Integrating ANN-LSTM Models for Enhanced Weather and Flood Forecasting with Optimized Evacuation Routing for Bacoor City

ALBA, Erica A.
Electronics Engineering Department
Technological University of the Philippines

ATAS, Marjorie Cattlyn D.
Electronics Engineering Department
Technological University of the Philippines

BATARIO, Bianca Victoria T.
Electronics Engineering Department
Technological University of the Philippines

BROSO, Elian Justin P.
Electronics Engineering Department
Technological University of the Philippines

OCAMPO, Eliza Mae R.
Electronics Engineering Department
Technological University of the Philippines

Engr. Edmund G. Monilar
Faculty
Electronics Engineering Department
Technological University of the Philippines

***Abstract*— In response to recurrent natural disasters, particularly floods and typhoons, in the Philippines, there's a critical need for localized forecasting and efficient evacuation routing at the barangay level. This research addresses these challenges by developing a real-time weather and flood monitoring system utilizing Machine Learning algorithm and evacuation routings. The ML component will utilize historical flood and weather data alongside real-time sensor inputs to predict flood events accurately. The research will explore the implementation of a combined model ANN-LSTM for improved flood prediction as well as accurate weather forecasting for a certain municipality. Additionally, user-friendly mobile applications will be developed to deliver localized weather forecasting and recommend the safest evacuation route using google maps. These applications will empower local communities and government agencies to implement effective Early Warning Systems (EWS) at the barangay level, enhancing disaster preparedness and reducing economic losses associated with natural disasters. By integrating ML algorithms, and evacuation routing strategies, this research aims to bolster community resilience in the Philippines against natural disasters, ensuring prompt and effective responses to mitigate risks and minimize impacts.**

Keywords— natural disasters, machine learning algorithm, evacuation routing, ANN-LSTM, google maps, Early Warning System, barangay level.

I. Introduction

The Philippines is among the countries that is most vulnerable to natural disasters, such as typhoons and floods, that present significant challenges to communities worldwide due to its geographical location. The Global Climate Risk Index 2021 ranked the Philippines as the fourth most vulnerable to extreme weather events such as tropical cyclones and flash floods [1]. With, timely evacuation is essential to reduce the loss of life and property. However, existing evacuation systems often falter in accurately adapting to rapidly changing weather conditions, highlighting the need for more precise forecasting and route optimization strategies [2].

The Disaster Risk Reduction and Management Act of 2010 (RA 10121) mandates the integration of disaster risk reduction (DRR) and climate change adaptation (CCA) into local development plans [3]. This study proposes an integrated approach utilizing Artificial Neural Network – Long Short-Term Memory (ANN-LSTM) models to improve weather and flood forecasting accuracy, aligning with the objectives outlined. Through the integration of advanced machine learning techniques with real-time surveillance data, the research aims to optimize evacuation routes, thereby providing reliable guidance during flood events and significantly transform disaster preparedness and response strategies.

II. Background of the Study

The intertwining of climate change and urban development has amplified the frequency and severity of weather-related disasters, particularly floods [4]. Conventional approaches to weather prediction and flood management have struggled to keep pace with these shifts, often resulting in delayed responses and ineffective mitigation strategies [5]. The urgency for advanced forecasting systems capable of issuing early, precise warnings has never been greater [6]. Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) models have emerged as potent tools in predictive analytics [7]. Their capacity to analyze extensive data sets and decipher intricate patterns renders them well-suited for forecasting meteorological phenomena. Through the fusion of ANN and LSTM models, researchers have initiated the development of more dependable and accurate forecasting systems, capable of predicting weather and flood events with heightened certainty.

The significance of forecasting extends beyond prediction alone. Ensuring the safe evacuation of at-risk populations during flood events is equally crucial [8]. Conventional evacuation routes may not always be viable or efficient amidst swiftly evolving flood scenarios [9]. Consequently, our research also concentrates on crafting an evacuation routing system that dynamically adjusts to real-time conditions, guaranteeing the safest passage to safety for affected individuals. It will provide the safest path by tracing a route that has the lowest readable water level on the street. This research endeavor aims to bridge the gap between advanced forecasting technology and practical disaster management applications, furnishing a comprehensive solution to the challenges posed by severe weather events.

III. Objectives

With, this journal aims the following:

1. To design and evaluate an ANN-LSTM model for accurate weather and flood forecasting using historical data.
2. To develop an evacuation route optimization which provides the safest route based on the lowest water level.

IV. Review of Related Literature

Table 1. Summary of Related Literature for Machine Learning

	Year	Parameters	Algorithm	Relevant Findings	Relationship to the Study
[10]	2018	Rainfall and Temperature	• Support Vector Regression (SVR) • Artificial Neural Networks (ANN)	ANN can produce the better results than the SVR with acceptable deviation of error rate.	Utilizing ANN offers a better result with its acceptable deviation of error rate.
[11]	2020	Rainfall	• Auto Regressive Integrated Moving Average (ARIMA) • Artificial Neural Networks (ANN) • Support Vector Regression (SVR) • Multilayer Perceptron (MLP) • Auto Encoders	Because of nonlinear relationships in rainfall datasets and the ability to learn from the past, Artificial Neural Network makes a superior solution to all approaches available.	Demonstrates that leveraging ANN provides a superior solution compared to other available approaches in terms of weather forecasting.
[12]	2020	Temperature, Humidity, and Air Pressure	• Long Short-Term Memory (LSTM) • Multilayer Perceptron (MLP)	The proposed models are good at prediction. MAE (LSTM) = 1.0561 MAE (MLP) = 0.7731	Both studies utilize the LSTM algorithm for predicting weather.
[13]	2011	Flood based on weather radar and/or rain gauge rainfall data	• Artificial Neural Networks (ANN)	Artificial Neural Networks (ANNs) provide significant speed improvements over conventional hydraulic simulators, particularly for flood severity classification. However, relying solely on rainfall for flood prediction does not yield operationally useful lead times.	Both studies employ ANN as an algorithm for predicting and analyzing flood forecasts.
[14]	2023	Flood based on precipitation	• Exponential Smoothing-Long-Short Term Memory (ES-LSTM) • Recurrent Neural Networks (RNNs) • Artificial Neural Networks (ANN) • Decision Tree (DT)	The study found that ES-LSTM and RNN achieved low mean absolute percentage error (MAPE) values of 3.17 and 6.42, respectively. In contrast, the ANN and DT models demonstrated high prediction accuracy rates of 96.65% and 84.0%, respectively. Overall, the ES-LSTM and ANN models performed best compared to other models.	Both research studies will concentrate on utilizing ANN for flood monitoring systems. Additionally, both studies integrate LSTM with other algorithms to enhance its robustness.

[10] *An Application of Data Mining and Machine Learning for Weather Forecasting*

This study evaluates the effectiveness of data mining and machine learning methods, specifically Support Vector Regression (SVR) and Artificial Neural Networks (ANN), for accurate weather prediction. The research utilized a 6-year historical weather dataset from the Chittagong metropolitan area, obtained from the Bangladesh Meteorological Department (BMD). The results indicate that SVR performs better than ANN in rainfall prediction, while ANN yields superior results compared to SVR.

[11] *Rainfall Prediction Using Machine Learning & Deep Learning Techniques*

This research paper introduces a Deep Learning Approach for rainfall prediction using Multilayer Perceptron and Auto-encoder Neural Network. The study compares architecture with existing state approaches (ARIMA, ANN, SVR). Accuracy is evaluated using Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). Additionally, the paper discusses various methodologies for rainfall forecasting, emphasizing the advantages of Artificial Neural Networks due to its ability to learn from historical data and handle nonlinear relationships in rainfall datasets.

[12] *Real-Time Weather Monitoring and Prediction Using City Buses and Machine Learning*

The study utilizes weather sensing data to train and verify two models: the Long Short-Term Memory (LSTM) model and the Multilayer Perceptron (MLP) model. These models predict temperature, humidity, and air pressure in a test environment. The performance of both models is comparable for temperature prediction, with MLP slightly outperforming LSTM from 8 a.m. to 6 p.m., while LSTM performs better in other time periods. For humidity and pressure, LSTM achieves superior tendency prediction compared to MLP. Although LSTM has a slight advantage over MLP, this may be due to differences in model depth or parameter usage.

The proposed prediction system is compared to existing architectures, including multiple linear regression (MLR). In terms of Mean Absolute Error (MAE), the proposed system with LSTM (MAE(LSTM) = 1.056) closely matches the MLR model in Parashar (MAE(MLP) = 1.10). The MLP model in the proposed system achieves the lowest MAE (MAE(MLP) = 0.7731), indicating strong predictive capabilities. Additionally, the proposed system provides past, current, and 24-hour weather forecast information.

[13] *Urban flood prediction in real-time from weather radar and rainfall data using artificial neural networks*

This research paper discusses using Artificial Neural Networks (ANNs) as Data-Driven Models (DDMs) for real-time urban flood prediction based on weather radar and rain gauge data. The study focuses on a sewer sub-network in Keighley, UK. An ANN is configured to predict flooding at manholes using rainfall input. In the absence of actual flood data, a hydrodynamic simulator provides target data for training the ANN. The ANN acts as a rapid surrogate for the simulator. While ANNs significantly improve speed over hydraulic simulators, flood prediction based solely on rainfall lacks operationally useful lead times. Efforts to extend prediction times are explored through radar rainfall feature extraction and time-series prediction using ANNs.

[14] *An Intelligent Early Flood Forecasting and Prediction Leveraging Machine and Deep Learning Algorithms with Advanced Alert System*

This research created a forecasting model for hourly precipitation using the exponential smoothing-long short-term memory (ES-LSTM) structure and recurrent neural networks (RNNs). Additionally, precipitation classification is performed using an artificial neural network (ANN) model and decision tree (DT) algorithm. The study utilizes the Historical Daily Weather dataset from the Australian Commonwealth Office of Meteorology. Results indicate that ES-LSTM and ANN achieve the best performance compared to other models, with low mean absolute percentage error (MAPE) and high prediction accuracy rates.

.

Table 2. Summary of Related Literature for Evacuation Routing

	Year	Relevant Findings	Relationship to the Study
[15]	2023	The research paper utilizes a map API which recognizes flood occurrence which then will provide an evacuation route to an evacuation shelter	Both research paper has a key feature which it shall provide an evacuation route from the user’s location towards an evacuation shelter
[16]	2020	The research paper utilizes GIS which classifies evacuation route and will adapt to flood event changes	Both research paper provides evacuation route in which it will based on the data gathered to trace the safest route towards the evacuation shelter
[17]	2023	The research utilizes GIS to analyze flood-prone areas, assess road networks, and identify optimal evacuation locations and routes.	Both research utilizes a system to provide an optimal and safest route towards the evacuation shelter as flood is present

Evacuation Routing involves strategically selecting the most optimal pathways to ensure the rapid and secure relocation of individuals during critical situations. This method aims to minimize the likelihood of injuries, loss of life, and damage to property by efficiently guiding people away from danger during emergencies. By meticulously planning evacuation procedures, the potential hazards faced by individuals are mitigated, ensuring they can promptly reach safety and minimizing their exposure to immediate threats. Additional measures such as designated assembly points, communication protocols, and emergency supplies distribution can further enhance the effectiveness of evacuation strategies, providing comprehensive protection for communities in crisis situations.

[15] *Map API-Based Evacuation Route Guidance System for Floods*

This study developed a Map API-Based Evacuation Route Guidance System to address the challenge of safely evacuating people from outdoor areas like forests and parks during floods. Their system leverages a map API to detect flood occurrences and calculate evacuation routes to the nearest shelters. It also adapts to changing conditions by updating the route if the initial path becomes impassable. The authors highlight the system's potential to enhance safety by providing real-time, location-specific evacuation guidance through smart devices. This approach represents a significant advancement in utilizing technology for disaster management in outdoor settings.

[16] *Flood Evacuation Routes Based on Spatiotemporal Inundation Risk Assessment*

A study where the researchers propose a methodology for determining evacuation routes considering both spatial and temporal aspects of flood inundation. Utilizing a non-linear auto-regressive neural network with exogenous inputs for flood prediction and a geographic information system for route planning, the study aims to enhance adaptability and safety during floods. The methodology was applied to a flood-prone area in Seoul, Korea, demonstrating the potential of artificial neural networks to expedite the flood prediction process and improve evacuation strategies based on dynamic hazard levels. This approach is significant for its contribution to disaster management by providing flexible and reliable evacuation guidance in response to changing flood risks.

[17] *GIS-based identification and analysis of suitable evacuation areas and routes in flood-prone zones of Nakhon Si Thammarat municipality*

The research focuses on utilizing Geographic Information Systems (GIS) to identify and analyze optimal evacuation areas and routes within the flood-prone zones of Nakhon Si Thammarat Municipality. The study integrates various data layers, such as slope angle, elevation, and distance from rivers, using the frequency ratio method to assess flood susceptibility. The findings indicate significant areas with high flood susceptibility and reveal that travel times can increase fourfold during flood scenarios. This research provides critical insights for emergency management authorities to develop comprehensive evacuation plans, enhancing resilience against future flood events in Thailand and potentially other Southeast Asian regions.

V. Methodology

The system utilizes different sensors for weather and flood monitoring. These sensors include humidity, wind speed, temperature, air pressure, and rainfall sensors for weather monitoring, as well as depth and water level sensors for flood monitoring. With, these parameters will serve as input for the machine learning model to predict weather and flood conditions over the next 6 hours.

Furthermore, the system offers both a mobile app that allows individuals to access weather forecasts and monitor flood situations in the chosen vicinity. Additionally, it incorporates flood prediction features, enabling users to track the potential flood risks within their community. Evacuation routing will then be incorporated beside the flood forecasting which will monitor the water level of certain streets to ensure a probable route towards the evacuation shelter.

The mobile app for weather prediction and flood detection, equipped with an early warning system, is a software solution tailored for smartphones. It utilizes advanced technologies such as meteorological data analysis, the utilization of google maps and machine learning algorithms to deliver precise weather forecasts and prompt flood alerts as well as offering an evacuation route to users located in the Philippines.

A. Block Diagram

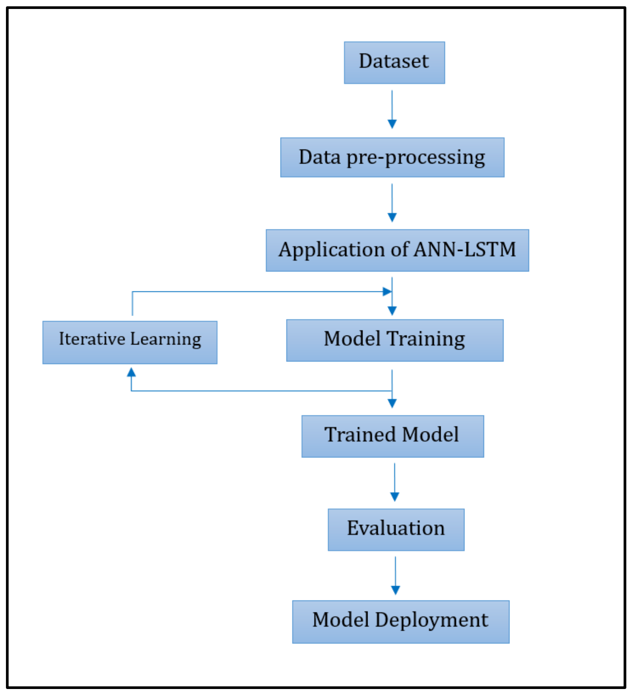


Figure 1. Simplified Block Diagram for Weather and Flood Forecast

The figure illustrates the proposed machine learning algorithm designed for both weather and flood prediction. The process begins with data pre-processing, where missing and duplicate values from the historical dataset are addressed. Next, the ANN-LSTM model is applied and iteratively trained. Finally, the trained model's performance is evaluated using metrics such as R-squared, Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE).

B. Research Design

The research utilized Descriptive Research Design. The study centers on developing a mobile application with a feature that provides an evacuation route, specifically the safest route for users and forecasts for both weather and flood systems—evaluated by calculating R-squared, RMSE and MAE. In addition, a User Acceptance Testing (UAT) will also be implemented in where the system is evaluated by the officials of Bacoor Disaster Risk Reduction Management Office (BDRRMO), barangay personnel and residents of the chosen Barangay to test the functionality, reliability, and efficiency of the system.

C. Software Design

Machine Learning Algorithm Selection

This study utilized Artificial Neural Network − Long Short-Term Memory (ANN-LSTM) model to process collected data from sensing nodes for both weather forecasting and flood monitoring. The ANN algorithm excels in handling nonlinear weather conditions and learning from historical data, making it a superior solution compared to other available approaches [11]. Additionally, the ANN model demonstrates effectiveness in predicting flood levels, achieving high prediction accuracy rates [14].

Furthermore, the LSTM model is trained using various combinations of weather parameters, including temperature, humidity, and pressure, to predict weather conditions [12]. Hence, integrating LSTM with other techniques enhances its robustness.

Evacuation Routing

This study utilizes Maps SDK for Android which is used for the integration of maps in android application as this study will use android as the mobile application. It shall use Google Maps data to provide map displays as well as respond to map gestures and also enhancing user's experience as it can add markers which will help the users to identify the position of evacuation shelter, the research flood nodes, and the user's position. The API used for tracing a route from the user's location towards the evacuation shelter is the Directions API. It shall offer a way to get the directions between locations and it can handle multipart directions with a series of waypoints to trace a route for the user.

Furthermore, this can be used in a way to provide a safest route for the users. It will make use of the data from the deployed flood node on the street to provide a safest route by reading which street has the lowest water level, which indicates that the street with the lower water level has a higher chance of being the safest route towards the evacuation shelter. Thus, providing a much safer direction for the user to pass through towards the evacuation shelter.

VI. Results and Discussion

The assessment utilized a range of crucial indicators for the analysis, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), R-squared Score, and Accuracy. These metrics were applied to evaluate forecast for both flood and weather systems to provide an accurate early warning.

Together, these metrics offered a comprehensive evaluation of the models' performance, highlighting its strengths and areas needing improvement.

A. Weather Node System

For the weather node system, the initial training data was from Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA)'s station – Sangley Pt., Station in Cavite City for it was considered as the nearest station to Bacoor City as per the PAGASA Climatology and Agrometeorology Division (CAD). It consisted of 8,036 data for the parameters: rainfall, maximum temperature, minimum temperature, relative humidity, wind speed, and wind direction. The maximum and minimum temperature were averaged to create a new column – temperature. The five columns of parameters (temperature, relative humidity, wind speed, wind direction, and rainfall) were then trained using the algorithm ANN-LSTM.

The post-deployment data was the collected data after the weather station was established and deployed. All its sensor were calibrated by PAGASA where it accumulated 59,825 rows of data at ten-second intervals. This data was also consisted of five column parameters: temperature, humidity, wind speed, wind direction, and rain intensity. Like the initial training data, the five columns and 59,825 rows of data were then trained using the ANN-LSTM algorithm.

Table 3. Comparison of Weather System's Initial and Post-Deployment Model Performance

	Initial Data Model Performance	Post-Deployment Data Model Performance
No. of Data	8,036	59,825
Mean Squared Error (MSE)	2.8798	0.5535
Root Mean Squared Error (RMSE)	1.6970	0.7440
Mean Absolute Error (MAE)	0.7953	0.1746
R-squared Score	0.9507	0.9920

Table 3 shows the comparison of the initial and post-deployment model performance for the weather node system. Based on the comparison of evaluation metrics, the post-deployment data performed better weather forecasting. It was trained on a substantially larger dataset (59,825) compared to initial dataset (8,036), which generally contributed to better model performance and generalization. It demonstrated significantly lower Mean Squared Error (MSE) of 0.5535 compared to initial model's 2.8798, and its Root Mean Squared Error (RMSE) is also much lower at 0.7440 versus 1.6970. Additionally, it also had a lower Mean Absolute Error (MAE) of 0.1746 compared to 0.7953, indicating more accurate predictions on average. Furthermore, post-deployment data gained a higher R-squared score of 0.9920, suggesting it explains more variance in the data compared to initial model's score of 0.9507.

Table 4. Weather System Post-Deployment's Comprehensive Model Performance

	Training Set Performance	Validation Set Performance	Test Set
Mean Squared Error (MSE)	0.2270	0.1812	0.5537
Root Mean Squared Error (RMSE)	0.4765	0.4257	0.7441
Mean Absolute Error (MAE)	0.1709	0.1729	0.1720
R-squared Score	0.9966	0.9972	0.9920

For table 4, it provides a comprehensive summary of the performance metrics for a machine learning model across three distinct data sets: the training set, validation set, and test set. The training set performance shows that the model has learned the patterns in the data well, with low error values and a high R-squared score of 0.997. The validation set performance is similar, indicating that the model generalizes well to unseen data used during the training phase. And lastly, the test set performance, while it is slightly lower, it still indicates good generalization with an R-squared score of approximately 0.992 and reasonable error metrics.

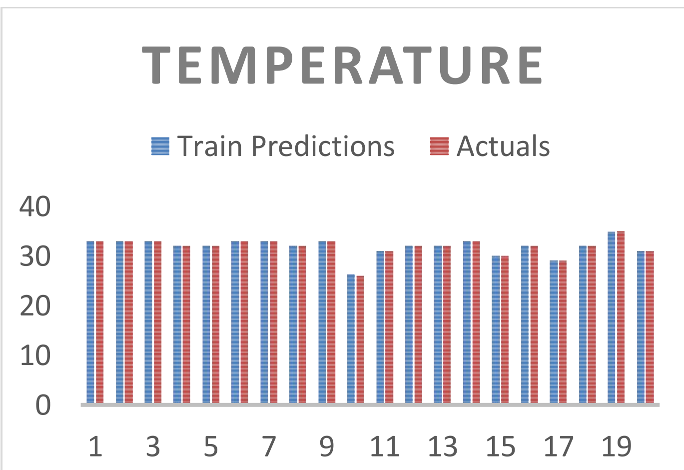


Figure 2. Comparison of Weather System's Model Performance on Training Set (Temperature)

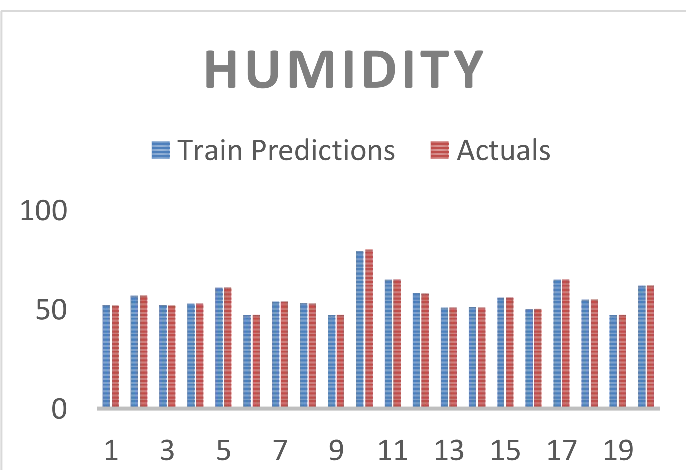


Figure 3. Comparison of Weather System's Model Performance on Training Set (Humidity)

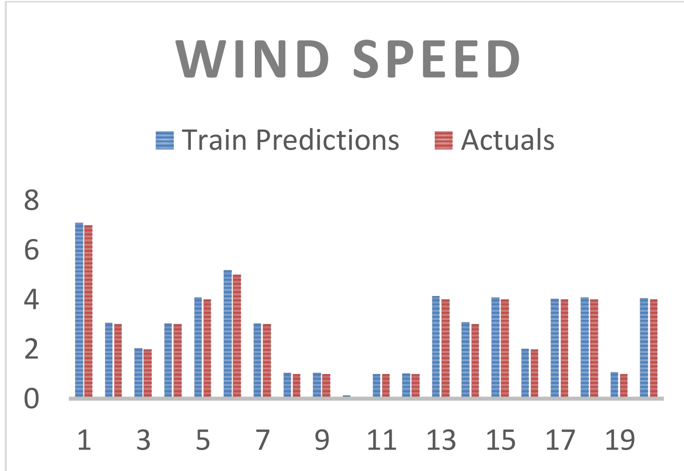


Figure 4. Comparison of Weather System's Model Performance on Training Set (Wind Speed)

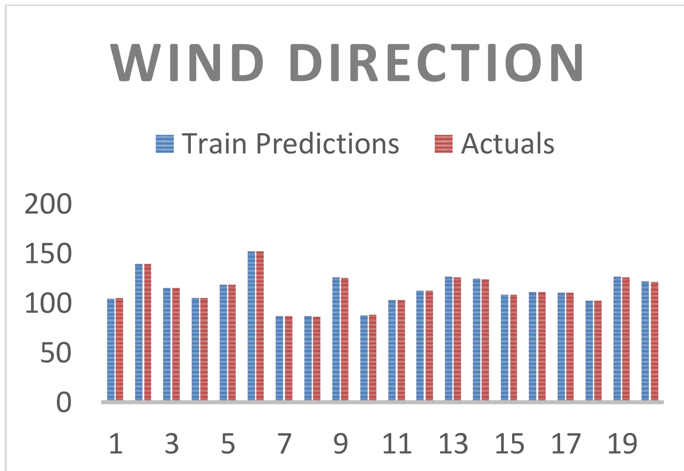


Figure 5. Comparison of Weather System's Model Performance on Training Set (Wind Direction)

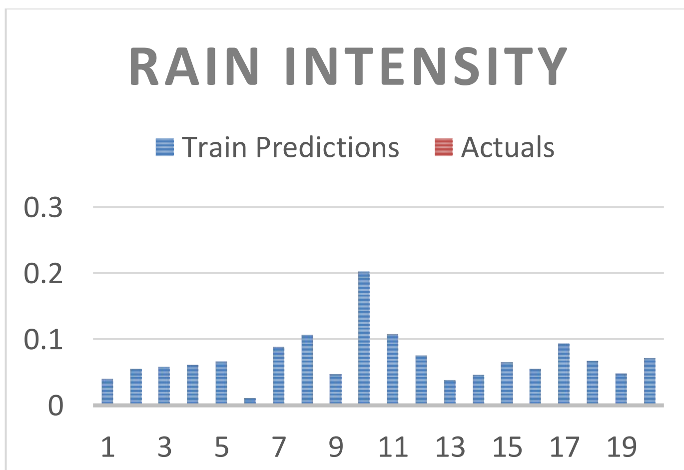


Figure 6. Comparison of Weather System's Model Performance on Training Set (Rain Intensity)

Table 5. Predictions and Actual Data of Temperature, Humidity, and Wind Speed at the Training Set

	Temperature (degC)		**Humidity (%)**		**Wind Speed (m/s)**	
Index	Train Predictions	Actuals	Train Predictions	Actuals	Train Predictions	Actuals
0	32.92537	33	52.09611	52	7.098402	7
1	32.99706	33	56.86482	57	3.07248	3
2	32.95482	33	52.08663	52	2.043482	2
3	31.96726	32	53.01989	53	3.026251	3
4	31.98885	32	60.90482	61	4.080995	4
5	33.0195	33	46.98618	47	5.188292	5
6	32.974	33	53.94244	54	3.045895	3
7	31.98161	32	53.14972	53	1.043676	1
8	32.98705	33	47.01876	47	1.053023	1
9	26.19324	26	79.53027	80	0.123103	0
10	30.96754	31	64.94891	65	0.990435	1
11	31.97127	32	58.08156	58	1.03371	1
12	32.00136	32	50.93933	51	4.130091	4
13	33.00658	33	51.00884	51	3.091485	3
14	30.06083	30	55.90755	56	4.076426	4
15	31.96909	32	50.0278	50	2.023978	2
16	29.04298	29	64.89447	65	4.020906	4
17	32.00839	32	54.95594	55	4.082115	4
18	34.89526	35	47.09547	47	1.077174	1
19	30.99823	31	61.9325	62	4.071104	4

Table 6. Predictions and Actual Data of Wind Direction and Rain Intensity at the Training Set

	Wind Direction (deg)		**Rain Intensity (mm/hr)**	
Index	Train Predictions	Actuals	Train Predictions	Actuals
0	104.2455	105	0.039745	0
1	139.0928	139	0.05523	0
2	115.1808	115	0.058051	0
3	105.0278	105	0.061228	0
4	118.3427	118	0.066429	0
5	151.9785	152	0.010255	0
6	87.01928	87	0.087951	0
7	86.51494	86	0.106565	0
8	125.4754	125	0.046551	0
9	87.20507	88	0.202358	0
10	103.0135	103	0.107931	0
11	112.1401	112	0.074805	0
12	126.3711	126	0.037948	0
13	124.4733	124	0.045671	0
14	108.2445	108	0.064897	0
15	111.1894	111	0.054505	0
16	110.3558	110	0.093197	0
17	102.2492	102	0.067356	0
18	126.2084	126	0.047929	0
19	121.5177	121	0.071288	0

The tables and figures above show that the predicted data aligns closely with the actual data, indicating only minor discrepancies. This visualization effectively supports the comprehensive metrics that measured the performance of the system. With, it results that the weather node system performs well in localized forecasting.

B. Flood Node System

Table 7. Comprehensive Post-Deployment Model Performance for Both Flood Node Systems

	Molino Node			**Prinza Node**		
	Training Set Performance	Validation Set Performance	Test Set Performance	Training Set Performance	Validation Set Performance	Test Set Performance
No. of Data	7,682			7,682		
Mean Squared Error (MSE)	0.2772	0.2728	0.2785	0.2625	0.2533	0.2654
Root Mean Squared Error (RMSE)	0.5265	0.5223	0.5278	0.5123	0.5033	0.5151
Mean Absolute Error (MAE)	0.2601	0.2608	0.2628	0.2684	0.2620	0.2715
R-squared Score	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999

Table 7 presented a detailed evaluation of the models' performance metrics for each node – Molino and Prinza, after deployment. Each node had 7,682 data points evaluated generated from its respective nodes. And just like the weather system, it was also then trained using the algorithm ANN-LSTM.

For the Molino Node, the performance metrics are consistently high across all sets, with an MSE around 0.2772 to 0.2785, RMSE approximately 0.5265 to 0.5278, and MAE about 0.2601 to 0.2628, coupled with a near-perfect R-squared Score of 0.9999. Similarly, the Prinza Node demonstrates robust performance, with slightly lower MSE and RMSE values compared to Molino, and comparable MAE and R-squared scores. Overall, the table highlights the model's strong and consistent performance across both nodes, ensuring reliable generalization across different datasets.

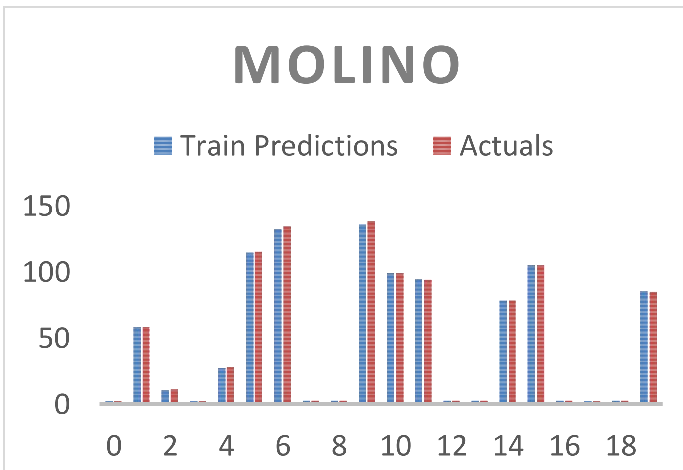


Figure 7. Comparison of Flood System's Model Performance on Training Set (Molino)

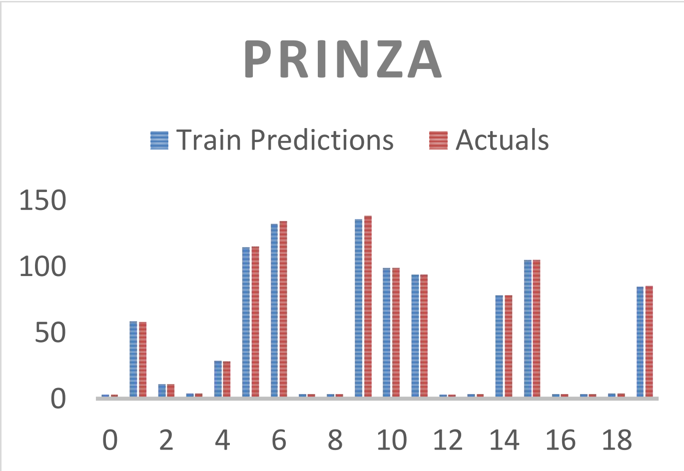


Figure 8. Comparison of Flood System's Model Performance on Training Set (Prinza)

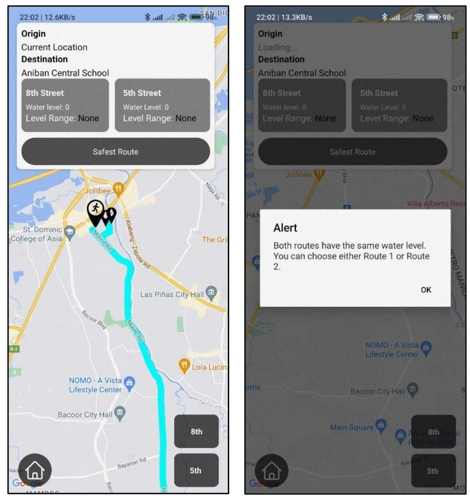


Figure 9. Both streets with the same flood level

Table 8. Predictions and Actual Data of Flood Level for both Molino and Prinza Dam at the Training Set

	Wind Direction (deg)		Rain Intensity (mm/hr)	
Index	Train Predictions	Actuals	Train Predictions	Actuals
0	2.1913	2.15	3.1304	3.17
1	58.0592	58	58.3121	58
2	10.5161	11	11.1078	11
3	2.0791	2.01	3.8578	3.91
4	27.3349	28	28.485	28
5	114.5037	115	114.4037	115
6	132.0186	134	132.2707	134
7	2.4428	2.45	3.6737	3.72
8	2.599	2.63	3.4791	3.52
9	135.6185	138	135.6637	138
10	99.0877	99	98.8965	99
11	94.1319	94	93.8786	94
12	2.6517	2.69	3.0704	3.11
13	2.4171	2.42	3.4888	3.53
14	78.0375	78	77.9753	78
15	104.9418	105	104.8388	105
16	2.4171	2.42	3.5759	3.62
17	2.2405	2.21	3.4404	3.48
18	2.4772	2.49	3.8864	3.94
19	85.0665	85	84.8734	85

Similar to the weather system, the tables and figures indicate that the predicted data also closely matches the actual data, with only minor discrepancies. This visualization effectively supports the comprehensive metrics used to measure the forecast of water level. Consequently, it shows that the flood node system performs also well in localized forecasting.

C. Evacuation Routing (Flood Node System – STREET)

The street flood node system is designed to update the safest and nearest route from point A to the evacuation center provided by the barangay officials.

Figure 9 shows that both Route A and Route B, comprising the node at 5th and 8th Street, have the same flood level, marked at the passable threshold. The system detected that the routes were safe and allowed the residents to choose either route with confidence, ensuring safe passage to the evacuation center despite the flooding situation.

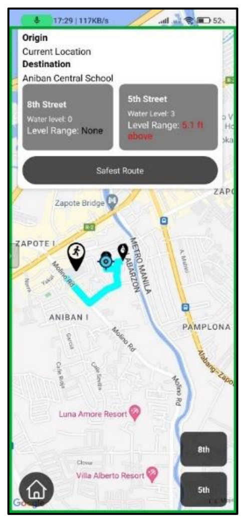
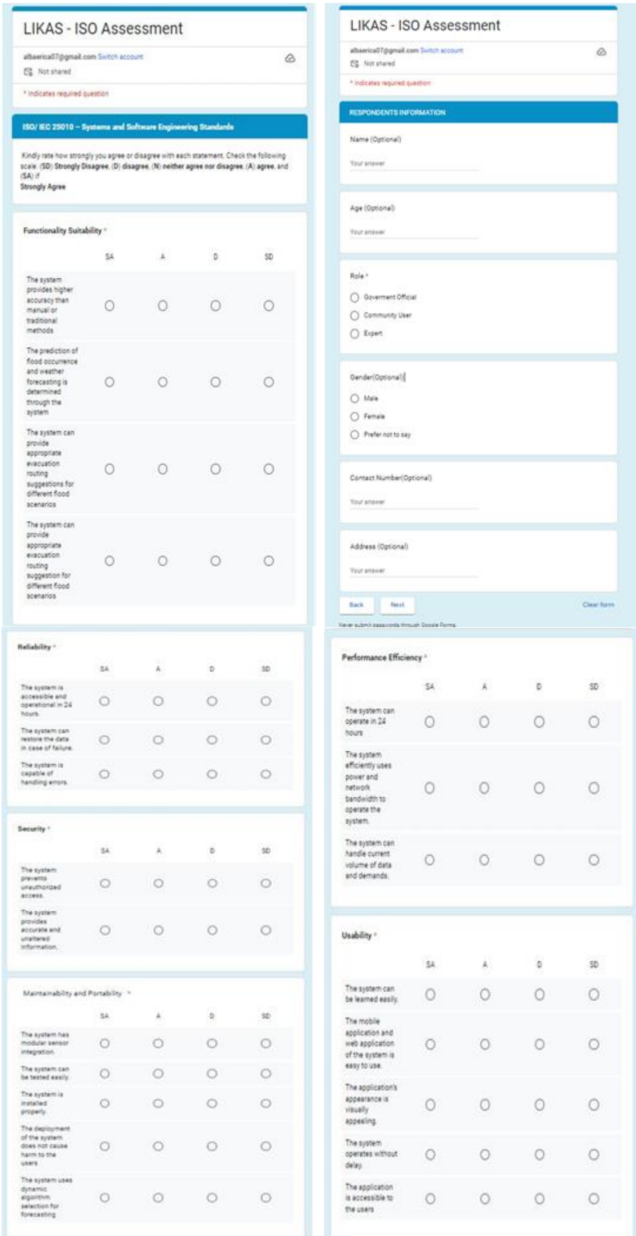


Figure 10. Two streets with the different flood level

Figure 10 illustrates two streets with different flood levels. The system evaluates these conditions and provides the safest route for users heading to the evacuation center. 5th Street has a higher flood level compared to 8th Street, which is closer to the passable threshold. Based on real-time data from sensors along these streets, the system identifies 8th Street as the safer option. Consequently, it directs the users to take 8th Street to ensure their safe passage to the evacuation center, prioritizing lower flood risks and enhancing community safety during the evacuation process.

D. User Acceptance Testing

A set of questionnaires was distributed to sixty respondents, five are field experts (Information Technology and Electronics Engineers), 15 are officials from Barangay BDRRMO, and 30 are residents. The questionnaire has 22 items consisting of six core evaluation: functionality suitability, performance efficiency, usability, reliability, security, and maintainability. These items are related to the usage of LIKAS and are rated based on a four-point Likert Scale. The findings of user acceptance were based on the average score of strongly disagree (1) and strongly agree (4).



Functionality Suitability Acceptance Results

Table 9. User Acceptance Testing result for Functionality

Functionality Suitability	SA	A	D	SD	Mean	Percentage
F1	14	35	1	0	3.26	81.5%
F2	15	35	0	0	3.3	82.5%
F3	18	32	0	0	3.36	84%
F4	20	30	0	0	3.4	85%
Total					13.32	83.25%

Note: Strongly Disagree (SD): 1-1.74, Disagree (D): 1.75 – 2.49, Agree(A): 2.5-3.24, Strongly Agree (SA): 3.25-4.00

The findings show that majority (81.5%) of the respondents strongly agreed that the system provides higher accuracy than manual or traditional methods, while 82.5% strongly agreed that the system can provide weather and flood forecasts. Furthermore, 84% of the respondents strongly agreed that the system can provide real-time data that are necessary for weather and flood monitoring, and among 85% strongly agreed that the system can provide appropriate evacuation routing for different flood scenarios. Analysis shows that there has no significant negative responses, indicating that the system is acceptable in terms of functionality with 83.25% of the respondents strongly agreed that the system can meet their functional needs in the occurrence of weather-related phenomena.

Performance Efficiency Acceptance Results

Table 10. User Acceptance Testing result for Performance Efficiency

Performance Efficiency	SA	A	D	SD	Mean	Percentage
P1	21	28	1	0	3.4	85%
P2	13	35	2	0	2.52	63%
P3	15	34	1	0	3.28	82%
Total					9.2	76.66%

Note: Strongly Disagree (SD): 1-1.74, Disagree (D): 1.75 – 2.49, Agree(A): 2.5-3.24, Strongly Agree (SA): 3.25-4.00

The findings show that majority (85%) of the respondents strongly agreed that the system operates in 24 hours. Additionally, 63% of the respondents agreed that the system uses efficient power to operate the system. Lastly, 82% of the respondents strongly agreed that the system can handle current volume of data and demands. Analysis shows that there has a high percentage of positive responses indicating that the system is acceptable in terms of performance efficiency. Overall, 76.66% of the respondents agreed that the system is designed and optimized for continuous, efficient, and effective operation, making it a cost-effective solution for handling ongoing data and operational demands.

Usability Acceptance Results

Table 11. User Acceptance Testing result for Usability

Usability	SA	A	D	SD	Mean	Percentage
U1	21	28	1	0	3.4	85%
U2	20	27	3	0	3.34	83.5%
U3	21	27	2	0	3.38	84.5%
U4	12	30	8	0	3.08	77%
U5	17	32	1	0	3.32	83%
Total					16.52	82.6%

Note: Strongly Disagree (SD): 1-1.74, Disagree (D): 1.75 – 2.49, Agree(A): 2.5-3.24, Strongly Agree (SA): 3.25-4.00

Based on the Likert Scale data shown, 85% and 83.5% of respondents strongly agreed that the system's applications are easy to learn and use, respectively. Additionally, 84.5% of the respondents strongly agreed that the application is visually appealing. Moreover, 83% of the respondents strongly agreed that the application is accessible to users. On the other hand, only 77% of the respondents agreed that the system operates without delay. Hence, the findings reveal that the system is well-designed in terms of usability, visual appeal, and accessibility, making it easy to learn and use. However, the performance delays are needed to address to improve the entire user experience and satisfaction. Nevertheless, the overall results shows that positive responses have high percentage which underscores the acceptability of the system in terms of usability with 82.6% of the respondents have strongly agreed to the evaluation.

Reliability Acceptance Results

Table 12. User Acceptance Testing result for Reliability

Reliability	SA	A	D	SD	Mean	Percentage
R1	20	30	0	0	3.4	85%
R2	8	39	3	0	3.1	77.5%
R3	9	36	5	0	3.08	77%
Total					9.58	79.83%

Note: Strongly Disagree (SD): 1-1.74, Disagree (D): 1.75 – 2.49, Agree(A): 2.5-3.24, Strongly Agree (SA): 3.25-4.00

The user acceptance testing results for reliability indicate strong positive feedback from respondents. A significant majority (85%) strongly agree that the system is accessible and operational 24 hours a day, highlighting its continuous availability. Additionally, 77.5% of users agree that the system can effectively restore data in case of failure, demonstrating robust data recovery capabilities. Furthermore, 77% of respondents believe the system can handle errors, suggesting effective error management processes. Overall, 79.83% of respondents provided positive responses, reflecting a high level of confidence in the system's reliability, continuous operation, data restoration, and error handling capabilities. This feedback suggests that users find the system highly reliable and effective in maintaining operational stability and data integrity.

Security Acceptance Results

Table 13. User Acceptance Testing result for Security

Security	SA	A	D	SD	Mean	Percentage
S1	13	31	6	0	3.14	78.5%
S2	14	34	2	0	3.24	81%
Total					6.38	79.75%

Note: Strongly Disagree (SD): 1-1.74, Disagree (D): 1.75 – 2.49, Agree(A): 2.5-3.24, Strongly Agree (SA): 3.25-4.00

The user acceptance testing results for security show strong positive feedback from respondents. For S1, which states that the system prevents unauthorized access, 78.5% of respondents agree or strongly agree, indicating that the majority find the system effective in securing access and protecting against unauthorized use. For S2, which states that the system provides accurate and unaltered information, 81% of respondents agree or strongly agree, reflecting high confidence in the system's ability to maintain data integrity and accuracy. Overall, the combined positive response rate is 79.75%, demonstrating that users generally perceive the system as reliable in safeguarding access and ensuring the accuracy of information. These results highlight the system's strong security features and its capability to protect user data effectively.

Maintainability and Portability Acceptance Results

Table 14. User Acceptance Testing result for Maintainability and Portability

Maintainability and Portability	SA	A	D	SD	Mean	Percentage
MP1	16	34	0	0	3.32	85%
MP2	19	29	2	0	3.34	83.5%
MP3	18	30	2	0	3.32	83.5%
MP4	20	30	0	0	3.4	83.5%
MP5	19	31	0	0	3.38	83.5%
Total					16.78	82.6%

Note: Strongly Disagree (SD): 1-1.74, Disagree (D): 1.75 – 2.49, Agree(A): 2.5-3.24, Strongly Agree (SA): 3.25-4.00

Users strongly agree (85%) that the system integrates sensors in a modular manner, showcasing its adaptability and flexibility in accommodating various sensor types seamlessly. In this context, the high level of agreement suggests that users have confidence in the system's capability to incorporate different sensor technologies efficiently, which enhances its versatility and usability across diverse applications. Additionally, a majority (83.5%) of users affirm that the system facilitates easy testing, indicating streamlined testing processes that enhance efficiency and effectiveness. This positive response underscores the system's user-friendly design and implementation, which enables testers to conduct tests with ease, ultimately contributing to the system's overall reliability and performance. Furthermore, 83.5% of users believe that the system undergoes proper installation, reflecting a smooth and satisfactory installation experience for users. This finding indicates that the system's installation process is robust and well-executed, ensuring that it functions optimally from the outset and minimizing potential disruptions or issues. Moreover, the high level of user confidence (83.5%) in the system's deployment, assuring users that its implementation does not pose any harm, underscores the system's commitment to safety and user well-being. This result reflects positively on the system's design and implementation practices, which prioritize user safety and satisfaction throughout the deployment process. Lastly, users acknowledge (83.5%) the system's utilization of dynamic algorithm selection for forecasting, ensuring accurate and reliable predictions through adaptive algorithmic approaches. This finding highlights the system's advanced capabilities and innovative features, which enhance its effectiveness in addressing complex forecasting tasks and adapting to changing environmental conditions. Collectively, these results demonstrate the system's robustness, safety, and innovation in ensuring maintainability and portability, fostering user trust and satisfaction in its performance and capabilities.

VII. Conclusion

The deployment and retraining of the weather and flood node systems have significantly enhanced their predictive capabilities. The weather node system for Bacoor City, after being retrained with a substantially larger dataset from the weather station, showed marked improvements in performance metrics, resulting in more accurate and reliable weather forecasts. Similarly, the flood node systems at Molino and Prinza exhibited strong model fits and low error metrics, ensuring precise flood predictions, with the Prinza node displaying marginally better performance. Overall, both systems have demonstrated excellent performance post-deployment, highlighting the efficacy of using larger, localized datasets and advanced algorithms like ANN-LSTM in environmental monitoring and prediction.

For the evacuation route feature, it was successfully developed in mobile application which provides the safest route from point A to the evacuation center. Through the integration of Google Maps Library, the mobile application was able to display the safest route towards the evacuation center during the occurrence of flood. The mobile application was able to provide accurate water level data along the two streets and update the users which among the routes are safe for the users to take.

Lastly, the system was evaluated using UAT in accordance with ISO/IEC 25010 - Systems and Software Engineering Standards, with participation from the government officials, community users, and experts from various sectors in Bacoor City. A comprehensive survey was conducted to evaluate the functionality, performance efficiency, reliability, usability, security, and maintainability and portability of the system. Analysis of the UAT revealed that the majority of the respondents provide positive feedback regarding the six core elements mentioned with majority agreement rates ranging from 76.66% to 83.25%. Overall, the findings indicates that the LIKAS system is acceptable and can be applied as an automated system for weather and flood monitoring which can significantly enhanced disaster preparedness and response capabilities in Bacoor City.

References

[1] D. Eckstein, V. Künzel, and L. Schäfer. 2021. Global Climate Risk Index 2021: Who Suffers Most from Extreme Weather Events? Weather Related Loss Events in 2019 and 2000–2019. Germanwatch e. V.

[2] Memorandum circular no. 122 series of 2018. https://dilg.gov.ph/PDF_File/issuances/memo_circulars/dilg-memocircular-201888_6862a1ddb0.pdf

[3] Republic act no. 10121 | Official Gazette of the Republic of the Philippines. https://www.officialgazette.gov.ph/2010/05/27/republic-act-no-10121/

[4] United Nations. (n.d.). Climate and weather related disasters surge five-fold over 50 years, but early warnings save lives - WMO report | UN news. United Nations. https://news.un.org/en/story/2021/09/1098662

[5] Mosavi, A., Ozturk, P., & Chau, K. (2018, October 27). Flood prediction using Machine Learning Models: Literature review. MDPI. https://www.mdpi.com/2073-4441/10/11/1536

[6] Early warning systems. UNESCO.org. (n.d.). https://www.unesco.org/en/disaster-risk-reduction/ews

[7] A.Al-azazi, F., & Ghurab, M. (2023). Ann-LSTM: A Deep Learning Model for Early Student Performance Prediction in MOOC. https://doi.org/10.2139/ssrn.4335519

[8] Sandink, D., & Binns, A. D. (2021, July 6). Reducing urban flood risk through building- and lot-scale flood mitigation approaches: Challenges and opportunities. Frontiers. https://www.frontiersin.org/journals/water/articles/10.3389/frwa.2021.689202/full

[9] Rudrawar, S. K., Ghorpade, P., & Sakhare, D. Y. (1970, January 1). Implementation of A* algorithm for real-time evacuation during fire situation. SpringerLink. https://link.springer.com/chapter/10.1007/978-3-030-69921-5_21

[10] Rasel, Risul Islam & Sultana, Nasrin & Meesad, Phayung. (2018). An Application of Data Mining and Machine Learning for Weather Forecasting. 169-178. 10.1007/978-3-319-60663-7_16.

[11] C. Z. Basha, N. Bhavana, P. Bhavya, and V. Sowmya, (2020). Rainfall Prediction using Machine Learning Deep Learning Techniques. Proc. Int. Conf. Electron. Sustain. Commun. Syst. ICESC 2020, no. Icesc, pp. 92–97, doi: 10.1109/ICESC48915.2020.9155896.

[12] Z. Q. Huang, Y. C. Chen, and C. Y. Wen, (2020). Real-time weather monitoring and prediction using city buses and machine learning. Vol. 20, no. 18, pp. 1–21, doi: 10.3390/s20185173.

[13] Duncan, A. P., Chen, A. S., Keedwell, E. C., DjordjeviĆ, S., & SaviĆ, D. A. (2011). Urban flood prediction in real-time from weather radar and rainfall data using artificial neural networks.

[14] Hayder, I.M., Al-Amiedy, T.A., Ghaban, W., Saeed, F., Nasser, M., Al-Ali, G.A., & Younis, H.A. (2023). An Intelligent Early Flood Forecasting and Prediction Leveraging Machine and Deep Learning Algorithms with Advanced Alert System. https://doi.org/ 10.3390/pr11020481

[15] Jeon, S., Jung, K., Kim, J., & Jung, H. (2023). Map API-based evacuation route guidance system for floods. Applied Sciences, 13(16), 9141. https://doi.org/10.3390/app13169141

[16] Lee, Y. H., Kim, H. I., Han, K. Y., & Hong, W. H. (2020). Flood evacuation routes based on spatiotemporal inundation risk assessment. Water, 12(8), 2271. https://doi.org/10.3390/w12082271

[17] Suwanno, P., Yaibok, C., Pornbunyanon, T., Kanjanakul, C., Buathongkhue, C., Tsumita, N., & Fukuda, A. (2023). GIS-based identification and analysis of suitable evacuation areas and routes in flood-prone zones of Nakhon Si Thammarat municipality. IATSS Research, 47(3), 416–431. https://doi.org/10.1016/j.iatssr.2023.08.004