Artificial Intelligence Methodologies Applied to Prompt Pluvial Flood Estimation and Prediction

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Abstract: Regarding urban flooding issues, applying Artificial Intelligence (AI) methodologies can provide a timely prediction of imminent incidences of flash floods. The study aims to develop and deploy an effective real-time pluvial flood forecasting AI platform. The platform integrates rainfall hyetographs embedded with uncertainty analyses as well as hydrological and hydraulic modeling. It establishes a large number synthetic of torrential rainfall events and their simulated flooding datasets. The obtained data contain 6000 sets of color-classified rainfall hyetograph maps and 300,000 simulated flooding maps (water depth) in an urban district. The generated datasets are utilized for AI image processing. Through the AI deep learning classifications, the rainfall hyetograph map feature parameters are detected and extracted. The trained features are applied to predict potential rainfall events, recognize their potential inundated water depths as well as display flooding maps in real-time. The performance assessments of the platform are evaluated by Root Means Square Error (RMSE), Nash Sutcliffe Efficiency Coefficient (NSCE) and Mean Absolute Percentage Error (MAPE). The results of RMSE and NSCE indicators illustrate that the methodologies and approaches of the AI platform are reliable and acceptable. However, the values of MAPE show inconsistency. Ultimately, the platform can perform and be utilized promptly in real-time and ensure sufficient lead time in order to prevent possible flooding hazards.

Keywords: artificial intelligence; deep learning; urban flooding; flash floods; hyetograph map; real-time flooding map datasets; pluvial flood forecasting

1. Introduction

The use of artificial intelligence (AI) technology for disaster prevention and early warnings is a new trend in recent years. In particular, convolutional neural network (CNN) technology can be applied to deal with urban flash floods. When the amount of rainfall induced flow exceeds the designed discharges of rivers, urban drainages, as well as sewer systems, the risks of urban flooding are substantially increased. For example, in September 2018, the maximum accumulated rainfall in Taipei City, Taiwan in 1-h was 123 mm, and in 3-h duration was over 200 mm [1]. The amounts of rainfall significantly exceeded the designed capacity of the city sewer system—i.e., about 78 mm/h. In Taiwan, the sewer outlets, in general, have been designed for a 2–5-year flood return period.

Several approaches exist nowadays in urban flooding and disaster prevention research, such as hydraulic methods, artificial intelligence or statistical analysis. In terms of hydraulic methods, many numerical models have been developed, such as HEC-RAS (US Army Corps. of Engineers) [2],
SOBEK or 3Di (Deltas) [3], MIKE (DHI) [4], SWMM (US EPA) [5,6], HDM-2D [6,7] and FLUval Modeling ENgine (FLUMEN) [7].

Among the numerical models, Bates et al. [8] describe the development of a set of equations, derived from 1D shallow water theory, which are used in a 2D storage cell inundation model in order to explicitly save computational cost. Moreover, it is widely recognized that quantification and reduction in uncertainty associated with the hydrologic forecast is an essential necessity for flood estimation and rational decision-making. By inducing a reasonable analytic-numerical computation method combined with predictive uncertainty assessment approaches [9], more accurate and reliable flood forecasts are acquired. On the other hand, for the purpose of real-time flood forecasts, the numerical model requires high-precision topographic data and short-time calculation capability. Thus, Cartesian grid cell processing is used to reduce the amount of calculation, by applying a 3Di approach over catchments [10]. Other research utilizes high-performance Graphics Processing Unit (GPU) clusters across heterogeneous platforms to shorten the computational execution [11]. However, it is difficult to achieve real-time flood warnings and inundation simulations over urban areas due to complex topography, drainage systems as well as data availability.

In artificial intelligence and statistical analysis methods, there are articles to identify relevant features or physics-based parameters prior to executing simulations. These methods execute data analyses via artificial neural network (ANN) and machine learning (ML) techniques in order to distinguish rainfall types and flooding characteristics [12,13]. The articles [12,13] address the aspects of technological progress in hydroinformatics including developing protocols for model integration and computer architectures of a modern modeling system as well as practical applications for solving various water-related issues. In addition, the two papers highlight the collaboration between data-driven modeling methods (i.e., ANN) and physically based models in order to improve the abilities of recognizing the co-evolution of social and hydrologic systems. By eliciting data mining and hybrid multimodeling methods, the model structure can be discovered and parameters can be optimized simultaneously. Regarding the deep learning of artificial intelligence methodologies, Szegedy et al. [14] demonstrated how factorizing convolutions and aggressive dimension reductions inside the neural network can result in relatively low computational cost while maintaining high accuracy. Furthermore, in study [15], the combination of a lower parameter count and additional regularization with batch-normalized auxiliary classifiers and label-smoothing allow the training of high quality networks on relatively modest sized training sets. Using the artificial intelligence technology to study urban flooding, Dawson et al. [16] compared the behavior and physical rationality of a generalized linear model with two neural network models for predicting median flood magnitude in rural catchments. The neural solutions demonstrate an encouraging degree of model performance and physical legitimacy. Similarly, Broad et al. [17] present a formalized qualitative process to evaluate a function to determine the most suitable meta-model scope so as to increase the likelihood of calibrating a high-fidelity meta-model and hence obtain ultimate results in a reasonable amount of execution time. The approach can be applied to risk-based optimization of water distribution systems and computationally intensive problem for real world systems. It is observed that artificial neural networks can be preferred in cases for which the multiple regression analysis predictions have not been met, and the analysis cannot be performed [18]. Furthermore, the study indicated that artificial neural networks have higher prediction accuracies in comparison with multiple regression analysis and yield results with lower error values.

Ghorbani et al. [19] investigate the applicability of artificial neural networks—i.e., multilayer perceptron (MLP) and radial basis function (RBF) models, and the support vector machine (SVM) model—for river flow predictions. The models’ results were compared using root mean square errors and the correlation coefficients. The outcomes indicate that MLP and RBF models predicted better than the SVM model for monthly river flow time series. However, most of the studies on floods or river flow discharges as well as water level forecasting were concentrated on relationships between rainfall and water level under a one-dimensional basin [20–23]. The papers [20–23] did not only apply a self-organizing map (SOM) cluster analysis, implement similarity classifications and explain flooding definitions and recurrences, but also utilized the nonlinear autoregressive with exogenous
algorithm methodology to predict the average flood depth over two-dimensionally flooded areas. Kim et al. [24] showed rainfall, overflow and inundation map data constructed as a database for training to predict the inundation area near Seoul. The real-time flood prediction with the hydraulic and probabilistic models suggested that this study improves the accuracy of the predicted flood inundation map and secures lead time.

In urban flooding risk management, Liu et al. [25] indicated that a physically based 2D cellular automation model integrates with Geographic Information System (GIS) software, including multiple parameters—i.e., precipitation, infiltration, water level, discharge to storm sewer inlets—which are considered to simulate flow dynamics in cities. Moreover, the flow depth at the catchment outlet is interpreted from street-monitoring closed-circuit television (CCTV) videos and verified by an on-site survey. Conventional sensing networks can only offer one-dimensional physical parameters measured by gauge sensors, whereas visual sensors can acquire dynamic image information of monitored sites and provide disaster prevention agencies with actual field information for decision-making. The visual sensing method established in Lo et al.’s [26] study provides spatiotemporal information that can be used for automated remote analysis for monitoring urban floods. The experimental results suggest that the visual sensing approach can be a reliable way of determining the water fluctuation and measuring its elevation and flood intrusion. Regarding the use of big data, Yu et al. [27] indicated the findings of several researchers on varied scientific and technological perspectives that have a bearing on the efficacy of big data in facilitating natural disaster management. In addition, the paper reviews major big data sources, associated achievements in different disaster management phases and emerging technology topics associated with leveraging the ecosystem big data to monitor and detect natural hazards, mitigate their effects, assist in relief efforts and contribute to the recovery and reconstruction processes.

The motivation of the study is to explore an effective and real-time urban pluvial flood early warning platform. The main purpose of the platform is to increase lead time of issuing warnings when a flood is imminent or already occurring. According to previous experiences, real-time flood simulation modeling is difficult and timeless. In order to conquer the barrier, the study delves into artificial intelligence of image recognition technology by transforming the real-time rainfall spatial distribution diagrams into predicted potential visualized inundation images. An actual case, in the regions of Nantun creek basin of Taoyuan City, Taiwan, is implemented. The relevant methods and approaches are illustrated step-by-step clearly in the following sections.

2. Methodologies and Implementations

The research develops and deploys datasets of rainfall intensity hyetographs and simulated inundated water depths over a designate district. Through the analyses of the similarities of rainfall patterns, searching and retrieving the correlated simulated flood depth(s) was conducted over the region, and therefore it can promptly predict the potential pluvial flood [28–32] incidences in real-time.

The analysis process of the study is presented in the research was divided into four stages as presented in Figure 1: the initial stage, the model setting, simulation and big data preparation stage, the AI learning and training stage, and finally the application and prediction stage by implementing a real scenario. The relevant steps are further illustrated as follows:

At the initial stage, the geographical and hydrological data were collected; the aggregated data were provided and utilized for modeling simulation. The data aggregating includes urban regions as well as time series and spatial of historical hydrological rainfall events such as Quantitative Precipitation Estimation and Segregation Using Multiple Sensors (QPESUMS) data [33]. The uncertainty analysis [34] was applied to the QPESUMS data in order to simulate the uncertainty distribution of each rainfall grid. The grid was combined, grouped and generated as 2D regional rainfall hyetograph maps embedded with corresponding coordinates (WGS 84). The process enters into the second stage—i.e., constructing large numbers of synthetic rainfall hyetographs and inundated water depth/map datasets over the designated region. The detailed generating procedures of the datasets are further illustrated in Section 2.3.
Figure 1. The analysis processes of the study.

The model setting, simulation and big data generating stage, in the beginning, included 1D, 2D SOBEK model set-up, calibration and validation. After inputting rainfall hyetograph maps into the model, the stage carried out the model simulation and output inundated water depths in ASCII (American Standard Code for Information Interchange) format. During the construction of rainfall hyetograph map datasets, Quantum Geographic Information System (QGIS) [35] tools were implemented to convert the time series and spatial rainfall hyetograph ASCII data into two-dimensional color-classified rainfall intensity JPG (Joint Photographic Group) images and produced a file system-based geographic map datasets. Similarly, applying the same process, via QGIS, to transform the SOBEK simulated inundated water depths of ASCII outputs into 2D colored image datasets and Keyhole Markup Language (KML) files. The KML files were imported into Google Earth and could be displayed and presented as flooding images over the designated region.

After establishing the databases of color-classified rainfall hyetograph image datasets and their corresponding simulated inundated water depth/map datasets, in the AI learning and training stage, these two databases combined with Inception V3 transfer learning [36] were further utilized to carry out feature extraction and classification. Inception V3 is a convolutional neural network; it is a special...
kind of multilayer neural network, designed to recognize visual patterns directly from pixel images as the databases constructed in the study. The process was executed as image recognition that, for a given rainfall hyetograph image, can correctly classify, detect and retrieve the corresponding predicted inundated water depth/image. In summary, in the AI learning and training stages, the AI platform utilized these two big data databases combined with Inception V3 transfer learning in order to carry out parameter analysis and learning between spatial datasets of rainfall and flooding, and extract the correlation between these two datasets.

Finally, the application and prediction stage implements the whole processes and applies them to a real scenario: (1) according to current (T) and previous 3-h rainfall patterns (T − 3, T − 2, T − 1) to train, evaluate and predict the subsequent 3-h (T + 1, T + 2, and T + 3) rainfall intensity map datasets (i.e., rainfall hyetographs) and (2) to calculate the corresponding anticipated simulated inundated water depth datasets, as well as (3) to display and present the flooding images—i.e., pluvial flood of the region, over Google Earth or Google Map. The implementation procedures are further illustrated in Section 2.5.3.

2.1. Study Area

The Nantun river basin in Taoyuan City, Taiwan, was selected as the study area. The geographical location of the region is indicated in Figure 2. The river is 21 km in length, the catchment area is approximately 228 km² and the average slope of the mainstream is 6/1000. Moreover, Taoyuan is a heavily populated city. There are more than 1 million people residing in this river basin. The types of land use include: an international airport, two industrial parks and intensively developed urban districts plus nine planned regions to cover metropolitan traffic, commercial and service industries. Therefore, once the amount of rainfall exceeds the capacity of designed river channels, drainages or sewer systems, flash floods will occur in the city.

The study case was focused on the three real torrential rainfalls, occurring on 11 June 2012, 16 May 2015 and 2 July 2019, respectively, comparing these three events including modeling calculation, data execution, prediction accuracy as well as performance evaluation.

2.2. Numerical Model Setup, Calibration and Validation

This section is further divided as the subheading. Deltras SOBEK version 2.15 was used as the hydrology, hydraulic and pluvial flood simulation model as presented in Figure 1. The model functions include the 1D hydraulic model (river, drainage, sewer, gates, pumping stations, or flood detention) and 2D pluvial flood model. Before executing the simulation, initial settings of the Sacramento model parameters in rural areas (i.e., upper zone tension water maximum (UZTWN), upper zone free water maximum (UZFWM), unit hydrograph (UH), etc.) need to be configured consistently to match with the actual physical properties of the designated site(s). The study area consists of 254 catchments, 222 open channels (Manning’s coefficient n = 0.02), 32 sewerage systems (n = 0.025) and 265 manhole covers. The total area of open channels and sewerage systems is 21.1 km². Evaluation of urban flood on surface runoff was conducted using the Soil Conservation Service Curve Number (SCS-CN) method. The Curve Number (CN) of the study area ranges between 59.57 and 97.23, and is partially listed in Table 1. The table actually contains 222 rows; the first 4 rows and the last row are presented. The CN value is based on the area’s hydrologic soil group, land usage, treatment and hydrologic condition. The Digital Elevation Model (DEM) grid cell size of the study area is 20 × 20 m.

With the SOBEK model initial settings completed, the model was calibrated and validated by historical flooding hydrological events in recent years. For example, two flooding events, on 11 June torrential rainfall in 2012 (11 June 2012) and on 16 May event in 2016 (16 May 2016), were selected for modeling calibration and validation. After completion of the settings and parameter suitability adjustments, the model was ready and used for simulating pluvial flood water depths.
Table 1. Watershed catchment area parameters.

| ID Number | Area (m²) | Slope  | Drainage Path Length | CN Value |
|-----------|-----------|--------|-----------------------|----------|
| EGCH-1    | 326,275   | 0.038  | 820.4                 | 62.5     |
| EGCH-2    | 7225      | 0.313  | 94.3                  | 78.1     |
| EGCH-3    | 133,025   | 0.042  | 768.8                 | 68.9     |
| EGCH-4    | 182,700   | 0.04   | 777.5                 | 68.2     |
| ...       | ...       | ...    | ...                   | ...      |
| EGCH-222  | 79,450    | 0.041  | 805.9                 | 92.8     |

The accuracy of the calibration, based upon these two flooding events, was evaluated by the formula as follows [37–42]:

$$A_d = \frac{A_c}{A_f + A_0 + A_c} \times 100$$  \hspace{1cm} (1)

where $A_d$ is the accuracy of the calibration; $A_c$ is the number of predicted flood grids which floods actually occurred; $A_f$ is the number of predicted non-flood grids, but floods occurred; $A_0$ is the number of predicted flood grids, but no flood occurred. The range of the accuracy is between 0% and 100%. Zero percentage means that the prediction completely failed, and a one hundred percentage means that the prediction was fully accurate.

In addition, the actual flooded zone was measured or calculated by the edges of monitored flooding regions. It ignored the altitude (or height) of the geographic feature in the regions. Therefore, from the empirical evidence, the actual flooded zone was overestimated compared to that of the model simulated one. This study area has complex topography. Because the altitude feature (topography) was not considered in this case, the accuracy of the calibration value needed to be set between 0.5–1.0—i.e., greater than 50%. Fifty percent is the practical value experienced in Taiwan. Thus, it can adequately predict the accuracy of flooded areas. During the calibration, if the validation
standard (or accuracy value) is not reached, the parameters of the model will be adjusted, and the calibration iterates repeatedly until the standard is achieved.

In Figure 3a indicates the torrential rainfall hyetograph on 11 June 2012 aggregated from rain gauges installed in the study area. Similarly, Figure 3b shows the rainfall hyetograph collected on 16 May 2016. In the diagram, Figure 3c,d display the actual pluvial flood areas of the rainfall events on 11 June 2012 and 16 May 2016, respectively. Based upon these two historical flooding events, applying the same calibration and validation standards, the accuracy of the simulated results, $A_o$ on 11 June 2012 flooding event is 59% as indicated in Figure 3e. Similarly, the accuracy of the simulated results, $A_o$ on 16 May 2016 event, is 52% in Figure 3f. Both accuracy values of calibration are greater than 50%; this results in the model being able to be applied for further simulation analyses of the research. The types of rainfall hyetographs can induce the differences of the accuracy of calibration as well. In general, a longer rainfall duration, such as the hyetograph on 11 June 2012, has a greater calibration value.

After the model is calibrated and validated, the model can be utilized for simulation and generate the big data repository of pluvial flood map datasets by inputting the results of uncertainty-analyzed rainfall hyetograph datasets. These rainfall big data and their corresponding pluvial flood depth/map datasets are provided for the AI learning and training.
2.3. Time Series and Spatial Rainfall Hyetographs Database

The rainfall intensity hyetograph database was aggregated and generated based upon the grid rainfall data (QPESUMS) of Taiwan’s top 21 major rainfall events (excluding rainfall events on 11 June 2012 and 16 May 2016), having a 16–72-h duration of precipitation from the years of 2008 to 2016 over the study river basin, Nantun. The multivariate Monte Carlo method [34] was implemented to introduce the uncertainty distribution of the rainfall grids and combine the grids with two-dimensional spatial random rainfall patterns. The multivariate uncertainties in the rainfall characteristics include rainfall duration, depth and storm pattern. For example, through the approaches, a total number of 6000 sets of hyetographs were created with 1-h quantitative rainfall distributions. These hyetograph datasets are in ASCII format embedded with coordinate attributes. In addition, by applying QGIS layer functions, these 6000 sets of rainfall hyetographs were converted and imposed on color-classified rainfall intensity distributions with 10 mm intervals, as indicated in Figure 4. As a result, nearly 300,000 (6000 events with 16–72 h duration on hourly basis) color-classified, in 10 mm increments, rainfall distribution image files were produced and stored as a file system-based map dataset. The image file, i.e., map dataset, was in JPG format that has three channels of RGB color, and the image size was 256 × 256 pixels. The datasets will be utilized for artificial intelligent image processing.
Figure 4. Time series and spatial of color-classified rainfall map datasets in 10 mm increments.

2.4. Urban Flooding Simulation and Flooding Map Datasets

The color-classified rainfall map datasets constructed previously were input into the hydrological hydraulic SOBEK model for pluvial flood simulation. The model was calibrated and validated as illustrated in Section 2.2.

The simulation was carried out by executing and allocating rainfall map datasets concurrently, which resided in the 6000 sets of hyetographs, into multiple virtual machines which were integrated as the Artificial Intelligent (AI) platform [43] of the research. The platform performed automated scheduling and generated outputs accordingly. After running for several days, approximately 300,000 datasets of simulated pluvial flood depths, in ASCII format, were created. Furthermore, by applying QGIS tools, the datasets were converted into 300,000 pluvial flood image datasets as JPG, Keyhole Markup Language Zipped (KMZ) files. The KMZ files, subsequently imposed on the Google Earth or Google Map platforms, could be displayed and presented dynamically as visual pluvial flood images over designated areas in real-time.

2.5. AI Learning and Training Approaches

After establishing file system-based databases of 300,000 colored-classified rainfall hyetograph map datasets and their corresponding 300,000 pluvial flood depth/map datasets as illustrated above, the AI learning and training processes were executed by implementing image recognition technology. In the recognition approaches, the AI platform integrated transfer learning algorithm, QGIS application and histogram similarity measures. In other words, the platform carried out the training pattern—i.e., feature extraction and classification portions as well as the prediction pattern as depicted in Figure 5. Once trained for a given rainfall hyetograph event, the platform can, in a timely manner, correctly classify, detect and retrieve a predicted pluvial flood map via image similarity comparing mechanism. The filenames of a rainfall hyetograph image and its associated pluvial flood depth/map dataset were named with the same suffix or extension. Thus, the former can retrieve the latter immediately via direct indexing.

2.5.1. Training and Predicting Patterns and Computing Environment

In the study, Inception V3 Convolutional Neural Network (CNN) technology was selected as the transfer learning algorithm. It is a special kind of multilayer neural network, designed to recognize
visual patterns directly from pixel images as the map datasets constructed previously. Python 3.6.3 version was the implementation programming language used to configure and integrate with the transfer learning method. The computing environment, a standard desktop, includes I7 CPU, 64 GB memory, 256 GB solid-state drive, 1070 GPU and Windows 10 Operating System.

In order to enhance the speed of execution, the generated 300,000 rainfall hyetograph datasets were divided into 20 categories in 10 mm rainfall intensity increments—i.e., 20 folders of image files, as presented in Figure 5. Each folder randomly allocated 80% of the files for algorithm training, 10% of the files for validation and 10% of the files for testing.

2.5.2. Prediction Pattern and Histogram Similarity Measure

To predict an pluvial flood map, in a timely manner, for a given rainfall event: (1) convert the rainfall event into a color-classified rainfall hyetograph image file; (2) according to the rainfall intensity, select a file folder having the same rainfall intensity, apply Inception V3 transfer learning algorithm, retrieve and select the maximum rainfall intensity; (3) calculate histogram similarity measures between the given image file with all of the rainfall hyetograph files individually in the selected folder; (4) compare and obtain the rainfall hyetograph file which has the highest value of similarity associated with the given one; (5) based upon the result, i.e., the most similar rainfall hyetograph intensity file, retrieve and predict the corresponding pluvial flood depth/map dataset by direct indexing via filename suffix and (6) display and present the pluvial flood image map file under Google Earth or Google Map in real-time.

The equation of histogram similarity measure is listed as below:

\[
SV = \frac{1}{N} \sum_{i=1}^{N} \left(1 - \frac{|g_i - s_i|}{\max(g_i - s_i)}\right)
\]

where \(SV\) is the similarity value; \(g_i\): number of pixels of a given rainfall image map and \(s_i\): number of pixels of one of the rainfall image files in the folder; \(N\) is the pixel value, i.e., 0-255. Similarity Value (SV) is the highest histogram similarity measure calculated by the given one and one of the files in the folder; the higher the similarity value, the closer of the two images.

![Figure 5. The architecture of the artificial intelligence platform of the study.](image-url)

2.5.3. Forecasting Method and Executing Flow Chart

In the study, a short-term ensemble rainfall forecasting method [44] was developed and deployed. In the method, four ensemble members were combined based on arithmetic average. For example, the rainfall forecast generated every hour included the antecedent three-hour rainfalls \((T - 3, T - 2, T - 1)\) at the current time \(T\). When the target time was three hours later, three different
rainfall forecasts were available at that target time. As a result, 3-h precipitation forecast images (T + 1, T + 2, T + 3) on hourly basis were created. The deployment diagram, implementation flow chart and a real-time example are described and depicted in Figures 6–8, respectively. Among the diagrams, examples of color-classified rainfall image datasets, in 10 mm increments, over the study area—at current, its antecedent 3-h measurement, and its next 3-h predicted measurement—are presented in Figure 6. The detailed short-term ensemble rainfall classification and pluvial flood forecasting approaches are illustrated step-by-step, as following, including the flow chart are shown in Figure 7. Furthermore, a scenario (the physical location indicated as the red square) of a rainfall hyetograph converted into a color-classified rainfall image dataset and retrieved from the corresponding flooding map dataset in real-time is displayed in Figure 8.

![Rainfall Forecast Images](image_url)

**Figure 6.** An example of current antecedent 3-h observed and next 3-h predicted color-classified rainfall intensity hyetographs over the study area.

Step 1—Input rainfall hyetograph image files to the AI platform:

Input a study district’s current and antecedent (prior) 3-h rainfall intensity maps (i.e., rainfall hyetograph map datasets T, T − 1, T − 2, T − 3) on an hourly basis.

Step 2—Transfer learning based upon these four image files:
Apply Inception V3 transfer learning algorithm and determine the folder of the maximum rainfall intensity.

Step 3—Calculate histogram similarity values:

Apply histogram similarity measure and calculate the similarity values between the T image file and individual map datasets in the rainfall intensity hyetographs folder (i.e., comparing T image file with each image file in the folder) and obtain a series of similarity values.

Step 4—Store rainfall intensity map with its corresponding similarity value:

After calculation, store the obtained similarity values into a list data type. This process iterates over Steps 2 and 3 until all maps in the database (i.e., folder) are compared.

Step 5—Sort similarity values and arrange their corresponding rainfall map datasets in descending order (individual map has its own time t):

At time T, sort similarity values and arrange their corresponding map datasets in descending order. Each individual map, in the order, has its own time t.

Step 6—Complete iterating of antecedent (prior) 3-h rainfall intensity maps (T − 1, T − 2, T − 3):

Calculate similarity values of rainfall intensity map of T − 1 with t − 1 map in the descending order of map datasets (only select the top 1000 maps in the folder). The similarity values of the map datasets are stored in a list data type. This process iterates Steps 2 and 3 until the top 1000 maps in descending order are compared. Repeat Step 6 for rainfall intensity maps of T − 2 and T − 3, respectively.

Step 7—Average similarity values (T, T − 1, T − 2, T − 3):

Average similarity values of (T, t), (T − 1, t − 1), (T − 2, t − 2), (T − 3, t − 3) of the top 1000 map datasets in descending order map datasets and store the values in a list data type.

Step 8—Select the highest average similarity value at time T and its corresponding rainfall intensity map:

In the list, select the highest average similarity value and obtain its corresponding rainfall intensity hyetograph (t) map. This time t and time T may not be the same values.

Step 9—Retrieve flooding map dataset from pluvial flood map datasets, i.e., database:

From Step 7, the rainfall intensity hyetographs map is obtained; search and retrieve the corresponding flood map in the flooding map datasets via direct indexing as indicated in Figure 9.

Step 10—Predict subsequent rainfall intensity map datasets:

To predict the subsequent 3 hours (T + 1, T + 2, and T + 3) of rainfall intensity map datasets, repeat the above Step 1–Step 8 processes.

Step 11—Display rainfall intensity map datasets and subsequent pluvial flood map datasets for time T, T + 1, T + 2, T + 3, on Google Map or Google Earth.
Figure 7. Rainfall map datasets and flooding map datasets developing, analyzing and predicting processes via Artificial Intelligence (AI) platform.

Figure 8. A scenario of rainfall intensity hyetograph converting into a color-classified image dataset and retrieving its corresponding flood map dataset in real-time.

2.6. Performance Indicators

The performance of assessments is based upon the following two indicators that quantify the error between observed and predicted measures [24,45,46]. First, the results of the predicted measures, obtained from AI platform methodology, were evaluated along with statistical analysis of the actually observed ones. The root means square error (RMSE) was used to evaluate and compare the actual observations with predicted results as a basic indicator and defined in Equation (3). The error of peak pluvial flood depth ($E_{dp}$) indicates the difference between the maximum observed and
the maximum predicted pluvial flood depths as defined in Equation (4). The error of time difference of the peak pluvial flood depths, \( ET_{dp} \), denotes the different occurrences of the maximum observed and the maximum predicted inundation depths as defined in Equation (5). The mean absolute percentage error (MAPE) is a measure of prediction accuracy of a forecasting method in statistics—for example, in trend estimation, also used as a loss function for regression problems in machine learning. It usually expresses the accuracy as a ratio defined in Equation (6). The equations of the indices are presented as below:

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{n}(d_{i,\text{observed}} - d_{i,\text{predicted}})^2}{n}}
\]  

\[
Ed_p = d_{p,\text{observed}} - d_{p,\text{predicted}}
\]  

\[
ET_{d,p} = T_{d,p,\text{observed}} - T_{d,p,\text{predicted}}
\]  

\[
MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{d_{i,\text{observed}} - d_{i,\text{predicted}}}{d_{i,\text{observed}}} \right| \times 100
\]

where:

- \( d_{i,\text{predicted}} \): predicted pluvial flood depth (m) at time \( t \);
- \( d_{i,\text{observed}} \): observed pluvial flood depth (m) at time \( t \);
- \( n \): number of measurements;
- \( d_{p,\text{predicted}} \): maximum predicted pluvial flood depth (m);
- \( d_{p,\text{observed}} \): maximum observed pluvial flood depth (m);
- \( T_{d,p,\text{predicted}} \): time when the maximum predicted pluvial flood depth occurs;
- \( T_{d,p,\text{observed}} \): time when the maximum observed pluvial flood depth occurs.

The Nash Sutcliffe Efficiency Coefficient (NSEC) [47] was used to evaluate the predictive performance of the model proposed in Equation (7). NSEC is a standardized value of the relative residual degree, with a range of \(-\infty < \text{NSEC} \leq 1\). The closer the NSEC value is to 1, the more accurate the predicted result becomes. If the value is close to 0, it indicates that the predicted (or simulated) results are close to the average of the observed ones. Thus, the overall result is credible. If it is much less than 0, the model is not credible which demonstrates an unacceptable performance.

In addition, from empirical experiences, when the NSEC value is between 0.5 and 0.9, it signifies that the trajectories of observed and predicted measurements are synchronized, and the gaps between the two measurements are narrow. On the other hand, when the NSEC value is between 0.1 and 0.5, the overall movements of the two measurements are similar over time, but the gaps between the two measurements are wider. In other words, the variations between the observed and the predicted values are larger.

\[
NSEC = 1 - \frac{\sum_{i=1}^{n}(d_{i,\text{observed}} - d_{i,\text{predicted}})^2}{\sum_{i=1}^{n}(d_{i,\text{observed}} - \bar{d}_{i,\text{observed.mean}})^2}
\]

3. Results and Discussion

This section provides a concise and precise description of the experimental results, their interpretation as well as a discussion that can be drawn from the study. According to the AI platform approach, a real scenario was implemented in the study area, i.e., Nantun river basin, Taoyuan City, Taiwan, as described previously. The hyetographs of three real torrential rainfall events, on 11 June 2012, 16 May 2016 and 2 July 2019, were conducted as the experiments to analyze, verify and validate the observed and predicted datasets via the developed AI platform and its methodologies.
3.1. Rainfall Hyetograph Map Datasets Similarity Analyses

Color is the most widely used attribute in image retrieval and object recognition. Rainfalls over the study region are imposed with QGIS tools and associated programming functions to convert the rainfall hyetographs into map layers and generate color-classified rainfall intensity map/image datasets.

The hyetographs of the heavy rainfall event, on 2 July 2019, resulted from an experiment conducted to measure the similarities of rainfall intensity images between the measured and the predicted datasets. Figure 9 indicates that the similarity values (SVs) of these two datasets fluctuate between 71% and 100% within a 24-h duration. The 100% SV was obtained because of no rain. The red stars exhibit the corresponding measured and predicted datasets and their related parameters at time \( t = 16 \).

![Figure 9. Similarity values of measured (obs) and predicted (pre) rainfall images in 24-h duration.](image)

3.2. AI Platform Real Case Application

A real practice has been investigated and implemented according to the rainfall event on 2 July 2019, with 30 monitoring stations (sensors) installed over the study region. Initially, Figure 10a indicates the distribution of measured pluvial flood depths in colors including layouts of sensors over the study area. Figure 10b is the CCTV image caught at monitoring station 15 while flash floods occurred. Figure 10c presents the AI predicted pluvial flood results which were imported into KML and KMZ files and displayed via Google Earth. The red circles, shown in three diagrams, indicate the same location, i.e., at station 15, while flash floods occurred. The maximum observed pluvial flood depth in the region is 0.4 m; the maximum predicted pluvial flood depth is 0.3 m.

Figure 11 illustrates the AI platform simulated pluvial flood depths at time T and its following three hourly predicted floods. Figure 11a displays the simulated results in color at 4:00 p.m. on 2 July 2019. The next 3-h predicted pluvial flood depths and their affected areas are presented in Figure 11b–d, respectively. Figure 11a,b indicate that the predicted flash flooding in the next hour increases. Figure 11b,c demonstrates that the flooding begins to recede. Figure 11c,d implies that the floods withdraw from the region. These forecast outcomes can be utilized and analyzed for traffic rerouting in urban districts while flash floods occur, especially after working hours to avoid traffic congestion. Furthermore, the forecasts can definitely provide inputs and strategies for decision-makers in order to mitigate the urban flash flooding damages.
Figure 10. (a) The actual measured pluvial flood depths distributed over the study region, (b) closed-circuit television (CCTV) image caught at monitoring station 15 and (c) the AI simulated/predicted results presented by Google Earth. The red circle indicates the same location, at station 15, in the study region.

Figure 11. Simulated (T) and predicted (T + 1, T + 2, T + 3) pluvial flood.
Figure 12 indicates that the rainfall hyetographs of current (T) and its antecedent 3-h (T − 1, T − 2, T − 3) rainfalls are measured (or observed) by collecting from rainfall gauges or monitoring stations. The predicted rainfall hyetographs of the next 3-h (T + 1, T + 2, T + 3) can be obtained from QPESUMS data. In other words, the predicted rainfalls were not generated by ensemble approaches as presented in this study case. This indicates that the research can be extended to obtain the predicted rainfalls from QPESUMS data directly as well, with the methodologies and implementations following the same approaches as presented at the left-hand side of the diagram.

Figure 12. Another approach by introducing Quantitative Precipitation Estimation and Segregation Using Multiple Sensors (QPESUMS) data as the next 3-h predicted rainfall hyetographs and following the methodologies as presented in the left-hand side of the diagram.

Figure 13 presents pluvial flood depths of observed ones (in red), SOBEK model simulated ones (in green) and AI platform predicted ones (in blue), during a 24-h period, at monitoring stations 4, 6, and 15, installed in the study region over three heavy rainfall events, 2 July 2019, 16 May 2016 and 11 June 2012, respectively. The diagrams, in general, compared with the observed pluvial flood depths and their trajectories, indicate that the AI predicted ones have higher accuracies than those of SOBEK model simulated ones at each monitoring station as well as under each rainfall hyetograph pattern. Moreover, the SOBEK model simulated pluvial flood depths have higher values with longer delays or lags of flooding occurrences than those of observed ones, especially for the event on 2 July 2019. On the other hand, the AI predicted pluvial flood depths are less than those of the observed ones, having earlier flooding occurrences than the actual observed timing. Furthermore, while the rainfall hyetograph has a longer duration and a rainfall intensity that is relatively evenly distributed, i.e., on 11 June 2012, the AI platform predicted results match closely with the measured ones as displayed in the diagram. However, for the skewed rainfall hyetographs, i.e., 16 May 2016 and 2 July 2019, either the predicted or simulated results are not matched accordingly with the observed ones.
Figure 13. The inundated water depths of observed (in red), SOBEK model simulated (in green) and AI platform predicted (in blue) at monitoring stations 4, 6 and 15 over the study area during three rainfall events.

3.3. Performance Evaluation and Methodologies Comparison

Error analyses between the AI platform methodology and the SOBEK model simulation based on the three rainfall events at monitoring stations 4, 6, and 15 are compared and presented in Table 2. In the table, the RMSE values of the two approaches are small, ranging from 0.02 to 0.44. This indicates that both approaches can accurately predict/simulate pluvial flood depths in the study area. For 11 June 2012 and 2 July 2019 events, the AI platform approach obtains higher accuracy than that of the model simulated. However, regarding the 16 May 2016 event, the model simulation results are marginally better than those of the AI platform approach. The peak pluvial flood depths, $E_{dp}$, of the AI platform method are slightly underestimated, compared with the observed ones, for all events at all stations. The $E_{dp}$ data of the simulated model are either slightly overestimated or underestimated. In addition, in general, the AI platform method can provide predicted pluvial flood occurrences hours in advance of the actual flooding instances during all rainfall events such as the $ET_{dp}$ values displayed in the table.

Table 2. Error analyses of the measured/predicted pluvial flood depths comparison.

| Rainfall Events | Station | RMSE (m) | Error of Peak Flood Depth (m) | Error of Time to Peak Flood Depth (h) |
|-----------------|---------|----------|-------------------------------|--------------------------------------|
|                 |         | AI       | Flood Model                   | AI                                   | Flood Model |
| 11 June 2012    | 4       | 0.13     | 0.17                          | -0.21                                | -0.06       | 1           | 0           |
|                 | 6       | 0.14     | 0.22                          | -0.22                                | -0.15       | 1           | 0           |
|                 | 15      | 0.33     | 0.44                          | -0.13                                | 0.11        | 1           | 0           |
| 16 May 2016     | 4       | 0.05     | 0.06                          | -0.09                                | 0.04        | 2           | 1           |
|                 | 6       | 0.24     | 0.17                          | -0.13                                | -0.10       | 1           | 1           |
The values of NSEC over the three rainfall events, evaluated at monitoring stations 4, 6, and 15, are presented in Table 3. The values characterize the agreement between the AI platform predicted inundated water depths and the observed ones of the experiment. In the table, all NSEC values, ranging between 0.15 and 0.84, are generally viewed as acceptable performance. For the 16 May 2016 rainfall event, the average NSEC value is 0.72; this reveals that the predictive model, i.e., the AI platform approach, is highly reliable, as described in [47]. If the NSEC value is close to 0, this indicates that the predicted results are close to the average of the observed ones. Thus, the overall results are credible to all three rainfall events.

However, the values of MAPE over the three rainfall events are inconsistent. For the 2 July 2019 event, the average MAPE value is 11.49. The average MAPE values of the other two events are greater than 50%. According to Figure 13, for events of 11 June 2012 and 16 May 2016, the observed inundated water depths (in red) are higher than the AI predicted ones (in blue) after the rain stopped. Apparently, the accumulated flooding water did not withdraw from the region and induced higher MAPE values. For 2 July 2019 event, both the observed inundated water depths and the AI predicted ones are zero while precipitation stopped.

Table 3. AI platform and Mean Absolute Percentage Error (MAPE) and Nash Sutcliffe Efficiency Coefficient (NSEC) performance evaluation.

| Station | 11 June 2012 Rainfall Event | 16 May 2016 Rainfall Event | 2 July 2019 Rainfall Event |
|---------|-----------------------------|-----------------------------|-----------------------------|
|         | MAPE (%) | NSEC | MAPE (%) | NSEC | MAPE (%) | NSEC | MAPE (%) | NSEC |
| 4       | 60.41    | 0.21 | 28.30    | 0.75 | 9.44     | 0.32 |
| 6       | 77.08    | 0.57 | 48.73    | 0.56 | 5.13     | 0.34 |
| 15      | 86.35    | 0.15 | 84.48    | 0.84 | 19.89    | 0.48 |
| Average | 74.61    | 0.31 | 53.84    | 0.72 | 11.49    | 0.38 |

The critical success index (CSI) was selected to validate the AI platform’s predicted flood grid (20 × 20 m per grid cell) accuracy ($A_r$), where $A_r$ is the number of predicted flood grids where floods actually occurred; $A_f$ is the number of predicted flood grids, but floods occurred; $A_o$ is the number of predicted flood grids, but no flood occurred. The range of the accuracy is between 0% and 100%. Zero percentage means that the prediction completely failed, and one hundred percentage means that the prediction is fully accurate. The AI platform CSI values of the three rainfall events are presented in Table 4. As seen in the table, the accuracies of the events ranged between 65% and 69%. This indicates that the AI platform can be applied to predict pluvial floods in urban areas.

Table 4. AI platform accuracy of validation by critical success index (CSI) [47].

| Rainfall Events | Observed Area (km²) | AI Area (km²) | $A_r$ (km²) | $A_f$ (km²) | $A_o$ (km²) | $A_s$ (%) |
|----------------|---------------------|---------------|-------------|-------------|-------------|-----------|
| 2 July 2019    | 0.41                | 0.38          | 0.31        | 0.10        | 0.07        | 64.58     |
| 16 May 2016    | 0.48                | 0.38          | 0.35        | 0.13        | 0.03        | 68.63     |
| 11 June 2012   | 2.58                | 2.43          | 2.02        | 0.56        | 0.41        | 67.56     |

4. Conclusions

The study aims to develop and deploy an effective real-time pluvial flood forecasting platform by applying prepared databases of rainfall intensity map datasets and their corresponding simulated flooding datasets, as well as through the mechanism of AI transfer learning classifications to extract feature parameters of rainfall images and detect potential flash floods in metropolitan regions. The approach can be performed and executed promptly in real-time and ensure sufficient lead time in order to prevent possible pluvial flood hazards.
In the study, the rainfall event datasets were generated according to the average of the current and the previous 3-h measured rainfall patterns to train, evaluate and predict the subsequent 3-h rainfall hyetographs. The research uses QGIS applications to convert rainfall hyetographs and pluvial flood depths into a geographic file system-based database integrated via Google Earth to provide interactive 3D visual effects of flooding over the study area.

However, the simulated flooding depths can be generated by any 2D pluvial flood model. Because the SOBEK model can be fully integrated with the Geographic Information System (GIS) layers, the depths of flooding were estimated and calculated by the SOBEK model. Furthermore, other simulation approaches, for example, each rainfall event being defined as a discrete event—discrete event simulation modeling—can be considered and investigated as well. The performance assessments of the study are based upon the RSME and Nash Sutcliffe Efficiency Coefficient (NSCE) indicators. The outcomes indicate that the methodologies of the AI platform are reliable and acceptable.

Apparently, the progress of flash flood predictions in terms of applying deep learning techniques will have numerous successes in the near future because the technique requires very little engineering by hand. Thus, the prediction process can easily take advantage of increases in the amount of available computation and data. In addition, new learning algorithms and architectures that are currently being developed for deep neural networks will only accelerate this progress.

According to the results, the AI platform approach can predict pluvial flood occurrence almost one hour earlier than when it actually happened. Therefore, the approach can provide, as a reference, decision-makers to respond promptly before flooding. In this study, the total execution time of the method is less than 6 minutes from the time taken to obtain the rainfall data to the time taken to display the flooding instance on web pages (including rainfall data preprocessing, image dataset conversion and analysis, as well as automated scheduling and computing). In the disaster prevention spectrum, the lead time and an imminent response are critical and essential in order to mitigate damages or losses.

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