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PREDICTION OF MAXIMUM AIR TEMPERATURE FOR DEFINING HEAT WAVE IN VARIOUS STATES OF PAKISTAN USING MACHINE LEARNING ALGORITHM

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Abstract
Temperature rise, associated with global warming, has increased the severity and frequency of heat waves worldwide. Several major states of Pakistan have been facing frequent heat waves in the past few years. The present study used a machine learning approach to predict the maximum air temperature (AT) for defining the heat wave occurrences in these states. The analysis was based on the monthly data of 13 parameters, collected from NASA's Giovanni and ERA5 reanalysis data during the summer season for the past 45 years. Three machine learning approaches were used in the study: multiple linear regression (MLR), support vector regression (SVR), and random forest (RF). It was observed that the maximum AT states were above the limits of the IMD criteria for defining heat wave occurrences. The performance of the models was evaluated using statistical metrics, comprising of root mean square error (RMSE) and coefficient of determination (R^2). Overall, the study shows that machine learning-based approaches can predict maximum AT for defining heat wave conditions with high accuracy. The RF method was observed to have the best results for predicting maximum AT. The study can have significant applications in different fields like climate modelling studies, urban planning and infrastructure, agriculture, etc., and it can help to implement appropriate measures to mitigate the adverse impacts of temperature rise.

INTRODUCTION

Global climate change has led to increased occurrences of heat waves, which significantly impact the environment, human health, economy, and agriculture (Pathak et al., 2018; Ebi et al., 2021). Heat waves intensify droughts and wildfires, leading to habitat destruction and loss of biodiversity (Fischer et al., 2014; Sutanto et al., 2020). Extreme heat poses health risks, causing heat-related illnesses and even fatalities, especially in vulnerable populations (Faurie et al., 2022). Moreover, the economy suffers as productivity decreases, energy demand surges, and infrastructure faces damage (Loucks, 2021; García-Leon et al., 2021). Agriculture bears the brunt, with crop failures and reduced yields, leading to food supply challenges and economic strain on farmers and consumers alike (Miralles et al., 2019; Bras et al., 2021). Due to the increase in global temperature during the past ten years, the incidence of heat waves has increased drastically. The heat waves also persist for a longer duration (Dosio et al., 2018). The danger of various forms of calamities can rise with extreme temperatures. Drought can worsen due to extended durations of heat, and wildfires can develop due to hot, dry weather (Sutanto et al., 2020). The change in land use in urban areas due to urbanization and industrialization has significantly raised the occurrence of heat waves in cities worldwide (Imran et al., 2021). The urban heat island effect may make cities up to 7°F hotter than surrounding areas, resulting from the heat absorbed by buildings, roads, and other infrastructure (Wang et al., 2016; Zhou et al., 2017). The production, distribution, and consumption of electricity are all impacted by rising temperatures. The ability of transmission lines to transmit power may be reduced because of high temperatures, which may result in concerns for the reliability of the supply of electrical power, such as rolling blackouts during heat waves (Hatvani-Kovacs et al., 2018). Heat wave definitions differ across nations; nevertheless, heat waves are typically characterized based on the typical weather and temperatures corresponding to a region's seasons, and they are said to occur when there is a significant departure from the region's normal temperature pattern. Extreme weather conditions occur widely and locally, impeding emergency response efforts. Due to the widespread occurrence of such severe weather conditions, response methods, such as the quick arrangement of emergency resources, are constrained. The increasing heat waves have severe effects on the ecosystem and biodiversity globally. Elevated temperatures disrupt habitats, change migration patterns, and jeopardize the survival of many plant and animal species (Upadhyay, 2020; Vincent, 2020).

The health and economic consequences of the current heat wave, including the number of hospitalizations and deaths, lost income, missed school days, and reduced working hours, are usually not known for months (Campbell et al., 2018; He et al., 2019). Sunburn, heat cramps, heat exhaustion, and heat stroke are potential effects of heat waves (Seema and Aigbavboa, 2018). As the Earth's average temperature rises, it will be more difficult for people to live in cities. In 2022, both Asian and European countries were affected by heat waves. Peak temperature in European cities was recorded as about 47°C in Pinhao, Portugal (Knight, 2022). The Indian Meteorological Department (IMD) deems a heat wave when the peak temperature at a station hits 40 °C or 30 °C, for plains and hilly regions, respectively (IMD, 2023a). Over the central, east, and north peninsular India as well as over the plains of northwest India (covering Punjab, Haryana, Delhi, Uttar Pradesh, West Bengal, Bihar, Jharkhand, Rajasthan, Madhya Pradesh, Odisha, Gujarat, and some portions of Andhra Pradesh, Maharashtra, Karnataka, and Telangana), heat waves often occur between March and June (Sharma et al., 2022; Srivastava et al., 2022; Ashrit et al., 2023). Heat waves often originate over northwest India and gradually extend eastward and southward, but not westward (Dodla and Satyanarayana, 2021). The maximum air temperatures in India have been registered between 45∘C (113 ∘F) and 50∘C (122 ∘F) in May 2022 (WMO, 2023) at various monitoring stations located throughout Rajasthan, Madhya Pradesh, East Uttar Pradesh, Vidarbha, large portions of Gujarat, Odisha, and some of Maharashtra (ESA, 2022; IMD, 2023b). Jaipur and Ahmedabad, two urban cities of India, had the highest recorded surface temperatures, with a maximum land surface temperature (LST) of about 65°C (Nandani, 2023). Similarly, the highest temperature in China was recorded above 40oC, and LST exceeded 60°C during the summer season (Liu et al., 2023).

Early forecasting of heat waves may be useful to pinpoint the location (likely to occur. However, very limited research has been conducted for predicting heat waves. Most of the studies were conducted to assess the rate of mortality induced due to the rise in heat waves. The majority of the studies were conducted at regional levels. Prediction of heat waves can help in addressing issues related to planning and mitigation. It is possible to anticipate heat waves using both statistical and dynamic methods (Nissan et al., 2017). The statistical method uses empirical models that connect large-scale ocean-atmospheric variables with heat waves. On the other

hand, dynamical methods rely on the physical interactions between the ocean, atmosphere, and land to construct the prediction model, making the model's development computationally costly. Consequently, statistical models are often employed for heat wave prediction models (Singh et al., 2018; Khan et al., 2019). It is difficult to address complex nonlinear prediction issues through a traditional statistical approach (Prasad et al., 2019). Various machine learning models were used in recent years to reliably forecast various natural events due to the capability of machine learning algorithms to comprehend multiple complicated processes (Khan et al., 2021; Slater et al., 2022). Wang et al. (2019) conducted a three-year study of predicting heatstroke occurrences in China using random forest regression. The study used meteorological parameters (i.e., temperature and humidity) for the prediction, and the results were more satisfying compared to the linear regression model. Fister et al. (2023) used a deep machine learning model to predict air temperature in Paris and Cordoba. Their study compared and ranked various machine learning models. Park et al. (2020) have compared the Quantile Regression Forests and Random Forest regression model.
The results show that QRF has a higher capacity than Random Forest regression.

The novelty of the present study
The novelty of predicting maximum air temperature for defining heat waves lies in several key aspects. Firstly, the study focuses specifically on cities of Pakistan with distinct geographical and ecological characteristics. Unlike many previous studies that considered only a limited set of parameters, this research incorporates a wide range of satellite data as input variables. These data, collected over a period of 45 years during the summer season, offer a comprehensive and detailed understanding of the factors influencing maximum air temperatures and heat wave occurrence in these regions. By utilizing these rich datasets, ML models can capture complex relationships and identify crucial predictors of heat waves with greater accuracy. The study also contributes to the field by comparing the performance of multiple machine learning algorithms, including Multiple Linear Regression (MLR), Support Vector Regression (SVR), and random forest (RF). This comparative analysis allows for a comprehensive evaluation of the prediction models and their suitability for capturing the specific dynamics of heat wave occurrence in different cities of Pakistan. Owing to the difference in geographical and climatic conditions of these areas and the high performance of the prediction models, the study is suitable for application to different regions.

Objective
The present study aims to develop a model for predicting maximum air temperature, which can be used for defining heat waves. MLR, SVR, and RF approaches were used for the model, which has been developed by utilizing data corresponding to different cities of Pakistan. These states have experienced frequent heat waves in the past decade. As the rate of heat wave incidents is rising every year, there is a need for a prediction model for better planning, management, and mitigation.

Methods and methodology
Data collection
The data of maximum air temperature, aerosol optical depth, black carbon, carbon monoxide, land surface temperature, relative humidity, normalized difference vegetation index, total column water vapor, boundary layer height, surface net solar radiation, surface pressure, east wind component, and north wind component were collected from NASA' Giovanni and ERA5 reanalysis data for the three months representing summer season (i.e., March, April, and May) for the past ten years (2013–2022). Giovanni is a NASA Goddard Earth Science Data and Information Services Centre's (GES DISC) Distributed Active Archive Centre (DISC) web application that makes it easy to visualize, analyze, and access Earth science remote sensing data (https://giovanni.gsfc.nasa.gov/giovanni/). ERA5 is the 5th generation atmospheric reanalysis global climate data provider of the European Centre for Medium Range Weather Forecasts (ECMWF). At reduced spatial and temporal resolutions, ERA5 contains information about all variables' uncertainty (Hersbach et al., 2020). ERA5 obtains data from

various satellite products, which is then made available after reanalysis.

Satellite imageries provide a comprehensive view of a large geographical area, including remote and inaccessible regions. This extensive coverage enables monitoring heat wave conditions over vast territories, including rural and less populated areas, where ground-based monitoring stations are usually scarce or absent. Satellite imagery provides near real-time data and thus may allow frequent updates on heat wave conditions, which can help in tracking the development and progression of heat waves. Continuous monitoring makes issuing timely warnings and advisories to the public and relevant authorities easier. Satellites provide a consistent stream of data over long periods, which is essential for studying heat wave trends, patterns, and changes over time. This historical perspective can be valuable for researchers and policymakers in understanding the impacts of climate change on heat waves. Satellite based monitoring does not require physical installations on the ground or human intervention, reducing the risk of data disruption and ensuring a continuous flow of information during extreme weather events. The methodology adopted in the present study gives a comprehensive approach that contributes to accurate and region-specific temperature predictions, enabling better heat wave preparedness, risk management, and climate adaptation efforts in all states.

Prediction of maximum at using the machine learning algorithms

Three different methods, MLR, SVR, and RF, were used to develop a model to predict AT. The effectiveness of machine learning predicted outcomes was assessed using coefficients of determination (R^2), and root means square error (RMSE). R^2 is a statistical measure used to evaluate the goodness of fit of a regression model. It represents the proportion of the variance in the dependent variable (the variable being predicted) that is explained by the independent variables (the predictors) in the model. It ranges from 0 to 1. If the R^2 value is close to 1, it suggests that the model provides a good fit to the data, as it explains a substantial portion of the variance. On the other hand, if the R^2 value is close to 0, it indicates that the model is not explaining much of the variance and may not be a good fit for the data. RMSE is used in statistics and machine learning to evaluate the performance of predictive models. It measures the average magnitude of the differences between predicted and observed values. RMSE calculates the square root of the average of the squared differences between predicted and actual values, effectively penalizing larger errors more heavily. Its principle lies in quantifying the accuracy and precision of a model's predictions, where lower RMSE values indicate better performance (Adnan et al.,2021; Singh et al., 2022). It also represents the capability of predicted models (Sheng et al., 2022).

MLR

MLR is an expansion of simple linear regression to explain the linear relationship between single dependent and multiple independent variables (Singh et al., 2023). The MLR formula is given in equation (i) below (Kuhn and Johnson., 2013).

$$y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots\ldots \beta_p x_n + e_i \qquad (i)$$

Where $i = 1, 2, 3, \ldots. n$, y_i, and x_i values are dependent and independent variables, respectively. e_i is the intercept.

SVR

The SVR algorithm predicts discrete values using the same methodology as support vector machines (SVMs). The idea behind SVR is to find the optimum fit line. This best-fit line in SVMs is an ideal hyperplane with most data points on the plane. The prediction from SVR was carried out using equation (ix) (Vickers, 2017).

$$F(X_i) = \sum_{i=1}^{n} (W_i \, \phi(x_i)) + b$$

Where b and W_i are the linear SVR function and nonlinear SVR function is denoted by $\varphi(x_i)$, SVR is classified into two types: linear SVM and nonlinear SVM. For the present study, nonlinear SVM model was used for the prediction. The kernel function, or $[K(x_i, x_j) = (\varphi(x_i) \cdot \varphi(x_j)]$, is the nonlinear SVR function is computed and used to produce interior products, assess the space, and examine the feature separating space.

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Random forest

The RF is an ensemble machine learning technique that creates many regression trees to help predict future outcomes. In RF, various trees generate different results. In RF, two methods boosting and bagging, can be applied to get a conclusion based on the results of each tree. The trees that can detect erroneous predictions are given greater weight in boosting, and the final prediction is determined by weighted voting. Regression trees are built using a bootstrap sample in bagging, and the prediction is derived from the outcomes of a majority vote (Yu et al., 2020; Zhang et al., 2021). The RF approach created the model linking AT with the selected variables. 90% of the data were randomly selected as training data, and the remaining 10% was used to test the model (Ma et al.,2021). In order to pick model parameters, the number of variables and decision trees were selected based on the maximum model R^2 for improved model fitting.

Results and discussion:

The Figure 1 illustrates the geographic distribution of average temperatures across 20 Pakistani cities, plotted using their latitude and longitude. The cities are color-coded based on their average temperatures, with blue shades representing cooler areas and red shades indicating warmer regions, as shown by the color bar. Southern cities like Karachi and Mirpur Khas exhibit higher average temperatures, while northern cities such as Mardan and Kohat experience cooler climates. Central cities, including Multan and Faisalabad, display intermediate temperatures, reflected in orange tones. This visualization highlights the spatial variation in average temperatures, showcasing the climatic diversity across Pakistan.

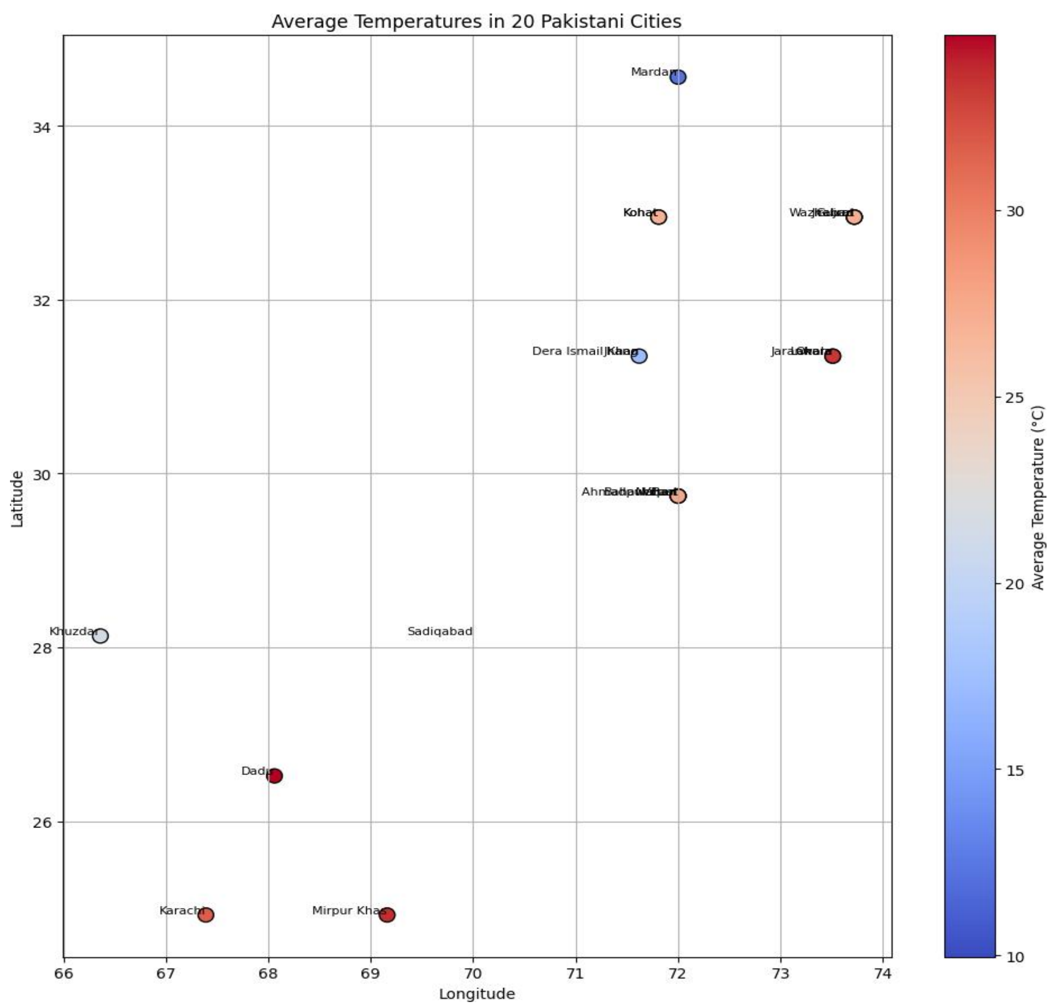

Figure 1: Average Temperatures in 20 Pakistani Cities

The graph in Figure 2, illustrates the historical trends in average temperatures across various cities in Pakistan, highlighting significant climatic shifts. Before the Industrial Revolution (marked by the red dashed line), temperatures remained relatively stable, but a notable upward trend began post-industrialization, especially after the mid-20th century (marked by the orange dashed line). Southern cities like Karachi and Hyderabad consistently exhibit higher average temperatures compared to northern cities, indicating the influence of geographic and climatic factors. The rising temperature trends align with global warming patterns, reflecting the impact of industrial activities and urbanization on Pakistan's climate.

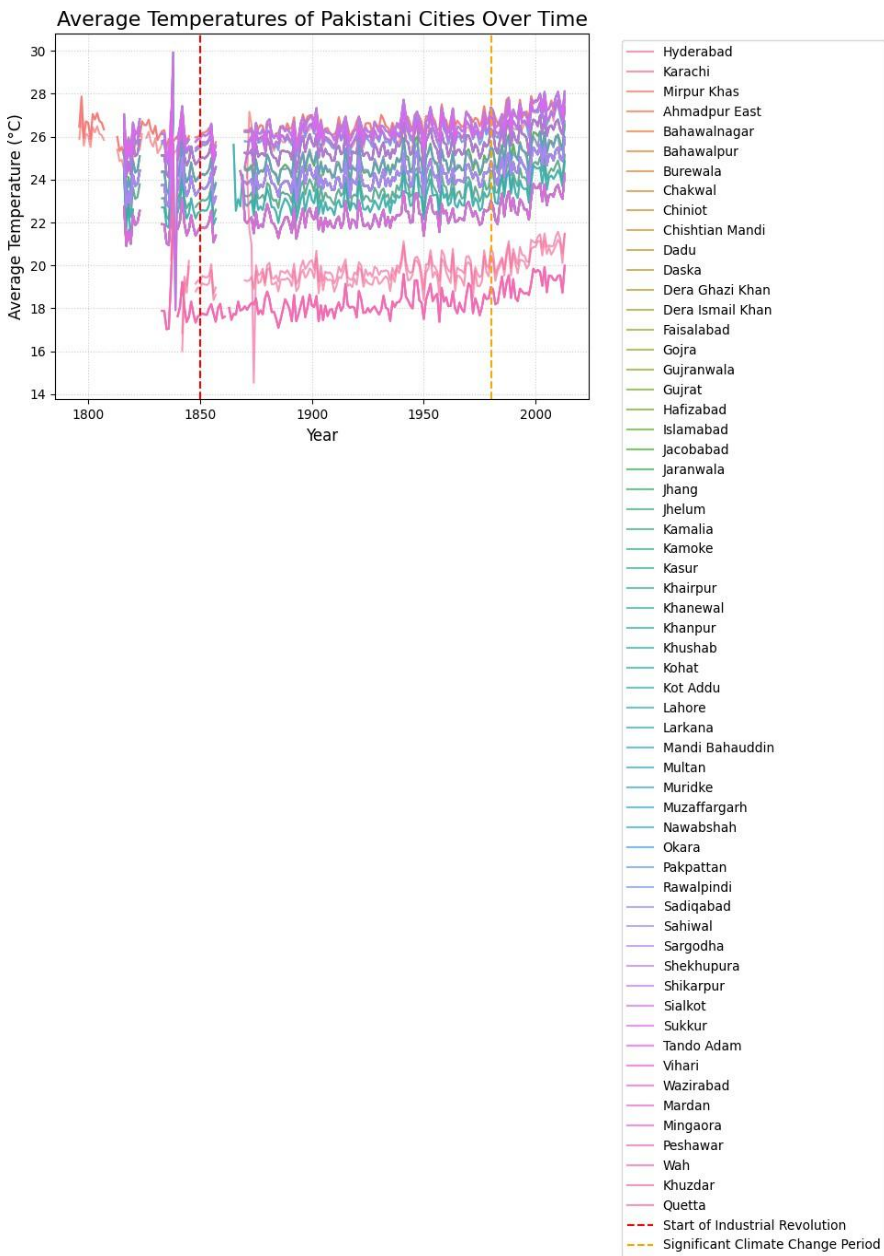

Figure 2: Average Temperature of Pakistani Cities over time

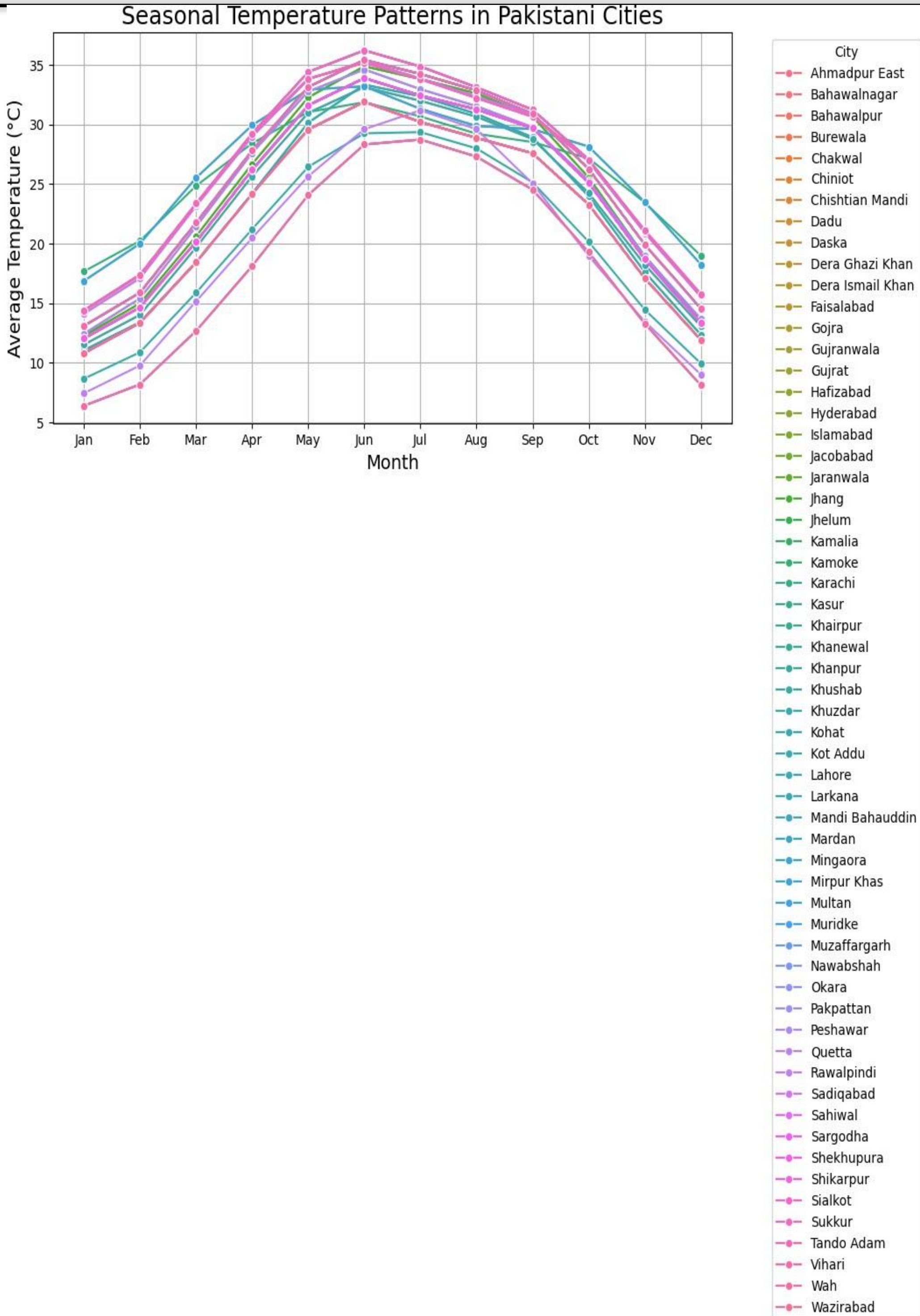

Figure 3: Seasonal Temperature Patterns in Pakistani Cities

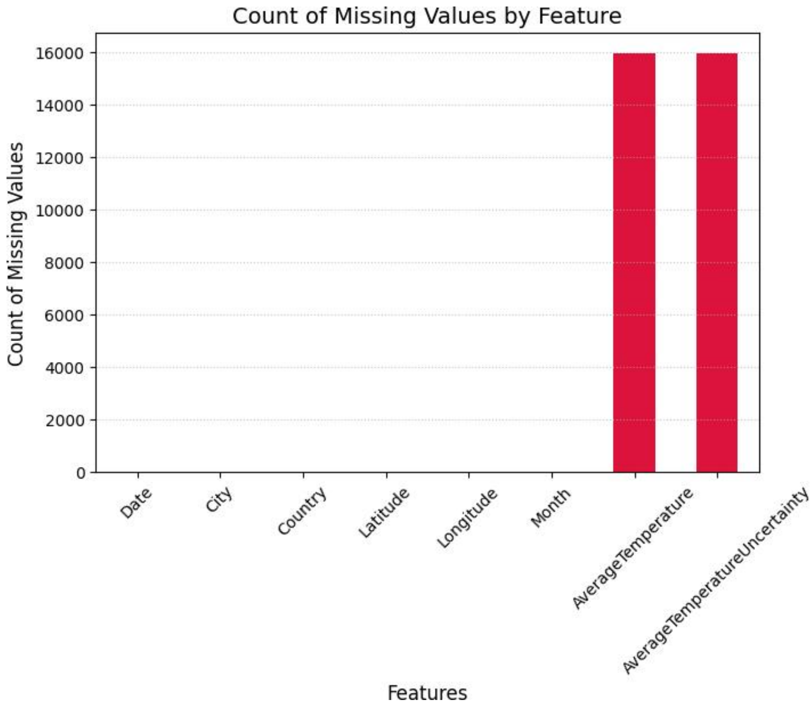

Figure 4: Count of Missing Values by Feature

The fifth image displays a box plot comparing temperatures across different seasons, offering a statistical summary of seasonal variations. It provides a clear visualization of the median temperature, interquartile range, and potential outliers for each season. Summer exhibits the highest median temperature and the widest range, reflecting greater variability in temperature extremes, while Winter shows the lowest temperatures with a more compact distribution. The presence of outliers in the data suggests occasional extreme temperature events, which could be linked to climate anomalies such as heatwaves or cold spells. These extremes may have significant socio-economic impacts, affecting agriculture, infrastructure, and public health. The box plot serves as a valuable tool for identifying patterns of variability and assessing the stability of seasonal temperature trends, aiding in better climate risk management and adaptation planning.

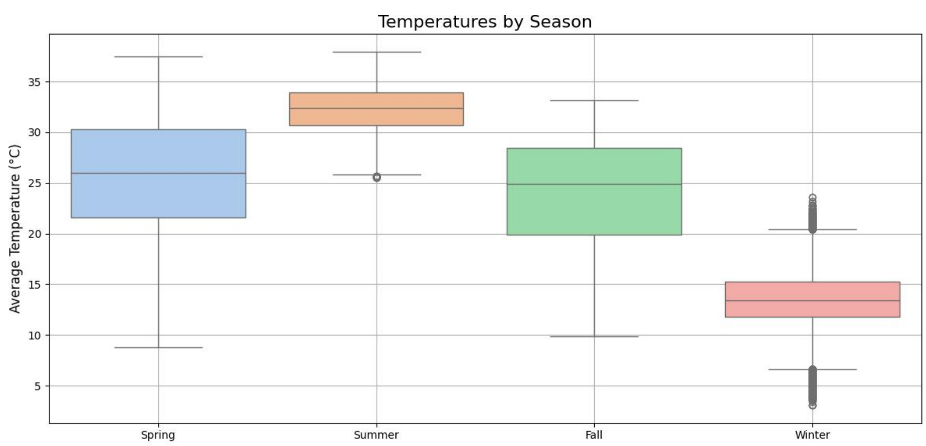

Figure 5: Temperature by Season

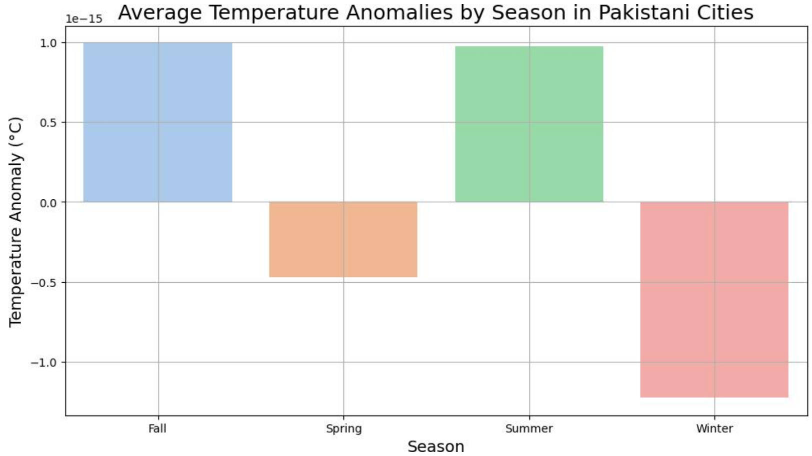

Figure 6: Average Temperature Anomalies by Season in Pakistani Cities

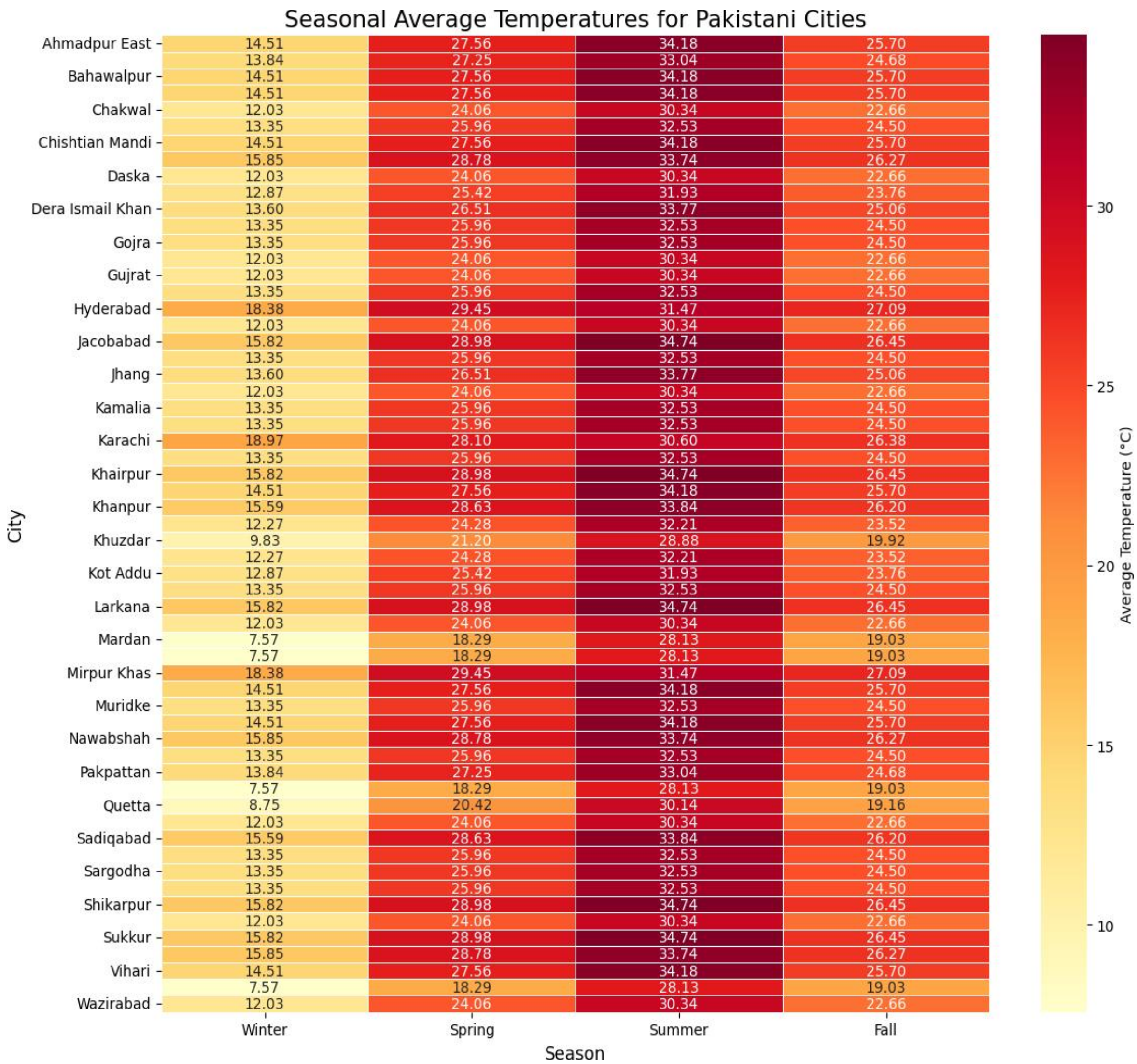

Figure 7: Seasonal Average Temperature for Pakistani Cities

The Figure 7 presents a heat map of seasonal average temperatures across various Pakistani cities, providing a comparative view of temperature distribution. Cities are listed along the y-axis, while seasons are represented on the x-axis. The heat map uses a color gradient to visually differentiate temperature intensities, with warmer colors indicating higher temperatures during Summer and cooler colors in Wint
er. Cities in southern Pakistan, such as Karachi, show consistently higher temperatures across all seasons compared to northern cities like Islamabad, which experience colder winters. This visualization highlights the geographical variations in temperature, emphasizing the need for region-specific climate policies and interventions. The heat map also serves as a useful tool for identifying climate trends, allowing policymakers and researchers to assess the impact of climate change on different regions and develop localized mitigation strategies.

Figure 8 shows a line plot depicting seasonal temperature trends in Pakistani cities from 1750 to 2013. It highlights seasonal variations, with Summer having the highest average temperatures and Winter the lowest. A significant drop in temperatures is observed around the mid-1800s, possibly due to climatic events such as volcanic eruptions or natural climate variability, followed by a steady warming trend across all seasons. The gradual temperature increase in recent decades may suggest the influence of global climate change, urbanization, and local environmental factors. The consistent rise in Summer temperatures indicates a potential intensification of heat waves, which could have implications for agriculture, water resources, and public health. This visualization provides a comprehensive perspective on historical temperature fluctuations and aids in understanding the long-term climate patterns affecting the region

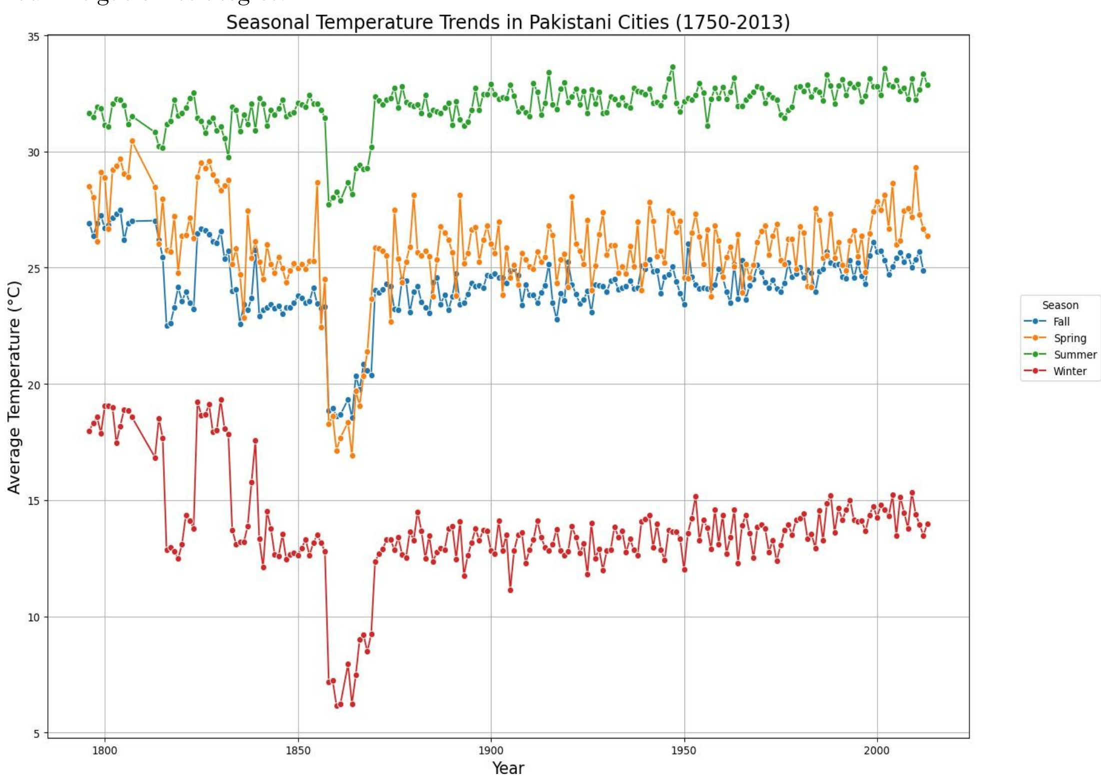

Figure 8: Seasonal Temperature Trends in Pakistani Cities (1750 - 2013)

The results highlight the performance of three regression models—Polynomial Regression, Random Forest, and Support Vector Regression (SVR)—in terms of their ability to predict the target variable, measured by R^2 scores and Root Mean Square Error (RMSE) on both training and testing datasets. Each model was optimized to its best hyper-parameters using grid search or a similar optimization technique. Polynomial Regression with the optimal degree of 4 demonstrates strong predictive capability, achieving a training R^2 of 0.9589 and a testing R^2 of 0.9587, indicating minimal overfitting. The RMSE values for the training and testing sets are nearly identical (7.5423 and 7.5144, respectively), reinforcing the model's stability and generalization across unseen data. However, The relatively higher RMSE compared to other models suggests that while Polynomial Regression captures complex relationships, it may not be as precise as other methods for this dataset.Random Forest regression emerges as the most effective model, with hyper-parameters tuned to a maximum depth of 20 and 150 estimators. This model achieves the highest R^2 scores for both training (0.9742) and testing (0.9736) datasets, demonstrating exceptional predictive accuracy. The RMSE values are significantly lower than those of the Polynomial Regression model, with 1.2629 for training and 1.2646 for testing, indicating both precision and robust generalization to unseen data. The negligible difference between training and testing metrics suggests that the Random Forest model successfully avoids overfitting while leveraging its ensemble nature to capture complex patterns in the data.

Support Vector Regression (SVR), optimized with a learning rate of 0.1 and 100 estimators, shows reasonable performance but falls short compared to the other models. The training R^2 score is 0.8867, and the testing R^2 is slightly lower at 0.8866. This close alignment of scores across datasets indicates a well-generalized model, but the lower R^2 compared to the Random Forest model suggests that SVR struggles to capture some nuances of the dataset. The RMSE values (2.5023 for training and 2.5144 for testing) are intermediate between the two other models, showing that while SVR offers good predictions, it is less precise than Random Forest in this context.

Overall, the Random Forest model outperforms both Polynomial Regression and SVR in terms of predictive accuracy and precision, making it the most suitable choice for this dataset. Polynomial Regression, despite its strong generalization and ability to model non-linear relationships, is less precise in prediction, while SVR provides a balanced alternative with moderate performance. These results underscore the importance of tailoring model selection to the dataset characteristics and prediction requirements.

Conclusions:

The effect of unbridled urbanization is being felt in the form of global warming throughout the world. Most parts of the world are facing unprecedented heat waves, which are causing a lot of discomfort to the residents, and their health is also being adversely affected. The heatwaves also cause a lot of stress on the energy infrastructure, with frequent power cuts and voltage fluctuations, especially in semi-developed/underdeveloped countries. It is very important to plan the measures to face extreme weather events, and predicting heat waves is one such step. Heat waves are associated with AT, and a heat wave is considered to occur when the AT remains unusually high for an extended period, and the temperature increase's duration and intensity determine the heat wave's severity. The present study was carried out to predict AT for defining heat wave occurrences in different states of Pakistan. The prediction was carried out using three machine learning approaches; MLR, SVR, and RF. The results show that maximum AT exceeded, on numerous occasions, the IMD limits for heat waves in states, indicating the heat wave occurrences. All three models performed well for states with moderate to high coefficient of determination values. It was observed that the RF method gave the best results for predicting maximum AT. The study can help to predict the maximum AT or heat wave episodes and help the government to develop a plan to mitigate this issue. Results of the present study are in line with few other studies reported in the literature while different results have also been observed. It can be interpreted that the performance of the model depends on climatic conditions, geography, topology, and vegetation. The study can be extended to include more parameters such as geopotential height, and sea level pressure etc. Predicting AT using machine learning model enables improved understanding and identification of heat wave events with higher accuracy and precision. Machine learning models can analyze historical weather data, atmospheric conditions, and other relevant factors to detect patterns and make reliable predictions, aiding in the early detection of heat waves. This early warning capability allows authorities to implement timely mitigation strategies, such as activating cooling centers, adjusting energy demand, and initiating public health interventions. Furthermore, machine learning models can provide localized predictions, considering specific geographic features and microclimates. Forecasting AT helps communities and organizations make their responses and allocate resources more efficiently. It also facilitates the identification of vulnerable areas and populations at higher risk during heat waves, allowing for targeted interventions and proactive measures to protect public health. The potential applications of predicting maximum AT for defining heat waves using machine learning approaches extend beyond states of Pakistan. This methodology can be applied to various case studies and regions worldwide. Predicting maximum AT can be useful in developing a comprehensive monitoring system for heat waves, enabling early warnings and informed decision-making at a global scale. Urban areas worldwide face the challenge of urban heat islands, where temperatures are significantly higher than those surrounding rural areas, and this study can aid in developing targeted strategies to mitigate urban heat islands, such as the placement of green spaces, cool roofs, and other heat-reducing interventions. AT predictions can support climate change adaptation efforts by providing valuable insights for developing strategies to protect vulnerable populations, enhance infrastructure resilience, and prioritize resource allocation. The study can also be used to evaluate the impact of the adaptation efforts for various scenarios. The present study also has application in agriculture as it can help farmers adapt selected practices, optimize irrigation, and adjust cropping patterns to mitigate the impacts of heat waves on agricultural productivity, contributing to global food security. Heat waves pose significant risks to public health, and the predictions can support public health planning and interventions. Authorities can develop targeted public health strategies, implement timely heat wave response plans, and allocate healthcare resources to mitigate heat-related illnesses and protect vulnerable populations. Mitigation works, and efforts for global warming issues are primarily concentrated in urban areas. Most of the monitoring network is concentrated in and around the cities. The present study can be useful in predicting the occurrence of heat waves by predicting AT for remote and isolated locations where such a monitoring network is not present.

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