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Machine Learning: Rain and Visible Moisture Prediction for Airport Safety

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ABSTRACT. *Accurate weather forecasting is of paramount importance in aviation operations, as weather conditions significantly impact flight safety. Various weather phenomena can pose risks to aircraft both in the air and on the ground at airports. This study focused on leveraging Machine Learning (ML) models to forecast the occurrence of rain at Seattle Tacoma International Airport and visible moisture (fog) at San Francisco International Airport. The weather data utilized in this research was obtained from the Iowa Environmental Mesonet (IEM), which maintained a comprehensive METAR-format weather database for airports in the United States. ML, a subset of artificial intelligence (AI), involves training machines or computers on extensive datasets to make predictions. Leveraging the exceptional processing speed of computers, ML offers substantial potential to enhance the efficiency of weather forecasting. In this study, the Python programming language and the JUPYTER notebook environment were employed to analyze weather data and train the ML algorithms. Both logistic regression and neural network (NN) models were developed for rain and visible moisture prediction, exhibiting promising results for both selected hub airports. These outcomes exemplified the significant impact of ML in advancing weather forecast capabilities in this specific domain.*

KEYWORDS - *weather forecast, flight safety, airport visibility, neural network*

I. INTRODUCTION

On August 2nd, 1985, Delta Airlines Flight 191 tragically crashed at Dallas-Fort Worth International Airport (DFW) at approximately 6:05 p.m. local time, resulting from severe wind shear [1]. During this timeframe, the wind speeds remained relatively stable until around 6:14 p.m., when they suddenly escalated to a remarkable 42 miles per hour within a span of only 9 minutes [1]. This devastating incident serves as a poignant illustration of the profound impact weather can have on aviation safety. Furthermore, weather conditions contribute to approximately 70% of flight delays each year [2], emphasizing the significance of comprehending weather dynamics within the aviation ecosystem. Although the atmosphere remains beyond human control, aviation entities can make informed adjustments, such as incorporating more flexibility into their flight schedules, through a better understanding of weather patterns. Machine Learning (ML) falls within the realm of artificial intelligence (AI) and involves training computers on datasets or images to predict desired categorical or numerical outcomes. ML algorithms, while lacking an understanding of the physical laws governing atmospheric behavior, excel in recognizing numerical values and patterns [3][4]. Hence, the aim of this study is to develop and deploy Machine Learning models to evaluate the feasibility of employing ML algorithms in forecasting and nowcasting various meteorological parameters across different airport.

II. LITERATURE REVIEWS

2.1 Internet of Things (IoT) and Machine Learning (ML) for Weather Prediction

ML has emerged as a valuable tool for driving business decisions and enhancing profitability, with its applications spanning various domains. Businesses leverage ML to predict consumer demand and preferences, while medical professionals employ it to aid in diagnosing diseases. One of the key advantages of ML is its ability to efficiently identify patterns within massive datasets, a task that would otherwise be laborious and inefficient using human or traditional formula-based calculations. Weather forecasting, traditionally reliant on complex models, satellite imagery, and weather station observations [5], now delves into the realm of ML. Before delving into the specifics of ML applications for weather, it is essential to introduce a powerful and innovative concept: the Internet of Things (IoT). Given the abundance of weather data from sources such as weather sensors, mobile apps, and the internet, effectively harnessing this data for accurate predictions and informed decisions is crucial. IoT leverages mobile devices and related devices to transmit data to cloud-based servers, enabling the extensive collection of data [5]. In the context of weather forecasting, these IoT devices encompass weather sensors capturing diverse meteorological parameters, mobile devices carried by individuals, as well as government weather sources. To determine the most suitable algorithm, researchers compared various options, including random forest, support vector machine, ridge regression, among others. The performance of the models was evaluated using root-mean-squared error (RMSE), which measures the deviation of temperature predictions from the true temperature values [5].

2.2 Visibility Forecast

Visibility plays a crucial role in aviation weather as it significantly impacts the feasibility of flight operations. In a study conducted by Kim and colleagues, they explored the use of different ML algorithms to predict low visibility. The input variables for these algorithms encompassed temperature, dew point, air pressure, wind direction, wind speed, relative humidity, and precipitation [6]. The researchers specifically applied tree-based algorithms, including random forest, extreme gradient boosting, and light gradient boosting, to forecast visibility. In order to assess the effectiveness of these algorithms, their performance was compared with predictions generated by the local data assimilation and prediction system (LDAPS) [5]. Although Kim's study highlighted a notable forecast error, it underscores the importance of Machine Learning algorithms in quickly discerning meaningful patterns within vast and diverse datasets. To enhance the predictive capabilities of ML algorithms for visibility, it is crucial to swiftly identify and learn significant patterns from extensive and diverse data sources.

Neural networks (NN) have emerged as one of the most powerful ML algorithms in use today. In a study conducted by Zhu and colleagues, meteorological data spanning from 2007 to 2016 was utilized. The data was randomly split, with 80 percent allocated for training and 20 percent for testing [6]. Two NN models were employed during the analysis. The first NN focused solely on using past visibility values to predict the visibility for the desired timeframe. Specifically, the mean absolute error ranged from 326.47 meters when using visibility one hour ago to 439.76 meters when using visibility 120 hours ago. The second NN incorporated all the previously mentioned input variables to predict the hourly dominant visibility [7]. The study concluded that the second NN performed better when the visibility range exceeded 1500 meters, while the first NN demonstrated better performance for visibilities below that threshold.

2.3 Predicting Wind Speed Using Machine Learning

Wind speed is undeniably another crucial meteorological parameter, particularly during the takeoff and landing phases of flight. It serves as a measure of air movement and plays a significant role in detecting weather events. Mandal and Sarode conducted experiments comparing three different models: multiple linear regression, random forest, and deep NN [8]. The study employed different data split ratios for training and testing including 70:30, 80:20 and 90:10 ratios. For the 70:30 split, the root-mean-squared errors were determined as 1.74, 0.37, and 1.44 for multiple linear regression, random forest, and deep NN, respectively. In the case of the 80:20 split, the respective errors were 1.50, 0.33, and 1.16. And, for the 90:10 split, the errors were measured as 1.65, 0.34, and 1.21 [8]. Based on these metrics, it appears that the 80:20 split yielded the most favorable results across all three algorithms.

Antor and Wollega's study was to predict the wind speed at Pueblo, Colorado using three algorithms: ridge regression, polynomial regression, and artificial NN [9]. During the algorithm application phase of the study, each model was run multiple times with different hyperparameters such as learning rate for ridge regression, degrees for polynomial regression, and neurons for the NN. The learning rate is a measure of how quickly one wants the algorithm to converge to reach the minimum error. For NN, the more layers and neurons, the better the performance on the training set, but for small datasets or low dimensional data, too many layers of neurons will overfit the data. Just like the previous studies analyzed, the evaluation metrics used were r squared score and root-mean-squared error. After applying all the algorithms, the r squared scores were approximately 0.5, 0.6, and 0.4 for ridge regression, polynomial regression, and NN respectively [9]. The root-mean-squared errors were approximately 3.4, 3.0, and 3.6 miles per hour for ridge regression, polynomial regression, and NN respectively. From these results, we can see that the polynomial regression outperformed the other 2 algorithms while the NN did not prevail.

Moradzadeh et al. (2021) examined variables: temperature, humidity, solar radiation, and wind direction to predict wind speed [10], both the multilayer perceptron NN and the group method of data handling (GMDH) model were used. The values of r score, root-mean-squared error, and mean absolute error for the multilayer perceptron NN were 0.9969, 0.0782 meters per second, and 0.0445 meters per second respectively and 0.9982, 0.0684 meters per second, and 0.0439 meters per second for the GMDH model. Both types of NN performed very well with the GMDH slightly outperforming the multilayer perceptron model [10].

2.4 Predicting Rainfall with Tree-Based Ensemble Algorithms and Simple Regression

Wet runways and heavy rainfall significantly affect aircraft braking action and airport runway visual range (RVR). In a 2021 study conducted in Bahir Dar City, Ethiopia, daily rainfall amounts were predicted using data from the local meteorological office's weather station [11]. The study employed three algorithms: random forest, XGBoost, and multiple linear regression. Evaluation metrics such as mean absolute error and root-mean-squared error were utilized, similar to previous studies. To identify features correlated with rainfall, the Pearson correlation coefficient was employed, considering values higher than 0.2 for inclusion in the final pool of input variables. The result showed that the highest correlation coefficient related to rainfall were evaporation, maximum daily temperature, minimum daily temperature, sunshine, relative humidity, with relative humidity and temperature showing the strongest correlation [11]. After feeding these input variables into each of the three algorithms, the XGBoost algorithm outperformed random forest and multiple linear regression as the root-mean-squared errors and mean absolute errors were calculated as follows: 3.58 and 7.58 for XGBoost, 4.49 and 8.82 for random forest, and 4.97 and 8.61 for multiple linear regression.

2.5 Research Question

In order to effectively forecast weather conditions at airports, ML techniques were applied, specifically utilizing NN, to compare against traditional linear regression analysis. The central research question addressed in this study was: How does Machine Learning predict weather conditions, specifically focusing on rain and visible moisture (fog) for airports?

III. RESEARCH METHODOLOGY

This study followed a systematic procedure, starting with the collection of multiple years of hourly weather data from the Iowa Environmental Mesonet (IEM) [12] for a specific airport. To process and analyze the data, Python's Pandas library was utilized, allowing for the data to be read into a tabular format within JUPYTER Notebook. To gain insights into the relationships between different variables and understand the weather phenomena specific to the airport under study, exploratory data analysis was conducted using Python's Seaborn and Matplotlib libraries. For the implementation of the artificial NN, the author employed the Tensorflow library.

IV. FINDINGS AND DISCUSSION

This part presented the results retrieved from the logistic regression model, artificial NN, and a dummy model created for rain and visible moisture (fog) prediction. The discussion will follow this order as well. The second portion with visible moisture prediction follows the same structure.

4.1 Rain Forecast - Atmospheric Pressure, Visible Moisture, and Cloud Height

During the data analysis phase, a comprehensive set of plots and charts was generated to explore the distinctive characteristics of time periods with and without rain. The initial step involved creating a line plot to examine the average atmospheric pressure values. A clear separation was observed, with no overlap between the values for rainy and non-rainy periods. Specifically, rainy periods exhibited consistently lower average atmospheric pressure values compared to non-rainy periods. The magnitude of the difference in average atmospheric pressure varied across months, ranging from over 6 millibars to approximately 3 or 4 millibars in most instances (refer to Chart 1).

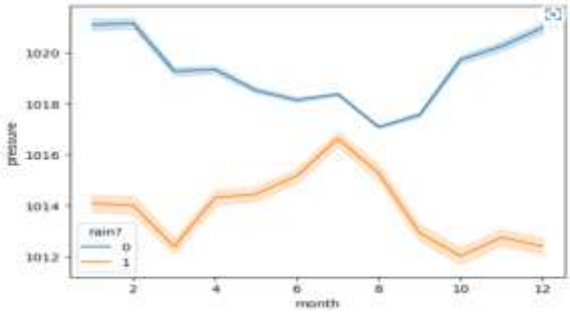
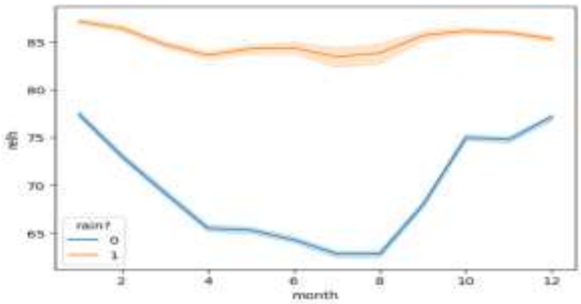


Chart 1. ***Atmospheric Pressure - Rainy vs. Non-rainy Days***

Note. “1” – Rainy; “0” – Non-rainy.

The analysis revealed minimal distinction in average pressure between the months of July (7) and August (8), with a marginal difference of approximately 1 millibar observed for both months. Similarly, a parallel line plot was generated to compare the average relative humidity values for rainy and non-rainy days across all months. The disparity in average humidity varied between 10% and 20%, contingent upon the specific month being examined (refer to Chart 2).

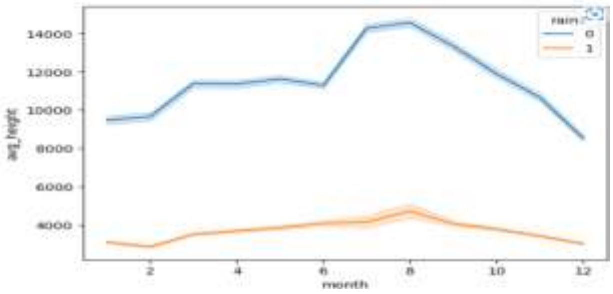
Chart 2. ***Visible Moisture - Rainy vs. Non-rainy day***



Note. “1” – Rainy; “0” – Non-rainy.

Another line plot was generated and revealed a significant distinction, with a substantial separation of at least 4000 feet observed in the average cloud heights. Rainy periods consistently exhibited lower cloud heights compared to non-rainy periods (refer to Chart 3). This finding highlighted the influence of rainfall on cloud formation and supports the notion that rainy conditions are associated with lower cloud heights (refer to Chart 3).

Chart 3. ***Cloud Height - Rainy vs. Non-rainy day***



Note. “1” – Rainy; “0” – Non-rainy.

During the feature engineering phase, the Pandas library was utilized to concatenate the three layers of cloud types, resulting in a consolidated sky condition feature. To visually depict the relationship between sky conditions and rainfall, a stacked bar chart was generated. This chart presents the proportion of rainy and non-rainy periods for each specific sky condition. The bar chart analysis revealed that rainy periods were commonly associated with certain sky conditions (single-layered overcast skies, dual-layered broken/overcast skies, triple-layered scattered/broken/overcast skies, and triple-layered few/broken/overcast skies) (refer to Chart 4).

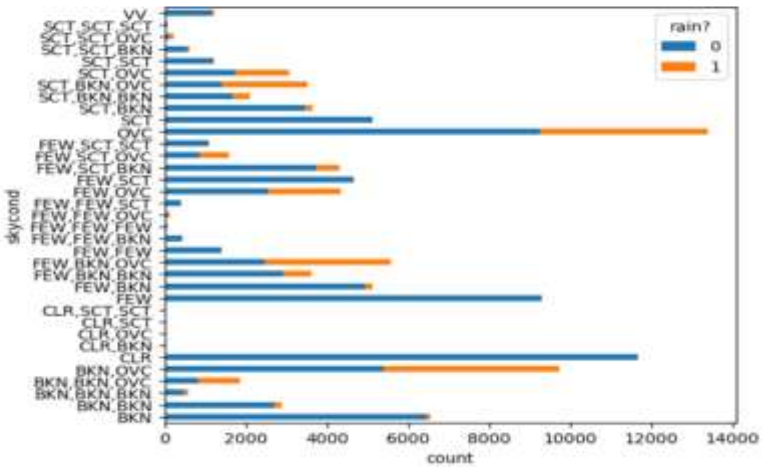
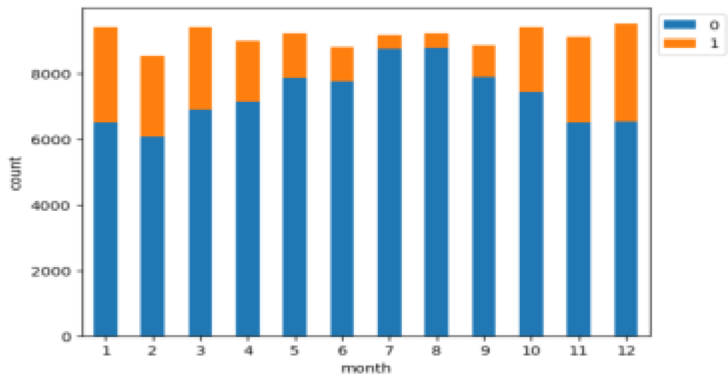


Chart 4. ***Rain vs. Cloud Types***

Note. “1” – Rainy; “0” – Non-rainy. SCT: Scattered; OVC: Overcast; BKN: Broken

Notably, sky conditions with triple-layered scattered/broken/overcast skies, triple-layered broken/broken/overcast skies, triple-layered few/broken/overcast skies, and dual-layered broken/overcast skies frequently accounted for approximately 50% or more of the time during rainy periods. Furthermore, a second stacked bar graph was generated to analyze the variations in the proportion of rainy and non-rainy days across all months. The graph demonstrated that the months from June (6) to September (9) exhibited a relatively lower proportion of rainy days compared to other months (refer to Chart 5). Collectively, these findings illustrated the relationship between cloud cover, sky conditions, and rainfall, while also highlighted the presence of seasonal variations in the proportion of rainy days throughout the year.

Chart 5. ***Logistic Regression Model Results for Rain Prediction***



Note. “1” – Rainy; “0” – Non-rainy

4.2 ***Rain Forecast – Logistic Regression Model***

During the preparation phase for applying the logistic regression algorithm, the data was split into training, validation, and test sets with a 90%, 5%, and 5% split. The overall accuracy for the training, validation, and test set were 87%, 87%, and 88% respectively. For the training set, the precision, recall, and F1 score for non-rainy periods were 0.9, 0.94, and 0.92, while for rainy periods, the values were 0.7, 0.6, and 0.64 respectively (refer to Table 1).

Table 1. *Training Set analysis - Rainy Days*

	precision	recall	f1-score	support
0	0.90	0.94	0.92	79274
1	0.70	0.60	0.64	19441
accuracy			0.87	98715
macro avg	0.80	0.77	0.78	98715
weighted avg	0.86	0.87	0.87	98715

For the validation set, the values of precision, recall, and F1 score for non-rainy periods are identical to the training set, and for rainy periods, the values are 0.69, 0.59, and 0.63 respectively (refer to Table 2).

	precision	recall	f1-score	support
0	0.90	0.94	0.92	4429
1	0.69	0.59	0.63	1055
accuracy			0.87	5484
macro avg	0.80	0.76	0.78	5484
weighted avg	0.86	0.87	0.87	5484

Table 2. *Validation Set analysis -Rainy Days*

Finally, for the test set, the precision, recall, and F1 score for non-rainy periods are 0.91, 0.94, and 0.93 respectively (refer to Table 3). For rainy periods, the values were 0.73, 0.62, and 0.67 respectively.

	precision	recall	f1-score	support
0	0.91	0.94	0.93	4409
1	0.73	0.62	0.67	1076
accuracy			0.88	5485
macro avg	0.82	0.78	0.80	5485
weighted avg	0.87	0.88	0.87	5485

Table 3. *Test Set analysis – Rainy Days*

The outcomes of training, validation, and test sets were very close and there was no overfitting occurred. Since training performance was decent, there did not appear to be signs of underfitting either. Additionally, a consistent trend of poor performance was observed for rainy periods across all sets. This was due to the data imbalance in terms of the proportion of rainy periods compared with non-rainy periods. To fix this issue, a secondary dataset consisting only of rainy data from 1/1/1960 to 1/1/2008 for Seattle Tacoma Airport (SEA) was combined with the original dataset. This bumped the proportion of rainy days up to 43.40%. To continue, the logistic regression algorithm was applied again to observe the new performance for all three datasets. For the second run of the logistic regression, the threshold was increased to 0.55 (> .50) for validation and test sets. The values of precision, recall, and F1 score for the training set were 0.9, 0.86, and 0.88 for non-rainy days. For rainy periods, the values are 0.82, 0.87, and 0.85 respectively (refer to Table 4). The overall accuracy was 86% (refer to Table 4).

	precision	recall	f1-score	support
0	0.90	0.86	0.88	79265
1	0.82	0.87	0.85	60854
accuracy			0.86	140119
macro avg	0.86	0.86	0.86	140119
weighted avg	0.86	0.86	0.86	140119

Table 4. *Training Dataset - Rainy Days Forecast at Seattle Airport (SEA)*

For the validation set, the precision, recall, and F1 score for non-rainy periods was 0.88 all cross, and for rainy periods the values were 0.84 all across (refer to Table 5). The overall accuracy was still 86%.

	precision	recall	f1-score	support
0	0.88	0.88	0.88	4433
1	0.84	0.84	0.84	3351
accuracy			0.86	7784
macro avg	0.86	0.86	0.86	7784
weighted avg	0.86	0.86	0.86	7784

Table 5. *Validating Dataset - Rainy Days Forecast at Seattle Airport (SEA)*

Finally, the test set precision, recall, and F1 score for non-rainy periods were 0.88, 0.87, and 0.87 respectively. The rainy period values were 0.83, 0.84, and 0.84 respectively and the overall accuracy was 86% (refer to Table 6). There is a substantial improvement in the rainy day forecast across all three sets of data.

	precision	recall	f1-score	support
0	0.88	0.87	0.87	4414
1	0.83	0.84	0.84	3371
accuracy			0.86	7785
macro avg	0.85	0.85	0.85	7785
weighted avg	0.86	0.86	0.86	7785

Table 6. *Test Dataset - Rainy Days Forecast at Seattle Airport (SEA)*

4.3 Rain Forecast - Neural Network (NN)

In this NN operation, a relatively simple architecture was implemented. The input layer consisted of fifteen (15) neurons, while the hidden layers were composed of ten (10), five (5), and three (3) neurons respectively. Each of these neurons was associated with the rectified linear unit activation function. The output layer comprised a single neuron, utilizing a sigmoid or logistic function for activation. The Adam optimizer algorithem with a learning rate of 0.001 was employed, and the loss function utilized was the binary cross-entropy function from TensorFlow. To enhance training efficiency, a total of 100 epochs were executed, with a batch size of 1000. Classification was determined using a threshold of 0.55. Evaluating the model's performance on the training set, the precision, recall, and F1 score values for non-rainy periods were determined as 0.89, 0.9, and 0.9, respectively (refer to Table 7). For rainy periods, the corresponding values were 0.87, 0.86, and 0.86. The overall accuracy of this NN model was 88%.

	precision	recall	f1-score	support
0	0.89	0.90	0.90	4433
1	0.87	0.86	0.86	3351
accuracy			0.88	7784
macro avg	0.88	0.88	0.88	7784
weighted avg	0.88	0.88	0.88	7784

Table 7 . *Neural Network - Training Set Analysis - Rainy Days*

During the validation phase, the precision, recall, and F1 scores for non-rainy periods in the validation set were found to be 0.88, 0.9, and 0.89, respectively. For rainy periods, the corresponding values were 0.87, 0.85, and 0.86 (refer to Table 8). It is noteworthy that the overall accuracy of the model remained consistent at 88%. This demonstrates the model's capability to maintain a reliable level of accuracy across different data subsets, providing consistent performance in predicting rainfall.

	precision	recall	f1-score	support
0	0.88	0.87	0.87	4414
1	0.83	0.84	0.84	3371
accuracy			0.86	7785
macro avg	0.85	0.85	0.85	7785
weighted avg	0.86	0.86	0.86	7785

Table 8 . *Neural Network - Validation Set Analysis – Rainy Days*

Finally, the test set non-rainy period values were 0.88, 0.87, and 0.87 respectively and rainy period values are 0.83, 0.84, and 0.84 respectively (refer to Table 9). The overall accuracy remains at 86%.

	precision	recall	f1-score	support
0	0.88	0.90	0.89	4414
1	0.87	0.85	0.86	3371
accuracy			0.88	7785
macro avg	0.88	0.87	0.87	7785
weighted avg	0.88	0.88	0.88	7785

Table 9. *Neural Network - Test Set Analysis – Rainy Days*

4.4 Rain Forecast - Dummy Model Verification

To assess the effectiveness of the applied ML models, a dummy model was created to simulate typical human performance without utilizing Machine Learning. This comparison aimed to evaluate whether the ML models would surpass the performance of the dummy model. If a Machine Learning model fails to outperform the dummy model, it indicates either the algorithm's ineffectiveness or a significant error during its implementation. The evaluation of the dummy model resulted in precision, recall, and F1 scores for non-rainy periods, which were determined as 0.96, 0.72, and 0.82, respectively (refer to Table 10). Furthermore, the overall accuracy of the dummy model was calculated as 75%. Comparing the performance of the ML models with the dummy model enabled a clear assessment of the superiority of the ML algorithms in predicting rainfall.

	precision	recall	f1-score	support
0	0.96	0.72	0.82	88112
1	0.43	0.87	0.58	21572
accuracy			0.75	109684
macro avg	0.70	0.80	0.70	109684
weighted avg	0.85	0.75	0.77	109684

Table 10. *Dummy Model for Rain Prediction Models*

The results of the analysis demonstrated that both NN and logistic regression models significantly outperformed the dummy model, indicating their ability to effectively learn and recognize patterns within the data. And the NN model exhibited a slight performance advantage of 2% over the simple logistic regression model at Seattle-Tacoma International Airport (SEA).

4.5 Visible Moisture Prediction

Another purpose of the project was to predict visible moisture (e.g., fog or mist). Data was collected for San Francisco International Airport (SFO) for the time frame 1/1/2009 to 1/1/2023 from IEM. During the initial phases of analysis, the proportion of foggy and misty periods was around 3.20% per the overall meteorological data. The variables used included: hour of day, month, relative humidity, temperature, wind speed, dew point, and pressure. A line plot comparing temperature gaps across the months for periods with and without visible moisture indicated that visible moisture had lower temperatures on average across all months with the exception of November to December (refer to Chart 7).

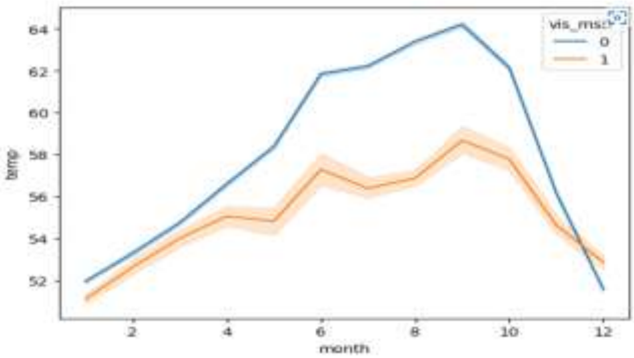


Chart 7. *Visible Moisture vs. Temperature San Francisco International Airport*

A line plot was generated to examine the relationship between relative moisture, wind speed, dew point, and atmospheric pressure. The analysis revealed that the majority of visible moisture occurrences coincided with the months between April and September, which also corresponded to higher wind speeds (refer to Chart 8). Notably, the historical record of dew point exhibited a less pronounced impact on visible moisture (refer to Chart 9). Conversely, atmospheric pressure displayed a stronger correlation with visible moisture occurrences (refer to Chart 10).

Chart 8. *Visible Moisture vs. Wing Speed - San Francisco International Airport*

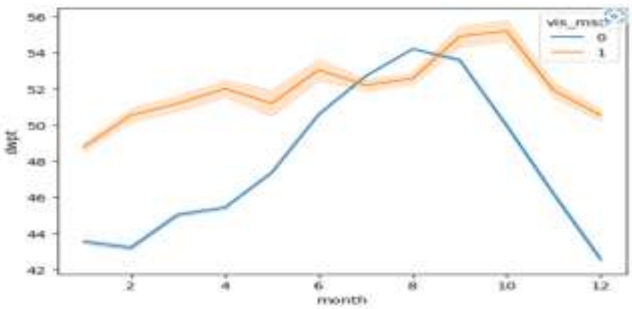


Chart 9. *Visible Moisture vs. Dewpoint - San Francisco International Airport*

Chart 10. *Visible Moisture vs. Atmospheric Pressure - San Francisco International Airport*

4.6 Visible Moisture - Logistic Regression Model

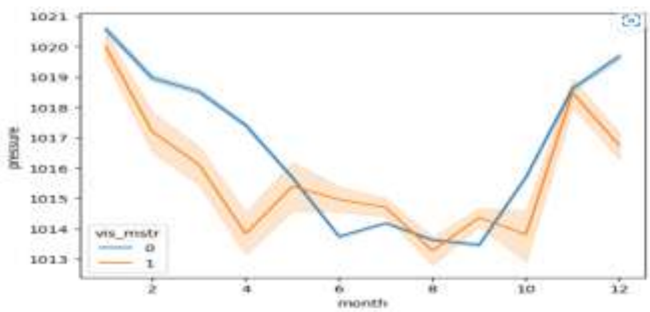
In this section, the needed variables were relative humidity and temperature. The authors divided the dataset into training, validation, and test sets. Input datasets were scaled and fed into the logistic regression algorithm. Similar to the previously rain forecast, the decision threshold was set to 0.5 for the logistic regression model, the initial application obtained a training precision, recall, and F1 score of the visible moisture scores were 0.38, 0.07, and 0.12 respectively (refer to Table 11). In the validating set, the periods with visible moisture obtained precision, recall, and F1 score of 0.28, 0.06, and 0.10 respectively (refer to Table 12).

Table 11. *Training Dataset – Humidity, Visible Moisture Forecast at SFO*

Note: SFO – San Francisco International Airport

	precision	recall	f1-score	support
0	0.97	1.00	0.98	5835
1	0.28	0.06	0.10	184
accuracy			0.97	6019
macro avg	0.62	0.53	0.54	6019
weighted avg	0.95	0.97	0.96	6019

Table 12. *Validating Dataset – Humidity, Visible Moisture Forecast at SFO*



For the test set, the performance for periods without visible moisture was again identical to the training set but the days of visible moisture showed scores of 0.32, 0.06, and 0.09 respectively for precision, recall, and F1 (refer to Table 13). The overall accuracy for all three datasets was 97%.

	precision	recall	f1-score	support
0	0.97	1.00	0.98	5821
1	0.32	0.06	0.09	198
accuracy			0.97	6019
macro avg	0.65	0.53	0.54	6019
weighted avg	0.95	0.97	0.95	6019

Table 13. *Test Dataset – Humidity, Visible Moisture Forecast at SFO*

For the temperature and visible moisture, a secondary dataset was created by combining visible moisture data from 1/1/1950 to 1/1/2008 with a random sample of 40,000 time periods without visible moisture. This combined dataset accounted for 32.93% of the data and was used for training the logistic regression algorithm. After reapplying the logistic regression algorithm, the training precision, recall, and F1 score for instances without visible moisture were 0.92, 0.91, and 0.92, respectively (refer to Table 14). For visible moisture, the scores were 0.83, and the accuracy rate was 0.89.

	precision	recall	f1-score	support
0	0.92	0.91	0.92	36059
1	0.83	0.83	0.83	17618
accuracy			0.89	53677
macro avg	0.87	0.87	0.87	53677
weighted avg	0.89	0.89	0.89	53677

Table 14. *Training Set – Temperature, Visible Moisture Forecast at SFO*

For the validating set, recall, and F1 score for instances without visible moisture were 0.92, 0.91, and 0.92, respectively and visible moisture scores were 0.83, 0.85, and 0.84 respectively (refer to Table 15).

	precision	recall	f1-score	support
0	0.92	0.91	0.92	1966
1	0.83	0.85	0.84	1017
accuracy			0.89	2983
macro avg	0.88	0.88	0.88	2983
weighted avg	0.89	0.89	0.89	2983

Table 15. *Validating Set - Temperature, Visible Moisture Forecast at SFO*

The test set performance for instances without visible moisture demonstrated precision, recall, and F1 scores of 0.91, 0.91, and 0.91, respectively (refer to Table 16). Additionally, the overall accuracy of the model

	precision	recall	f1-score	support
0	0.97	1.00	0.98	104873
1	0.38	0.07	0.12	3466
accuracy			0.97	108339
macro avg	0.68	0.54	0.55	108339
weighted avg	0.95	0.97	0.96	108339

on the test set was calculated as 88%. These metrics indicate that the model performed consistently well in correctly predicting the absence of visible moisture. The result simultaneously showcased its reliability and effectiveness in discerning visible moisture conditions.

	precision	recall	f1-score	support
0	0.91	0.91	0.91	1975
1	0.82	0.83	0.82	1007
accuracy			0.88	2982
macro avg	0.87	0.87	0.87	2982
weighted avg	0.88	0.88	0.88	2982

Table 16. *Test Set - Temperature, Visible Moisture Forecast at SFO*

4.7 Visible Moisture Forecast - Neural Network

Using Neural Network (NN), the structure consisted of four (4) layers with seven (7) neurons, five (5) neurons, three (3) neurons, and one (1) neuron for the input, hidden, and output layers respectively. The results obtained from the NN closely resembled those of the simple logistic regression model, as depicted in Table 17. This suggested that both models yielded comparable performance in the classification task.

	precision	recall	f1-score	support
0	0.92	0.91	0.92	1966
1	0.83	0.85	0.84	1017
accuracy			0.89	2983
macro avg	0.88	0.88	0.88	2983
weighted avg	0.89	0.89	0.89	2983

Table 17. *Neural Network - Visible Moisture Forecast at SFO*

4.8 Visible Moisture Forecast - Dummy Model

The dummy model employed in this study aimed to predict the presence of visible moisture based on a simple rule: predicting visible moisture when the relative humidity reached 90% or higher, given the average humidity values were approximately 90%. Evaluating the performance of the dummy model, precision, recall, and F1 scores for instances without visible moisture were determined as 0.98, 0.96, and 0.97, respectively. For instances with visible moisture, the corresponding values were 0.29, 0.50, and 0.37 (refer to Table 18). Furthermore, the overall accuracy of the dummy model was calculated as 95%.

	precision	recall	f1-score	support
0	0.98	0.96	0.97	116529
1	0.29	0.50	0.37	3848
accuracy			0.95	120377
macro avg	0.64	0.73	0.67	120377
weighted avg	0.96	0.95	0.95	120377

Table 18. *Dummy Model - Visible Moisture Forecast at SFO*

4.9 Discussions

If we compared the dummy model metrics to the initial application of logistic regression, the dummy model outperformed the logistic regression model for visible moisture. However, the second run of the logistic regression model significantly outperformed the dummy model and achieved a great balance between scores for periods with and without visible moisture. As a result, the logistic regression analysis was the preferred model for visible moisture prediction. The logistic regression process was also faster and the test results were identical to the NN.

V. CONCLUSION

The primary objective of this study was to assess the applicability of ML algorithms in predicting hazardous weather conditions for aviation operations, focusing specifically on rain and visible moisture. To achieve this, a subset of weather variables obtained from IEM for SEA and SFO airports was utilized. The study employed two key algorithms, namely logistic regression, and Neural Network (NN), for both rain and visible moisture prediction. The evaluation of these algorithms allowed for the identification of the optimal approach to be employed in weather prediction. By leveraging ML techniques, the study aimed to enhance the accuracy and reliability of weather forecasts, thus enabling better decision-making for aviation operations.

The initial phase of the study centered around rain prediction specifically for Seattle-Tacoma International Airport (SEA). Through the inclusion of an ample amount of rainy data, significant enhancements were achieved in the accuracy of rain forecasts. The findings unveiled that the Neural Network (NN) model surpassed the logistic regression model by 2% in terms of overall accuracy, and similar improvements were observed in category-specific metrics such as the F1-score. The subsequent segment of the study entailed the prediction of visible moisture at San Francisco International Airport (SFO). Both the logistic regression algorithm and the artificial Neural Network (NN) were employed for this purpose. In the initial application, the logistic regression model performed below expectations, failing to surpass a dummy model created for comparison. However, by augmenting the dataset with additional visible moisture data, the logistic regression model exhibited a substantial improvement, outperforming the dummy model and achieving a favorable balance in predictive performance for data with and without visible moisture. Simultaneously, the NN model displayed comparable performance to the logistic regression model. Considering the logistic regression model's ease of implementation and practicality, it was chosen as the model for visible moisture prediction at San Francisco International Airport (SFO).

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