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Research Article

Hybrid CNN-LSTM Model for Accurate Long-Term and Short-Term Temperature Prediction: A Case Study for Bingöl and Tunceli

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Abstract: Extreme and sudden weather events experienced with global warming and climate change reveal the importance of accurate air temperature prediction. For this reason, it can be used to optimize decision-making processes for a wide range of applications from health and agricultural planning to energy consumption strategies. Artificial intelligence methods are successfully applied in many application areas due to their flexibility and efficiency. Traditional weather forecasting models are inefficient in detecting sudden fluctuations and complex, irregular patterns in data. Artificial intelligence methods overcome these limitations thanks to their ability to process big data and capture long-term temporal dependencies. In this study, the aim is to predict future temperature changes more accurately by capturing patterns in past data with the developed CNN-LSTM hybrid model. The developed hybrid model is compared in detail with RF, SVM, CNN, and LSTM. The compared models were tested using daily average temperature data between 1961-2024 and hourly temperature data between 2020-2024. Experiments have shown that CNN-LSTM outperforms the compared models with R^2 value above 0.97 in all scenarios.

Keywords: air temperature prediction; deep learning; machine learning; CNN; LSTM

Uzun ve Kısa Vadeli Sıcaklık Tahmini İçin Hibrit CNN-LSTM Modeli: Bingöl ve Tunceli İçin Bir Vaka Çalışması

Özet: Küresel ısınma ve iklim değişikliği ile birlikte yaşanan aşırı ve ani hava olayları, hava sıcaklığının doğru bir şekilde tahminin önemini ortaya koymaktadır. Bu sebeple sağlık ve tarımsal planlamadan enerji tüketim stratejilerine kadar geniş bir uygulama alanı için karar verme süreçlerinin optimize edilmesinde kullanılabilir. Yapay zekâ yöntemleri, esneklikleri ve verimlilikleri sebebiyle birçok uygulama alanında başarılı bir şekilde uygulanmaktadır. Geleneksel hava tahmin modelleri, verilerdeki ani dalgalanmaları ve karmaşık, düzensiz örüntüleri tespit etmede verimsiz kalmaktadır. Yapay zekâ yöntemleri büyük verileri işleme ve uzun-vadeli zamansal bağımlılıkları yakalayabilme kabiliyetleri sayesinde bu sınırlılıkların üstesinden gelmektedir. Bu çalışmada geliştirilen CNN-LSTM hibrit model ile geçmiş verilerdeki örüntüleri yakalayarak gelecekteki sıcaklık değişimlerini daha doğru bir şekilde tahmin etmek amaçlanmıştır. Geliştirilen hibrit model RF, SVM, CNN ve LSTM ile detaylı bir şekilde karşılaştırılmıştır. Karşılaştırılan modeller 1961-2024 tarihleri arasındaki günlük ortalama sıcaklık verileri ve 2020-2024 tarihleri arasındaki saatlik sıcaklık verileri kullanılarak test edilmiştir. Deneyler, CNN-LSTM'nin tüm senaryolarda 0,97'nin üzerinde R^2 değeri ile karşılaştırılan modellerden daha başarılı olduğunu göstermiştir.

Anahtar Kelimeler: hava sıcaklık tahmini; derin öğrenme; makine öğrenmesi; CNN; LSTM

1. Introduction

Since the beginning of human history, weather conditions have significantly affected human life. People began to make weather predictions, observe, and predict in ancient times [1]. In ancient times, observations were based on the positions of celestial bodies and stars [2]. Weather prediction methods and accuracy have also increased with technological developments. From the first observations to the present day, the development of technologies has led to a significant development of weather prediction methods. Today, weather prediction is essential in many areas of our lives. Sectors such as agriculture, transportation, energy production, and tourism make plans using weather prediction data [3]. In addition, weather prediction is also essential for predicting and preventing natural disasters. For example, weather prediction data helps to predict natural disasters such as storms, hurricanes, floods, and avalanches in advance and to take the necessary precautions. Meteorology can now make much more detailed and accurate predictions thanks to technological developments [4]. In addition, weather prediction data has become instantly accessible through smartphones and other devices. In this way, people can follow weather conditions and plan accordingly.

Weather prediction is the study of predicting meteorological events that can be seen in a particular country, region, or center within a certain period using subjective or objective methods based on observations and analyses [5]. Weather prediction has three stages: observation, analysis, and prediction [6]. In weather prediction, observations are obtained from ground observations, ship observations, upper atmosphere observations, radar data, satellite images, and data from meteorological stations. The collected ground level and upper atmosphere observation data are processed on maps during the analysis process [7]. Experts evaluate the ground, sky, satellite, radar, and numerical prediction analyses during the prediction process, create weather prediction reports, and make meteorological inferences.

Weather predictions from analyzing meteorological observation data directly affect decision-making processes in many application areas such as agriculture, economy, daily life, tourism, transportation, and energy management [3]. Accurate weather prediction is vital in increasing efficiency and effectiveness in the mentioned sectors and minimizing the risks that natural disasters may cause. In the tourism sector, route planning depends on weather conditions, possible disruptions in transportation, and crop growth and harvest in agricultural activities depend on temperature and weather conditions [8]. Similarly, animal health and meat and milk yield in animal husbandry activities are directly related to weather conditions and temperature. In addition, increased air conditioning use in high temperatures and increased natural gas and fossil fuel use in low temperatures are directly related to air quality and energy management [9].

Traditional methods used in air temperature prediction are based on statistical, mathematical, and physical models. However, traditional models may be inefficient in dealing with increasing data [10]. For this reason, artificial intelligence methods are prominent in weather prediction. With the increasing effects of climate change, the consistency of weather predictions is becoming more critical.

The role of artificial intelligence in increasing the consistency rate in predictions also comes to the fore. Artificial intelligence can make more accurate, more precise, and more efficient weather predictions than traditional methods with its speed and ability to analyze past weather events [11]. Thanks to its capacity to process big data and its ability to learn complex relationships, artificial intelligence methods overcome the limitations of traditional methods. Artificial intelligence methods can determine future temperature trends for a specific city or region by analyzing past weather data [12]. In addition, artificial intelligence methods increase prediction performance with new data provided since they can learn without requiring human intervention. In this way, it can quickly adapt to changing climate conditions or sudden weather events.

In this study, the CNN-LSTM hybrid model was created to increase weather prediction performance and efficiency. The developed model was compared extensively with RF, SVM, CNN, and LSTM. The novelty of this study can be summarized as follows:

- A data-driven approach was presented for predicting 65-year daily mean temperature values and 5-year hourly temperature values for Bingöl and Tunceli.
- A hybrid CNN-LSTM model was created for long-term and short-term weather temperature prediction.
- CNN-LSTM was compared in detail with efficient and popular methods such as RF, SVM, CNN, and LSTM.
- This is the first study in the literature using this dataset.

2. Related Works

Aydin et al. presented a comparative analysis of deep learning models using air quality data from 15 stations located in the central Anatolia region and its surroundings [13]. In the study, an LSTM-based model was developed for predicting PM_{10} concentration. Experiments showed that the LSTM outperformed the compared deep learning model.

Bekkar et al. presented a comparative analysis of deep learning models for air quality prediction [14]. In the study, hybrid models were created using CNN and LSTM and CNN and GRU models. The created hybrid models were compared with base models and Bidirectional LSTM. Experiments showed that CNN-LSTM outperformed the benchmark models with 0.989 R^2 in daily forecasting and 0.979 R^2 in weekly forecasting.

Ay, and Ekinci presented a comparative analysis of XGBoost, LSTM, and Artificial Neural Network (ANN) models to predict ozone levels in Kocaeli, Sakarya, and Çanakkale cities [15]. The study used approximately four years of hourly observation data between 2018-2021. Polluting parameters PM_{10}, SO_2, NO, NO_2, and O_3 were used as inputs for the modeling. Experiments showed that LSTM has 0.94 R^2 for Kocaeli, 0.83 R^2 for Sakarya, and 0.94 R^2 for Çanakkale.

Karabulut and Topçu presented a comparative analysis of SVM and LSTM to predict the air temperature of Kars province [16]. The study used monthly and daily observation values between 2010 and 2021. Experiments showed that LSTM outperformed SVM, with 0.9867 R^2 in monthly prediction and 0.9937 R^2 in daily prediction.

Subbiah et al. proposed the BFS-Bi-LSTM model for wind speed estimation, which eliminates non-linearity, dimensionality, uncertainty, and overfitting problems [17]. They compared the proposed model with LSTM, BFS-LSTM, MLP, and BFS-MLP models. The developed model showed better performance than the compared models with 0.530 MAE, 0.784 RMSE, and 0.8766 R^2.

Shakya et al. developed a prediction model using Gated Recurrent Unit and Encoder-Decoder models for predicting $PM_{2.5}$ concentrations in New Delhi [18]. Approximately three years of New Delhi's 1-hour, 8-hour, and 24-hour data were used in the study. Experiments were carried out for different combinations of parameters: meteorological data, motor vehicle data, and emission values. The developed model was compared with XGBoost, LSTM, ANN, and RF. Experiments showed that the created model had the most successful results, with 0.959 R^2 in the 1-hour weather forecast.

Esager and Ünlü presented an applied analysis of CNN, GRU and LSTM for the prediction of hourly $PM_{2.5}$ concentrations of Tripoli [19]. The dataset used in the study consists of 3-month, hourly $PM_{2.5}$ observation data. Experiments were performed with different node numbers for the compared models. Experiments showed that CNN outperformed the compared models with 0.04 Mean Absolute Percentage Error (MAPE).

The studies in the reviewed literature demonstrate the advantages and effectiveness of various deep-learning models in weather and air quality forecasting. The literature has consistently shown that models such as LSTM, CNN-LSTM, and hybrid methods outperform traditional methods in terms of accuracy and efficiency. Deep learning models are more effective for processing complex patterns in nonlinear and large datasets.

The CNN-LSTM hybrid model developed in this study is a significant step forward in improving temporal and spatial weather prediction accuracy. This model's success underscores the potential of combining deep learning architectures to enhance forecasting performance in complex weather systems. It also reinforces the promising trajectory of related studies in this field, offering optimism for the future of weather and air quality prediction.

3. Material and Method

This section explains the dataset used, compared traditional methods and created hybrid CNN-LSTM model in detail. It explains the analysis of 65-year daily average temperature values and 5-year hourly temperature data belonging to Bingöl and Tunceli provinces and the data pre-processing process. It emphasizes the basic structures of the traditional prediction methods LR, RF, SVM, CNN, LSTM, and CNN-LSTM models and their performances in temperature prediction. Finally, the structure and development process of the hybrid CNN-LSTM model created in this study are explained.

3.1. Dataset

This study used real-time air temperature data provided by the 13th Regional Directorate of Meteorology, Elazığ. The daily average temperature data provided cover the period of April 1961-2024. Hourly air temperature data cover April 2020-April 2024. Figure 1 shows the daily average temperature values change for Bingöl and Tunceli for 1961-2024.

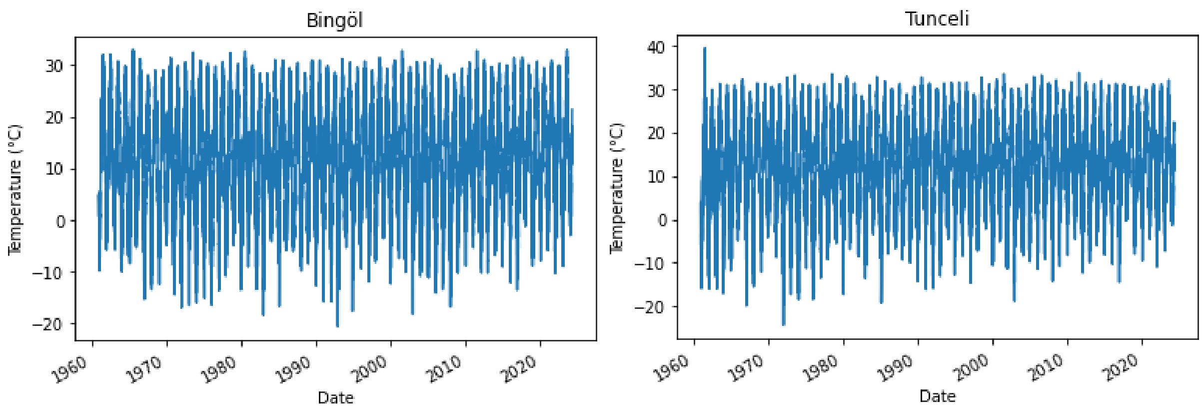

Figure 1. The change in daily average temperature values for Bingöl and Tunceli for the period of 1961-2024

Figure 2 shows the change in hourly temperature values for Bingöl and Tunceli for the date range April 2020-April 2024.

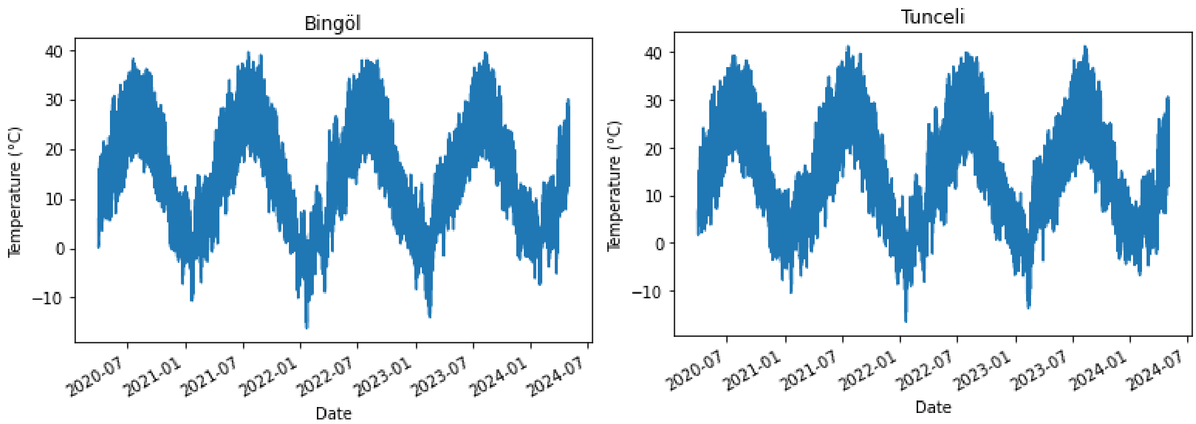

Figure 2. The change in hourly temperature values for Bingöl and Tunceli for April 2020-April 2024

Table 1 shows the minimum, average and maximum temperature values for daily average temperature values (1961-2024) and hourly temperature values (April 2020-April 2024).

Table 1. *Temperature values*

Temperature	Daily average temperature (1961-2024)		Hourly temperature (2020-2024)	
	Bingöl	Tunceli	Bingöl	Tunceli
Min	-20.70	-24.40	-16.20	-16.50
Mean	12.24	12.79	13.96	14.08
Max	33.00	39.50	39.50	41.20

As seen in Table 1, the column with daily average temperature values shows the lowest, mean, and highest average temperature values for Bingöl and Tunceli. The hourly temperature column shows the lowest, mean, and highest temperature values observed according to hourly temperatures.
The lowest average temperature between 1961-2024 was recorded as -20.70 for Bingöl and -24.40 for Tunceli. These temperature values show the average, and it is concluded that night temperatures are lower, especially. According to the hourly temperature values between 2020-2024, the lowest temperature was measured as -16.20 for Bingöl and -16.50 for Tunceli. However, the most alarming trend is the increase in summer and winter temperatures in recent years due to the effect of global warming.

3.2. Prediction Models

LR is a machine learning model used to express a dependent variable with a linear model by one or more independent variables [20]. The main purpose is to understand the relationship between the dependent variable and the independent variables and to predict the value of the dependent variable using this relationship. LR uses $y_i = \beta_0 + \beta_1 * x_i + \varepsilon$ equation. In this equation, x_i refers to the observations of the independent variable and y_i the observations of the dependent variable. The β_0 fixed coefficient refers to the β_1 slope coefficient. ε refers to the difference between real values and predicted values. *X* refers to the independent variable and *Y* refers to the dependent variable [21].

RF is a machine learning model that is formed by combining many decision trees. Each decision tree is trained on a randomly sampled subset of data, and these trees are created with random features [22]. This process ensures that the trees are independent of each other and can make different decisions. Each decision tree makes its prediction. In classification problems, each tree makes a class prediction, and the class with the most votes is the final prediction of the model. In regression problems, the final result is obtained by taking the average of the predictions of the trees [23].

SVM is used to classify data as belonging to a particular class. SVM works to separate data with a line or hyperplane [24]. This line or hyperplane is chosen to separate the data as best as possible. SVM works by maximizing the distance between two classes on this line or hyperplane. SVM can be used to classify both linear and non-linear data. Linear data is data that a line can separate. Non-linear data cannot be separated by a line [25]. SVM uses different kernel functions to classify non-linear data as well.

CNN, which is used in the form of 1D in the time series, effectively removes local patterns in the data [26]. In the time series context, trends and patterns in the data are removed at a particular time. Convolution layers make the property subtraction by processing the data in a rocking window of a specific size. Pooling layers reduce the data size to learn more general features [27]. Full-linked layers are used to learn the features of higher levels than those extracted by conviction, and pooling layers are used to learn and create final predictions.

The primary purpose of the LSTM is to solve the problem of learning long-term addictions in Recurrent Neural Network (RNN) models. Although RNNs theoretically have the potential to learn long-term addictions, they may encounter problems with the disappearance of a gradient in practice [28]. LSTM can solve these problems with unique cell structures (forgetting, input, and output), keep the information in memory for long periods of time, and use it when necessary [29]. These cells determine what to remember and what to forget. If the incoming input is trivial, it is forgotten; if it is essential, it is transferred to the next stage. Decide which information will be kept or forgotten. Information from the previous hidden layer and current information passes through the Sigmoid activation function [30]. The closer the value is to 0, the more forgotten it will be; the closer to 1, the more it will be held.

3.3. Developed Hybrid Prediction Model

The dataset used in this study is a time series data consisting of daily and hourly air temperature observation values. For this reason, it is necessary to transform the dataset into regression problem structure. The sliding window method was used for this purpose. This method ensures that the given input is set to the specified window size, and the data point in the next time step is set as output. For instance, if the window size is 3, t_1, t_2 and, t_3 will be the input, and t_4 will be the output, as shown in Fig. 3.

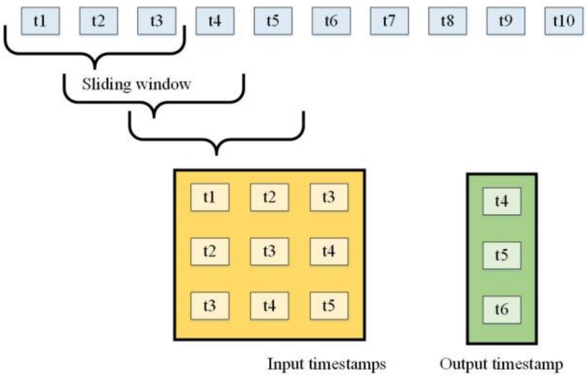

Figure 3. Transform the dataset into regression problem

Experimental studies showed that the lowest error rates were obtained when the sliding window size was 9. After transforming the data into the regression problem structure, it was scaled using MinMaxScaler. 20% of the dataset was used for testing and 80% for training. 10% of the train data was used for hyper-parameter optimization. For each compared model to achieve the most successful result, the hyper-parameters of the models were adjusted using grid search. Grid Search attempts to find the best combination of certain hyperparameters to improve the performance of models. This method systematically tries all possible combinations of the specified hyperparameter ranges and selects the most suitable parameter set. When applying Grid Search, the hyperparameter space is first determined. Then, parameter values are defined and all combinations are tried and the most successful hyperparameter combination is selected. Developed CNN-LSTM model architecture is seen in Figure 4.

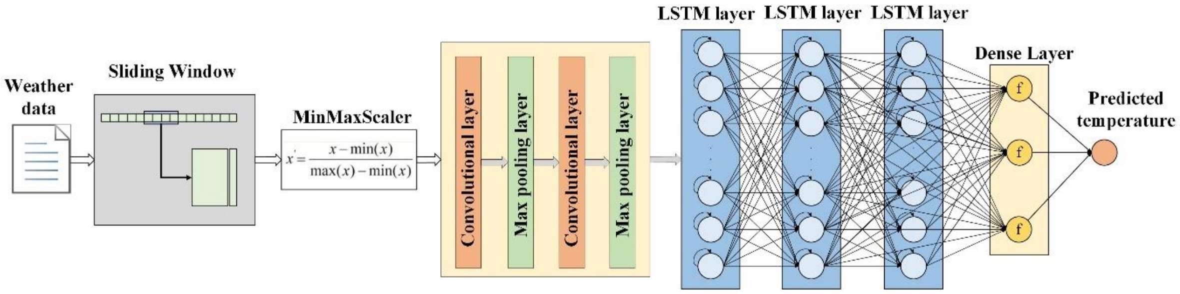

Figure 4. Developed hybrid CNN-LSTM model

CNN is responsible for extracting features in time series data and learning the relationships and patterns between the data. LSTM enables increasing prediction performance by learning long- and short-term dependencies between data. CNN-LSTM takes daily or hourly air temperature observation values as input. After the data is transformed into a regression problem structure using a sliding window, it is scaled using the MinMax scaler. The CNN component uses convolution layers to discover patterns in the data and perform feature extraction. The LSTM component models complex relationships in the data by processing feature maps sent from the CNN. In this way, LSTM learns the data's long and short-term dependencies. Grid search is used to optimize the hyper-parameters of CNN-LSTM. The number of convolutional layers for the CNN component is 2; the activation function is ReLU, the pool size is 2, and the number of filters is 64. The LSTM component has 128 neurons, and the Adam optimizer was used. The dropout rate is 0.2, the epoch is 50, and the batch size is 64.

4. The Experimental Results

In this study, RMSE, MAE and R^2 metrics were used to evaluate the models. RMSE, MAE, and R^2 are statistical metrics used to measure the predictive performance of a model. They are used to analyze the difference between the predicted values and the actual values, especially in regression problems. RMSE is the root mean square of the errors between the predicted values and the actual values. MAE is the mean of the absolute values of the differences between the predicted values and the actual values. R^2 measures how well the model explains the relationship between the independent variables and the dependent variable. R^2 expresses the explanatory power of the model.

Experimental results for the average temperature values for Bingöl and Tunceli between 1961-2024 are shown in Table 2 and Figure 5.

Table 2. *Experiments for the average temperature values for Bingöl and Tunceli between 1961-2024*

	Bingöl			Tunceli		
Model	RMSE	MAE	R^2	RMSE	MAE	R^2
LR	1.650	1.253	0.973	1.635	1.248	0.976
RF	1.600	1.217	0.975	1.576	1.214	0.977
SVM	1.597	1.215	0.975	1.565	1.209	0.978
CNN	1.559	1.178	0.977	1.501	1.149	0.980
LSTM	1.462	1.160	0.981	1.351	1.050	0.985
CNN-LSTM	0.864	0.695	0.996	0.850	0.667	0.994

As seen in Table 2 and Figure 4, the CNN-LSTM hybrid model had 0.864 RMSE, 0.695 MAE and 0.996 R^2. For Tunceli, CNN-LSTM had 0.850 RMSE, 0.667 MAE and 0.994 R^2. Experiments showed that CNN-LSTM was quite successful in predicting the air temperature with an accuracy of approximately +- 0.6 °C and a success rate of over 0.99 in daily average temperature prediction.

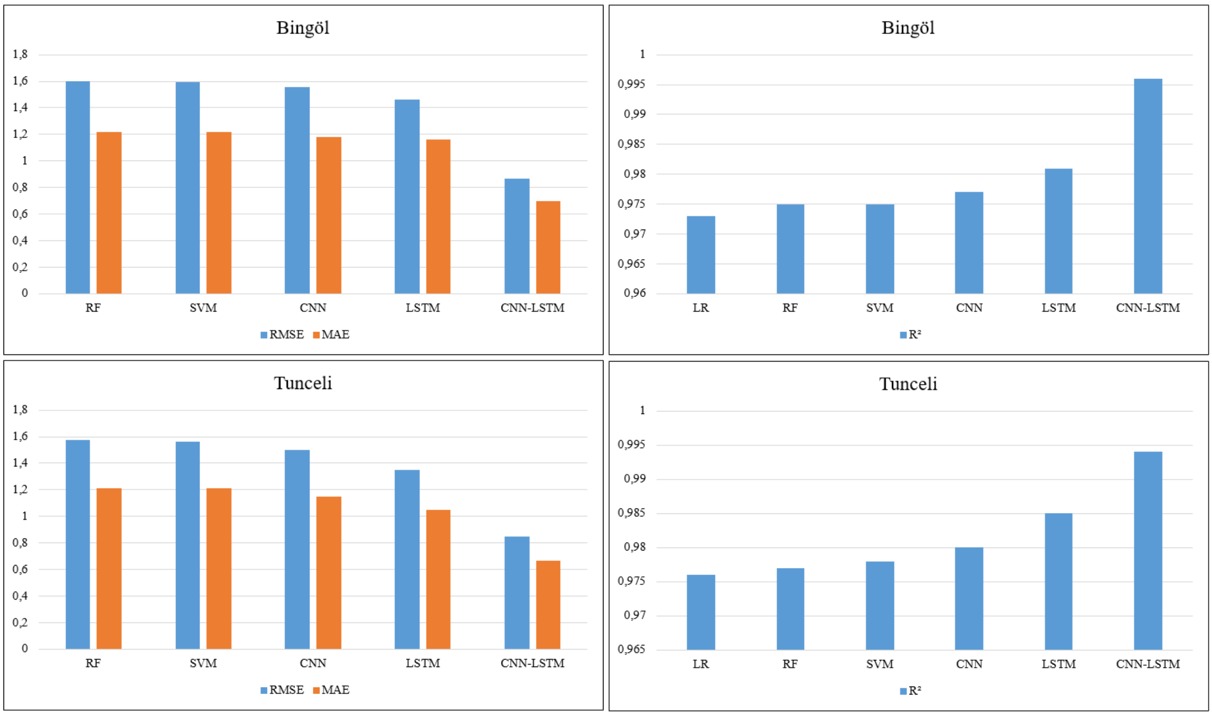

Figure 5. Experimental results for the average temperature values for Bingöl and Tunceli between 1961-2024

Experimental results for the hourly temperature values for Bingöl and Tunceli between 2020-2024 are shown in Table 3 and Figure 6.

Table 3. *Experiments for the hourly temperature values for Bingöl and Tunceli between 2020-2024*

	Bingöl			Tunceli		
Model	RMSE	MAE	R^2	RMSE	MAE	R^2
LR	0.987	0.700	0.990	1.138	0.814	0.987
RF	0.967	0.672	0.991	1.118	0.802	0.988
SVM	0.938	0.659	0.992	1.069	0.766	0.989
CNN	0.950	0.665	0.991	1.061	0.776	0.989
LSTM	0.836	0.612	0.993	1.011	0.730	0.991
CNN-LSTM	0.617	0.478	0.997	0.808	0.584	0.998

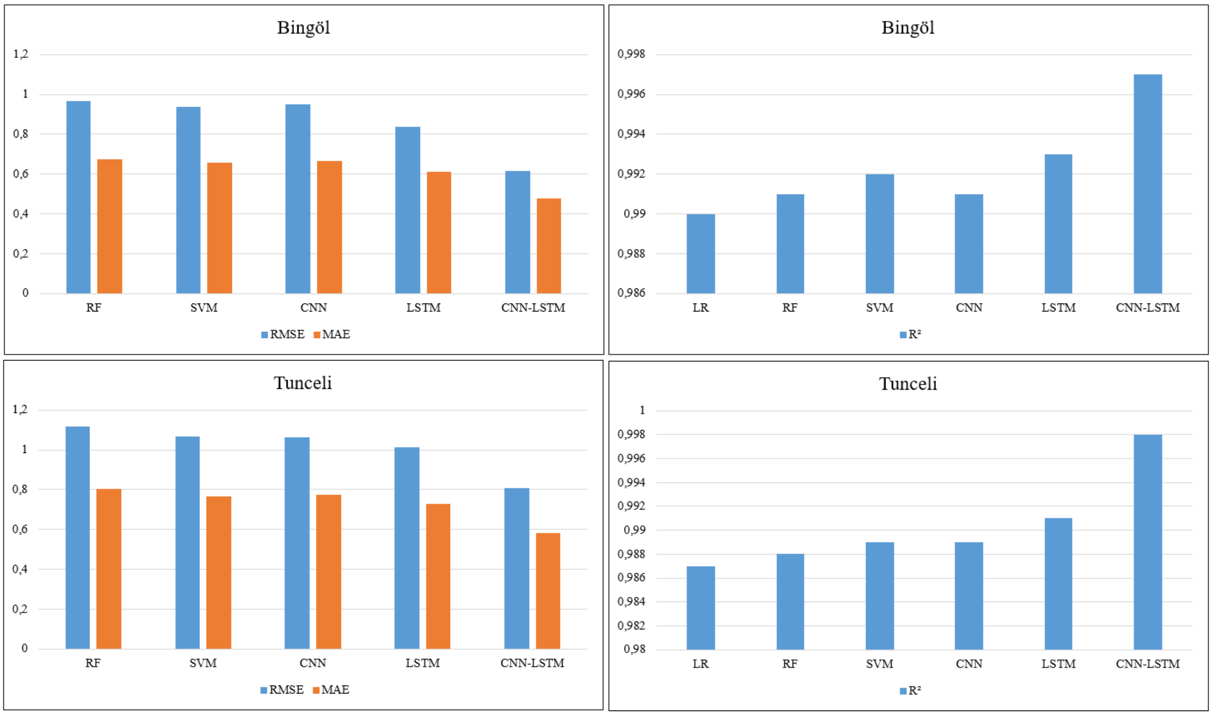

Figure 6. Experimental results for the hourly temperature values for Bingöl and Tunceli between 2020-2024

As seen in Table 2 and Figure 5, the CNN-LSTM hybrid model had 0.864 RMSE, 0.695 MAE and 0.996 R^2. For Tunceli, CNN-LSTM had 0.850 RMSE, 0.667 MAE and 0.994 R^2. Experiments showed that CNN-LSTM was quite successful in predicting the air temperature with an accuracy of approximately +- 0.6 °C and a success rate of over 0.99 in daily average temperature prediction.

CNN-LSTM outperformed the compared models due to its ability to capture complex temporal and spatial patterns. CNN is an effective model for extracting spatial and local patterns in data. By filtering the noise, CNN extracts important features from noisy and sudden weather data. LSTM improves the prediction quality by using the temporal patterns in this processed data. LSTM is effective in learning long-term temporal dependencies. From temperature data, CNN extracts essential features such as geographical changes, seasonal fluctuations, and abnormal weather events, enabling LSTM to process this information throughout the time series. Combining CNN and LSTM in a hybrid model enabled effective learning of both spatial and temporal patterns.

5. Conclusions

Air temperature forecast directly affects human behavior and the activities of various sectors. It is essential to accurately predict air temperature for tourism and daily activity planning, as well as for children, the elderly, and people with chronic diseases who are at risk in terms of health. In the agricultural sector, the growth and maturation of crops and the harvest time change according to the air temperature. Agricultural producers decide on irrigation, fertilization, and harvesting processes according to the estimated air temperature values. In the transportation sector, sudden weather changes such as icing or extreme heat in air, land, and sea transportation negatively affect transportation safety and cause disruptions in transportation. Similarly, in the energy production sector, air temperature is directly effective. Temperature changes in the summer and winter increase energy consumption; therefore, planning for energy production and distribution is related to air temperatures.

With global warming and climate change, the importance of air temperature forecasts is increasing today. Climate anomalies increase the frequency of major temperature changes and extreme weather events. Therefore, making accurate long-term and short-term air temperature forecasts is important for predicting natural disasters and reducing their effects. For this reason, this study aims to increase forecast accuracy by using artificial intelligence methods. A hybrid CNN-LSTM model was developed using the prominent and efficient features of CNN and LSTM. The potential impact of this model on various sectors is significant. The developed model was comprehensively compared with RF, SVM, CNN, and LSTM. The compared models were tested using the average temperature data of Bingöl and Tunceli between 1961-2024 and hourly temperature data between 2020-2024. Experiments showed that CNN-LSTM was more successful than the compared models with above 0.97 R2 in all scenarios. This success underscores the potential of the CNN-LSTM model to revolutionize air temperature predicting and its impact on various sectors.

Conflict of Interest

The author reports no conflict of interest relevant to this article.

Research and Publication Ethics Statement

The author declares that this study complies with research and publication ethics.

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