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Research Article

Maximum Temperature Forecasting with an Automatic Forecasting Method Based on Deep Dendritic Artificial Neural Network (AutoDeepdenT)

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ABSTRACT

Due to the global ecological crisis, accurate temperature prediction has become increasingly important, especially for environmental sustainability worldwide. The main motivation for this research is the increasing importance of temperature prediction due to the global ecological crisis. Considering the impacts of climate change and environmental sustainability, making accurate temperature predictions has become a critical necessity for the conservation of natural resources and the fight against climate change. In addition to traditional statistical techniques, the success of deep learning methods in solving complex relationships has become the focal point of research in this field. A large number of statistical techniques are used to predict air temperatures, but deep learning methods have recently become popular for complex relationships. More layers distinguish Deep Artificial Neural Networks (DANNs) from traditional Artificial Neural Networks (ANNs). Since they have multi-layered designs, they perform high-level inference in data analysis. This research has predicted temperature values using the Dendritic Neuron Model-Based Explainable Feedback Deep Artificial Neural Network (DeepDenT) architecture. The study consists of 412 monthly maximum temperature data covering 1991 to 2022 from the Giresun province. According to the results, the AutoDeepDenT method obtains more accurate predictions than all other tested models. This highlights the effectiveness of advanced deep learning techniques in temperature prediction and their importance for environmental sustainability.

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1. INTRODUCTION

Today, one of the most pressing global issues is climate change, primarily driven by rising average temperatures and increasing concentrations of greenhouse gases in the atmosphere. The escalation of air temperatures leads to significant environmental challenges, including climate change and drought. Accurate predictions of changes in air temperatures are crucial for formulating sustainable environmental policies and implementing necessary precautions (Fister et al., 2023; Seager et al., 2019; Doblas-Reyes et al., 2013). In this context, temperature estimates and climate forecasts, which serve as indicators of global warming, have emerged as vital areas of research. Climate predictions aim not only to analyze current climate parameters but also to provide insights into future conditions. The results of these predictions guide policymakers in various domains, such as agriculture, disaster risk management, and energy planning (Salcedo-Sanz et al., 2024; Pepler et al., 2015). Air temperature, a fundamental physical variable of the atmosphere, influences not only the functioning of climate systems but also the vital activities of humans and other living organisms (Tajfar et al., 2020; Valipour et al., 2020). Furthermore, temperature data play a critical role in accurately predicting other meteorological variables, such as evaporation, runoff, and solar radiation (Jovic et al., 2018; Marzo et al., 2017; Tang et al., 2012).

In recent years, methods for forecasting air temperatures have shifted from traditional statistical models to artificial intelligence-based approaches. Deep Learning (DL), a powerful machine learning technique, facilitates the extraction of meaningful patterns from complex datasets through the use of multilayered artificial neural networks (Deng & Yu, 2014). Deep Artificial Neural Networks (DANNs) outperform conventional artificial neural networks by incorporating additional hidden layers, thereby enabling the processing of complex, high-dimensional data and allowing for the extraction of more abstract features (Schmidhuber, 2015). The learning process typically involves minimizing a loss function through the backpropagation algorithm (Rumelhart et al., 1987).

In the research conducted by Eğrioğlu and Baş (2025), a deep learning model derived from the Dendritic Neuron Model, named AutoDeepDenT, was implemented to forecast monthly temperature maxima for Giresun province in Turkey. This model was specifically developed for subsequent applications in other environmental predictive modeling challenges. Unlike conventional deep learning systems, this model enhances synaptic functions by incorporating additional nerve-like units, thereby simulating a more realistic dendritic processing. Moreover, the feedback loop is known to improve accuracy over time due to recurrent learning. As previously mentioned, the motivation for this research lies in utilizing DeepDenT across different domains with environmental datasets to achieve greater effectiveness in problem-solving. The current objective is to evaluate the effectiveness of AutoDeepDenT on the entire temperature dataset to promote broader acceptance of the model.

For this study, data were primarily collected from the Trabzon Meteorology Regional Directorate, which includes 412 monthly maximum temperature readings spanning from 1991 to 2022. The estimation process was conducted using an automatic prediction tool developed in MATLAB by the authors (The MathWorks, 2024). Temperature prediction is critical in areas such as climate change, agriculture, energy planning, and disaster management. In this context, artificial neural networks (ANNs) and deep learning-based methods are widely employed. The literature encompasses studies conducted across various geographical regions, utilizing different data types and time intervals, thereby revealing the complexity and diversity of the temperature prediction problem. In this regard, the performance of ANNs and deep learning models has been assessed in terms of hidden layer configurations and application areas.

Traditional ANNs have long been favored for temperature prediction. Ustaoglu et al. (2008) tested backpropagation ANN (FFBP), radial basis function (RBF), and generalized regression neural network (GRNN) models using daily average, maximum, and minimum temperature data from Turkey between 1989 and 2003. They produced daily temperature forecasts with varying hidden layer configurations. Similarly, Afzali et al. (2012) developed a single hidden layer (15-neuron) ANN model using daily and monthly temperature data from Iran between 1961 and 2004, making predictions for one day and one month ahead. Dombayci and Golcu (2009) utilized a Levenberg-Marquardt algorithm-based ANN model to generate daily average temperature predictions using monthly, daily, and previous day's average temperature data from 2003 to 2006. These studies illustrate that while ANNs are effective for time series data, their capacity to learn complex patterns is limited due to the restricted number of layers. In addition to ANN-based models, studies integrating geographic and meteorological variables have also gained attention. Bilgili and Şahin (2009) performed monthly temperature predictions using a multi-layer perceptron (MLP) model that incorporated latitude, longitude, elevation, and month data from Turkey between 1975 and 2006, utilizing a single hidden layer (32-neuron) structure. Similarly, Kisi and Shiri (2014) applied a single hidden layer (four neurons) ANN model with the same variables using data from Iran between 1956 and 2010. Sahin (2012) developed single hidden layer ANN models with 14 and 24 neurons, leveraging city, month, elevation, latitude, longitude, and monthly average land surface temperature data from Turkey between 1995 and 2005. These studies demonstrate that integrating geographical data into temperature prediction models enhances accuracy.

Deep learning approaches stand out compared to traditional ANNs due to their ability to handle more complex data structures. Tran et al. (2021) compared traditional ANNs, recurrent neural networks (RNNs), and long short-term memory (LSTM) models using daily maximum temperature data from South Korea between 1976 and 2015. They reported that LSTM with 1-20 hidden neurons and 1-3 hidden layers performed superiorly in predictions ranging from 1 to 15 days ahead. Zhang and Dong (2020) developed a convolutional recurrent neural network (CRNN) with four past temperature data maps from China spanning 1952 to 2018, utilizing three convolutional layers, one LSTM, and one dense layer to predict future temperature maps. These studies indicate that deep learning models, particularly LSTM and convolutional networks, offer high accuracy for time series and spatial data. Regional diversity is an important factor in designing temperature prediction models. De and Debnath (2009) developed a single hidden layer (2 neurons) ANN model using maximum and minimum temperature data from India between 1901 and 2003, focusing on predicting the monsoon months (June-August). Another study by Salcedo-Sanz et al. (2016) employed an MLP model using data on the previous month's temperature, Southern Oscillation Index (SOI), Indian Ocean Dipole (IOD), and Pacific Decadal Oscillation (PDO) from Australia and New Zealand between 1900 and 2010 to produce monthly average temperature forecasts. These studies emphasize that regional climate characteristics and additional meteorological variables enhance model performance.

Among deep learning models, LSTM, CNN, and hybrid architectures are frequently preferred for time series prediction. Lee et al. (2020) compared MLP (6 hidden layers), LSTM (2 hidden LSTM + 3-6 dense layers), and CNN (5 convolutional + 2 dense layers) models using multiple variables such as temperature, humidity, and solar radiation from South Korea between 2009 and 2018. They noted that LSTM yielded better results in predicting daily average, minimum, and maximum temperatures. Kreuzer et al. (2020) tested single and multivariable LSTM and ConvLSTM models with temperature, humidity, cloud cover, and wind data from Germany between 2009 and 2018, reporting that a ConvLSTM model with 6 convolutional layers, 2 LSTM layers, and 2 dense layers achieved high accuracy in 24-hour temperature predictions. Roy (2020) compared MLP (2 layers, 16 neurons), LSTM (16 hidden neurons), and CNN+LSTM (32 convolution filters+16-neuron LSTM) models using seven-day meteorological data from New York between 2009 and 2019, highlighting the superior performance of the CNN+LSTM model for one-day and ten-day predictions. Abhishek et al. (2012) employed a 5-hidden-layer ANN model using 10 years of historical data to perform daily maximum temperature predictions in Canada between 1999 and 2009. Bas et al (2024) proposed the dendritic neuron model artificial neural networks from being affected by the outliers in the data set; a robust learning algorithm based on Talwar's m estimator, median statistics to prevent the effect of outliers in the inputs, and a new data preprocessing method are used together in a network structure. These studies underscore the effectiveness of ANN models in multivariable and short-term predictions.

In contrast to the previously mentioned studies, the proposed AutoDeepDenT model offers an explainable feedback-based deep artificial neural network architecture grounded in a dendritic neuron model. In this research, AutoDeepDenT was utilized to predict temperatures based on 412 monthly maximum temperature records from Giresun province between 1991 and 2022. The model achieved high accuracy in 12-month forecasts when evaluated using the RMSE metric. This study advances the current literature by introducing AutoDeepDenT as a novel, effective, and explainable AI framework for accurate temperature prediction.

2. METHODOLOGY

2.1. Dataset

The dataset used in this study consists of monthly maximum temperature data from Giresun province located in the Eastern Black Sea Region of Türkiye. Located between the Coastal Mountains and the Black Sea, Giresun is one of the important cities of Türkiye with agricultural diversity, characterized by a humid subtropical climate. Agricultural products grown in special climate conditions, especially hazelnuts, tea and kiwi, are significantly affected by air temperature. Therefore, accurate modeling of temperature trends in the region is extremely important for agricultural planning and crop productivity. The dataset used in this study covers the 32-year period between January 1991 and December 2022 and consists of a total of 412 monthly observations. The data were obtained with special permission from the Trabzon Meteorological Regional Directorate affiliated to the General Directorate of State Meteorological Services of Türkiye. Before modeling the data, the dataset was divided into training, validation and test subsets to ensure a more accurate and objective evaluation of the forecast performance.

2.2. DeepDenT Automatic Forecasting Method

To forecast the highest monthly temperatures in Giresun province, this study employs the DeepDenT model, which is a sophisticated deep artificial neural network inspired by the dendritic neuron model developed by Egrioglu and Bas (2024). One of the key advantages of DeepDenT is its ability to minimize reliance on subjective opinions, providing predictions that are purely data-driven and unbiased. The model integrates dendritic cells (DnCs) into its deep feedback artificial neural network framework. At its core, DeepDenT features an output layer built on a classical fully connected (FC) layer that uses an additive aggregation function. What sets DeepDenT apart from traditional neural networks is its partially connected structure, where DnCs are arranged in a sequential and hierarchical manner. The automatic forecasting method introduced by Eğrioğlu and Baş (2024) streamlines the prediction process by removing the need for practitioners to tackle complex technical details, thus allowing for more efficient forecasting solutions (Eğrioglu & Bas, 2024). The architecture of DeepDenT is illustrated in Figure 1.

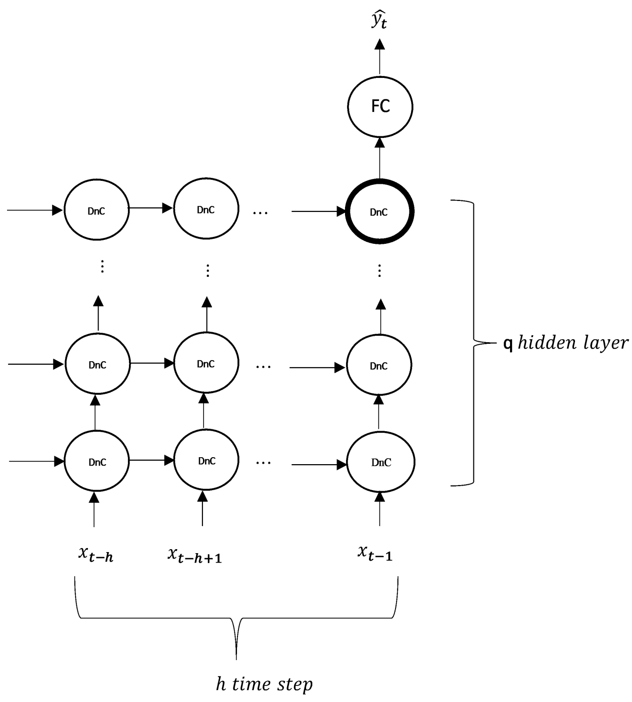

Figure 1. DeepDenT Architecture (Egrioglu & Bas, 2024)

The automatic estimation method used in this study was developed based on the DeepDenT architecture in Bas and Egrioglu (2025). It was designed to minimize the need for manual intervention, allowing users to systematically carry out the modeling process. The method aims to improve estimation performance through a structure that incorporates steps such as statistical controls, determination of lag variables, and hyperparameter optimization. The steps of the automatic estimation method defined are listed below:

Step 1: Determination of Hyperparameter Ranges

- Number of Hidden Layers: Minimum and maximum values are defined.
- Number of Dendritic Cells: The values m_{min} and m_{max} with in each cell.
- Time Steps***:*** Minimum and maximum values h_{min} and h_{max}
- ***N***umber of Repetitions for Random Initial Weights::n_{repeat}
- Number of Training, Validation, and Test Data Samples:: $\boldsymbol{n_{train}}, \boldsymbol{n_{val}}$ **ve** $\boldsymbol{n_{test}}$
- Time Series Period:$\boldsymbol{s}$
- Bootstrap Repetition Count: $\boldsymbol{n_{bst}}$
- Number of Forecasts: $\boldsymbol{n_f}$

Step 2: The real-time series consisting of a total of n observations, $X_t = \{x_1, x_2, \dots, x_n\}$, is divided into three sets: training, validation, and test sets:

$$X_t^{train} = \{x_1, x_2, \dots, x_{ntrain}\} \quad (1)$$
$$X_t^{val} = \left\{x_{n_{train}+1}, x_{n_{train}+2+}, \dots, x_{n_{train}+n_{val}}\right\} \quad (2)$$
$$X_t^{test} = \left\{x_{n_{train}+n_{val}+1}, x_{n_{train}+n_{val}+2+}, \dots, x_n\right\} \quad (3)$$

Step 3: Stationarity in the time series is checked. If the time series is not stationary, stationarity is achieved by differencing. First, it is investigated whether there is stationarity arising from seasonality. If the condition given in Equation (4) is satisfied, seasonal differencing is applied using Equation (5) to achieve stationarity.

$$|ACF_m| > 1.645\sqrt{\frac{1 + 2(ACF_1 + \sum_{i=2}^{m-1} ACF_i^2)}{n}} \quad (4)$$
$$z_t = (1 - B^s)^D x_t \quad (5)$$

Subsequently, s represents a seasonality period. After examining non-stationarity related to seasonality, non-stationarity caused by trends is investigated using unit root tests. The Augmented Dickey-Fuller test is applied to the time series. If the series contains a unit root, the differencing process is applied according to Equation (6).

$$w_t = (1 - B)^d z_t \quad (6)$$

Step 4: Partial autocorrelation coefficientsr_{kk} $(k = 1,2, \dots, nlag)$ and the variances of these coefficients are calculated to determine the confidence intervals for the time series.

$$r_k = \frac{\frac{1}{n_{trn} - k}\sum_{t=k+1}^{n_{trn}}(x_t - \bar{x})(x_{t-k} - \bar{x})}{\frac{1}{n_{trn}}\sum_{t=1}^{n_{trn}}(x_t - \bar{x})^2} \quad (7)$$

Partial autocorrelation coefficients are calculated using Equation (8).

$$r_{kk} = \frac{r_k - \sum_{j=1}^{k-1} r_{k-1,j} r_{k-j}}{1 - \sum_{j=1}^{k-1} r_{k-1,j} r_j} \quad (8)$$

The variance of these coefficients is expressed as in Equation (9).

$$V(r_{kk}) = \frac{1}{n_{trn}} \pm 2\sqrt{V(r_{kk})} \quad (9)$$

Lags corresponding to partial autocorrelation coefficients outside the bounds are determined, and these lags form the elements of the $LagK$ set. The membership function for the$LagK$ set is defined by Equation (10) for, $k = 1,2, \ldots, nlag$.

$$\mu_{LagK}(k) = \begin{cases} 1, & if\ r_{kk} > 2\sqrt{V(r_{kk})}\ or\ r_{kk} < -2\sqrt{V(r_{kk})} \\ 0, & otherwise \end{cases} \quad (10)$$

Step 5: Validation and test performances are calculated for all possible hyperparameter combinations(m, q, h). The number of combinations is calculated based on the defined ranges.
Step 5.1: Random initial weights are generated a specific number of $\mathrm{n_{repeat}}$ times.
Step 5.2: The significant inputs are determined for each random weight set.
Step 5.3: The best validation results obtained with different initial weights are selected.
Step 6: The hyperparameter set with the best performance is determined.
Step 7: The test performance is evaluated for the selected hyperparameter set, and the process is completed by calculating predictions from the model.

3. RESULTS AND DISCUSSION

In this study, we utilized monthly maximum temperature records from Giresun province spanning 1991 to 2022 to generate forecasts using the DeepDenT model. The dataset, containing a total of 412 monthly observations, provides a robust basis for analyzing temperature trends over more than three decades. The initial and final ten values of the dataset, presented in Table 1, illustrate the fluctuations in maximum temperatures throughout this period, highlighting both seasonal variations and potential long-term trends.

Table 1. Dataset (First and Last 10 Values)

City	Data Order	Year	Maximum Temperature
Giresun	1	1991	14.6
Giresun	2	1991	18.8
Giresun	3	1991	22
Giresun	4	1991	26
Giresun	5	1991	30
Giresun	6	1991	26.6
Giresun	7	1991	29
Giresun	8	1991	29.3
Giresun	9	1991	25
Giresun	10	1991	27.2
Giresun	403	2022	31.7
Giresun	404	2022	19.9
Giresun	405	2022	19.7
Giresun	406	2022	21.9
Giresun	407	2022	34.6
Giresun	408	2022	26.5
Giresun	409	2022	29.7
Giresun	410	2022	29.6
Giresun	411	2022	32.2
Giresun	412	2022	32.5

The modelling process involved uploading the dataset to an automatic forecasting application, where essential parameters were meticulously specified. Given the monthly frequency of the data, we defined the time series period as 12 months. Each of the training, validation, and test sets was allocated 12 observations, ensuring a balanced approach to model evaluation. Furthermore, the configuration of the model was carefully calibrated, with the number of dendritic cells set to 4 and the forecast horizon determined to be 12 months. The optimal configuration of the DeepDenT model, identified through rigorous training, included a time step (h) of 1, one hidden layer (q), one dendrite (m), and a significant lag of 12. This configuration reflects a thoughtful adaptation of the model to the inherent characteristics of the temperature data. The actual time series values were visualized in Figure 2, providing a clear representation of the temperature trends over the years. The RMSE value obtained for in-sample prediction performance when applying the AutoDeepDenT method was 4.0973. The error metrics obtained for the test set in out-of-sample performance are given in Table 2.

Table 2. Out of Sample Performance of AutoDeepDenT

RMSE	MAPE	SMAPE	MASE	REIMAE
7.1492	114.2208	50	0.905943	1.279655

Additionally, in Figure 3, multi-step forecasts were obtained for out-of-sample performance and compared with actual values. Following the training of the DeepDenT model, the forecast values were plotted against the actual values, as shown in Figure 3. This comparison not only illustrates the model's predictive capabilities but also serves as a visual verification of its performance. Upon examining Figure 3, it is observed that there is a notable similarity between the actual values (blue line) and the predicted values (orange line); however, the predicted values fall short of the actual values during certain periods. Both lines exhibit fluctuations, with significant increases in actual values particularly noted at the 5th and 10th positions. Overall, while the predicted values trend closely to the actual values, it is evident that the predictions lag behind, especially at the 3rd and 11th positions. This situation serves as an important indicator for assessing the predictive success of the model.

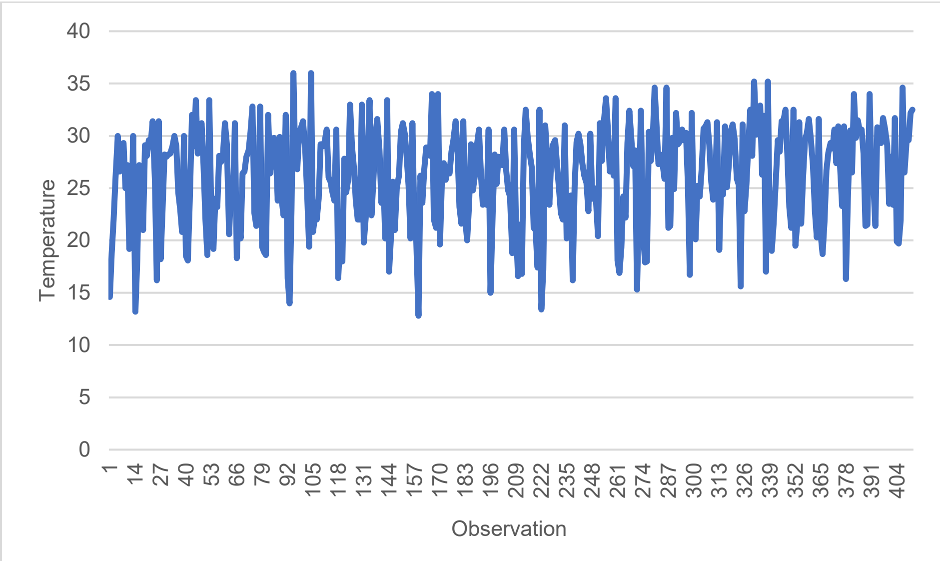

Figure 2. Real Time Series (1991-2022)

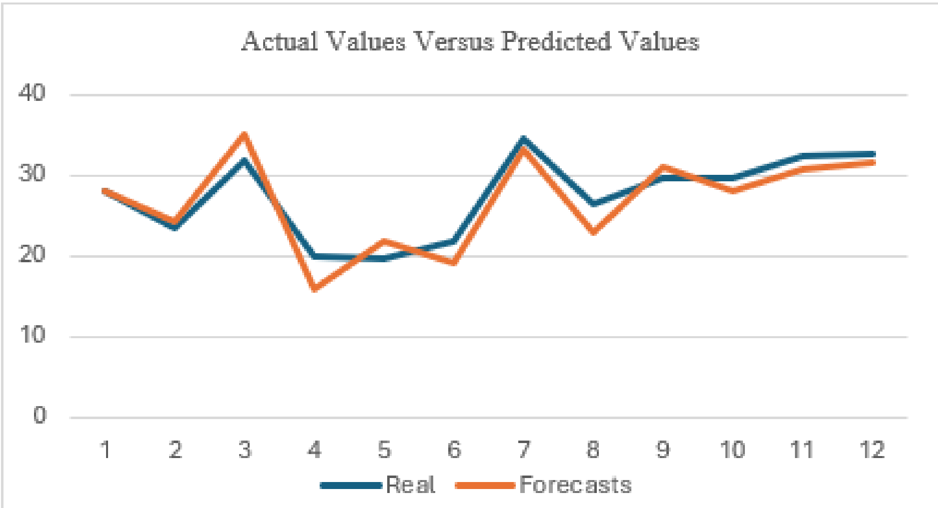

Figure 3. Actual Values Versus Forecasted Values for Test Set (Last 12 Values)

The effectiveness of the DeepDenT model was quantitatively assessed using the Root Mean Square Error (RMSE) criterion. This metric is crucial for understanding the accuracy of temperature predictions, as it provides a straightforward means of evaluating model performance (Salaudeen et al., 2023). In our analysis, the AutoDeepDenT model outperformed traditional forecasting techniques and contemporary machine learning methods. The RMSE values for various models, summarized in Table 3, offer insight into the comparative effectiveness of each approach. Notably, the AutoDeepDenT model achieved the lowest RMSE of 5.191, demonstrating superior forecasting accuracy relative to other methods.When compared to the Multilayer Perceptron (MLP) model, which recorded the highest RMSE of 5.955, it is evident that AutoDeepDenT not only excels in terms of accuracy but also highlights the limitations of MLP in capturing the complexities of temperature data.

This superiority can be attributed to the unique architecture of DeepDenT, which incorporates a dendritic neuron model that enhances its ability to simulate realistic biological processes, thereby improving its predictive performance. Table 3 shows that the methods have an error of around 5°C in predicting the maximum temperature of a day. The performance of the models in predicting the maximum temperature is similar, but it can be seen that the AutoDeepDenT method provides an improvement of between 3% and 14% compared to the other methods.

Table 3. Comparison of Results for Test Data with Different Prediction Methods

Method	Root Mean Square Error (RMSE)
Linear Regression	5.5767
Stepwise Linear Regression	5.3676
Tree (Medium)	5.6799
Linear SVM	5.5483
Efficient Linear SVM	5.5767
Ensemble Boosted Trees	5.3649
Neural Network (MLP)	5.9553
AutoDeepDenT	5.1917

The implications of these findings are particularly significant in terms of climate science and environmental management. The DeepDenT model's ability to predict maximum temperatures more accurately than other models will directly assist policymakers in developing effective policy recommendations. As the frequency of sudden changes in weather conditions increases, reliable temperature predictions are becoming an indispensable tool for effective disaster risk management, agricultural planning, and energy resource allocation. The model's depth and power are evident: DeepDenT adapts better to the structure and characteristics of the data compared to other methods, thereby performing much better on complex data structures. This is because the model can automatically extract features and thus learn important features more effectively. The fundamental strength of this deep learning approach is that the model is designed to have more layers and neurons than traditional networks. This deep architecture allows it to analyze not only basic patterns but also extremely complex and abstract relationships within the data. This advanced and detailed learning process ultimately enables the model to develop superior generalization capabilities that can be applied to new data with high accuracy.

4. CONCLUSION

This study successfully predicted maximum temperature data for the province of Giresun using DeepDenT, a new deep neural network model. The model's effectiveness and accuracy were comprehensively evaluated, confirming that the automatic prediction method yields superior results compared to existing neural networks and classical methods. Accurate temperature and drought predictions are of vital importance for agricultural regions such as Giresun, especially considering their significant role in hazelnut, tea, and kiwi production in Turkey. Furthermore, Giresun's location in the Eastern Black Sea region, which receives high rainfall, means it faces a high risk of natural disasters such as floods and landslides. Therefore, accurate temperature and precipitation predictions are critical for the region, primarily to reduce loss of life and support agricultural production. In recent years, rising temperatures caused by climate change have negatively affected many regions, and these changes have particularly impacted agricultural production. Therefore, accurate temperature forecasts are essential for developing sustainable and appropriate agricultural policies. Accurate forecasts enable policymakers to develop the right strategies for sustainable agriculture; for example, farmers can be protected by implementing measures such as switching to more resilient crop varieties or optimizing irrigation systems. In the Eastern Black Sea region, which is highly susceptible to landslides due to high rainfall, the accuracy of meteorological forecasts is critical for taking preventive measures before such disasters occur. Landslides cause both loss of life and damage to agricultural areas. Maximum temperature forecasts can affect the quality of agricultural products and the supply-demand balance in the market. Predictable temperature changes allow farmers to better plan their crops, reducing economic losses. Furthermore, accurate forecasts can minimize price fluctuations in agricultural products. Advanced forecasting systems encourage more effective use of technology in agriculture; these applications not only increase productivity but also support the spread of sustainable agricultural practices. Future work plans include testing the proposed model with larger datasets in different regions and optimizing processing time and costs for real-time forecasts. Overall, the findings indicate that maximum temperature predictions can be made more accurately and reliably. The method proposed in this study was applied to maximum temperature data and produced better prediction results compared to other machine learning methods. This approach can be extended to other fields such as finance, tourism, and health data.

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CONFLICT OF INTEREST
The authors declare no conflicts of interest.

AUTHOR CONTRIBUTION
Mehmet Akif Kara: Conceptualization, methodology, software, formal analysis, investigation, writing original draft, and editing. Abdulkadir Keskin: Data curation, writing original draft, supervision, review and editing. Erol Egrioglu: Software, formal analysis, review and editing.

DATA AVAILABILITY
The datasets generated during and/or analyzed during the current study are not publicly available due to restrictions imposed by the Ministry of Environment, Urbanization and Climate Change of Türkiye, as the data were obtained under a special permit. Data are however available from the corresponding author on reasonable request and with permission of the Ministry of Environment, Urbanization and Climate Change of Türkiye.

DECLARATION OF GENERATIVE AI
Not applicable.

ETHICS
Not applicable.

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