HabagatPlus: Providing Recommendations for Localized Class Suspension in Schools During Inclement Weather Conditions Using Naive Bayes Classifier

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***Abstract*—With tens of typhoons visiting the Philippines annually, there are multiple instances that classes in its schools are being suspended. To ensure the safety of the students during times of unfavorable weather conditions, there are existing guidelines that schools and universities in the Philippines follow, depending on the severity of the weather, indicated by a storm warning signal in an area. In the absence of a storm warning signal, a localized class suspension can take effect, in which local government units (LGUs) can decide. Various LGUs have different criteria on their decision to suspend classes, as well as their levels of urgency; some local officials declare early, while some announcements are delayed. To aid in decision making for the LGUs, the concept of HabagatPlus was created, a recommendation service for use during times of turbulent weather conditions. It aims to give recommendations on class suspensions based on historical data. This research project explores on the feasibility of using the Naïve Bayes classifier algorithm in building a machine learning model for HabagatPlus. Utilizing various datasets such as historical weather data, class suspensions data, and geolocation information in the Philippines, HabagatPlus makes an analysis of the trends and patterns based on previous weather conditions and related class cancellations. The developed model achieved an 82.05% accuracy rate, while having 56.58%, 41.31%, and 45.53% for its precision, recall, and F1 score, respectively.**

Keywords—Localized class suspension, recommendation system, weather data, machine learning, data analysis, Naïve Bayes classifier

I. Introduction

Being a tropical country located in the Northwest Pacific Ocean, the Philippines is one of the countries that experience strong typhoons and thunderstorms each year. The Philippines is hit by twenty typhoons on an average basis annually; five of which prove to be destructive [1]. In response to the threats posed by these weather phenomena, the Philippine Atmospheric, Geophysical, and Astronomical Services Administration (PAGASA), home to the country's weather bureau, is the government agency tasked to monitor weather disturbances and provide appropriate advisories and warnings [2]. Once a potential tropical cyclone makes its way towards the Philippine Area of Responsibility (PAR), PAGASA is tasked to categorize such weather system, assess its strength and magnitude, and inform the public on how it could possibly affect the country. Depending on the maximum speed and velocity of the weather system, PAGASA informs the public of its intensity and possible impact by raising appropriate storm warning signals, also known as the tropical cyclone wind signal (TCWS) based on their monitoring, forecasts, and observations. These wind signals range from Signal No. 1 being the lowest, to Signal No. 5 being the highest [3].

On January 9, 2012, Presidential Executive Order No. 66 was signed and promulgated, implementing automatic class cancellations depending on PAGASA's raised TCWS in a province, city, or municipality. Upholding the Filipino people's constitutional rights to life and safety, this order prescribes rules on the suspension of classes due to weather disturbances. Under the said order's guidelines, class sessions in the preschool level will be automatically cancelled once an area is under Signal No. 1; classes in the elementary and high school levels for those under Signal No. 2; while classes in the tertiary level for those under Signal No. 3 and above [4]. For areas that are not under any TCWS, the local government units (LGUs) are the ones delegated with the assessment. Provincial governors, as well as city and municipal mayors make the decision, depending on certain factors experienced first-hand by residents. There can be varying criteria in the LGUs that could affect their decision, which can also become subjective and confusing at times. Moreover, time is of essence during extreme weather conditions. Given this however, there are instances that the decision on localized class suspension gets very delayed, to the point that the students are already in their respective classrooms before the declarations are handed down. These situations lead to inconveniences, with the safety and well-being of those affected getting compromised.

Fig. 1. Various depictions of class suspension caused by inclement weather conditions in the Philippines

In order to address the aforementioned issues, the idea of an online service that can be utilized by LGUs as reference on deciding class suspensions during heavy rains and typhoons was idealized in the form of HabagatPlus. Analyzing historical weather data on days when actual class suspensions happened due to inclement weather, HabagatPlus incorporates several factors including rainfall amount, wind speed, and temperature, in order to create a recommendation model. Two major datasets were used, namely: (1) historical weather data sourced from PAGASA, and; (2) historical class suspensions data gathered from internet articles posted by prominent news and government agencies, which also served as training and testing data for the classifier algorithm. After processing the current weather information within the trained model, HabagatPlus will then return a recommendation on the suspension of classes. The name of the system, HabagatPlus, comes from the word "*habagat*" which translates as "southwest monsoon" [5] in the Filipino language; the prevailing winds in the Philippine islands during the third and early fourth quarter of each year which brings heavy rains and winds to the country.

This research project seeks to investigate the feasibility of utilizing the Naïve Bayes classifier in creating the recommendation model for HabagatPlus, with historical weather and historical class suspensions data as its training and testing datasets. This endeavor also explores on the developed model's metrics for accuracy, precision, recall, and F1 score.

II. LITERATURE REVIEW

A. *Storm warning signals and class cancellations*

From time to time, it is inevitable to suspend class sessions especially when the weather condition is severe. In the Philippines, PAGASA is constantly on stand-by for tracking incoming tropical cyclones that form across the oceans that surround the country. Tropical cyclones are "rapid rotating storms originating over tropical oceans from where it draws the energy to develop" [7]. Meteorologists are usually extensively observing once a tropical cyclone is already within the Philippine Area of Responsibility (PAR), which is the innermost monitoring domain closest to the Philippine islands boundary [8]. The classification of a tropical cyclone depends on its degree of intensity, which is according to the strength of the winds associated with it [3]. The following table shows the criteria PAGASA uses in classifying cyclones that enter the Philippines:

TABLE I. PHILIPPINE TROPICAL CYCLONE WARNING SYSTEM (TCWS)

Classification	Maximum sustained winds (kph)	Nautical miles per hour (knots)	Tropical cyclone warning signal (TCWS) number
Tropical depression (TD)	~61	~34	1
Tropical storm (TS)	62 - 88	35 - 47	2
Severe tropical storm (STS)	89-117	48-63	3
Typhoon (TY)	118-184	64-99	4
Super typhoon (STY)	185~	100~	5

As shown in the above table, an equivalent tropical cyclone warning signal (TCWS) is hoisted on the basis of the cyclone's classification. According to PAGASA, the TCWS is a warning to the public of how strong the winds can be felt in a particular area. TCWSs are usually raised on a per-province, -highly urbanized city, or -independent component city level, with the exception for Metro Manila which is collectively placed under a single warning signal. In case that certain situations require, a TCWS can also be issued at the city- or municipality-level. With the TCWS being a tiered system, the escalation or de-escalation of warning signals permits skipping of levels [3]. For example, places under Signal No. 1 can be upgraded directly to Signal No. 3 without becoming Signal No. 2. The most recent version of the TCWS system has been in place since March 23, 2022, replacing its 2015 version [9].

With the overall safety of students in consideration, Executive Order No. 66 [4] was issued in 2012 in order to implement automatic class cancellations depending on the raised TCWS in a particular locality. This means that for instance, once PAGASA declares a province to be under Signal No. 2, classes in preschool, elementary, up to high school in that province will be automatically cancelled. The Philippines' Department of Education (DepEd) released its Order No. 43 of the same year, issuing guidelines on the implementation of the executive order [10]. DepEd Order No. 43, s. 2012 mentions that in the absence of any TCWS from PAGASA, the local chief executives can declare localized cancellation/suspension of classes in both public and private schools.

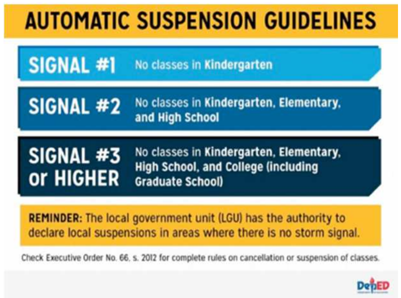

Fig. 2. Guidelines on automatic class suspensions, released by the Philippine national government in 2012.

B. *Delayed class cancellation announcements*

Although there are already guidelines in place, it is not without its flaws. Every now and then, when localized class cancellations are necessary, there are numerous instances wherein the suspensions are announced very late. The Department of Interior and Local Government (DILG) reported in 2018 on receiving numerous complaints and feedback from private individuals on the late suspension of classes by some LGUs. This has resulted in the students' inconveniences and exposure to various safety risks. For instance, during Luzon's bout with Tropical Depression "Henry" (international name: Son-Tinh) in July 2018, class cancellations were announced when the students were already in school, having to wade through filthy flood waters in order to return to safety [11]. Moreover, several students expressed their dismay on the late announcement of class cancellations in select cities in Metro Manila. A TV Patrol report [12] of ABS-CBN News echoed the disadvantages of these delayed class suspensions to school-goers. According to the news report, the frustration roots from the effort of going to school, added with the hassle of getting en route. Yet upon reaching school, only to know that classes will be suspended. Interviewed students insinuated that classes should have been cancelled and announcements relating to such were made prior to the start of their scheduled school sessions.

On the side of the local chief executives, LGUs mentioned that they have basis, with the use of scientific data, to decide on class cancellations during heavy rains and typhoons. According to them, the National Disaster Risk Reduction and Management Council (NDRRMC) and PAGASA steer their decision. Quezon City's disaster risk reduction and management (DRRM) mentioned that they monitor cloud formation through PAGASA's website, in coordination with concerned officials as well. They said that they usually analyze, cite, and present their recommendations to the mayor. A consultation with the head of city schools is also done. According to LGUs, they also put a lot of effort in ensuring accuracy in their decision-making during disasters [13]. They are also dependent on PAGASA's raised signals; hence, they cannot announce any suspension in the absence of any rainfall advisory. PAGASA also justified that certain thresholds are being followed, and that they also cannot raise warnings without any data to back their claim [12].

C. *Recommendation systems and machine learning*

Pham [14] defines recommendation systems, also known as recommender systems, being software engines created to make suggestions to users on the basis of previous preferences, interactions, and engagements. In the released Journal of Big Data, Roy and Dutta [15] expounds recommendation systems as useful mechanisms for filtering online information which is widespread owing to personalization trends and users' changing habits.

To make the most significant suggestions, recommendation systems make use of machine learning algorithms and techniques, by analysis of the data it was provided. Given this, the initial phase of data processing for recommendation systems is data collection, which involves the accumulation of important pieces of data for the creation of a prediction model. Other processes involved are data storage, analysis, and filtering. Having enough data is important in model training; that is, with the availability of more quality data for the algorithms leads to more effective and relevant suggestions. After which, the process entails picking the most appropriate data filtering approach, and implementing the proper algorithm to train a model [16].

D. *Synthesis*

Based on the literature gathered and reviewed, the need for an online service that could provide recommendations on localized class suspensions is of imminent importance. Based on the current guidelines in place, this service can be used by LGU leaders for their decision on class suspension during days with unpleasant weather conditions. With the Naïve Bayes classifier being used in recommendation systems and weather-based predictions, this algorithm can also be utilized for the creation of the recommendation model.

III. METHODS

Using the experimental-exploratory type of research, this study follows the scientific research design. Performed in a controlled environment, this research methodology may include a problem statement, a configurable variable, and factors that can be calculated, measured, and compared. The exploratory component of this study seeks to answer the question of its feasibility, and address a phenomenon [17].

A. *The Naïve Bayes classifier*

Used for classification tasks, the Naïve Bayes classifier is a supervised machine learning algorithm. Based on the assumption that the attributes of the input data are independent from one another, this facilitates the algorithm to create predictions promptly and correctly. An application of Bayes' theorem, the Naïve Bayes classifier can validate the probability of an event occurring given historical events as its basis. It is very simple, can be built easily, efficient for high volumes of data, and is proven to exceed the performance of even highly-sophisticated machine learning and classification algorithms [18].

The formula for the Naïve Bayes classifier [19] is as follows:

$$P(c|x) = \frac{P(x|c)P(c)}{P(x)}$$

$$P(c|x) = P(\, x_1|c) \times P(\, x_2|c) \times \dots \times \, P(\, x_n|\, c) \times P(c) \tag{1}$$

where:

- P(c|x) stands for the posterior probability of class (target) given predictor (feature)
- P(c) as the prior likelihood of class
- P(x|c) being the probability of the predictor given class, and;
- P(x) as the prior probability of predictor.

Among the various machine learning algorithms, the Naïve Bayes classifier is widely used when categorical data and classification tasks are involved. Being a popular with having a simple approach in machine learning, it is a probability theorem that facilitates the calculation of conditional probabilities. Sethi [20] demonstrates building a simple Naïve Bayes classifier using the GaussianNB algorithm to predict whether to do certain activities based on weather conditions. Overall, Naïve Bayes classifiers are beneficial for quick and efficient predictions [21].

B. *Collection of relevant data*

There are two major groups of historical data collected for this research project: (1) historical weather data and (2) historical class suspensions data. The historical weather data included daily record of rainfall amount; relative humidity; minimum, maximum, and average temperatures; wind speed, and; wind direction from seventeen (17) weather stations across the Philippines.

date	province	city_municipality	preschool	elementary	junior_high	senior_high	tertiary
2019-07-02	METRO MANILA	MUNTINLUPA	1	1	0	0	0
2019-07-02	METRO MANILA	MARIKINA	1	1	0	0	0
2019-07-02	METRO MANILA	MANDALUYONG	1	1	0	0	0
2019-07-02	METRO MANILA	MALABON	1	1	0	0	0
2019-07-02	METRO MANILA	MAKATI	1	1	0	0	0
2019-07-02	METRO MANILA	LAS PIÑAS	1	1	0	0	0
2019-07-02	METRO MANILA	CALOOCAN	1	1	0	0	0
2019-07-02	METRO MANILA	MANILA	1	1	0	0	0
2019-07-02	PAMPANGA	SAN LUIS	1	1	0	0	0
2019-07-02	PAMPANGA	MACABEBE	1	1	1	1	0
2019-07-02	PAMPANGA	ANGELES	1	1	1	1	0
2019-07-02	PAMPANGA	SAN SIMON	1	1	1	1	0
2019-07-02	PAMPANGA	GUAGUA	1	1	1	1	0
2019-07-02	CAVITE	TRECE MARTIRES	1	1	1	1	1
2019-07-02	CAVITE	TAGAYTAY	1	1	1	1	1
2019-07-02	CAVITE	IMUS	1	1	1	1	1
2019-07-02	CAVITE	GENERAL TRIAS	1	1	1	1	1
2019-07-02	CAVITE	DASMARIÑAS	1	1	1	1	1
2019-07-02	CAVITE	CAVITE	1	1	1	1	1
2019-07-02	CAVITE	CARMONA	1	1	1	1	1
2019-07-02	CAVITE	BACOOR	1	1	1	1	1

Fig. 3. Sample rows from the class suspensions dataset

Meanwhile, the historical class suspensions data were gathered from internet articles published by major and reputable news agencies and government websites in the Philippines. Only class suspensions that are caused by inclement weather conditions such as heavy rainfall, tropical depression, storms, and typhoons were included. The historical class cancellations data were further categorized into two separate subgroups: (a) announcements-based, and; (b) TCWS-based. The process of collecting historical data for class suspensions involved the following steps:

- *Gathering information on yearly Pacific typhoon season*. For each year, information on all tropical cyclones that went through the Philippine islands were collected.

- *Acquiring data on each tropical cyclone with TCWS.* Based on the guidelines from Executive Order No. 66 / DepEd Order No. 43, a raised TCWS would indicate an automatic class suspension in an area. The information gathered for this phase forms the TCWS-based class suspensions dataset.

- *Obtaining data on class suspensions based on LGU announcements*. Extensive search was done for capturing localized class suspensions announced by LGUs using the social media hashtag "#WalangPasok" (meaning "no classes" in the Filipino language) for each day that a tropical cyclone is within the PAR. This constitutes the announcements-based class suspensions dataset.

Each of these dataset portions were stored in an online database for accessibility and ease of use. Online resources for this information were manually read and reviewed, with pertinent details logged into the database. This involved recording the (a) date of the class cancellation; (b) province and (c) city or municipality where the class cancellation took effect, and; (d) the school levels covered by the cancellation, if it is applicable to preschool, elementary, high school, or tertiary level.

In parallel with the implementation of Presidential Executive Order No. 66 / DepEd Order No. 43, series of 2012, this research study's coverage included data from January 1, 2012 up to December 31, 2021 only; spanning a total of nine (9) years' worth of historical weather and class suspensions data.

Other miscellaneous datasets were incorporated in this research endeavor, particularly the localities dataset. This provides a reference of all provinces in the Philippines, with their respective cities and municipalities. In addition, this also comes with their geolocation information. This dataset would eventually be vital in determining approximate weather conditions in a given area.

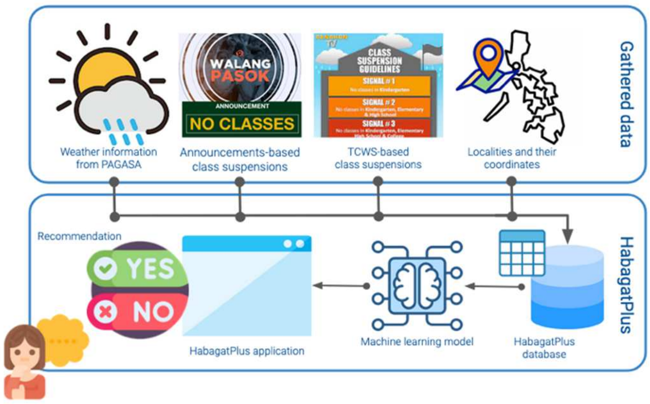

Fig. 4. Process flow of the HabagatPlus service

C. Data pre-processing

After collection of the necessary data, appropriate cleansing procedures were applied to the gathered datasets. The procedures included trimming of whitespaces, elimination of special characters, replacement of null values, uppercasing of all alphabetic characters, among others.

The availability of latitude and longitude values in the localities dataset provides the ability for HabagatPlus to trace the nearest weather station for each city and municipality, of every province in the country, using the haversine formula. An important equation in navigation [22], the haversine formula calculates the shortest distance between two points in a sphere, given their known coordinates.

$$haversine(\theta) = sin^2\left(\frac{\theta}{2}\right) \tag{2}$$

$$haversine\left(\frac{d}{r}\right) = haversine(lat_2 - lat_1) + cos(lat_1) \times cos(lat_2) \times haversine(long_2 - long_1)$$

For the implementation [23] of the haversine formula and its integration with HabagatPlus, a special external script was used in determining the nearest weather station for each locality. Written in PHP, the script traverses through all the records of provinces, cities, and municipalities, and determines the nearest weather station based on their coordinates.

```
class haversine {
     private $latitude_value;
     private $longitude_value;

     public function __construct($latitude_value,
$longitude_value) {
          $this->latitude_value = deg2rad($latitude_value);
          $this->longitude_value = deg2rad($longitude_value);
     }

     public function getLatitudeValue() {
          return $this->latitude_value;
     }

     public function getLongitudeValue() {
          return $this->longitude_value;
     }

     public function getDistance(haversine $other_value) { //
          $earth_radius = 6371;

          $diff_latitude_value =
$other_value->getLatitudeValue() - $this->latitude_value;
          $diff_longitude_value =
$other_value->getLongitudeValue() - $this->longitude_value;

          $x = sin($diff_latitude_value / 2) ** 2 +
               cos($this->latitude_value) *
               cos($other->getLatitudeValue()) *
               sin($diff_longitude_value / 2) ** 2;

          $z = 2 * asin(sqrt($x));
          $distance_in_meters = $earth_radius * $z;

          return $distance_in_meters;
     }
}
```

Fig. 5. Implementation of the haversine formula in PHP code

In order to merge the historical weather data with the historical class cancellations data, the weather station served as the key component in joining them, since each city and municipality is assigned their respective weather station.

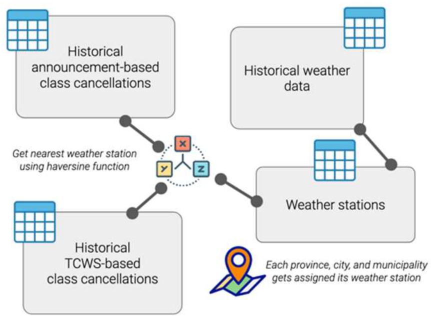

Fig. 6. A diagram showing how the class cancellations data and historical weather data are joined through the weather station information

A given city or municipality will then refer to the weather data of its assigned weather station, forming the denormalized version of the dataset used in model training and testing.

date	province	city_municipality	max_level_suspended	rainfall_amount	temp_mean	wind_speed	suspended
2012-08-10	RIZAL	CAINTA	SENIOR HIGH	19.4	27.7	1	YES
2012-08-10	BULACAN	MALOLOS	ALL LEVELS	19.4	27.7	1	YES
2012-08-10	METRO MANILA	PASIG	ALL LEVELS	19.4	27.7	1	YES
2012-08-10	METRO MANILA	MARIKINA	ALL LEVELS	19.4	27.7	1	YES
2012-08-10	METRO MANILA	MALABON	SENIOR HIGH	19.4	27.7	1	YES
2012-08-10	METRO MANILA	NAVOTAS	ALL LEVELS	19.4	27.7	1	YES
2012-08-10	METRO MANILA	CALOOCAN	ALL LEVELS	19.4	27.7	1	YES
2012-08-10	METRO MANILA	VALENZUELA	SENIOR HIGH	19.4	27.7	1	YES
2012-08-10	RIZAL	TAYTAY	SENIOR HIGH	19.4	27.7	1	YES
2012-10-03	METRO MANILA	MUNTINLUPA	SENIOR HIGH	58	24.4	2	YES
2012-10-03	CAVITE	MENDEZ	ALL LEVELS	58	24.4	2	YES
2012-10-03	METRO MANILA	TAGUIG	SENIOR HIGH	58	24.4	2	YES
2012-10-03	CAVITE	KAWIT	ALL LEVELS	58	24.4	2	YES
2012-10-03	CAVITE	AMADEO	ALL LEVELS	58	24.4	2	YES
2012-10-03	CAVITE	NOVELETA	ALL LEVELS	58	24.4	2	YES
2012-10-03	METRO MANILA	PASAY	SENIOR HIGH	58	24.4	2	YES
2012-10-03	METRO MANILA	MANILA	SENIOR HIGH	53.6	24.6	1	YES
2012-10-03	METRO MANILA	MARIKINA	SENIOR HIGH	53.6	24.6	1	YES
2012-10-03	CAVITE	TANZA	ALL LEVELS	58	24.4	2	YES
2012-10-03	CAVITE	GENERAL EMILIO AGUINAI	ALL LEVELS	58	24.4	2	YES
2012-10-03	CAVITE	TRECE MARTIRES	ALL LEVELS	58	24.4	2	YES

Fig. 7. Denormalized version of the dataset used in training and testing of the HabagatPlus recommendation model

After forming its denormalized version, the dataset was further subdivided into four (4) sub datasets, namely: (1) preschool, (2) elementary, (3) high school, and (4) tertiary. In the application, depending on the school level for suspension, the appropriate sub dataset will be referenced. The train-test-validate splitting methodology was done in order to distribute the dataset accordingly. The following table shows the actual dataset distribution:

TABLE II. DATA DISTRIBUTION PER DATASET CATEGORY

Dataset	**Total record count**	**Training records 70 %**	**Testing records 20 %**	**Validation records 10 %**
Preschool	87,011	60,907	17,402	8,701
Elementary	48,584	34,009	9,717	4,858
High school	64,205	44,944	12,841	6,421
Tertiary	65,054	45,538	13,011	6,505

D. *Classification model training and evaluation*

Using the GaussianNB function in Python's scikit-learn library, the Naïve Bayes classifier was applied to the datasets. After necessary transformations and splitting done to the datasets, the model was designed to predict with a set of sample values for its attributes.

```
attributes = ["rainfall_amount", "wind_speed", "temp_mean"]
target = "suspend"

attributes_training, attributes_testing, target_training,
target_testing =
train_test_split(class_suspend[attributes],class_suspend[target
],test_size = 0.30, random_state = 10)

model = GaussianNB()
model.fit(attributes_training, target_training)
pred = model.predict(attributes_testing)

recommendation = model.predict([[in_rainfall_amount,
in_wind_speed, in_temp_mean]])

if recommendation == "YES":
    interpretation = "SUSPEND"
elif recommendation == "NO":
    interpretation = "DO NOT SUSPEND"
```

Fig. 8. Code portion for providng recommendation using the GaussianNB function in Python's scikit-learn library

The HabagatPlus machine learning model based on the Naïve Bayes classifier was executed over each of the prepared datasets and gained the following ratings in terms of its accuracy, precision, recall, and F-1 score:

TABLE III. HABAGATPLUS RECOMMENDATION MODEL METRICS

Dataset	**Accuracy**	**Precision**	**Recall**	**F-1 score**
Preschool	66.40 %	74.03 %	38.24 %	50.43 %
Elementary	97.56 %	9.15 %	26.42 %	13.59 %
High school	83.22 %	73.05 %	53.37 %	61.68 %
Tertiary	81.02 %	70.10 %	47.20 %	56.42 %
Average	**82.05 %**	**56.58 %**	**41.31 %**	**45.35 %**

With an average accuracy rating of 82.05% across all the dataset groups, this shows that the HabagatPlus machine learning model can provide a fairly accurate recommendation on class suspensions based on historical weather and class cancellations data. However, ratings garnered in the precision, recall, and F-1 score shows that the recommendation service still needs further improvement when it comes to identifying true positive, true negative, false positive, and false negative outcomes.

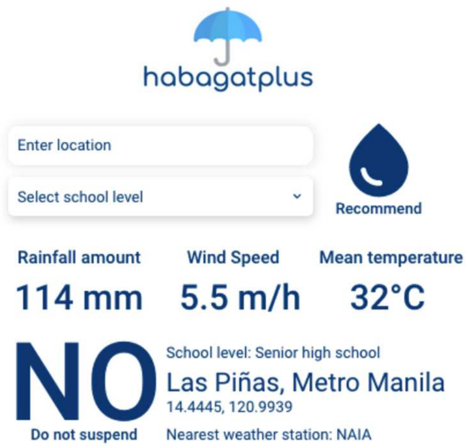

Fig. 9. Interface mockup for the HabagatPlus recommendation service

IV. RESULTS

An array of different trial sets were devised as input to the HabagatPlus recommendation model. These trial sets served as a functional test to the proposed service, gauging on what recommendations will it provide given values for the following attributes: (1) rainfall amount, (2) wind speed, and (3) mean temperature. Usually by default, the expectation is for HabagatPlus to recommend "no" or "do not suspend" for low numeric values for these attributes. As the values get higher, the observation is that HabagatPlus changes its recommendation to "yes", equivalent to "suspend".

TABLE IV. TRIAL SET SAMPLES FOR HABAGATPLUS

#	**Dataset**	**Input Values**			**Recommendation**
		Rainfall amount	Wind speed	Mean temp	
1	Preschool	50.00	2.00	28.00	No, do not suspend
2	Preschool	100.00	5.00	30.00	No, do not suspend
3	Preschool	300.00	9.00	34.00	Yes, suspend
4	Elementary	100.00	5.00	32.00	No, do not suspend
5	Elementary	300.00	8.00	35.00	No, do not suspend
6	Elementary	600.00	12.00	37.00	No, do not suspend
7	High school	200.00	5.00	34.00	No, do not suspend
8	High school	300.00	7.00	36.00	No, do not suspend
9	High school	500.00	9.00	38.00	Yes, suspend
10	Tertiary	150.00	5.00	34.00	No, do not suspend
11	Tertiary	200.00	7.00	35.00	No, do not suspend
12	Tertiary	250.00	9.00	36.00	Yes, suspend

Based on the trials done, the HabagatPlus recommendation model changes its decision upon reaching certain thresholds. Very high values for rainfall amount and wind speed causes the suggestion of HabagatPlus to switch from an initial “no” to an eventual “yes” value. Combining a very low value for rainfall amount with a very high value for wind speed, and vice versa, also leads to this course of action by the developed model.

V. CONCLUSION AND RECOMMENDATIONS

The HabagatPlus recommendation model created using the Naïve Bayes classifier can provide suggestions on the suspension of classes based on the historical class suspensions and historical weather data. Particularly for the high school and tertiary level suspensions, the HabagatPlus recommendation model shows encouraging results in its model metrics, particularly for its accuracy.

Although exhibiting a promising outcome, HabagatPlus can still be further enhanced. With its obtained metrics, the recommendation model can still be further optimized with the following next endeavors:

- *Inclusion of more weather stations*. The current iteration of the project only involved 17 out of the 116 PAGASA weather stations available throughout the Philippines. A wider coverage would be much favorable for data analysis.
- *Integration of other weather-related natural calamities such as floods*. A new set of guidelines for the automatic cancellation of classes have been released under DepEd Order No. 37, s. 2022, rainfall warnings integrated with the conventional TCWS. Incorporating data on flood levels can also be done.
- *Full automation of the data gathering mechanism*. Gathering the historical class cancellations data, the entire process took an estimated total of 45 days to complete. Natural language processing (NLP) techniques can be incorporated in order to make the process of collecting these information faster and easier.
- *Exploration of other machine learning algorithms*. While the Naïve Bayes classifier implementation proves to be feasible in providing recommendation on class suspensions, it would be worth investigating other available machine learning algorithms as well.
- *Continuous improvement*. The study's scope for its dataset is from 2012 up to 2021 only. Constantly updating the HabagatPlus database with the most recent data will be helpful.

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