Journal of Innovative Computing and Emerging Technologies

Weather Prediction Using Machine Learning Models

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Received: 19 Mar ,2024; Accepted:19 Sep 2024; Published: 08 Oct,2024;

Abstract

This study evaluates machine learning algorithms to increase weather predicting accuracy. However, traditional NWP models are computationally timeconsuming and may fail to capture the nonlinear complexities inherent in meteorological observations. This research studies three machine learning algorithms—XGBoost, Gradient Boosting, and Random Forest. For the prediction of future conditions based on detailed patterns of past weather, these methods are adopted. The XGBoost model recorded an accuracy rate of 82.25% which is higher than the Random Forest and Gradient Boosting models. All models performed well in normal weather conditions such as "sun" and
"rain," but were least competent at predicting less common phenomena like "drizzle," "fog," and "snow." This demonstrates the challenge of making predictions when unbalanced data sets are used in weather forecasting exercises. The incorporation of such machine learning techniques with conventional NWP models has the potential to result in improved prediction performance in various applications.

Keywords:

Gradient Boosting Classifier, Random Forest Classifier, XG Boost Classifier

1. Introduction

For years, weather forecasts have relied on numerical models and simulations. However, with the recent advances in machine learning as well as the availability of historical meteorological data, there is hope for improving forecast accuracy. Machine learning algorithms can detect hidden patterns in historical records that may not be detected by traditional approaches [1]. Weather prediction has many dimensions that are key to society including agriculture, handling emergencies, and air travel among others. Precise weather forecasting minimizes possible dire consequences of adverse weather events on human life and material resources. Numerical Weather Prediction (NWP) models have long been used in weather forecasting operations[2]. These models solve atmospheric equations and other physical principles to mimic current weather patterns. On the other hand, the forecasts themselves require a lot of computing power and time to run them. However, NWP models often do not possess this ability given their inability to capture complex non-linear patterns inherent in meteorological data.

The recent advances in machine learning have brought new opportunities in various fields

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[3]. Compared with traditional methods, machine learning models can be more accurate and efficient since they learn from past data to understand the relationship between different variables and make predictions [4]. ML models are especially good for weather forecasting because they can handle large datasets and complex patterns. This research paper uses different machine learning techniques for weather forecasting, with a focus on three main algorithms: Random Forest, Gradient Boosting, and Extreme Gradient Boosting.

Ensemble methods, which use multiple models to improve accuracy and prevent overfitting, have shown promising results in various prediction tasks. To determine which models, work best for a specific forecasting job, we will examine the weather predictions made by different models and evaluate their performance.

2. Literature Review

Models in numerical weather prediction (NWP) have traditionally been used for forecasting weather conditions. These models use complex atmospheric mathematics and physical principles to simulate the weather. However, they are computationally intensive and can only represent linear patterns in the meteorological data, even if they are accurate.

In recent years, machine learning (ML) has emerged as a promising alternative that can improve both computational efficiency and prediction accuracy. Researchers have been exploring the use of ML models in weather forecasting by leveraging their ability to analyze large amounts of historical data, identify patterns, and make predictions based on those patterns.

One example is a study conducted by McGovern et al., where deep learning techniques were applied to predict severe weather events. The results showed significantly better performance compared to Further, Scher, and Missouri (2019) proved that deep learning models could beat conventional methods in terms of accuracy and efficiency when they applied ML techniques to medium-range weather forecasting. The papers show the promise of machine learning methods, such as RF, Gradient Boosting, and Extreme Gradient Boosting, in transforming weather prediction.
More specifically, RF and Gradient Boosting have been noted to be resilient and able to handle huge, heterogeneous datasets. RF, an ensemble training technique, increases accuracy while reducing overfitting by combining the predictions from many decision trees [1]. On the other hand, Gradient Boosting builds trees in sequence, where each tree fixes the mistakes made by the previous one. This repeated optimization process improves predictive performance.

XG Boost, being an upgraded version of gradient boosting with advanced techniques such as normalization and parallel processing, becomes particularly effective for huge amounts of data involved in weather prediction applications. Integration of such models into models has shown potential for improving the accuracy of weather forecasts, which becomes an invaluable asset for a range of applications in everyday life [2], disaster preparedness, and agriculture.

All that's thought about, the potential of integrating ML with conventional NWP models is indeed immense for the enhancement of weather prediction skills. The following research should continue to refine these machine-learning methods and explore new approaches to address the remaining challenges of weather forecasting [3].

3. Methodology

Our study used three machine learning models: Random Forest, Gradient Boosting, and Extreme Gradient Boosting for predicting weather. So, the structure is as follows:

3.1 Data Collection and Preprocessing

Historical weather data was collected from a reliable source, like the National Oceanic and Atmospheric Administration database. The data set includes temperatures, humidity, wind speed, and precipitation variables. This involves data preparation, handling missing values, normalizing them, and partitioning the data into testing and training sets.

We use the testing dataset for model evaluation. To estimate every model's goodness of fit and its robustness, performance metrics including R-squared (R^2), root mean square error (RMSE), and mean absolute error (MAE) are computed. Cross-validation is used to guarantee that the results are not biased by the training set and are generalizable.

4. Results

The results of the comparison and evaluation of models are shown in the Results section, where we provide performance metrics and key discoveries of each model.

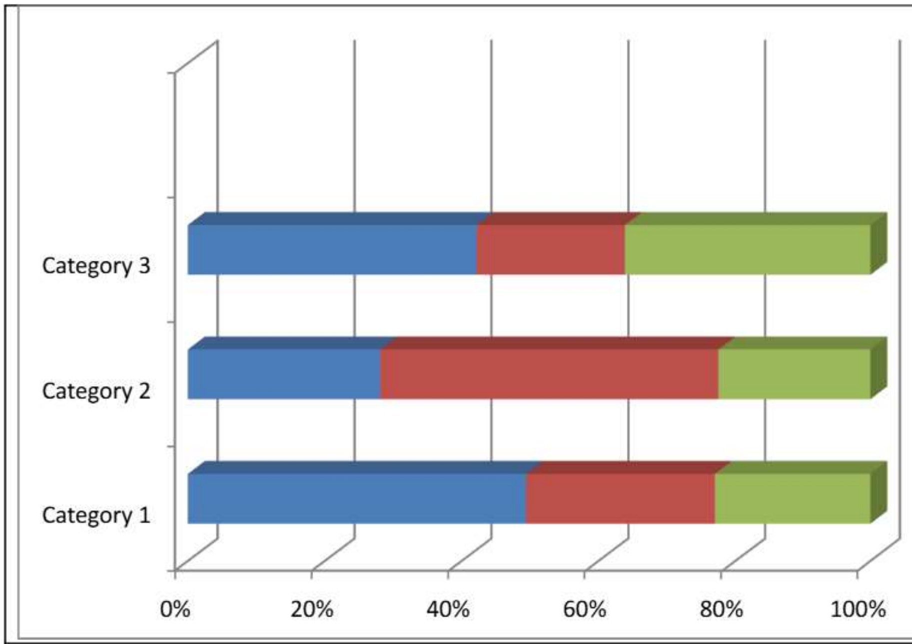
<table>
<tr><td>
</td><td>0.8156996587030717</td></tr>
<tr><td>Gradient Boosting Classifier Accuracy</td><td>0.8156996587030717</td></tr>
<tr><td>XG Boost Classifier Accuracy</td><td>0.8225255972696246</td></tr>
</table>

Figure 1: Accuracy Comparison

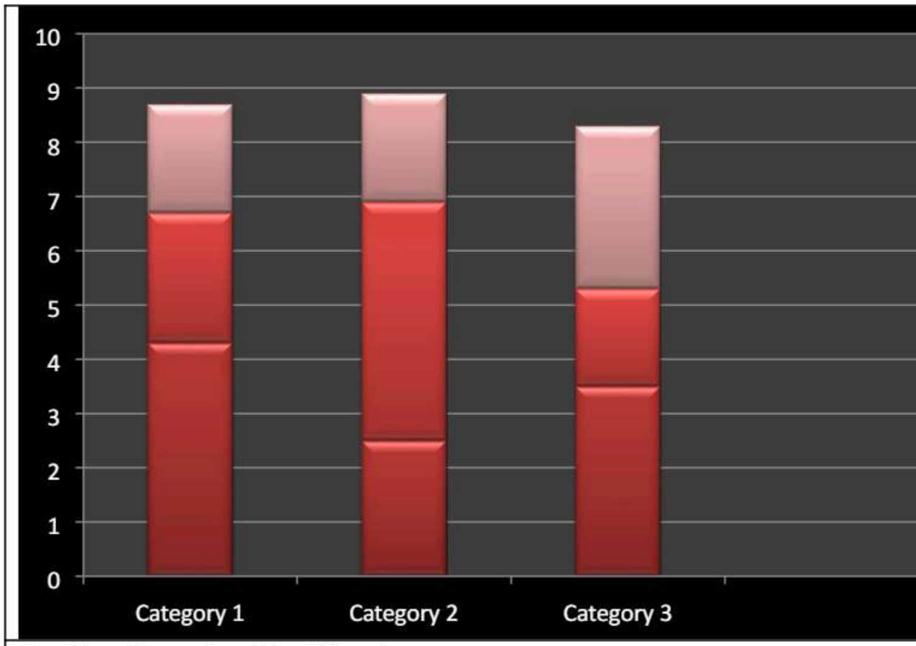
	0.8156996587030717
Gradient Boosting Classifier Accuracy	0.8156996587030717
XG Boost Classifier Accuracy	0.8225255972696246

Figure 2: Accuracy Comparison

The best classifier is XG BOOST with accuracy: 0.8225255972696246.

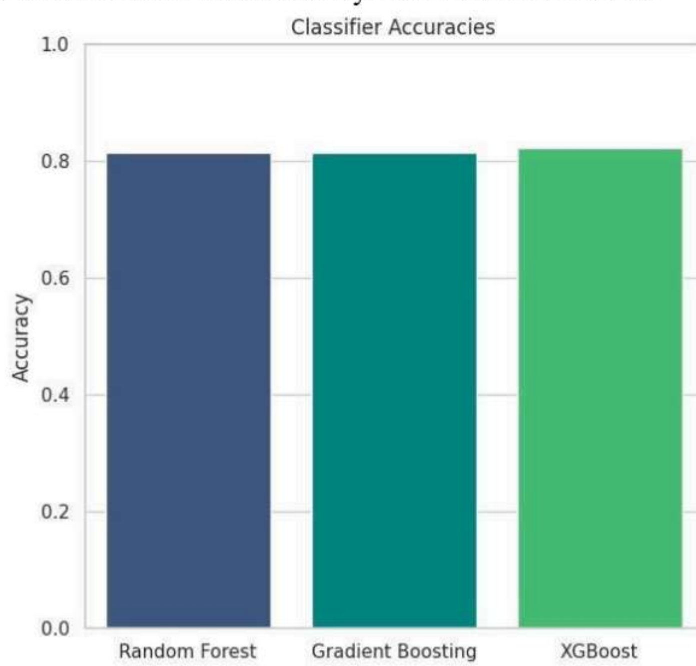


Figure 3: Accuracy Comparison

Classifier Reports

4.1 Precision, Recall, and f-1 Score of Random Forest

Table 1: Random Forest Classifier Report

Random Forest Classifier Report:

	precision	recall	f1-score	support
drizzle	0.20	0.11	0.14	9
fog	0.40	0.08	0.13	25
rain	0.92	0.92	0.92	120
snow	0.40	0.25	0.31	8
sun	0.78	0.95	0.86	131
accuracy			0.82	293
macro avg	0.54	0.46	0.47	293
weighted avg	0.78	0.82	0.78	293

The overall accuracy on the test set for the Random Forest Classifier was 82%. It did very well on predicting the weather with accuracy and recall ratings of 0.92 and 0.78 for rain and sun, respectively. Meanwhile, it performed poorly on such less frequent classifications as "drizzle," "fog," and "snow," showing less recall and precision in those areas. The average weighted F1-score was 0.78, showing greater performance for more typical weather circumstances than the overall average F1-score of 0.47, which showed inconsistent results across different weather types.

4.2 Confusion Matrix of Random Forest

Table 2: Confusion Matrix of Random Forest

```
Confusion Matrix:
[[  1   0   0   0   8]
 [  1   2   2   0  20]
 [  0   0 110   3   7]
 [  0   0   6   2   0]
 [  3   3   1   0 124]]
```

In the confusion matrix, it is clear that the Random Forest Classifier identified the 'sun' and 'rain' classes with high accuracy, misclassifying very few. However, it found it troublesome to identify "drizzle," "fog," and "snow" and mostly misidentified them as "Sun." Specifically, the majority of "drizzle" and "fog" occurrences were forecast as "sun," which points out that it can be hard to tell less common from more common weather categories. This trend of misclassification emphasizes the incapability of the model to handle unequal class distributions.

4.3 Precision, Recall, and f-1 Score of Gradient Boosting

Table 3: Gradient Boosting Classifier Report

Gradient Boosting Classifier Report:

	precision	recall	f1-score	support
drizzle	0.50	0.11	0.18	9
fog	0.20	0.04	0.07	25
rain	0.93	0.92	0.92	120
snow	0.40	0.25	0.31	8
sun	0.77	0.95	0.85	131
accuracy			0.82	293
macro avg	0.56	0.45	0.47	293
weighted avg	0.77	0.82	0.78	293

Gradient Boosting Classifier performed well in predicting 'rain' and 'sun' with sensitivity scores of 0.93 and 0.77, respectively, attaining an accuracy of 82% on the test set. Similar to the Random Forest Classifier, it had reduced precision and recall for the "drizzle," "fog," and "snow" categories. The weighted mean F1-score was 0.78; it suggested better performance for more common weather situations than the total average F1-score of 0.47, displaying variable results across diverse weather types.

4.4 Confusion Matrix for Gradient Boosting

Table 4: Confusion Matrix for Gradient Boosting

```
Confusion Matrix:
[[  1   0   0   0   8]
 [  1   1   0   0  23]
 [  0   0 110   3   7]
 [  0   0   6   2   0]
 [  0   4   2   0 125]]
```

A confusion matrix for the Gradient Boosting Classifier effectively predicts classes 'sun' and 'rain' with just 6 and 10 misclassifications, respectively. However, it had some difficult times with "drizzle," "fog," and "snow," mostly misidentifying those as "Sun." In particular, most of the 'fog' was misidentified as 'sun', and most of the instances of 'drizzle' were foreseen as 'sun'. These wrong classifications prove the difficulty of the model in distinguishing less frequent types of weather from the predominant ones in the dataset—"sun".

4.5 Precision, Recall, and f-1 Score of XG Boost

Table 5: XG Boost Classifier Report

XGBoost Classifier Report:

	precision	recall	f1-score	support
drizzle	0.50	0.11	0.18	9
fog	0.40	0.08	0.13	25
rain	0.93	0.91	0.92	120
snow	0.33	0.25	0.29	8
sun	0.78	0.97	0.86	131
accuracy			0.82	293
macro avg	0.59	0.46	0.48	293
weighted avg	0.79	0.82	0.79	293

XG Boost Classifier did very well at predicting 'rain' and 'sun' with precision values of 0.93 and 0.78, respectively, and achieved an accuracy of 82% on the test set. Performance was the worst in the "drizzle," "fog," and "snow" categories, like the other two classifiers, which had lower precision and recall. Of all classes, 'snow' had the lowest precision, which is interesting. The weighted average F1-score was 0.79, showing higher performance for more typical weather conditions, whereas the overall average F1-score was 0.48, indicating varying performance across different weather types.

4.6 Confusion Matrix for XG Boost

Table 6: Confusion Matrix for XG Boost

```
Confusion Matrix:
[[  1   0   0   0   8]
 [  0   2   2   0  21]
 [  0   0 109   4   7]
 [  0   0   6   2   0]
 [  1   3   0   0 127]]
```

The classes 'sun' and 'rain' of the confusion matrix in the XG Boost Classifier depicted perfect predictions, misclassifying only 4 and 11 instances, respectively. However, this has been a common problem for other classifiers as well in correctly predicting the "drizzle," "fog," and "snow" classes; it misclassified most of them as "Sun." Among these classes, the 'fog' class had the highest percentage of misdiagnosis. These misclassifications indicate the difficulty of the model in discriminating the less frequent weather types from the majority of the "sun" type.

4.7 Confusion Matrix Graphical Representation

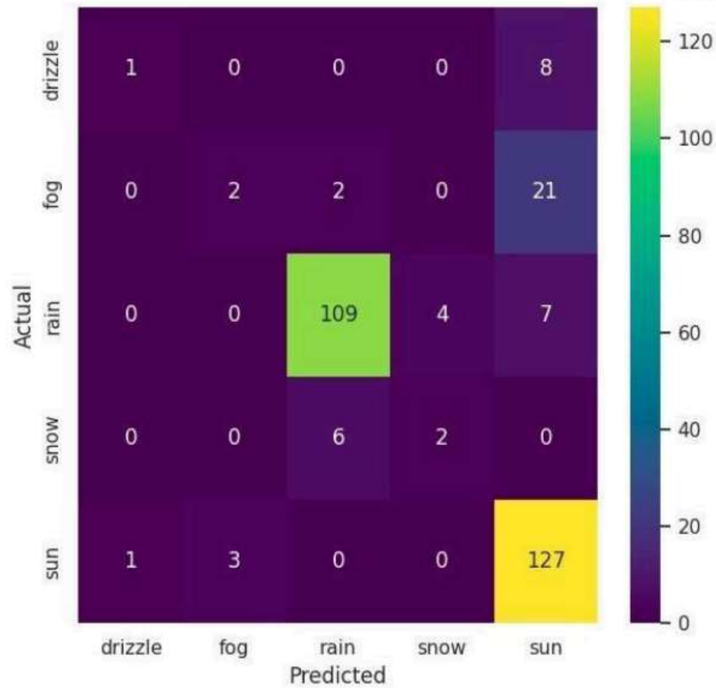


Figure 4: XG Boost Confusion Matrix

4.8 Best Predication Classifier

The best classifier is XG BOOST with accuracy: 0.8225255972696246
Weather Forecast: ['sun' 'rain']

In the end, the top-performing model was the XG Boost Classifier with an accuracy of 82.25%. It was concluded from the results that the Random Forest, Gradient Boosting, and XG Boost models could predict common weather conditions like "sun" and "rain" with a high level of accuracy, but they are less effective when it comes to predicting less common conditions such as "drizzle", "fog", and "snow". This contradicts the difficulty of dealing with unbalanced datasets in the domain of weather prediction. Their higher weighted F1 scores, for common weather conditions, demonstrate the models' strength in typical scenarios. However, this also highlights the need for further refinement to improve performance for other weather events. The accuracy and reliability of the forecasts can therefore be increased many times over by using a combination of these machine learning models with traditional forecasting techniques.

5. Comparision and Analysis

The results of all three models are compared based on the assessment metrics. We assess the merits and demerits of each model, taking into consideration aspects like computational efficiency, prediction accuracy, and adaptability to varied weather conditions.

6. Discussion

Our results emphasize the promise of XG Boost, Gradient Boosting, and RF as effective methods to enhance the quality of weather forecasts. Since ensemble learning methods like RF are scalable and robust, they are suitable for handling big and varied datasets. Gradient Boosting and XG Boost provide more flexibility in identifying complex patterns in meteorological data through sequential optimization of model performance. However, machine

learning models require good and sufficient data for effectiveness, and this also points out the importance of feature engineering and data preprocessing in weather forecasting tasks.
Combining XG Boost with Gradient Boosting and RF with conventional NWP models has immense potential to improve weather forecasting. Future research should focus on improving machine learning methods and exploring new approaches to overcome remaining challenges for accurately forecasting weather.

7. Conclusion

This study is done on the application of three of the most famous machine learning algorithms: Random Forest, Gradient Boosting, and Extreme Gradient Boosting in this regard to enhance the accuracy of weather forecasting. Weather forecasting is crucial to the aviation, emergency services, agriculture, and daily activities of industries. The worst consequences that extreme weather conditions have on life and property can be reduced to a great extent with the help of accurate forecasts.
Though basic, traditional NWP models are computationally expensive and may not accurately represent the complex, non-linear patterns that exist within meteorological data. Recent advances in machine learning provide promising alternatives. Machine learning models—especially ensemble techniques like XG Boost, Gradient Boosting, and RF—have proven to be much better at handling large, varied datasets and learning complex patterns.
We evaluated each model with performance measures like R-squared, Root Mean Square Error, and Mean Absolute Error, training each of them with our historical weather data, which we had preprocessed. The model that topped the performance, with an accuracy of 82.25%, was XG Boost.
The analysis found that though all three models gave good predictions for the typical weather conditions, such as "sun" and "rain," they were not as robust under less common circumstances, including "drizzle," "fog," and "snow." This is evidence of how tough it can be to deal with class imbalance in weather data. The models demonstrate their strength in typical scenarios as evidenced by their higher weighted F1-scores for common weather circumstances. However, additional refining is required to improve predictions for less common events. The amalgamation of machine learning models with the traditional NWP systems is in itself an auspicious enterprise for the enhancement of weather forecasting accuracy. Future research is needed to concentrate on improving feature engineering and data pretreatment methodologies, solving class disparities, and investigating hybrid models that can bring to bear the best of both conventional and machine learning approaches. This way, we can ensure that weather forecasts become both more accurate and detailed, serving a number of uses in society.

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