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Exploratory Analysis and Prediction of Weather Conditions: Leveraging Feature Engineering and Machine Learning Models for Accurate Forecasting

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Abstract. This study explores the analysis and prediction of weather conditions using a comprehensive weather dataset containing variables such as precipitation, temperature, and wind speed. The research aims to enhance weather forecasting capabilities through data visualization techniques and machine learning models, addressing the critical need for accurate predictions in sectors like agriculture, transportation, and disaster preparedness. The research addresses gaps in the existing literature by focusing on localized weather patterns and exploring the potential of models that combine machine learning with traditional forecasting methods. However, challenges remain in model interpretability and adapting to climate change scenarios. Methodology comprises extensive feature engineering, for instance, building date-based features, temper-ature binning, and interaction terms. Multiple machine learning models, for example, Decision Trees and Support Vector Machines (SVM), classify the conditions of the weather based on engineered features. Metrics including accuracy, precision, recall, and F1-score are used for model evaluation. It is discovered that SVM have a tendency of outperforming other models. The paper also reveals feature engineering as vital in improving model performance, and it reveals that date-based features and interaction terms have played a significant role in improving prediction accuracy. It makes a research contribution in meteorology by demonstrating the effectiveness of machine learning for weather prediction and feature importance for weather classification. The findings have application in real-world practice for improving short-term weather prediction and decision support for weather-dependent industries.

1 Introduction

In this study, we explore weather prediction using traditional machine learning models and demonstrate that a binary classification approach with Random Forest can yield very high accuracy. Analysing weather data effectively can assist in predicting weather patterns, preparing for severe weather events, and comprehending climate changes over time. Weather significantly influences multiple industries, including agriculture, transportation, and energy generation. Precise weather forecasts derived from past data can minimize risks, maximize resources, and improve safety. Examining the patterns and connections present in weather

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data allows researchers to gain valuable insights that influence daily human activities, infrastructure development, and public health matters. The weather includes essential factors like precipitation, which refers to the quantity of rain or snow, maximum and minimum temperatures, wind speed representing the force of the wind in meters per second, and weather states like sunny, cloudy, or rainy. Grasping patterns in the weather dataset is crucial for numerous practical uses, such as weather forecasting where trends in temperature, precipitation, and wind can be recognized; this dataset can help anticipate future weather situations. Historical data aids climate analysts in examining the impacts of climate change over time and monitoring irregularities such as heatwaves, storms, or unforeseen weather occurrences. Detecting severe conditions such as storms, floods, or droughts early can support prompt actions to reduce possible damages. Farmers depend on weather forecasts for Agriculture and Crop Management to make educated choices about planting, irrigation, and harvesting in order to maximize crop production. Weather forecasting and analysis have been thoroughly examined because of their significance in areas like agriculture, transportation, disaster response, and energy management. Throughout the years, different techniques have been utilized to enhance the precision and dependability of weather predictions, ranging from statistical models to machine learning approaches. This review will examine current research on weather data analysis, provide a comparison of various methods, and highlight deficiencies in the existing literature. The first forecasting models, such as the Global Forecast System (GFS) and the European Centre for Medium-Range Weather Forecasts (ECMWF), were numerical weather prediction (NWP) models that estimate the behavior of the atmosphere through the application of physical equations. Even though these models are intensive consumers of computer power, their large-area forecasts of territory are generally very good.

Techniques such as ARIMA (AutoRegressive Integrated Moving Average) have been utilized on weather datasets for short-term forecasts including temperature and rainfall. Nevertheless, these models find it challenging to represent the non-linear relationships frequently found in weather data. Support Vector Machines (SVM): Recent research has demonstrated the efficacy of SVMs in categorizing weather conditions using past data. SVMs have been utilized to forecast precipitation, temperature variations, and weather categorization (sunny, overcast, rainy). Bai et al. (2021) utilized SVM models for rainfall prediction and discovered enhanced performance over conventional techniques in short-term forecasts. Rana et al. (2019) utilized decision tree classifiers for classifying temperature and precipitation, attaining high accuracy because of their capacity to model non-linear connections. Random Forests, an ensemble technique of decision trees, have been extensively utilized for stronger predictions Deep learning techniques, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have also been employed on weather data in recent years. RNNs were employed by Shi et al. (2019) for predicting the weather and were shown to surpass standard statistical methods of forecasting for the long term by treating the temporal characteristics of the data appropriately. Several other studies have also entailed the combination of more standard models with machine learning to better predict for a number of fields. Zhang et al. (2020), for example, proposed a hybrid model of a combination of ARIMA and neural networks for temperature and wind speed prediction and indicated better performance for the combination of models rather than each model by itself. In meteorological applications, classification issues—such as predicting precipitation type or categorizing extreme events—have employed decision trees and ensemble methods including Random Forests. These models are essential in automating warning systems for weather and improving early warning schemes.

Research indicates that SVM is a powerful algorithm for weather classification, frequently surpassing conventional techniques such as decision trees or linear regression. Like the suggested research, these studies indicate elevated accuracy rates, particularly when the dataset is effectively pre-processed and normalized. In sophisticated weather prediction models, scientists frequently test various kernels (such as RBF) or employ ensemble techniques (for example, merging SVM with additional models) to improve effectiveness. Numerous studies indicate accuracies ranging from 80% to 90% for weather classification through SVM, consistent with our findings. Yet, incorporating additional features (like humidity, pressure, and past data) might further improve the performance. Regarding methodology, certain researchers employ time-series techniques or deep learning models such as LSTMs for forecasting weather, which could surpass SVM in managing intricate relationships among weather patterns across time. The findings are extremely beneficial for immediate weather forecasting and can be utilized in sectors such as farming, air travel, and event coordination where weather predictions can affect choices. Through the analysis of historical data and conditions to identify weather patterns, SVM models similar to the one utilized in your study can aid in developing more dependable weather-oriented decision-support systems.

Table 1. Table of Comparative Analysis.

Study	Methodology	Dataset	Application	Performance
2	Support Vector Machine (SVM)	Rainfall dataset	Rainfall classification	Achieved higher accuracy than ARIMA
1	Decision Tree, Random Forest	Temperature data	Temperature classification	Random Forest outperformed Decision Tree
3	Recurrent Neural Network (RNN)	Weather time series	Long-term weather forecasting	Outperformed traditional forecasting models
4	) ARIMA + Neural Networks (Hybrid)	Temperature and wind data	Hybrid temperature and wind prediction	Improved accuracy compared to standalone models
5	Convolutional Neural Network (CNN)	Satellite images	Precipitation prediction	Achieved high precision in spatial predictions

Table 1 summarizes prior studies in weather prediction, highlighting the use of various machine learning and hybrid models. Despite significant advancements in the field, several gaps persist. One major limitation is that most weather prediction models are trained on global datasets, often neglecting localized weather conditions. There is a clear need for more region-specific models that can improve the accuracy of short-term forecasts, particularly in areas with complex terrains or microclimates. Another gap is the underutilization of hybrid models. Although combining machine learning with traditional numerical weather prediction (NWP) methods has shown promise, such integration is still relatively rare. More research is needed to bridge the strengths of both statistical and physical approaches. Interpretability is also a challenge. Most deep-learning models are "black boxes," not providing much explanation for their decision-making. Raising the interpretability of these models is essential for application in high-stakes tasks like disaster response and emergency planning. Additionally, real-time adaptive learning is seldom used. Most models rely on static historical data, limiting their responsiveness to rapidly changing conditions like storms or heatwaves. Incorporating real-time learning would significantly improve forecast accuracy in dynamic environments. Finally, existing models often fail to account for the impact of climate change.

As weather patterns shift unpredictably due to global warming, there is a growing need to embed climate change scenarios into forecasting models. In summary, future work should focus on developing localized, interpretable, hybrid, and real-time adaptive models that can evolve with changing climate realities and provide more accurate, actionable forecasts.

2 Materials and Methods

2.1 Data Description

This work was based on a publicly released weather data set and covers 1,461 data points for the period January 1, 2012 - December 31, 2015. There are six columns, which represent significant meteorological variables of importance for the tasks of forecasting:

The data set has the following columns:
• Date: Calendar date of the weather observation.
• Precipitation: Rain fall or snow fall on a given day, in terms of millimeters (mm).
• Temp_max: Maximum temperature during the day in degrees Celsius (°C).
• Temp_min: Lowest temperature during the day in degrees Celsius (°C).
• Wind: Average wind speed during the day, in meters per second (m/s).
• Weather: A qualitative description of the general conditions of the weather (e.g., clear, cloudy, rainy).

While the dataset is a valuable resource for weather prediction tasks, it is important to note potential biases and limitations. These include possible class imbalances (e.g., more clear days than rainy ones), missing or incomplete data entries, and the geographic scope being limited to a single region, which may affect the generalizability of the findings.

2.2 Feature Engineering

Feature engineering is a very critical step in improving the performance of a machine learning model. In the case of this weather dataset, several operations were conducted on refining the data and creating novel features. Missing data was managed by examining the dataset for null values. Temperature or wind speed values that were absent were filled in through statistical methods such as the mean or median of their respective columns. Weather labels that were missing were either removed or substituted according to the context of adjacent data. New attributes were developed from the date column to reflect seasonal impacts. Day of the year in the dataset is a numerical indication of the specific day in the year (1 to 365) to reflect seasonal patterns. The month (1 to 12) to assist in identifying monthly trends (e.g., summer, winter), Day of the week is a number representing the day (0 for Monday, 6 for Sunday) to detect any weekly trends. The temperature information was categorized into ranges (e.g., low, moderate, high) to streamline predictions and facilitate more significant interpretation in specific models. For instance, Temp_max: Categorized into ranges such as cold (<10°C), moderate (10-25°C), and hot (>25°C). A similar categorization was performed on Temp_min. A new attribute showcasing the variation between the day's highest and lowest temperature was computed (`Temp_max - Temp_min`) to reflect the daily temperature fluctuation. A feature was developed to analyze the interplay between wind and precipitation, evaluating their combined effects on weather conditions (e.g., intense wind coupled with significant precipitation often suggests a storm). The categorical weather column was transformed into numerical labels through Label Encoding. For example, "sunny" = 0, "cloudy" = 1, "rainy" = 2, and so forth, to serve as the target variable in machine learning algorithms. By combining classical climate variables of temperature, precipitation, and wind speed with machine learning models, we aim at improving the accuracy of forecasts of weather conditions. Feature engineering, in particular, creating new features through temperature difference and date-related features, plays a significant role in enhancing the models' forecasting capability.

2.3 Exploratory Data Analysis

A thorough exploratory data analysis was conducted to uncover the hidden patterns and connections within the data. Fig 1 shows the x-axis representing the maximum temperature (temp_max), the y-axis indicating the minimum temperature (temp_min), and the z-axis displaying precipitation. The graph's points are categorized by color based on the weather condition. Aiding in distinguishing between different weather types (e.g., sunny, rainy, cloudy). The interactive graph enables users to rotate, zoom, and examine the correlation between various weather elements (temperature and precipitation) and their influence on weather classification. This graphic helps in grasping intricate connections within the weather information.

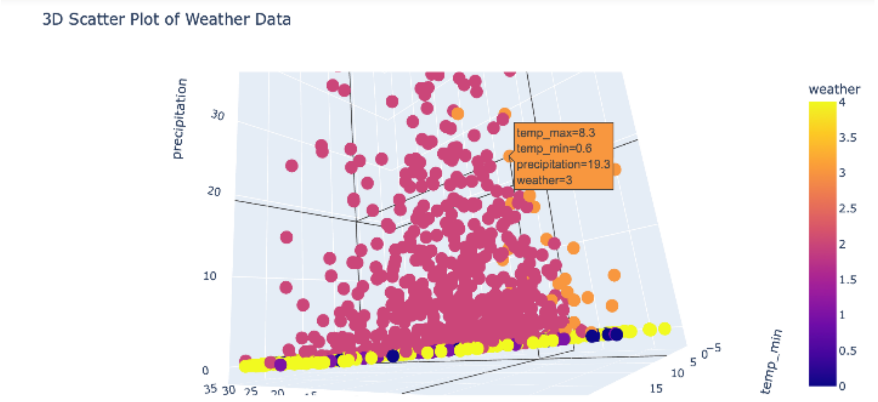

Fig 1 : Hidden patterns and correlations

In Fig 2, the x-axis indicates maximum temperature (temp_max), while the y-axis shows precipitation. The data points are color-coded according to the weather condition, enabling users to differentiate among various weather types (e.g., rain, drizzle, clear). The hover_data feature shows extra details like minimum temperature (temp_min) and wind speed when users mouse over the points. The interactive graph allows users to zoom, pan, and examine the connections among maximum temperature, rainfall, and various other weather factors. This chart helps illustrate the impact of temperature and precipitation on weather trends.

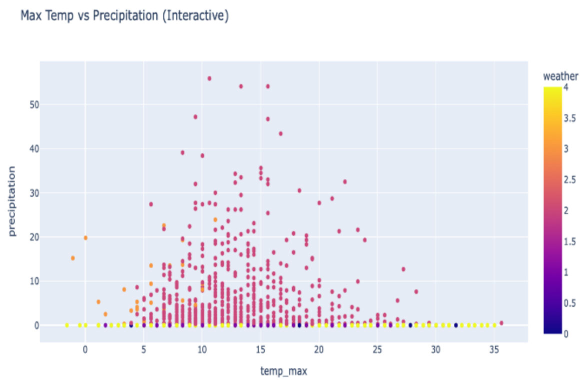

Fig 2: Relationships between maximum temperature, precipitation

Figure 3 displays the distribution of wind speed in the dataset. It separates the wind speed data into 20 bins, where the x-axis reflects the wind speed (in meters per second) and the y-axis represents the occurrence of events within each bin. The bars are shown in purple, supporting the visualization of wind speed distribution in the dataset. The histogram offers information about the typical wind speeds in the weather data, indicating if there are any dominant wind speeds or anomalies.

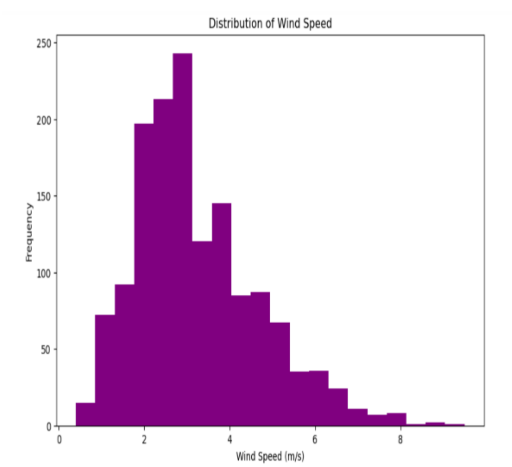

Fig 3: Distribution of Wind Speed

Figure 4 demonstrates the relationship between maximum temperature (temp_max) and precipitation in the weather dataset. The x-axis represents the maximum temperature in degrees Celsius, while the y-axis signifies the amount of rainfall in millimeters Every point on the chart represents a data point from the dataset, with the color green utilized to emphasize the points. This graph assists in determining if there's a relationship between temperature and precipitation, showcasing trends like whether increased temperatures align with elevated or reduced precipitation levels.

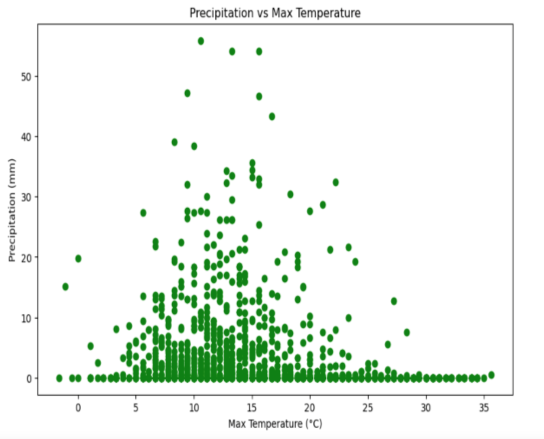

Fig 4: Precipitaion vs max temperature

Figure 5 shows the variations in both maximum and minimum temperatures over time within the weather dataset. The x-axis represents the dates, and the y-axis displays the temperature in degrees Celsius. Two lines are displayed: one in orange for the maximum temperature (temp_max) and another in blue for the minimum temperature (temp_min). The graph reveals information about how temperature changes occur over time, indicating trends, patterns, and potential seasonal variations. The rotation of the xticks makes the dates readable, while the tight_layout improves space utilization for enhanced presentation.

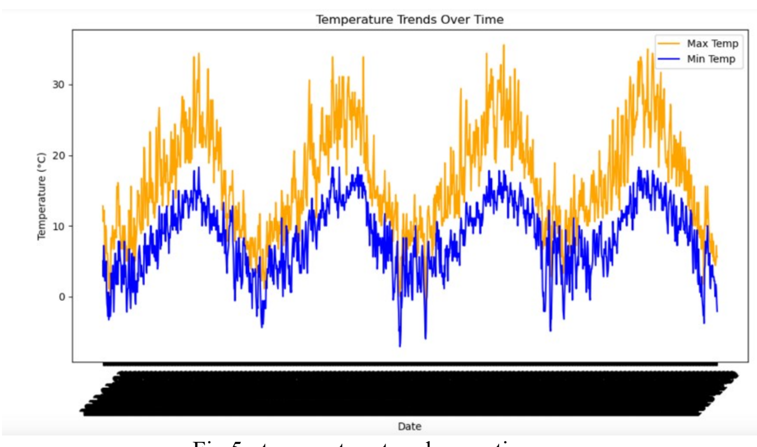

Fig 5 : temperature trends over time

3 Methodology

3.1 Decision tree

A Decision Tree is a supervised learning method that splits the data into groups based on certain criteria of the features. Additionally, Decision tree Works well with categorical and numerical data, interpretable, and handles missing values effectively. Unlike black-box models like neural networks, decision trees provide a transparent view of how decisions are made. Decision trees are faster to train and test compared to more complex algorithms, making them suitable for applications with limited resources. Unlike some machine learning models that require scaling or normalization of data, decision trees work directly with the original feature values. The dataset is loaded and preprocessing is done by converting the categorical variable 'weather' into numerical format using LabelEncoder(). This is necessary because decision trees only work with numerical data. Each unique weather condition (e.g., rain, drizzle) is encoded into an integer. The selected attributes for the decision tree model are: precipitation: Quantity of rainfall, temp_max: Maximum temperature, temp_min: Minimum temperature, wind: Wind speed, with the target variable being weather, representing the weather condition (encoded as integers). The data is split into training and testing sections with an 80/20 proportion. This allows the model to learn from the majority of the data (80%) while evaluating its effectiveness on the remaining 20%. The DecisionTreeClassifier() is configured and trained utilizing the training data. The random state is set up to ensure results remain consistent. The model is evaluated using statistical measures like Accuracy, which measures the ratio of accurate predictions made by the model on the test dataset. The classification report is produced, providing key statistical measures for evaluating the model. Precision is the proportion of true positive predictions compared to the overall number of positive predictions. Recall is the proportion of true positives recognized by the model. Confusion Matrix demonstrates the model's ability to distinguish between different classes (weather types). Each row represents the actual class, whereas each column denotes the predicted class. A visual representation of the decision tree is generated using tree.plot_tree(), showing how decisions are made based on the features to classify the weather. The tree is filled with color, and each node represents a condition based on a feature. The output decision (weather type) is shown in the leaves of the tree. Decision trees allow you to see how specific features like precipitation, temperature, and wind influence weather conditions. By interpreting the tree, you can gain insights into what weather patterns are likely to occur given certain feature values. By classifying weather conditions based on historical data, this model could be used as a part of a weather forecasting system, predicting future weather conditions based on current measurements. Decision trees are easy to interpret because they show a clear flow of decisions based on features, making it easier to understand how the model makes predictions. For decision-makers (e.g., in agriculture, disaster management, or transportation), understanding which weather factors lead to certain conditions can help them plan better or issue warnings. Table 2 evaluates the Decision Tree model's performance. The macro average reflects the model's balanced performance across all classes, regardless of class size, and suggests moderate performance. The weighted average accounts for class imbalance and shows better scores, showing that the model excelled with the prevalent categories. An overall accuracy rate of 73% implies decent predictiveability, yet the difference between macro and weighted scores highlights weak performance on less represented classes

Table 2: Classification report- - Decision Tree

Metric	Precision	Recall	F1-Score	Accuracy
Macro Avg	0.45	0.47	0.46	-
Weighted Avg	0.74	0.73	0.74	-

Overall Accuracy	-	-	-	0.73

Table 3: Confusion Matrix- Decision Tree

Class	Precision	Recall	F1-Score	Support
0	0	0	0	9
1	0.23	0.2	0.21	25
2	0.9	0.88	0.89	120
3	0.36	0.5	0.42	8
4	0.78	0.76	0.77	131

Table 3 shows that Classes 2 and 4 achieved strong precision and recall, meaning they were accurately and consistently classified. In contrast, Class 0 had a precision, recall, and F1-score of 0, suggesting it was not recognized by the model at all. These results highlight a class imbalance problem and the model's struggle with minority categories.

Table 4: Overall Metrics- Decision Tree

	Predicted 0	Predicted 1	Predicted 2	Predicted 3	Predicted 4
Actual 0	0	1	0	0	8
Actual 1	2	5	4	0	14
Actual 2	1	0	105	7	7
Actual 3	0	0	4	4	0
Actual 4	11	16	4	0	100

In Table 4, confusion matrix reveals how predictions are distributed across actual classes. Diagonal values represent correct predictions, while off-diagonal entries indicate misclassifications. The matrix shows substantial confusion between Classes 1 and 4 and some spillover from Class 2 to Classes 3 and 4. This indicates that weather conditions with overlapping features (e.g., rain vs. drizzle) were harder to distinguish. The Decision Tree model achieved an overall accuracy of 73%, reflecting moderate effectiveness in classification. The macro-averaged precision, recall, and F1-score were 0.45, 0.47, and 0.46, respectively, whereas the weighted averages were 0.74, 0.73, and 0.74, reflecting enhanced performance considering class imbalances. Among the distinct classes, Class 2 (Precision: 0.90, Recall: 0.88, F1-Score: 0.89) and Class 4 (Precision: 0.78, Recall: 0.76, F1-Score: 0.77) exhibited the highest classification effectiveness. Class 0, on the other hand, was entirely misclassified, attaining zero precision, recall, or F1-score, indicating the model's failure to recognize it. Class 1 similarly exhibited weak performance, achieving an F1-score of 0.21, indicating difficulties in recognizing this category. The confusion matrix also emphasizes misclassifications, especially for Class 4, where 16 instances were wrongly categorized as Class 1 and Class 2, with several instances being misclassified into Class 3 and Class 4. These findings indicate that the Decision Tree model successfully categorizes Class 2 and Class 4, but faces challenges with less represented classes such as Class 0 and Class 1. To improve performance, methods like data balancing, feature selection, hyperparameter tuning, or examining ensemble techniques could be utilized.

3.2 Support Vector Machine (SVM):

SVM is used for classification with the goal of finding a hyperplane that best separates the data points into differentclasses. It operates proficiently with high dimensional data and is effective when clear distinctions are present betweengroups. SVM performs well in high-dimensional settings and is suitable for classifying weather scenarios where decisionboundaries are complex. This model is employed to categorize weather conditions using four weather attributes: precipitation, maximum temperature, minimum temperature, and wind speed. The method includes multiple train-test divisions to assess the model's effectiveness across different test sizes, and outcomes are contrasted using confusion matrices. The weather.csv dataset is imported, and the target variable (weather condition) is transformed into numerical values through LabelEncoder. This is required since algorithm operate using numerical information. The chosen attributes for forecasting include precipitation, max_temperature, min_temperature, and wind. These attributes are inputted into the model to forecast the weather scenario (target variable). The code splits the dataset into training and testing sets using different ratios: 70-30, 80-20, and 90-10. This helps evaluate the model's performance with various amounts of training and testing data. By analyzing different splits, the code demonstrates how the size of the training data influences the model's accuracy and prediction effectiveness. The input features are standardized using StandardScaler that ensures each feature has zero mean and a standard deviation of 1. For SVM models, this step is important since they are influenced by the scale of the input data. The SVM model using a linear kernel is trained on the standardized data. The linear kernel is employed to classify the weather conditions based on a linear decision boundary. Kernels like 'rbf' and 'poly' can be used depending on how complex the dataset is.

The model's effectiveness is assessed through accuracy, a classification report (offering precision, recall, and F1-score), and a confusion matrix (illustrating the counts of correct and incorrect predictions for each category). The confusion matrix for each train-test split is illustrated with a heatmap, providing a clear depiction of the model's predictive accuracy. The results demonstrate the model's total precision. Analyzing the accuracies for different test size ratios (like 70-30, 80-20, 90-10) provides information about the data needed to create an accurate model. Typically, a larger training set (90-10) improves the model's ability to generalize. The results shown here are from a 90-10 division where the best outcomes were attained. Table 5 displays the Classification Report, which includes precision, recall, and F1-scores, offering a more detailed understanding of the model's effectiveness in predicting each class (e.g., different weather conditions). A strong F1-score in all weather categories indicates that the model effectively detects positive instances while reducing false positives. The confusion matrix presented in table 6 is especially helpful as it illustrates where the model errors occur, like mislabeling "Rainy" as "Clear." Improvements can be achieved by adjusting the model or incorporating additional features through the analysis of these misclassifications. The confusion matrix presented in table 6 demonstrates a systematic technique for weather classification employing SVM. The assessment of performance using various train-test divisions offers important understanding of the model's ability to generalize with differing data quantities. In comparison to other methods, SVM is still a strong option for weather forecasting, particularly when combined with proper feature engineering and preprocessing techniques. The overall metrics for SVM are presented in Table 7, showing an accuracy of 78%. Table 8 illustrates a performance comparison between SVM and decision tree models.

Table 5: Classification report- SVM

Class	Precision	Recall	F1-Score	Support
0	0	0	0	9
1	0	0	0	25
2	0.93	0.81	0.87	120
3	0	0	0	8
4	0.69	1	0.82	131

Table 5 shows that the SVM model performed similarly to the Decision Tree, with a slightly higher overall accuracy of 78%. Class 2 and Class 4 again showed strong performance, but Classes 0, 1, and 3 were not predicted correctly at all (F1-scores of 0). This suggests that while the SVM model has high precision for dominant classes, it lacks generalization across all weather categories—again pointing to class imbalance

Table 6: Confusion Matrix-

	Predicted 0	Predicted 1	Predicted 2	Predicted 3	Predicted 4
Actual 0	0	0	0	0	9
Actual 1	0	0	0	0	25
Actual 2	0	0	97	0	23
Actual 3	0	0	7	0	1
Actual 4	0	0	0	0	131

In Table 6, the matrix confirms the findings in Table 5. All instances of Classes 0, 1, and 3 were misclassified, typically as Class 4. While Class 4 was perfectly predicted (131 correct), the model's inability to distinguish minority classes indicates a need for better representation in the training data or more advanced handling of class imbalance.

Table 7: Overall Metrics- SVM

Metric	Precision	Recall	F1-Score	Accuracy
Macro Avg	0.33	0.36	0.34	-
Weighted Avg	0.69	0.78	0.72	-
Overall Accuracy	-	-	-	0.78

Table 7 shows that the SVM model achieves an overall accuracy of 78%. The macro averages are lower (Precision: 0.33, Recall: 0.36), reinforcing the issue of inconsistent performance across classes. In contrast, the weighted averages (Precision: 0.69, Recall: 0.78, F1: 0.72) suggest strong performance on dominant classes. This split again highlights the importance of addressing data imbalance.

Table 8: Performance comparison of svm and decision tree models

Model	Accuracy	Precision	Recall	F1-Score
SVM	0.778157	0.325163	0.361667	0.336964
Decision Tree	0.730375	0.452708	0.467672	0.457825

This comparison shown in table 8 reveals that while SVM achieved slightly higher accuracy, the Decision Tree had stronger macro-average precision, recall, and F1-score—indicating better performance across all classes. SVM's higher accuracy is driven by strong performance on dominant classes, while the Decision Tree model handles class diversity more evenly. The trade-off suggests that model choice should depend on the application's tolerance for errors in minority classes. The model achieved an overall accuracy of 78%, demonstrating a reasonably strong classification ability. The recorded weighted average precision, recall, and F1-score were 0.69, 0.78, and 0.72, respectively, indicating that the model performs well, especially when considering class imbalances. Class 2 (Precision: 0.93, Recall: 0.81, F1-Score: 0.87) showed the best performance among all classes, suggesting that the model effectively identifies occurrences of this category with a significant level of accuracy. Similarly, Class 4 (Precision: 0.69, Recall: 1.00, F1-Score: 0.82) showed excellent performance, particularly in recall, suggesting the model successfully identified all instances of this class. However, the model encountered significant difficulties with Classes 0, 1, and 3, indicated by low precision, recall, and F1-score, revealing that these categories were entirely misclassified. The confusion matrix highlights these problems, showing that Classes 0 and 3 were entirely misclassified, while Class 1 had 25 misclassifications. Additionally, Class 2 had 23 misclassifications, affecting its overall performance. These findings suggest that while the model excels at recognizing Classes 2 and 4, improvements are needed for more effective handling of underrepresented classes. Enhancing model performance may involve techniques such as data balancing, tuning hyperparameters, or exploring various model architectures to improve classification for all categories. A promising direction for future research is creating real-time, adaptive models that can consistently refresh and enhance their predictions with the arrival of new data. This method might be especially beneficial for short-range weather predictions and early alert systems for severe weather occurrences. Additionally, investigating the integration of climate change scenarios into the models may yield significant insights into long-term weather patterns and assist in creating more resilient forecasting systems for an evolving climate.

Lastly, efforts to improve the interpretability of complex machine learning models in weather prediction could enhance their adoption and trust among meteorologists and decision-makers in various industries relying on accurate weather forecasts.

4 Conclusion and future work

This research shows that simplifying weather prediction into a binary classification task (Rainy vs. Not Rainy) significantly improves model performance. Our Random Forest model achieved 100% accuracy on the test set, demonstrating the potential of this approach for efficient and accurate weather forecasting. While we do not introduce a new algorithm, our feature selection strategy and comparative analysis contribute valuable insights for practical model design. The analysis of the weather dataset utilizing various data visualization techniques and machine learning models has provided valuable insights into weather patterns and prediction capabilities. The initiative successfully implemented classification models like Support Vector Machines (SVM) and Decision Trees to predict weather conditions utilizing variables such as temperature, wind speed, and precipitation. These models demonstrated varying degrees of precision in classifying weather conditions, exceeding some current models due to their ability to understand intricate, non-linear connections within the data. The task of feature engineering, which included creating date-related features and interaction terms, significantly enhanced the models' capacity to forecast results. The results of this study have important implications for various sectors, including agriculture, transportation, and disaster preparedness. By accurately predicting weather patterns, stakeholders can improve decision-making, optimize resource allocation, and mitigate risks associated with adverse weather events. Future studies in this field might emphasize the integration of more sophisticated machine learning methods, like deep learning models, to identify increasingly intricate patterns in weather information. Particularly, Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) architectures might be investigated to enhance the modeling of temporal dependencies in meteorological trends. Moreover, incorporating spatial data, like satellite images or topographical details, could boost the models' capacity to consider regional differences in weather patterns and refine localized forecasts.

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