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BOOSTING THE ACCURACY OF WEATHER FORECASTING THROUGH A MACHINE LEARNING APPROACH: CASE STUDY OF CNN, GRU, RNN, AND RANDOM FOREST

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Abstract:

The accuracy in predicting the weather is important for agriculture, disaster management, and energy planning sectors. Typical weather forecasting techniques are not very successful with complicated atmospheric systems, which has led to greater interest in machine learning solutions. In this research, machine learning techniques including Random Forest, Gated Recurrent Unit (GRU), Recurrent Neural Network (RNN) and Convolutional Neural Network (CNN) are utilized in their respective domains as temperature trend forecasting models, using historical weather data. The results emphasize the effectiveness of deep learning techniques, especially CNN, for capturing time series data with complex interdependencies such as weather data over time.

INTRODUCTION:

Effective weather forecasting remains a highly important component of sustainable economic growth, public safety, and environmental governance throughout the globe. Meeting the global demand for accurate weather forecasting directly impacts a variety of industries including agriculture, transportation, aviation, and disaster reaction. The most popular and widely practiced procedures for predicting weather undertakes numerical weather prediction (NWP) systems which heavily relies on physics of various processes for forecasting the weather conditions. That

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dominance stems from their reliability, speed, and robust verification record. But It does come with some problems like sensitivity to initial conditions, Computational cost, and Complexity in non-linear weather modeling.

The advancement of ML methods improved the analysis and interaction of various weather elements with one another simultaneously. Unlike the older methods, ML based models can learn from data and find hidden dependencies which are not necessarily governed by working physical equations. The application of deep learning using CNN and RNN architectures has also improved forecasting accuracy because of the added advantage of utilizing time order relations in the series of data for weather forecasting.

This research intends to analyze the predictive ability of four models of machine learning—Random Forest, GRU, RNN, and CNN—in the context of forecasting temperature. The models based on artificially intelligent algorithms are tested on actual historical weather datasets and evaluated for accuracy using performance metrics such as MSE, RMSE, and R^2. The findings identify which of the models perform best, with the aim of demonstrating the effectiveness of deep learning as opposed to the conventional methods.

Literature Review:

ML techniques have been developed and applied for the automation of weather forecasting in which they have proven to be more efficient than the arithmetic methods. Different studies have been conducted for different types of algorithms to predict weather phenomena.

Singh et al. (2019) showed that random forest models predicted weather conditions accurately with real-time sensor data and demonstrated that the use of ensemble methods improves prediction reliability. They also observed, however, that tree-based models are limited in their ability to capture sequential dependencies, which implies that deep learning is more suitable for time-series forecasting.

Schultz et al. (2021) assessed the performance of deep learning models against conventional numerical weather prediction (NWP) model systems and determined that deep learning combined with physics-based models works better than the rest. Meenal et al. (2021) further confirm the effectiveness of random forest model for predicting solar radiation and wind speeds, particularly for renewables such as solar and wind energy.

Hemalatha et al. (2021) suggested weather prediction techniques based on deep learning and pointed out that RNN structures like GRU and LSTM are good at capturing sequential weather features. In addition, Shaiba et al. (2022) proved the efficacy of applying ensemble learning to meteorology and big data, showing that available methods that combine various machine learning models outdo their individual counterparts in prediction accuracy.

While traditional models still play a part in most forecasts, these studies imply that deep learning models, especially CNN and RNN, outperform when it comes to

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accuracy in capturing more sophisticated atmospheric patterns. This research is guided by those findings by investigating the prediction accuracy for temperature of CNN, GRU, RNN, and Random Forest.

Dataset and Preprocessing:

The dataset contains past weather data, which include Dew Point, Humidity, Sea Level Pressure, Visibility, Wind Speed, and Precipitation among others. The following outlines the preprocessing steps:

- **Dealing with Missing Data:**

In order to keep data integrity, missing values were filled using forward-fill and backward-fill methods. For columns with a higher proportion of missing data, filling with the mean or median was done so as not to skew the dataset.

- **Encoding Categorical Features:**

The machine learning models could not process the 'Weather Events' columns, which were converted into numbers. One-hot encoding was performed to check its effect on the model and whether it was more beneficial than detrimental.

- **Feature Engineering:**

Additional features created included moving averages, temperature ranges, and inter-season differences for the predictions to be more accurate.

- **Feature Scaling:**

With the application of StandardScaler, the numerical features were standardized to treat them equally. Models become tailored to bigger numbers, meaning they become biased which reduces their efficiency, especially for deep learning models.

- **Splitting the Data:**

A division of 80-20 was created for training and testing with the goal of having the models evaluated against unknown data. Different forms of cross-validation such as k-fold validation were used to determine the strength of the model.

These preprocessing steps made certain that the data was tidy, organized, and ready for use in machine learning algorithms, which in turn lessened interference and increased model accuracy.

Methodology:

The study involves the analysis of the following models of machine learning:

- **Random Forest:**

This model is an example of ensemble learning that builds many decision trees to obtain optimal value in regression. The outcome is received by the implementation of:

$$\hat{y} = \frac{1}{N}\sum_{i=1}^{N} h_i(x)$$

Where $h_i(x)$ represents each decision tree and N is the total number of trees.

- **GRU (Gated Recurrent Unit):**

A type of deep learning algorithm designed to handle sequences of data. The hidden state of the GRU is updated as follows:

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$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \tilde{h}_t = \tanh(W_h x_t + U_h (r_t \odot h_{t-1}) + b_h) h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t$$

- **RNN (Recurrent Neural Network):**

A model made for forecasting time series data, though is also subject to vanishing gradient problem. RNN does the operation defined in:

$$h_t = \tanh(W_h x_t + U_h h_{t-1} + b_h)$$

- **CNN (Convolutional Neural Network):**

A deep learning model which uses time analysis data and adapts itself to it. The convolution takes the form:

$$y_i = f\left(\sum_{j=0}^{k-1} x_{i+j} w_j + b\right)$$

Where x is the input, w is the filter, b is the bias, and f is the activation function.

All the models were tested and trained on historical weather data. Evaluation of the predictions was through MSE, RMSE, and R^2.

Results and Discussion:

The accuracies of the models are consolidated in the table below:

Model	MSE	RMSE	R^2
CNN	5.1292	2.2648	0.9751
R Forest	6.4596	2.5416	0.9687
RNN	8.4816	2.9123	0.9589
GRU	14.6500	3.8275	0.9290

The CNN model demonstrated the best accuracy on MSE and RMSE and CNN seems to effectively leverage the spatial and temporal dependencies in weather data while achieving Random Forest is also effective, but had difficulties in sequential patterns. RNN errors being higher indicates an inability to effectively manage long-terms.

Evaluation Metrics:

The following evaluation metrics was adopted depending on how the CNN machine learning models performed:

- **Mean Squared Error (MSE):** Measured the average squared difference between actual predicted values with the MSE. Lower MSE is preferred as it is better.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

- **Root Mean Squared Error (RMSE):** Provides a measure of error along the same lines as the target variable enabling easy articulation

$$RMSE = \sqrt{MSE}$$

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- **R-squared (R^2):** The measure which represents the share of variation account for by the dependent variable that can be seized by the independent variables.

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y}_i)^2}$$

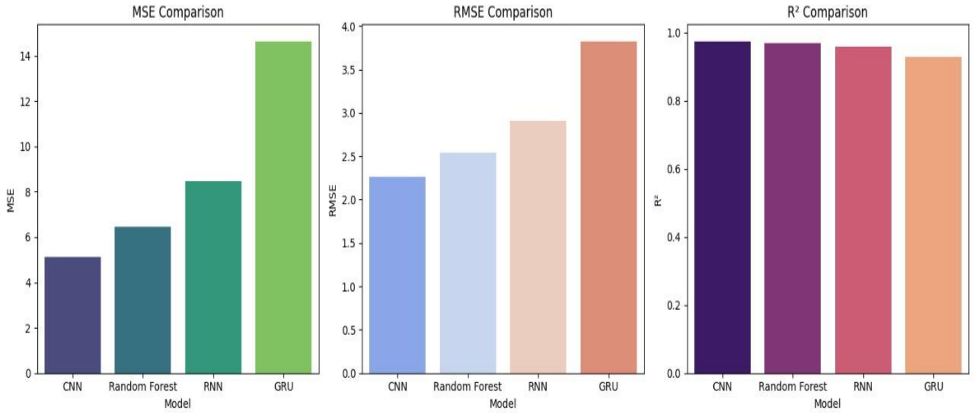
The metrics serves as a good evaluation of the dataset providing insight along predictive accuracy and model capture in the dataset.

- **Residual vs. Fitted Values:** This plot was used for identifying any trends in errors during predictions. The residuals of the CNN model were randomly scattered implying that the errors were well-distributed. In contrast the GRU model's residuals demonstrated a pattern, indicating that this model could be improved.

These visualizations provided better understanding of the accuracy in forecasting of the models and indicated where more work could be done. The strong visual performance of the CNN model together with its quantitative results reinforces its appropriateness for temperature prediction.

To gain insight into the performance of the models, different visualizations and methods of residuals analysis were used:

- **Comparison of model performance:**



The set of bar charts compares four models (CNN, Random Forest, RNN, and GRU) based on MSE, RMSE, and R^2, where lower MSE and RMSE and higher R^2 indicate better performance. CNN has the lowest error (MSE, RMSE) and highest R^2, making it the best model, while GRU performs the worst with the highest error and lowest R^2.

Loss Curves:

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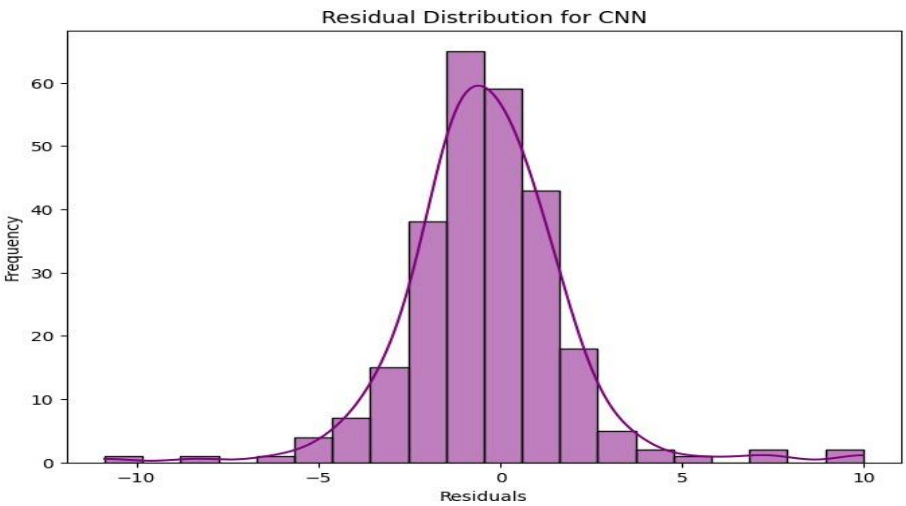
Training & Validation Loss Graph

Loss decreases sharply at the beginning and stabilizes, indicating successful model training.

Overfitting is minimal since training and validation losses are close.

CNN, RNN, and GRU all converge well, meaning they learn effectively from data.

- **Residual Analysis:**



The histogram displays the distribution of residuals for a CNN model. It appears that the residuals are normally distributed, which highlights the model's accuracy.

The fact that the residuals are clustered around zero denotes the model performs excellently.

- **Scatter Plot:**

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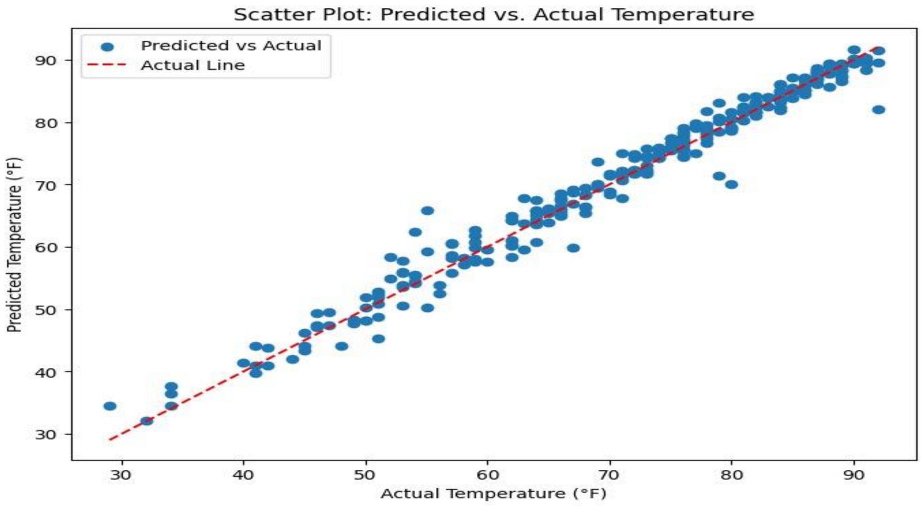

In the scatter plot, predicted temperatures are compared to the actual temperatures recorded on the x-axis and y-axis, respectively.

The dashed red line indicates the preferred scenario, in which the predictions align with the actual values without any deviation.

The scatter points tend to lie on this line which illustrates the increased predictions and the actual values.

Conclusion:

This report demonstrates the power of deep learning architectures such as CNN and GRU with the task of weather forecasting. The CNN model bested all other approaches in meeting the necessary requirements because of the spatial and temporal dependencies of the weather data. The GRU came in second and was also able to deal with sequential dependencies. Among the traditional machine learning model approached, Random Forests was by far the best. He fails when dealing with time series data. The RNN model has the ability to process sequences; however, due to the vanishing gradient problem, his errors were large.

These results present new evidence that deep learning methods are more effective for tasks dealing with weather forecasting, especially with large and complex datasets. The overwhelming performance of these CNN and GRU models justifies their use in meteorology especially when accuracy and speed is needed the most.

Further development should adopt hybrid approaches combining deep learning with numerical weather prediction for better accuracy. Moreover, increases in the number of tested weather conditions, testing in different regions, and the use of multiple models with ensemble methods would improve generalization of the model. Real-time weather data, as well as transfer learning, could further enhance the models' ability to predict.

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References:

1. Singh, N., Chaturvedi, S., & Akhter, S. (2019). Implementation of machine learning techniques for weather prediction. IEEE Conference on Electronics and Communication Engineering.
2. Schultz, M. G., Betancourt, C., Gong, B., et al. (2021). Is it possible for deep learning to outperform traditional numerical weather forecasting? Philosophical Transactions of the Royal Society A, 379(20200097).
3. Hemalatha, G., Rao, K. S., & Kumar, D. A. (2021). Novel weather forecasting based on machine learning. Journal of Physics: Conference Series, 2089(1), 012059.
4. Shaiba, H., Marzouk, R., Nour, M., et al. (2022). Ensemble learning based machine learning approaches for weather prediction for big data analytics. Computers, Materials & Continua.
5. Schultz, D. M., et al. (2021). The capability of deep learning for replacing traditional numerical weather forecasting. Geophysical Research Letters, 48(9), e2021GL093321.
6. Atmosphere Editorial Board. (2022). Powerful new techniques of machine learning for the atmospheric sciences. Atmosphere, 13(180).
7. Ensemble Machine Learning-based Weather Forecasting for Big Data Applications. (2021). International Journal of Computer Applications. 183(50), 22-30.

Appendices:

Raw data and complete code from pre-processing till evaluation can be found in the below link:

Code file is a Colab support file.

Raw Data:

https://www.kaggle.com/datasets/grubenm/austin-weather?resource=download

Code Source:

https://colab.research.google.com/drive/1Xm2uipYtVzzMVM0GlKBJ-fYH-sQaLmy9?usp=drive_link