(RESEARCH ARTICLE)

Accurate weather forecasting with dominant gradient boosting using machine learning

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Abstract

This Paper examines the interesting topic of weather forecasting using ML. From kaggle.com, there is an extensive list of daily weather records for a Seattle dataset. In this chapter, gradient boosting outcomes are revealed as a result of careful data preparation and thorough examination of several machine learning models such as K-Nearest Neighbors, Support vector machine, Gradient Boosting, XGBOOST, logistic regression, and random forest class Its 80.95% accuracy was outstanding. ML traverses atmospheric dynamics that form a basis for weather predictions. It uses a highly developed method that enables it to predict the complex trends in the weather. In addition, machine learning algorithms are increasingly important for detecting non-linear relationships and patterns from large sets of complex data with time. It is critical for meteorologists in overcoming uncertainties associated with atmospheric dynamics to improve prediction. Gradient Boosting – a weather forecasting perspective in an interdisciplinary landscape involving weather science and machine learning. The current research on ML for weather forecasting has been very useful.

1. Introduction

Weather prediction traces its roots way back during the 19th Century. Another notable event was in NWP system usage which took place in 1970-1980's [1]. Such relations were also confirmed in other models like k-nearest neighbours model, support vector machine, gradient boosting, XGBoost, logistic regression, and Random Forests Classifier [2]. This is largely as a result of reporting from meteorological stations. Hence, this way has provided a big picture on the current weather situation [3]. Although weather can never be foretold or forecasted, efforts have often been made towards its study and prediction. In addition, this quest keeps recurring, more so at present as there arise increasing complexity and intensity of weather conditions. The first chapter signifies that the time of meteorology has arrived, implying weather prediction also. A 'Gordian knot' of puzzles of atmospheric dynamics". This is a fourteenth scale research data collecting in Seattle, one of many complicated meteorological processes zones [4]. The A1 model support is based on daily recorded and highly reliable weather information, which constitute the core of these modelled databases.

The method of machine learning possesses an exceptional ability to navigate the intricate choreography of weather patterns, surpassing the limitations of human understanding to uncover concealed connections within vast and intricate datasets [5]. This is the focal point of its work. Basically, the models discussed consist of numerical values. The computer programme is utilised to determine these equations and track changes in meteorological attributes. It is completed gradually, either day by day or with some days of advance planning. This chapter shows the synergistic relationship between Gradient Boosting, a breakthrough machine learning method, and weather forecasting. Exciting advancements are being made in the field of atmospheric science, as researchers explore the enormous strength of machine learning methods. These investigations are uncovering remarkable insights into the intricate workings of atmospheric dynamics,

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redefining our comprehension of weather forecasting. Grasping the mechanisms that govern the intricate symphony of the atmosphere forms the foundation of weather prediction. Simply estimating the future is insufficient; this is the very heart of weather forecasting.

These are among others, air pressure, temperature, wind speed and direction, moisture content in air (humidity), etc. It makes observations by means of sea observation, ground observation, radar observation among others. Weather forecasting involves using the data for a number of applications and models which in turn discover different patterns. The subject of weather forecasting is highly interesting and may result in plenty of practical activities including aviation, agriculture and tourism. Other problems surrounding weather forecasting include interpreting trends with large quantities of weather information for instance. Then developing an appropriate model to make projections into concealed phenomena within these many data sets [7]. Machine learning finds its way through atmospheric dynamics, when models predict with an accuracy of 80.95%. Unlike other data analysis methods, machine learning has the capability of disentangling complicated connections and detecting the patterns within massive datasets whose understanding was challenging with traditional analytic procedures. It assists meteorologists in addressing the intricacies involved in atmospheric behaviour studies, thereby providing improved predictions of the weather. This makes them important sources of information for business, communities and governments that need dependable weather projections.

Although significant progress has been made towards using artificial intelligence and deep learning to forecast weather patterns, moving away from traditional numerical weather prediction approaches comes with its own set of hurdles. Despite the impressive speed of the latest AI models on advanced graphics processing units, they continue to face challenges in achieving the same level of accuracy and reliability as the combined forecasting system of the European Centre for Weather Forecasts. Understanding the intricacies of the atmosphere and the behaviour of weather systems can be quite challenging. AI models struggle to grasp the complex interconnections and relationships within the atmosphere, posing a significant limitation. The traditional approaches to weather prediction require solving complex equations to accurately depict the dynamic changes in the atmosphere across a grid. Yet these approaches are expensive computationally and may require high processing times using supercomputers. Their strength lies in speed with which they can handle the data but precision suffers for it.

This variation in the precision, especially apparent in the long-term predictions such as root mean square error, highlights the essential need for improvements in state-of-the-art AI approaches. The fourcasternet root mean square error values for a five day 500 hPa geopotential forecast is however much larger than the 195.6 from ecmwf's operational ifs. However, despite current advances in AI-based models, they are still unable to fully capture the complex, unsolved atmospheric phenomena that give rise to numerous errors and miscalculations. The following sections of this chapter will discuss data preparation [9], and model testing, model performance and accuracy, machine learning's crucial role in weather prediction, meteorology's transformative impact, and Gradient Boosting singular impact on weather forecasting's future. Weather forecasting plays a important role in the lives of many individuals, as it has the potential to affect various sectors such as agriculture, irrigation, and marine trade [10]. The future of weather forecasting will be greatly influenced by the insights gained from these multidisciplinary approaches. Additionally, accurate weather predictions can help prevent unforeseen accidents and ultimately save lives [11].

2. Related Works

Wang et al. suggested that gradient boosting regression trees can be utilized to improve accuracy of weather prediction models [12]. A different paper by Lee et al. proposed Team learning techniques using ensemble learning methods in weather forecasting and prediction discusses the resolution of weather prognostics problems through ensemble learning approaches [13]. An array of diverse machine-learning methodologies inclusive but not limited to gradient-boosting have been discussed by Cifuentes as well as Marulanda in their critique named "Air temperature forecasting using machine learning techniques: a review" [14]. These authors in particular emphasis on the practical application of these methods in meteorological forecasting processes. By evaluating various machine learning tactics among which is included 'gradient boosting', Markovics together with Mayer review each one's performance within climate prediction circumstances through their article titled "Comparison of machine learning methods for photovoltaic power forecasting based on numerical weather prediction. Renewable and Sustainable Energy Reviews"[15]. In other research, Stensrud and Brooks focus on the ensemble method [16] in order to increase the accuracy of short-range climate forecasts [17].

Using XGBoost in forecasting weather conditions, Dong et al. proposed an application of gradient boosting for weather predictions [18]. In the comprehensive exploration "Weather Classification Model Performance: Using CNN, Keras-TensorFlow." was done by Sharma, A., & Ismail, Z. S. employed in the weather prediction models [19]. A comparative study on the application of deep-learning techniques on climatic foresight.

It also uses a very reliable tool which is referred to as a graduate boosting machine for the accurate prediction of rainfall of Wu et al [20]. Dong et al. titled "Enhancing short-term forecasting of daily precipitation using numerical weather prediction bias correcting with XGBoost in different regions of China'' includes the following: Gradient boosting approach for short term weather forecast improvement [21]. "Comparison of Support Vector Machine and Extreme Gradient Boosting for predicting daily global solar radiation using temperature and precipitation in humid subtropical climates" by Fan et al. [22]. A new ensemble approach for weather forecasting based on or forecasting main meteorological parameters is proposed by Karvelis et al. [23]. Ghorbani and Khatibi alongside FazeliFard proposed "short-term wind speed predictions with machine learning techniques", a comparative analysis comparing different types of machine learning models which include a specially designed Gradient-Boost model aimed at high predictability wind speed forecasting [24].

Further detailing on this topic is Park alongside Hwang discussing assessment of Light GBM through research stated as "A two-stage multistep-ahead electricity load forecasting scheme based on LightGBM and attention-BiLSTM" refers to the evaluation of a common boost scheme often noticed in climatic disciplines and other applied fields associated with climate forecasts [25]. Dewi et al. proposed Fog prediction using artificial intelligence [26]. D'Agostino and Schlenker titled the paper "Recent weather fluctuations and agricultural yields: implications for climate change" [27]. Gradient boosting algorithm for predicting temperature changes on this paper. Fouillet and Rey's proposed article titled "A predictive model relating daily fluctuations in summer temperatures and mortality rates" includes the following: This article is about the accurate prediction forecast of temperature swings using a gradient boosting machine [28].

Grover and Kapoor have jointly penned an article entitled " A deep hybrid model for weather forecasting [29]. They discuss a concept of 'Integrating Gradient Boosting' that highlights their combined efforts in defining hybrid models and using gradient boosting to advance weather prediction. Olson and Kenyon have authored another research piece that delves into the topic of "Improving wind energy forecasting through numerical weather prediction model development" [30].

A Journal entitled "Design and evaluation of adaptive deep learning models for weather forecasting," by Abdulla and Demirci informs the audience how adaptive methods that involve improved boosting algorithms work in helping accurately predict climates [31]. A paper by Andrade and Bessa called 'improving renewable energy forecasting with a grid of numerical weather predictions' is a collaborative effort by these two authors [32]. The research titled Multivariate monthly water demand prediction using ensemble and gradient boosting machine learning techniques. authored by Banda et al. highlights an evaluation of yields achieved in deployment efficiencies used while forecasting multivariable weather [33]. Lastly, this gives an authority to a thesis focused on the spatial aspect that has been narrated with emphasis emphasising space benefits related to current tool redevelop techniques and aims to improve or develop existing approaches. Exploring different methodologies for weather forecasting has resulted in the development of new approaches, especially in the field of artificial intelligence (AI) and machine learning. In recent years, there has been a shift towards using machine learning techniques, such as neural networks and support vector machines, to model weather phenomena. This approach is becoming increasingly popular and is being utilised in conjunction with traditional physics-based simulations and differential equations.

When it comes to machine learning for weather prediction, neural networks appear to be the preferred option according to the reviewed papers. While neural networks were the focus of two of the investigations, support vector machines were the focus of the third publication. Because of their superior comprehension of complicated, non-linear links between historical weather patterns and future atmospheric conditions, neural networks have found extensive use in weather forecasting. Neural networks, in contrast to simplistic linear regression models, take into account more than just the data's linear relationships. This suggests that they are better able to anticipate outcomes since their thought processes are less rigid and more open to other possibilities. There were two separate methods that researchers addressed neural network applications. Another group depended entirely on neural networks for weather prediction, while a third group integrated neural networks with concepts from meteorological science. On the other hand, the support vector machine method [34] took a different tack, deciding to utilise a classifier specifically for weather prediction. What made that study stand out was how it used meteorological concepts in conjunction with neural networks [35]. It effectively merged the capabilities of neural networks with a profound comprehension of weather dynamics. On the other hand, the utilisation of neural networks in a separate study demonstrated their remarkable ability to comprehend intricate patterns in data without relying on explicit weather regulations. However, it is crucial to acknowledge that support vector machines have certain limitations in predicting the weather, particularly when compared to the capabilities of neural network-based methods, despite demonstrating promising potential. It appears that support vector machines could face challenges in capturing the diverse and complex relationships inherent in the data. Many of these papers compare the performance of gradient boosting against other machine learning models for weather forecasting tasks [36], with a focus on algorithmic comparisons. They examine how gradient boosting

regression trees, xgboost, lightgbm, and ensembles that employ gradient boosting would improve short- and long-term prediction abilities respectively. Another huge number of publications concentrate on the quantity of moisture, temperatures, the rate of winds and precipitation. They analyse how gradient boosting models can capture these components, showing that these algorithms can get good predictions depending on specific weather. Researchers have also noted the use of gradient boosts within hybrid mixture or ensemble models. These studies are aimed at enhancing the precision in weather prediction by incorporating individual model strong points. The authors investigate the synergies that can exist among GB with other techniques and how it can be exploited to improve prediction accuracy. Therefore, several publication articles in the field of weather forecasting highlight the importance of considering both space (time plus place and then space) when trying to predict weather conditions. These findings reveal that the gradient boosting methods can be altered to tackle spatio-temporal data leading to enhanced accuracy when it comes to predicting weather patterns in varied settings.

3. Materials and Methods
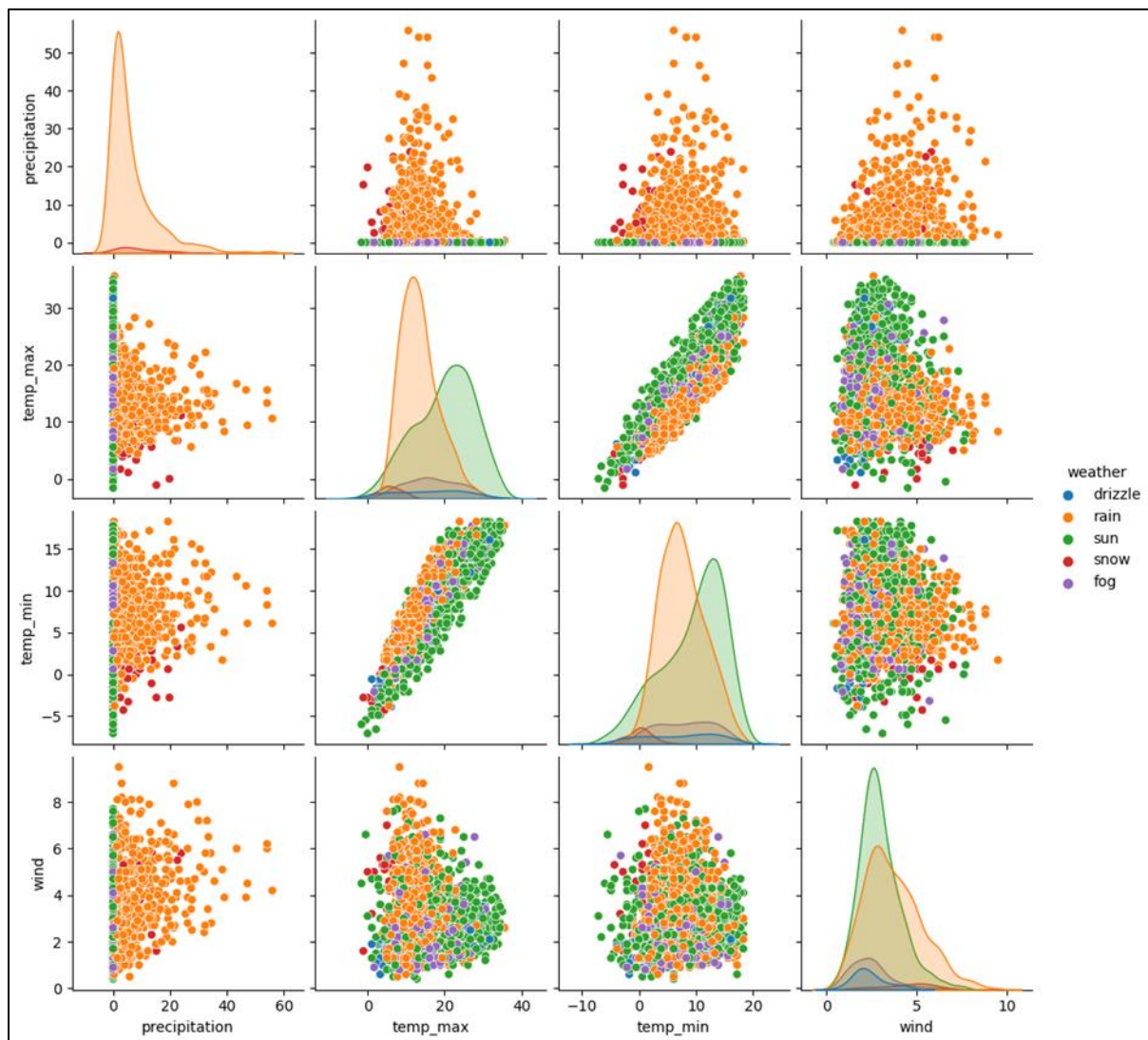
3.1. Dataset

Figure 1 Scatterplot visualisation of correlations within a dataset

The Kaggle dataset weather prediction is used to incorporate actual data [37]. In the data set, columns for rainfall, snowfall, and other precipitation indicate the quantity that happened during the time. This dataset includes temp_max and temp_min, the highest and lowest temperatures measured in the same time period. It appears that the column wind contains wind velocity or condition data. To conclude, the weather section groups current weather conditions like sunny, wet, overcast, etc. This information is essential for evaluating weather patterns, identifying seasonal variations,

and maybe constructing models that can anticipate weather conditions based on the attributes presented. Further analysis of this data may reveal the complex dynamics and effects of these factors on different climates [38]. The comprehensive display enables the concurrent analysis of variable distributions and correlations across different weather conditions. This visualisation approach demonstrates the interplay of weather elements and how they might impact on each other under different atmospheric circumstances by identifying potential trends or patterns in the dataset, as depicted in the Figure. The Seaborn pairplot tool generates a scatterplot grid to visualise correlations within a dataset as shown in Figure 1. Colour-coding the data points for the dataset (df) in accordance with the categories in the 'weather' column after creating scatterplots for each pair of numerical columns (precipitation, temp_max, temp_min, and wind).

Weather forecasting has a range of applications that affect different aspects of our lives. Industries, transportation systems, disaster management and energy management all depend on weather predictions. Meteorologists are currently, at the forefront of an era, where they are moving from dealing with uncertainties in the atmosphere to using predictive analytics. This shift will enable us to anticipate and adapt to the nature of weather with accuracy and foresight. The use of machine learning algorithms is driving this transformation. The actual data seems to be contained in the Kaggle dataset. Precipitation in the data set denotes a column which shows the amount of rainfall, snow falling or any other incident.

The concurrency between the exploring and developing technology for weather forecast to unlock the mysteries of the music in the air.

Thus, seaborn's countplot produces bar plots. The DataFrame's 'weather' column includes distinct categories, and this visualisation demonstrates their frequency is shown in Figure 2. The figure depicts the dataset's weather categories and the count of events associated with each. This visualisation technique helps explain the dataset's composition and atmospheric conditions.
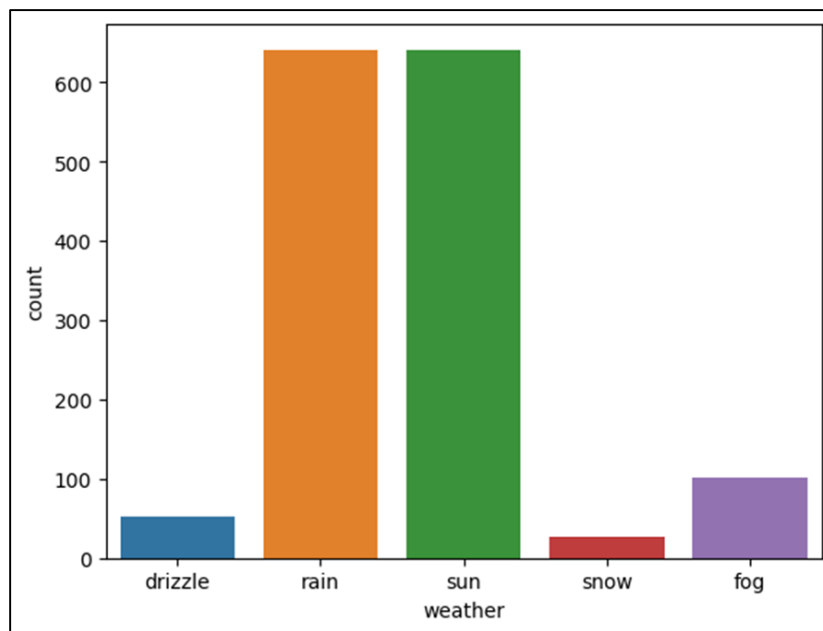

Figure 2 Visualisation dataset's frequency for weather prediction

There is a pattern in the scatter plot showing relationships among precipitation, temperature, wind and humidity is shown in Figure 3. As can be seen in this graph, the higher the temperature the lower the probability of rainfall. This is logical since warm air contains more moisture and therefore decreases rain chances. Despite this, some researchers argue that high winds may be accompanied by a rise in humidity level [39]. This might be implied that an incident of high wind causes evaporation of water thereby contributing to high levels of humidity in the region. A total description of a scatter plot enables people to understand the relationship between these four variables that constitute the environment.
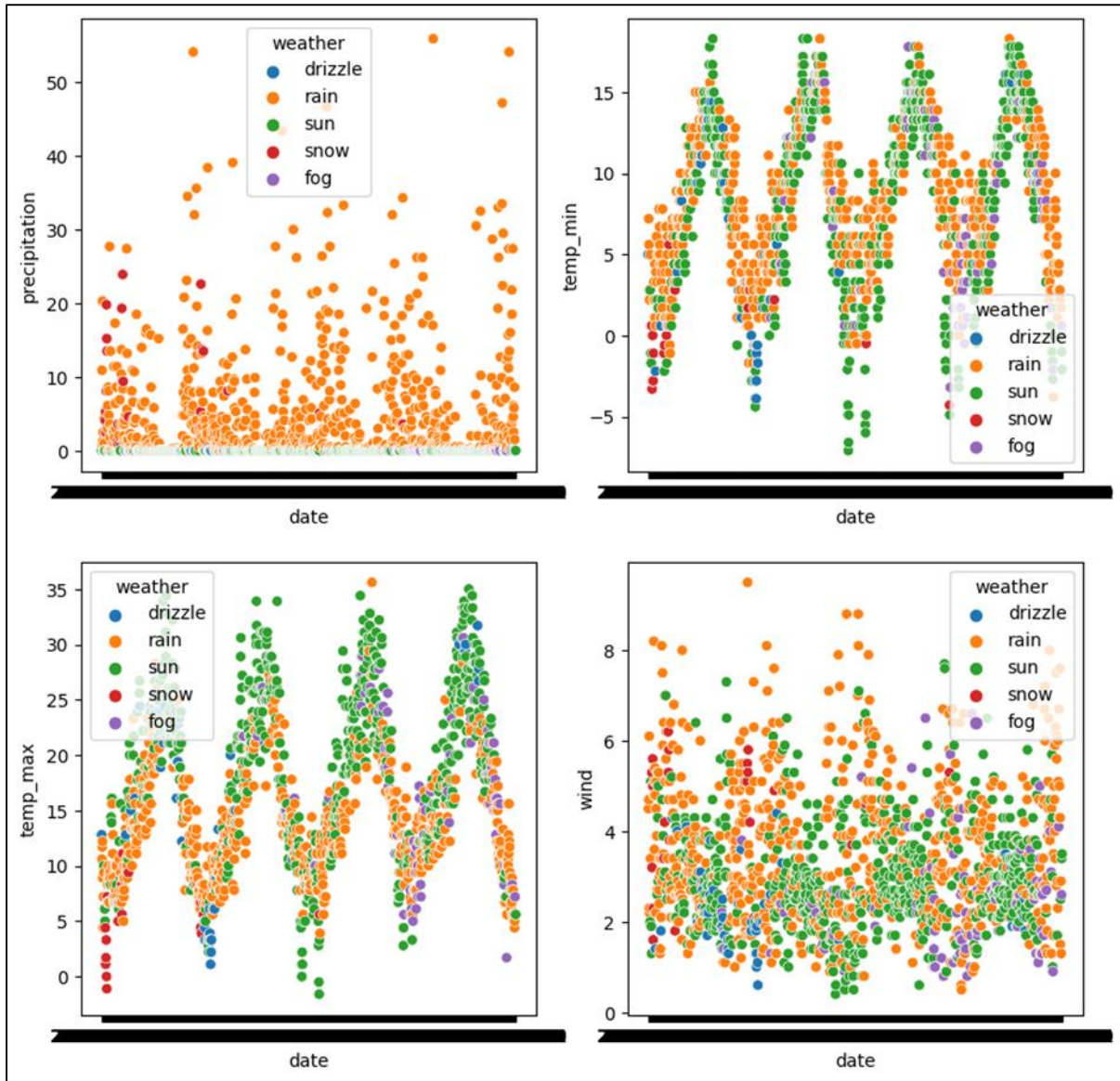
Figure 3 Scatter plot visualisation of relationships among precipitation, temperature, wind and humidity

As for various weather components shown in Figure 4 for a certain area during an interval, the box plot illustrates it pictorially [40]. In the first plot depicting precipitation, most of the bulk measurements ranged from zero to half an inch while there were a few spike measurements that exceeded one inch illustrating some extreme precipitation periods. The second box diagram denotes temp_max demonstrating a skewed distribution trending toward the warm side. Unlike the first one, temp_max shows the same pattern but at a reduced lower spectrum scale. Finally, again, through the fourth chart the way that wind is presented depicts different values just as the previous time – reflecting on the natural inconsistencies of life at each stage.

These sketches can help reveal the variability for the different meteorological factors, while also pointing out the possibilities and potential effects in relation to the predicted weather event itself. Together, they provide insight into what is likely to happen next, and offer early warning of such hazards and potential.
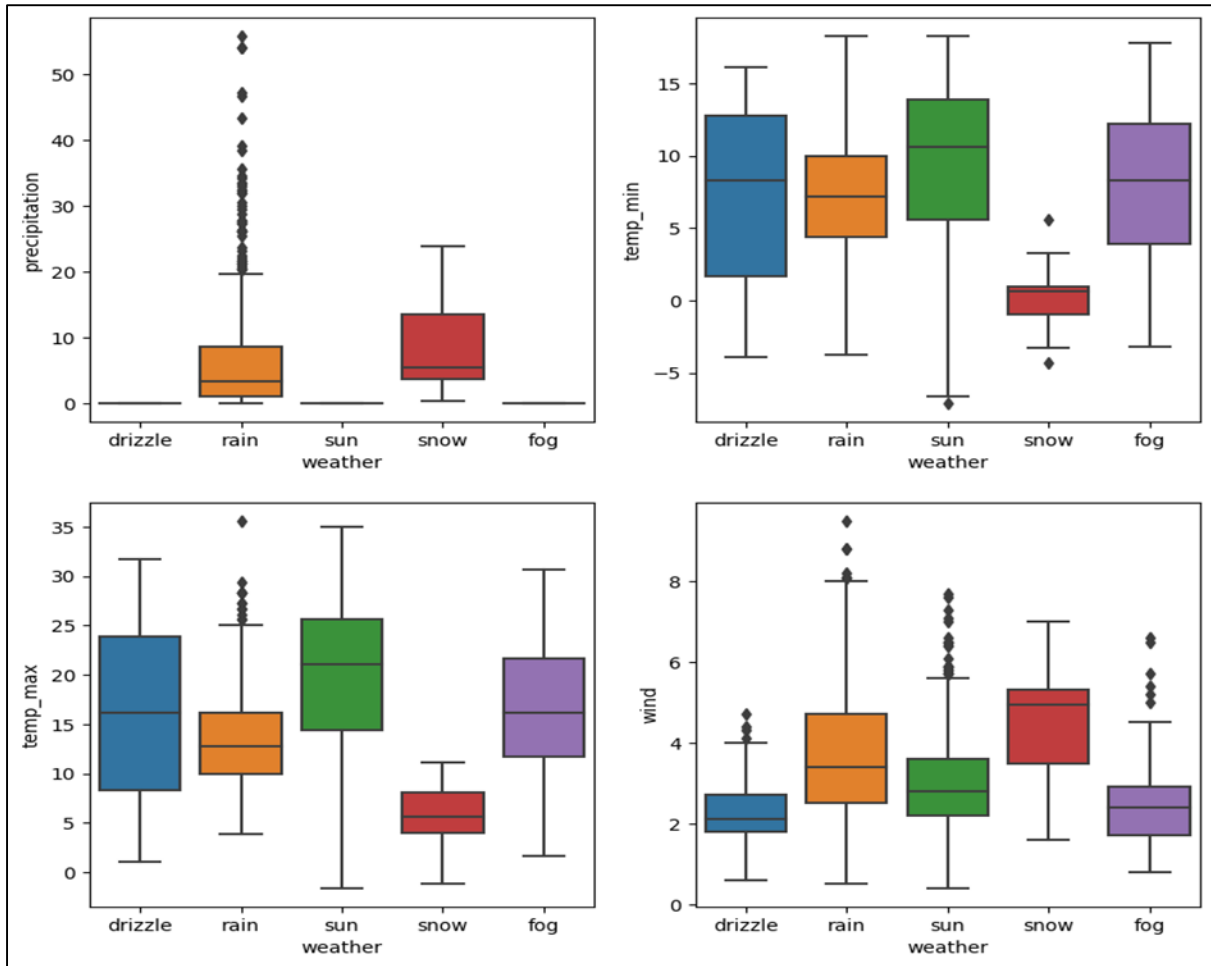
Figure 4 The box plot illustrates weather components of precipitation, Temperature_min, Temerature_Max, and Wind

All these procedures that preceded the proper analysis are part of establishing machine learning for a meteorological set. Turning weather categories into readable numbers using the LabelEncoder tool is a great part of Python's scikit-learn library toolbox that we successfully performed. The 'weather' section was renovated, with various kinds of weather being transformed to separate numerical symbols. The "remove" process involved deleting the 'date' for the reason that it could not be quantified or help in identifying a single mission.

Elements plucked out of this aforementioned data set formed part of the new feature matrix simply referred to as x with a slight exception being the 'weather' compartment that was not illuminated. These imported features transform readily into one organised algebraic field known as X with emphasis at Target (Y) variables around it connected only now with codified characterization that will shine at its best in predicting the reasons for the crucial elements.

The preprocessing sequence formed an important step when preparing this dataset for scrutiny by machine learning. Transforming categorical data into numerals; structuring the feature matrix and establishing a relation with the target variable were the critical early steps. This preprocessing is fundamental for the data to fit in the machine learning algorithm requirements paving way for correct and expeditious model training and consequent prediction of weather patterns derived from the data set.

3.2. Machine Learning Classifiers.

The system consists of six machine learning classifiers for precise analysis and forecasting.

3.2.1. Logistic Regression (LR):

Logistic Regression (LR) is a dependable and essential tool in statistics that is mainly utilised to ascertain the membership of something in one group or another. LR prioritises the classification of items into various groups rather than offering exact numerical predictions, even though its name might suggest a link to numbers. It functions by

analysing different factors that may affect the outcome and then calculates the probability of something belonging to a specific category. LR accomplishes this by utilising a blend of mathematical calculations and logical reasoning. It presents the information in a way that guarantees the final result is between 0 and 1, resembling a measure of probability or certainty. It's extremely convenient when the connections between these factors and the categories are evident or can be simplified, making it a preferred choice because of its easy-to-use nature, simplicity, and capacity to prioritise factors in category decisions.

Surprisingly, logistic regression is helpful in classifying problems rather than their solution or management as would be implied by its name. The procedure involves mimicking the possibility that a particular subgroup will occur or take place. For instance, when applying meteorological surveillance tasks such as binary classifications, if properly utilised, it can predict rainfall through various inputs.

3.2.2. Random Forest Classifier(RF):

The Random Forest Classifier (RF) operates as a collective of knowledgeable individuals collaborating in the field of machine learning. They generate numerous decision trees, each targeting various aspects of the problem by utilising random pieces of information. When you require a response, every tree generously shares its insights, and collectively they reach a consensus through a democratic voting process to determine the optimal solution. This team excels in managing large volumes of data, tackling diverse challenges, and demonstrating a keen ability to prioritise what truly matters, without getting bogged down by insignificant minutiae. In addition, their collaborative efforts ensure that decisions are not influenced by the perspective of a single tree, resulting in a more dependable final decision. RF combines several decision trees that have their outcomes merged together, thus, enhancing precision but at the same time avoiding overfitting. It is strong enough to handle high dimensional data and it was therefore helpful because of several factors that are related to weather forecasting.

Gradient Boosting Classifier(GBC) : The Gradient Boosting Classifier (GBC) is comparable to a collaborative teammate in the field of machine learning, adopting a systematic approach to enhance its prediction capabilities. It has a unique approach, functioning as a team captain that leads its team towards success. Instead of operating in isolation, the team members collaborate and continuously enhance their skills by learning from one another's errors. If a team member makes an error, the captain diligently focuses on that particular area to ensure that the next member performs it correctly. In this manner, their capabilities continue to improve, particularly when it comes to managing complex patterns within the data. GBC is widely recognised for its ability to deliver precise forecasts when handling intricate data. However, it requires careful attention to prevent excessive fixation on specific details and overfitting during the process. This is one other similar fusion approach which builds on the prior errors sequentially with every tree. A similar model provides satisfactory prediction with which important features and subtler forecasts concerning weather conditions can be traced.

Decision Tree Classifier(DT): The Decision Tree Classifier (DT) operates as a perceptive researcher, unraveling a mystery by asking a series of relevant inquiries. It's a simple yet clever approach that works like a game of 20 questions, where each question narrows down the data using the most important clues. The questions continue to expand until the detective arrives at a final conclusion. One of the remarkable aspects of DTs is their incredible versatility. They have the ability to process various types of information, ranging from numerical data to categorical data, and they are remarkably straightforward to comprehend. However, at times, they can become overly fixated on the minute details of the case, potentially overlooking the broader perspective. That's why it's important to provide some assistance, such as pruning, to prevent them from becoming overly fixated on details and ensure their ability to effectively tackle new cases. Nevertheless, detectives - I mean, Decision Trees - continue to be a favoured option due to their simplicity and ability to solve various classification puzzles. The decision trees split data sets by specific features attempting to produce branching patterns in conclusions. This is why they are appreciated mainly as simple, understandable, straightforward visualisations that are perfect for investigation of relationships between different atmospheric variables and their consequences.

Support Vector Classifier(SVC): The Support Vector Classifier (SVC) is highly skilled at separating different groups of friends at a party. Imagine a remarkable individual who possesses the uncanny ability to strategically delineate boundaries on the dance floor, ensuring that various groups remain separate while still allowing everyone ample room to move and groove. This approach focuses on identifying the most effective method for categorising individuals into various social groups, strategically establishing boundaries to ensure clear distinctions between these groups. SVC invests significant effort in employing mathematical techniques called kernels to enhance its perspective and streamline the process of identifying optimal line placements. However, in certain situations, like when the party gets crowded and

different groups interact often, it can be difficult to set boundaries without some help. In simple situations, though, it is very good at setting clear limits, which makes it a popular choice for organising things in the field of machine learning.

SVC is a powerful method of class separation to find appropriate hyperplanes. It successfully differentiates and hence is important for finding navigable climate observations; mostly in unusual cases it can separate undesirable weather conditions that are vital.

KNearestNeighbors(KNN): The KNearestNeighbors (KNN) algorithm in the world of machine learning is similar to having a helpful neighbour who assists you in making decisions by observing the actions of your closest friends. This method is straightforward and efficient, as it categorises new data points by analysing the dominant class of its neighbouring data points. KNN operates by storing a comprehensive collection of cases and categorising new cases by evaluating their similarity, typically employing distance metrics. If you want to determine the group to which a new data point belongs, KNN algorithm examines its nearest neighbours and identifies the group that the majority of them belong to. The number of neighbours that KNN consults is denoted by the letter "K". Increasing the value of K means that more neighbours are considered for advice. Although KNN is generally considered to be a simple and intuitive algorithm, it may encounter challenges when dealing with large datasets or when there is ambiguity in distinguishing between different classes. This is because KNN heavily depends on local data relationships. However, its straightforwardness and adaptability have made it a favoured option for classification tasks in machine learning. KNN algorithm [41] is particularly effective when working with simple algorithms. This is because it has a good grouping basis and dominates its neighbourhood in this respect, which is important for meteorological services who want to identify variations of a typical representation of local demographics that result spectacularly.

There are various performance metrics available to evaluate the efficiency of machine learning models. Here are a few important ones:

- Precision: This metric assesses the overall precision of the model's predictions. The precision is calculated by dividing the number of correctly predicted instances by the total number of instances in the dataset. The calculation of precision is performed using the following formula:

Precision= True Positives / (True Positives + False Positives)

- Accuracy: Accuracy is a way to evaluate the accuracy of a model's positive predictions. The frequency of accurate predictions of positive events is examined in relation to the overall predictions made by the model. When these positive predictions could have significant impacts, accuracy is important.

Accuracy= Number of Correct Predictions / Total Number of Predictions

- Recall is a crucial measure for gauging a model's ability to identify true positives. Imagine it as a means for assessing how well the model detects positive occurrences. This metric measures the precision of positive forecasts compared to the true positive results. Ignoring these valuable advantages could have major repercussions, so it's essential to weigh the potential impact carefully.

Recall= True Positives / (True Positives + False Negatives)

- The F1-Score is a crucial evaluation metric that takes into account precision and recall simultaneously. Striking a delicate balance between accurately predicting specific outcomes and representing real-life events is vital. This score provides a comprehensive understanding of the model's performance, taking into account both false positives and missed actual events. It is calculated using a simple formula that efficiently combines precision and recall.

F1-Score=2× Precision×Recall / (Precision+Recall)

Having an accurate model is crucial for predicting the timing and location of events like rain or storms. It's our utmost priority to ensure the accuracy of our model's forecasts. In addition to accuracy, the model's ability to recall true positives, such as accurately identifying and predicting storms or rain, is also important. From this perspective, the F1-Score effectively combines the strengths of both accuracy and recall, allowing us to gain a deeper understanding of the model's ability to predict specific weather events and accurately represent real-life occurrences.

4. Results and Discussions

The performance of this logistic regression model varies among the different classes presented in Table 1. It is accurate in predicting classes 2 and 4, achieving a high precision, recall, and F1-score. Nevertheless, when it comes to class 0 and 1, it has a very hard time achieving this feat as all measures, including precision, recall, and F1-scores, are at 0.00, implying no success in detecting cases from within this range. Overall, the model's accuracy comes to 81%, meaning it can predict about 81% instances in all the classes. Nonetheless, the macro average metrics showcase a lesser performance in terms of precision, recall, and F1 scores that are about 0.53, 0.43, and 0.44, respectively. The balanced accuracy measure hints that there is a better balanced view of the model's overall performance on all classes.

Table 1 Performance parameters of logistic Regression Classifiers for weather prediction

Logistic Regression	Precision	Recall	F1-score	Support
0	0.00	0.00	0.00	5
1	0.00	0.00	0.00	5
2	0.94	0.82	0.88	79
3	1.00	0.33	0.50	6
4	0.68	0.33	0.50	52
Accuracy	0.81			147
Macro avg	0.53	0.43	0.44	147
weighted avg	0.79	0.81	0.78	147

Performance of Gradient-Boosted Classifiers differs across the classes presented in Table 2. Precision, recall and F1 for classes 2 and 4 reveal its ability to predict instances in these classes sufficiently. However, it has challenges with Classes 0 and 1, in which its precision, recall, as well as F1-score score becomes lower. However, class 3 is characterised by high precision score and lesser recall which results in high f1-score. An 81% accuracy would mean more than 80% of all classes predicted correctly. The model was fair on all classes by having macro average metrics with a precision of 0.56, recall of 0.53, and an F1 score of 0.53.

Table 2 Performance parameters of Gradient-Boosted Classifiers for weather prediction

Gradient Boosting Classifier	Precision	Recall	F1-score	Support
0	0.00	0.00	0.00	5
1	0.33	0.20	0.25	5
2	0.97	0.81	0.88	79
3	0.80	0.67	0.73	6
4	0.68	0.96	0.80	52
Accuracy	0.81			147
Macro avg	0.56	0.53	0.53	147
weighted avg	0.81	0.81	0.80	147

The Random Forest Classifier is varied in its performance across different classes as presented in Table 3. It shows a good level of performance on class 2 with regard to precision and recall which shows its potential in predicting instances in this class. Nevertheless, the precision, recall, and F-1 scores are generally reduced for class 0, class 1 and class 3 which indicates it is difficult to correctly identify examples classified in those classes. Class 4 shows relatively high precision, recall, as well as F1-score. Overall accuracy of the model is 73%, which means the model correctly identifies about 73% of occurrences for each class. Regarding the macro average metrics that equally consider every class, the precision,

recall, and F1– scores are 0.49, 0.48, and 0.48, respectively, representing an unevenly balanced yet moderate overall outcome for each class.

Table 3 Performance parameters of Random Forest Classifier for weather prediction

Random Forest Classifier	Precision	Recall	F1-score	Support
0	0.00	0.00	0.00	5
1	0.10	0.20	0.13	5
2	0.87	0.84	0.85	79
3	0.80	0.67	0.73	6
4	0.68	0.69	0.69	52
Accuracy	0.73			147
Macro avg	0.49	0.48	0.48	147
weighted avg	0.74	0.73	0.73	147

In all classes, the Performance of the Decision Tree Classifier is presented in Table 4. Class 2 has a relatively high precision and recall. Therefore, it is accurate at predicting cases of class 2. However, precision, recall, and F1 for the sets zero, one, and three scores poorly indicate hardness determining correctly for set 0, set 1, and set 3. Precision at moderate level, Recall at moderate level and macro average F1 at moderate level for Class 4. As such, this total accuracy would be 70%. And translates into about 7 cases among the 10 being right for every class. The macro average metrics treat every class equally, achieving precision of 0.44, a recall of 0.47, and an overall F1-score of 0.45, which shows sufficient but average classification results for all groups.

Table 4 Performance parameters of Decision Tree Classifier for weather prediction

Decision Tree Classifier	Precision	Recall	F1-score	Support
0	0.00	0.00	0.00	5
1	0.08	0.20	0.11	5
2	0.88	0.81	0.84	79
3	0.57	0.67	0.62	6
4	0.69	0.65	0.67	52
Accuracy	0.70			147
Macro avg	0.44	0.47	0.45	147
weighted avg	0.74	0.70	0.72	147

K-nearest neighbours (KNN) classifiers vary in the performance of different classes as presented in Table 5. The precision and recall are also high on class 2 showing that the system identifies the instances properly. Nevertheless, for zero and one classes, precision, recall, and F1-scores are quite small, which may be a sign of difficulty in precisely predicting cases in this set of classes. Moderate precision, recall, and F1-score as well as for class 4. Based on the above findings the model has an overall accuracy score of 77%. This implies that the model gets the correct results across all the classes, almost 77%. Based on the macro average metrics that give equal weight to every class, the precisions, recalls, and F1-scores of 0.47, 0.44, and 0.45 show only mild results in the overall evaluation.

Table 5 Performance parameters of KNearestNeighbors Classifier for weather prediction

KNearestNeighbors Classifier	Precision	Recall	F1-score	Support
0	0.00	0.00	0.00	5
1	0.00	0.00	0.00	5
2	0.92	0.84	0.87	79
3	0.75	0.50	0.60	6
4	0.68	0.85	0.75	52
Accuracy	0.77			147
Macro avg	0.47	0.44	0.45	147
weighted avg	0.76	0.77	0.76	147

Correctly forecasting weather conditions is important in predictive weather. Out of the models evaluated, logistic regression and gradient boosting classifier had the best performance at 80.95% accuracy. The logistic regression applies a set of historical data in order to predict probability of weather outcome for different models while the gradient boosting builds individual models one after another with intention of overcoming errors done during earlier constructions. The matching accuracies they show point out their ability to resolve delicate structures inherent to weather data. It is closely followed by the Support Vector Classifier (SVC) with 77.55%, which also does fairly well in selecting the optimal hyperplane for classifying weather patterns. On the other hand, the decision tree mode revealed an accuracy of 70.07% thus illustrating a bit lesser precision ascertained through the datasets characters. On the other hand, random forest and k-nearest neighbours came up to be in a middle range showing about moderate success in ensemble learning and proximity based classification for weather prediction.

Table 6 Performance Accuracy comparison of different classifiers for weather prediction

Classifier	Accuracy (%)
Decision Tree	70.07
Random Forest	72.79
K-Nearest Neighbors	76.87
Support Vector Classifier	77.55
Logistic Regression	80.95
Gradient Boosting Classifier	80.95

The accuracy metrics of these models shed light on how well each model can predict weather patterns is presented in Table 6. One of the models that performed excellently was Logistic regression followed by gradient boosting. But each had their own special approach and costs associated with them. Other aspects of an accurate model, including its interpretability, the level of computational complexity associated with it, and ability to be adapted in variable weather conditions should also be considered when choosing the most appropriate model for practical weather prediction applications. Finally, the suitability of the selected model depends on finding that balance between successful prediction and the particular weather prediction requirements that are needed to ensure real life practicality.

5. Conclusion

This chapter emphasises the significance of the re-designed Gradient Boosting model to our forecasting weather systems. The data was obtained from a Kaggle dataset, where it is specified how many days are sunny or cloudy in a single day in Seattle. During our research we compare with Logistic regression, Random forest, Decision tree and so on machine learning algorithms. The best performer was the gradient boosting with a precision measure of 80.23% out of them all. It illustrates different simple performance metrics of its efficacy for the weather. For example, it entails producing intricate spatial designs which can be vague in meteorological data. It is also portable across a massive and

comprehensive data set having dependencies. These values outperformed Support Vector classifier, K-NN, and logistic regressions giving accuracies of 77.55%, 76.87%, and 80.95%, respectively.

Machine learning is essential whereas air dynamics establishes this basis for weather forecasting. Hence, due to this, weathering becomes complex and strong measures are required to properly handle voluminous data as well as subtle fluctuations that are not important in usual meteorological models. Thus, another piece of additional input which can be incorporated to the bag of forecast accuracy in meteorology could be the gradient boosted regression. The area of machine learning, among others, serves as the benchmark for creation of novel technology. This will be one evaluation that graduate boosting meteorology students will make to link their technology to their studies. It shows how various ML-based studies can predict weather. These challenges can be solved by enhancing ensemble mode and going deeper into combining different machine learning algorithms leading to better predictive models. A possible step could include studying techniques like model-stacking or model-blending. Such practices provide weak points an opportunity for reduction while simultaneously elevating accuracy predictions to unprecedented levels.

As such, this becomes a chance to unearth alternative potential variables (features) that would enhance the models' effectiveness.

The other crucial direction is to put together the space factor and time aspect into predictive models. More sophisticated time series analysis or microscale modelling of past evolution of weather situations in such regions as microclimatology could produce more accurate predictions for microevolutions of local weather in near future. It is possible to discover such complex interrelations that go beyond classical ML solutions by using recurrent and convolutional NN based deep learning approaches for big weather datasets. For this reason, predictive models need both validity and practical utility as they become the basis for incorporating domain knowledge to ML predictions and thereby increasing their logical and reliable nature. In addition, collaboration with meteorologists and professionals continues to be necessary. These are some of the key paths that collectively provide a recipe for enhancing the service quality and ultimately have an impact on various parts of society.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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