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Using Machine Learning Methods to Predict Temperatures in Iraq (Baghdad)

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Abstract:

Temperature forecasting is an important tool for understanding climate patterns and for helping societies adapt to climate change. Predictive models play a role in mediating decision-making across various fields. In the present study, we used three methods of machine learning - Support vector machine (SVM), artificial neural networks (ANN), and Extreme gradient boosting (XGBoost) regression - for predicting mean July temperatures in Baghdad (1941–2009). The results showed the predictive ability of these methods, while the XGBoost model was the most effective. Which achieved the highest accuracy, outperforming SVM and ANN. The results highlight XGBoost's superior ability to capture complex patterns in temperature data, while SVM and ANN provide moderate predictions. When clustering and nested trees were used, the results showed that XGBoost was better suited to the dataset's complexity, while SVM performed well but was less accurate than XGBoost. In the end, we recommend researching the features of additional data and improving accuracy in future predictions during model refinement.

Keywords: Machine learning, XGB model, ANN model, SVM model, Temperature forecasting

1-Introduction

Baghdad temperature forecasts aim to improve energy management and adapt to health risks posed by extreme weather, facilitating more effective decision-making across sectors and enhancing resilience to climate change. Forecasts can be implemented using machine learning techniques; one algorithm is logistic regression (LogReg), which uses classification to estimate the probability of customer churn. However, this algorithm performs poorly on imbalanced data [2]. XGBoost is a popular and effective algorithm among machine learning experts, with 17 of the 29 winning solutions in the 2015 Kaggle competition using XGBoost as part of their ensembles [3]. XGBoost uses a boosting approach and is expected to contribute to more accurate and efficient predictions, especially when working with imbalanced data. A study compared the performance of the XGBoost and LogReg algorithms for predicting customer churn rates with imbalanced data [1].

Liu and colleagues focus on the importance of innovation in computation, particularly in its applications such as financial risk management and stock price forecasting. They also discuss two key algorithms that play a prominent role in stock price forecasting: ANNs and SVMs, emphasizing their vital role in improving the accuracy of forecasts and predictions in this field [5]. A recent study compared the performance of two neural networks, an ANN and a CNN, in predicting above-ground biomass [6]. Machine learning algorithms have shown promise in predicting heart disease using patient data. A machine learning-based model for predicting these diseases was presented, using SVM techniques and artificial intelligence [7]. Wen et al. simulated and predicted lunar landing features using the XGBoost model. They used Bayesian optimization to fine-tune the key parameters of the model, which in turn helped improve the prediction [8].

Temperature forecasting is a critical tool for understanding climate patterns and facilitating societal adaptation to climate change. Predictive models play a pivotal role in mediating decision-making across diverse sectors, including public health, agriculture, energy management, and urban planning [11]. The increasing frequency of extreme weather events, such as heatwaves and droughts, underscores the urgency of developing accurate and scalable temperature prediction systems [12].

Recent advancements in machine learning (ML) have demonstrated remarkable potential in climate science, particularly in handling non-linear relationships and high-dimensional datasets. For instance, ensemble methods such as XGBoost have outperformed traditional statistical models in predicting environmental variables, thanks to their ability to capture complex interactions [13]. Similarly, ANNs and SVMs have been widely adopted for their robustness in modeling spatial and temporal climate data [14]. In the context of Baghdad, where rising temperatures pose significant challenges to infrastructure and public health, accurate forecasting is indispensable. Previous studies have highlighted the efficacy of ML methods in similar arid regions, with XGBoost achieving superior performance in temperature prediction tasks [15]. However, gaps remain in optimizing these models for localized datasets and addressing overfitting, particularly in ANNs [16].

Recent studies have evaluated the performance of various machine learning models in predicting temperature. A comprehensive analysis by Singh and Rawat compared XGBoost, SVM, and Random Forest (RF) using a 45-year dataset from Visakhapatnam airport. The study found that SVM and RF exhibited slightly superior performance over XGBoost across several metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R^2 score, Mean Absolute Percentage Error (MAPE), and Explained Variance Score [17, 24]. Similarly, a study by Rahman assessed Gradient Boosting, AdaBoosting, ANN, Stacking Random Forest, Stacking Neural Network, and Stacking K-Nearest Neighbors (KNN) using a 20-year dataset from Dhaka city. The findings highlighted the remarkable achievements of these models, providing valuable insights into their performances and feature correlations [18].

Additionally, a study by Quayesam compared Ridge Regression, LASSO, Random Forest, and XGBoost for predicting Sea Surface Temperature in the Great Barrier Reef region. The results revealed that while LASSO and Ridge Regression performed well, Random Forest and XGBoost significantly outperformed them in terms of predictive accuracy, as evidenced by lower MSE, MAE, and Root Mean Squared Prediction Error (RMSPE) [19]. These findings align with our study, which evaluates XGBoost, ANN, and SVM for predicting July temperatures in Baghdad, providing a foundation for assessing model performance and identifying the most reliable approach.

As for the rest of our paper, in Part 1, we demonstrate the necessity of measuring temperature to improve prediction accuracy. In Part 2, we develop several machine learning methods for prediction. In Parts 4, 5, and 6, we demonstrate XGBoost, a powerful predictive tool; ANN, which excels at modeling complex data; and SVMs, which are effective for regression tasks, respectively. In Part 7, we present a practical approach for predicting temperatures in Baghdad Province, Iraq, using machine learning methods. Finally, we present the results of this research.

This study makes the following main contributions: First, it applies three machine learning methods (XGBoost, ANN, and SVM) to Baghdad's July temperature dataset covering the years 1941–2009. Second, it provides a comprehensive comparative evaluation of these models' predictive accuracy using multiple performance metrics, including MSE, RMSE, MAE, and R^2. Third, it identifies that XGBoost is the most effective model for capturing complex, nonlinear climate patterns in Baghdad's temperature data, while ANN and SVM deliver moderate performance. Finally, it establishes a foundation for future research on localized climate forecasting, highlighting the need for improved model refinement and the integration of additional explanatory variables to enhance predictive accuracy.

2. Related Work

Temperature forecasting is critical for understanding climate patterns and supporting decision-making in sectors such as energy management, public health, and urban planning. In recent years, machine learning (ML) techniques have been increasingly applied to climate and environmental forecasting due to their ability to model complex, nonlinear relationships in high-dimensional datasets.

Several studies have explored the use of ensemble and neural network methods for temperature prediction. Singh and Rawat compared XGBoost, SVM, and Random Forest for predicting daily temperatures in Visakhapatnam, India, using a 45-year dataset. Their results showed that SVM and Random Forest slightly outperformed XGBoost across metrics such as MSE, RMSE, MAE, and R^2, demonstrating the value of these ML methods for accurate temperature forecasting [17]. Similarly, Rahman et al. evaluated Gradient Boosting, AdaBoost, ANN, and stacking-based ensembles in Dhaka, Bangladesh. The study highlighted the strong performance of ensemble methods like Gradient Boosting and XGBoost for modeling local climate data [18].

Early fire detection systems using convolutional neural networks (CNNs) and surveillance cameras have been developed to minimize human and material losses. These systems are more accurate and cost-effective than traditional approaches [24]. Artificial intelligence (AI) and deep CNN models showed high performance in liver disease classification, with ResNet50 achieving 97.94% accuracy. Image preprocessing and segmentation play a vital role in enhancing diagnostic accuracy [25].

Deep learning with transfer learning was applied to SAR images for oil pipeline leak detection. The Xception model combined with an SVM achieved 99.8% accuracy, surpassing other methods [26].

Quayesam et al compared Ridge Regression, LASSO, Random Forest, and XGBoost for predicting sea surface temperatures in the Great Barrier Reef region. XGBoost and Random Forest significantly outperformed linear models, demonstrating their ability to capture complex patterns in environmental datasets [19]. Other research has demonstrated the effectiveness of ANNs in modeling nonlinear temperature and precipitation patterns [20, 21] and the utility of SVMs in handling regression tasks for climate variables [22].

Based on these studies, XGBoost has been selected in this work due to its ensemble-based boosted tree structure, robustness to nonlinearities, and ability to handle complex datasets effectively. SVM and ANN are included for comparison, as they have shown robust predictive performance in similar environmental and climate prediction studies. This comparative framework allows for assessing model performance on Baghdad's historical temperature data and determining the most accurate approach for forecasting July temperatures.

3-The Necessity of Temperature Measurement

High temperatures directly impact our public health, environment, industry, and scientific research. Measuring temperature represents both a major challenge and a golden opportunity, especially in Baghdad, which faces diverse environmental and health conditions. It effectively contributes to improving productivity in the industrial, agricultural, and other sectors. This makes temperature measurement an essential element in developing policies and strategies aimed at improving the quality of life and responding to environmental and health challenges more efficiently and effectively.

4-Machine Learning (ML) Methods for Prediction

Machine learning focuses on analyzing algorithms and utilizing mathematical and statistical techniques. It uses various methods to analyze data, extract patterns, and make predictions in various fields.

Furthermore, intelligent systems rely on machine learning to deliver more effective services, improving people's lives and generating significant economic and scientific benefits across sectors. As various machine learning methods have emerged and improved over time, we encounter different approaches that allow us to solve problems based on the problem type, data, and required learning. Machine learning methods vary widely, and in our research, we used three methods: ANN, SVM, and extreme gradient boosting (XGB). We will briefly introduce the above methods.

4.1 Extreme Gradient Boosting (XGBoost)

XGBoost was developed by combining concepts from gradient descent and boosting, resulting in a gradient boosting machine (GBM). Boosting is an ensemble learning algorithm that assigns different weights to the training dataset at each iteration to improve model performance and increase prediction accuracy. In each boosting iteration, weights are added to misclassified error samples and subtracted from correctly classified samples, effectively altering the training data distribution [4].

GBM utilizes second-order gradient statistics to minimize the regularized objectives outlined in the following equation:

$$\mathcal{L}(\phi) = \sum_{i} l\,(\hat{y}_i, y_i) + \sum_{k} \Omega\,(f_k) \tag{1}$$

where

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \parallel w \parallel^2 \tag{2}$$

Note that l is a differentiable convex loss function it is obtained by:

$$l(\hat{y}_i, y_i) = \hat{y}_i - y_i \tag{3}$$

Since $\parallel w \parallel^2$ is the L2 norm of the weights w, λ is the regularization parameter, and γ is the complexity penalty associated with the number of leaves T in the trees [3].

4.2 Development of XGBoost

The GBM algorithm aims to identify optimal candidate split points in large datasets. Chen and Guestrin proposed a novel distributed weighted quantum block diagram algorithm capable of handling weighted data with a provable theoretical guarantee, resulting in a new, scalable, and efficient algorithm called XGBoost [3]. XGBoost is also available R, Julia, and Python.

4.3 ANN model

The network consists of a set of interconnected nodes. We can represent each node by an activation function f. Assuming x_i is the input of node j, the output of node j is given by:

$$y_j = f\left(\sum_{i=1}^{n} w_{ij}\, x_i + b_j\right) \tag{4}$$

Where b_j is the bias for node j, and w_{ij} is the weight between input i and node j.

ANNs rely on learning algorithms to update weights. The update equation can be expressed as:

$$w_{ij}^{(t+1)} = w_{ij}^{(t)} - \alpha \frac{\partial L}{\partial w_{ij}} \tag{5}$$

Where L is the loss function that measures the difference between predicted and actual values and α is the learning rate.

ANNs are used to recover complex patterns from data, which can be mathematically represented by the expression:

$$\hat{y} = f(x) \tag{6}$$

where x is the noisy input data, and $\hat{y}$ is generated to reconstruct the original patterns, even when the data is contaminated.
ANN is based on a model inspired by the biological neural network, which resembles an interconnected network of nodes, made up of units resembling biological neurons that function similarly in processing information and performing computational operations.
Shallow networks usually consist of one or two hidden layers and are suitable for simple classification or regression tasks, while deep networks with three or more hidden layers are typically applied in more complex domains such as image recognition, speech processing, and natural language processing. The number of neurons in each hidden layer is not fixed and is generally determined through experimentation, with common choices including 32, 64, or 128 neurons. Various activation functions can be used within these networks. The sigmoid function, which outputs values between 0 and 1, was common in early networks but suffers from vanishing gradient issues. Similarly, the tanh function, which outputs between -1 and 1 and is zero-centered, also faces this limitation.
Non-adaptive neural networks demonstrate the ability to represent datasets and can reconstruct patterns even when the data contains corrupted or noisy elements, enhancing their flexibility and effectiveness in handling imperfect data.
The basis of the SVM classifier is linear data classification, and in linear data partitioning, we try to choose a hyperplane with a higher confidence margin.
Understanding the relationship between input and output data in temperature forecasting is often considered a complex process. After explaining the process of developing networks for temperature prediction, we focus on static and dynamic methods. We also review data preparation, model efficiency, and the mechanism for selecting the number of neurons in a layer to achieve the lowest error rate. We then apply the MLP network method to predict temperatures in Baghdad, Iraq, contributing to accurate estimates of climate change in the region amid rapid and dynamic environmental changes.

4.4 SVM model

SVM is a classification model whose principle is to find a hyperplane that separates different classes [9, 10]. Suppose we have two points y_1 and y_2 in an n-dimensional space. We express the hyperplane as:

$$h^T y + b = 0 \tag{7}$$

Where h is the direction of the hyperplane and b is the bias term.

The confidence margin represents the distance between the hyperplane and the nearest points from the different classes, and is calculated using:

$$\text{Margin} = \frac{2}{\| h \|} \tag{8}$$

The goal is to maximize the margin during training, which helps minimize the risk of model complexity and avoids overfitting.

SVMs use different types of kernels to map data into higher-dimensional spaces and create effective decision boundaries. The linear kernel, defined as

$$K(x_i, x_j) = x_i \cdot x_j, \tag{9}$$

is best suited for linearly separable data. The polynomial kernel, expressed as

$$K(x_i, x_j) = (\gamma x_i \cdot x_j + r)^d, \tag{10}$$

is useful for handling curved decision boundaries, with the degree d determining the complexity of the curve. The radial basis function (RBF) kernel, given by

$$K(x_i, x_j) = \exp(-\gamma \parallel x_i - x_j \parallel^2)\ , \tag{11}$$

is the most commonly used and highly effective for non-linear problems. Another option is the sigmoid kernel,

$$K(x_i, x_j) = \tanh(\gamma x_i \cdot x_j + r)\ , \tag{12}$$

which behaves similarly to activation functions in neural networks. In addition to kernel choice, SVM performance depends on key parameters. The regularization parameter C controls the trade-off between achieving a wide margin and allowing misclassifications, while γ (gamma) defines how far the influence of a single training point extends, which is especially important for the RBF kernel. For polynomial kernels, the degree d serves as a critical parameter that affects the flexibility of the decision boundary. Table 1 summarizes the key parameters of ANN and SVM, along with their common options and examples.

Table 1. Key Parameters of ANN and SVM

Model	Key Parameter	Options / Examples
ANN	Hidden Layers	1–n layers, neurons per layer (32, 64, 128, …)
	Activation Functions	Sigmoid, Tanh, ReLU, Leaky ReLU, Softmax
SVM	Kernel Type	Linear, Polynomial, RBF, Sigmoid
	Parameters	C, γ (gamma), Degree (for polynomial)

4.5 The XGBoost algorithm

Te XGBoost algorithm takes as input training data $\{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$, a differentiable loss function $L(y_i, F(x))$ and a learning rate α. Then, based on the following process, the final model is produced.

1. The first weak model is a constant number that minimizes the loss function:

$$\hat{f}_0 = arg_\gamma\, min \sum_{i=1}^{N} L(y_i, \gamma) \tag{13}$$

2. For m from 1 to M, do the following:

a) Compute the gradient and Hessian as follows:

$$\hat{g}_m(x_i) = \left[\frac{\partial\, L(y_i, f(x_i))}{\partial f(x_i)}\right]_{f(x)=\hat{f}_{m-1}(x)} \tag{14}$$

$$\hat{h}_m(x_i) = \left[\frac{\partial^2\, L(y_i, f(x_i))}{\partial f(x_i)^2}\right]_{f(x)=\hat{f}_{m-1}(x)} \tag{15}$$

b) Train the model using the data:

$$\left\{(x_i, -\frac{\hat{g}_m(x_i)}{\hat{h}_m(x_i)})\right\}_{i=1}^{N} \tag{16}$$

$$\hat{\phi}_m = arg_{\phi\in\Phi}\, min \sum_{i=1}^{N} \frac{1}{2}\hat{h}_m(x_i)\left[-\frac{\hat{g}_m(x_i)}{\hat{h}_m(x_i)} - \phi(x_i)\right]^2 \quad (17)$$

$$\hat{f}_m(x) = \alpha\hat{\phi}_m(x) \quad (19)$$

c) Construct the model as follows:

$$\hat{f}_m(x) = \hat{f}_{m-1}(x) + \cdots + \hat{f}_0(x) \quad (20)$$

3. The final model is:

$$\hat{f}(x) = \sum_{i=0}^{M} \hat{f}_i(x) \quad (21)$$

5-Practical aspect: Using machine learning methods to predict temperatures in Baghdad Province, Iraq

We will examine the predictions made by these methods and compare them with those made using multi-layer neural networks, Support Vector Machine, and the XGB algorithm. Table 2 represents the average temperatures for July in Baghdad, Iraq. We aim to use this data to measure temperature to enhance the accuracy of predictions using the machine learning methods mentioned above in the theoretical aspect.

Data source: Baghdad weather data. This data represents daily maximum and minimum temperatures in Baghdad during July from 1941 to 2009. For more details on the data, please visit [23]. The intensity and summertime characteristics of Baghdad during July, which is considered one of the hottest months of the year, show high temperature fluctuations and significant heat stress, making it an ideal sample for studying high variability and assessing climate sustainability. The availability of summer data in meteorological records also makes July more stable and available than other months, reducing the impact of time gaps and improving comparability.

The training error shows significant fluctuations, indicating that the model may be learning well in some epochs. The testing error remains relatively stable but higher than the training error, indicating a discrepancy between performance on the training and testing data. Figure 1 provides insight into how the model has performed over epochs and helps identify potential problems in the training process.

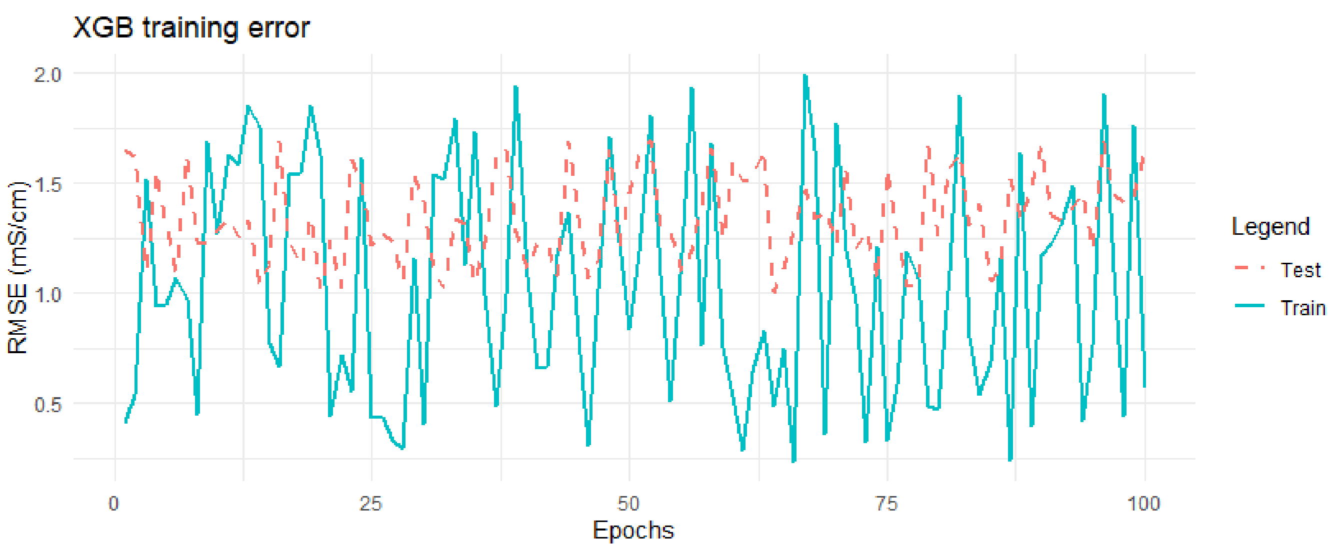

Figure 1. Training and testing error of XGBoost model over years.

The evaluation results indicate that the proposed model achieves a Mean Squared Error (MSE) of 0.42, reflecting a relatively low level of squared prediction error. The Root Mean Squared Error (RMSE) of 0.65 °C suggests that, on average, the model's predictions deviate from the observed temperatures by less than one degree, which is considered a reasonable level of accuracy in climate forecasting applications. Similarly, the Mean Absolute Error (MAE) of 0.52 °C confirms that the average prediction error remains small, further supporting the reliability of the model's outputs. However, the coefficient of determination ($R^2 = 0.467$) indicates that the model explains approximately 46.7% of the variability in the temperature data. This demonstrates that while the model captures a substantial portion of the observed variation, there is still unexplained variance, suggesting the potential for improvement through the inclusion of additional explanatory variables or further model refinement. The predicted temperature for 2026 is 34.70°C.
The Figure 2 illustrates the comparison between actual mean temperatures (red line) and those predicted by the ANN model (dashed blue line) from 1941 to 2009. The actual temperatures display various fluctuations throughout the years, reflecting climatic changes. The predicted values from the ANN generally follow the trend of the actual data but do not capture all the specific variations, especially the peaks and valleys. The MSE for the mean temperature using ANN is 1.10. This value indicates the average of the squares of the errors, providing a measure of how closely the predicted values align with the actual temperatures. A lower MSE suggests better predictive performance.

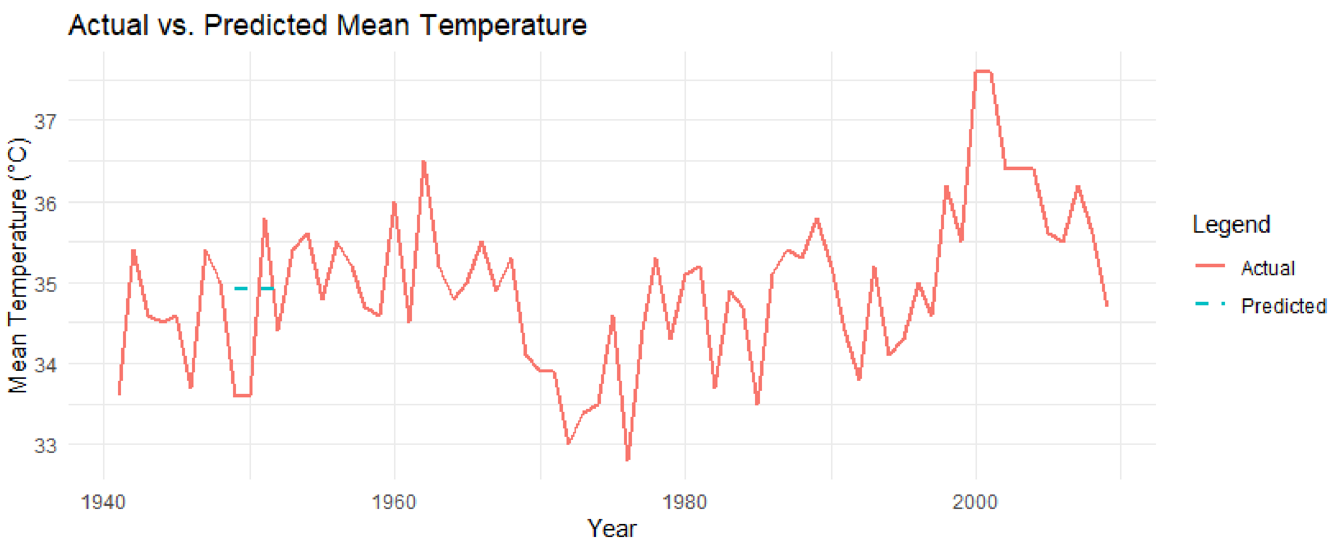

Figure 2. Training and testing error of ANN model over years.

The evaluation results indicate that the model achieved a Mean Squared Error (MSE) of 1.10, corresponding to a Root Mean Squared Error (RMSE) of approximately 1.05. This suggests that, on average, the predicted mean temperatures deviate from the observed values by about one degree Celsius. The Mean Absolute Error (MAE) was estimated at 0.83, indicating that the magnitude of prediction errors remains relatively low across most observations. Furthermore, the coefficient of determination (R^2) was calculated to be 0.395, implying that the model explains roughly 40% of the variance in the temperature data. These results demonstrate a moderate predictive capability, with reasonable error margins, although a substantial proportion of variability remains unaccounted for. The predicted temperature for the year 2026 is approximately 35.13 °C, indicating an expectation of a slight increase in mean temperatures compared to previous records.

Table 2. Mean Temperatures for July in Baghdad, Iraq (1941-2009)

year	Mean temperature	year	Mean temperature
1941	33.6	1976	32.8
1942	35.4	1977	34.4
1943	34.6	1978	35.3
1944	34.5	1979	34.3
1945	34.6	1980	35.1
1946	33.7	1981	35.2
1947	35.4	1982	33.7
1948	35.0	1983	34.9
1949	33.6	1984	34.7
1950	33.6	1985	33.5
1951	35.8	1986	35.1
1952	34.4	1987	35.4
1953	35.4	1988	35.3
1954	35.6	1989	35.8
1955	34.8	1990	35.2
1956	35.5	1991	34.4
1957	35.2	1992	33.8
1958	34.7	1993	35.2
1959	34.6	1994	34.1
1960	36.0	1995	34.3
1961	34.5	1996	35.0
1962	36.5	1997	34.6
1963	35.2	1998	36.2
1964	34.8	1999	35.5
1965	35.0	2000	37.6
1966	35.5	2001	miss
1967	34.9	2002	36.4
1968	35.3	2003	miss
1969	34.1	2004	miss
1970	33.9	2005	35.6
1971	33.9	2006	35.5
1972	33.0	2007	36.2
1973	33.4	2008	35.6
1974	33.5	2009	34.7
1975	34.6		

Figure 3 compares actual (Observed) and predicted (SVM) mean temperatures from 1941 to 2009. Red Line: Repre sents actual recorded temperatures over the years, showing fluctuations with noticeable peaks and valleys.́ Dashed Blue Line: Represents temperatures predicted by the SVM model. While it captures some general trends, it does no t follow all the precise fluctuations of the actual data. The model has managed to capture some overall trends, such as the gradual increase in temperatures during certain periods. However, there are points where predictions are less accurate, reflecting a general trend rather than actual temperature variations.

The SVM model achieved a Mean Squared Error (MSE) of 0.85, corresponding to a Root Mean Squared Error (RM SE) of approximately 0.92. This indicates that, on average, the predicted mean temperatures deviate from the obser ved values by just under one degree Celsius. The Mean Absolute Error (MAE) was calculated as 0.78, suggesting that the magnitude of prediction errors remains relatively low across most observations. The coefficient of determination (R^2) was 0.224, indicating that the model explains approximately 22.4% of the variance in the temperature data. Overall, these results demonstrate a moderate predictive performance, with reasonable accuracy, although a significant portion of variability remains unexplained.

This indicates that the model predicts an average mean temperature of around 35.13 °C for the year 2026. The prediction suggests a slight increase in mean temperatures compared to recorded values in prior years, reflecting the general trend of rising temperatures in the historical data. The performance metrics of the three models are summarized in Table 3.

Table 3. Performance comparison of XGB, ANN, and SVM models for mean temperature prediction.

Model	MSE	RMSE	MAE	R^2
XGB	0.42	0.65 °C	0.52 °C	0.467
ANN	1.10	1.05 °C	0.83 °C	0.395
SVM	0.85	0.92 °C	0.78 °C	0.224

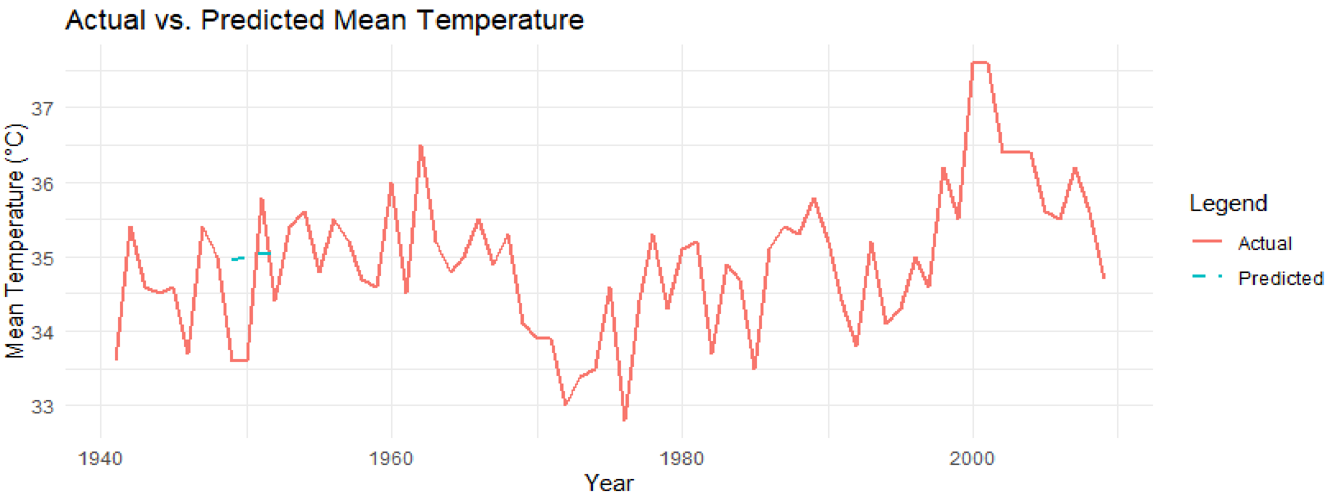

Figure 3. Training and testing error of SVM model over years.

5- Conclusion

In this study, three machine learning methods—ANN, SVM, and XGB—were used to predict temperatures in Baghdad using July data spanning 1941 to 2009. The dataset was randomly divided into training and testing sets. The best-performing model based on MSE values was XGBoost, which outperformed both SVM and ANN, making it the most effective choice for predicting mean temperature in this case. This finding is consistent with previous studies [17, 18, 19], which show that ensemble models such as XGBoost demonstrate superior ability to capture complex climate patterns compared to ANN and SVM. The XGBoost model benefited greatly from its boosted trees and clustering approach, enabling it to more efficiently handle the dataset's complexities and significantly improve prediction accuracy. In contrast, the SVM model performed reasonably well, capturing underlying temperature trends, while the ANN model showed weaker performance, consistent with findings that neural networks may overfit small or noisy climate datasets [16]. Overall, the XGBoost model demonstrates superior predictive accuracy and variance explanation compared to ANN and SVM. Both ANN and SVM provide moderate predictions, but XGBoost is clearly the most reliable choice for this dataset.

Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this research. All analyses, results, and interpretations presented in this study were conducted with full academic integrity and without any commercial, financial, or personal relationships that could have influenced the outcomes.

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