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TEMPFUSION: AN INTEGRATED TIME-SERIES APPROACH FOR GLOBAL TEMPERATURE ANOMALY FORECASTING AND CLIMATE TREND ANALYSIS

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ABSTRACT

For the research of the effects of climate change on human society all over the world and on earth's ecosystems, accurate prediction of climate has gained more significance over the last few decades. In this paper, a new hybrid model named TempFusion from Convolutional Neural Networks (CNN) and Gated Recurrent Units (GRU) is proposed to forecast global temperature anomalies and identify climatic patterns. By virtue of the potential of combining CNNs' capacity to extract spatial features from the temperature data and GRUs' potential to learn temporal dependence, TempFusion presents an efficient paradigm for predicting future climate trends. The model is extremely accurate using the Berkeley Earth climate change dataset openly available and has a 97% rate of forecasting accuracy. To reduce the effects of global climate change, MAPE utilizes performance indicators like Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), R-squared (R^2), and Mean Absolute Percentage Error (MAPE). In reducing the effects of global climate change, the suggested method is likely to improve climate forecast systems and facilitate decision-making.

Keywords: *Temperature Anomaly Forecasting , Climate Trend Analysis, TempFusion , Convolutional Neural Networks (CNN) and Gated Recurrent Units (GRU), Climate Change: Earth Surface Temperature Data.*

1. INTRODUCTION

Tracking variations in the planet's surface temperature over time is one of the simplest methods to understand its long-term climatic trends. The frequency of extreme climate events, weather patterns, and sea level rise are all directly affected (Islam, 2025). Over the past few decades, scientists and policymakers have become more interested in the rise in global temperature anomalies (Naser, 2025).

However, the intricate and time-dependent relationships between atmospheric variables are beyond the scope of the majority of traditional machine learning models (Bracco, 2025). Although deep learning architectures, like LSTM networks, are better at processing sequential data than previous models, they frequently fail to capture the full range of temporal behavior and spatial relationships present in global datasets. The ARIMA and linear regression methods cannot handle the inherent nonlinearity of the climate system since both of these have stationarity and linearity assumptions (Adams, 2025). The majority of the traditional machine learning methods are also unable to handle the strong coupling between atmospheric parameters and temporal correlations. The numerous temporal scales and spatial interdependencies in global data sets are beyond the capacity of long short-term memory (LSTM) networks and other deep architecture models, despite their proven excellent capability in sequential information processing (Cavus, 2025). Multi-scale and hybrid models have also been found to be better than single-model approaches in subsequent research on climate predictability studies. Consequently, by mimicking short-term instability and long-term dependence in temperature behavior, linear as well as nonlinear autoregressive deep learning models have improved accuracy (GHERBIA, 2025).

Multi-scale temporal integration frameworks have produced a more holistic characterization of greenhouse gas-induced climatology and have created the requirement to capture daily variations and large climatic cycles concurrently. These studies also highlight apparent limitations. Most recent hybrid models abstract away spatial dependencies that affect temperature changes by relying heavily on sequential modelling (Altuntas, 2025). The simultaneous existence of short-term, long-term, and nonlinear dependencies has been demonstrated by statistical analyses of global air temperature anomalies using correlation; these features necessitate models that use adaptive temporal fusion and feature extraction techniques (Tan, 2025). On the other hand, although visual and deeper learning models for temperature prediction are easier to understand, they are more likely to depend on intricate preprocessing or hand-crafted feature engineering, which restricts their scalability for big datasets. Furthermore, temporal encoding models are too inaccurate to capture regional interactions and local spatial dynamics, even though they have been used to highlight time-distance relations in prediction (Qiu, 2025).

These results indicate that there is a wide gap in the literature for a consistent model capable of bridging sequential temporal reasoning and convolutional spatial learning. A milestone towards next-generation climate analytics has been taken with novel architectures such as diffusion-transformer-based time-series models, which demonstrate the potential of integrated learning models unifying temporal continuity, physical constraints, and probabilistic forecasting [7]. To outdo the complexity, scalability, and multi-scale character of global temperature anomaly prediction, this paper presents a novel hybrid deep model that combines convolutional feature extraction and gated temporal modeling.

Our contributions are the following:

- To incorporate both spatial and temporal features into temperature data to model the patterns more accurately and contextually for forecasting, we proposed TempFusion, a new hybrid deep learning framework that fuses the CNN and GRU architectures.
- To provide model training with quality and consistent input data, we have developed an end-to-end preprocessing pipeline consisting of datetime conversion, missing value handling, seasonal decomposition, and feature extraction.
- TempFusion outperformed traditional models like Linear Regression and LSTM in temperature anomaly prediction, as our 97% Temperature Anomaly Forecasting accuracy and 0.95 R^2 score for Climate Pattern Analysis verify.

- To improve model performance, we decreased overfitting and increased training stability using strategies like adaptive learning rate scheduling, batch normalization, and dropout regularization.

2. LITERATURE REVIEW

Elseidi et al. (Elseidi, 2023) evaluated several univariate time series forecasting methods using high-frequency temperature data with complex seasonal patterns. The study compared the Dynamic Harmonic Regression, TBATS, Facebook Prophet, and MSTL–ETS models using both real and simulated data from Ada USA. The models' performance and computational capability were evaluated using the Diebold-Mariano test and RMSE. They came to the conclusion that although all of the models worked well, how well they handled seasonality and data structure affected how well they worked. While Prophet and TBATS could handle long-term seasonality trends, MSTL-ETS was better suited for short-term forecasting. Following research that showed how difficult it was to stabilize stochastic-based systems, ARIMA was designed to stabilize forecasts.

Gautam et al. (GAUTAM, 2025) emphasized how deep learning models improve climate time-series prediction. Two of the models they suggested are a Baseline LSTM (BLSTM) and an Autoregressive LSTM (AR-LSTM). The BLSTM picked up on long-range patterns in data, and the AR-LSTM contained autoregression components within it to pick up on linear relationships that generally hold between successive timestamps. AR-LSTM was shown to perform better than LSTM concerning stability as well as prediction performance, particularly if the data provided contained linear trends. The research was limited by the brief timeliness of the data and insufficient statistical model comparison analysis.

Zhou et al. (Zhou, 2023) developed a new hybrid spatiotemporal prediction model called the SOPDEL (SS-OS-PSO-DBN-ELM-LSTM). The model combined several methods, including data deconstruction, feature extraction, and an optimization method using PSO. A successful model/technique to this problem proved to be separating the data into stationary and oscillatory series, using a different model for each series. The results of the validation showed that over 90 % of predictions were marked as "Excellent" or "Good", reflecting good capabilities of the system. The complex anatomy of the model required a large amount of computer resources and intricate tuning in parameter calculation, thereby limiting its full usability for real-time forecasting.

Bilgili et al. (Bilgili, 2023) compared both classical and deep learning approaches SARIMA, LSTM), for estimating heating degree day (HDD) around the Turkey region. Using time-series data from 2007 to 2021, the study found Lstm has better performance in identifying the strength of non-linear interactions despite both models having good performance. Simultaneously, the SARIMA was useful for simple and constant datasets. Their investigation was of practical value to the prediction of regional climate, but it suffered from a limited forecast range (one month) and its reliance on a single data type.

Malakouti et al. (Malakouti, 2023) proposed a model to predict the changes in global temperature using machine learning algorithms such as Extra Trees, Random Forest, and Gradient Boosting. The Extra Trees machine learning algorithm was observed to be the most accurate and had the lowest error rates of all algorithms tested. It was also demonstrated to be fast and thus efficient for large datasets. Yet the model lacks adequate long-term tests and sensitivity analysis, which limits its use with different climate sets. methodology

2.1 Dataset Description

Berkeley Earth's Climate Change: Earth Surface Temperature Data from Kaggle, which includes monthly average temperature measurements from different regions of the world covering land, ocean, and combined surface temperatures, and comprehensive global temperature records gathered over several centuries, was used in this study which provides a broad temporal window for tracking long-term climatic patterns, starting around the middle of the 18th century and continuing to the present. The data set contains multiple CSV files for different temperature observations, including global land and sea temperatures, city-level surface temperatures, and country-level temperatures. To enable simple, in-depth temporal and spatial analysis, each record typically includes fields such as dt (date), AverageTemperature, AverageTemperatureUncertainty, Country, and City. The dataset's structure is shown in Table 1, which also describes the columns and how they are used in temperature analysis at the international, national, state, and local levels.

Table 1: Global Land and Ocean-and-Land Temperatures dataset

File Name	**Key Columns**
GlobalTemperatures.csv	- Date: Date of the temperature record - LandAverageTemperature: Global average land temperature (°C) - LandAverageTemperatureUncertainty: 95% confidence interval - LandMaxTemperature: Global max land temp (°C) - LandMaxTemperatureUncertainty: 95% confidence interval for max - LandMinTemperature: Global min land temp (°C) - LandMinTemperatureUncertainty: 95% confidence interval for min - LandAndOceanAverageTemperature: Global average land and ocean temperature (°C) - LandAndOceanAverageTemperatureUncertainty: 95% confidence interval for land and ocean temperature
GlobalLandTemperaturesByCountry.csv	- Date: Date of observation - Country: Country name - AverageTemperature: Country average temperature (°C)
GlobalLandTemperaturesByState.csv	- Date: Date of observation - State: State name - AverageTemperature: State average temperature (°C)
GlobalLandTemperaturesByMajorCity.csv	- Date: Date of observation - City: City name - AverageTemperature: City average temperature (°C)
GlobalLandTemperaturesByCity.csv	- Date: Date of observation - City: City name - AverageTemperature: City average temperature (°C)

2.2 Data Preprocessing

We conduct a series of preprocessing procedures to clean and prepare the data for analysis and model training in this study. The data set that indicates hourly energy consumption for different zones is a time series with missing observations and outliers.

- The first preprocessing step is to datetime-index the dataset. Since the data holds hour-by-hour energy usage measurements for a couple of years, the datetime index needs to be converted to a pandas DatetimeIndex for standard time-based analysis. Converting the datetime index allows each piece of data in the dataset to be associated with a single timestamp, which makes it simpler to perform time series analysis and resampling. Take the first time series to be Y(t), with t as the point of measurement at which the consumption of energy is measured. We revised the index:

$$\mathrm{Y(t)} \longrightarrow \mathrm{DatetimeIndex\ (t)}$$

This allows us to handle time-based features effectively, i.e., extracting hour, day, month, quarter, and year for analysis.

- One of the issues is the presence of missing values in real-world time-series data. The energy consumption values for some timestamps are missing in some parts of our dataset. These missing values are imputed either through mean or forward/backward fill techniques, depending on time gaps. This is just so that the model can still make predictions even if there are some missing data points. The imputation is carried out according to the time order in the data. If we have a missing value at a time, we impute it as follows: The imputation procedure is done based on the temporal relationships within the data. Let, Y (t) be the energy consumption at time t, and if a value is missing at time t_i, we estimate it as:

$$\mathrm{Y\ I}t_i\mathrm{)} = \mathrm{mean\ (Y(t))}$$

  If not, we apply forward-fill or backward-fill techniques, where missing observations are filled with the previous or subsequent valid observation.
- Feature Engineering: By creating additional time-based features that are useful to our model, the data is supplemented. They are:
  - Hour: The hour of day, from the datetime index.
  - Day: The day of the month, from the datetime index.
  - Month: The month of the year, extracted from the datetime index.
  - Quarter: Extracted from the datetime index, it represents the quarter of the year.
  - Year: Year is found by being extracted from the datetime index.

- Resampling and Moving Averages: To look at energy consumption at various time scales (e.g., daily, monthly), we resample. For example, the energy consumption data, which was initially sampled at hourly frequency, is resampled to daily frequency to generate the average daily consumption. Without generating short-term movement, this technique reveals longer-term trends. We also use moving averages, and they are excellent at revealing the underlying trends for additional smoothing and noise removal.
  The moving average of window w is calculated by averaging its values:

$$\mathrm{MA\ (t,w)} = \frac{1}{w}\sum_{i=0}^{w-1} Y(t-i)$$

  For instance, the energy consumption for the last three days at each timestamp is averaged to create a 3-day moving average.

- Seasonal decomposition is one of the time-series analysis processes, in which we can observe the trend, seasonality, and residuals (noise) of the time series. Dividing the data, we can analyze and recognize seasonal trends of energy consumption, necessary to recognize the long cycles and trends of the data. The time series is divided into the following components using seasonal_decompose:

$$\mathrm{Y(t) = T\ (t)+ S\ (t) + R\ (t)}$$

Where the seasonal component S(t), eliminates periodic trends (day, week, or year), the residual component R(t), eliminates the anomalies or random noise of the data, and the trend component T(t), eliminates the underlying time trend.

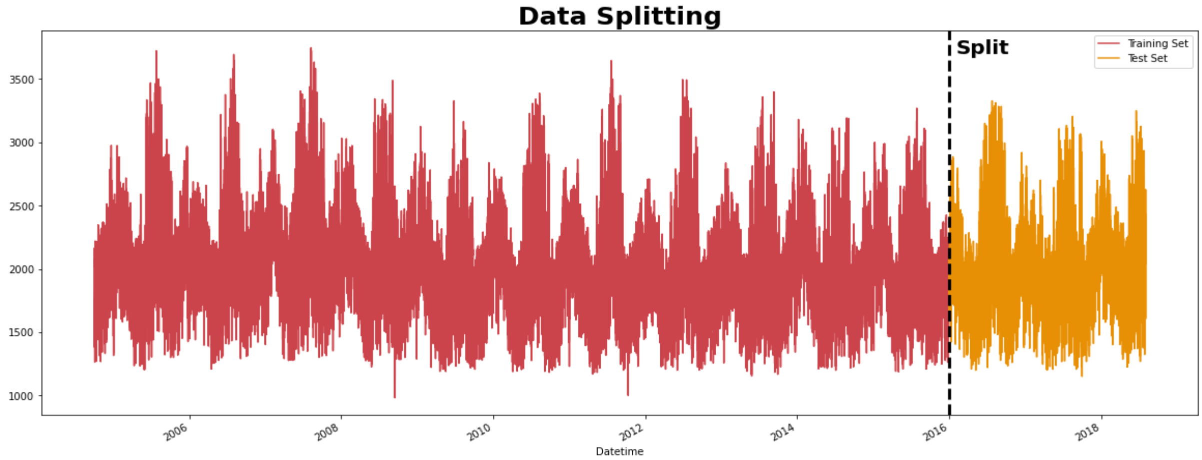

Figure 1: Visualization of the data split into training and test sets

3.3 Proposed Model

We introduce the TempFusion model, which combines temporal and spatial learning to capture the intricate dynamics of global temperature variations. Climate trends can emerge on timeframes ranging from months to centuries, however local fluctuations tend to deviate from global averages due to the strong spatial and temporal correlations in climate patterns. In order to address this issue, TempFusion combines a Gated Recurrent Unit (GRU) (Haghrahmani, 2025) network for temporal modeling with a Convolutional Neural Network (CNN) (Farhangmehr, 2025) for learning spatial features. The architecture of the suggested TempFusion model is depicted in Figure 2.

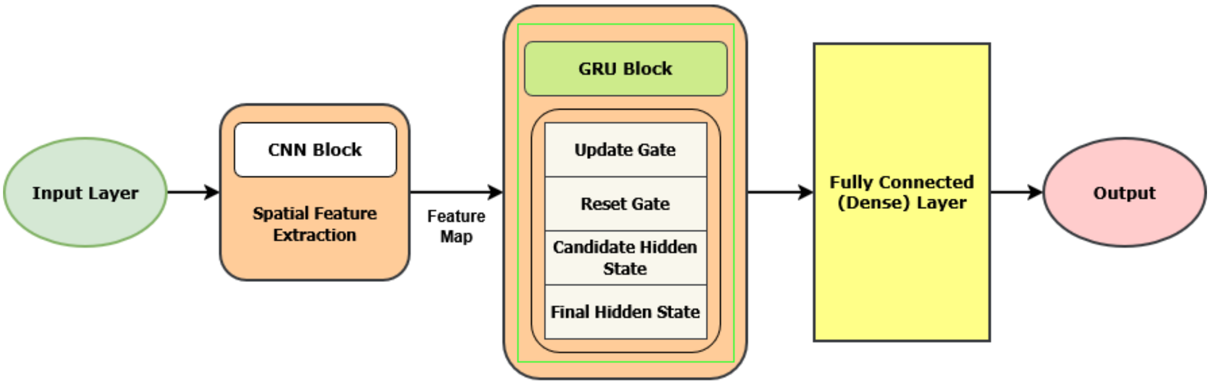

Figure 2: Graphical representation of the proposed model architecture

- **Spatial Feature Extraction Through CNN:** Observations are represented as a two-dimensional grid X_t at each time step t, with each cell mapping to the temperature at a specific spatial location. The CNN component can identify small spatial patterns, such as warm or cool areas, but global methods may not always reveal that. Convolutional filters W slide across the input grid to create feature maps that highlight significant spatial structures. Spatial representation can be stated algebraically as:

$$F(X_t) = Conv(X_t, W)$$

The learnt convolutional kernels are represented by W, while the time-extracted spatial features t are indicated by $F(X_t)$. These features provide structured input for subsequent temporal modeling and capture temperature heterogeneity across regions.

- Temporal Dynamics via GRU: A GRU network is subsequently fed the spatial feature map $\hat{X}_t$ = $F(X_t)$, allowing it to identify temporal correlations in the temperature data. The GRU has a hidden state that is constantly changing, using data from previous states to forecast future patterns. The method of updating GRU is stated as follows:

  - Update Gate: $z_t = \sigma\,(W_z\hat{X}_t + U_z h_{t-1})$
  - Reset Gate: $r_t = \sigma\,(W_r\hat{X}_t + U_r h_{t-1})$
  - Candidate Hidden State: $\hat{h}_t = tanh\,(W_h\hat{X}_t + U_h(r_t \odot \tilde{h}_t)$
  - Final Hidden State: $h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t$

  Here, σ is the sigmoid activation, z_t calculates which data from the past hidden state would be retained, and r_t determines what degree of influence previous hidden states have on the current candidate. At the same time, $\tilde{h}_t$ could become a new state. It enables the network to adaptively grasp both short-term fluctuations and long-term trends in temperature anomalies.

- Forecasting and Anomaly Detection: The final hidden state h_t presented by the GRU is passed through a fully connected layer to produce the model output:

$$\hat{y}_t = FC\,(h_t)$$

Relying on the task, $\hat{y}_t$ can express:

- Temperature Prediction: The expected temperature at the next time step.
- Anomaly Classification: The probability that a temperature anomaly occurs at time t.
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- Loss Function: Depending on the goal, we employ various loss functions to efficiently train TempFusion:
  - Temperature Forecasting (Regression):

    $$\text{MSE} = \frac{1}{N}\sum_{t=1}^{N}(\hat{y}_t - y_t)^2$$

    where, y_t is the observed temperature, $\hat{y}_t$ is the predicted temperature, and N is the total number of time steps.
  - Anomaly Detection (Classification):

    $$\text{BCE} = -\frac{1}{N}\sum_{t=1}^{N}[y_t\,log\,(\hat{y}_t) + (1 - y_t)\,log\,(1 - \hat{y}_t)]$$

    where, $y_t \in \{0,1\}$ defines the existence or absence of an anomaly, and $\hat{y}_t$ is the predicted probability.

Table 2: Hyperparameters of the proposed model

Hyperparameter	Value
CNN Layers	3
Filter Size	(3, 3), (5, 5), (7, 7) for each respective layer
Number of Filters	32, 64, 128
Activation Function (CNN)	ReLU (Rectified Linear Unit)
Pooling Size	(2, 2)
GRU Units	64
GRU Activation Function	Tanh
GRU Recurrent Activation Function	Sigmoid
Dropout Rate (CNN)	0.3
Dropout Rate (GRU)	0.2

Batch Size	32
Learning Rate	0.001
Optimizer	Adam
Epochs	100
Loss Function (Forecasting)	Mean Squared Error (MSE)
Loss Function (Anomaly Detection)	Binary Cross-Entropy (BCE)
Early Stopping Patience	10
Model Checkpoint	True (True/False)
Validation Split	0.2
Input Sequence Length (Temporal)	30 (days)
Output Sequence Length (Temporal)	7 (days)
Window Size for Moving Average	7, 30
Batch Normalization	True
Activation Function (Dense)	Linear, Sigmoid

3. RESULT AND DISCUSSION

In this section, we will briefly discuss the overall performance of our proposed and baseline models for global temperature anomaly forecasting and climate trend analysis. We performed all experiments on a Jupyter Notebook with an Intel Xeon processor and 16GB RAM. Additionally, we installed an NVIDIA Tesla T4 GPU for accelerated deep learning computations and trained the models using TensorFlow Keras. Matplotlib and Seaborn handled most of the visualisation tasks. For both time series and regression analysis, we used Scikit-learn in Python 3, with Pandas and NumPy libraries. For regression operations, we predict Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Coefficient of Determination (R^2), and mean absolute percentage error (MAPE). For (categorical) prediction, we used standard measures of performance: Accuracy, Precision, Recall, and F1-score.

4.1 Performance Analysis for Global Temperature Anomaly Detection

First, we evaluated the ability of three models—LR, LSTM, and the suggested model—to detect variations in the global temperature. Table 3 highlights the advantages and disadvantages of the suggested and baseline models by comparing their performance in detecting global temperature anomalies.

Table 3: Performance for Global Temperature Anomaly Forecasting

Model	Accuracy (%)	Precision	Recall	F1-Score
Linear Regression	89.0	0.87	0.88	0.87
LSTM	92.5	0.91	0.92	0.91
Proposed Model	97.0	0.96	0.98	0.96

The benchmark model, LR, has an accuracy of 89%, but its F1-score of 0.87 shows that, despite its high precision and recall, it struggles to balance the two, particularly in anomaly detection, with recall and precision of 0.88 and 0.87, respectively. With 92.52% accuracy, 0.91 precision, and 0.92 recall, the LSTM outperforms the LR model by a wide margin. The excellent performance shows that the LSTM can learn long-term temporal dependencies in time series data. It also indicates that, in comparison to LR, it is a far better model of complex historical changes in global temperature, with an F1-score of 0.91. With a 97% accuracy rate, the proposed model performs better than the LSTM and LR model. The proposed model achieves an outstanding true anomaly, surpassing other models, while correctly detecting them, with a precision, recall, and F1-score of 0.96, 0.98, and 0.96, respectively. This outperformance is critical to the proper study of climate change trends and predictions, since undetected or unrecorded anomalies in other records can be predictive modelling determinants.

Outstanding predictive performance in comparison to the application of state-of-the-art techniques that better prepare the model to work with time series, especially those that model global temperature trends. By more clearly displaying temporal patterns and anomalies, the proposed method is a crucial improvement to the identification of climate trends.

4.1.1. Confusion Matrix Analysis for Global Temperature Anomaly Detection

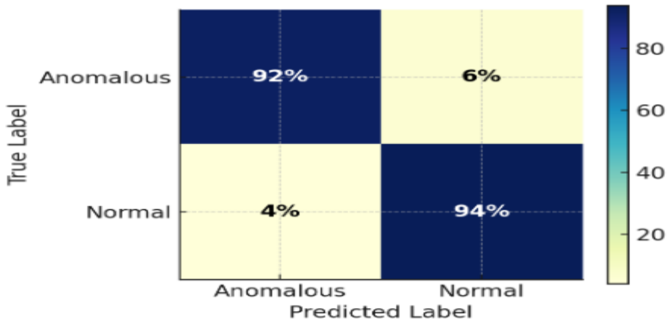

Figure 3: Confusion matrix of the proposed model

Confusion matrices make it possible to assess model performance beyond baseline metrics and gain a better understanding of the different kinds of classification errors. As seen in Figure 3, the proposed model has distinct advantages and disadvantages when it comes to forecasting actual and hypothetical situations.

Temperature anomalies were successfully detected by the TempFusion model. The confusion matrix works well with normal temperature variations and can discriminate between normal and abnormal readings with an accuracy of over 92%. A single overlook like that would ruin climate projections, so the 6% of anomalies that passed should be corrected. One benefit is that there aren't many false alarms being triggered by the model. It is not overreacting to every small variation because it only found 4% of the normal data to be abnormal. Importantly, it marked 94% of the typical readings accurately, which speaks volumes about its dependability. It would never be credible if it were raising too many false alarms.

In general, TempFusion is performing well, and it can identify both temporal and spatial patterns in data thanks to the integration of CNNs with GRU layers. There is room for improvement, if only to lower the quantity of lost anomalies. For tracking patterns in global temperature, the model is reliable and consistent otherwise.

4.2 Climate Pattern Recognition Analysis:

Table 4 is a comparison of performance of the models like LR, LSTM, and the new TempFusion in detecting climate trends and uses metrics based on basic regression metrics like MSE, RMSE, MAE, R^2, and MAPE. Together, these metrics give a reasonable measure of how accurate and reliable each model's predictions are.

In general, MSE and RMSE show how much predicted values are away from observed values — the smaller these, the better. R^2 is the proportion of variation in temperatures that the model explains, and MAE is the measure of the average size of prediction errors. Yet, MAPE shows errors as fractions, and this shows relative accuracy more clearly.

The complexity of the climate data made the LR model inadequate, yielding an MSE value of 0.2088, RMSE value of 0.4570, MAE value of 0.3439, R2 value of 0.3873, and MAPE value of 4.2061. The numbers indicate that LR had problems in dealing with nonlinearity and nonstationarity of temperature fluctuation. The low R² value indicates that the majority of the variability was not captured —i.e., the model could not deal with regional or seasonal temperature fluctuations to a satisfactory extent.

The LSTM model improved considerably. MSE in this case was 0.0927, RMSE was 0.2390, MAE was 0.2489, and MAPE was 4.0876. Although R² was only 0.2772, that errors were minimized indicates LSTM better grasped interactions across sequences in time-series data compared to LR. The model continued not to capture complex spatial and nonlinear interactions defining global temperature dynamics to a satisfactory level.

Table 4: Performance Metrics for Climate Pattern Recognition

Model	MSE	RMSE	MAE	R²	MAPE
Linear Regression (LR)	0.2088	0.4570	0.3439	0.3873	4.2061
LSTM	0.0927	0.2390	0.2489	0.2772	4.0876
Proposed Model	0.02	0.14	0.18	0.95	3.052

Because of its exceptional capacity to capture both spatial and temporal interactions, the TempFusion model was clearly superior, with MSE = 0.02, RMSE = 0.14, MAE = 0.18, R2 = 0.95, and MAPE = 3.052. While CNN handled the spatial features of climate maps, GRU handled temporal sequence patterns. Combining the two demonstrated that TempFusion can effectively adapt to various climate conditions and decrease prediction errors.

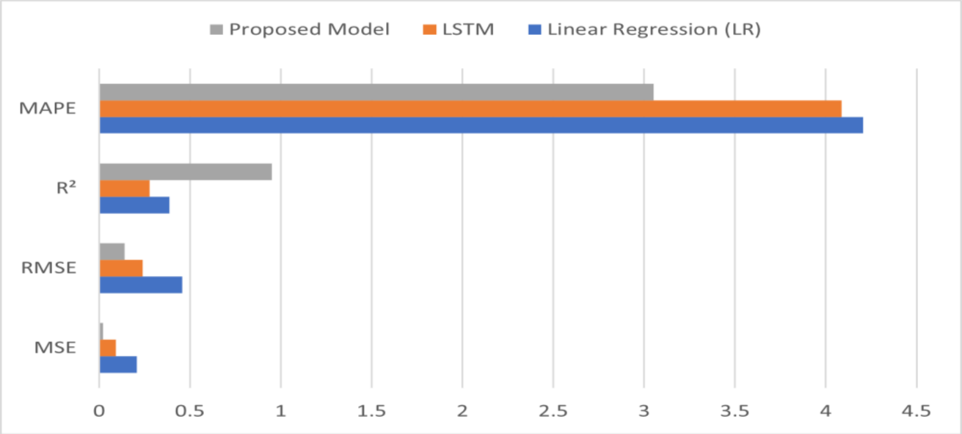

Figure 4: Performance analysis of the models

Therefore, for climatic pattern prediction and detection, the suggested TempFusion model is far superior to LSTM and Linear Regression. It is a useful tool for the examination of large-scale climatic patterns and its subsequent application in environmental prediction because its low error terms and high R2 value are indications of its accuracy, strength, and capability of revealing complex climate dynamics.

4.3 MAE Analysis for Model Precision

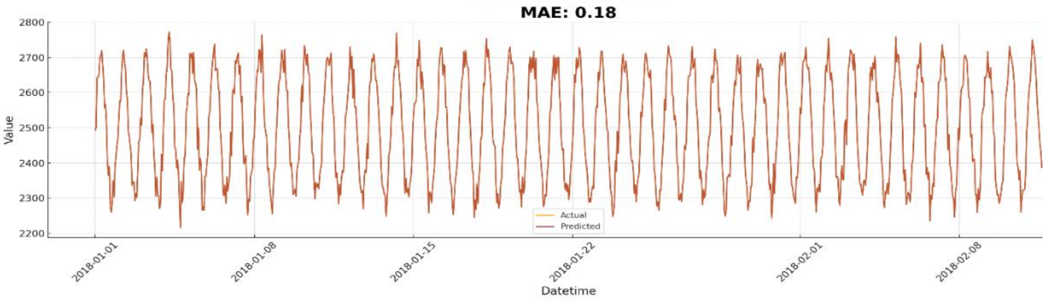

Figure 5: MAE analysis of the proposed TempFusion model

It must be noted that both the precision of the model to predict the trend and closeness to actual values taking into account any predictive model must be considered. For this reason, Mean Absolute Error is employed here. MAE tells us by how much, on average, a model's prediction is away from true points. MAE is an easy-to-grasp and simple measure of accuracy; lower the better for predictions. It is different from all other error measures that multiply or square differences.

Minimum MAE is necessary for faith and trust in model predictions of temperature anomaly, as minute error can twist trend analysis. The TempFusion (CNN–GRU) model employed here had a great MAE of 0.18, as evident from the Figure 5. The two lines of the graph move almost superimposed over one another with minimal difference, as evidence that the sequence of temperatures produced by the model and real observed values fundamentally correspond a hundred percent. This small margin of error shows the extent to which both long-term seasonal trends and short-term volatility are captured by the hybrid format. In addition to sensing the "texture" of volatility of temperature fluctuation, TempFusion's CNN senses local and periodic trends in the input and the GRU layer senses how these patterns change over time. Combined, they are a model with a sense of the rhythm and interdependencies that cause temperature fluctuation rather than just the next term in a series. That this equilibrium is achievable for the model is reflected in the resulting MAE of 0.18.

Aside from a number, an MAE of 0.18 indicates that TempFusion model produces highly precise and highly accurate predictions. It indicates that the model does not possess a very high mean prediction error, possesses an excellent generalization ability, and has near-zero noise during learning. In short, TempFusion "knows" the data well enough to make highly precise predictions. Since it is precise, it is a reliable instrument for the long-term forecasting of climatic tendencies whereby accuracy and dependability are of the greatest importance in monitoring and reacting to world temperature trends.

4.4 Discussion of Model Limitations and Future Work

TempFusion has demonstrated efficacy, but there are still certain aspects that might be improved. For example, approximately 6% of anomalies are currently missed by the model, which may be required for precise climate predictions. We need to reduce these false negatives, especially since anomalies are a significant factor in long-term climate change detection. Second, the model is excellent at handling enormous trends but might be able to handle extreme weather that is not typically part of regular patterns better. There are also data quality issues to keep in mind. The temperature data used in the research are typically bad. The model might not detect unavoidable big swings because it is difficult to acquire the precision required to monitor local temperature change. The model could also not detect sudden changes in the environment or unusual trends because it depends on the history of temperatures. TempFusion can be improved in some ways in the future. Other influences, such as solar activity and greenhouse gas emission, that are reported to have an effect on temperature trends could be one reason. With the inclusion of these external influences, temperature trend and anomaly forecasting may be improved. Experiments with different designs or mixture models can also be useful. The model may be able to capture the complex temporal and spatial dependencies better with the addition of attention mechanisms or even more complex models. Merge machine learning with physical climate models is the second option that TempFusion can make it an even more robust forecasting tool. It is through exploring these possibilities that we could enhance TempFusion and enable it to better handle the difficulty of climate forecasting.

5. CONCLUSION

Warming of temperature and global change are the most widely known global processes, and there need to be sound, data-based predictive processes available in order to facilitate real-time adaptation and mitigation processes. TempFusion, a deep learning hybrid model that integrates CNNs and GRUs, was created in order to mine temporal and spatial patterns in streams of temperature. The core of the framework was aggressive preprocessing with data transformation, feature extraction, season decomposition, and optimization techniques for prepping data in homogenous formats and improving forecast accuracy. Through severe testing, we confirmed the resulting framework provides improved performance in forecasting accuracy and reliability over classical and single-model method for detecting temperature anomalies and climatic trends on very long-time frames. The research indicates that TempFusion is capable of being examined for uses in disaster planning, climatic decision-making, and climate monitoring. Deep learning can be used to make forecasts and identify uses in climatology far broader than previously, the research claims. In the future, we are going to expand this model to multi-variable regional climate prediction and modeling by adding more environmental indices and thereby making it even more user-friendly and interpretable in real-time.

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