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Enhancing The Effectiveness Of Weather Forecasting Using Ensemble Machine Learning Techniques

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Accurate weather forecasting is essential for managing the consequences of climate change and erratic weather conditions affecting various sectors such as agriculture, transportation, and public safety. This study presents a novel approach to improving weather prediction by integrating advanced machine learning techniques. The proposed model consists of Base Model 2 which combines Long Short-Term Memory (LSTM), eXtreme Gradient Boosting (XGBoost) using Ensemble approach. The output is then compared with Base Model 1 which combines K-Nearest Neighbor (KNN), Decision Tree (DT), Multi-Layer Perceptron (MLP) using Stacking Approach. The results from both Base Models are compared on the basis of accuracy and prediction time. The proposed methodology involves comprehensive data collection, rigorous preprocessing, feature selection, and development of an ensemble model using various machine learning models. The ability to capture intricate, nonlinear relationships in weather data is enhanced by this strategy, resulting in more precise and trustworthy forecasts. The model was evaluated using several metrics and achieved a high accuracy of 0.9608, MCC of 0.8850, and F1-score of 0.9602. The findings suggest that the integration of intelligent techniques significantly improves the accuracy and reliability of weather forecasting. Future research could extend this model to different regions and incorporate additional meteorological factors. This study contributes to the ongoing efforts to develop more sophisticated weather forecasting models, offering valuable insights for decision-makers in weather-sensitive industries.

Keywords: Weather Forecasting, Recursive Feature Elimination (RFE), K-Nearest Neighbor (KNN), Decision Tree (DT), Multi-Layer Perceptron (MLP), eXtreme Gradient Boosting (XGBoost), Long Short-Term Memory (LSTM).

1. Introduction

Forecasting weather is the practice of predicting future weather conditions [1] based on real-time information like temperature, humidity, and pressure from numerous sensors [2]. This practice has been crucial throughout history, supporting both personal decisions and large-scale industrial planning. Weather forecasts at the individual level determine safety protocols [3], including refraining from engaging in hazardous outdoor activities during adverse conditions and taking health precautions in extreme temperatures [4]. In agriculture, forecasts are essential for planning planting, harvesting, and irrigation schedules, ultimately maximizing crop yields and maintaining stable food supply chains [5-9]. The transportation industry also benefits from precise weather predictions, as they help plan and schedule flights, train routes, and maritime activities, reducing delays and enhancing safety procedures [9-11]. The construction and infrastructure sectors are dependent on weather forecasting [12][13]. Accurate predictions help avoid project delays and quality issues, ensuring efficient project management. Predicting severe weather phenomena such as hurricanes and typhoons is essential for disaster relief [14]. Early alerts can significantly reduce casualties and property damage. Climate prediction, although often overlooked in the short term, is vital for addressing long-term issues like sea level rise due to global warming [15]. Advanced climate models provide insights into potential future impacts, facilitating the development of targeted mitigation strategies [16]. Thus, weather and climate forecasting remain indispensable tools in managing both everyday activities and long-term planning for human society [62][70].

Weather forecasting can address various problems in multiple sectors, including agriculture, transportation, construction, and disaster relief, making it an essential instrument for human life and societal processes [17]. Its importance cannot be overstated, as it has a decisive role in various domains and aids in decision-making, planning, and preparedness [18]. Climate change poses significant threats to biodiversity by altering the geographic range of many species. Accurate climate models, which incorporate factors like atmospheric pressure, ocean currents, and biosphere interactions, are essential for understanding these environmental changes [19]. Hence, accurate long-term climate forecasts are crucial for planning and adapting to these changes, ensuring sustainable resource management of land, water, and forests. For example, predictive models can forecast water shortages, enabling proactive water management practices. Climate change also affects public health, increasing the spread of infectious diseases and heatwave occurrences. Detailed climate models help public health organizations allocate resources and create effective response plans. A widely accepted and upheld agreement to address the problem of climate change is the Paris Agreement [20]. In contrast to the temperatures recorded prior to the emergence of industrialization, the goal is to keep the rise in the global average temperature well below 2 °C, ideally to 1.5 °C. The "Green Deal" in Europe has the objective of achieving carbon neutrality by 2050, which means reducing net emissions of greenhouse gases to zero [21]. These international efforts aim to mitigate these impacts by limiting global warming and reducing greenhouse gas emissions.

The socioeconomic effect of weather forecasting and changing climates is significant and cannot be underestimated [22-23]. Numerical Weather Prediction (NWP) models have had a significant societal impact, revolutionizing weather forecasting [24]. These physics-based models use data assimilation techniques [25]-[26] to include observations from many sources, including satellite data. However, the high density of satellite observations requires data thinning. Typically, using a higher geographic resolution in NWP models is believed to lead to more realistic weather predictions, especially for predicting rainfall [27-31]. However, traditional computing approaches have limitations for achieving convection-permitting spatial resolutions in global NWP models. As a result, studies investigated alternate systems for computing that utilize Graphical Processing Units (GPUs) [32]. Weather forecasting frequently uses a number of AI algorithms. Based on patterns and trends, supervised machine learning methods [60] [61] such as Support Vector Machine (SVM), Random Forest (RF), and neural networks may evaluate historical weather data and predict current and future conditions.

RF has been employed in weather prediction [33] because of its capacity to manage multidimensional data and nonlinear relationships [34], although it has challenges when making predictions beyond the observed data. SVM is employed for forecasting rainfall and classifying weather conditions. Despite being computationally expensive and needing meticulous hyper-parameter adjustment for best performance, it demonstrates favourable outcomes with data that cannot be separated linearly [35]-[36]. Deep Learning (DL) [37] is currently gaining recognition as an effective development of neural networks. Deep learning is a data-centric approach that leverages reference input datasets and corresponding labelled output data to reveal complex connections between the input and output data. It has the potential to exceed standard models that are traditionally designed [38]. Employing DL approaches appears to be an appropriate fit for the Earth system research domain, which includes weather forecasting and satellite remote sensing [39]. The increasing number of Earth Systems data sets from multiple sources, including EO satellites [40] and crowdsourced sensors [41], presents opportunities for DL algorithms to extract valuable insights and improve weather forecasting models [42]-[43]. The ability of neural networks, like deep learning models, to identify complex patterns and provide accurate predictions has made them very popular. They have been useful in weather forecasting for predicting humidity, precipitation, and temperature. Neural network training can be computationally costly because of the large amount of labelled data required. In order to address these challenges a unique approach is proposed in this study for improving the efficiency of weather forecasting by leveraging these advanced DL techniques [63]-[64].

1.1 Importance of the Research

Accurate weather predictions can mitigate the impact of adverse weather conditions, improve agricultural productivity, ensure safe transportation, and save lives during natural disasters. The proposed methodology enhances weather forecasting by leveraging advanced machine learning techniques, thereby providing more reliable and precise weather predictions. This research addresses the growing demand for improved forecasting accuracy, which is essential for planning and decision-making processes across various industries and communities.

1.2 Problem Description

Current weather forecasting models often struggle with accuracy and real-time applicability due to limitations in data processing, feature selection, and model capabilities. Traditional approaches fall short in handling the complexity and variability of meteorological data, leading to imprecise forecasts, especially under rapidly changing conditions. Feature selection in these models can be suboptimal, including irrelevant data and excluding crucial predictors, further reducing accuracy. These limitations underscore the need for advanced forecasting systems that integrate sophisticated data processing, dynamic feature selection, and Ensemble learning techniques to enhance adaptability and accuracy.

1.3 Research Contributions

This study introduces several novel contributions to the field of weather forecasting:

- This study combines LSTM and XGBoost models within an ensemble framework, leveraging the strengths of both time-series and gradient-boosting techniques to enhance overall predictive accuracy.
- The proposed model captures essential patterns in the data while reducing computational complexity by feature selection methods like recursive feature elimination.
- The proposed system can dynamically adapt to new patterns and improve its predictive performance, making weather forecasts more reliable and timelier by incorporating mechanisms for continuous learning and real-time feedback.
- The proposed system including LSTM and XGBoost in Base Model 2 is then compared with Base Model 1 which consists of KNN, DT, MLP.

Section II describes the review of literature. The next section discusses the research methodology, which includes the approaches employed in the study as well as the recommended framework for constructing a weather forecasting system. The proposed technique's results are reported in section IV under the result and discussion heading. Section V highlights the study's findings as well as its future scope [65]-[66]-[67].

2. Literature of review

There is an extensive amount of literature available that discusses a wide range of data analysis and statistical approaches used for weather forecasting [44]-[45]. Researchers have explored various statistical and data mining methods, such as regression analyses, decision trees, neural networks, and clustering, to identify the most effective real-time data analytics method for weather forecasting. Multiple authors have presented their findings on weather forecasting. Holmstrom et al. introduced a method for predicting the highest and lowest temperatures for the upcoming week based on the weather data from the previous two days [46]. The study employed a linear regression model together with a modified version of a functional linear regression method. The study demonstrated that expert weather forecasting services excelled both models in predicting weather conditions for a period of up to seven days. However, their approach had superior performance in predicting future days or extended periods. Hybrid model is used in [47] for weather forecasting that utilized neural networks. Guo et al. [48] employed SVMs for recognizing patterns in weather classification.

Yadav et al. [49] suggested a predictive model based on data mining to determine the changing trends of weather conditions. The previous data pattern is utilized to estimate the forthcoming weather conditions. Further, several studies employed the hidden Markov model and k-means clustering techniques to forecast and analyze weather observations [50]-[51]. The study in [52] introduced a hybrid technique for weather forecasting. This approach blended discriminatively trained forecasting algorithms with deep neural networks to simulate the combined characteristics of a set of weather-related parameters. Montori et al. performed a study that included crowdsensing, a method in which individuals contribute their smartphone data to gather information about environmental events [53]. SenSquare is an architectural solution designed to manage data from various sources, including IoT devices and crowdsensing platforms. It provides an integrated display of this data to users. This data is utilized to analyze the surroundings in a smart city.

3. Research Methodology

This section outlines the techniques and processes employed in the study along with the proposed framework.

3.1 Technique used

The specific techniques and methods that are utilized in the proposed methodology are given as follows:

(i) Recursive Feature Elimination (RFE)

Irrelevant features are common in large datasets. Recurring features impact the inefficiency of the classification algorithm. This could lead to less accurate predictions. Determine which variables are crucial for making accurate forecasts using RFE. This preserves the valuable characteristics acquired from the more refined feature sets while reducing the dataset's dimensionality. A method that iteratively searches for a target number of attributes is "recursive". RF classifiers rank attributes in descending order of priority after establishing their significance. Next, the model is retrained with the updated feature set to improve classification accuracy and remove less important features. The loop continues as long as there are additional features to be included [54].

(ii) Long Short-Term Memory (LSTM)

Long-term dependencies are difficult for conventional recurrent neural networks (RNNs) to capture, mostly because of problems like gradient vanishing. LSTM overcame this challenge by introducing gate operations that control the flow of data. The fundamental structure of LSTM is shown in **Figure 1**.

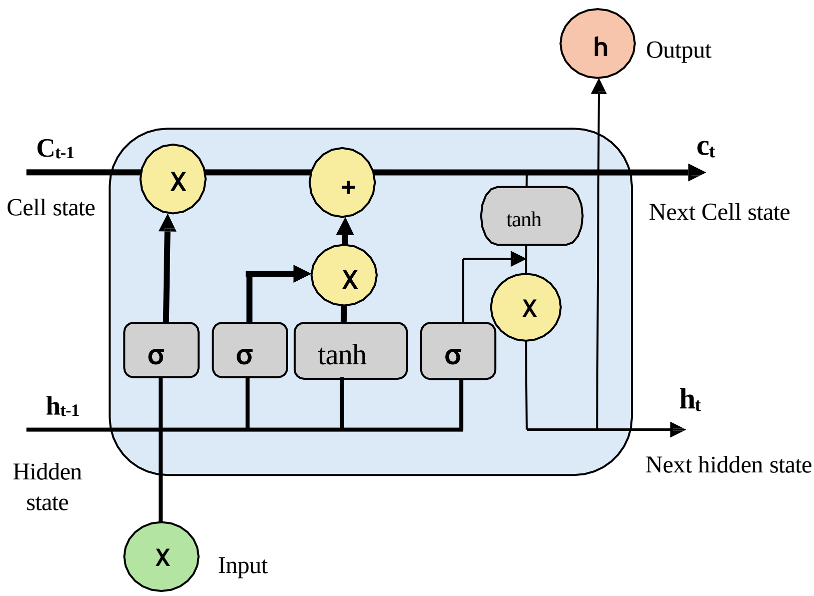


Figure 1. LSTM model [55]

In weather forecasting, LSTMs are particularly effective because they can learn from historical weather patterns and use this information to predict future conditions. The ability to maintain long-term dependencies allows LSTMs to capture the temporal dynamics of weather data, such as seasonal changes and trends. By training on extensive datasets that include past weather observations, LSTMs can generate forecasts that consider the complex, nonlinear relationships inherent in weather phenomena.

They are therefore a useful tool for enhancing the precision and reliability of weather predictions over various time horizons [56].

(iii) eXtreme Gradient Boosting (XGBoost)

XGBoost has gained prominence for its performance and efficiency in predictive modeling. In order to prevent overfitting, XGBoost uses an increasingly regularized model than previous implementations.

Here is the minimized XGBoost objective function [57]:

$$obj^{(t)} = \sum_{i=1}^{n} \left(y_i - \left(\hat{y}_i^{(t-1)} + f_t(x_i)\right)\right)^2 + \sum_{t=1}^{T} \Omega(f_t) \tag{1}$$

To increase model performance, a greedy decision tree model is added, denoted by $f_t(x_i)$, and penalize model complexity with the regularization term Ω (f_t), where y_i is the desired outcome for the i-th instance, and $\hat{y}_i^{(t)}$ is its predicted value at the t-th iteration. By incorporating XGBoost into a weather forecasting system, meteorologists can leverage its strengths to produce more precise short and long term forecasts [58].

3.2 Proposed methodology

The proposed framework for improving the effectiveness of weather forecasting is shown in **Figure 2**. The proposed methodology enhances weather forecasting accuracy by incorporating intelligent techniques. The steps involves data collection, encompass historical weather data. The data undergoes preprocessing followed by feature selection to extract the most relevant information. Advanced models, including LSTM and XGBoost, are trained on this refined data. By combining their strengths through an ensemble approach, the methodology aims to produce highly accurate predictions. The models are evaluated using various performance metrics.

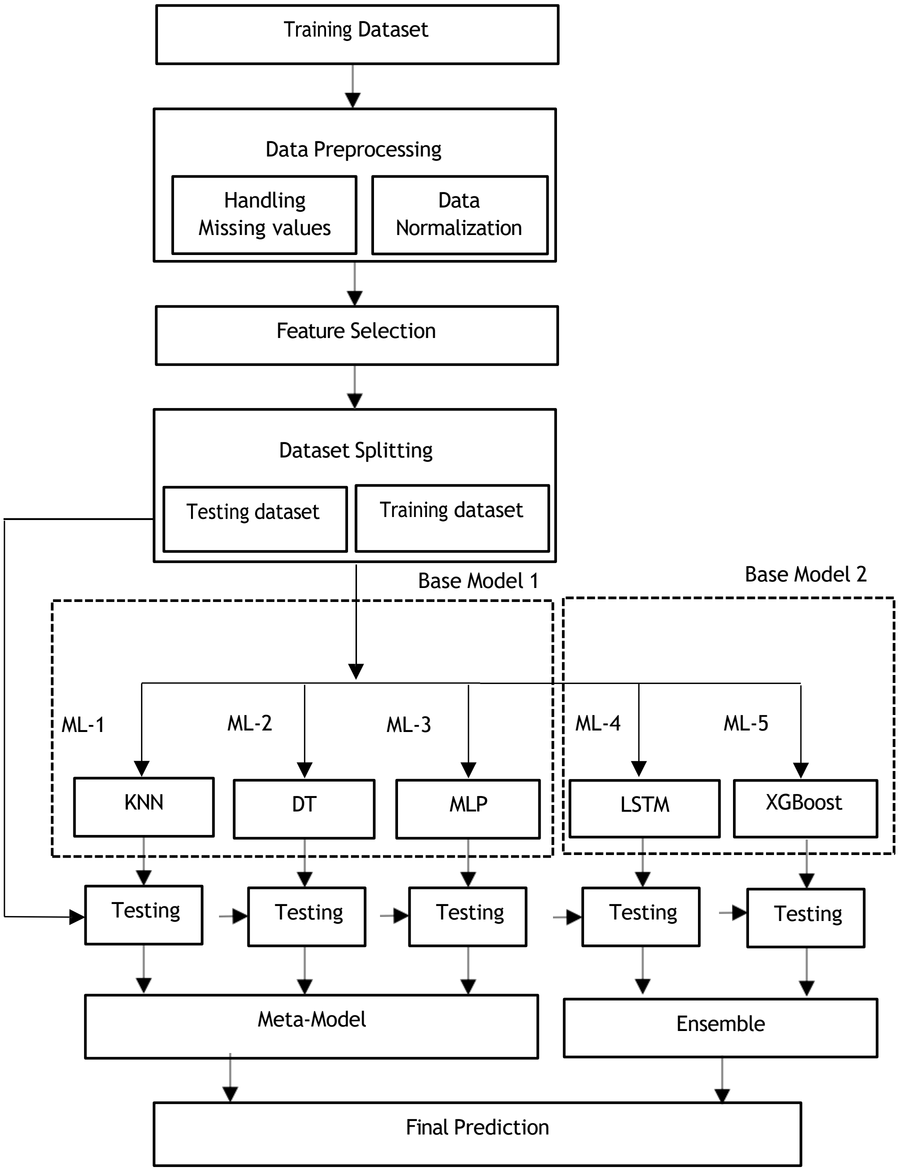


Figure 2. Proposed methodology

The proposed methodology involves several key steps, which are given as follows:

1. **Data collection**

- **Weather dataset:** This step involves gathering historical weather data from a reliable dataset.

2. **Data Processing:**
   - **Clean data to handle missing values and noise:** Techniques used to handle missing values, outliers, and noisy data.
   - **Transform data by scaling features:** Normalize or standardize the data to bring all features to the same scale.
3. **Feature engineering:**
   - **Select relevant features:** Employ RFE to select the most significant features for modeling.
4. **Dataset Splitting:**
   - **Training and testing sets:** Create Training and testing subsets, typically using a 70%-30% split.
5. **Model Development:**
   - **Define and train the LSTM model:** Create and train an LSTM neural network model for time-series forecasting.
   - **Define and train XGBoost model:** Create and train an XGBoost model for robust performance.
   - **Create an ensemble model:** Combine the predictions of the LSTM and XGBoost models using an ensemble technique.
6. **Model evaluation**
   - **Evaluate models using evaluation metrics:** Evaluate the models using the given metrics, accuracy, F1-score, precision and recall.

4. Results and Discussion

This section provides the Dataset description and Result analysis for the Proposed model.

4.1 Dataset Description

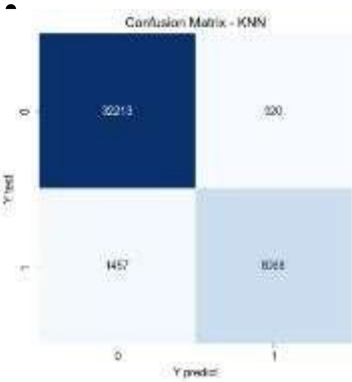
The dataset is a comprehensive weather dataset [59], containing 142,193 entries and 24 columns. The dataset includes a diverse set of variables, including date, location, minimum temperature, maximum temperature, sunshine, rainfall, evaporation, wind gust direction, wind gust speed, wind direction, wind speed, humidity, atmospheric pressure, cloud cover and temperature. Additionally, it includes binary indicators for whether it rained today or if it rains tomorrow, as well as a risk measurement (RISK_MM). The dataset contains a mix of continuous and categorical data, with certain columns such as evaporation, sunshine, and cloud cover having a significant amount of missing values.

4.2 Result analysis

Detailed analysis of the results obtained by the proposed algorithms:

(i) <u>Base Model 1:</u>

- **<u>KNN</u>**: Figure 3(a) represents a confusion matrix, a performance measurement tool for a classification model. Figure 3(b) shows models performance for test set with an accuracy of 0.94, MCC of 0.83, F1 Score as 0.94, Precision of 0.90 and Recall of 0.85.

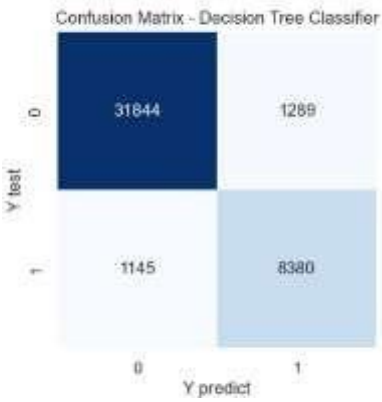



```
Model performance for Test set
- Accuracy: 0.9442777439167331
- MCC: 0.8366337350892984
- F1 score: 0.9436935494760115
              precision    recall  f1-score   support

          No       0.96      0.97      0.96     33133
         Yes       0.90      0.85      0.87      9525

    accuracy                           0.94     42658
   macro avg       0.93      0.91      0.92     42658
weighted avg       0.94      0.94      0.94     42658
```

(a) Confusion matrix – KNN (b) Testing results of KNN Model

Figure 3: Overall KNN results

- **<u>DT</u>**: Figure 4(a) represents a confusion matrix. Figure 4(b) shows models performance for test set with an accuracy of 0.94, MCC of 0.83, F1 Score as 0.94, Precision of 0.87 and Recall of 0.88

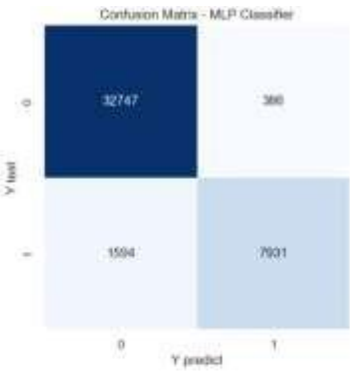



```
Model performance for Test set
- Accuracy: 0.9429415349992968
- MCC: 0.8364206559688829
- F1 score: 0.9430934403789083
              precision    recall  f1-score   support

          No       0.97      0.96      0.96     33133
         Yes       0.87      0.88      0.87      9525

    accuracy                           0.94     42658
   macro avg       0.92      0.92      0.92     42658
weighted avg       0.94      0.94      0.94     42658
```

(a) Confusion matrix – DT (b) Testing results of DT Model

Figure 4: Overall DT results

- **<u>MLP</u>**: Figure 5(a) represents a confusion matrix. Figure 5(b) shows models performance for test set with an accuracy of 0.95, MCC of 0.86, F1 Score as 0.95, Precision of 0.95 and Recall of 0.83.

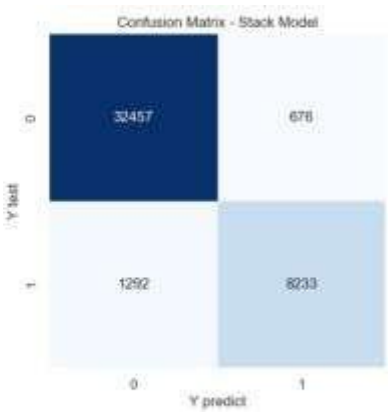



```
Model performance for Test set
- Accuracy: 0.9535843218153688
- MCC: 0.8630117072123978
- F1 score: 0.952428519864223
              precision    recall  f1-score   support

          No       0.95      0.99      0.97     33133
         Yes       0.95      0.83      0.89      9525

    accuracy                           0.95     42658
   macro avg       0.95      0.91      0.93     42658
weighted avg       0.95      0.95      0.95     42658
```

(a) Confusion matrix – MLP (b) Testing results of MLP Model

Figure 5: Overall MLP results

<u>**Stack Model**</u>: It utilizes the advantages of KNN, DT and MLP by merging their prediction using a Meta-Model layer. Figure 6(a) represents a confusion matrix. Figure 6(b) shows models performance for test set with an accuracy of 0.95, MCC of 0.86, F1 Score as 0.95, Precision of 0.92 and Recall of 0.86.



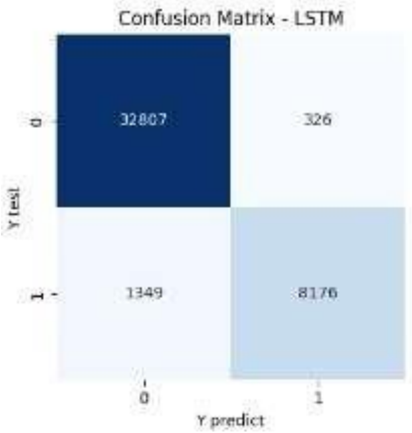

```
Model performance for Test set
- Accuracy: 0.9538656289558817
- MCC: 0.8646431139258587
- F1 score: 0.9533072586177894
              precision    recall  f1-score   support

          No       0.96      0.98      0.97     33133
         Yes       0.92      0.86      0.89      9525

    accuracy                           0.95     42658
   macro avg       0.94      0.92      0.93     42658
weighted avg       0.95      0.95      0.95     42658

Training time: 395.2737536430359s
```

(a) Confusion matrix – Stack Model (b) Testing results of Stack Model

Figure 6: Overall Stack Model results

(ii) <u>Base Model 2:</u>

- <u>**LSTM**</u>**:** Figure 7(a) represents a confusion matrix. Figure 7(b) shows models performance for test set with an accuracy of 0.96, MCC of 0.88, F1 Score as 0.95, Precision of 0.96 and Recall of 0.86.

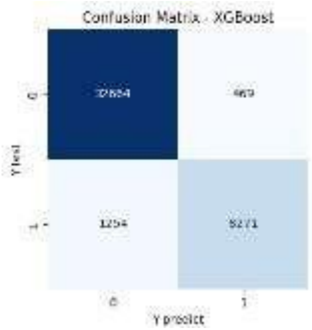



```
Model performance for Test set
- Accuracy: 0.9607342116367387
- MCC: 0.884581492115758
- F1 score: 0.9599185604611002
              precision    recall  f1-score   support

           0       0.96      0.99      0.98     33133
           1       0.96      0.86      0.91      9525

    accuracy                           0.96     42658
   macro avg       0.96      0.92      0.94     42658
weighted avg       0.96      0.96      0.96     42658
```

(a) Confusion matrix – LSTM (b) Testing results of LSTM Model

Figure 7: Overall LSTM results

- **XGBoost:** Figure 8(a) represents a confusion matrix. Figure 8(b) shows the models performance for test set with an accuracy of 0.95, MCC of 0.88, F1 Score as 0.95, Precision of 0.95 and Recall of 0.87.

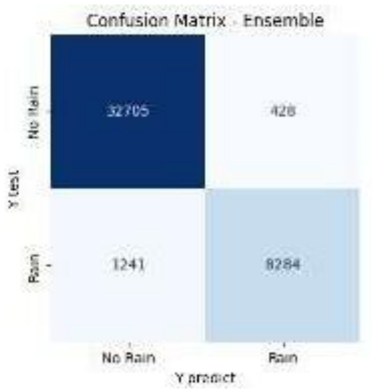



```
Model performance for Test set
- Accuracy: 0.959608983074687
- MCC: 0.8813475976143215
- F1 score: 0.958977452001162
              precision    recall  f1-score   support

           0       0.96      0.99      0.97     33133
           1       0.95      0.87      0.91      9525

    accuracy                           0.96     42658
   macro avg       0.95      0.93      0.94     42658
weighted avg       0.96      0.96      0.96     42658
```

(a) Confusion matrix – XGBoost Model (b) Testing results of XGBoost Model

Figure 8: Overall XGBoost results

Ensemble model: Figure 9(a) represents a confusion matrix. Figure 9(b) shows the models performance for test set with an accuracy of 0.96, MCC of 0.88, F1 Score as 0.96, Precision of 0.95 and Recall of 0.87.




```
Model performance for Test set
- Accuracy: 0.9608748652069952
- MCC: 0.8850868233779885
- F1 score: 0.9602398708610878
              precision    recall  f1-score   support

           0       0.96      0.99      0.98     33133
           1       0.95      0.87      0.91      9525

    accuracy                           0.96     42658
   macro avg       0.96      0.93      0.94     42658
weighted avg       0.96      0.96      0.96     42658
```

(a) Confusion matrix – Ensemble Model (b) Testing results of Ensemble Model

Figure 9: Overall Ensemble Model results

The Stack Model results after combing KNN, DT, MLP is shown in Table 1(a) and Ensemble Model results after combing LSTM, XGBoost is shown in Table 1(b). The Test Analysis of Stack Model and Ensemble Model in terms of Accuracy, MCC and F1-score in shown in Figure 10.

	Accuracy	MCC	F1
knn	0.944278	0.836634	0.943694
dt	0.942942	0.836421	0.943093
mlp	0.953584	0.863012	0.952323
stack	0.953866	0.864643	0.953307

	Accuracy	MCC	F1
lstm	0.960734	0.884581	0.959918
xgboost	0.959608	0.881347	0.958977
ensemble	0.960874	0.885086	0.960239

(a) Base Model 1: Stack Model Results (b) Base Model 2: Ensemble Model Results

Table 1: Stack Model vs Ensemble Model results

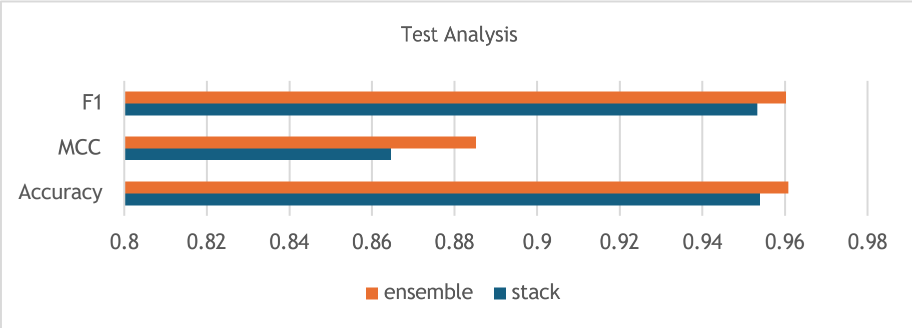


Figure 10: Test Analysis of Stack Model and Ensemble Model

Ensemble Model performs noticeably better than Stack Model by an accuracy of 0.9608, MCC of 0.8850, and F1-score of 0.9602 as shown in Table 2. But the Prediction time of Ensemble Model is higher than Stack Model as shown in Figure 11. These results show the effectiveness of Ensemble Model, in enhancing predictive accuracy and robustness in Weather prediction [68]-[69]-[70].

	Accuracy	**MCC**	**F1**	**Prediction Time**
stack	0.953866	0.864643	0.953307	395.273753s
ensemble	0.960874	0.885086	0.960239	1130.277192s

Table 2: Result comparison of Stack Model and Ensemble Model in terms of Accuracy, MCC, F1-score and Prediction Time

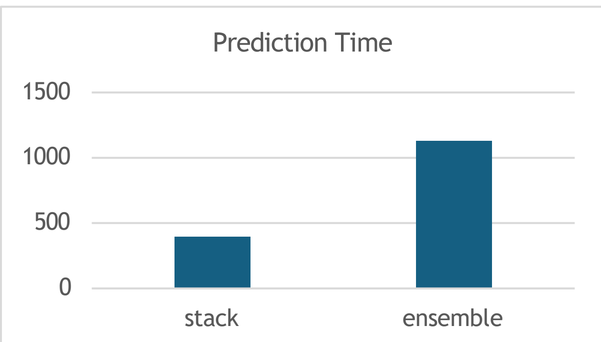


Figure 11: Prediction Time of Stack Model and Ensemble Model

5. Conclusion

Weather forecasting is the science of predicting atmospheric conditions based on data analysis. This study addresses the growing need for more accurate weather predictions to mitigate the impact of extreme weather events. The objectives include enhancing prediction accuracy using advanced machine learning models. The assessment models employed in this study are RFE, with Base Model 1 and Base Model 2. The Base Model 2 which combines LSTM and XGBoost using Ensemble Techniques improves the prediction performance compared to Base Model 1which combines KNN, DT and MLP. But at the cost of Prediction time which is higher for Base Model 2 compared to Base Model 1. The Ensemble model achieved an accuracy of 0.9608, MCC of 0.8850, and F1-score of 0.9602, indicating robust performance. Future research could explore further optimization and application to different geographical regions.

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