StormMind
AI based Web-Service for Storm Damage Prediction

Bachelor Thesis

ZHAW School of Engineering
Institute of Computer Science

Submitted on:
06.06.2025

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Computer Science

Declaration of Authorship

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I have no limitations.
— Thomas Shelby

To our parents…

Abstract

Extreme weather events cause considerable damage to infrastructure, the economy and the environment worldwide. Predicting such damage can help to optimize preventive measures and reduce costs. In this project, a neural network is being developed that analyzes historical weather data and damage reports to predict potential storm damage in Switzerland based on new weather forecasts. Using modern machine learning techniques, relevant patterns are recognized in order to train a predictive model. The model is tested for accuracy and optimized to enable reliable predictions.

Key words: Machine Learning, Neural Network, Storm Damages

Acknowledgements

We would like to thank Andreas Meier for his valuable support and guidance throughout this project. Additionally, we would like to thank to Dr. Katharina Liechti which has provided us with valuable insights about the sciences of weather and storm damages. For providing and collecting data to make this project possible, we also like to thank to the Swiss Federal Institute for Forest, Snow and Landscape Research WSL.

Preface

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Key words:

Contents

List of Abbreviations

FNN	Feedforward Neural Network	**RNN**	Recurrent Neural Network
LSTM	Long Short Term Memory Neural Network	**VGP**	Vanishing Gradient Problem
NN	Neural Network		

1 Introduction

1.1 Motivation

Why do we do this?

1.2 Work Outline

What do we want to predict etc.

2 Theoretical Background

2.1 Weather Research

2.1.1 Reason for Flooding

- Drought Followed by Heavy Reain
- Snowmelt in Spring

2.1.2 Reason for Landslide

- Slope, Water, Soil Condition

2.2 Machine Learning

Machine Learning has gained increasing popularity in recent years, particularly through advancements in Neural Networks (**NNs**). These developments have significantly expanded the capabilities of automated data-driven modeling across various domains. In this chapter, we focus primarily on **NNs** architectures, as they form the core modeling approach used in this project.

2.2.1 Feedforward Neural Networks

Feedforward Neural Networks (**FNNs**) are a class of machine learning models inspired by the structure and function of the human brain. In biological systems, neurons are interconnected through synapses, and their strengths change in response to external stimuli—a process that underlies learning. **FNNs** mimic this behavior by using computational units, also called neurons, connected by weighted links. These weights are adjusted during training to improve the model's predictions, analogous to synaptic strength adjustments in the brain.

Each artificial neuron receives inputs, scales them using learned weights, applies a non-linear activation function, and forwards the result to subsequent neurons. Through this architecture, an **FNN** models complex functions by propagating signals from input to output layers. Learning in **FNNs** occurs via exposure to training data consisting of input–output pairs. The network adjusts its weights to reduce the difference between its predictions and the target outputs, thereby minimizing the prediction error.

While the biological analogy is imperfect, it has historically guided the development of neural architectures. More formally, **FNNs** can also be viewed as compositions of simple mathematical units—such as logistic or linear regressors—structured into a computational graph. Their expressive power arises from stacking these units into deeper networks, enabling them to approximate highly non-linear relationships in data. This capacity to learn from examples and generalize to unseen inputs makes **FNNs** a powerful tool in modern machine learning.

Architecture

An **FNN** trained with backpropagation, which is discussed in Section 2.2.2, can be illustrated as a directed acyclic Graph with inter-connections. It contains a set of neurons distributed in different layers.

- Each neuron has a activation function.
- The first layer, shown on the left side in Figure 2.1, is called the input layer and has no predacessors in the inter-connection graph. Additionally, is their input value the same as their output value.
- The last layer, shown on the right side in Figure 2.1, is called the output layer and have no successors in the inter-connection graph. Their value represents the output of the Network
- All other neurons are grouped in the so called hidden layers. In Figure 2.1 this is represented by the layer in the middle. A neural network can have an arbitrary amount of hidden layers.
- The edges in the inter-connection graph, are so called weights, which represent an arbitrary number in $\mathbb{R}$. These weights are updated during the trianing process.

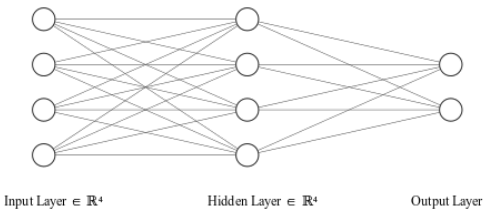

Figure 2.1 – Illustration of a Neural Network with 3 layers. Illustrated with [1]

Computation of the Output

The calculation of the output of the **FNN** is also called a forward pass. To do so, the value of each neuron needs to be calculated. This is done by summing all the inputs and then put

this value into a given activation function. Mathematically, this process can be represented as: $y = f\left(\sum_i^n \xi_i\right)$ wher f represents the activation function of the neuron and ξ_i the input or also called the potential of a neuron. To compute a full forward pass, this is done for each neuron from the input layer towards the output layer. When a value is passed throughtouh a weight to a successor neuron, the value is multiplied by the value of the weight. This process can then be summarized to:

$$\begin{aligned} y_1 &= f\left(\sum_i^n w_{ij} x_i\right) \text{ [input to hidden layer]} \\ y_{j+1} &= f\left(\sum_i^n w_{ij} y_j\right) \forall j \in \{1...k-1\} \text{[hidden to hidden layer]} \\ o &= f\left(w_{ij+1} y_j\right) \text{ [hidden to output layer]} \end{aligned} \tag{2.1}$$

[2] where j denotes the layer, ascending from input layer to output layer, f activation function, w_{ij} weight at index i and layer j, x as input at index i. The state of the neuron in the output layer o can then by denoted as the output vector.

2.2.2 The Backpropagation Training Algorithm

Objective: To identify a set of weights that guarantees that for every input vector, the output vector generated by the network is identical to (or sufficiently close to) the desired output vector.

Note: The actual or desired output values of the hidden neurons are not explicitly specified by the task.

For a fixed and finite training set: The objective function represents the total error between the desired and actual outputs of all the output neurons for all the training patterns.

Error Function

$$E = \frac{1}{2} \sum_p^P \sum_i^N \left(y_{ip} - d_{ip}\right)^2 \tag{2.2}$$

[3]

where P is the number of training patterns, N the number of output neurons, d_{ip} is the desired output for pattern p, y_{ip} the actual output of the neuron i and output neuron i.

Procedure

1. Compute the actual output for the presented pattern
2. Compare the actual output with the desired output
3. Adjustment of weights and thresholds against the gradient of the error function (Equation (2.2)) for each layer from the output layer towards the input layer

Figure 2.2 – Training Procedure of the backpropagation algorithm

Adjustment Rules

$$
\begin{aligned}
w_{ij}(t+1) &= w_{ij} + \Delta_E w_{ij}(t) \\
\Delta_E w_{ij} &= -\frac{\partial E}{\partial w_{ij}} = -\frac{\partial E}{\partial y_j}\frac{\partial y_j}{\partial \xi_j}\frac{\partial \xi_j}{\partial w_{ij}}
\end{aligned}
\tag{2.3}
$$

[3]

where $\Delta_E w_{ij}$ denotes the change of the Error Function with respect to w_{ij}, E the Error Function, y_j the output of the output neuron j, ξ_j the potential of the neuron j and w_{ij} the weight with index i at layer j.

2.2.3 Recurrent Neural Networks

The feedforward **FNNs** discussed in Section 2.2.1 are inherently limited to fixed-size, unordered input representations. This makes them unsuitable for sequential data, where both the order and length of the input can vary. To address this limitation, we introduce a class of models specifically designed to process variable-length sequences: Recurrent Neural Networks (**RNNs**)

Architecture A **RNN** consits of the following components:

- Input signal: The external data which is fed into the network at a timestep n and represent the current information which the network is processing.
- State signal: Also known as the hidden state, represents the memory of the **RNN** for a given neuron. It contains information about the past inputs in the sequence and is updated at each time step based on the current input and the previous state. The hidden state is updated with the following formula: $h_t = f(h_{t-1}, x_t)$. After the update, the hidden state of neuron i serves as input into the neuron $i + 1$
- Weights: The weights of the **RNN** neurons are shared among all different states.
- Output: Each neuron has a output, which is denoted as y_1 - y_4 in Figure 2.4. This output can serve as the output for the current state or as input into the next neuron.

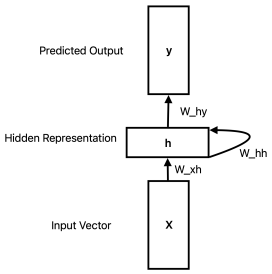

Figure 2.3 – **RNN**

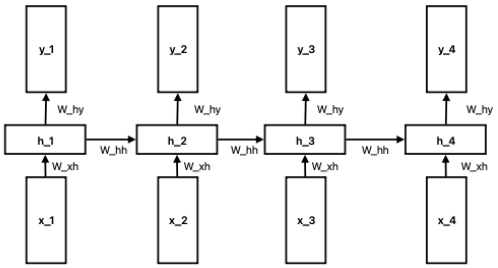

Figure 2.4 – 4 times unrolled **RNN**

Vanishing Gradient Problem

The Vanishing Gradient Problem (**VGP**) is a challenge encountered during the training of of **RNNs**, particullary dealing with deep **RNNs** and long input sequences. It arieses from the way how gradients are updated during the backpropagation algorithm (discussed in Section 2.2.2), which updates the network's paramertes / weights by propagating gradients backward through each time step. In backpropagation, gradients are computed via the chain rule, resulting in repeated multiplication of weight matrices and derivatives of activation functions across time steps. When these values are consistently smaller than one, the gradients exponentially decrease as they traverse earlier layers or time steps. Consequently, the gradients become vanishingly small, leading to negligible updates for earlier parameters and impairing the network's ability to learn long-range dependencies. The same principle aries, when the gradients become too large. In this case, the problem is called the exploding gradient problem.

2.2.4 Long Short Term Memory Neural Networks

Long Short Term Memory Neural Networks (**LSTMs**) are a special form of **RNNs** designed to address the problem of Vanishing Gradients while having a more fine-grained control over the previous input data. **LSTMs** are an enhanement of **RNNs**, because the recurrence conditaions of how the hidden state h_t is processed. To achieve this aim, we introduce a new hidden state of the same dimesion as h_t, which is called the cell state and is denoted as c_t. The

key innovation of the **LSTM** lies in its ability to control the flow of information using a set of gating mechanisms. These gates regulate how information is added to, removed from, or exposed from the cell state. Each gate is implemented as a sigmoid-activated neural layer and serves a distinct role in the update process.

Architecture

At each time step t with a given input vector x_t, previous hidden state h_{t-1} and previous cell state c_{t-1}, the **LSTM** performs the following computations:

- Input Gate: Decides which new information will be added to the cell state and is calculated as:
  - $i_t = \sigma(w_i[h_{t-1}, x_t] + b_i)$
- Forget Gate: This gate decides which parts of the previous cell state should be forgotten. The value of the forget gate is calculated as:
  - $f_t = \sigma\big(w_f[h_{t-1}, x_t]\big) + b_f)$
- Candidate Cell State: Computes possible candidates $\tilde{c_t}$ which can be added to the cell state, computed as:
  - $\tilde{c_t} = \tanh(w_c[h_{t-1}, x_t] + b_c)$
- Cell state update: Given the candidates, the cell state can be updated as:
  - $c_t = f_t \cdot c_{t-1} + i_t \cdot \tilde{c_t}$
- Output Gate: Determines which part of the cell state influences the hidden state and therefore the output. It is computed with:
  - $o_t = \sigma(w_o[h_{t-1}, x_t] + b_o)$
- Hidden state update: The final hidden state is computed by applying the output gate to the activated cell state. It is computed with:
  - $h_t = o_t \cdot \tanh(c_t)$

Note: w_x represents a complete weight matrix for each gate, b_x denotes the bias for the corresponding gates, and σ denotes the sigmoid function.

[2], [4], [5], [6]

2.3 Software Engineering

3 Methodology

3.1 AI Engineering

3.1.1 Data

3.1.2 Data Cleaning

3.1.3 Deep Learning Experiments

The goal of the experiments was to identify the most suitable deep learning architecture for predicting storm damage events based on weather-related input features. We evaluated different types of neural networks, beginning with a baseline Feedforward Neural Network (**FNN**), and compared their performance on a held-out test set.

Datasets

As shown in Table 3.1 dataset was temporally split into training, validation, and test sets to simulate realistic forecasting scenarios and prevent information leakage. The training set spans the years 1971–2002, the validation set covers 2003–2013, and the test set includes data from 2013–2023.

Table 3.1 – Datasets splits

Set	Nr of patterns	Years
Train	10014	1971 - 2002
Validation	3132	2003 - 2013
Test	3132	2013 - 2023

3.1.3.1 Feedforward Neural Network

Our first experiment employed a baseline Feedforward Neural Network (**FNN**), whose architecture is illustrated in Figure 3.5. The network consists of 10 fully connected layers with ReLU activation functions. The model was trained using the Adam optimizer and crossentropyloss.

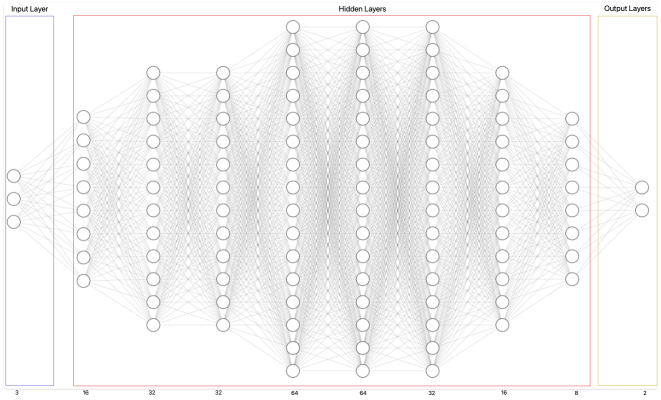

Figure 3.5 – Illustration of the used **FNN**

Input features

The input to the **FNN** consisted of three weather-related variables: mean temperature at 2 meters, total rainfall, and snow accumulation. All features were normalized to zero mean and unit variance, as described in Section 3.1.2, and were provided on a weekly basis for each coordinate in the dataset.

Training

The Feedforward Neural Network was trained to minimize the weighted cross-entropy loss, using class weights computed via sklearn's [7] compute_class_weight function. This approach addresses class imbalance in the training data by assigning higher loss penalties to underrepresented classes. The computed class weights were passed to the PyTorch [8] CrossEntropyLoss function, allowing the model to pay more attention to minority class predictions.

We used the Adam [9] optimizer with a learning rate of $1e^{-4}$, as it provides adaptive learning rate updates and has been shown to work well in practice for deep learning tasks involving sparse gradients. To further improve training stability and avoid overfitting, we employed a learning rate scheduler (ReduceLROnPlateau), which reduces the learning rate by a factor of 0.5 if the validation loss does not improve for 5 consecutive epochs.

Training was performed over 100 epochs using mini-batches of 64 patterns per batch. After each epoch, the model was evaluated on the validation set to track performance metrics including accuracy, F1 score, precision, and recall. These metrics allowed us to monitor not

only the raw predictive performance, but also the model's balance between false positives and false negatives, which is particularly important in the context of storm damage prediction.

This training setup was chosen to ensure stable convergence, account for class imbalance, and enable dynamic adjustment of the learning rate during training.

3.1.3.2 Long Short Term Neural Network

TBD

3.2 Software Engineering

3.2.1 Backend

3.2.1.1 Technologies

3.2.1.2 Architecture

3.2.2 Fronttend

3.2.2.1 Technologies

3.2.3 Test Concept

4 Results

4.1 Results of AI Engineering

To evaluate model performance, we conducted x experiments based on the configurations detailed in Section 3.1.3. The first experiment, using a standard feedforward network, serves as the baseline. The setup was described in Section 3.1.3.1

———

INSERT COMPARISON OF ALL MODELS TABLE

——-

4.1.1 Feedforward Neural Network: Results

The feedforward network achieved stable training behavior across 100 epochs, as shown in . Both training and validation loss converged early and remained relatively flat, suggesting a well-calibrated optimization setup. While the training loss steadily decreased, the validation loss plateaued, indicating that the model did not overfit and generalized reasonably well to unseen data.

Performance metrics such as accuracy, F1 score, precision, and recall also stabilized early during training, as shown in Figure 4.6. The final validation accuracy reached approximately 66%, with an F1 score around 0.59. This balance between precision and recall suggests that the model was able to capture patterns in both classes despite class imbalance.

The confusion matrix () further illustrates the model's performance. Class 0 (no storm damage) was predicted with high accuracy (1730 true positives vs. 492 false positives), while Class 1 (storm damage) showed moderate performance (534 true positives vs. 376 false negatives). Although the model exhibits a slight bias toward the majority class, it still correctly identifies a significant proportion of storm damage events, which is critical for real-world risk prediction.

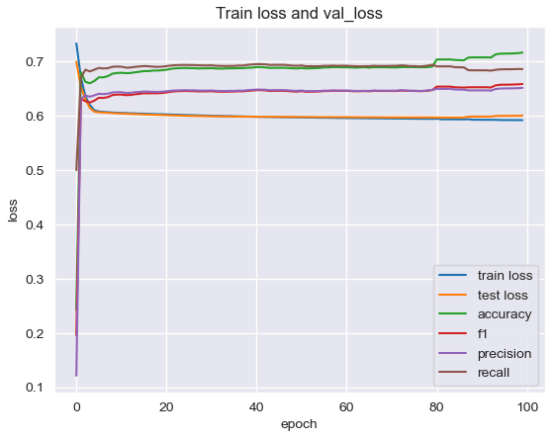

Figure 4.6 – Training of the FNN

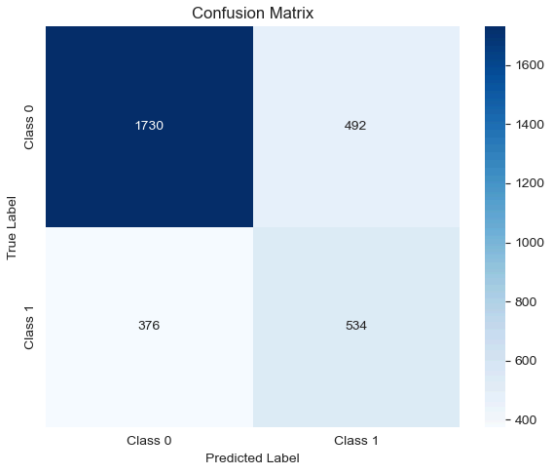

Figure 4.7 – Confusion Matrix of the FNN

Overall, the feedforward network serves as a solid baseline, offering balanced generalization and a reliable starting point for evaluating more complex architectures.

4.1.2 LSTM Neural Network

4.2 Software Results

5 Discussion and Outlook

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A Appendix

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