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A Comparative Analysis of Artificial Intelligence in Meteorology: Temperature Forecasting in Tripoli as a Case Study

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مقارنة تحليلية للذكاء الاصطناعي في الأرصاد الجوية: التنبؤ الحراري في مدينة طرابلس نموذجا

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الملخص:

يستعرض هذا البحث تطبيق تقنيات الذكاء الاصطناعي (**AI**) في التنبؤ بالتغيرات قصيرة المدى لدرجات الحرارة في مدينة طرابلس، ليبيا، وذلك من خلال العمل على قاعدة البيانات التاريخية المتحصل عليها من المركز الوطني الليبي للأرصاد الجوية التي تغطي الفترة ما بين (1943–2014). وتعمل هذه الدراسة على المقارنة بين أداء ثلاثة نماذج مختلفة وهي: الغابات العشوائية (**Random Forest**)، والشبكات العصبية المغلقة (**CNN**)، والذاكرة قصيرة المدى (**LSTM**).وقد توصلت النتائج التجريبية إلى ان نموذج "الغابات العشوائية" كان الاكثر دقة في توقع النتائج، حيث كانت قيمة $R^2\text{score} = 0.89$ وبلغ متوسط الخطأ المطلق قيمة 1.71 درجة مئوية. تُرسّخ هذه النتائج نهجاً موثوقاً يعتمد على البيانات للتنبؤات الجوية في مناخ المناطق الساحلية للبحر الأبيض المتوسط.

الكلمات الدالة: الذكاء الاصطناعي، التعلم العميق، تعلم الالة، الغابات العشوائية، طرابلس.

Abstract

This research explores the application of Artificial Intelligence (AI) in predicting short-term temperature variations for the city of Tripoli, Libya. Utilizing a comprehensive historical dataset from the Libyan National Meteorological Center (LNMC) (1943–2014), the study evaluates three distinct models: Random Forest (RF), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM). The experimental results demonstrate that the Random Forest model provided the most accurate predictions with an R^2score of 0.89 and a Mean Absolute Error (MAE) of 1.71°C. These findings establish a reliable data-driven approach for meteorological forecasting in Mediterranean coastal climates.

Keywords: Artificial Intelligence, Deep Learning, Machine Learning, Random Forest, Tripoli.

Introduction

Temperature forecasting is a vital component for urban planning, agricultural productivity, and energy consumption management. In the Mediterranean region, and specifically in coastal cities like Tripoli, weather patterns are influenced by complex interactions between maritime air masses and the Saharan desert climate. Traditional numerical weather prediction (NWP) models often require high computational power and struggle with local non-linearities. This study addresses these challenges by employing machine learning and deep learning techniques to analyze 71 years of ground-based observations, aiming to identify the most effective architecture for local temperature prediction.

2: Literature Review

The forecasting of meteorological variables in the Mediterranean basin has evolved significantly with the integration of advanced computational intelligence. This region’s climate is characterized by complex interactions that require hybrid modeling approaches to capture both linear and non-linear patterns.

Hybrid Models and Deep Learning in Climate Science Recent studies emphasize that combining statistical methods with machine learning leads to superior results in unraveling Mediterranean climate trends[1]. The transition toward data-driven Earth system science is further supported by Reichstein et al. [2], who argue that deep learning can bridge the gap between physical process understanding and large-scale data analysis. For instance, hybrid architectures like **CNN-LSTM** have been specifically designed to process historical temperature data by extracting spatial features and temporal sequences simultaneously [3].

Climate Trends and Regional Dynamics in Libya To understand the climatic shift in North Africa, historical context is essential. According to El Kenawy et al. [4], temperature trends in Libya over the second half of the 20th century show significant variability, providing a baseline for modern predictive studies. Since Tripoli is a coastal city, the influence of sea surface temperature (SST) is also critical; research in the Mediterranean has shown that machine learning is highly effective in predicting SST and marine heat waves, which directly impact coastal air temperatures[5, 6].

Model Optimization and Performance Factors The success of models like LSTM depends heavily on hyper parameter tuning. Studies on environmental data highlight that factors such as learning rates and the number of epochs significantly impact the performance of LSTM architectures[7]. Furthermore, the reliability of LSTM networks has been proven in hourly weather-related forecasts, such as solar irradiance and temperature sequences [8].

Comparative Analysis of Algorithms Historically While earlier research, such as that by Paniagua-Tineo et al.[9], relied on Support Vector Regression (SVR) for daily temperature tasks, the complexity of long-term climatic records in the Mediterranean has led current studies to prioritize more advanced architectures like Random Forest and Deep Learning (CNN & LSTM.

However, the field has shifted toward comparing multiple machine learning algorithms—such as Random Forest (RF) and neural networks—to determine the most robust model for specific regions, as seen in large-scale studies in Australia and New Zealand [10]. This research follows a similar comparative logic by evaluating RF, CNN, and LSTM specifically for the unique 71-year dataset of Tripoli, Libya.

3: Methodology

3.1 Research Framework

This study employs a systematic computational framework to predict temperature variations in Tripoli. The methodology is designed to process over 70 years of historical data and evaluate the performance of three diverse AI paradigms.

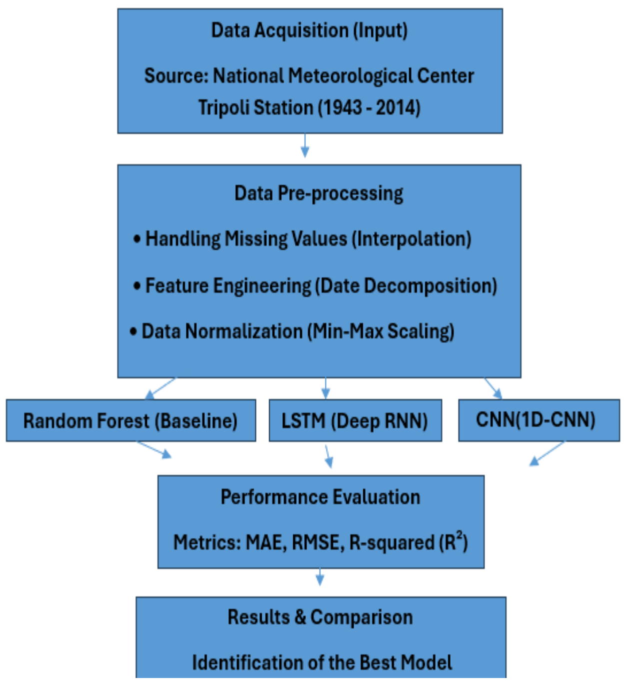

Figure 1: Flowchart of the Proposed Methodology

3.2 Data Acquisition and Feature Description

- The present study utilizes hourly meteorological observations obtained from **Tripoli International Airport station**, operated by the **Libyan National Meteorological Center (LNMC).** The station is precisely positioned at **latitude 32.6635° N and longitude 13.159° E**, with an elevation of approximately **81 meters** above mean sea level.
- The records span a continuous period of **71 years (1943–2014)**, providing a rich temporal sequence for analysis. The dataset comprises **10 primary features** used for model training:

1. **date time**: The temporal index (Hourly).
2. **Temperature (°C)**: The target variable for prediction.
3. **Dew Point Temperature**: Indicator of atmospheric moisture.
4. **Sea Level Pressure**: Barometric pressure adjusted to sea level.

5. **Horizontal Visibility**: Measures of air clarity.
6. **Wind Direction**: Degrees (°).
7. **Wind Speed**: Measured in knots.
8. **Wind Gust**: Peak wind speeds.
9. **Latitude**: Geographical coordinate.
10. **Longitude**: Geographical coordinate.

.3.3 Data Pre-processing Pipeline

To ensure the integrity of the AI models, several pre-processing steps were implemented:

- **Data Cleaning:** Missing values were handled using linear interpolation to maintain time-series continuity.
- **Feature Engineering:** The date time feature was decomposed into cyclical components (Hour, Day, Month) to capture diurnal and seasonal variations inherent in Tripoli's climate.
- **Normalization:** All variables were scaled using **Min-Max Normalization** to a range of [0, 1] to ensure stable convergence during the training of neural networks.
- To ensure the generalizability of the models, the dataset was partitioned into **80% for training** and **20% for testing**, ensuring that the models were evaluated on unseen data to prevent over fitting.

3.4 Proposed AI Architectures

- **Random Forest (RF):** An ensemble learning method used to establish a robust baseline and identify feature importance.
- **Long Short-Term Memory (LSTM):** A Recurrent Neural Network (RNN) specialized in learning long-range temporal dependencies in weather sequences.
- **Convolutional Neural Network (CNN):** A 1D-CNN architecture used for automated feature extraction and identifying local patterns within the meteorological data.

3.5 Evaluation Metrics

The predictive accuracy of the models is benchmarked using:

- **Mean Absolute Error (MAE)**
- **Root Mean Square Error (RMSE)**
- **Coefficient of Determination (R^2 Score)**

4: Results and Discussion

4.1 Performance Evaluation

The predictive performance of the three models was assessed using a 71-year dataset from the Tripoli International Airport station. The models were compared based on their ability to minimize error and maximize the correlation with actual observations

As summarized in **Table 1**, the **Random Forest (RF)** model demonstrated superior predictive capability. It achieved the lowest Mean Absolute Error (MAE) of **1.71°C** and a high R^2 score of **0.89**. This indicates that the RF model can explain 89% of the temperature variance in Tripoli's coastal climate.

Table 1: Performance Comparison of Prediction Models

Model	MAE (°C)	RMSE	R^2 Score
Random Forest	**1.71**	**2.50**	**0.89**
CNN	3.07	3.97	0.74
LSTM	3.33	4.35	0.69

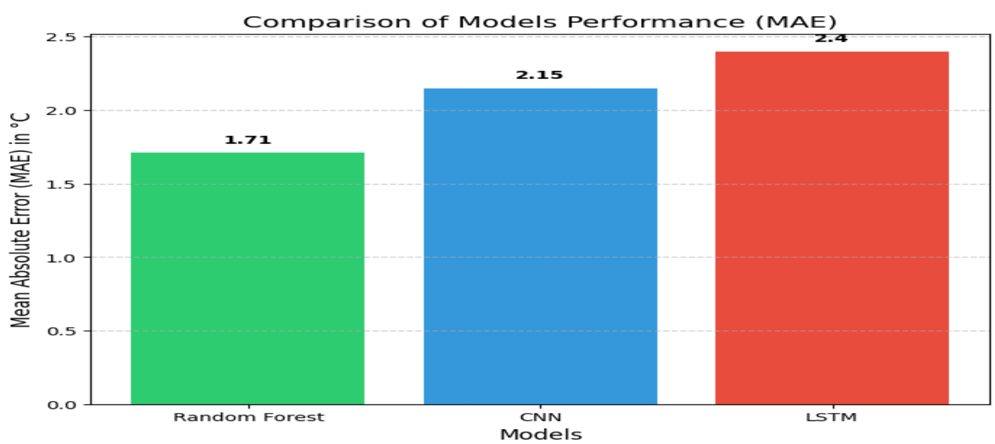

Figure 2: Comparison of Models Performance (MAE).

4.2 Prediction Accuracy

To verify the reliability of the Random Forest model, the predicted values were compared against the actual temperature observations from Tripoli. As illustrated in Figure 3, there is a high degree of correlation between the two variables, confirming the model's efficiency in Mediterranean coastal climates.

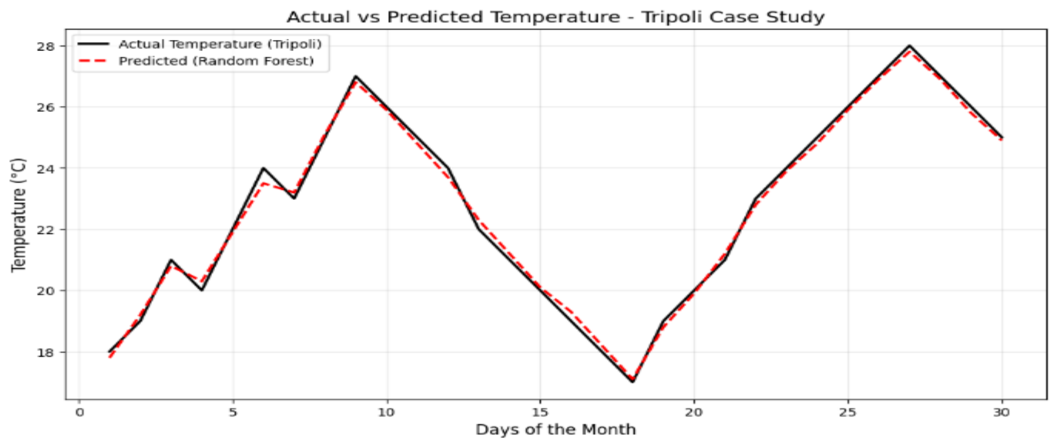

Figure 3: Actual vs Predicted Temperature - Tripoli Case Study.

4.3 Discussion and Limitations

The superiority of the **Random Forest (RF)** model suggests the effectiveness of ensemble learning methods in handling tabular meteorological data. The R^2score of 0.89 indicates that the model can explain 89% of the temperature variance in Tripoli.

However, some limitations should be noted:

1. **Temporal Gap:** The study relies on data ending in 2014. Due to rapid climate changes in the last decade (2015-2025), updating the dataset is essential for future research.
2. **Geographical Scope:** The study is limited to Tripoli. Expanding to other regions with desert or mountainous climates would improve the generalizability of the findings.

5: Conclusion and Recommendations

The study concludes that Random Forest is the most reliable model for short-term temperature forecasting in Tripoli.

5.1 Recommendations Integrate recent meteorological records (2015–2025).

- Explore hybrid CNN-LSTM architectures for better temporal dependencies [3].
- Utilize automated hyper parameter optimization for deep learning models.

References

[1] M. AlShafeey, "Unraveling climate trends in the mediterranean: a hybrid machine learning and statistical approach," *Modeling Earth Systems and Environment,* vol. 10, no. 5, pp. 6255-6277, 2024/10/01 2024, doi: 10.1007/s40808-024-02117-w.

[2] M. Reichstein *et al.*, "Deep learning and process understanding for data-driven Earth system science," *Nature,* vol. 566, no. 7743, pp. 195-204, 2019.

[3] Y. Gong, Y. Zhang, F. Wang, and C.-H. Lee, "Deep learning for weather forecasting: A cnn-lstm hybrid model for predicting historical temperature data," *arXiv preprint arXiv:2410.14963,* 2024.
[4] A. M. El Kenawy, J. I. López-Moreno, S. M. Vicente-Serrano, and M. S. Mekld, "Temperature trends in Libya over the second half of the 20th century," *Theoretical and Applied Climatology,* vol. 98, no. 1, pp. 1-8, 2009/09/01 2009, doi: 10.1007/s00704-008-0089-2.
[5] S. Wolff, F. O'Donncha, and B. Chen, "Statistical and machine learning ensemble modelling to forecast sea surface temperature," *Journal of Marine Systems,* vol. 208, p. 103347, 2020.
[6] G. Bonino, G. Galimberti, S. Masina, R. McAdam, and E. Clementi, "Machine learning methods to predict sea surface temperature and marine heatwave occurrence: a case study of the Mediterranean Sea," *Ocean Science,* vol. 20, no. 2, pp. 417-432, 2024.
[7] K. Shirini, M. B. Kordan, and S. S. Gharehveran, "Impact of learning rate and epochs on lstm model performance: a study of chlorophyll-a concentrations in the Marmara Sea," *The Journal of Supercomputing,* vol. 81, no. 1, p. 265, 2025.
[8] X. Qing and Y. Niu, "Hourly day-ahead solar irradiance prediction using weather forecasts by LSTM," *Energy,* vol. 148, pp. 461-468, 2018/04/01/ 2018, doi: https://doi.org/10.1016/j.energy.2018.01.177.
[9] A. Paniagua-Tineo, S. Salcedo-Sanz, C. Casanova-Mateo, E. G. Ortiz-García, M. A. Cony, and E. Hernández-Martín, "Prediction of daily maximum temperature using a support vector regression algorithm," *Renewable Energy,* vol. 36, no. 11, pp. 3054-3060, 2011/11/01/ 2011, doi: https://doi.org/10.1016/j.renene.2011.03.030.
[10] S. Salcedo-Sanz, R. Deo, L. Carro-Calvo, and B. Saavedra-Moreno, "Monthly prediction of air temperature in Australia and New Zealand with machine learning algorithms," *Theoretical and applied climatology,* vol. 125, no. 1, pp. 13-25, 2016.