DESIGN AND IMPLEMENTATION OF MACHINE LEARNING MODELS AND ALGORITHMS FOR FLOOD, DROUGHT AND FRAZIL PREDICTION

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Abstract

Design and Implementation of Machine Learning Models and Algorithms for
Flood, Drought and Frazil Prediction

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Natural calamities like floods and droughts pose a significant threat to humanity, impacting millions of people each year and incurring substantial economic losses to society. In response to this challenge, this thesis focuses on developing advanced machine learning techniques to improve water height prediction accuracy that can aid municipalities in effective flood mitigation.

The primary objective of this study is to evaluate an innovative architecture that leverages Long Short Term Networks - neural networks to predict water height accurately in three different environmental scenarios, i.e., frazil, droughts and floods due to snow spring melt. A distinguishing feature of our approach is the incorporation of meteorological forecast as an input parameter into the prediction model. By modeling the intricate relationships between water level data, historical meteorological data and meteorological forecasts, we seek to evaluate the impact of meteorological forecasts and if any inaccuracies could impact water-level prediction. We compare the outcomes obtained by incorporating next-hour, next-day and next-week meteorological data into our novel LSTM model. Our results indicate a comprehensive comparison of the usage of various parameters as input and our findings suggest that accurate weather forecasts are crucial in achieving reliable water height predictions.

Additionally, this study focuses on the utilization of IoT sensor data in combination with ML models to enhance the effectiveness of flood prediction and management. We present an online machine learning approach that performs online training of the model using real-time data from IoT sensors. The integration of live sensor data provides a dynamic and adaptive system that demonstrates superior predictive capabilities compared to traditional static models. By adopting

these advanced techniques, we can mitigate the adverse impacts of natural catastrophes and work towards building more resilient and disaster-resistant communities.

Acknowledgments

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List of Acronyms

IoT Internet of Things. 2, 3, 5, 32–34, 36

LSTM Long Short Term Memory. 2–4

ML Machine Learning. 2–5, 36

Chapter 1

Introduction

1.1   General Background and Motivation

Natural catastrophes, like floods and droughts, have long been a significant concern for human societies worldwide. These events result in widespread devastation, causing loss of life, displacement of populations and substantial economic losses. Floods, in particular, are among the most devastating natural disasters, affecting millions each year and causing billions of dollars in damages. In Canada, flood losses totaled $405 million between 1983 and 2008 and cost $1.8 billion between 2009 and 2017 [27]. Flood prediction is critical to mitigating floods' impact, minimizing human casualties, preventing infrastructure loss, and preserving ecosystem imbalance. As climate change intensifies, the frequency and severity of such disasters are expected to increase, making it crucial to develop effective strategies for prediction, prevention, and management.

Historically, water height prediction models have relied on traditional physics based models or statistical approaches and simplistic forecasting techniques. Flood prediction techniques used by various forecasting agencies involve the usage of physically based deterministic hydrological models like HYDROTEL [16] at the *Direction de l'Expertise Hydrique et de l'Atmosphere (in English; Center for Water and Atmosphere Expertise)*(DEHA) of Quebec (Canada); Distributed Hydrological Soil Vegetation Model [59] at the Advances Hydrologic Prediction Services, associated with the National Oceanographic and Atmospheric Administration in the USA. Pagano *et*

al. [50] highlights that these models utilize high computational resources and have difficulty accurately modeling fine spatial resolutions. This limitation was further resolved by data-driven flood prediction models, which used machine learning techniques [15, 35] that can capture complex relationships between the hydrological parameters and accurately predict water height. ML models, particularly those based on neural networks like Long Short Term Memory (LSTM), have shown promising capabilities in capturing intricate patterns and dependencies in time series data. However, incorporating meteorological forecast data into the prediction process has been an area of relatively less exploration.

The motivation for this research lies in the potential benefits of fusing meteorological forecast data with water level data to improve prediction accuracy. Meteorological forecast provide valuable information on precipitation, temperature, and other meteorological factors that directly influence water levels in rivers, lakes, and other water bodies. By integrating this dynamic weather data into ML-based prediction models, we can enhance the model's ability to anticipate water height fluctuations and respond to evolving weather patterns.

Moreover, the rise of the Internet of Things (IoT) has opened up new possibilities for collecting real-time data from a network of interconnected sensors. These IoT sensors can provide a wealth of information about environmental conditions, water levels, and other relevant parameters, contributing to a more comprehensive and up-to-date dataset. Leveraging this IoT data in combination with ML models allows for continuous and adaptive model training, enabling the system to adapt to changing environmental conditions and provide more accurate predictions.

In Quebec, there are multiple initiatives are underway to observe water-levels in rivers and monitor flood events. The first initiative is with Hydro Meteo and Geosapeins and the E-nundation product [17] which relies on water-sensors only and these sensors are powered by electric cables and necessitate the installation of dedicated electric poles to function effectively. Their prediction model only relies on historical water-levels. The second initiative is with CMM - Communauté Métropolitaine de Montréal and the Grand Crues project [13]. Their plan is to install 29 measurement stations in various locations across the metropolitan area. These stations will gather information about water levels. The objective is to observe the patterns of water bodies and predict

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future trends for a three-day period. These stations are operated using electrical connections and rely solely on past water level data to make projections about water levels. Thus, there lies a drastic need for more advance tools to predict water-level which could utilize multiple parameters and further data collection of multiple parameters from IoT sensors could be utilized for more accurate prediction.

The potential impact of accurate water height predictions and effective flood management is far-reaching. Timely and precise forecasts can facilitate better preparedness and response measures, allowing authorities to issue timely warnings and evacuate vulnerable areas. Additionally, improved predictions can aid in optimizing water resource management, preventing water shortages during droughts and minimizing the damage caused by floods.

In summary, the general background and motivation for this research stem from the urgent need to enhance water height prediction models to better address the challenges posed by natural catastrophes like floods and droughts. By combining ML techniques, LSTM models, weather forecast data, and IoT sensor information, this study aims to develop an innovative and effective approach for predicting water height which could help reduce the impacts of devastating floods, ultimately contributing to increased resilience and safety for communities at risk.

1.2   Key references

The first key contribution is a publication. We review below the key references, and readers can find a more detailed literature review in the paper, embedded in Chapter 2. In the domain of water-level prediction, several studies have contributed to establish a comprehensive understanding of flood prediction with different techniques. While an in-depth analysis of these references can be found in the paper, this brief literature highlights their significance and relevance. Initial works [16, 32] leveraged physical and statistical models that relied on data from various hydrological and meteorological parameters fed into mathematical and physical models. Later, with the advent of machine learning, experiments were carried out to evaluate the performance of ML models for flood prediction. Chau *et al.*[9] compared the performance of artificial neural networks with adaptive network

based fuzzy inference systems (ANFIS) and observed ANFIS performed well compared to genetic algorithm based ANN. Gude *et al.*[19] explored the river gauge height prediction using statistical and machine learning models like Auto Regressive Integrated Moving Average (ARIMA) , Long Short Term Memory (LSTM) networks and showed that machine learning models are more accurate than the physical and statistical models. Several studies have proposed the usage of LSTM based models for water-level prediction like Borwarnginn *et al.*[5] who proposed a combination of LSTM-SVR (Support Vector Regressor) for river-water height prediction for 6h and 12h intervals and used rainfall, cumulative rainfall for his works but did not explore various meteorological parameters that could influence water-level prediction. Further, works involving meteorological forecasts, like Kurian *et al.*[34] where he combined rainfall forecasts from physical models with ANNs for streamflow prediction and showed the benefit of combining forecasts with ML models. These key references have significantly shaped the trajectory of our research and building on the foundations laid by these works, our paper addresses existing gaps and we propose novel way to predict water-level leveraging various meteorological parameters as well as meteorological forecasts.

The second contribution is described in Chapter 3 and include a section dedicated to the literature review with respect to the contribution of that last chapter.

1.3 Contributions of the Thesis

The thesis makes several notable contributions to the field of water level forecasting and flood mitigation:

- Our publication includes the comparision of various ML methods and a novel LSTM based water-level forecasting approach using meteorological forecasts. The major contribution of this paper includes :

    – A novel LSTM Model, incorporating weather forecasts with historical weather data and water-level.

- Evaluation in Impact of model performance using various combinations of meteorological parameters.

- Explored the usage of Online Machine Learning approach for flood prediction using IoT sensor data.

- Improved Flood Prediction with IoT Sensor Data and Online ML Training

- Conducted a comparative analysis of performance of water-level prediction models using Online Vs Batch training to observe effectiveness of Online training.

1.4   Organization of the Thesis

The thesis is organized as follows. Chapter 2 is made out of a paper (to be shortly submitted) on batch ML models Flood forecasting. It involves a novel LSTM model incorporating meteorological forecasts and comparision with other ML models learned via batch training. Chapter 3 investigates the use of online machine learning and compares the results to traditional Batch training approach. This latter chapter includes a brief overview of online machine learning, the proposed online machine learning architecture, and then the comparative numerical results. It is a joint work with another M.Comp.Sci. student, Meet Mehta, and common to both thesis. Meet developed the IoT framework and carried out the data collection process, while Bhargav worked on experimentation of various libraries and design of Online Machine Learning algorithm in the use case of this system. The experiments on real-time data and comparisons to Batch-ML were performed together. Input data of the online ML algorithm is collected using the IoT sensor platform developed in the M.Comp.Sci. thesis of Meet Mehta [42] with data collected in the Rivière Le Boulé at Lac Superieur. We present the results of these experiments in the end of Chapter 3. Chapter 4 presents the conclusions of the thesis and future research directions.

Chapter 2

ML Methods for Flood Prediction

2.1 Introduction

Natural disasters, like earthquakes, hurricanes, floods, and droughts, can result in significant losses at national and regional levels. The occurrence of torrential rains and subsequent flooding in Quebec during the spring of 2017 and 2019 resulted in aggregate losses exceeding 576 million (CAD) $ [27]. Events like floods have far-reaching consequences, including loss of life, displacement of people, damage to homes, businesses, infrastructure, and disruption of essential services such as transportation, power and water supplies.

Flood frequency analysis shows that there has been an increase in floods in rivers across Quebec (Canada) region in recent decades [49, 58]. Roy *et al.* [54] studied the impact of climate change and seasonal floods in Quebec and reported 250% increase in the water discharge and water levels in some scenarios providing evidence for significant increase in typical flood level.

A variety of factors contribute to development of floods; in Quebec, the the main factors leading to favourable conditions for flood development are season dependent. In spring time, the runoff associated with heavy rainfalls combined with the snow-melts are considered to be the main culprits. In winter months, ice-jams, primarily related to frazil ice, are the most common phenomena leading to floods (Zahmatkesh *et al.* [63]). A review of multiple climate models reported a positive relationship between the observed increase of rainfall amounts in the period between January to

April and September to December and higher volume of runoff in winter and spring months. In the summer periods on the other hand, increased temperatures leading to increase in evaporation rates combined with decrease in rainfall amounts contribute towards the occurrence of droughts, see Mailhot *et al.* [40]. Recently in 2022, concerns for severe droughts were reported in parts of southern Quebec (CBC News, 2022). Thus our study tries to predict water level during various periods influenced by different phenomenons in Quebec.

Given the escalating flood risks, accurate and timely flood prediction near inhabited areas can have a significant contribution towards disaster mitigation tools such as early warning systems, and evacuation planning. However, achieving such accurate flood prediction remains challenging due to the intricate and nonlinear nature of hydrological processes governing floods.

A variety of methodologies for flood predictions have been discussed in the literature. Traditional methods in flood prediction studies typically rely on mathematical models aiming to capture the physics of underlying hydrological processes associated with floods. Such mathematical models have been proposed for for floods [12], storms [11], for rainfall associated runoff [7, 8], for atmospheric circulation patterns [38] including coupled effects of ocean and floods [12]. Physical models like HYDROTEL [16], WATEFLOOD [32] are employed at various provincial River Flood and Forecasting Centers (RFFC) [63]. Despite the impressive capabilities demonstrated by this type of models in predicting diverse range of floods scenarios, they require high spatial resolution data sets, while the mathematical computation involved in these complex physical models necessitates intensive computational power [12, 63]. Kim *et al.* [29] states it is highly challenging to find expertise since these models need supervision for calibration and effectively carry out modelling.

More recently, a variety of data-driven approaches, including but not limited to Machine Learning (ML) models, have been implemented in flood prediction literature. Generally, such approaches can mitigate the limitations of physical models due to their relative implementation simplicity. These models have gained popularity because they can capture non-linearity using just historical data without explicit understanding of underlying physical processes. Recent studies

use machine learning (ML) models and algorithm that involve prediction of various flood variables such as water level [5, 19, 30], soil moisture, rainfall amounts [5, 5, 39], discharge rates [10, 28, 30] , rainfall-runoffs [30] and many more. Several ML techniques like Artificial Neural Networkds (ANNs), Support Vector Regression (SVR), Recurrent Neural Networks (RNNs) have been examined to predict these flood variables. Chau *et al.* [9] compared the performance of of artificial neural networks with adaptive-network-based fuzzy inference system (ANFIS) in the Yangtze River and observed that ANFIS performed well in simulations with RMSE of 0.214m compared to 0.226m for Genetic Algorithm based ANN. Hipni *et al.* [22] compared SVR with ANFIS and concluded that SVR performs better than ANFIS using parameters like rain and dam water-level. Zhang *et al.* [64] suggested using 2 hour inputs for forecasting 4 hour ahead values using ANN, ANFIS and SVM and mentioned that ANFIS was robust to capture information with differnt lag inputs while SVM showed better performance in extreme typhoon events.

Although the conventional ML methods showed satisfactory results, the rise of time series-based models such as RNN and LSTM networks has led to increased popularity in flood prediction. Le *et al.*[35] leveraged LSTM for flow forecasting for one-day, two-day and three-day with Nash–Sutcliffe efficiency (NSE) values greater than 86%. NSE is generally used to determine the predictive skill of hydrometric model further explained in Section 2.2.5. Borwarnginn *et al.* [5] proposed a combination of LSTM - SVR model which performed slightly worse than LSTM to predict river water height, but authors mention that the novel approach could detect rapid changes in water that are higly prevalent in events of floods, typhoons, etc. Recent works on transformer based models have also been leveraged for flood prediction, Castangia *et al.*[6] shows that transformers work slightly better than LSTMs. For 3 days forecasting of water-level transformers achieve NSE of 0.93 while LSTM have NSE 0.91. Despite achieving 4% better results on transformers the model sizes increased by 1400% from 198k parameters in LSTM to 3M in transformers [6]. Thus leveraging these huge models can be computationaly expensive espesially on remote flood monitoring sites having small IoT devices with memory and computational limitations.

In the recent years, several studies have incorporated the use of meteorological forecast data for the coming days to predict upcoming events of floods. This approach has been the subject of

several recent studies, which have demonstrated the potential of meteorological data to improve the effectiveness of flood forecasting systems. [39] utilized radar rainfall prediction data from National Meteorological Observatory of China to effectively show the improvement on real-time river water-level changes. [18] utilized an ensemble of weather forecast models and a probabilistic graphical model to estimate flood warning levels based on impact evaluation parameters. The hybrid rainfall forecast proposed in [46] showed significant improvements of 39% in accuracy and 63% and 25% in the Sejong Rainfall-runoff model (SURR). [34] combined physical models with artificial neural networks to create a hybrid model involving rainfall forecast data. The NSE increased from 0.91 to 0.95 and also illustrated that the proposed hybrid model could be used to generate forecasted streamflow hydrograph corresponding to a full flood event well in advance.

While the literature has focused on specific type of flood events, our work tried to predict water-level year-round including events of floods and droughts at a specific location for different time durations of 1hour, 1 day and 1 week. In this paper, the authors present water level prediction using river-water height data paired with various meteorological parameters at few sites in Terrebonne (Greater Montreal Area, Quebec, Canada) for three periods: Droughts, spring Ice Melt, and Frazil. The categorization of periods is based on the occurrence of natural events during specific seasons of the year. The authors propose and compare a novel approach to utilize the temporal information of meteorological forecasts and combine them with historical data to predict water-level.

The paper is organized as follows. Section 2.2 presents the background and problem statement, including an overview of the LSTM architecture. In Section 2.3, we describe various improved LSTM models for flood forecasting. Section 2.4 showcases the results obtained from implementing the proposed LSTM architecture. In Section 2.5, we draw conclusions of our study.

2.2 Background and Problem Statement

This study is the result of a collaboration with the municipality of Terrebonne, which was interested in predicting three environmental events: frazil (usually in January), flooding due to snow

melt during the spring, and drought during the summer. Water level of the river bordering Terrebonne was collected by Hydrometeo [25] and is described in next section. Since prediction of environmental events corresponds to prediction using time series, we next recall the key features of LSTM [23], before describing the improved LSTM model used in our study.

2.2.1 Problem Statement: Meteorological Event Predictions

In the sequel, we are interested in the prediction of three meteorological events: drought during the summer, frazil during the winter, and flood due to ice-melt periods. We therefore partitioned the dataset into three distinct seasonal periods, each associated with the prediction of one of these events, see Table 1.
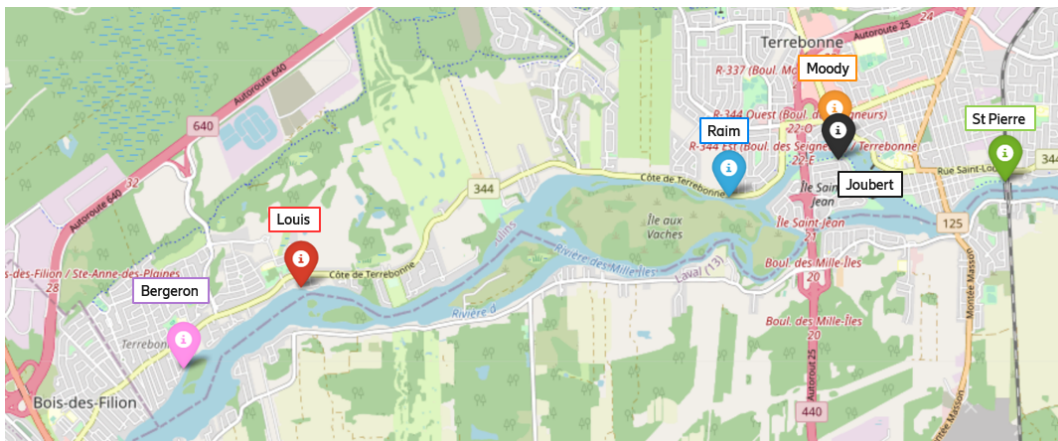
Figure 1: Location of the 6 hydrometric stations managed by Hydro Meteo nearby Terrebonne.

The drought period corresponds to the summer months characterized by high temperatures and limited rainfall, leading to potential drought conditions. In the scope of the current study, this period was defined to span from May 15 to November 1st. While some areas of Quebec receive moderate rainfall during this period, others experience significantly lower precipitation, intensifying the drought-like conditions.

The frazil period refers to the time when frazil Ice forms on water bodies, influencing the behavior of rivers. Data collected between November 1st and February 15th falls within this period.

On the other hand, the ice-melt period encompasses data captured from February 15 to May 15.

During this period, the melting of frozen water from ice caps and frazil Ice causes river levels to rise. Multiple meteorological and horological factors contribute to the observed variability during this period.

It is important to highlight that the categorization of data into periods, such as drought period, frazil period, and flood due to ice-melt period, is based on patterns observed in Quebec and may vary in different geographical locations. It encompasses the time periods needed to correctly predict their occurrence, based on past weather conditions conducive to their occurrence.

Periods	Dates between
Drought	May 15 - November 1
Frazil	November 1 - February 15
Flood	February 15 - May 15

Table 1: Seasonal Distribution and Corresponding Dates of Phases

By dividing the dataset into these distinct seasonal phases, the model can focus on the specific parameters associated with each meteorological event, enhancing their prediction and the associated water-level fluctuations.

2.2.2 Water Data

We used the water-level data sets collected by Hydro Meteo [25] at 6 of their hydrometric stations, each located at a potential flooding location on the Rivière des Mille Îles, a channel of the Ottawa River in southwestern Quebec, Canada, that runs into the Rivière des Prairies. It flows eastwards from the Lake of Two Mountains and is 40 km long, containing small islands that are part of the Hochelaga Archipelago. The locations of the six hydrometric stations (Bergeron, Louis, Raim, Joubert, Moody, St. Pierre) are indicated in Figure 1. When archived, data were kept only for 30-minute intervals, while initially collected at 5-minute intervals.

Location	Start Timestep	End Timestep
Bergeron	2018-10-31 2:35:00 PM	2022-06-30 4:00:00 PM
Louis	2008-12-11 8:35:00 PM	2018-11-30 5:45:00 PM
Raim	2008-12-01 3:45:00 PM	2018-11-20 12:55:00 PM
Joubert	2011-01-13 2:30:00 PM	2021-01-01 11:40:00 AM
Moody	2014-06-11 1:15:00 PM	2022-07-04 3:15:00 PM
St Pierre	2010-02-18 5:00:00 PM	2020-02-07 2:10:00 PM

Table 2: Start and end time stamps of the six hydrometric stations for the water-level data collection.

Data ranges vary for each hydrometric station location, as compiled in Table 2. To ensure consistency across all data, the collected data was extrapolated using the nearest neighbor from previous or subsequent hour values to reflect 5-minute intervals at each location for all time periods. This resulted in 12 observations per hour and 288 observations per day for each hydrometric station. The dataset had a significant number of missing values, likely due to outages caused by connectivity issues, faulty hardware, or unforeseen circumstances. To address this issue, we used spline interpolation [31] to fill in the gaps in the data. It is known to effectively capture the underlying patterns of datasets, providing a reliable and accurate estimation of the missing values. We also experimented with other interpolation techniques like polynomial, k-nearest neighbors, but spline interpolation proved to be the most successful.

2.2.3 Meteorological Data

Meteorological data was obtained from Open-Meteo [48], which has historical weather data from reanalysis models like ERA5 [21] for the parameters mentioned in Table 3. Reanalysis is a systematic approach of producing comprehensive and consistent datasets for climate monitoring and research. It involves assimilation of past short-range forecasts with observations for a variety of observations of the atmosphere, land surface, and ocean [20]. Various different weather datasets

are combined into one regularly spaced grid to compensate for inconsistency incurred by biases in measurement taken by different instruments at different points in history

The closest Open-Meteo weather station (45.6999° N, -73.6° W) to Terrebonne (45.6930° N, 73.6331° W), i.e., about 18km away, was used for the data collection of this meteorological data. Historical data for meteorological forecasts is only kept for the past month and thus we could not use the website of Open-Meteo to access forecast data associated with the water data in the time period mentioned in Table 2. However, based on estimated errors of forecast vs. real values, we generate forecast values as described in the next paragraph.

Meteorological forecast data was collected for the duration of one month from 5th February 2023 till 6th March 2023. Each file of meteorological forecast contains prediction of various meteorological parameters for 7 days(1 week) from various agencies GEM(Canadian Weather Service),IFS(European Centre for Medium-Range Weather Forecasts), GFS(Global Forecast System), JMA (Japan Meteorological Agency), ICON(Deutscher Wetterdienst) and Arpege (MeteoFrance) [48]. From data of all these various forecast agencies, best suitable models observed for Terrebonne site are combined by Open-Meteo and considered as 'best-match' which are then compared to real meteorological data. As mentioned in Equation (1), We compute residual error by comparing the forecast value of next 7 days with real values obtained for the same 7 days. Further, mean and standard deviation of the residual error ε is calculated for all the forecast data from 5th February 2023 till 6th March 2023. Determining the exact distribution of this error between forecast values and real values, over the course of a year is challenging and therefore for the purpose of this experiment we making an assumption that it follows normal distribution. Equation (3) outlines the method we use to make estimation in forecasts for time periods mentioned in Table 2. We randomly sample the error as mentioned in Equation (2) and subtract it from the real values y_{obs} of meteorological parameters to obtain estimated forecast $y_{estimated forecast}$. The process mentioned above is performed for all the meteorological parameters mentioned in Table 3 to obtain an estimation of meteorological forecasts.

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$$error(\varepsilon) = y_{obs} - y_{forecast} \qquad (1)$$

$$e = X \sim \mathcal{N}(\mu_\varepsilon, \sigma_\varepsilon) \qquad (2)$$

$$y_{estimated\,forecast} = y_{obs} - e \qquad (3)$$

Parameter	Unit	Description
Temperature (2m)	°C	Air temperature at 2 meters above ground
Relative humidity (2m)	%	Relative humidity at 2 meters above ground
Dewpoint (2m)	(°C)	Dew point temperature at 2 meters above ground
Rain	mm	Only liquid precipitation of the preceding hour including local showers and rain from large scale systems.
Snowfall	cm	Snowfall amount of the preceding hour in centimeters.
Mean sea-level pressure	hPa	Atmospheric air pressure reduced to mean sea level (msl)
Surface pressure	hPa	Pressure at surface
Cloudcover	%	Total cloud cover as an area fraction
Windspeed (10m)	km/h	Wind speed at 10m above ground
Soil temperature (0 to 7cm)	°C	Average temperature of different soil levels below ground between 0 and 7 cm.
Soil temperature (7 to 28cm)	°C	Average temperature of different soil levels below ground between 7 and 28 cm.
Soil moisture (0 to 7cm)	m³/m³	Average soil water content as volumetric mixing ratio at 0-7 cm depth
Soil moisture (7 to 28cm)	m³/m³	Average soil water content as volumetric mixing ratio at 7-28 cm depth
Direct radiation	W/m²	Direct solar radiation as average of the preceding hour on the horizontal plane and the normal plane (perpendicular to the sun)

Table 3: Meteorological parameters used and their description.

2.2.4 LSTM Machine Learning Models

Long Short-Term Memory (LSTM) Models have been widely used in time-series predictions and several studies mentioned in Section 2.1 have proven their effectiveness. While more recent and sophisticated models like transformers have gained prominence, LSTMs have demonstrated remarkable performance in capturing temporal dependencies and patterns within sequential data. Our goal of this study was focused on experimenting inclusion of meteorological forecast and further use similar models on microcontrollers; thus the maturity and availabitlity of resources in LSTMs played a role in our choice. Although transformers offer advanced capabilities, the complexity of their implementation and excessively large model sizes [6] could lead to difficulties to export them onto microcontrollers and thus these drawbacks outweighed their benefits for our research goals.

In this section, we describe the key ideas of LSTM network, before describing the additions we made for our particular prediction problem.

LSTM was designed by Hochreiter and Schmidhuber [23] and is a type of recurrent neural networks capable of capturing long-term dependencies LSTM contains three gates - an input gate, an output gate and forget gate -, inside a unit called memory cell. These gates regulate the flow of information in LSTM to solve the vanishing gradient problem observed in RNN. The input vectors are defined as $X = [x_1, x_2, \ldots, x_n]$ and output vector $Y = [y_1, y_2, \ldots, y_n]$.

The state at each time t, is represented by c_t, while h_t represents state of the hidden layers at t. The forget gate, see Equation (4)), which is controlled by f_t,

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{4}$$

is essential in determining whether data is removed from the memory block or used by the output gate to produce outputs for the current time steps or propagate that to the next time steps.

The input gate, denoted by i_t, regulates what new information from the current time step t should be added to memory. A new memory vector $\hat{C}$ is also generated using information from

both - input data from current time step x_t and context from the previous hidden states- $h_t - 1$.

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{5}$$

$$\hat{C}_t = \tanh(W_c[ht - 1, x_t] + b_c). \tag{6}$$

The memory cell C_t at time step t is updated by combining important information from the previous cell state C_{t-1}, and adding new information from the new candidate cell state $\hat{C}$. The information which is necessary from previous cell state, is regulated by the forget gate output f_t which is multiplied to C_{t-1}. The new candidate cell state is multiplied with the input gate i_t which triggers what new memory is to be added to the cell state.

$$C_t = f_t \odot C_{t-1} + i_t \odot \hat{C}_t. \tag{7}$$

The output o_t for the current memory cell is generated through the past memory as well output vector generated from x_t:

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o).. \tag{8}$$

Updating of h_t at time step t, which is a combination of output gate along with memory cell state with tanh activation which controls the magnitude and range of the information propagated in the hidden state. The value of h_t also denotes the forecast value (output) of current cell which is symbolically represented by y_t

$$y_t = h_t = o_t \otimes \tanh(c_t). \tag{9}$$

Figure 2 represents the data flow in LSTM, which is calculated iteratively at all time steps.
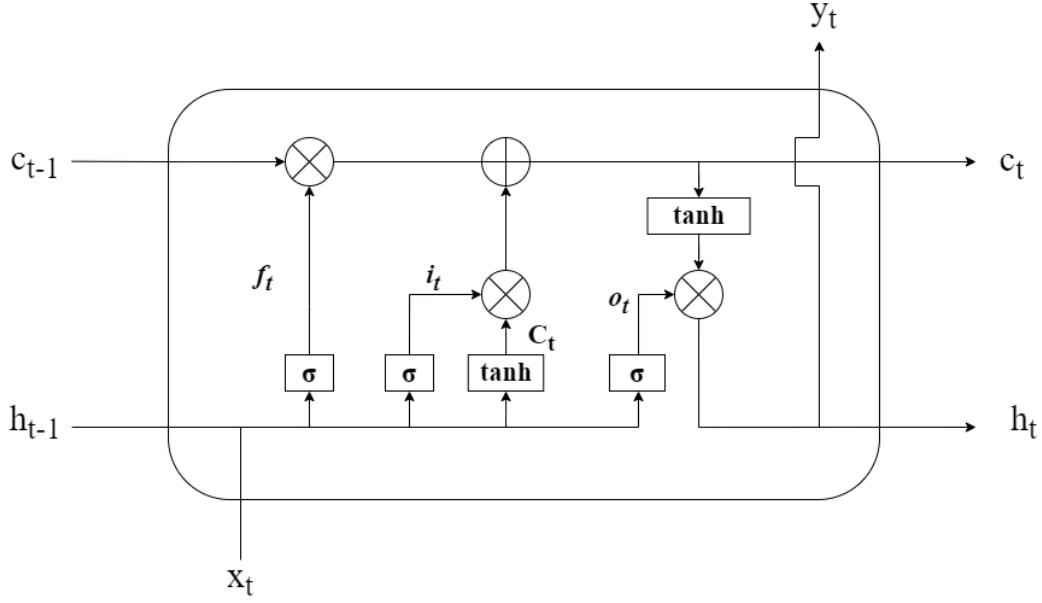
Figure 2: Long Short-Term Memory (LSTM) cell architecture

2.2.5   Performance Evaluation Criteria

The performance of the models was quantitatively compared on 2 quantitative indices, Nash–Sutcliffe efficiency (NSE) and Root Mean Square Error(RMSE). Nash–Sutcliffe efficiency (NSE) is a metric mainly used in hydrological and water-quality models to compare simulated(here forecasted) values with observed values to quantify the model ability to capture variability compared to observed data. Root Mean Square Error(RMSE) is another widely used performance indicator in machine learning algorithms where the average difference between predicted values and actual values is evaluated.

The mathematical expressions of the above mentioned metrics are as follows:

$$\text{NSE} = 1 - \frac{\sum\limits_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum\limits_{i=1}^{n}(y_i - \bar{y})^2}, \qquad \text{RMSE} = \sqrt{\frac{1}{n}\sum\limits_{i=1}^{n}(y_i - \hat{y}_i)^2}. \tag{10}$$

where n is the number of samples, y_i and $\hat{y}_i$ are the actual and predicted values of water level at time interval i. $\bar{y}$ is average of the actual water-level. NSE is widely used in evaluation of hydrological models [41] and the value of NSE lies in the range of [-1,1] where 1 is the best value for

a model. RMSE is commonly used metric in machine learning whose value ranges between $[0,\infty)$ and the best value for RMSE is 0. By employing both types of indices, a comprehensive and nuanced assessment was achieved, providing a more sophisticated understanding of the performance exhibited by the various models described in Section 2.3.

2.3 Proposed ML Models

In this section, we mention the three different machine learning LSTM models used for water level forecasting in the context of weather conditions, for each of the environmental events mentioned earlier. Each model has different data inputs and is capable of forecasting the water-level values for the same number of time steps.

Water-level-LSTM (WaLSTM), discussed in Section 2.3.1, utilizes only water level data for forecasting. In Section 2.3.2, we present LSTM model incorporating historical Meteorological parameters (MetLSTM) which is a refinement of the basic LSTM model mentioned in Section 2.3.1. In Section 2.3.3, we propose the model (FMLSTM), which integrates meteorological forecast data as mentioned in Section 2.2.3, into the deep learning framework and thus highlight transfer of temporal information from meteorological data in upcoming timesteps. By comparison of performances of FMLSTM with WaLSTM and MetLSTM we could evaluate the impact of using meteorological forecast as an input parameter to the model. Furthermore, the potential influence of inaccuracies in meteorological forecasts on the precision of water-level predictions could be investigated.

2.3.1 Water-level (WaLSTM) Model

We now describe the initial LSTM model that exclusively employs water level data for prediction of water-level for upcoming timesteps and acts a baseline for comparison. This model utilizes a sequential approach, where a series of i timesteps of water level data is provided as input. The architecture of this model is motivated from similar LSTM model used by Borwarnginn *et al.*[5] for water-level predictions, 6h and 12h ahead. Our model has one more LSTM layer to capture

more complex information for predictions 1 week ahead. Along with that, the number of units of LSTM is variable for different periods and prediction lengths to optimize it with respect to site.

The first LSTM layer consists of m units, while the second layer incorporates double the number of units $2m$. The final LSTM layer comprises m units. Subsequently, the output of the last LSTM layer is passed through a dense layer, which enables the prediction of water levels for n future timesteps. The number of LSTM units m in each layer is optimized while training the model using Optuna [1]. Figure 3 shows a diagram representation of the proposed model.
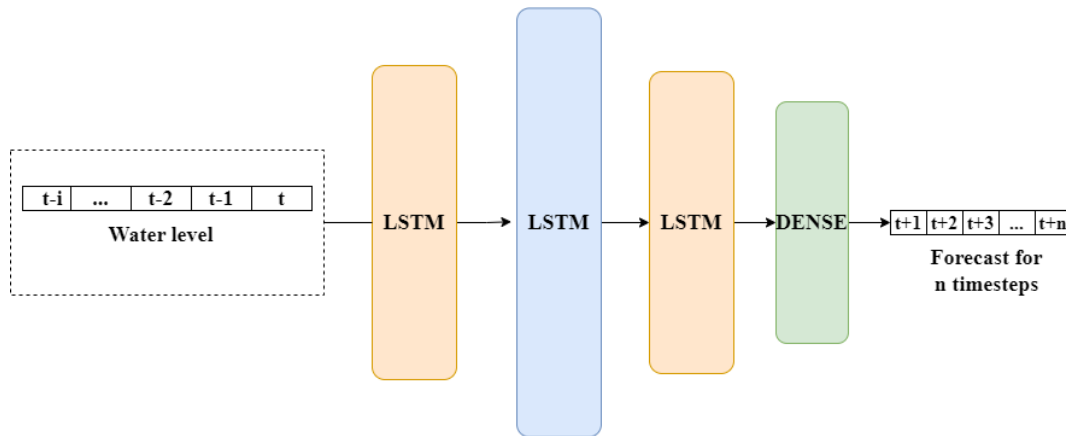
Figure 3: Model Architecture for Water-level LSTM(WaLSTM)

2.3.2   Water-level with Meteorological Data (MetLSTM) Model

MetLSTM, is an extension of framework presented in Section 2.3.1. This model takes into account the historical meteorological data in conjunction with water level measurements, thereby encompassing the influence of diverse weather parameters like temperature, pressure, rainfall, snowfall, and more. By incorporating these features, the input for each timestep of the model expands to encompass p weather parameters alongside the water level parameters, resulting in a total of $p + 1$ input parameters. This expanded input is then processed using the LSTM architecture, following the methodology similar to Section 3.2.1 as outlined in Figure 4.
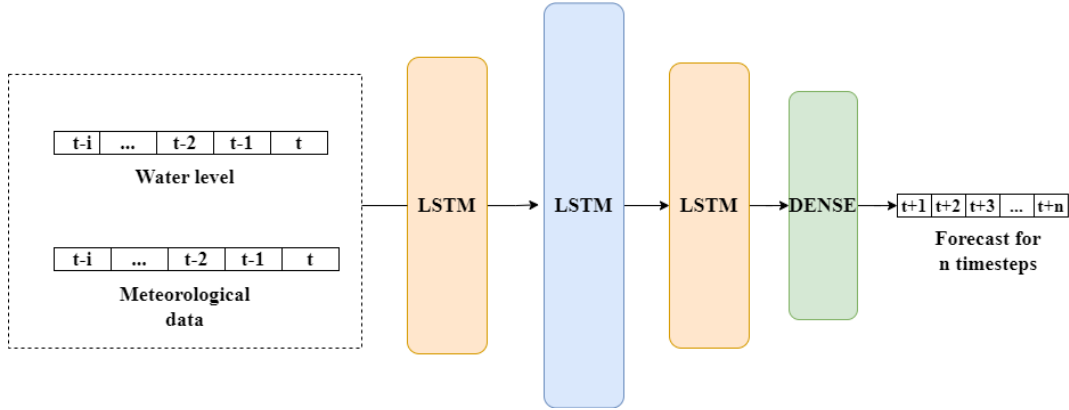
Figure 4: Model Architecture for LSTM-Model using Water-level with Meteorological Data (MetLSTM)

The model outputs the prediction of water levels for n future timesteps. Through the integration of weather parameters with water level data, this model can get a comprehensive understanding of the meteorological impact on the fluctuations and variations observed in water levels. This enriched comprehension provides valuable insights into the intricate interplay between weather conditions and the dynamics of water levels and thus could assist in prediction of water-level.

2.3.3 Water-level with Meteorological Data and Meteorological Forecast (FML-STM) Model

We investigate the inclusion of meteorological forecasts in addition to historical water level data and corresponding meteorological data in an LSTM model, while previous studies considered historical meteorological data only. The model input consists of the water level data and meteorological data from time steps $t - i$ to t, comprising $p + 1$ parameters as mentioned in the previous section 2.3.2. Additionally, the meteorological data for forecast horizon with q parameters includes information on the weather for the time steps $t + 1$ to $t + n$ taken into consideration by the model. This input can also be replaced with meteorological forecasts for same period to help model gain temporal information of these parameters in forecast horizon. Here, time step $t + 1, t + 2, ..., t + n$ represent the specific time intervals for which water level predictions are made.

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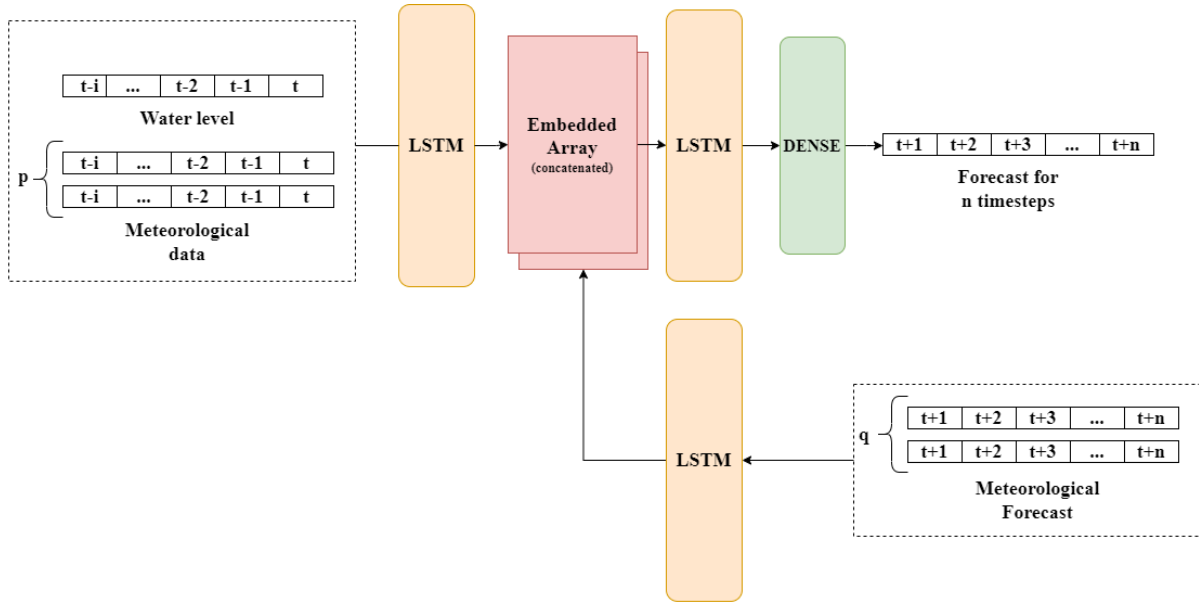
Figure 5: Model Architecture for LSTM model comprising Water-level, historical meteorological data and Meteorological Forecast data (FMLSTM)

As shown is Fig. 5, q features of meteorological forecast data are integrated using a single LSTM layer that processes their temporal information. The resulting array is then concatenated with the array generated by passing the water level and meteorological data through a single layer of LSTM. Subsequently, this concatenated array is passed to another LSTM layer, followed by a dense layer, which predicts the water level output for the n timesteps.

One approach could be using meteorological forecasts along with the input to the MetLSTM model. But FMLSTM first encodes the meteorological forecast using a different LSTM layer which enables us to use different sized arrays of input for (historical water-level , meteorological data) and (meteorological forecast). For example, we take the training window size as past 2 weeks to predict for the next 1 week. In this case, $i = 4096$ and $n = 2048$ and the shape of both inputs would be different where (historical water-level, meteorological data) would contain 4096 timesteps while (meteorological forecast) would contain only 2048 timesteps. Thus FMLSTM model has an advantage of using different window size of meteorological data and meteorological forecast data, compared to traditional model where all three inputs were combined.

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By comparing these models, we aim to determine the effectiveness of incorporating meteorological forecasts in water level forecasting using FMLSTM and evaluate the impact of different input combinations on the predictive performance.

Predicted timesteps (n)	Timesteps used per training sample (i)
1 hour (12 timesteps)	1 week (2,048 timesteps)
1 day (288 timesteps)	1 week (2,048 timesteps)
1 week (2,048 timesteps)	2 weeks (4,096 timesteps)

Table 4: Number of timesteps predicted by the model corresponding to the number of training timesteps.

2.4   Results

In this section, we present the results of experiments conducted on the data from various sites of the city of Terrebonne, see the map in Figure 1 of Section 2.2. We evaluate the performance of the WaLSTM,MetLSTM and FMLSTM models, summarize the results in this section. Two experimental approaches that were used to run the FMLSTMModel where different datasets were used as input.

For comparision of model performance with statistical models like Auto Regressive Integrated Moving Average (ARIMA), we evaluated the ARIMA model with (p,d,q) values (2,1,1) but this experiment made us realize the limitation of statistical models that for each 1 week period (training window), there could be different values of (p,d,q) obtained by selecting lowest AIC(Akaike Information Criteria) and BIC(Bayesian Information Criteria) and thus leading to different optimization for each training sample. (p,d,q) are the various parameters in ARIMA which are used to define the orders of the autoregressive (AR), differencing (I), and moving average (MA) components, respectively. A more longer period could be considered in this case to reduce the number of optimizations required, but since there are also different periods like droughts, frazil and ice-melt, such bifurcation would thus lead to non-continuous data, further leading to difficulties in creating

such models. For example, we evaluated the performance of model keeping (p,d,q) = (2,1,1) and observed that for drought period, water-level prediction for one week, one training window observed 'nan'(error or invalid number) prediction while NSE values was observed 0.348 on average for others. On comparison to the NSE value of 0.8512 for FMLSTM and 0.8186 of WaLSTM, we see that these statistical models not only have limitation on parameters selection and their complex optimization but also lag performance for better forecasting. We further compare the ARIMA model but for shorter durations, more 'nan' values were increasingly observed thus making the comparison ineffective. We further continue discussion about results on comparison of various models.

The first experimental approach(A1) considered true meteorological data for the duration we are predicting water-level is considered as one of the inputs to FMLSTM model. It consists the ground truth values of meteorological parameters for timesteps $t+1, t+2...t+n$. This approach is mentioned in Figure 6.
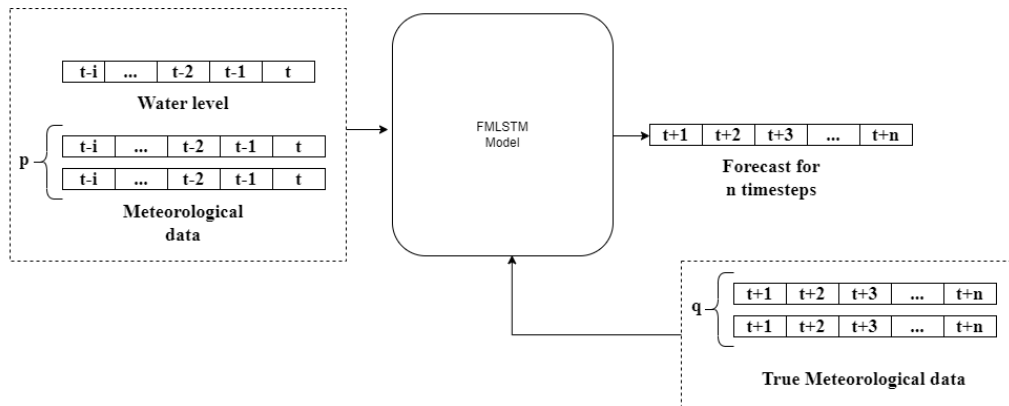
Figure 6: Approach 1 - Using True Meteorological data for prediction duration

The second approach (A2) involved using the meteorological forecasts calculated by estimation as input as mentioned in Figure 7,

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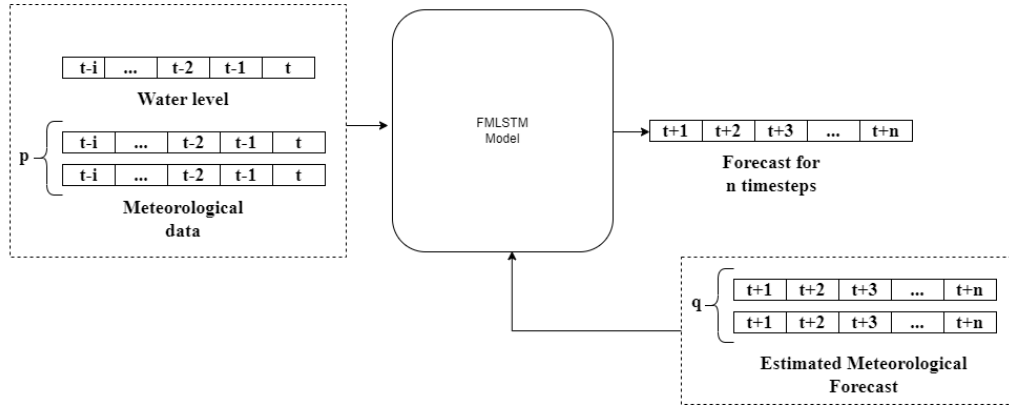
Figure 7: Approach 2 - Using Estimated Meteorological Forecast for prediction duration

We examined the impact of using all the meteorological parameters (as mentioned in Table 3) compared to using only a subset of these meteorological parameters (temperature, relative humidity, rainfall, pressure, and snowfall). Based on the number of meteorological parameters considered for input, this section is further divided into 2 subsections. Both experiments are carried out on 3 time periods, each associated with a particular weather condition (drought, frazil and flood due to snow melt) to observe the performance of our approach in all three weather events.

2.4.1 Comparison of Model Performance using All Meteorological Parameters

We evaluate the models on data from Bergeron (Table 5) and Louis site (Table 7). We Predict for 1 hour, 1 day and 1 week for Bergeron site using Approach 1 and results are mentioned in Table 5. This improvement is attributed to the incorporation of meteorological data for the duration of the prediction. For example, rainfall and temperature in the FMLSTM model could demonstrate their influence on river water-level possible due to gradual snowmelt in winter caused by high temperatures in the forthcoming days, or increased rainfall leading to runoff from surrounding areas, thereby introducing the potential for abrupt water-level changes.

Table 5: Results at Bergeron site with all meteorological parameters using true meteorological data (approach 1)

	One Hour			One Day			One Week		
	WaLSTM	MetLSTM	FMLSTM	WaLSTM	MetLSTM	FMLSTM	WaLSTM	MetLSTM	FMLSTM
Drought									
RMSE	0.0039	0.0056	0.0081	0.0135	0.0175	0.0193	0.0649	0.1663	0.0588
NSE	0.9995	0.9990	0.9980	0.9946	0.9910	0.9892	0.8186	-0.1905	0.8512
Frazil									
RMSE	0.0030	0.0056	0.0039	0.0248	0.0257	0.0302	0.1090	0.2171	0.1155
NSE	0.9986	0.9951	0.9975	0.9072	0.9002	0.8617	-0.0499	-0.1520	-0.1788
Ice-Melt									
RMSE	0.0038	0.0068	0.0046	0.0223	0.021	0.0199	0.1253	0.2262	0.1172
NSE	0.9999	0.9966	0.9984	0.9645	0.9686	0.9717	-0.1608	-0.0468	-0.0161

We also predict for 1 day and 1 week using Approach 2, comprising of estimated meteorological forecast and compare the results to other models. The results are summarized in Table 6. By observing Tables 5 and 6, we also observe that the performance of FMLSTM model deteriorates with estimated forecasted values compared to using true meteorological data for duration of prediction. This was expected as there persists an error in meteorological forecasts caused by inaccurate forecast by weather stations, which is then amplified to predict water level.

Table 6: Results at Bergeron site with all meteorological parameters using estimation of meteorological forecast (approach 2)

	One day			One week		
	WaLSTM	**MetLSTM**	**FMLSTM**	**WaLSTM**	**MetLSTM**	**FMLSTM**
	Drought					
RMSE	0.0135	0.0175	0.0188	0.0649	0.1663	0.0620
NSE	0.9946	0.9910	0.9897	0.8186	-0.1905	0.8343
	Frazil					
RMSE	0.0248	0.0257	0.0501	0.1090	0.2171	0.2011
NSE	0.9072	0.9002	0.8949	-0.0499	-0.1520	-0.1205
	Ice-Melt					
RMSE	0.0223	0.021	0.0404	0.1253	0.2262	0.2266
NSE	0.9645	0.9686	0.9678	-0.1608	-0.0468	-0.0517

Further to verify this, we predict water-level for 1 day and 1 week at Louis site using approach 1, whose results are mentioned in Table 7. At Louis, We observe for both one day and one week using meteorological ground truth values in (FMLSTM) showed compelling performance. Specifically, when evaluating the RMSE values and NSE values for the Frazil(0.0268,0.9388) and Ice Melt (0.0208,0.9862) period within a one-day timeframe, the FMLSTM model exhibited equal or superior performance compared to WaLSTM and MetLSTM. On the other hand, for a one-week timeframe, FMLSTM outperformed the WaLSTM and MetLSTM models with comparatively large margins. Results from Table 5, Table 6 and Table 7 show that when using all meteorological parameters, as the time horizon is extended FMLSTM model outperforms other models and the additional information provided by meteorological data for the upcoming days offers valuable insights into the trend that might persist in the future.

Table 7: Results at Louis site with all meteorological parameters using true meteorological data (approach 1)

	One day			One week		
	WaLSTM	**MetLSTM**	**FMLSTM**	**WaLSTM**	**MetLSTM**	**FMLSTM**
	Drought					
RMSE	0.0299	0.0168	0.1634	0.098	0.0643	0.0427
NSE	0.9936	0.9909	0.9914	0.9216	0.8484	0.933
	Frazil					
RMSE	0.0564	0.0317	0.0268	0.2364	0.1237	0.1049
NSE	0.9396	0.9143	0.9388	0.1107	-0.0952	0.2135
	Ice-Melt					
RMSE	0.0506	0.024	0.0208	0.0346	0.1706	0.1394
NSE	0.9819	0.9816	0.9862	0.1526	0.0768	0.3833

2.4.2 Comparison of Model Performance using selective meteorological parameters

We verify the performance on a subset of meteorological parameters previously used. We use Temperature, Humidity, Rain, Pressure for all periods and include snow data exclusively for frazil and ice-melt periods. The experiment is performed on water-level data from Bergeron site , 1 day and 1 week timesteps are predicted using the 3 models. The results of this experiment using True meteorological data(approach 1) are mentioned in Table 8 while the results for estimated (approach 2) are mentioned in Table 9. We observe that the results for One Week of Drought and Ice-Melt period, the FMLSTM model outperforms other models while performance in Frazil period is comparatively same.

Table 8: Results at Bergeron site with Temperature, Pressure, Humidity, Rain and Snow* using true meteorological data (approach 1)

	One day			One week		
	WaLSTM	**MetLSTM**	**FMLSTM**	**WaLSTM**	**MetLSTM**	**FMLSTM**
			Drought			
RMSE	0.01354	0.0158	0.0173	0.0649	0.0819	0.053
NSE	0.9946	0.9937	0.9913	0.8186	0.7115	0.8761
			Frazil			
RMSE	0.0248	0.0256	0.0265	0.1090	0.1098	0.1095
NSE	0.9072	0.9004	0.8937	-0.0499	-0.0639	-0.0586
			Ice-Melt			
RMSE	0.0223	0.0215	0.0208	0.1253	0.1207	0.0871
NSE	0.9645	0.9671	0.9691	-0.1608	-0.0775	0.4388

Table 9: Results at Bergeron site with Temperature, Pressure, Humidity, Rain and Snow*. using estimation of meteorological forecast (approach 2)

	One day			One week		
	WaLSTM	**MetLSTM**	**FMLSTM**	**WaLSTM**	**MetLSTM**	**FMLSTM**
Drought						
RMSE	0.01354	0.0158	0.0171	0.0649	0.0819	0.0508
NSE	0.9946	0.9937	0.9915	0.8186	0.7115	0.8886
Frazil						
RMSE	0.0248	0.0256	0.0507	0.1090	0.1098	0.2125
NSE	0.9072	0.9004	0.8926	-0.0499	-0.0639	-0.1045
Ice-Melt						
RMSE	0.0223	0.0215	0.0394	0.1253	0.1207	0.1855
NSE	0.9645	0.9671	0.9693	-0.1608	-0.0775	0.2952

2.5 Conclusion

We studied new machine learning models, as well as the impact of using weather forecasts instead of precise weather conditions (as in literature articles) to predict the water level of rivers in the context of designing tools for predicting events related to floods.

Although the experiments were conducted using either actual meteorological data or estimated meteorological forecasts due to the unavailability of meteorological forecasts dataset, experiments show that inaccuracy in meteorological forecasts (in case of estimated forecasts) impacts the quality of water-level prediction. With more accurate meteorological forecasts, better water-level prediction tools could be devised using models similar to FMLSTM.

By including meteorological data for timesteps for which we are predicting water-level, we aid the model with the information on various weather patterns or phenomenons likely to happen

that could lead to water-level fluctuations and thus better understand the relation of meteorological elements and dynamics of water level.

Moreover, this experiment was carried out using meteorological data from a weather station away from the river banks. Thus, there may be marginal deviations in observed values of temperature, wind and other meteorological parameters at the site where water-level data was collected. Thanks to the weather station in the IoT platform, it will be possible to collect on-site meteorological data thus aiding more reliable results. Even using meteorological data with high spatial resolution could help in this problem.

This work currently employs a historical water-data dataset provided by Hyro-Meteo thus, errors in the accuracy of the water-level sensor could propagate in the prediction results. Also because an external source of data-provider, real-time meteorological forecast could not be experimented with the limitation of real-time water-level data. In future, we believe our approach can be easily implemented for real-time water-level predictions using data from IoT sensors and this could help signal water-level alerts to prevent floods or other natural calamities due to water-level changes. Currently there is no open-source data store for weather forecasts for a specific region beyond the past month thus experimentation was limited to assuming the meteorological data for prediction intervals as meteorological forecast data or estimation of meteorological forecasts. Experiments could be carried out to test various meteorological forecast models and use their forecasts as input to our models along with historical hydrological and meteorological data. These meteorological forecast models contain inaccuracies termed as *model error* in [3]. *M.R. Allen et al.* mentions that sometimes modellers may be accustomed to expecting an increase in model resolution or improved parameterisations would improve the behaviour of their forecast mode but sometimes, it could be attributed to the *model error* of underlying tools. Thus, it is important to note that error of the prediction system can be directly influenced with error propagated by the meteorological forecast models thus it is important to test out this before deploying such models at flood critical mission centers.

2.6 Acknowledgement

Chapter 3

Online Machine Learning for Flood Prediction

3.1 Introduction

Machine learning has been widely used in the modern world with abundant data and applications in artificial intelligence and data analytics. Conventional machine learning paradigms have often worked through batch or offline learning capabilities where a model is trained by some learning algorithm from the entire training dataset at once (over multiple epochs) and then deployed for inference without (or seldom) performing any update afterward. In contrast, online learning is an area of research under machine learning where the model learns incrementally from data sequentially.

Implementing batch training in such flood forecasting models requires substantial datasets comprising historical records of multiple hydrological variables. However, for remote Internet of Things (IoT) based flood forecasting systems, constraints in storage capacity and uncertainty in connectivity pose significant challenges in accessing such extensive datasets. Consequently, online machine learning methodologies are deemed more suitable for remote IoT flood prediction, enabling real-time processing of newly acquired data without depending on local storage.

Numerous studies [2, 4, 44, 57] from different geographical locations across the globe have

documented the fact that the frequency, severity, and duration of flood disasters are experiencing an increasing trend due to climate change, land use dynamics, and increasing human activities. The costs related to flooding have quadrupled in the past 40 years [27], and with the temperature rise by 2-6°C expected in Canada, the hydrological cycle is anticipated to be impacted [15]. With the increasing frequency and intensity of extreme weather events in recent years, the importance of flood prediction models to evolve with these changes becomes extremely important. Traditional batch learning methods become expensive when re-training the model on new data and may not adapt well to changing patterns or evolving data distributions. However, online machine learning overcomes the drawbacks of batch learning since the model is updated regularly with new incoming data. In the case of flood prediction, when data from IoT weather sensors is continuously streamed, an online learning model can adapt to the changing weather patterns and provide up-to-date predictions without the need for costly re-training processes. This enables more accurate and timely predictions in dynamic environments where the data distribution evolves over time.

In this chapter, we propose an online learning approach for flood forecasting to continuously learn the changing water-level patterns utilizing the real-time data collected from IoT sensors. We evaluate the performance of Online Machine learning approach for next timestep and next 1 hour predictions. We also compare the results to traditional batch machine learning paradigm for next timestep prediction and observe that online machine learning improves flood forecasting capabilities with continuous training.

3.2   Literature Review

Online learning is closely related to other areas like adaptive learning, continual learning, incremental learning, sequential learning, and these terminologies may often be confused with one another.

The learner in adaptive learning attempts to adapt the learning model for dynamically changing environments and models can utilize online learning in such environments but it is not limited to online learning and heuristic adaptation or modifications of batch learning algorithms can be

utilized which evolve to respective environment changes [24]. Continual learning is often termed as 'lifelong learning' and inspired from humans ability to continuously learn new tasks while being good at other tasks through our lifetime. While continuous learning is closely related to online learning, existing studies follow paradigm of batch training to learn on existing tasks or new tasks. Incremental learning refers to learning from stream of data samples in constrained spaces to address efficiency and scalability. Incremental learning can be viewed as a branch of online learning and extension for adapting traditional offline learning techniques in data-stream settings [52]. Sequential learning revolves around the learning from sequential training data in which the order of data is very important [14]. Sequential learning can be solved using either batch or online learning algorithms.

Several Neural networks-based learning approaches [36, 60] followed this branch of online learning, and the Perceptron could be viewed as the simplest form of online learning. One extensively studied approach in online/stochastic gradient descent utilizes the efficient back-propagation algorithm for online learning [36]. With advancements in machine learning, several attempts have been made to make deep learning compatible with online learning [37, 66]. Sahoo *et al.* [55] proposed Hedge backpropagation to learn deep neural networks in an online setting and address slow convergence of deep networks through dynamic depth adaptation. Hoi *et al.*[24] provides a comprehensive overview of online learning techniques, covering various algorithms and methodologies with a main focus on approaches in online supervised learning and online learning with partial feedback.

In this section, we highlight the developments mainly focused on online machine learning, and their applications in IoT-based environments.

3.2.1 Online learning in time series

Online learning is used for time-series problems where data arrives sequentially and needs to be processed and predicted in an ongoing manner, such as IoT sensor data [26, 33], stock prices [56], and network traffic [45], among others. Kraemer *et al.*[33] simulated online machine learning training to predict 1-day photovoltaic energy. Improvement of 56% is observed on the online machine

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learning model using Random Forest Regressor(RFG), compared to persistent predictor (termed LAG). Singh *et al.* [56] compared incremental learning using linear regression with online-offline learning approach utilizing a wide range of deep learning models like LSTM, Stacked LSTM, Bi-LSTM, CNN, and CNN-LSTM. Results showed that BiLSTM performed the best compared to other Incremental learning approaches. The online-offline model used by Singh *et al.*[56] was trained at the end of every trading session. Melgar *et al.*[43] devised a novel forecasting algorithm for streaming time series called StreamWNN. StreamWNN utilizes K-Nearest neighbors and starts with an offline stage in which a forecasting model is created based on historical data, and further, the model is incrementally updated in the online stage with buffer data. One-day updates on model-trained electrical energy consumption performed better than no updates or updating the model monthly or quarterly. Multiple studies have demonstrated improvements in training time-series data using online machine-learning approaches, motivating further experimentation to evaluate the performance of online machine-learning on our specific dataset.

3.2.2 Flood forecasting systems using online learning

Yu *et al.*[62] used an ensemble method comprising dynamic evolving neural-fuzzy inference system or DENFIS. DENFIS utilizes Evolving Clustering Method (ECM) where clusters get regularly modified during online learning. This approach fails when the observed water-level values have never occurred in the training or update phase, and time-order not being maintained in cluster organization. Thus prediction would be inaccurate compared to other supervised models. [61] compared the performance of Support Vector Machines (SVM) and Gated Recurrent Unit(GRU) model on the historical dataset (1981-1986) with online learning (termed as incremental updates) and showed that improvement was observed in the rainfall-runoff prediction.

3.2.3 Online learning with microcontrollers

Internet of Things (IoT) based machine learning systems integrate connected devices and sensors with machine learning algorithms to enable data collection, analysis, and real-time decision-making. Online Machine Learning has been tested on microcontrollers integrated into the IoT in diverse domains, including agriculture [47], mobile and wearable devices [26], energy sensors [33], and other areas. Due to Microcontrollers' limited storage capacity and low energy consumption, online machine learning is a suitable option for these devices. Tiny Online Machine Learning(TinyOL) [53] libraries are developed for incremental training on-device for streaming data. Such libraries aim to run training of ML models on low compute hardware of 64MHz CPU with 256 KB RAM along with battery consumption of 0.1W.

Despite the progress in algorithms and libraries for IoT-based online machine learning systems, there is a limited amount of research in the literature that integrates real-time online machine learning methods using water-level data from IoT sensors for flood forecasting. Our aim is to address this gap with our work.

3.3 Online Machine Learning

Online learning represents a distinct paradigm in machine learning, differing from the traditional batch learning approach. In the batch learning method, the learning process relies on having the entire training data available beforehand, and the training occurs offline due to its resource-intensive nature [24]. However, this approach has inherent drawbacks, such as inefficiency in terms of time and space costs and limited scalability for large-scale applications, as the model needs to be re-trained entirely when new data arrives.

In contrast, online learning is a dynamic and sequential method that handles data in a streaming fashion. As new data instances arrive individually, the learner continuously updates its predictive model to adapt to the latest information. This real-time adaptation makes online learning highly efficient and scalable, particularly for big data applications with high data velocity. By instantly updating the model with each new data instance, online learning overcomes the limitations of

batch learning, providing a more agile and adaptive approach to machine learning tasks. This makes online learning a valuable choice for real-world data analytics applications where data arrive continuously and in large volumes.
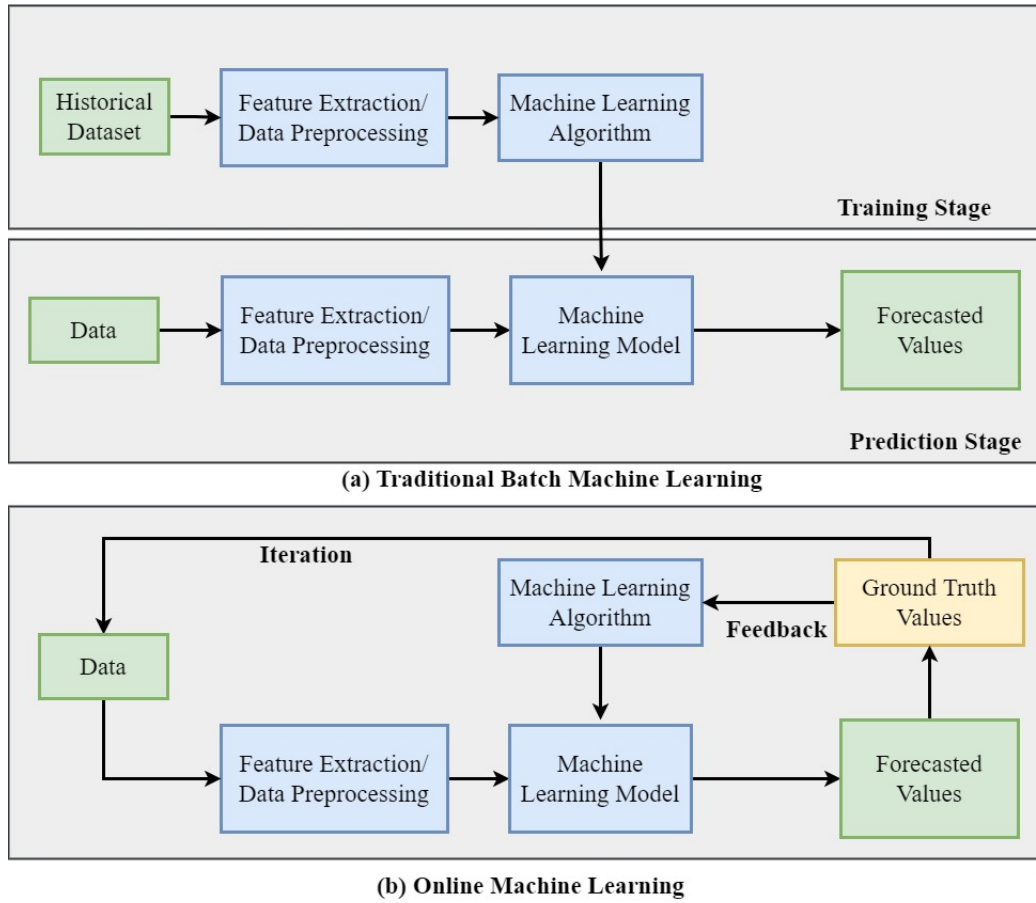
Figure 8: Batch vs. Online Machine Learning inspired from figure in [65]

3.3.1 Data Collection

This section summarizes the data collection process carried out from the IoT modules via the HY-DROSIGHT system developed by Meet[42]. It involves retrieving real-time sensor data from the Water Level Sensor (MX2001-01-SS-S) of the HYDROSIGHT system deployed at various physical locations. The Water Level Sensor communicates through the Water Level Sensor Module (RXMOD-W1) via a 4G network, enabling seamless data transmission. Water-level data is transmitted in regular intervals of 5 minutes via the 4G network to the Data Logger Station (RX3004)

which plays a crucial role in this process. The data logger station accumulates the water level data daily and exports it to the backend server for further processing and analysis. A scheduled cron job is executed on the server to collect and pre-process the water level data. The pre-processing process involves quality checks like checking null and negative values, verifying the correctness of data based on parameters like sensors installation height, and defining minimum and maximum values for each measurement. The pre-processed data is then stored in a time-series database to enable efficient retrieval and management of the sensor readings.

The time-series database stores the water level data separated by 5-minute intervals, capturing detailed and frequent measurements. This data is utilized for training and testing the online machine-learning model. The model continuously updates and adapts its predictions based on the real-time data from the Water Level Sensor, allowing for accurate and timely forecasting of water level heights.
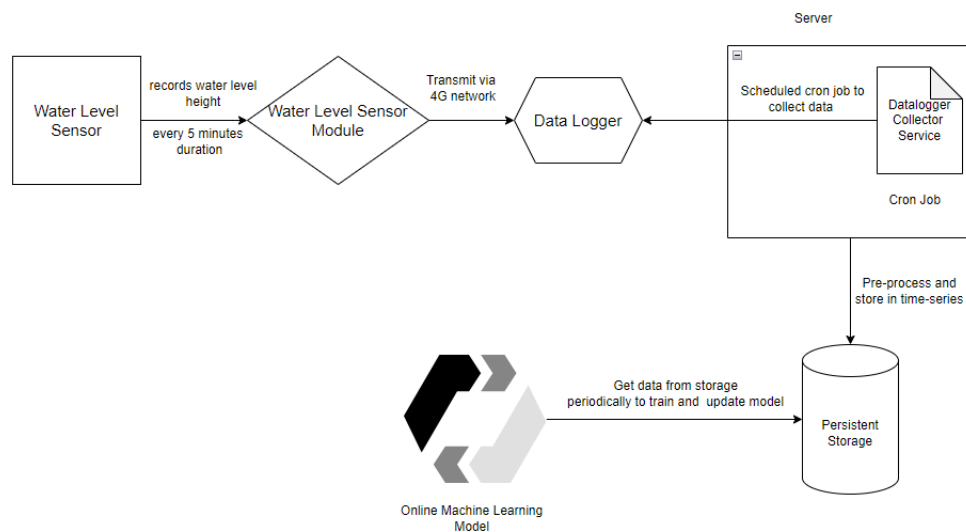

Figure 9: Data Collection for Online Machine Learning Model

3.3.2 Proposed Online Machine Learning Model

In this section we mention the Online machine learning model used to achieve accurate water-level forecasting using time series data collected from the HYDROSIGHT system. The data is gathered at five-minute intervals and stored in a dedicated database on a server. The methodology involves training a machine learning model to forecast the water level for the next time step based on the information from the last ten time steps in the database.

Before inputting the data into the model, several pre-processing techniques are applied to ensure data quality. These techniques include verifying values and correcting any missing entries. The data is also scaled using MinMaxScaler [51]. to improve the model's performance.

Algorithm 1: Online Machine Learning Algorithm

---

1 **Initialize**: $w_1 = 0$;   `// Initialization of model weight w₁`

2 **for** t = 1, 2, .., T **do**

3   Learner receives incoming sensor data x_t;

4   Learner predicts next value: $\hat{y}_t = f(x_t; w_t)$;

     Output: $\hat{y}_t$

5   True value y_t received from sensor ;

6   Learner calculates the loss: $l = MSE(y_t, \hat{y}_t)$;

7   **if** $loss(\varepsilon) > 0$ **then**

8   Update the learner;

9          $w_{t+1} = w_t + \delta(w_t, (x_t, y_t))$;

Once the data is processed and scaled, the model utilizes its prior training to predict the water level for the next step. At the beginning of the training process, the model's weights are random, but as it progresses, it continuously learns and refines its predictions through online learning. The forecasted value, denoted as $\hat{y}_t$, is then compared to the actual water-level value, y_t, to calculate the prediction error. However, due to the 5-minute sensor reading delay, the error calculations occur after this duration.

Following error calculation, the online training of the model begins. The model is trained on a

single training sample of the last ten time steps, allowing it to continuously improve and enhance its forecasting capabilities for the next step. After training, the model is stored in a model registry, which efficiently manages and versions the models.

For subsequent water-level forecasting tasks, instead of deploying the model directly, the latest version of the model is retrieved from the model registry. This ensures that the most up-to-date and refined model is always used for making predictions. Due to resource constraints, only one model is stored in this system. However, if storage for multiple models is available, the model registry allows for tracing back to a model with better accuracy in case of very high error in the current model.

This cyclic online training, evaluation, and deployment process enables the proposed approach to adapt continuously to dynamically changing river water-level data, ensuring accurate forecasts over time. As a result, this approach provides an efficient and practical solution for real-time water-level forecasting, which is crucial for various water resource management applications.
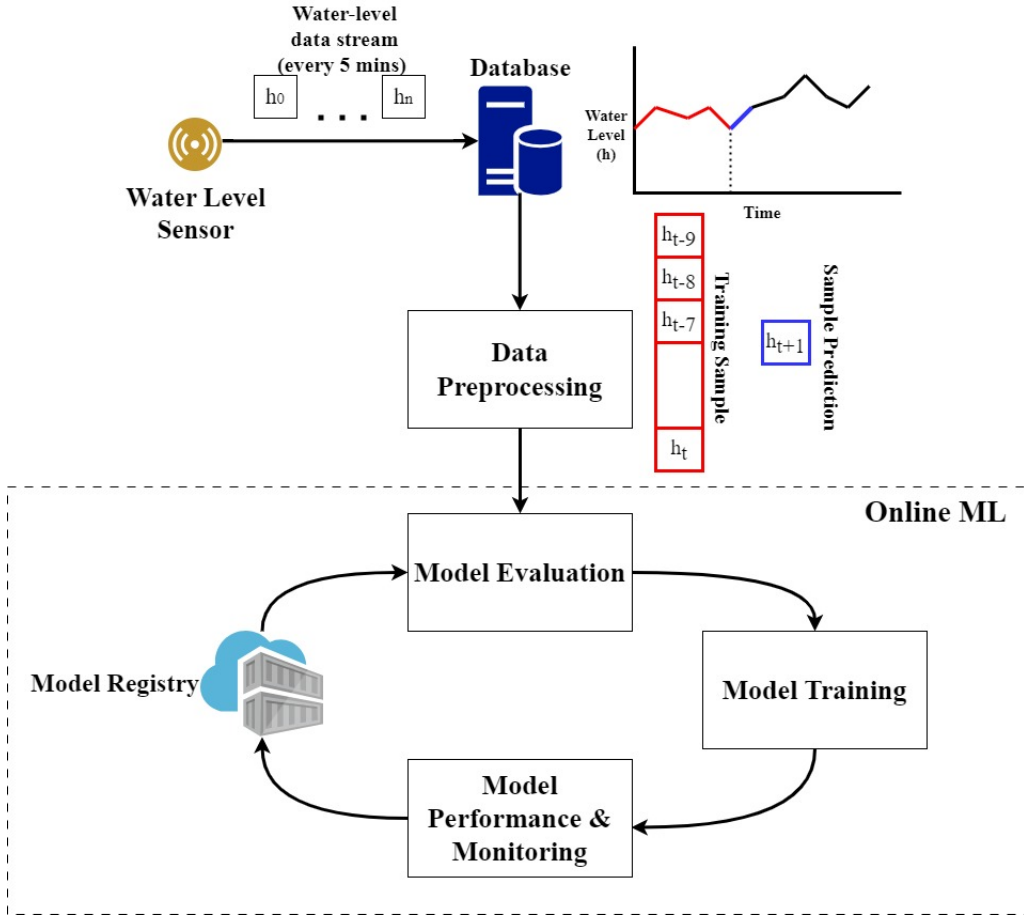
Figure 10: Online Machine Learning Architecture for Water Level Forecasting

3.4 Results

Our approach was evaluated using time series data, collected at Lac-Supérieur, one of the test sites where the HYDROSIGHT system was deployed for testing. Unfortunately, the system deployed at Terrebonne and Ericsson facility while fully operational today, was not fully functional at the time of our experiments, and could not utilized for the testing of the on-line algorithm. To assess the performance of the online machine learning model, we divided the experiment into two phases, Phase-1 and Phase-2. Training was performed in 2 subsequent phases to evaluate the enhancement in model performance through continuous online training. In Phase-1, water level measurements from 5th June 2023 to 25th June 2023 were used as training datasets. For Phase-2, the model was

further trained with data up to 30th June 2023 to incorporate more varied water level measurements. The online machine learning model's performance was evaluated for two forecasting durations: 5 minutes and 1 hour, using a testing dataset spanning from 30th June 2023 to 4th July 2023.

Figure 11 illustrates the dataset distribution with end-dates for end of training of phase I and II as well as the testing phase. It was crucial to account for the rapidly changing environment and the continuous evolution of data distributions in our evaluation. The time gap of more than five days between the evaluation data and the testing phase significantly impacted the Mean Squared Error (MSE) results. This highlighted the necessity of regularly updating the model to accommodate the transient changes in river water levels.
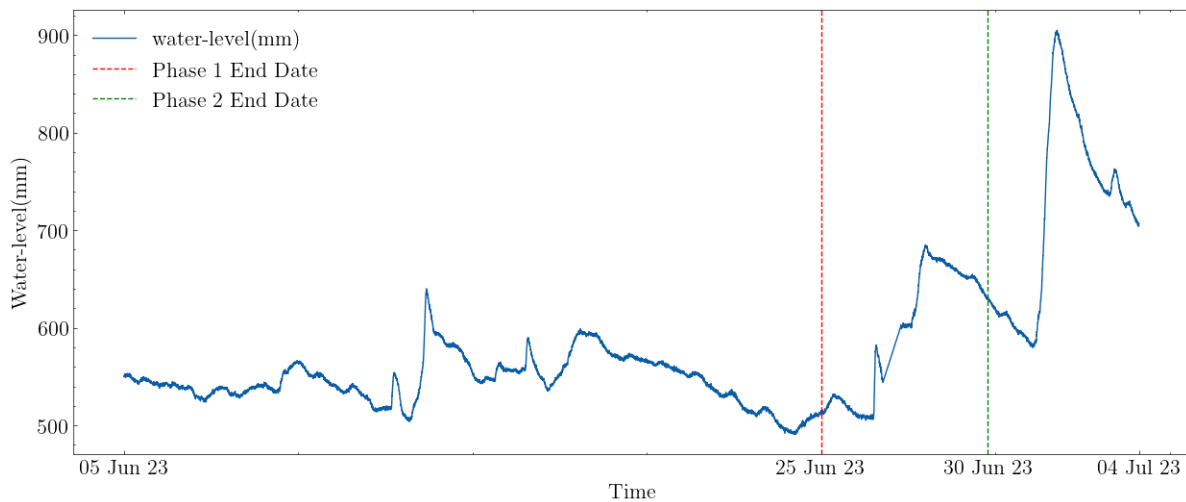
Figure 11: Visualization of water-level collected from Lac Superior and corresponding training phase dates

The results presented in Table 10 show a notable difference between the MSE of the testing phase. However, with Phase-2, where the model was continuously updated with incoming data until 30th June 2023, we observed a significant enhancement in the test error. The MSE decreased from 0.047 to 0.012, representing an impressive 74% decrease compared to the scenario where the model was not continuously updated. The same trend was observed in the results for forecasting water levels with a 1-hour duration. The continuous updating of the model resulted in improved accuracy and performance.

Forecasting Duration	Training	Testing Mean Squared Error(MSE)
Next timestep (5 minutes)	Phase-1	0.04796
	Phase-2	0.01235
1 hour	Phase-1	0.05049
	Phase-2	0.01331

Table 10: Results of water level forecasting using online learning approach

To gain initial insights into the applicability of Online ML for water level forecasting in contrast to Traditional Batch learning, we conducted an experiment focusing on forecasting water level heights for a 5-minute duration. We compared the results obtained from the Online ML approach with those derived from the Traditional Batch learning approach.

As shown in Table 11, the experiment's outcomes clearly demonstrate the benefit of the online ML paradigm, particularly in Phase-2. The online ML model exhibited more effective forecasting capabilities than the traditional batch learning model. This improvement can be attributed to the online ML model's ability to adapt and continuously update with incoming data, thus making it better suited to handle the rapidly changing environment and evolving data distributions in water level measurements.

These preliminary findings indicate the promising potential of online ML in the context of water level forecasting and underscore the advantages it holds over the more conventional traditional batch learning approach.

Machine Learning Approach	Training	Testing Mean Squared Error(MSE)
Batch ML	Phase-1	0.043801
	Phase-2	0.028732
Online ML	Phase-1	0.047962
	Phase-2	0.012355

Table 11: Comparison of batch and online ML approach for water level forecasting

Chapter 4

Conclusions and Future Work

In conclusion, this thesis has successfully addressed the challenges of water height prediction by proposing an innovative LSTM-based model in Chapter 2 that incorporates meteorological data from forecast horizon. Through a comprehensive evaluation, we demonstrated the significant improvement in prediction results using FMLSTM on the accuracy of water height predictions, particularly for longer forecasting horizons, like one week.

The chapter on Online Learning 3 showcases an online learning approach for flood forecasting, leveraging IoT for real-time water level predictions. Preliminary tests demonstrate a significant improvement in flood forecasting capabilities compared to traditional batch learning. The adaptive nature of online learning allows continuous model updates based on changing environmental conditions. The promising results from our preliminary tests open up new possibilities for future research and developments in the field, ultimately aiming to mitigate the devastating impacts of floods and protect vulnerable communities.

4.1 Future Work

The work presented in this thesis can serve as motivation for further developments in online learning-based applications leveraging water-level and other hydrological sensors for flood prediction. While the current focus is on a single sensor, future work can involve training models

with data from multiple sensors, such as rain, snow, and pressure. This expanded approach will enhance the accuracy and reliability of flood prediction systems, leading to more effective preventive measures. Further combination of this work could lead to an ensemble method for water-level forecasting comprised of meteorological forecasts and also with online training (Figure 12. This integrated system would leverage real-time updates through online learning to adapt and improve continuously.
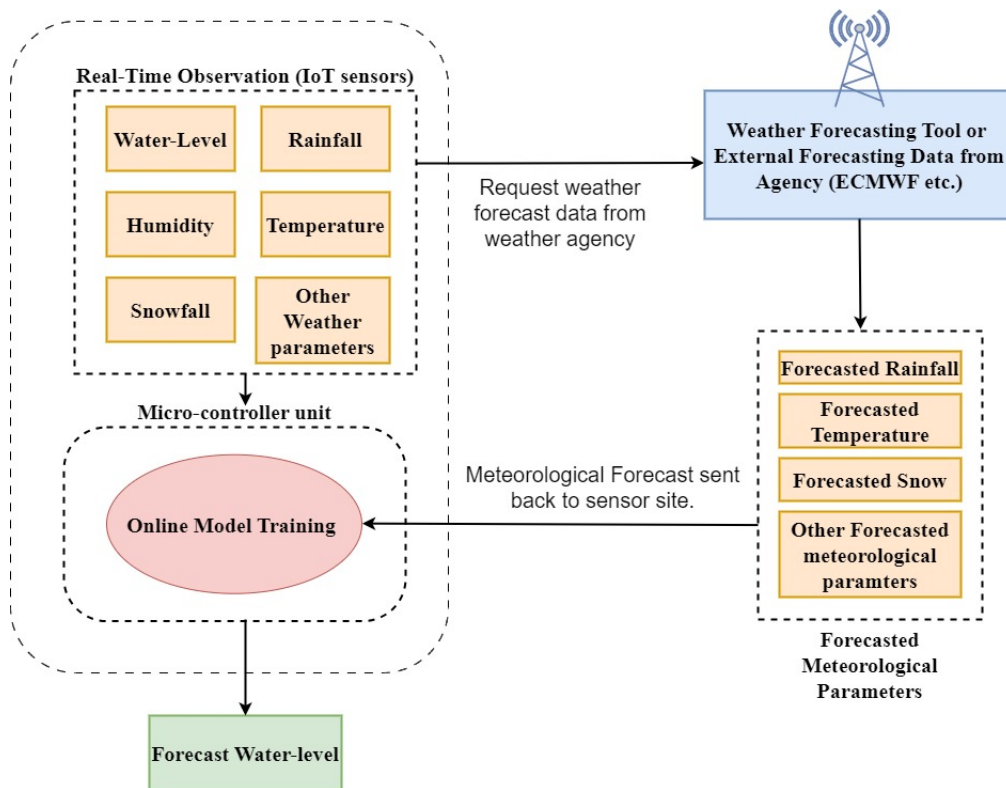
Figure 12: Proposed system for online training for Water-prediction with meteorological forecast

While this thesis has made significant progress in enhancing water height prediction and flood mitigation, there are several avenues for future research and improvement:

- Currently, the weather forecasts Chapter 3 utilize weather data from open-source meteorological sites and we also estimate forecast using errors computed from the same data. The model could be further optimized with stored meteorological forecast data or forecast data coming in from local meteorological provided by the municipalities or IoT sensors could be

leveraged to collect this information making it completely self reliant.

- Explore the application of transfer learning techniques to leverage knowledge gained from one region's data for predicting water heights in a different geographical location. This approach could enhance the model's generalization capabilities and make it adaptable to various regions.

- Optimize the placement of IoT sensors in the monitoring network to maximize the accuracy and coverage of data collection. A well-designed sensor network can improve the quality of real-time data and enhance the model's performance.

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