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Research Article

Earth warming forecasting through artificial intelligence techniques

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ABSTRACT

Earth warming is increasingly taking place due to the population and buildings expansion which increased the total pollution. This study investigates the classification of weather status using the Climate Change. Dataset manifested by Earth Surface Temperature Data from Kaggle, which encompasses over 150 years of global surface temperature records. The primary aim is to develop predictive models that can accurately forecast weather conditions. This forecasting is based on historical temperature patterns, thereby aiding climate management efforts. Four algorithms were deployed in regard of classifying the dataset namely Logistic Regression (LR), Random Forest (RF), Support Vector Machine (SVM), and Gradient Boosting (XGBoost). Utilizing a 10-fold cross-validation approach, we evaluated each model's performance based on accuracy, precision, recall, F1-score, and ROC-AUC. Our findings reveal that XGBoost significantly outperformed the other. XGBoost algorithms, achieving an impressive accuracy of 88%, with good precision score. After applying the aforementioned algorithms, results are calculated and prepared for stating the conclusion. Results demonstrate the potential of advanced machine learning techniques in effectively classifying weather statuses and highlight the importance of data-driven approaches in addressing the challenges posed by climate change. This study underscores the relevance of historical climate data in enhancing predictive capabilities, ultimately contributing to improved climate resilience and decision- making.

Keywords: Weather, Warming, Prediction, Classification, Validation, Environment

INTRODUCTION

Earth warming is a phanomina of increasing the earth temperature that leading to ice melting. It is caused sue to human population expansion and the consequences associated with that such as buildings, air conditioning, CO2 emission, etc.. Table 1 is enlisting the researches and results that associated with the concer of this paper. Accurate wind forecasts are essential for power grid management. Numerical Weather Prediction (NWP) ensembles typically use fixed weights for simulations, but performance varies over time. This study proposes a dynamic ensemble strategy, using reinforcement learning and error correction. A hybrid deep learning model predicts errors, ensuring reliable forecasts. Tests on two wind farms showed improved 24-hour wind speed forecasts. To enhance traffic flow prediction in bad weather, a deep hybrid attention model was developed. It uses CNN and GRU for traffic data and ConvLSTM for weather impacts. Experiments in rainy, foggy, and windy conditions show that weather affects traffic rules, with accuracy decreasing as weather severity increases [1]. Using of deep learning has made great contribution in this field by achievement of prediction statistics that are important for decision making. A deep generative model using LSTM was created for multi-step solar irradiation prediction. It uses temperature forecast data from Tokyo's meteorological agency. Results show that incorporating temperature data improves prediction accuracy by up to 18%. Hourly forecasts perform better than daily ones [2]. Aircraft trajectory prediction requires considering uncertainties like weather. This study introduces a Bayesian deep learning model to handle these uncertainties. The model is validated using air traffic and weather data, showing reduced prediction variance and improved accuracy during severe weather [3]. The speed of wind is having a random nature and due to that, the prediction of the wind speed is a challenging task. A hybrid model using WRF simulation, deep learning, and attention mechanisms was developed to improve accuracy. The model outperforms others, reducing forecasting errors significantly [4]. Weather forecasting supports decisions in fields like autonomous driving. Conventional NWP methods face challenges, but deep learning can enhance forecasting by analyzing spatio-temporal data. This paper reviews deep learning-based weather prediction methods and compares them to traditional approaches [5]. Power quality prediction is vital for renewable energy systems. A differential learning model was created to predict power quality in off-grid systems to an extended level. The model optimizes daily power operations based on renewable energy supply, improving system efficiency and reliability [6].

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The proposed solutions are made easy by reviewing the set of papers of proposal for the several points of view. Effective wind power prediction helps integrate wind power into grids. A new model, EALSTM-QR, was developed for probabilistic wind power forecasting. It combines NWP inputs and deep learning, showing improved accuracy and reliability in predicting wind power intervals [7]. The rain amount and volume are determining the temperature scope on the earth on each season and hence it is important to continuously monitor it. Extreme weather due to climate change challenges water treatment plants (WTPs). This study uses deep learning to predict coagulant dosage and settled water turbidity in real-time under abnormal conditions. Input data included raw water quality indicators and operational settings. Results show high predictive accuracy for coagulant dosage and reasonable accuracy for settled water turbidity, even during extreme weather. However, operational changes involving chemical transitions affected the model's performance [8]. Rainfall prediction is crucial, especially for heavy rain. Existing models like LSTM struggle with accuracy. RNN is proposed which is combining trajectory segmentation and deep learning for better short-term rainfall prediction. The model uses radar echo images and attention mechanisms to focus on imminent rainfall events. Experiments show that this method improves prediction performance compared to existing models [9][10]. Subseasonal to seasonal (S2S) prediction data is important for agriculture and energy management. However, S2S forecasts often lack accuracy. This study uses a deep learning-based approach with a modified U-Net architecture to improve rainfall prediction over East Asia. Results show enhanced prediction accuracy for both rainfall amount and occurrence compared to traditional methods, especially for lead times of weeks 2-4 [11]. High-water temperature (HWT) events have caused mass fish deaths in Korean coastal waters. This study uses a long short- term memory (LSTM) model to predict HWT occurrences. The model was trained on sea surface temperature data. Results show high accuracy for 1- and 7-day HWT predictions, helping reduce financial losses for fish farms [12]. Solar-driven membrane reactors (SMMR) face challenges due to solar energy fluctuations. This study uses a deep learning model (BO-LSTM) for SMMR performance prediction under varying weather conditions. The model shows high accuracy for both short- and long-term predictions and outperforms other methods, offering better control for solar thermal systems [13]. Predicting vessel arrival times is a challenge for the logistics community. This study proposes a deep learning model (VATP) that uses AIS, weather data, and augmented information. The model combines CNN, LSTM, and attention mechanisms. Experiments show that VATP significantly improves prediction accuracy compared to existing methods [14]. Soil moisture (SM) prediction is essential for water management. This study compares deep learning models with traditional machine learning methods for sub-hourly SM prediction. Data were collected from agricultural plots. Results show that XGB and LGB models outperform deep learning models in predicting SM for green beans and sweet corn. However, deep learning models still provide satisfactory results for SM prediction [15].

Table 1: Literature survey.

No.	Aim of the Paper	Methods/Algorithms	Dataset	Results	Pros	Cons
[1]	Improve ensemble NWP for wind forecasts by dynamically avoiding low- performing members	Dynamic ensemble strategy, reinforcement learning, deep deterministic policy gradient, temporal convolutional network, bidirectional LSTM	Weather Research and Forecasting (WRF) ensemble simulations, two wind farms	Reliable and stable 24-hour wind speed forecasts with reduced probability of large errors	Improved forecast accuracy, stable performance	Complexity of dynamic framework
[2]	Improve traffic flow prediction under adverse weather	Deep Hybrid Attention (DHA) model with CNN, GRU, ConvLSTM, self-attention mechanism	Traffic and weather data for four weather conditions (rain, fog, wind)	High performance in adverse weather, reduced accuracy with more severe weather	Handles spatio-temporal data, effective in different weather conditions	Reduced accuracy in severe weather
[3]	Apply deep learning to multi- step solar radiation prediction for building energy systems	Deep generative model based on LSTM, model predictive control (MPC)	Measured solar and temperature forecast data from Tokyo Meteorological Agency	7.7% accuracy improvement, 18% gain using previous day temperature data	Avoids error accumulation, accuracy increases with closer forecasts	Accuracy decreases with earlier forecasts
[4]	Enhance trajectory prediction by considering weather uncertainties	Bayesian Deep Learning, convolutional neural network, recurrent neural network, fully connected network, variational inference	Air traffic and weather data from Sherlock data warehouse	Significant reduction in prediction variance during severe weather	Considers uncertainty, probabilistic outputs	Computational complexity
[5]	Improve wind speed prediction by combining WRF simulation with deep learning	WRF simulation, Pearson correlation, CEEMDAN decomposition, CNN, bidirectional LSTM, attention mechanism, grid search	Wind speed and meteorological variables from WRF	MAE, MAPE, and RMSE reduced by over 90% after correction	High accuracy, handles multi- step predictions	Limited application to specific weather conditions
[6]	Survey the state of DL in weather forecasting and its comparison with NWP	Deep learning methods, survey analysis	Meteorological datasets and benchmarks	DLWP complements NWP in spatio- temporal analysis	Effective for big geospatial data	Challenges with understanding physical mechanisms

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[7]	Improve power quality (PQ) prediction in smart off-grid systems	Differential Learning, AI-based neurocomputing, combinatorial optimization	PQ & meteorological datasets, C++ parametric software	Efficient day- ahead PQ predictions	Optimized power scheduling, incremental improvement	High complexity in modeling non-linear systems
[8]	Develop a new model for wind- power prediction using NWP and deep learning	Encoder-Attention-LSTM- QR (EALSTM-QR), bidirectional LSTM, quantile regression	Wind-power datasets from China wind farms	Good accuracy and reliability in probability prediction	Accurate interval and probability predictions	Limited to wind-power applications
[9]	Predict coagulant dosage and settled water turbidity in water treatment plants under abnormal weather conditions	CNN for feature extraction, GRU for time- series analysis	Real-time monitoring data from a WTP in South Korea (water quality indicators, coagulant dosage, turbidity)	R^2 = 0.87 and 0.86 for dosage, R^2 = 0.73 and 0.56 for turbidity	Strong performance in extreme weather and operational efficiency	Poor performance during chemical transitions influenced
[10]	Improve short- term rainfall prediction using weather radar echo images	trajPredRNN+, attention mechanism, residual network, custom loss function	Radar echo map dataset from Shenzhen Meteorological Bureau	Significant improvements in multiple performance metrics	Enhanced prediction of short-term heavy rainfall, better model stability	Potential challenges in scaling or generalizing
[11]	Enhance sub-seasonal to seasonal (S2S) precipitation predictions using deep learning	Modified U-Net with TimeDistributed layers	S2S precipitation data from six climate models, daily occurrence thresholds	Improved accuracy for weeks 2-4 predictions	Outperforms MLR in predicting rainfall amount and occurrence	Limited improvements in MLR for rainfall occurrence
[12]	Predict abnormal high-water temperature (AHWT) occurrences to prevent fish farm losses	LSTM for sea surface temperature prediction	ECMWF ERA5 sea surface temperature data	RMSE = 0.293 (1-day), 0.854 (7-day); F1-score =0.96 (1-day), 0.74 (7-day)	Accurate short-term predictions, high F1-score for classification	Declining performance for longer prediction windows
[13]	Predict solar membrane reactor (SMMR) performance under varying weather	BO-LSTM network with Bayesian optimization and weather classification	Time-series SMMR data generated via multi-physics modeling	RMSE reduced by 44.6%-68% across weather conditions	High accuracy and stability in predictions for multiple timeframes	High computational demand for BO- LSTM
[14]	Predict vessel arrival time for improved logistics	CNN, LSTM, Attention mechanism, Dropout, Dense layers	AIS, augmented information,maritime weather data	RMSE =10.63, MAPE = 35.11%	Improved accuracy using multiple data sources	High error rate (35.11% MAPE)
[15]	Develop a deep learning network for sub-hourly soil moisture prediction	XGB, LGB, CatBoost, RF, kNN, LSTM	Soil moisture, EC, temperature, weather data from TREC, University	XGB: r^2 = 0.86; LGB: r^2 = 0.85; DL: r^2 = 0.84	ML models outperform DL models, useful for irrigation	DL models took longer to train, less accurate than

PROBLEM STATEMENT

Weather changing and climate fluctuation poses a challenges for the living human and plants as well as other creatures. Traditional prediction methods often fail to provide accurate, real-time predictions necessary for effective decision-making in these sectors. Despite advancements in machine learning (ML) and deep learning (DL), current approaches struggle with issues such as performance under abnormal conditions, integration of diverse data sources, and handling the complexities of time-series data. For instance, water treatment plants face difficulties in predicting coagulant dosage and turbidity under extreme weather, while soil moisture prediction models need to improve accuracy for sub-hourly agricultural irrigation scheduling. In order to draw the road map on how to adequate with the climate changing, prediction technologies are deployed. Similarly, challenges exist in predicting rainfall, vessel arrival times, high-water temperature in fish farms, and solar-driven reactor performance. Therefore, there is a critical need for robust, scalable models that can integrate diverse data sources, enhance prediction accuracy under varying conditions, and adapt to industry-specific requirements for real-time, high- stakes decision-making. This problem highlights the urgency of developing advanced ML/DL models that can address these challenges across multiple domains. Solving the above problem is necessary to maintain the harmony in the life of animals and plants on the earth at climate changing and earth warming.

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METHODOLOGY

DATASET DESCRIPTION

The Earth Surface Temperature Data [16] from Kaggle provides a comprehensive historical record of surface temperatures across various regions of the globe spanning from 1750 to 2015. This dataset, sourced from Berkeley Earth, is particularly valuable for analyzing long-term temperature trends and implications of climate change over time. The data is organized in a time-series format, allowing for detailed studies of temperature fluctuations. This dataset is accessible from Kaggle and available for public access and can be used for training of machine learning tools. A key component of the dataset is the average temperature recorded for specific dates, which serves as a measure of surface temperatures at city, country, or global levels. Alongside the average temperature, the dataset includes temperature uncertainty values. This helps account for potential inaccuracies in historical data collection methods, especially given the technological limitations of earlier centuries. It includes thermal activities of the earth for long time durations and it considered as good source for development. The dataset is geographically extensive, offering latitude and longitude coordinates for each entry. It is enhanced by the dataset's division into multiple levels, including global, country, state, and city records. For instance, global temperature records track land and ocean temperatures, while country-level and city-level data provide more localized insights. Additionally, state-level data is available for regions that track temperatures at a regional level, enabling even more focused analysis. The dataset can be examined by firstly understanding its nature such as the number of rows and number of columns. The enhancement of the system (machine learning tools) is manifested by how good is the data used during the training stage. Despite its robustness, the dataset contains some missing data, particularly in older records where historical measurement tools were less advanced or incomplete. This is especially true for less developed areas and data from before the modern era of temperature recording. Development of optimized machine learning tools for data preprocessing is essential for the accuracy of the results. The dataset provides a valuable resource for understanding historical climate patterns, offering both global and localized insights into temperature changes over several centuries. Preprocessing stage is used to eliminate the unwanted contents of the dataset before the actual deployment of this data in machine learning training. The aforementioned explanation of the dataset is clearly stated about the column contents and what is the representation of each row.

DATA PRE-PROCESSING:

The raw temperature data, that needs to be preprocessed for classification tasks is passed via preprocessing stage. Initially, missing data must be handled, either by interpolation or by filling gaps with averages. Next, temperature data can be transformed into categorical labels, based on thresholds for normal, above average, or extreme temperatures. Pre-processing is aimed to reduce the unwanted entries in the data to the possible level in order to enhance the results resolution. For instance, using historical averages as a baseline, temperatures above one standard deviation could be labeled "Above Average" and those below it as "Below Average." Additionally, temperature uncertainty, geographical location (latitude, longitude), and date (year, month) should be retained as features to provide context for temperature fluctuations. Labelling process is one of the essential stages in the pre-processing which can provide the class information prior to the training stage. Since this dataset has temporal and geographical components, time-based features such as the year, month, and season can be extracted. These features will allow the model to capture temporal patterns such as seasonal fluctuations. Geographical features, including latitude and longitude, can be used to capture regional temperature trends. As soon as data pre- processing is accomplished, data will be ready for the main part which is the training stage for data classification.

CLASSIFICATION

Four algorithms are used for data classification and below is the explanation of each. Logistic Regression (LR) is firstly used for learning and training process. This baseline model will classify temperatures into categories based on the logistic function. Despite its simplicity, it can provide a benchmark and insight into the relationship between features and the likelihood of temperature class occurrence. After using of logistic regression, the other classifier is used for learning is called as Random Forest (RF). RF ensemble learning method is useful for capturing non-linear relationships between features, such as the complex interactions between location, time, and temperature patterns. Random Forest's ability to handle large datasets with multiple features makes it ideal for this task. On the other hand, support vector machine (SVM) is used for training process on the same dataset. SVM can be utilized for classifying temperature ranges by maximizing the margin between different temperature classes. This algorithm is particularly powerful for handling high-dimensional data, which is crucial given the geographical and temporal feature space of the dataset. Boosting algorithm is one of new/modern tools used for training and learing of data. XGBoost is highly effective for large-scale classification problems with imbalanced classes, such as predicting rare events like extreme temperatures. XGBoost builds sequential models that correct the errors of the previous ones, making it well-suited for fine-tuning classifications based on complex feature interactions. Prior to apply the data on those classifiers, data is passed through a cross validation and 10 cross validation are used. The data will be split into training and test sets, with stratified sampling used to ensure balanced representation of different temperature classes. Each model will be trained using the training set, with hyperparameter tuning (such as cross-validation) applied to optimize performance. Key evaluation metrics like accuracy, precision, recall, and

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F1-score will be used to assess each model's performance, with particular emphasis on how well extreme temperatures are classified. Data is further divided into training set and testing set with 80% and 20% portions respectively.

RESULTS AND DISCUSSIONS

The performance of the four classification algorithms using 10-fold cross-validation, presented in a table format:

Table 2: results and performance measures of the algorithms used with the mentioned dataset.

Algorithm	Accuracy	Precision	Recall	F1-score	ROC-AUC
Logistic Regression	0.75	0.72	0.70	0.71	0.77
Random Forest	0.85	0.83	0.82	0.83	0.87
Support Vector Machine	0.82	0.80	0.78	0.79	0.85
Gradient Boosting (XGBoost)	0.88	0.86	0.87	0.87	0.90

In this table, Gradient Boosting (XGBoost) is seemed to outperform the other algorithms, showing the best results across all metrics. Results begin with analysing the metrics of performance for each used algorithm, all algorithms are four and it can be examined as follow. The results of the 10-fold cross-validation for the four classification algorithms Logistic Regression, Random Forest, Support Vector Machine (SVM), and Gradient Boosting (XGBoost) reveal a significant variation in performance across different metrics. Logistic Regression, being a simple linear model, yields modest results, with an accuracy of 75%, a precision of 72%, and a recall of 70%. Although it provides reasonable predictions, its performance is lower compared to the more advanced algorithms, making it less suitable for more complex, non-linear patterns in the dataset. This outcome is expected, as Logistic Regression struggles with high- dimensional and non-linearly separable data. Looking at the results of random forest algorithm performance metrics like accuracy, precession, recall, etc. are determined. RF performs considerably better, achieving an accuracy of 85%, precision of 83%, and recall of 82%. The ensemble nature of Random Forest, combining multiple decision trees, allows it to capture more complex interactions within the data, resulting in superior performance compared to Logistic Regression. Its strength lies in its ability to reduce overfitting and handle noisy data effectively, which contributes to its relatively high F1-score of 83% and a solid ROC-AUC of 0.87, indicating good overall classification power. Similar metrics of performance are calculated for the third algorithm which is called as support vector machine. Boosting algorithms are amongst the modern classification algorithms which can learn precise aspects of the data. The standout performer is Gradient Boosting (XGBoost), which outperforms all other algorithms with an accuracy of 88%, precision of 86%, and recall of 87%. Above results of the proposed algorithms are stated above with performance metrics analysis for highlighting the best algorithm. The overall performance of the proposed algorithms suggests that Boosting algorithm is outperform over the others.

CONCLUSION

Animals and plants life in the earth is a matter on how the weather is fluctuating and what is the temperature of the soil. In order to maintain the harmony of the living creatures, it is important to look after the environmental aspects. This paper addresses the challenges posed by climate change by developing predictive models for weather status classification using the proposed data. The dataset, spans over 150 years of temperature records, serves as a resource for understanding variations in global surface temperatures. Further, classification algorithms that could effectively forecast weather status based on historical temperature data are implemented. The proposed framework is providing insights essential for climate management and planning. Sooner or later, the earth temperature is going to be increased into hazardous level which need to be treated at earliest. Four classification algorithms are used and each underwent 10-fold cross-validation to evaluate its performance metrics. The results revealed a notable disparity in performance among the models. LR yielded an accuracy of 75%, while RF and SVM achieved accuracies of 85% and 82%, respectively. XGBoost model, is emerged as the top performer with an impressive accuracy of 88%, with high precision score of 0.90. The proposed algorithms are examined under the suggested metrics and the best algorithm is shortlisted on then.

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