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Towards A Smart City Concept - Machine Learning Smarts for the Estimation of Future Temperature Rise in Tabuk City

Eman Khaled Albalawi
Spatial Science Department of Geography, Umm Al-Qura
University, Makkah, Saudi Arabia.

Abstract:

In the Middle Eastern peninsula especially in Saudi Arabia, there is a varsity temperature variation among the individual regions. As far as the city of Tabuk is concerned, no study has been conducted, regarding climate change (the temperature rise) in the Tabuk region and its implications on society and for the flagship "Future Smart Cities" concept. In this paper, machine learning algorithms are used to predict the future temperature values in the Tabuk region. The machine learning algorithms were trained on the data collected from the real-time weather radar stations of the region. Different features from the dataset are used for machine learning models to predict the future temperature. These unique features, for example, humidity and pressure, impact the accurate predictability of the temperature. Temperature prediction is modelled as a regression problem due to the nature of the data, therefore, different machine learning regression models were developed, i.e., Multi-layer Perceptron (MLP) or Artificial Neural Network (ANN), Decision Trees (DT), K-Nearest Neighbours (KNN), and Support Vector Regression (SVR). The preliminary results shown in this paper are encouraging and produced 90% accuracy on the testing dataset. We envisage that the findings will inform decision-makers of the Climate and Weather Ministry of Tabuk City, eventually providing a step towards the Smart City's Concept in Future.

Keywords: Temperature prediction, Climate change, Machine learning, Smart cities.

Introduction:

Vision 2030, the transformative blueprint for Saudi Arabia's future, paints a vibrant picture of sustainable and resilient urban environments. Smart cities, powered by innovative technologies, stand as pivotal elements in realizing this vision, offering solutions to pressing challenges that are particularly acute in arid regions like the Kingdom. One such challenge - accurately predicting future temperature variations - assumes paramount importance due to the escalating global phenomenon of climate change.

Arid regions like Tabuk City, with its scorching summers and low precipitation, are especially vulnerable to the adverse effects of rising temperatures. Increased heat stress, water scarcity, and detrimental impacts on infrastructure and ecosystems pose significant threats to the city's well-being. Recognizing this urgency, Saudi Arabia is pioneering innovative climate resilience and mitigation strategies within its smart city initiatives. Saudi Arabia's commitment to smart city development, coupled with its focus on innovation and technological advancements, positions it at the forefront of utilizing machine learning for temperature prediction. The successful implementation of such initiatives holds the potential to not only safeguard its cities from the detrimental effects of rising temperatures but also offer valuable lessons and best practices for other arid regions grappling with similar challenges.

Machine learning has become a promising method for time-series prediction like temperature prediction (Gulrez, T. (2021), Poh, C. et al. (2021, March)). By harnessing the power of historical weather data and incorporating relevant contextual factors, sophisticated algorithms can be trained to deliver accurate predictions of future temperature variations. This study paves the way for robust and accurate temperature predictions, informing critical decision-making towards building a resilient and climate-smart future for Tabuk. The selection of the most suitable model for temperature prediction in Tabuk will depend on factors like data complexity, interpretability needs, and computational resources. Evaluating the performance of these algorithms based on metrics like mean-squared error and R-squared will provide valuable insights into their effectiveness in this specific context.

Machine Learning Model Development:

Popular machine learning models for temperature prediction include Regression-based models (Linear Regression, Decision Trees, Random Forests), Time Series models (ARIMA, LSTM, GRU), Support Vector Machines (SVM), and ensemble methods. In this paper, we have developed an ensemble machine learning model which incorporates the effect of all machine learning algorithms and in the end produces an ideal model for the prediction tasks.

In this work a data driven model was developed while utilising the features of the historic climate dataset e.g. a classical Multi-layer perceptron (MLP) or an Artificial Neural Network (ANN). The efficacy of ANNs for temperature prediction is bolstered by several empirical studies including, Gulrez, T., et al. (2023, March), Culpepper, J. B., & Gulrez, T. (2023, October) conducted a comparative analysis, testing ANN architectures – alongside the traditionally employed Multi-Layer Perceptron (MLP) regression. Their findings revealed firstly possibility of MLP as multi-input multi-output and notable improvements in predictive accuracy achieved by the ANN models compared to MLP, highlighting the potential of these non-linear approaches for capturing complex relationships within different datasets. Similar to a study by Azari et al. (2022), who investigated temperature prediction in the southern region of Memphis, Tennessee, USA. They conducted a comparative evaluation of five algorithms: Linear Regression (L.R.), Support Vector Machine (SVM), k-nearest Neighbour (kNN), Adaptive Boosting (AdB), and Random Forest (R.F.). Notably, the Artificial Neural Network outperformed all other methods, demonstrating its superior ability to learn and model the intricacies of temperature variations in this specific context.

Although standalone machine learning algorithms offer valuable tools for temperature prediction, the quest for enhanced accuracy compels researchers to explore beyond their capabilities. Hybrid models, which synergistically combine multiple machine learning algorithms or seamlessly integrate them with physical models, therefore, have emerged as a promising avenue (Hou et al., 2022). Their appeal lies in their ability to leverage the strengths of diverse approaches, potentially overcoming the limitations inherent in individual models (Moosavia et al., 2020). Moreover, along side ensembling of machine learning methods, the time is ripe to introduce machine learning models which require less data. This new approach could be derived from psychophysics or psychology e.g. Perceptual control architecture as proposed by Marken, R., et al. (2022), Gulrez, T., et al. (2022) and Kavaliauskaitė, D. et al. (2023).

Uncertainty and Confidence Intervals:

The importance of incorporating uncertainty quantification into temperature predictions has been increasingly recognized amidst advancements in forecasting methodologies (e.g., Gulrez, T., et al. (2007, June)). This shift stems from a growing awareness of the limitations inherent in point estimates, which fail to account for the inherent variability and unpredictable nature of future climate scenarios. To address this crucial need, researchers have developed sophisticated techniques for generating confidence intervals and uncertainty estimates that provide valuable insights into the reliability and range of potential outcomes associated with a given prediction. Uncertainty quantification also fosters continuous model improvement. By meticulously analyzing situations where predicted temperatures fall outside the established confidence interval, researchers can pinpoint potential weaknesses in their models and refine their methodologies. This iterative process paves the way for the development of ever-more reliable and robust temperature prediction models, enhancing our ability to navigate the complexities of a dynamic climate system.

The primary objective is to identify a robust and efficient weather forecasting model capable of generating highly accurate temperature predictions. To achieve this, we will leverage a diverse set of associative machine learning algorithms, including Artificial Neural Network (ANN), Decision Trees (DT), K-Nearest Neighbours (KNN), and Support Vector Regression (SVR). By meticulously applying these algorithms to relevant climate data, we aim to conduct a comprehensive comparative analysis of their effectiveness in predicting future temperature variations in Tabuk. Ultimately, this analysis will culminate in the selection of the algorithm that delivers the best overall performance, paving the way for the development of a more powerful and accurate weather forecasting model for Tabuk City.

Methodology:

The Tabuk region is situated in north-west Saudi Arabia, Geographically, the region is defined by coordinates spanning from 28°23' to 28°39' north latitude and 36°35' to 36°57' east longitude.

Data sourced from the General Presidency of Meteorology and Environment Protection, of Tabuk meteorological station (ID 40375) (Figure 1). The dataset encompasses daily observations of various temperature variables, offering a comprehensive record of the region's climatic fluctuations. To leverage this rich data source for enhanced temperature prediction, we employ a rigorous machine learning approach.

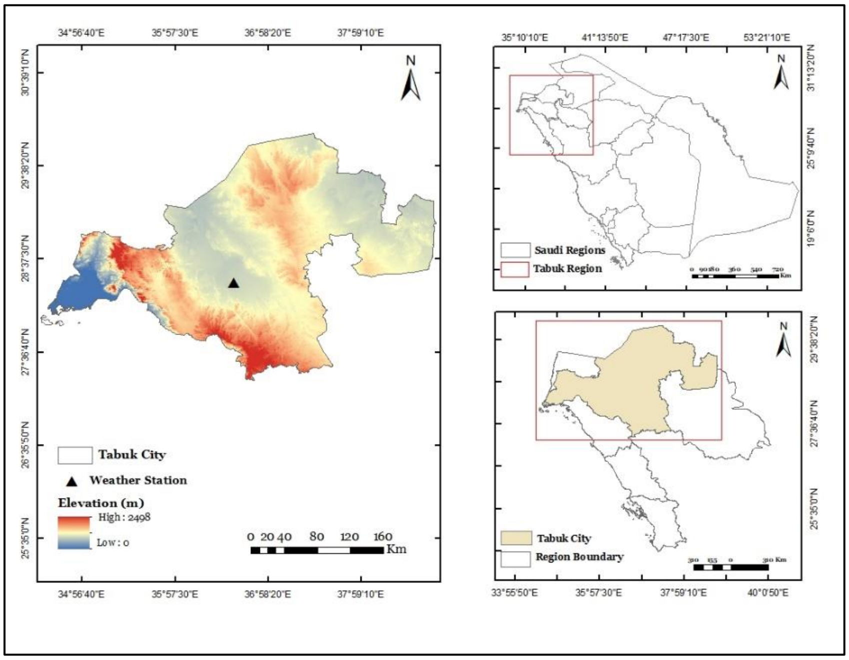

Figure 1. A map of the Tabuk region and weather station was chosen for temperature prediction.

Data Preparation:

In any machine learning project, the quality of the output crucially relies on the initial step: data pre-processing. This is where we ensure the data's validity and accuracy, laying a solid foundation for subsequent analyses. In this case, our dataset consists of key parameters like pressure, wind direction, and humidity, all relevant to the prediction task. Particularly, including additional information like humid wind vapour could further enhance the model's performance. However, it's equally important to identify and remove irrelevant features, a process called feature selection, to prevent overfitting and improve efficiency. To achieve this balance, Principal Component Analysis (PCA) was employed (as shown in Gulrez, T., et al. (2014)). By reducing the data's dimensionality while preserving its informative essence, PCA allows to streamline processing time and boosts the algorithm's effectiveness.

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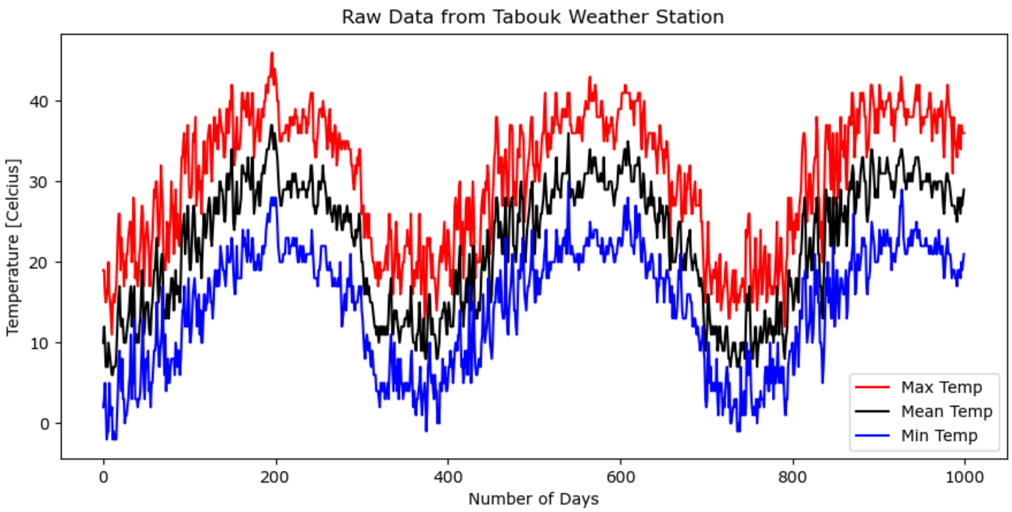

Figure 2. Tabuk Temperature (°C) Data Sample: First 1000 Days of Daily Max, Mean, and Min Values.

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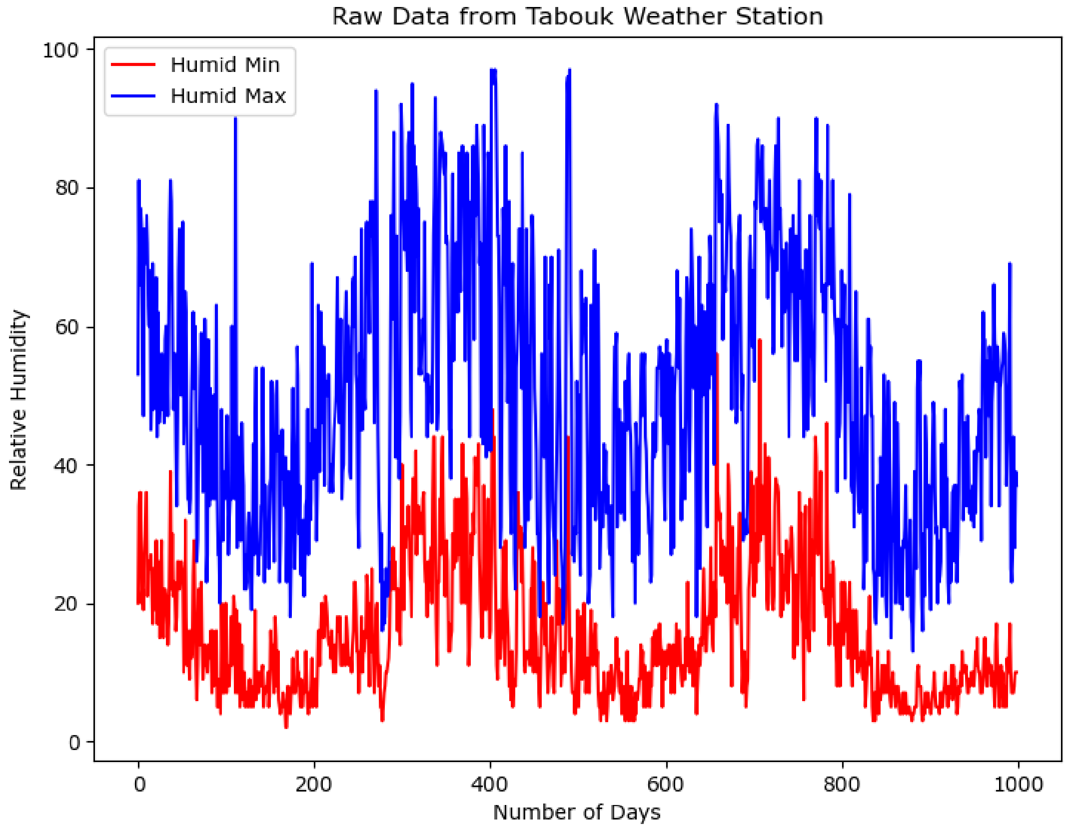
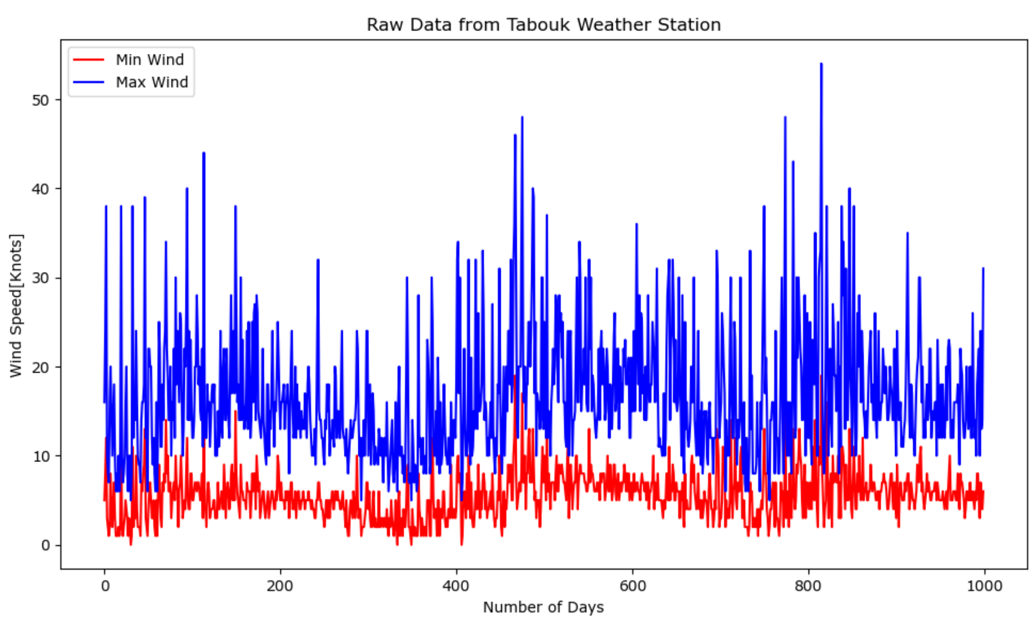
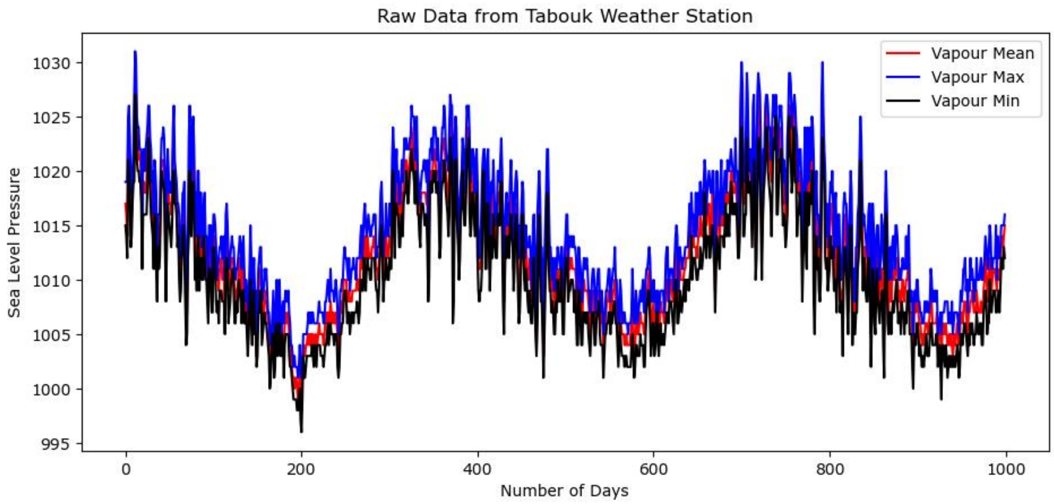
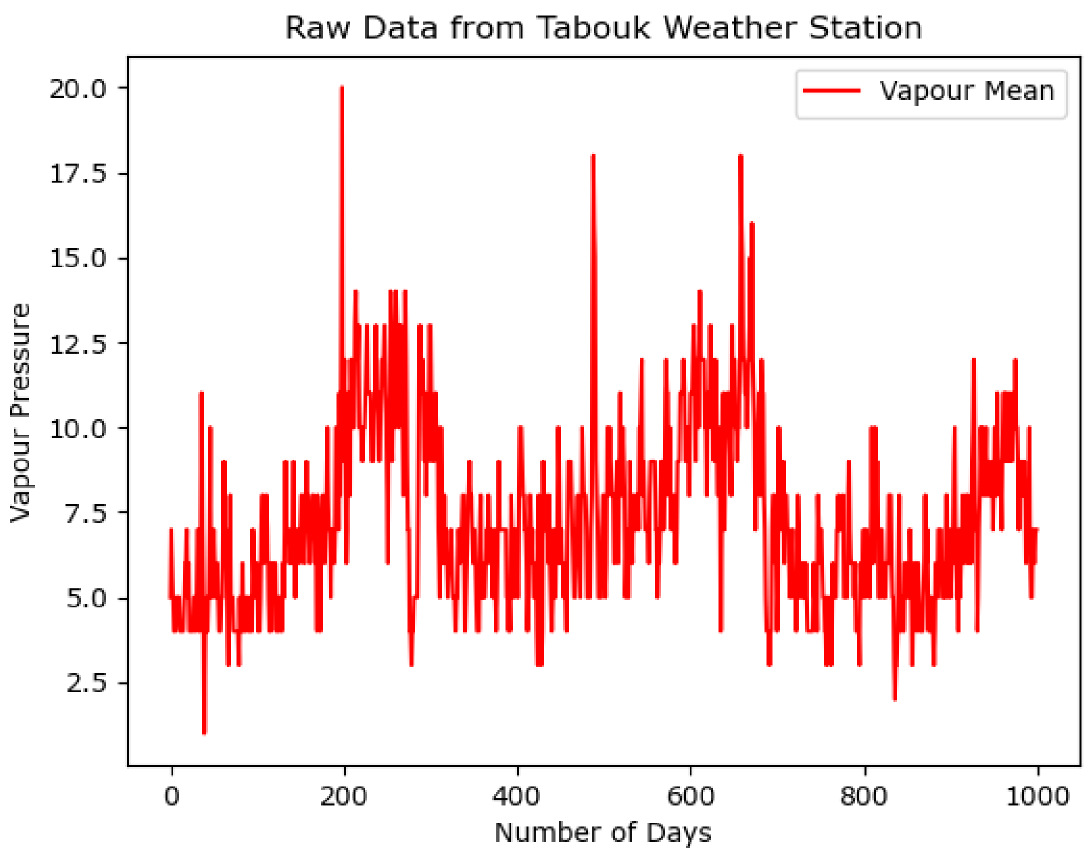








Training and Testing the Models:

This paper presents a novel analysis of historical weather data collected from the Tabuk weather station, in Saudi Arabia spanning the past three decades. The dataset is meticulously divided into two distinct partitions: a training set comprising 70% of the data and a testing set encompassing the remaining 30%. This strategic division ensures that the models are trained on a representative subset of the historical data while reserving a separate portion for unbiased evaluation of their predictive performance. We then subject the training data to a battery of diverse hybrid machine-learning algorithms, each combining the strengths of multiple machine-learning techniques. By exploring this rich ensemble of approaches, we aim to identify the model that yields the optimal balance of accuracy and error minimisation in the context of Tabuk's temperature prediction. Through a meticulous comparative analysis of the results generated by each hybrid model, we strive to identify the most effective approach for predicting future temperature variations in Tabuk. This rigorous evaluation will not only elucidate the most suitable model for this specific task but also contribute valuable insights into the broader field of temperature prediction using hybrid machine learning methods.

Evaluation Metrics for Model Predication Performance

Common evaluation metrics include Mean Absolute Error (MAE) and a learning curve for assessing the accuracy of temperature predictions. The effectiveness of the proposed model, therefore, was rigorously evaluated using established strategies such as the Learning Curve and comparisons with Mean Absolute Error (MAE).

MAE quantifies the average absolute deviation between predicted and actual temperatures. Its simplicity fosters interpretability, yet it downplays the impact of large errors compared to small ones. The Mean Absolute Error (MAE) doesn't have a single equation, but rather a formula that calculates any two datasets (y_true and y_predicted):

$$MAE = 1/n * \Sigma |y\_true\_i - y\_predicted\_i|$$

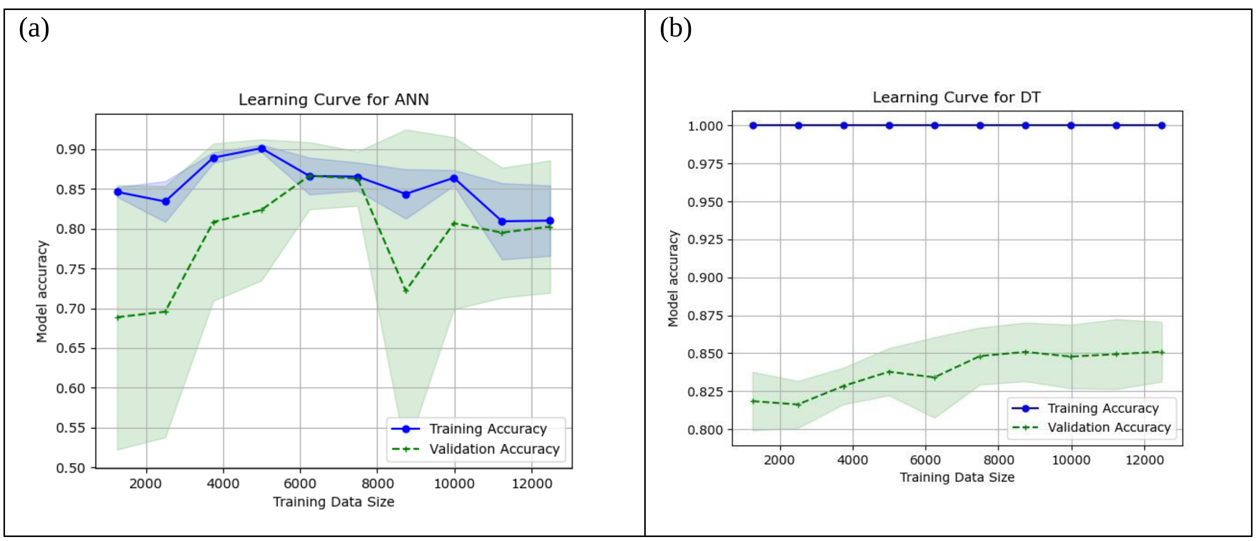
Where:

n is the total number of data points in your dataset.
y_true_i is the actual value of the i-th data point.
y_predicted_i is the predicted value of the i-th data point by your model.
Σ is the summation symbol, meaning you sum the absolute difference between each actual and predicted value for all data points.
This formula essentially calculates the average of the absolute differences between your model's predictions and the actual values, providing a measure of how accurate your model is overall. The lower the MAE, the better your model's performance.

Results, Discussion and Models Performance

The learning curve analysis reveals promising results for the ANN model. Both training and validation accuracy exhibit a positive trend with increasing training data size, highlighting the model's effective learning capacity. The training accuracy reaching 0.90 signifies strong performance on the observed data. While the validation accuracy peaks at around 0.85, suggesting good generalization to unseen data, it remains slightly lower than training accuracy. This relatively small gap (around 0.05) between training and validation accuracy indicates a low risk of overfitting, a desirable outcome for robust model performance. The rapid initial increase in accuracy with growing data size demonstrates the model's fast learning rate. The curves suggest an optimal data size range of 8000-10000, where accuracy gains begin to plateau. This indicates that further increasing training data beyond this range might not offer significant performance improvements. Notably, the model demonstrates a promising ability to generalize to new data, achieving a validation accuracy of 0.85. This suggests its effectiveness in applying the learned patterns to unseen scenarios, a crucial characteristic for real-world applications.

In contrast, a striking feature of the DT model curve is the training accuracy reaching a perfect score of 1.000, suggesting complete memorization of the training data. However, this comes at the potential cost of overfitting, as evidenced by the gap between the flat blue training curve and the fluctuating green validation curve, which peaks at around 0.850 but dips as low as 0.825. While the validation accuracy remains respectable, it suggests the model might not generalize well to unseen data. The initial rise in validation accuracy followed by a plateau and slight decline indicates that the DT model might benefit from regularization techniques to mitigate overfitting and improve its generalizability. This could involve limiting the tree depth, implementing early stopping, or employing techniques like data augmentation to diversify the training data. Overall, the DT model exhibits a strong learning ability but raises concerns about overfitting.



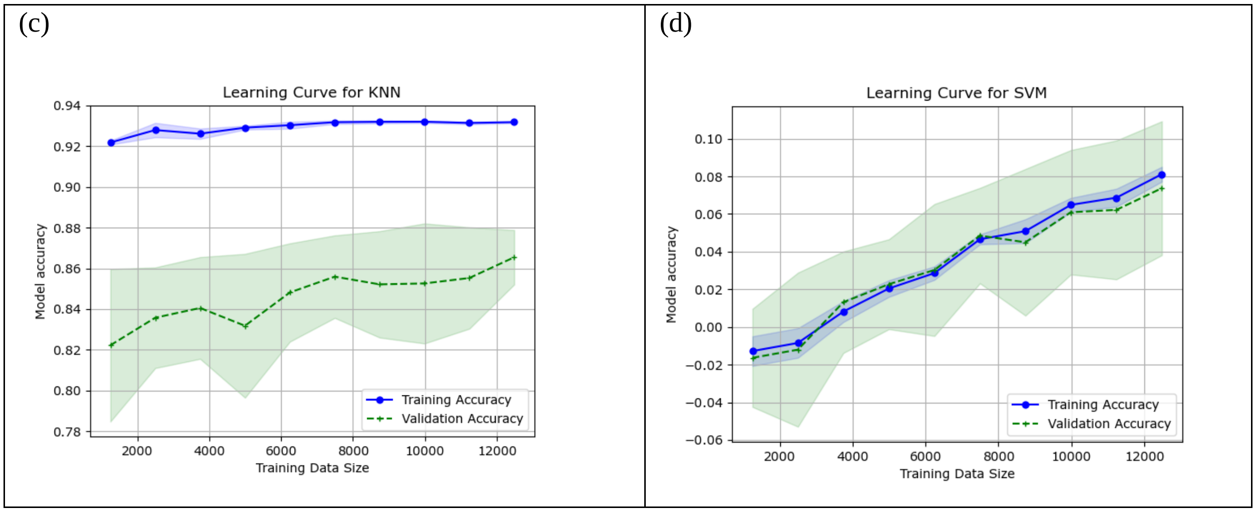


Figure Presents the learning curve and accuracy of four models: ANN (a), Decision Tree (b), KNN (c), and SVM (d).

A notable feature in the KNN model is the training accuracy starting at a relatively high value of 0.92 and gradually increasing to reach a peak of 0.93. This suggests strong initial learning and good performance on the training data. The validation curve also exhibits encouraging behaviour, consistently rising from a starting point above 0.82 to reach its highest point of more than 0.86. This gradual upward trend indicates that the KNN model effectively balances learning from the training data with generalizability to unseen data, minimizing the risk of overfitting. Overall, the KNN model's learning curve paints a picture of effective learning, good generalization, and minimal overfitting risk.

Calculating the mean and standard deviation of the four models' MAE scores can provide a comprehensive understanding of their generalization to unseen data. The figure reveals significant discrepancies in the temperature forecasts generated by the four models for the Tabuk station. Remarkably, the ANN model exhibits superior performance, suggesting its enhanced capability in capturing underlying patterns within the data series.

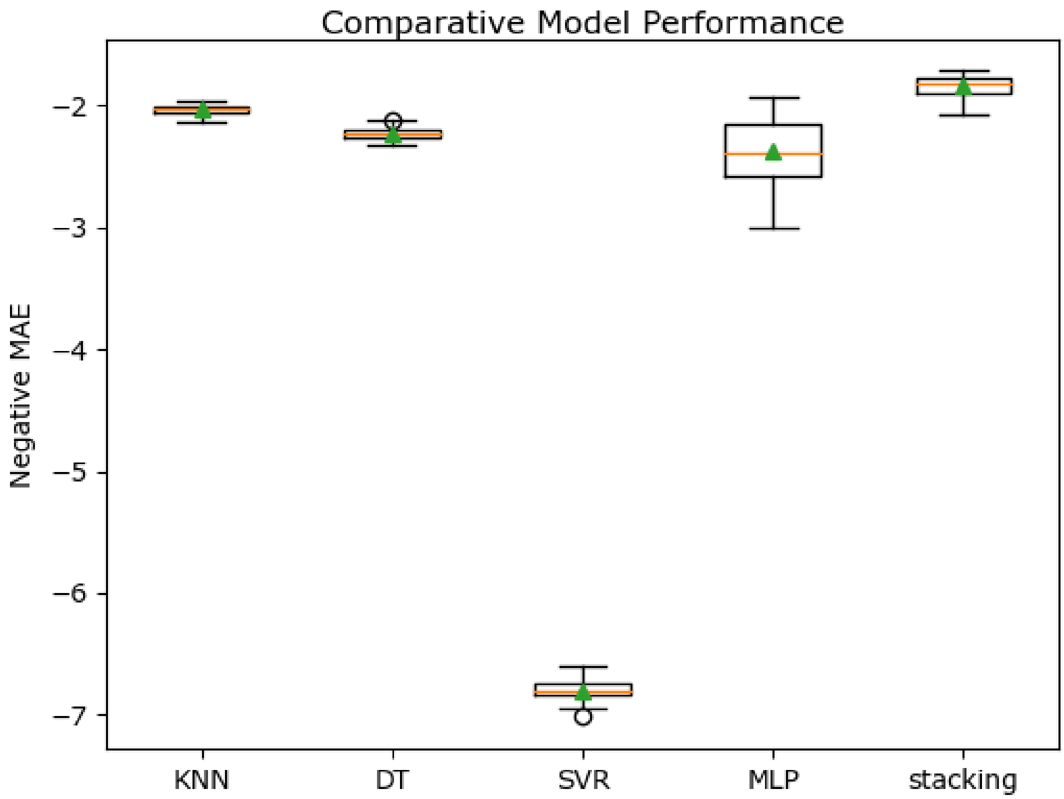


Figure: Comparison of Model Performance (MAE) for ANN, Decision Tree, KNN, and SVM

Conclusion:

This study investigated the application of various machine learning models, including ANNs, Decision Trees (DTs), K-nearest neighbours (KNNs), and Support Vector Regression (SVR), for temperature prediction within the context of smart cities. While previous works have explored SVM's potential for weather forecasting, our comparative analysis revealed that ANNs emerged as the most efficacious model for this specific task.

The inherent strengths of ANNs for smart city temperature prediction lie in their exceptional ability to navigate the intricacies of the task. Unlike simpler models like decision trees and k-nearest neighbours, ANNs can readily capture the inherent non-linearity of temperature fluctuations driven by complex interactions between diverse factors like air pressure, humidity, wind patterns, and seasonal variations. Additionally, smart city environments generate a variety of data from various sources, and ANNs excel at seamlessly integrating these diverse features into the prediction process, leading to more comprehensive and nuanced models compared to SVR, which often require cautiously pre-defined features. Furthermore, the dynamic nature of smart cities necessitates adaptable models that can learn and refine themselves continuously, a challenge in which ANNs shine with their superior generalizability to unseen data compared to static models like decision trees and k-nearest neighbours. While DT and other models still hold merit in specific applications, our findings suggest that ANNs represent a valuable tool for temperature prediction in smart cities due to their exceptional ability to handle non-linearity, integrate diverse features, and adapt to dynamic environments. This advantage opens doors for numerous applications in smart city development, including weather forecasting, resource management, and even climate-adaptive infrastructure design.

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