the frequency and intensity of extreme weather events is already a reality due to global warming. In order to better inform the disaster management teams about the upcoming flooding situation in an urban catchment, the research project KIWaSuS (AI-based warning system for heavy rain and urban flash floods) is going to develop three models with artificial intelligence (AI) for precipitation nowcasting, forecasting of sewer overflow and forecasting of inundation areas. In comparison to a usual rainfall nowcasting model for a specific heavy rainfall event, the first developed AI precipitation prediction model can deliver better results for forecast horizons between 20 and 60 minutes. It can also maintain its performance constant up to a lead time of 35 minutes. In the first investigations for the flood prediction model, it was analysed whether the inclusion of other inputs additionally to precipitation information could improve the performance of the AI model. It is demonstrated that the addition of sewer overflow information improves the model performance, which corroborates the planned coupling of these three AI models to achieve the goals of the research project KIWaSuS.

KEYWORDS

Artificial Intelligence, Flash Flood, Forecast, Rainfall, Urban Catchment

1 INTRODUCTION

Heavy rainfall events which inevitably lead to severe flooding are expected to be more frequent in the future as a consequence of climate change. In July 2021, several localities in the German states of North Rhine-Westphalia and Rhineland-Palatinate were affected by extreme rainfall and floods. Attribution analyses indicate that the intensity and return period of this event were increased by 3 – 19% and 1.2 – 9, respectively, compared to the world before the increase in average temperature of 1.2 °C due to climate change (Kreienkamp et al., 2021).

Extreme events are characterized by their high dynamics and rapid onset times, which can jeopardize the action of disaster management teams taken by surprise by the fast development of rainfall and flood events. Accurate and early warnings about the probable progress of heavy rainfall events and flash floods in urban catchments is, therefore, of great importance to enhance the preparedness of these teams prior and during these events.

In this context, the research project KIWaSuS (AI-based warning system for heavy rain and urban flash floods) aims to develop a warning system to inform actors of disaster management about the probable flood situation with a lead time of up to two hours. In order to provide more detailed and on-time information on susceptible areas to flooding due to upcoming heavy rainfall event, three models will be developed to forecast rainfall (nowcasting), overflow of the sewer system and the resulting flooding (Figure 1). Within the vast field of artificial intelligence (AI), appropriate methods of machine learning (ML) will be selected and applied to the three models, so that they can learn from historical relevant events. The end product of the research project will be an iterative map of the probable flooding situation of the study area, which will be placed at the disposal of the disaster management teams for further decision-making process regarding the most appropriate plan of action.

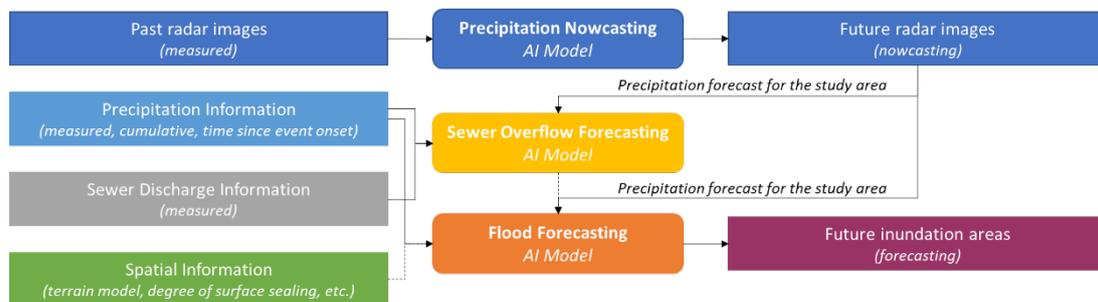


Figure 1: Systematic view of the AI models within the warning system of KIWaSuS

2 DEVELOPMENT OF THE AI MODELS

2.1 Rainfall Nowcasting

2.1.1 Data description and preparation

For the development of the rainfall nowcasting model, radar data of the product DX of the German Weather Service (DWD) from the radar station Essen are used as input. The product DX (DWD, 2016) delivers raw radar data with a time resolution of five minutes, which is clipped to a range of 80 km around the radar station, sufficiently covering the study area in the city of Gelsenkirchen, Germany. The raw data is subsequently corrected for clutter removal and signal attenuation effects, and converted into rain intensity values.

Also necessary for the development of the AI model is the product DX-Offline (Treis et al., 2016). The DX-Offline data is a radar dataset for the German state North Rhine-Westphalia which provides extensively corrected radar data, including also correction with rainfall measurements of precipitation sensors. This dataset is used as “label” in the model training, as it has a substantially higher quality than usual radar data and it is available for historic events. As preparation for the model training, radar data for the years 2004 – 2010 and 2012 – 2019 were evaluated, in order to select relevant historic heavy rainfall events with duration from 15 to 240 minutes and with a minimal return period of three years.

2.1.2 Preliminary results with first model architecture

As a first model architecture, a convolutional neural network (CNN) with 3D convolutional layers was trained with the samples from years 2012 – 2019. Twelve radar images, corresponding to one hour, were given as input, and twelve radar images of the upcoming hour were given as label for the network training. In spite of the prior selection of relevant heavy rainfall events, the majority of the pixels in the radar images correspond to null values,

forming an extreme unbalanced dataset. To minimize the effect of the skewness of the data distribution upon the model training, two different data transformation strategies were tested: log transformation and cube root.

The 3D-CNN model was trained twice for 50 epochs, once for each data transformation function. The results were evaluated considering continuous (Mean Square Error – MSE) and categorical (Critical Success Index – CSI) metrics. The 3D-CNN model with the log transformation presented better results than the same model with the cube root transformation. Higher CSI values were obtained for all lead times for the rainfall intensity thresholds of 10, 15 and 30 mm/h. Moreover, the average MSE over all samples was smaller for the log transformation ($1,30 \text{ (mm/h)}^2$) compared to the error with the cube root transformation ($1,37 \text{ (mm/h)}^2$).

The forecasts of the 3D-CNN model with the log transformation were compared to the forecasts of a nowcasting model with Lagrangian Persistence (DenseRotation, Ayzel et al. 2019), which is used as baseline model. The 3D-CNN model offers better results for forecast horizons between 20 and 60 minutes, and also maintains a constant performance up to a lead time of 35 minutes for all the rainfall intensity thresholds, as shown in Figure 2.

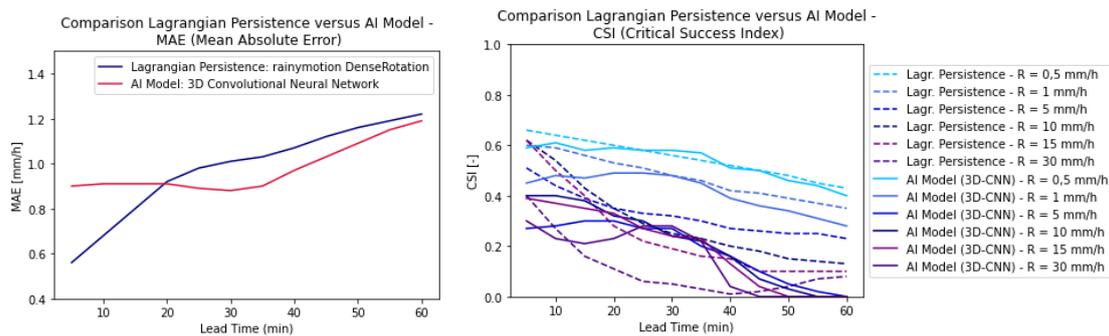


Figure 2: Comparison of the AI Model to a Lagrangian Persistence Model according to the evaluation metrics MAE and CSI

2.2 Flood Forecasting

2.2.1 Data description

The flood forecasting model is developed to cover the 3 km^2 study area in the city of Gelsenkirchen. As neither sewer overflow at manholes nor flooded areas are currently measured to the required extent, there is not yet historical measurement data for the training of this model. Therefore, these datasets were computed for the study area through a coupled 1D-2D hydrodynamic (HD) inundation model built with MIKE+ software (DHI, 2021).

Since sewer networks in Germany are designed for return periods of sewer overflow in the range of 2 to 10 years according to DIN EN 752:2017 and DWA-A 118 (2006), precipitation events that lead to overloading of the sewer system are quite rare. However, the flood prediction model under development is addressed exactly to these events and should predict as accurately as possible the full range of all likely overload events. For this reason, precipitation data from eight stations close to the study area were used to generate the dataset of historic precipitation events. Additionally, model rains were created to include in the best way possible rare events with high return periods ($T > 100a$) into the dataset. The final training dataset consists of 105 model rainfall events and 153 historical rainfall events for which overflow hydrographs and inundation areas were calculated.

2.2.2 Preliminary results for the flood forecasting model

First, a model for the prediction of inundation areas was developed. In later operation, the model will be able to derive the inundation areas as a temporal sequence of raster images for the same forecast horizon of the precipitation nowcasting model. The goal is to minimize the error between the simulations generated by the HD model and the forecasts of the ML model as much as possible. While the target value is clearly defined to be the future inundation areas, several variables are available to be used as input of the ML model. These include not only precipitation information (fallen precipitation, predicted precipitation, cumulative precipitation, elapsed time since event onset), but also the overflow hydrographs, which are currently obtained from the HD model. An additional source of information is spatial information, such as terrain models or the degree of surface sealing. These variables provide the model with additional information about the system and also facilitate model transferability to a different study area (Guo et al., 2021; Löwe et al., 2021). Thus, three potential inputs are available for the forecasting model. The goal of the initial investigations is to determine the combination of the most relevant input variables from these potential inputs. For this purpose, a total of four models were

developed: the first model with only precipitation as input, the second one with precipitation and spatial information, the third one with precipitation and overflow information, and the last model with all three input variables. Artificial neural networks with an autoencoder architecture were selected as the ML method. In case of multiple inputs, these were merged at the model bottleneck layer.

All models were trained for 100 epochs and the model for the iteration with the lowest error on the validation dataset were saved in each case. A test dataset of 26 events was utilized to evaluate the models, and the Root Mean Squared Error (RMSE) and CSI were applied as metrics. The results are shown in the figure 3 below. The boxplots show the distribution of the metrics over all 26 test events. It can be seen that the additional consideration of overflow leads to better results. Although spatial information is important in terms of model transferability, it leads to poorer values of the metrics.

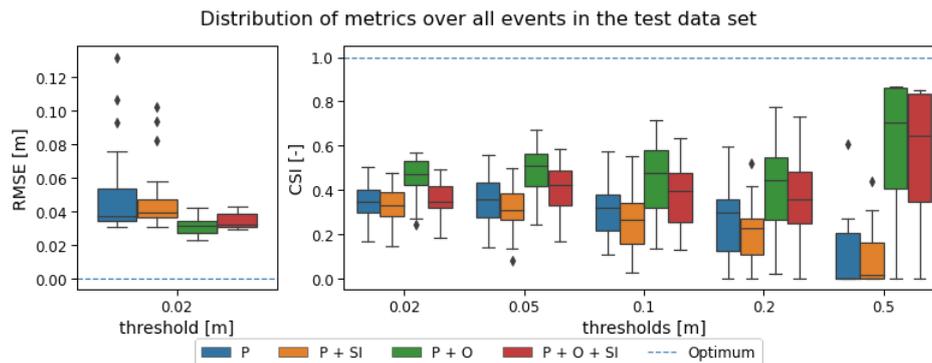


Figure 3: Evaluation of the different models with the inputs precipitation (P), spatial information (SI) and overflow (O). The threshold value indicates the water levels above which pixels are included in the metric calculation.

3 CONCLUSIONS

The preliminary results show important steps in the development of the AI models. For the precipitation nowcasting, other model architectures are planned to be trained in order to improve upon the performance of the 3D-CNN model. Regarding the flood forecasting model, it has been demonstrated that the consideration of overflow information improves the model performance, corroborating the benefits of coupling the three AI models. This next step is planned to take place as soon as the final versions of all models are defined and trained.

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