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Original Paper

SMART WEATHER PREDICTION FROM SENSOR DATA USING MACHINE LEARNING

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ABSTRACT

In this study, we implemented a weather prediction model using multiple classification algorithms like logistic regression, KNN, SVM, Decision Tree, Naive Bayes, and XGBoost. Notably, the Random Forest classification model emerged as the most effective for forecasting diverse weather parameters like drizzle, rain, sun, snow, and fog. Leveraging historical data, machine learning enhances weather forecasting accuracy by identifying patterns and handling complex relationships, integrating various data sources like satellite imagery. The model, utilizing a dataset with features such as temperature, humidity, wind speed, and atmospheric pressure, underwent preprocessing for missing values and feature normalization. The Random Forest algorithm demonstrated an 86% accuracy, validated by the confusion matrix analysis during training and evaluation. This study underscores the Random Forest algorithm's efficacy in multiclass weather prediction, emphasizing its potential to revolutionize forecasting accuracy and planning capabilities, outperforming existing strategies in precision and computational efficiency.

KEYWORDS

Weather Prediction, Machine Learning, Parameters, Random Forest, Forecasting

1. INTRODUCTION

Weather forecasting has greatly benefited from advancements in machine learning techniques. Machine learning models are now being used to enhance the accuracy and efficiency of weather predictions. These models analyze vast amounts of historical weather data, including temperature, humidity, wind speed, and atmospheric pressure, to identify patterns and make predictions about future weather conditions. [3] One of the primary advantages of using machine learning in weather forecasting is its ability to handle complex and nonlinear relationships within the data. Traditional forecasting methods often rely on simplified mathematical models that may not capture all the intricate factors influencing weather patterns. Machine learning models, on the other hand, can consider a wide range of variables and interactions to generate more accurate predictions. Various machine learning algorithms are applied in weather forecasting, including naive Bayes decision trees, random forests, support vector machines, and neural networks. These algorithms are trained on historical weather data and then tested and refined to improve their predictive capabilities. As new weather data becomes available, the models can be updated to incorporate the latest information, ensuring the forecasts remain up to date. Weather forecasting plays a crucial role in numerous domains, ranging from agriculture and transportation to disaster management and daily decision-making. Recently, machine learning (ML) algorithms have shown promising results in improving the accuracy of weather forecasting. This research paper aims to investigate the application of the ML algorithm in weather prediction and assess its effectiveness in forecasting key weather parameters.

The dataset utilized in this research comprises records of maximum temperature, minimum temperature, humidity, precipitation, wind speed, atmospheric pressure, and other pertinent features. To ensure the quality and consistency of the input data for the Random Forest model, preprocessing techniques were employed to handle missing values and normalize the dataset.

Some of the key points we will cover in this research paper include:

- Utilizing the Random Forest and multiple ML algorithms for weather forecasting.
- Acquiring and preprocessing a comprehensive dataset encompassing multiple years and diverse meteorological parameters.
- Employing performance evaluation metrics like [4] Accuracy, precision, recall, f1score, confusion matrix, ROU, and AUC curves, etc. to assess the performance of the Naive Bayes model.
- Conducting a comparative analysis of the Random Forest algorithm with other ML algorithm techniques in the field of weather prediction.

This study highlights the Random Forest ML algorithm's efficacy in weather prediction, boasting an impressive 86.0% accuracy, surpassing other ML algorithms. These results underscore the superiority of the Random Forest approach in accurate weather forecasting, offering valuable insights for its implementation in diverse weather-related applications. The findings contribute to enhanced decision-making, resource allocation, and risk management strategies in various contexts. Additionally, the study involves continuous sensor monitoring of pH, dissolved oxygen, ammonia, and turbidity, with actuators adjusting water conditions based on the collected data.Pest and Disease Management: Utilizing image recognition and chemical cues, smart sensors detect pests and diseases, prompting actuators to deploy targeted solutions.

- Water and Resource Management: Soil moisture sensors prevent overwatering and optimize irrigation, with actuators automating irrigation based on real-time moisture data.
- Labor Intensity Reduction: Smart actuators automate fish feeding through automated feed dispensers, reducing manual tasks.

2. LITERATURE SURVEY

S.no	Paper Title	Year of Publication	Methodology	Results	Limitations
1	Prediction and Classification of Weather Using Machine Learning	2022	Logistic Regression, SVM model	Regression (e.g., temperature) achieved 95% accuracy with logistic regression, while weather classification (e.g., cloudy, sunny) reached 96% accuracy using SVM models with different kernels	Generalization to diverse weather conditions and regions may vary.
2	Weather Prediction Using Machine Learning Algorithms	2022	Random Forest, Decision Tree, MLP classifier, Linear regression, and	Analyzing features like temperature, apparent temperature, humidity, wind speed, wind bearing, visibility, and cloud cover.	Dependence on historical data and feature relevance for accurate machine learning-based weather prediction.

			Gaussian naive Bayes.		
3	Weather Prediction using Advanced Machine Learning Techniques	2019	FCNN model	FCNN model possesses the learning and generalization ability that captures the dataset's non-linear characteristics of input features. The model produced an OA of 87.83% as tested with the IMD dataset.	Exclusive focus on FCNN model performance over- looks at potential ensemble techniques and external factors impacting predictions.
4	Smart Weather Prediction Using Machine Learning	2022	Classification Models	Smart weather prediction by implementing various classification models and got the highest accuracy in the Gradient Boosting algorithm with 81% accuracy.	81% accuracy was achieved in smart weather prediction using diverse classification models, with Gradient Boosting performing best.
5	Machine learning techniques for weather forecasting by William Samuel sanders	2018	Random Forest Model	Weather prediction system using various machine learning models and found that the random forest model got the lowest error rate in the prediction system.	Potential oversight of model generalization and external variables in Sanders' study on weather prediction using machine learning.
6	Smart Weather Forecasting Using Machine Learning: A Case Study in Tennessee	2018	Random Forest Model	Random Forest Regression (RFR) using various regression techniques, including RMSE evaluation, proved superior for predicting continuous temperature values.	The applicability of find- ings to other regions or weather parameters might vary.
7	Prediction of Weather Forecasting By Using Machine Learning	2020	Machine learning Algorithm	A weather forecasting model using a machine learning algorithm and a framework for weather prediction produced an accuracy of 70%.	Achieved 70% accuracy in weather forecasting using machine learning, suggesting potential room for improvement.
8	Weather Forecast Prediction: An Integrated Approach for Analysing and Measuring Weather Data	2018	Naïve Bayes and Chi- Square algorithms	Time series weather prediction employs Naïve Bayes and Chi-Square algorithms, enhanced by a Java based web application framework for accurate forecasts.	Reliance on Naïve Bayes and Chi-Square algorithms may overlook certain complex weather patterns.
9	Artificial intelligence in weather and climate prediction Learning atmospheric dynamics	2020	ANN, CNN, ML	The AI-based system uses ANN, CNN, and machine learning for precise weather and climate prediction across regions.	Reliance on historical data quality and model generalization for AI-driven weather and climate prediction.
10	Weather forecasting model using Artificial Neural Network	2012	Artificial Neural Network (ANN)	Multi-layer neural network with tan-sigmoid activation on raw weather data shows improved prediction and potential for broader applications.	The complexity of neural network architecture, potential overfitting, and data handling challenges.

11	Machine Learning in Weather Prediction and Climate Analyses Applications and Perspectives	2022	Systematic Literature Review	Machine learning methods are becoming increasingly important in climate and numerical weather prediction research.	This is limited by its focus on a specific period and a specific set of methods.
12	Machine Learning for Applied Weather Prediction	2018	Blending approach	DI Cast is an AI-based weather forecasting system that outperforms individual NWP models by 10-15%.	DI Cast in development, is still imperfect with accuracy limitations due to data requirements and challenges in certain areas.
13	Deep Learning-Based Weather Prediction	2021	Systematic literature review.	Deep learning-based weather prediction (DLWP) has the potential to improve the accuracy and efficiency of weather forecasting.	DLWP's effectiveness hinges on data quality/quantity but can be complex, inaccurate for extremes, limited in applicability, and demanding computing resources.
14	A Dynamic Convolutional Layer for Short-Range Weather Prediction	2015	Experimental research.	A new dynamic convolutional layer enhances short-term weather prediction accuracy by generating adaptive filters per input.	Dynamic convolutional layer may be less robust to noise, and outliers, and harder to interpret compared to conventional counterparts.
15	The Analysis of Data Mining Techniques for Weather Prediction	2016	Data Mining.	The study compared algorithms for weather prediction, finding random forest with the AdaBoost ensemble most effective, offering regional weather condition prediction using historical data.	Weather prediction accuracy hinges on historical data availability; complex models need ample data, posing challenges for rare or widespread events.

3. PROPOSED SYSTEM

In this proposed system, we leverage the power of machine learning, specifically the Random Forest classification model, to enhance weather prediction accuracy. Our system aims to forecast various weather parameters such as drizzle, rain, sun, snow, and fog with a high level of precision. Fig 1, explains that a Weather warning system collects weather data from sensors and sends an alarm if the data is above the danger level, displaying precautions to the public.

Weather monitoring system (WMS): This system monitors the weather with the following sensors

- Temperature detector: measures temperature through an electrical signal
- Atmospheric pressure detector/barometric sensor: a device that measures atmospheric pressure. When air pressure increases, it indicates a rise in the barometer, and decreases in air pressure indicate a fall in the barometer.
- Humidity sensor: a device that senses, measures, and reports air's relative humidity (RH).
- Rain sensor: It is a device that accurately measures rainfall in the atmosphere. This compact rainfall detector module measures rainfall on a real-time basis.

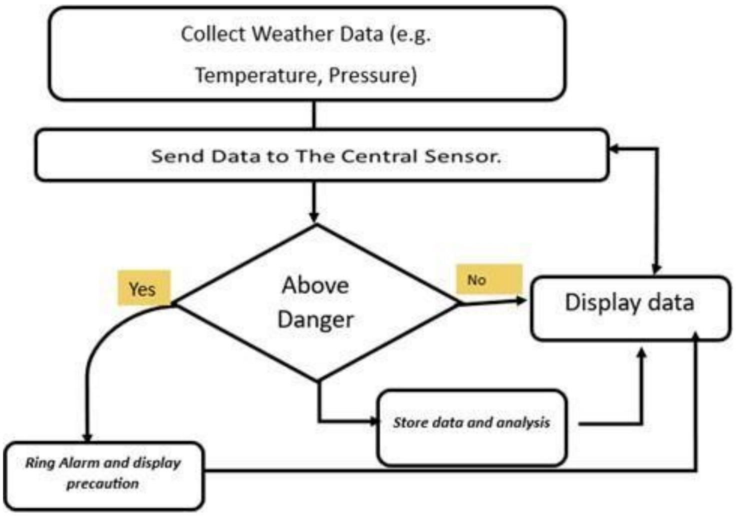


Figure 1: Data flow diagram to measure Weather data.

4. OVERVIEW OF MULTI-CLASS LABEL CLASSIFICATION

Multiclass label classification is a widely used technique in machine learning that can be used for weather forecasting. In this process, we classify the weather patterns into multiple classes, such as drizzle, rain, sun, snow, or fog. To recognize the patterns in the input data, such as temperature, humidity, and wind speed, and predict the relevant weather conditions for new, unseen data, we train the model according to that. It has many practical applications, such as weather forecasting agriculture, speech recognition, Disease Diagnosis, and autonomous driving, using different recording types. Accurate weather prediction can help farmers make informed decisions about crop planting, irrigation, fertilization, and pest control, leading to improved crop yields, reduced resource wastage, and better overall farm management.

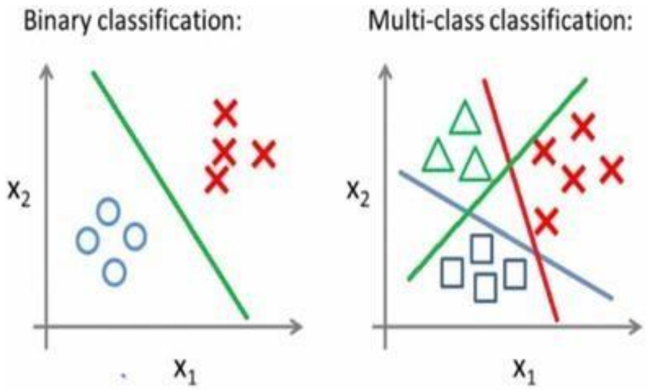


Figure 2: Multi-class label classification.

Fig. 2, explains the difference between binary and multi-class classification. Binary classification is a type of machine learning where the outcome can be one of two possibilities, such as ”yes” or ”no”, ”true” or ”false”, ”healthy” or ”sick”. Multi-class classification is a type of machine learning where the outcome can be one of more than two possibilities, such as ”red”, ”blue”, ”green”, or ”yellow”. Many machine-learning algorithms, including decision trees, support vector machines, neural networks, and random forests, can be used for multiclass label classification in weather prediction. The selection of an algorithm is determined by factors such as the dataset's size and complexity, as well as the specific requirements of the application at hand. Weather prediction using multiclass label classification faces challenges such as data availability, imbalanced classes, complex interactions, uncertainty, and the need for accurate feature selection and engineering. Various techniques such as improving data quality, oversampling, under-sampling, using advanced models or class weighting can be used to overcome this problem. The performance of multiclass classification models for weather prediction can be evaluated using metrics such as accuracy, precision, recall, F1 score, and confusion matrix. These parameters measure the model's ability to predict the weather class of the test data.

5. DATASET DESCRIPTION

The provided data frame consists of 1461 observations, each containing five weather-related variables. The "date" variable denotes the specific date of the observation. The "precipitation" variable records the amount of precipitation in millimeters (mm) during that observation. The "temp max" variable represents the maximum temperature in degrees Celsius (°C) recorded on that day. The "temp min" variable indicates the minimum temperature in degrees Celsius (°C) observed. Lastly, the "wind" variable denotes the average wind speed in meters per second (m/s) measured during the observation. These variables collectively capture essential aspects of weather conditions, allowing for comprehensive analysis and modeling to gain insights into the observed weather patterns and trends. We are predicting 5 different kinds of weather conditions using the above-given parameters like Date (year, month, day), minimum temperature, maximum temperature, wind speed, and precipitation. Data visualization of the dataset for more detailed information in this type of study can be used to gain more insights. It can also be used to identify which type of prediction model is to be used so that we gain or build an accurate and efficient model that is more suitable for our data.

Table 1. Weather conditions

S.No.	**Weather condition**
1	Drizzle
2	Rain
3	Snow
4	Sun
5	Fog

Table 2. Information about input variables

Input variable	**Data type**	**Measuring units**
Date	date	date of the observation
Precipitation	Double	Amount of precipitation (mm)
Temp min	Double	Minimum temperature (°C)
Temp max	Double	Maximum temperature (°C)
Wind	Double	Average wind speed (m/s)

The following graph gives information about each class's count in the weather column (multi-class dependent variable).

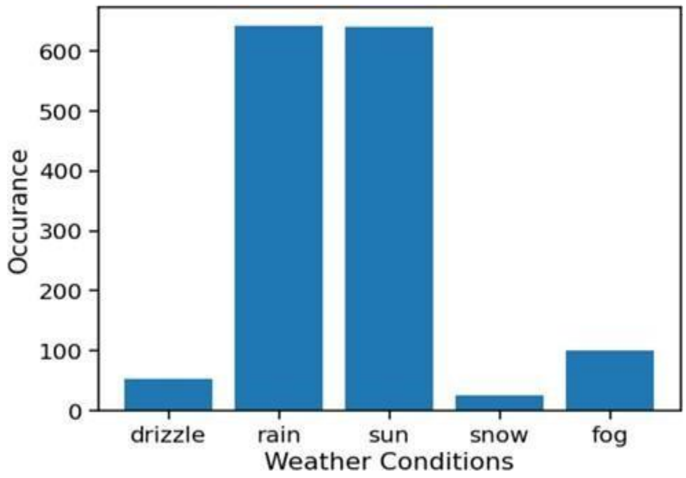


Figure 3. Weather Class Count

The following graph will show the histogram distribution of each independent variable in the dataset.

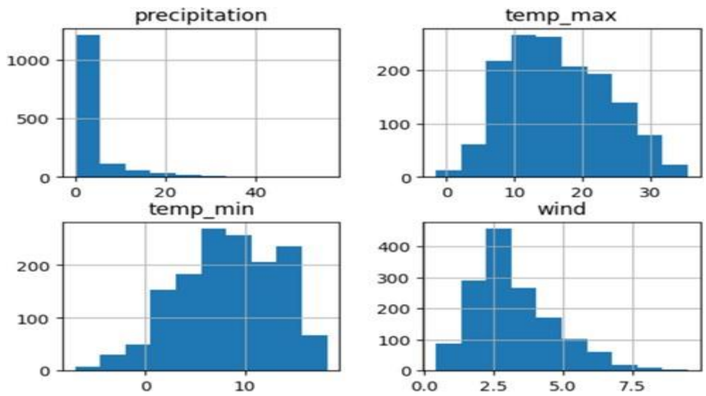
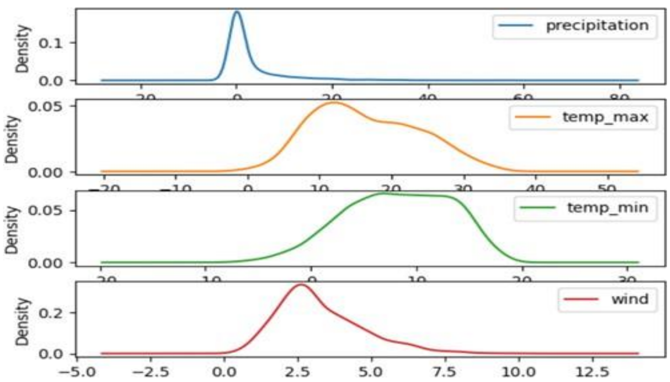


Figure 4: Histogram Distribution of Independent Variables

The following graph will show the density distribution of each independent variable in the



dataset.

Figure 5: Density Distribution of Independent Variables

The following graph will show the correlation between each independent variable and the correlation of each independent variable on the dependent variable. This information is used for knowing the correlation between all the variables. We can easily eliminate problems like multi-collinearity and find the correlations between them.

Figure 6: Correlation Matrix of Independent Variables

6. ALGORITHM APPROACHES

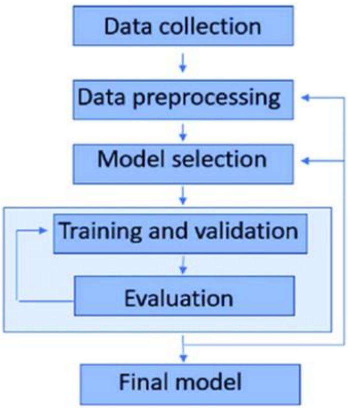


Figure 7: Algorithm approach

6.1 Data Collection

Weather data collection sensors are strategically placed in different areas to capture various weather patterns. The dataset covers a wide geographic area and includes data collected over many years. The frequency of data collection varies based on sensor type and location, with some sensors collecting data hourly and others daily.

6.2 Data Preprocessing

After gathering weather reports with different kinds of attributes, the weather dataset underwent preprocessing. The dataset consists of 1462 days of weather reports, providing comprehensive coverage of the weather conditions. To ensure data integrity and accuracy, missing values were removed from the dataset to mitigate any potential errors in the analysis.

6.3 Data Exploration and Visualization

We used exploratory data analysis techniques to thoroughly investigate the data and uncover any interesting trends or patterns. To help with our analysis and understanding, we visualized the data using graphs and charts. We paid particular attention to spatial and temporal patterns in the data, looking for any connections or relationships between the different weather variables.

6.4 Feature Engineering

We found that the features present in our dataset were highly suitable for training our model. During testing, when allthe features were combined, we achieved an impressive accuracy rate of 86 percentage. Therefore, we decided to utilize all13 features of the dataset to perform weather prediction, as they proved to be significant contributors to the accuracy of our predictions.

6.5 Data Labeling

In our weather dataset, we employ a multiclass labeling approach to assign different weather conditions to each data point. The labels are determined based on specific criteria, including temperature and precipitation thresholds. These labels play a crucial role in training our machine-learning models for accurate weather forecasting. After careful consideration, we have chosen the decision tree and random forest models as our final machine-learning approaches for accurate weather prediction. These models were selected based on their ability to effectively analyze the dataset and generate reliable forecasts. The decision tree model offers interpretability, while the random forest model harnesses the power of ensemble learning, both contributingto improved accuracy in weather predictions.

6.6 Decision Tree

Decision tree models (DTs) are powerful non-parametric supervised learning algorithms that can be applied to various classification and regression problems. They make predictions by following a series of decision rules based on the input data. The construction of decision trees relies on the calculation of entropy, which quantifies the level of uncertainty or impurity inthe data. This allows the models to effectively partition and classify the data based on different

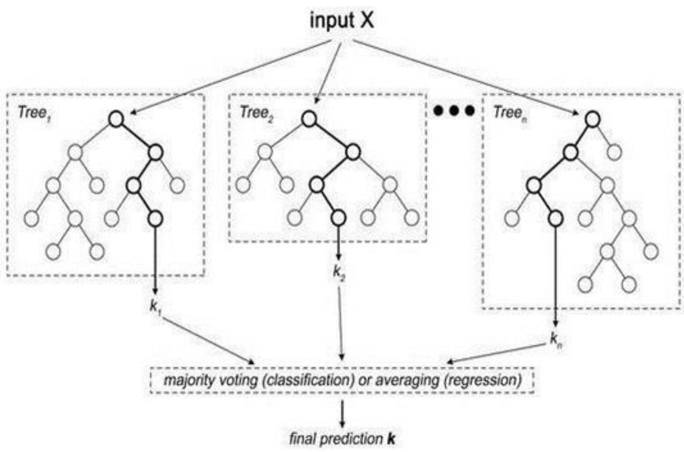
$$G = 1 - \sum_{i=1}^{n} p_i^2$$

features, resulting in accurate predictions.

6.7 Random Forest

Random Forest is a powerful machine learning algorithm that takes a collective approach to make predictions. It combines multiple decision trees, each trained on different subsets of the data and features, to create a diverse set of predictors.

By considering the predictions from each tree, Random Forest produces more accurate and reliable results. This algorithm is especially useful for handling complex datasets and achieving high levels of predictive accuracy, making it a popular choice in various applications. In Fig. 8,



the random forest is an ensemble of three decision trees, each of which is trained on a different random subset of the data and features to reduce over fitting and improve performance.

Figure 8: Random Forest Structure

6.8 Na¨ıve Bayes

Naive Bayes is a simple machine-learning algorithm that is used for classification tasks. It is based on Bayes' theorem, which states that the probability of an event A happening, given that event B, has already happened, is equal to the probability of event A happening times the probability of event B happening given that event A has already happened, divided by the probability of event B happening.

$$P(c|x) = P(x|c)P(c)/P(x)$$

Naive Bayes assumes that all the features are independent of each other. This means that the probability of a feature occurring does not depend on the occurrence of any other feature. This assumption makes the algorithm much simpler to train and implement but can also lead to over fitting.

6.9 XG Boost

XGBoost is a machine learning algorithm that is used for classification and regression tasks. It is a gradient-boosting algorithm, which means that it builds a model by adding new trees to an existing model one at a time. Each new tree isdesigned to correct the errors made by the previous trees.

$$L(y, f(x)) = \sum_{i=1}^{n} L(y_i, f(x_i)) + \Omega(f)$$

6.10 Logistic Regression

Logistic regression is a machine learning algorithm that is used for binary classification tasks. It is a type of regression analysis that uses a logistic function to model the probability of an event happening.

$$P(y = 1|x) = \frac{1}{1 + e^{-(a+bx)}}$$

The logistic function is a sigmoid function that converts any real number to a probability between 0 and 1. This makes itsuitable for modeling binary events, such as whether a customer will click on an ad or not.

6.11 SVM

SVM stands for Support Vector Machine. It is a supervised machine-learning algorithm that can be used for both classification and regression tasks. SVM works by finding the hyperplane that best separates the two classes of data.

$$J(w, b) = \frac{1}{2}||w||^2 + C\sum_{i=1}^{n} \max(0, 1 - y_i(w^T x_i + b))$$

6.12 KNN

KNN stands for k-nearest neighbors. It is a non-parametric machine learning algorithm that can be used for both classification and regression tasks. KNN works by finding the k most similar instances to a new instance and then predicting the label of the new instance based on the labels of the k nearest neighbors.

$$\hat{y} = \frac{1}{k}\sum_{i=1}^{k} y_i$$

The k value is a hyperparameter that needs to be set by the user. The value of k can affect the accuracy of the model. A small value of k may lead to overfitting, while a large value of k may lead to underfitting.

7. Results and Discussion

We have used various performance evaluation metrics to calculate the performance and efficiency of the model. Theclassification model that we have used for this prediction is Random Forest. We have considered the following metrics:

- 1. Confusion Matrix
- 2. Accuracy score
- 3. Precision
- 4. Recall
- 5. F1

7.1 Confusion Matrix

A confusion matrix is a useful tool for evaluating the performance of a classification model. It provides a summary of the model's predictions compared to the actual labels, showing the number of correct and incorrect predictions. This matrix helpsus understand how well the model performs for different classes, enabling us to assess its accuracy and effectiveness.

In Fig 9, we present the confusion matrix for our weather prediction model.
Table 3 is used to represent how the label encoding is done on each weather condition (classes) and also shows which valueis assigned to what class.

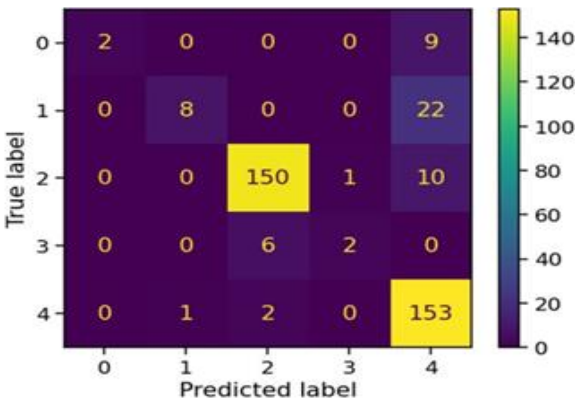


Figure 9: Confusion matrix

Table 3: encoded information

Class	Encoded Value
Drizzle	0
Rain	2
Sun	4
Snow	3
Fog	1

7.2 Accuracy Score

Accuracy Score is a metric that measures the proportion of correct predictions made by a classification model. It reflects the model's ability to accurately classify instances into their respective classes. While high accuracy is desirable, it's important to consider other evaluation metrics for a comprehensive assessment of the model's performance.

Table 4 is used to give detailed information about the performance of each class. We have considered 4 main performance evaluation parameters they are Accuracy, Precision, Recall, and F1-score. Support indicates the number of occurrences of each class in the testing data. The performance of multiple classification models on the same data split is mentioned in the below table.

Table 4: Performance of each classification model

Models	Accuracy score
Random forest	0.86
Na¨ıve Bayes	0.844
XG Boost	0.83
Logistic Regression	0.79
Decision Tree	0.78
SVM	0.74
KNN	0.69

7.3 PRECISION

Precision is a metric that measures the accuracy of positive predictions made by a model. It indicates the proportion of correctly predicted positives and helps evaluate the model's ability to minimize false positives.

7.4 RECALL

Recall is a measure of how good a model is at finding all of the positive cases in a dataset. It is important in applications where it is critical to identify all positive cases, even if it means making some false positives.

7.5 F-MEASURE

The F-measure, or F1 score, combines precision and recall into a single metric. It provides a balanced measure of amodel's performance, considering both false positives and false negatives. A high F-measure indicates a model that achievesa good balance between precision and recall.

With the help of the information and formulas that were mentioned above, wehave calculated the performance of our model. We used Python programming language for coding and applying the machine learning models and using this concept of random forest for building the heart disease prediction system.
Table 5 summarizes the performance of the random forest classification model on various metrics, including accuracy, precision,recall, and F1 score.

Table 5: Information on the random forest classification model performance

	Precision	Recall	F1-score	Support
Drizzle	1.00	0.18	0.31	11
Rain	0.95	0.93	0.94	161

Sun	0.79	0.98	0.87	156
Snow	0.67	0.25	0.36	8
Fog	0.89	0.27	0.41	30
Accuracy	-	-	0.86	366
Macro avg	0.86	0.52	0.58	366

8. CONCLUSION

By the information provided in Table 4 we can conclude that out of all the classification algorithms, the random forest algorithm performed well. The Random Forest algorithm for weather prediction yields a respectable accuracy of 86 percentage. This algorithm proves to be a powerful tool, leveraging an ensemble of decision trees to generate reliable forecasts. With its ability to handle large datasets, capture complex relationships, and account for missing data, Random Forests excel in predicting weather patterns. While 86 percentage accuracy is commendable, it is crucial to acknowledge that there may still be room for improvement. Further research and exploration of advanced techniques could enhance the accuracy and precision of weather predictions, leading to more reliable forecasts for practical applications.

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