

# Flood Prediction through Artificial Neural Networks

A case study in Goslar, Lower Saxony

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**Abstract**—In this project, a system was developed, which allows a flood prediction based on given data sets for a level measuring station in the Goslar area for a period of four hours. First, existing neural networks, which were developed during a seminar at the TU Clausthal, were extended with the help of the framework Tensorflow and investigated whether larger water level values and further flood scenarios allow good qualitative prognoses. Furthermore, the influencing factors of possible floods were identified based on past scenarios. In addition to gauge and precipitation measuring stations in the immediate vicinity of Goslar, weather data from the Institute of Electrical Information Technology (IEI), which have been available every 15 minutes since 2003, were also taken into consideration. These data sets were processed and evaluated accordingly, so that a qualitative prediction can be made for exact water gauge heights. In addition, in order to reduce the training time, a dimension extraction was performed using a Principal Component Analysis (PCA), in which main components were identified and the data set examined for patterns in order to determine the possibility of a dimension reduction. In order to transfer the neural network to further scenarios, a prediction was made for the area of Bad Harzburg, where two measuring stations with additional weather data were used as inputs.

**Keywords**—Machine learning; Neural networks; PCA; Feedforward neural networks; Flood prediction.

## I. INTRODUCTION

Floods are events, which, depending on the region and their characteristics, can have devastating consequences for people and their homes. At first, it is not always quite clear which exact interrelationships have been involved in the development of these events and have led to the subsequent catastrophe. Even if several flood events have occurred in the same region over the years, different reasons may have led to the individual incidents. This also applies to the area around Goslar, a town in the northwestern part of the Harz in the federal state of Lower Saxony. In July 2017, probably the most devastating natural disaster of the last century occurred here. Within only two days, 306 l/m<sup>2</sup> (according to the records of Harzwasserwerke GmbH at the Eckertalsperre) of rainfall fell in the immediate vicinity. This rainfall could be recorded at the gauging stations installed there in the period from 24.07. 9:00 am to 26.07. 12:00 pm [1]. The reason for this high precipitation could be found quickly and can be traced back to

the low-pressure area “Alfred”, which led to many floods in other areas in the northern Harz.

Another example concerned 10 May 2018 (Ascension Day). Here, precipitation of up to 100 l/m<sup>2</sup> fell within a few hours, with the Abzucht, a tributary river of the Oker, which was still largely responsible for the flood in the previous year, remaining far below the critical limit. Both situations show that although precipitation can play an important role, it is limited to a certain catchment area and can lead to flooding due to the direction of water flow in the local environment. Experience has also shown that other variables, such as soil moisture or snow melting must also be considered in order to be able to make accurate statements about whether there is a risk of flooding.

An evaluation of all theoretically possible parameters and measuring stations would take a lot of time and is currently already being implemented by an external warning system from the “Harzwasserwerke”. Different predictions e.g., for precipitation and temperatures are compiled and evaluated manually. The problem that arises at this point is the resulting warning time of approx. 20 minutes. This period is not sufficient for a complete preparation of the local fire brigade. In order to increase this early warning time and to be able to make a qualitative statement about a future flood, a self-learning neural network will be created which automatically predicts a future (possible) exceeding of a threshold value at a water gauge measuring station. For this purpose, historical weather data as well as water level and rainfall data from the immediate vicinity of Goslar are used, which are fed into the neuronal network and used for training. The network optimizes the data based on the previously processed data and then provides information on whether there is a risk of flooding for another independent set of test data.

In the beginning existing work was taken up to check whether a flood can be predicted. These were evaluated and improved in order to be able to predict exact water levels with a maximum deviation of 5cm. Finally, a transfer to another scenario in Bad Harzburg takes place, where a flood prediction for another environment is made using another measuring station.

Section 2 starts with two related works, which have already dealt with similar topics. In section 3 a short explanation of the preliminary work is given, which has already investigated this topic in the context of a seminar at the TU Clausthal. Based of this works, a forecast of floods in Goslar is finally

made. This serves to investigate whether an improvement of their algorithms can be made. Then a prediction of exact water levels is made. This forecast is then examined for dimensional reduction using a Principal Component Analysis (PCA) and evaluated for another scenario in Bad Harzburg. Section 4 briefly lists and compares two further alternative learning methods. In the end section 5 concludes with an explanation of the further outlook.

## II. RELATED WORK

In this section, two related works are taken up, which deal with similar topics. The first work deals with a service provided by Google, which is part of the Google Public Alerts Program and can use Artificial Intelligence (AI) to predict floods in the Indian region and then send warnings to the inhabitants [2]. The second work deals with an AI technology for reliably predicting earthquakes in different parts of the world [3].

### A. Google Public Alerts

In 2017, Google provided special warning services within Google Maps, Google Now and in the normal Google search to warn affected people of imminent disasters. These include storm warnings, hurricane evacuation alerts, forest fires and earthquakes. The data is made available by the cooperation partners from the USA, Australia, Canada, Colombia, Japan, Taiwan, Indonesia, Mexico, the Philippines, India, New Zealand and Brazil, collected by Google and displayed for all users worldwide. Only early flood warnings were not made available to users on this platform. Since these were not offered by the cooperating partners, Google has developed its own service, which uses Artificial Intelligence to predict flood catastrophes. Using historical weather and flood events, as well as river level measurement stations and terrain conditions, these data are processed and fed into a neural network and then simulated on maps [4]. The subsequent prediction results are stored in Google Public Alerts with the severity of the event.

For a first test with real data, Google Public Alerts was released in September 2018 in the Patna region in India and first floods were successfully predicted. India's central water authority is working closely with Google to achieve better results in the future, which can be better achieved by Google than by the authorities themselves due to its technical expertise and the computing power it provides. In the future, cooperation's with Europe will also be realized in order to make similar predictions and make them available to users. In this case, interfaces would have to be created to enable Google to have permanent access to data.

### B. Artificial Intelligence based techniques for earthquake prediction

A second elaboration [3] also deals with an early warning system, which was built based on Artificial Intelligence. Here, the prediction was not of floods but of earthquakes, whereby different approaches for the realization of such systems were compared with each other. Basically, earthquakes can be characterized by two properties. This is on the one hand the magnitude and on the other hand the depth. Those that are

classified as fundamentally dangerous are those that are at a shallow depth and have a high magnitude. These are weighted correspondingly higher in the neuronal network. Based on input data from southern California, archived in the Southern California Earthquake Data Center (SCEC), earthquakes were tested in a Probabilistic Neural Network (PNN) of various strengths, of which 102 out of 127 earthquakes were successfully detected in the test data sets of classes 1 to 3. Stronger earthquakes were also used in the test data sets. These were not successfully detected according to the paper, so instead of PNNs RNNs (Recurrent Neural Networks) for magnitudes from 6.0 were investigated [5]. In data preprocessing, the area is divided into smaller regions and the time in which the earthquake occurred into several time slots. Subsequently, these sections were processed including their relation to larger earthquakes in the investigated region. Another scenario presented here concerns Chile. For this purpose, a Novel Neural Network, which predicts whether an earthquake will occur or not over the next five days [6]. The earthquakes used for this purpose were taken from two earthquake catalogues [7] and [8], which record all seismological activities in South America. Earthquakes from a magnitude of 4.5 in the period from 1957 to 2007 were used for this purpose.

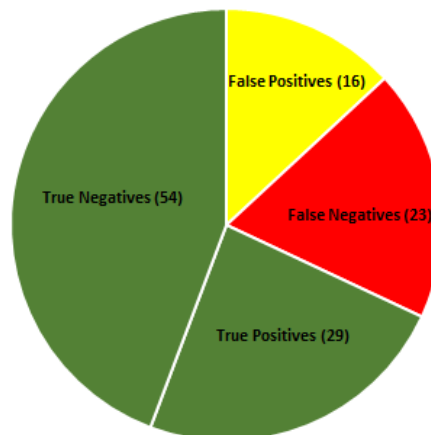


Figure 1. Pie chart for the earthquake forecast of the Chile Peninsula [6]

The training and test procedure took place in various regions in Chile, whereby different warning times and earthquake magnitudes were used. On average, results were close to 71%. From the 122 earthquakes defined in the test data, a pie chart was created, which is shown in Figure 1. Here, not only the occurrence of an earthquake was predicted, but also its strength, whereby a deviation of 1% flowed into the result.

## III. IMPLEMENTATION AND RESULTS

### A. Preliminary work

In the context of a seminar at the Clausthal University of Technology, three seminar papers on this topic were written, which dealt with the help of different AI frameworks (CNTK from Microsoft, Tensorflow from Google and Caffe from the University of California, Berkeley) and the previously defined



Figure 2. Used measuring stations: source (modified): openstreetmap.org

problem [9] [10] [11]. It was their task to create a neural network based on given data and to determine the data and result quality on this basis. It should be identified if that framework is suitable for this problem and how the result can still be improved. Two data sets were provided:

- A training data set from 01.11.2003 to 03.12.2012 consisting of approx. 80000 data points in 1-hour intervals
- A test data set from 14.06.2015 to 01.01.2018 consisting of approx. 22000 data points in 1-hour intervals

Both data sets contained the water levels (cm) and flow rates (m<sup>3</sup>/s) at the water level measuring stations Sennhütte and the Margarethenklippe, rainfall data (mm) in Hahnenklee and the Granetalsperre. In addition, weather data were provided by the Institute for Electrical Information Technology at Clausthal University of Technology. These contained the temperature, the humidity, the air pressure, the solar radiation, the wind speed and the wind direction, whereby an average over the period of one hour took place. In addition, each data point was assigned a label  $\epsilon \in [0,1]$  indicating if flooding had occurred. Decisive for this was the water level at the water level measuring point Sennhütte, whereby it was defined that the water level of 40cm marked a flood. The measuring stations are shown in Figure 2 on a map (A: Hahnenklee, B: Granetalsperre, C: Margarethenklippe, D: Sennhütte).

The task was to make a flood prediction for the location Sennhütte with an early warning period of one or 48 hours. In order to achieve this, the provided data was processed. The average values of the last 2, 4, 8, 16 and 32 hours of rainfall were used for the input vector by a supposed connection between the water quantities in the rivers and the past precipitation values. The same procedure was used for the temperature values. Similarly, the seminar participants

formed the averages of the individual water levels and air pressures over 1, 2, 3 and 4 hours. After processing, the data was fed into the neuronal network.

For all three seminar papers, the results for the prediction of one hour are presented in the Figures 3-5. For this purpose, a confusion matrix was created, which compares the results of the prediction and the results in the test data set. The correctly predicted results were highlighted in green, while the false alarms (false positives) were highlighted in yellow and the false negatives in red. This has the background that the false-negative results should be avoided altogether, as they would have devastating consequences by an incoming flood. The false positives should also converge towards 0, as this would result in unnecessary deployment of the emergency services. The consequences, however, would be manageable and have a lower damage potential.

Confusion matrix		Label	
		Flood	No Flood
Prediction	Flood	54	2
	No Flood	9	11008

Figure 3. Result with Framework Caffe [9]

Confusion matrix		Label	
		Flood	No Flood
Prediction	Flood	62	57
	No Flood	1	11053

Figure 4. Result with Framework CNTK [10]

Confusion matrix		Label	
		Flood	No Flood
Prediction	Flood	80	47
	No Flood	3	11031

Figure 5. Result with Framework Tensorflow [11]

In all three elaborations, a two-hour and four-hour forecast was discussed in more detail following the 1-hour forecast. Similar results could be achieved, which only worsened significantly with an increase to eight hours. For this reason, the further investigation of this work will concentrate on a 4-hour forecast, which would represent a considerable improvement in view of the warning time currently in use.

### B. Prediction for higher water levels

Based on the preliminary work of the seminar participants, their algorithms should first be examined for major flood hazards. For this purpose, the water levels, which characterize floods, were increased to 50, 60, 70 and 80 cm. For better results, the data from the measuring stations were processed at 15-minute intervals instead of one hour. Like the preliminary work, the precipitation data at the measuring stations of the Granetalsperre and Hahnenklee were averaged over 1, 2, 4, 8, 16 and 32 hours and fed into the net as additional parameters. The values of the last 1, 2, 3, 4 and 5 hours were calculated for the outflow and water level measurements at the Margarethenklippe and the Sennhütte and fed into the neuronal network as additional dimensions.

In order to guarantee an even better quality, the same weather data set was used that was already used in the seminar papers. From these the average temperatures of the last 1, 2, 4, 8, 16, 32 hours were calculated and transferred together with the air humidity, the air pressure at the considered time, as well as before 1, 2, 3 and 4 hours into the input vector. The considered solar irradiation value and the wind speed were taken over in addition.

For the prediction of higher water levels, moving averages were formed which, in contrast to the arithmetic mean, are not formed over all data records, but only over a selected period. In this case, for example, this applies to temperatures of up to 32 hours and 128 data records. For the classification of the network, a label was created, which can be used for different Scenarios indicated if there was a flood (0=no flood, 1=flood). In order to consider data sets that indicate a flood hazard during the training process of the neural network more, an additional field is added to the input vector called "weight". This tells the network how often this data set should be trained in comparison to the data that do not represent a flood hazard. It is calculated from the ratio between the data sets with the label 1 and the label 0 used in the training data set. In addition to the data preparation, the scenarios to be tested were also determined. These were a total of 12, whereof the water levels of 50, 60, 70 and 80cm with a warning time of 1, 2 and 4 hours were considered. Good forecasts were achieved for all forecasts. This also affected the events with a four-hour warning time.

Two hidden layers with a neuron count of 128 and 64 neurons were used for the network architecture. The sigmoid function was used as activation function, which carried out the training with a learning rate of 0.001 and 10000 training steps. The optimization function for this case was the Proximal Adagrad-Optimizer. Figure 6 shows the confusion matrix at a water level of 50cm and an hour warning time.

Confusion matrix		Label	
		Flood	No Flood
Prediction	Flood	195	413
	No Flood	0	156024

Figure 6. Confusion matrix at 50cm water level and one hour warning time

The number of false negatives could be completely reduced to zero. This applies to all scenarios listed above in the same way. In addition, 413 results were issued as false alarms, which, like the preliminary work, was largely due to a better early warning period, in which the occurrence of a flood event was predicted too early. Since the confusion matrices for the other eleven scenarios contained similar values, these are not listed here.

### C. Prediction for concrete water levels

After the prediction of flood events for different scenarios, the prediction of exact water levels will be dealt in the following. The same data basis was used as for the previous prediction. The forecast was made for the gauging station in Sennhütte. Since only a few floods were available in the database from 2003 to 2018 and their level levels varied, two

different training and test data sets were distinguished for this prediction:

- A test data set from 2014 to 2018 and a training data set from 2003 to 2013
- A test data set from 2003 to 2008 and a training data set from 2009 to 2018

Since a neural network can only learn the water levels that were made available to it in the training set, it was not possible in the first case to correctly predict the water levels of the 2017 flood because these were outside the value range. For this reason, the order was reversed and this flood was integrated into the training data set.

In order to enable the neural network to correctly learn less frequently occurring water levels in the training set, all data points have been assigned a weight indicating how often the corresponding water level should be trained in the data set. The rarer the water level appears in the entire training data set, the higher the number of training runs in the neural network for this one data set.

In contrast to the prediction for higher water levels more neurons were used in this scenario. For the first hidden layer these were 512 and for the second hidden layer 256 neurons. Furthermore, the sigmoid function was used again as activation function and the Proximal Adagrad-Optimizer as optimization function, again with a learning rate of 0.001. Only the number of training steps was adjusted in the parameters. So, this has increased from 10000 training steps to 100000 steps, because the best prediction results could be achieved.

For the test cases, 170 (largest measured water level) different classes were created, which were used as classification basis for the data sets. In the prediction, the neural network finally assigned each data point to a class, whereby the actual and target states could be compared with each other. Tables 1 and 2 show the results of both predictions.

TABLE 1 PREDICTION FOR 2014-2018 (157611 RECORDS)

Difference greater than [cm]	Number of data sets	Accuracy [%]
0	7429	95.29
1	356	99.77
2	184	99.88
3	147	99.91
4	127	99.92
5	113	99.93

TABLE 2 PREDICTION FOR 2003-2008 (181026 RECORDS)

Difference greater than [cm]	Number of data sets	Accuracy [%]
0	12571	93.056
1	1741	99.04
2	740	99.59
3	367	99.8
4	207	99.89
5	131	99.93

On the one hand, the tables contain the number of data sets whose values in the prediction differ from those in reality by a certain amount and on the other hand the ratio of these to the total number of data sets. Both tables show good results, which show an accuracy of 99% at a water level difference of 1cm

*D. Principal Component Analysis (PCA)*

From the amount of data used so far, it is not possible to deduce which attributes have the greatest impact on the training and results of the neural network. An identification of the most important influencing factors allows a reduction of the input data and computing time, as well as a de-noising of the data set. An overfitting of the network is also limited by the dimension reduction, since a larger number of dimensions leads to a larger adjustment of the neural network. to get better results.

In the following, a Principal Component Analysis (PCA) is presented, which calculates possible main components based on linear combinations and enables a dimension reduction on of these. For this purpose, the original dimensions  $p$  are reduced to a smaller number of dimensions  $q$ , which summarize the essential information of the  $p$  dimensions.

First, the data set is standardized in order to ensure a correct distribution of the individual characteristics and to realize independence from the value ranges. From this standardized data set, a covariance matrix is created, which contains the covariance of each attribute with every other attribute. The eigenvalues and eigenvectors are calculated from this covariance matrix. The eigenvectors form the main components, while the corresponding eigenvalues signal how much information is contained in them [12]. The  $p$  eigenvectors with the largest eigenvalues are then filtered out. This serves to form a transformation matrix  $T$  consisting of  $m$  rows (number of dimensions) and  $p$  columns (number of eigenvectors). The following 12 attributes were selected for the realization of the PCA in this paper: rainfall from Hahnenklee and the Granetalsperre, outflow and water levels of the Margarethenklippe and the Sennhütte, as well as weather data consisting of temperature, air humidity, air pressure, radiation, wind speed and wind direction, in each case in the interval of one hour, resulting in 102040 data records. The first main component is obtained by minimizing the sum of the squared deviations of all variables. In other words, to extract the first component, the portion of variance that the component can explain across all variables is maximized. The remaining variance is then explained step by step. This means that the second component should clarify as much residual variance as possible. This procedure continues until the total variance of all data is theoretically explained by the main components.

The first seven main components of the Principal Component Analysis would be sufficient to maintain 90 percent variance. These account for 93.27 percent of the total variance, so a reduction from twelve to seven dimensions would only result in a 6.73 percent loss of information. Using these results, it can be concluded that all data from the measuring stations would be sufficient to have a large part of the information. The weather data only have an influence of

6.73 percent on the total information content and could therefore be discarded.

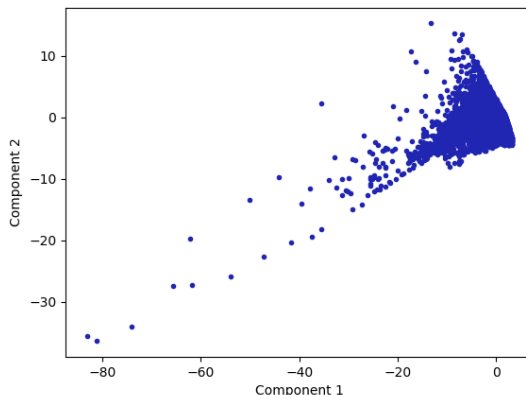


Figure 7. Reduction to 2 dimensions

The Reduction means that the computation time and memory problems can be decreased, as fewer dimensions are included in the calculation without a significant loss of the prediction quality. Figure 7 shows a reduction to two dimensions, with clustering of the data points around the coordinate origin.

*E. Bad Harzburg area*

The following is a review of the neural network for a further Scenario outside the previously considered catchment area. For this purpose, the region around Bad Harzburg with one precipitation and one outflow/level measuring station each installed at the Baste was examined more closely. Since in contrast to Goslar only two measuring points were available, the values for soil moisture (only derived), air temperature and precipitation, provided by the “Deutschen Wetterdienst” at 10-minute intervals, were also used. In total, this resulted in 520128 data records.

The task was to predict water levels of 50, 60, 70 and 80cm for one, two and four hours and to evaluate them by the flood from 24.07.2017 to 27.07.2017. After the data preparation, the data set was labelled. All data points which exceeded the flood threshold value were assigned the code number 1. All other data points were given the value 0. Another field contained a weight that trained data sets that signaled flood hazard more frequently in the network than data that did not.

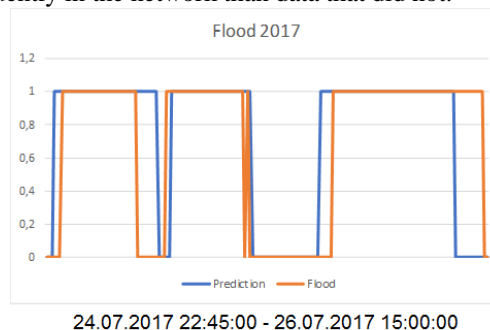


Figure 8. Prediction for Bad Harzburg at a water level of 80cm and two hours

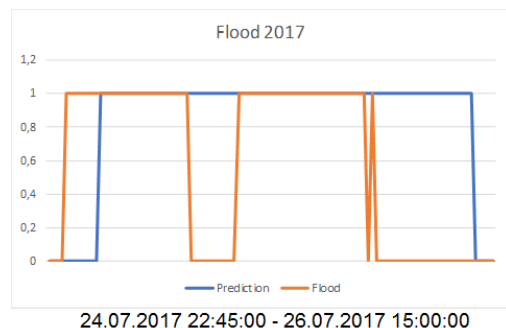


Figure 9. Prediction for Bad Harzburg at a water level of 80cm and four hours

The results of the prediction presented at Figure 8 and 9 are exemplary for a two- and four-hour prediction for a threshold value of 80cm. At first glance, it is clear that good results were obtained for an advance warning time of two hours, but that these results clearly deteriorated with an increase to four hours.

In order to enable a comparability with the results of the level measuring station Sennhütte, the same parameters were used for the creation, the training and the testing of the neuronal network. These parameters included the learning rate (0.001), the number of training sessions (10000) and the number of hidden layers (2 with a neuron count of 128 and 64 neurons). The activation function was the sigmoid function and the optimization function the Proximal Adagrad-Optimizer. For this reason, it can be concluded that the number and location of the gauge, outflow and precipitation measuring stations have a major impact on the quality of the results and that it might be advisable to add more for better results.

#### IV. ALTERNATIVE METHODS

This paper deals with Artificial Neural Networks (ANN), which in this case were excellently suited for supervised learning. There are also alternative methods such as Regression Trees or Ensemble Learning that can also be used. Regression Trees belong to the group of decision trees and deal with the mapping of decision rules to a branched tree, which is then traversed from the root to the individual leaves based on various decisions.

With regression trees a continuous value is mapped on the individual leaves (e.g., a time series analysis), so the aim of this method is the prediction of continuous values. This has the advantage that for small amounts of data it is easy to understand which decision is made at which moment. However, this clarity decreases considerably with an increasing number of decisions. A further problem here is the overfitting, in which the error increases continuously with new test data records at a certain point [13].

In contrast to other methods, Ensemble Learning uses several different learning algorithms at the same time. A set of predictors (ensemble) is formed, which together form an average (ensemble average). In this way, certain outliers can be corrected by other learning methods. If there is a method that is best suited to the problem, it will outperform most other

learning methods in ensemble learning. Furthermore, the more methods used, the more difficult it will be to interpret the results. The biggest restriction, however is the learning time. The more methods are used, the longer the algorithm needs to calculate the prediction result, which is the reason why this work is limited to only one learning procedure [14].

#### V. CONCLUSIONS

The aim of this work was to establish, train and evaluate a neural network for the detection of flood hazards and concrete water levels in the area around Goslar. In addition, existing works were examined, trained and tested for the recognition of flood inlets starting from a higher water level. Increasing the warning time to four hours produced very good results. All floods in the period from 2003 to 2018 were successfully detected and predicted accordingly. A reduction of false alarms was successfully achieved, but some were left over time, which in some cases resulted in false positive predictions. This, however, was usually related to a danger that had already occurred shortly before. Further water level, precipitation and outflow measuring stations could be used to identify further floods outside the area (here: Sennhütte). For example, the flood of 10 May 2018 did not appear in the data, but was defined as a flood hazard.

In addition to the identification of floods, the prediction of exact water levels was also a task of this work. The same data sets as for the flood prediction were used to divide the data into two scenarios. For each scenario, it was necessary to predict the water levels at the Sennhütte with a maximum deviation of 5cm. The results showed an accuracy of close to 99% from a difference of 1cm, only higher water levels, which were either outside the value range of or only with a very small number in the training datasets were not detected and were above the 5 cm deviation limit. In order to obtain better results for the higher water levels, further floods in the training data would be necessary.

The consideration of a dimension reduction for the selected data set with 12 dimensions has shown that seven dimensions would be enough for over 90 percent variance conservation. As an alternative classification method an LDA [15] can be used. When using a discriminant function two or more groups can be examined simultaneously for a plurality of characteristic variables. Furthermore, new objects whose class affiliation is not known can be rearranged. Later collected data can be easily assigned.

The evaluation for the area of Bad Harzburg was also able to precisely detect and predict floods up to a warning time of two hours. When this time was increased to four hours, the accuracy was no longer sufficient. An addition of further measuring stations to determine the water levels, outflow quantities and precipitation could produce a similar result quality as for the area around Goslar.

Until now, the measurement of the prediction quality has only been calculated using confusion matrices, which did not provide a meaningful evaluation of false alarms. For a better determination of the quality of the neuronal network, another method can be used, called cross-validation method [16]. The most frequently used method is k-fold cross-validation. At the beginning there is a division of the data into k equal parts, also

called folds. Subsequently, the network is run through  $k$  times, where  $k-1$  folds are used as training data set and the remaining fold as test data set. With each further run a different fold is used as test data set, so at the end of the validation procedure  $k$  accuracies are available from which the arithmetic mean will be formed. The multiple runs of the net with different folds provide information about the sensitivity of the net, since each data point in the data set was available exactly once in the test data set.

The preprocessing of the time series of the different measuring stations and weather data can also be replaced by a recurrent neural network. Here, the data of the past time points are stored in the input layer. A recurrent neural network can use this information, which are stored internally.

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