ENGG 680 - Deep Learning Approaches to Flood Forecasting of Kampala, Uganda

Final Project Report

(GROUP – 10)

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1. Introduction

One of the most common and damaging natural disasters in the world, flooding causes a great deal of death, damage to infrastructure and environmental deterioration. According to the World Bank, flooding affects over 2 billion people annually, with annual economic losses exceeding $100 billion and a yearly death toll in the thousands (Rentschler & Salhab, 2020). Rapid urbanization, coupled with inadequate surface drainage infrastructure and intense rainfall events, exacerbates the risk of flooding, particularly in urban areas, where it threatens public safety, health and infrastructure (Mukwayaet al., 2012).

Kampala, Uganda's capital city, has a current population of 4 million and a predicted population of 21 million by 2040. It is highly vulnerable to floods, particularly during the two rainy seasons (March-May and October-December) (International Rescue Committee, 2018). While Kampala lacks significant rivers, it is specifically prone to pluvial flooding. Pluvial flooding, also known as flash flooding or overland flooding, occurs when rainfall exceeds the ability of both the soil to absorb it and the stormwater drainage systems to withstand it.

The Nakivubo Channel, Kampala's major drainage system, was constructed in the 1950s to prevent pluvial floods by diverting stormwater and wastewater away from industrial and residential areas. It is a 9-kilometer-long river that drains waste and storm water into the Nakivubo Swamp, a natural wetland, which in turn then flows into Lake Victoria. Recent rapid urbanization and floodplain expansion, spurred by population pressure and lax enforcement of wetland preservation legislation, have increased runoff into the channel (Gideon & Bernard, 2018). The issue is exacerbated by the accumulation of both municipal waste and sediment directly within the channel and its tributaries, reducing hydraulic capacities throughout the entire network. These compounding factors cause the network to become overwhelmed during heavy rainfall events (Abo, 2024; Olsson, 2024). In flood-prone areas of Kampala, 69% of households have experienced flooding due to the current infrastructure and urban planning deficiencies (Olsson, 2024).

Despite ongoing efforts by the Kampala Capital City Authority (KCCA) to improve drainage infrastructure, the city continues to experience significant flood-related disruptions. Between January 2019 and November 2024, the UN's Global Disaster Alert and Coordination System (GDACS) recorded six major flooding events in Kampala, along with one landfill slope failure that resulted in substantial loss of life in 2024 (GDACS, 2019-2024). As climate projections suggest an increase in future rainfall intensity, the frequency of pluvial flooding in Kampala is expected to rise unless adequate infrastructure is developed to manage these extreme weather events (Mukwaya et al., 2012).

For flood predictions, Uganda currently uses GloFAS which stands for the Global Flood Awareness System. GloFAS was created by the European Union's Copernicus Program and is supported in Uganda by the Uganda National Meteorological Authority (UNMA) and the Ugandan Red Cross Society (URCS). Forecasting pluvial flood events in urban settings is thought to be beyond the scope of the GloFAS model, which is largely focused on river flooding. In addition, the model's low temporal coverage and coarse geographical resolution make it difficult to produce the localized, real-time predictions needed for efficient urban flood risk management (Boelee et al., 2018; Umer et al., 2018). As such, GloFAS is not suitable for smaller urban systems like Kampala, even though it works well for catchments with a larger scale. The current flood forecasting capabilities for the city's urban landscape are therefore seriously lacking (Mulangwa, 2023).

A promising answer to this problem is provided by recent developments in machine learning (ML). ML models can identify intricate patterns in real-time by evaluating vast amounts of hydrological and meteorological data, which increases the precision of flood forecasts.

The goal of this project is to use meteorological data from the Trans-African Hydro-Meteorological Observatory (TAHMO) network to create an ML-based forecast model for Kampala. Five weather stations run by TAHMO in Kampala gather comprehensive data on wind speed, surface air temperature, relative humidity, precipitation, atmospheric pressure, lightning, soil moisture and temperature. To increase the precision and promptness of flood forecasts in Kampala, this data will be used as one of the two inputs for a deep learning model that looks for relationships between meteorological factors and pluvial flood events.

In terms of a metric to quantify the pluvial flood events, the absence of stream gauge data in Kampala is a significant challenge. Several instream monitoring stations were formerly present on the Nakivubo Channel, but they have been poorly maintained and are no longer functional. Several new stations that were sponsored by the UN in 2019 had not yet been deployed as of 2022 (Musoke, 2022). Another possible source of data is the URCS, which has set up several stream gauge stations in rural areas, however URCS does not have stations in Kampala's urbanized districts. As such, the capacity to accurately forecast urban flood events may be hampered by this data deficit.

To tackle this deficiency, we sourced two alternative data options: (1) Dr. Seith Mugume's intensity-duration-frequency (IDF) curves for Kampala, and (2) flood event records from the GDACS database (Olsson, 2024; GDACS, 2019-2024). After discussion, we chose to utilize the historical flood event data over the IDF curves as, while the IDF curves provided a generalized estimation of rainfall intensity and frequency, they might not capture the full

Complexity of local flooding events. Whereas the historical flood data allowed us to directly correlate observed flood occurrences with specific weather conditions. Further, the IDF curves are based on rainfall data from 1943-2019, which, may not fully reflect current or future flood risk patterns under evolving climate change conditions. Finally, the IDF curves were derived using daily rainfall data, which may not adequately represent the short-duration, intense rainfall that often drives flash floods, particularly in urban areas with poor drainage systems. In contrast, historical flood data captures the actual flooding events and their specific dynamics, offering a more accurate and contextually relevant source for flood prediction. Thus the decision was to move forward with historical flood events as a metric of flood conditions.

The purpose of this study is to develop a machine learning-based, early warning system for predicting flash floods and enhancing public safety in Kampala

2. Literature Review

Rainfall prediction has long been regarded as one of the most important jobs in meteorology and climate science, as it is closely related to several challenges such as water management, agricultural productivity, and catastrophe avoidance. Rainfall prediction could eventually play a key part in disaster management, with early warnings allowing governments, humanitarian groups, and rescue teams to plan ahead of time in flood-prone areas. With the development of AI and machine learning, new techniques have been developed to predict and classify data based on their analysis. The author has identified that using long-short-term memory (LSTM) networks, the authors demonstrate superior performance in predicting rainfall with high accuracy and address the challenges of nonlinear data (Sankaranarayanan & Krishnan, 2020) . The integration of artificial intelligence allows for effective flood management by enabling early warnings, precise resource allocation, and improved water management. The author in [3] explores the application of machine learning (ML) algorithms for flood forecasting in Malaysia's Dungun River Basin, revealing an increasing frequency of flooding linked to rainfall patterns and intensities (Babar et al., 2022,). The research demonstrates that artificial neural networks (ANN) achieved the highest prediction accuracy at 90.85%, outperforming other models like Random Forest (75.61%) and Logistic Regression (48.78%). By analyzing rainfall and water level data, the study highlights that most flooding events occur at rainfall levels between 1 and 500 mm, with a peak frequency of 110 events at 250 mm of rainfall. The study highlights in that India faces severe flood risks, with temperature and rainfall intensity being critical parameters for early flood prediction, yet underutilized in existing models. A Deep Neural Network (DNN) model demonstrated the highest accuracy (91.18%) compared to machine learning algorithms like SVM, KNN, and Naïve Bayes, emphasizing its capability in flood forecasting. The research showcases the importance of leveraging seasonal data for early predictions, allowing preemptive measures to mitigate flood impacts on human lives and infrastructure. Some of the main challenges for rainfall prediction arise from the nonlinearities in weather data. Normally, temperature, humidity, wind speed, and cloud formation interact to influence rainfalls through relationships that cannot always be straightforwardly modeled with conventional methods. Findings reveal that the DNN approach effectively reduces prediction errors, making it a valuable tool for disaster management and early warning systems in flood-prone regions. Deep learning approaches, notably Long Short-Term Memory (LSTM) networks, attempt to accomplish exactly that. In these findings underscore the importance of ML models, particularly ANN and Random Forest, for enhancing flood forecasting accuracy and supporting proactive risk management strategies (Hadi et al., 2024,).

3. Methodology

3.1. Data Collection

The source of the main data in this study is the Trans-African Hydro-Meteorological Observatory-TAHMO, operating a network of five stations across Kampala. This dataset provided high-resolution records of relative humidity, precipitation, maximum temperature, minimum temperature, and mean temperature, which we used for the flood prediction. These are the meteorological and hydrological variables that precede flood events and have been deemed essential for an accurate urban flood forecast by Musoke et al. (2022) and the International Rescue Committee (2018).

3.2. Data Preprocessing

The preprocessing is also another important aspect of this project. We merged five stations data into one which can represent the whole of Kampala. Missing data values were imputed, and outliers were removed to ensure dataset quality. The data was labeled by 7 flood events for the model to learn. Standardization of variables via normalization ensures uniform scales, enhancing the model's performance.

3.3. Model selection

For flood prediction in Kampala, we utilized Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) models. RNN's main distribution lies in its ability to model and process sequential data, unlike traditional neural networks that handle inputs independently. Its recurrent nature and hidden state give it a significant edge in tasks requiring temporal understanding, though it comes with challenges in training and efficiency for long sequences. LSTMs are superior to RNNs because they can capture long-term dependencies and mitigate the vanishing gradient problem. This makes LSTM more suitable for handling hourly data, which involves extensive temporal dependencies. For this flood prediction study, LSTMs are optimal due to their robust gating mechanisms, which enable them to learn from detailed, sequential data. LSTM is particularly effective for managing non-linear relationships and avoiding vanishing gradient issues, making it ideal for rainfall prediction tasks (Haidar & Verma, 2018; Babar et al., 2022).

3.4. Model Validation

The dataset was divided into subsets for testing and training, each serving a distinct purpose in model development (Hastie et al., 2009). The training set is used to adjust the model's internal parameters by minimizing the error during learning. The validation set guides the tuning of hyperparameters, such as learning rates, dropout rates, and hidden layer configurations, helping to prevent overfitting and improve generalization. The testing set, at the end, verifies that the model generalizes well when exposed to previously unseen data and works reliably in real-world situations. This formalized approach balances the fitting of data with predictive accuracy.

3.5. Model Evaluation

The performance was evaluated on several key metrics to ensure accuracy and reliability such as the Confusion Matrix. The F1 Score balances precision (correct flood predictions) and recall (detecting most flood events), ensuring the model provides dependable flood event predictions (Chollet, 2017).

3.6. Python Libraries

This project used several Python libraries. Pandas is used for data manipulation and analysis, providing efficient tools for handling structured data. Sklearn (Scikit-learn) is used for machine learning, offering algorithms for classification, regression, clustering, and evaluation metrics. Torch (PyTorch) is also used, which is a deep learning framework that enables building and training neural networks with flexibility. Seaborn and Matplotlib are visualization libraries, with Seaborn specialized in statistical graphics and Matplotlib providing comprehensive plotting capabilities for data analysis.

4. Data Processing

As mentioned, this project uses 5 different weather data hourly with 5 stations from TAHMO. To represent the whole of Kampala, this project simply merged 5 stations into 1, then imputed missing values and removed the outliers to ensure the data quality. Then, the final data is prepared, which is the features for the model in this project.

timestamp	precipitation (mm)	relativehumidity AVG (-)	temperature AVG (degrees Celsius)	temperature MAX (degrees Celsius)	temperature MIN (degrees Celsius)
2019-12-06 17:00	0.0	0.815138888888889	22.558333333333300	22.9	22.266666666666670
2019-12-06 18:00	0.0	0.835472222222220	22.122222222222200	22.5	21.866666666666700
2019-12-06 19:00	0.0	0.865111111111110	21.747222222222220	22.03333333333330	21.53333333333330
2019-12-06 20:00	0.0	0.878805555555560	21.35555555555560	21.666666666666700	21.033333333333300
2019-12-06 21:00	0.0	0.879666666666670	21.29722222222220	21.433333333333300	21.133333333333300
2019-12-06 22:00	0.0	0.884361111111110	21.447222222222200	21.6	21.26666666666670
2019-12-06 23:00	0.0	0.894333333333330	21.33888888888890	21.566666666666700	21.133333333333300
2019-12-07 00:00	0.0	0.903305555555560	21.158333333333300	21.333333333333300	20.966666666666700
2019-12-07 01:00	2.300333333333330	0.926194444444440	20.3	21.3	18.4
2019-12-07 02:00	6.549333333333330	0.987416666666670	17.702777777777800	18.166666666666700	17.400000000000000
2019-12-07 03:00	2.375333333333300	0.995555555555560	17.688888888888900	17.833333333333300	17.533333333333300
2019-12-07 04:00	1.972	0.999166666666670	17.744444444444400	17.86666666666670	17.633333333333300

Figure 1: Five different weather data hourly as features.

Meanwhile, this project found 7 major flood events in Kampala from the UN. Precisely, the flood's duration.

```
① 2019-12-07 00:00 to 2019-12-13 00:00
② 2020-09-08 00:00 to 2020-09-12 00:00
③ 2021-08-09 00:00 to 2021-08-10 00:00
④ 2021-11-04 00:00 to 2021-11-06 00:00
⑤ 2022-12-20 00:00 to 2022-12-22 00:00
⑥ 2023-01-10 00:00 to 2023-01-14 00:00
⑦ 2024-07-24 00:00 to 2024-08-11 00:00
```

Figure 2. Seven major flood events in Kampala.

So, the very next step is how to design the problem. Simply, this project chose to make it a binary classification. As can be seen from the figure below, added a new column at the end of the data to be the label. In this column, -1 stands for there is no flooding in Kampala at this hour, while 1 is there is flooding.

timestamp	precipitation (mm)	relativehumidity AVG (-)	temperature AVG (degrees Celsius)	temperature MAX (degrees Celsius)	temperature MIN (degrees Celsius)	label
2019-12-06 17:00	0.0	0.8151388888888889	22.5583333333333300	22.9	22.2666666666666670	-1
2019-12-06 18:00	0.0	0.8354722222222220	22.1222222222222200	22.5	21.8666666666666700	-1
2019-12-06 19:00	0.0	0.8651111111111110	21.7472222222222220	22.0333333333333330	21.5333333333333330	-1
2019-12-06 20:00	0.0	0.8788055555555560	21.3555555555555560	21.6666666666666700	21.0333333333333300	-1
2019-12-06 21:00	0.0	0.8796666666666670	21.2972222222222220	21.4333333333333300	21.1333333333333300	-1
2019-12-06 22:00	0.0	0.8843611111111110	21.4472222222222200	21.6	21.2666666666666670	-1
2019-12-06 23:00	0.0	0.8943333333333330	21.3388888888888890	21.5666666666666700	21.1333333333333300	-1
2019-12-07 00:00	0.0	0.9033055555555560	21.1583333333333300	21.3333333333333300	20.9666666666666700	1
2019-12-07 01:00	2.3003333333333330	0.9261944444444440	20.3	21.3	18.4	1
2019-12-07 02:00	6.5493333333333330	0.9874166666666670	17.7027777777777800	18.1666666666666700	17.4000000000000000	1
2019-12-07 03:00	2.3753333333333300	0.9955555555555560	17.6888888888888900	17.8333333333333300	17.5333333333333300	1
2019-12-07 04:00	1.972	0.9991666666666670	17.7444444444444400	17.8666666666666670	17.6333333333333300	1

Figure 3. Labeling the data.

5. Modeling

The modeling of this project is mainly based on PyTorch. Designed a deep learning LSTM network with 2 hidden layers, then continued with a linear layer to map the output of the LSTM to the final prediction. In the end, applied the sigmoid function to obtain the probability value, which is from 0 to 1.

```python
# LSTM
class LSTM(nn.Module):  2 usages
    def __init__(self, input_size=5, hidden_layer_size=100, output_size=1):
        """
        LSTM for binary classification
        :param input_size
        :param hidden_layer_size
        :param output_size
        """
        super().__init__()
        self.hidden_layer_size = hidden_layer_size
        self.lstm = nn.LSTM(input_size, hidden_layer_size, num_layers=2, dropout=0.4)
        self.linear = nn.Linear(hidden_layer_size, output_size)
        self.sigmoid = nn.Sigmoid()

    def forward(self, input_x):
        input_x = input_x.view(len(input_x), 1, -1)
        hidden_cell = (torch.zeros(2, input_x.size(1), self.hidden_layer_size),  # sha
                       torch.zeros(2, input_x.size(1), self.hidden_layer_size))
        lstm_out, (h_n, h_c) = self.lstm(input_x, hidden_cell)
        linear_out = self.linear(lstm_out.view(len(input_x), -1))  # =self.linear(lstm
        predictions = self.sigmoid(linear_out)
        return predictions
```

Figure 4: Main part of the LSTM network.

For the loss function, this project uses the Binary Cross Entropy (BCE) for binary classification. Then uses Adam from PyTorch, which is an optimization algorithm often used in training neural networks, this may help update the parameters of the model efficiently and enable the model to converge quickly.

```python
loss_function = nn.BCELoss()  # loss
optimizer = torch.optim.Adam(model.parameters(),
                             lr=0.0001)  # optimizer
```

Figure 5: Loss function and optimizer.

6. Training and Testing

For model training, the project used last year hourly data, because it has the largest flood duration, from October 2023 to October 2024, which is great for the model to capture more flood features.

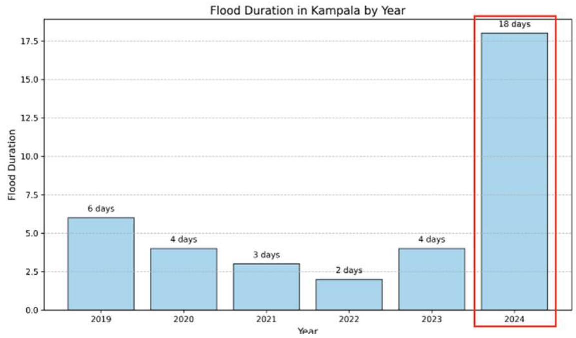


Figure 6: Flood duration in Kampala by year.

The training loss with BCE is shown in the figure below. Basically, the project stopped training the model at about 160 epoch, when it satisfied the condition.

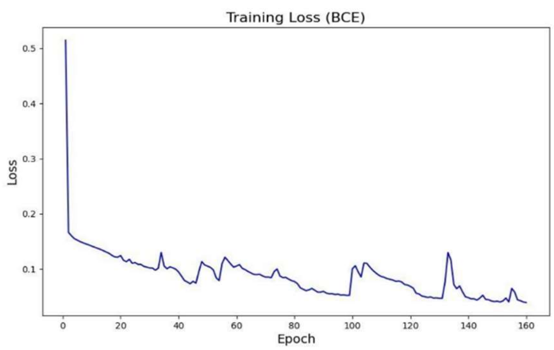


Figure 7: Training loss with BCE.

In the testing part, the project operated 2 testings. For the first testing, used 2 months hourly data from August 2020 to October 2020. The figure below is the label, which also serves as ground truth. Can be seen from the figure that there is a flood duration from 8th September to 12th September.

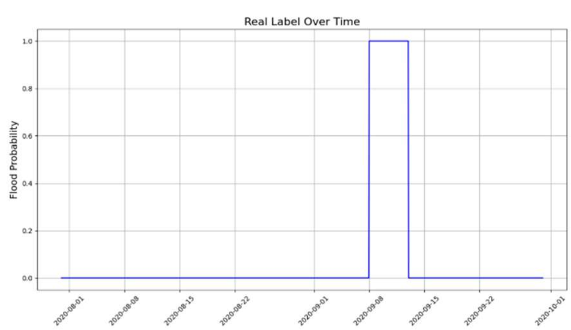


Figure 8: The label of the first test.

From the confusion matrix and evaluation metrics below, can tell that the accuracy and precision are high, indicating the model can predict almost all the no flood hourly data correctly. However, the recall is not that ideal, meaning the not that good performance of the model on flooding data.

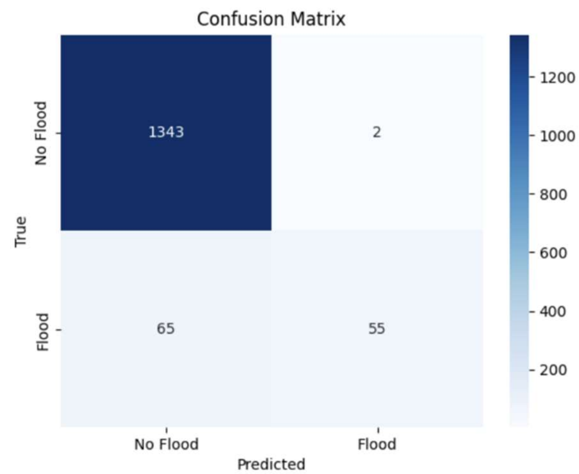


Figure 9: Confusion matrix for the first testing.

```
Accuracy: 0.9543
Precision: 0.9649
Recall: 0.4583
F1 Score: 0.6215
```

Figure 10. Evaluation metrics for the first testing.

The figure below is the comparison between the model prediction and ground truth. Overall, on the first testing, the model works though there are some gaps. It can predict almost all the no flood hours correctly, and also can predict the flooding with low accuracy.

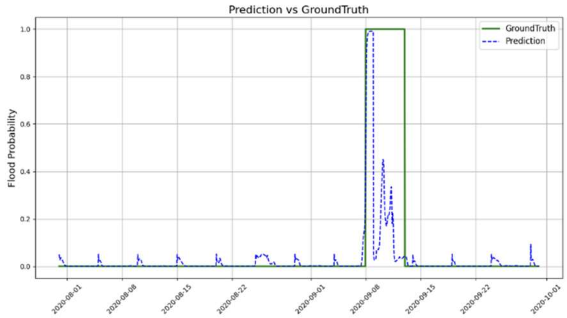


Figure 11: The comparison between the model prediction and ground truth in the first testing.

For the second test, the project used 5 months of hourly data. There are 2 flood events during these 5 months, which also can be seen from the figure below.

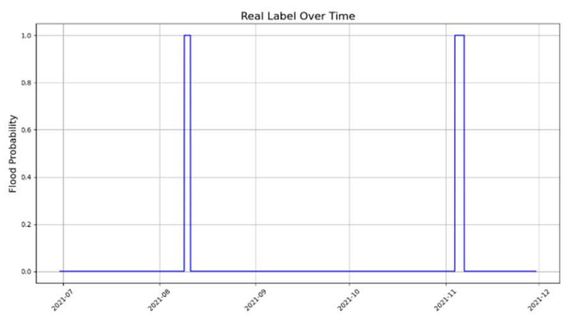


Figure 12: The label of the second test.

Same as the first testing, the accuracy and precision are high, suggesting the really good performance of the model on the no flood data. Meanwhile, the recall is still low, but 0.6 is better than the first test, indicating that the model predicted more flooding data correctly in this test.

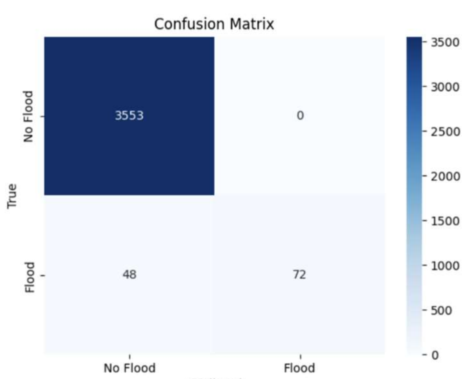
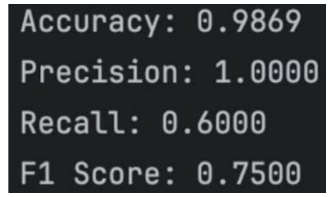


Figure 13. Confusion matrix for the second testing.



Accuracy: 0.9869
Precision: 1.0000
Recall: 0.6000
F1 Score: 0.7500

Figure 14: Evaluation metrics for the second testing.

From the comparison between the prediction and ground truth below, the model performance on the second flood was great, but could not predict the first flood.

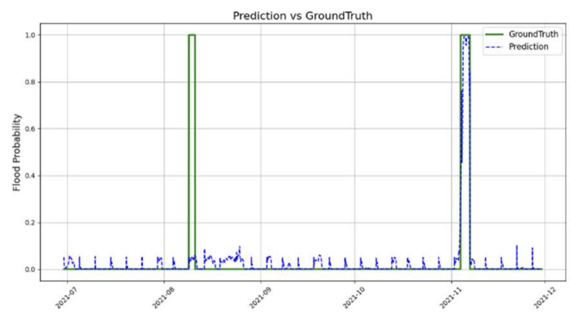


Figure 15. The comparison between the model prediction and ground truth in the second testing.

7. Discussion

This project used open source data and labeled them, then used the deep learning model LSTM to fit in the data to do flood forecasting. Overall, the model works, its performance on the no flood data is really good. But on the flooding data, its performance is unstable with the evidence of the second testing.

The unsteady performance of the model is mainly due to the imbalanced data. The figure below shows the flood and no flood hourly distribution for the data. There are about 43000 hours with no flood, but only 1056 hours with flood, which results in the unstable performance of the model on the flooding data.

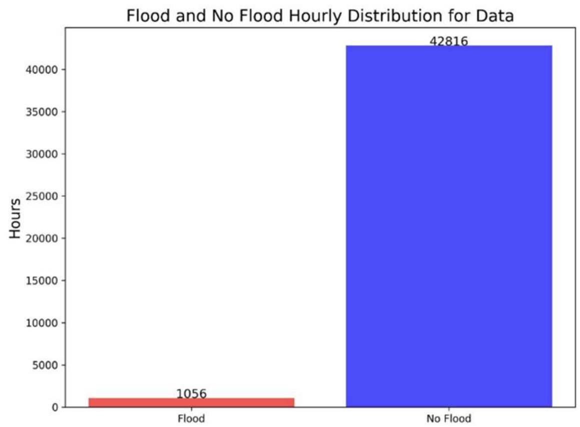


Figure 16: Flood and no flood hourly distribution for the data.

In the future, to improve the performance of the model for flood prediction, the very first consideration is to collect more data, this may help the model to capture more flood patterns. Secondly, optimizing the model using transfer learning, simplifying the architecture, or using different training strategies like regularization, loss function weighting, and cross-validation can help prevent the model from over fitting and enhance its stability.

8. Conclusion

The primary goal of this project was to develop a machine learning-based, early warning system to predict flash floods and enhance public safety in Kampala. Despite significant challenges, particularly in the area of data acquisition, the use of Long Short-Term Memory (LSTM) networks proved to be an effective tool in achieving this goal. The lack of stream gauge data and the limited scope of the UN flood database, which primarily contained catastrophic events, presented difficulties in building a balanced and comprehensive dataset. These limitations, along with the absence of hourly rainfall data and the complexities of urban flood dynamics, contributed to some gaps in model performance, particularly in recall and F1 scores. However, the **LSTM model** demonstrated high accuracy and precision, which is promising for future flood forecasting applications in the region.

One of the key successes of the project was the innovative approach of using the historical flood event data from the GDACS database in the absence of real-time stream gauge data. While the model performed reasonably well, expanding the flood occurrence dataset to include all flooding events—not just the most catastrophic—could enhance the model's ability to learn from a more diverse set of scenarios, improving its overall performance and predictive power. Moving forward, the integration of higher-resolution data, such as **hourly rainfall** data and more granular flood records, will be crucial in refining the model for more accurate, real-time flood forecasting, ensuring better flood risk management in Kampala's rapidly urbanizing landscape.

9. Acknowledgements

"We thank the Trans-African Hydro-Meteorological Observatory (TAHMO) for the provision of meteorological data. Interested parties may contact info@tahmo.org for these data"

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