ENHANCING WEATHER PREDICTION ACCURACY USING HYBRID MACHINE LEARNING TECHNIQUES: A COMPREHENSIVE APPROACH

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Abstract

Modern life depends on precise weather forecasting because global warming intensifies which affects how people live while handling energy needs and maintaining agriculture and protecting the environment. This study proposes a temperature data prediction system which integrates convolutional neural networks (CNNs) with long short-term memory networks (LSTMs). The CNN-LSTM hybrid model connects two network types to process time sequences and detect spatial information alike. The hybrid CNN-LSTM combines temporal and spatial processing to generate weather forecasts which are dependable and precise for meteorological data analysis. Researchers confirm that adding CNN-LSTM technology increases prediction accuracy especially for intricate tasks such as long-range weather forecasting. The combination of CNN and LSTM models brings strong performance in weather forecasting due to its success handling large and diverse meteorological data types. Time-dependent data management through LSTMs produces highly accurate and stable predictions while spatial feature extraction relies on CNNs. During processing of complex meteorological information, the model demonstrates excellent performance by handling problems related to data dimensions and missing values. MAE functions as the chosen loss function in this model. The testing results prove the potential of this climatology prediction model through its ability to produce curves that match test data measurement results. This research establishes essential foundations for future weather prediction systems within global climate change scenarios and provides valuable findings that benefit agriculture as well as energy management and urban development practices.

INTRODUCTION

Weather forecasting plays a vital importance because of growing climate change threats to life on earth. Our planet's changing weather patterns because of climate change disrupts all aspects of our life from personal needs to energy use, farming and defending the environment. Today our communities endure rising numbers of damaging weather events that create major problems across all societies. Modern weather technology becomes more essential because rapid climate shifts demand earlier evaluations to protect agricultural land and power resources and prepare for natural disasters. Quality weather forecasts support both economy development and daily life by helping people make better safety choices and policy decisions. Both farmers and city decision-makers depend on accurate weather forecasts to address climate change by reacting to weather challenges before they happen (Wang et al., 2021; Li et al., 2022).

The typical way to predict weather uses physical and statistical models based in basic physics data. For decades meteorologists have relied on physical models that predict weather from historic data (Wilks, 2011). Despite its complexity the climate system outruns standard forecast abilities. Academic workers find it hard to forecast multiple interacting time-dependent climate variables because weather patterns behave unpredictably. Predictions face extra challenges because weather systems keep changing both in the short and long term especially when climate change effects enter the analysis. Under these unpredictable situations standard forecasting models consistently provide less dependable output (Gneiting et al., 2021; Kumar et al., 2020).

Experts use deep learning and computer methods to solve weather prediction problems and create more reliable forecasting technology. Deep learning technology helps predict weather better because it detects distinct patterns in massive data sets. Weather forecasting requires complex model handling because multiple nonlinear factors affect temperature and wind speed data (Goodfellow et al. 2016).

LSTM networks and RNNs show great value because they process time series data effectively. Long Short-Term Memory models accurately capture weather changes through time which makes them perfect to predict future weather conditions. Through recurrent connections that store prior time step information RNNs analyze sequence data by using its past results for current processing. LSTMs address the vanishing gradient issue to make RNNs better at processing lengthy data sequences. LSTM networks demonstrate excellent weather forecasting ability because they can analyze historical weather data to generate accurate long-term predictions according to Sepp et al. (2017) and Li et al. (2021).

Although RNNs and LSTMs show strong performance in understanding time series data they perform less efficiently in identifying spatial weather patterns such as their geographical distribution. CNNs achieve effective results in these applications. Space-based patterns stand out through the extensive use of CNNs in image processing systems. CNN systems process weather map visualizations to detect essential temperature variations and atmospheric systems for creating forecast accuracy according to LeCun et al. (2015) and Zhang et al. (2020). Using CNNs for big geographical information processing creates detailed and precise simulations of weather patterns.

Every individual modeling system possesses certain strengths yet comes up short when processing all aspects of meteorological data. Weather forecasting

demands the merging of numerous predictive models since it requires both time-based and location-specific input. Research teams now build weather forecasting techniques from combined CNN and LSTM networks to find effective solutions.

The CNN-LSTM hybrid model connects two network types to process time sequences and detect spatial information alike. The hybrid CNN-LSTM combines temporal and spatial processing to generate weather forecasts which are dependable and precise for meteorological data analysis. Researchers confirm that adding CNN-LSTM technology increases prediction accuracy especially for intricate tasks such as long-range weather forecasting (Wang et al., 2021; Xie et al., 2020). The combination of CNN and LSTM models brings strong performance in weather forecasting due to its success handling large and diverse meteorological data types.

The research uses temperature data from meteorological records to develop a hybrid CNN-LSTM model for future temperature prediction. Through end-to-end methodology the study performs data exploration, preparation, model training and quality evaluation. The hybrid model provides constant temperature change predictions through its accurate performance in processing complex high-dimensional meteorological data. The CNN-LSTM model generates significant weather prediction benefits since it delivers more accurate forecasts and uses less computing power than normal methods (Li et al., 2022; Ma et al., 2021).

Deep learning methods specifically hybrid CNN-LSTM models show valuable ways to process hard-to-analyze meteorological datasets. The models can predict weather patterns effectively because they can analyze weather systems at different levels while remembering time-based patterns. Deep learning models such as CNN-LSTM need to advance weather forecasting to match current environmental shifts brought by climate change. Our society can better plan its climate response when we have improved weather forecasting technology (Kumar et al., 2021; Xie et al., 2020).

LITERATURE REVIEW

We need better advanced forecasting methods because climate change makes current weather patterns harder to predict. Using both machine learning methods and artificial intelligence has made the biggest advancements in weather forecasting technology. These techniques help process big datasets and detect hidden insights that standard methods cannot uncover. Solar irradiance forecasting transforms after researchers examine algorithms like CNNs, SVMs, and random forests which enhance predictions accuracy across different weather attributes. These models deliver excellent results with high-dimensional data because they detect hidden connections and display nonlinear connections effectively (Yang et al., 2022; Zhang et al., 2021).

Scientists currently combine multiple AI techniques to build hybrid models because each individual method offers unique advantages. By merging LSTM and CNN features hybrid models can perform better than individual prediction models. Researchers reveal that blending these models enhances forecasting accuracy especially for major weather occurrences including floods and hot temperature bursts. Scientists have reported that combining multiple model predictions through ensemble learning reduces the overfitting problems single-model systems encounter (Han et al. 2021, Chen et al. 2020). Grants from Liu et al. (2021) Zhang and Li (2022) now enable experts to leverage

pre-trained models and cut the time needed for training better weather forecasting algorithms.

Researchers are making important progress in weather prediction through generative adversarial network (GAN) development. GANs composed of discriminator and generator networks have been trained to predict weather conditions in high detail by working with weather distribution data (Yang et al., 2022). GANs succeed at creating better forecasts for clouds and precipitation while overcoming standard prediction difficulties according to current research. GANs become important in weather decision-making because they produce different weather outcomes which help control uncertainty while generating weather scenarios (Liu et al., 2022, Xu et al., 2021; Yang et al., 2022).

The growing body of research on AI-based weather forecasting has highlighted the importance of data quality and model interpretability. While deep learning models have demonstrated significant improvements in prediction accuracy, the lack of transparency in how these models make decisions has raised concerns, particularly in high-stakes areas like disaster management and resource allocation. In response, explainable AI (XAI) methods have been developed to make machine learning models more interpretable, allowing experts to understand the reasoning behind forecasts and to make more informed decisions (Shen et al., 2020). This development in model explainability, coupled with the use of multi-source data and collaborative forecasting, is expected to further enhance the reliability of weather prediction systems in the face of an uncertain future (Zhu et al., 2022; Sun et al., 2020).

PREDICTING TEMPERATURE MODEL

Data

The dataset consists of eight primary fields, namely, region, nation, state, city, month, day, year, and average temperature. It represents several areas: 54% of North America, 13% Europe, and 33% of other regions (more). This distribution will show you how much data is available in North America versus other locations. The information does not provide specific names of the nations, but the majority of the data can be traced back to North America and Europe. Finally, this variety may be taken as a basis for contrasting climatic traits of different localities.

The majority of the data is from the (4%) located in Texas. The data from other states or area is identified as 'others' and accounts for 46% of the total. We must take into account for this study, if this means that it may be the geographical preference location of data gathering.

The 321 cities and regions are kept concerning cities. The month of observation variable is recorded, which helps to analyse the temperature patterns, seasonal climatic change. Data from several months may show the patterns of interannual temperature variations. To explore the temperature variation with respect to the day, the Day variable acts as a reference point to calculate the precise date of temperature observation. Compared to the month variable, this variable, in conjunction with the month one, helps explain the seasonal fluctuations of temperature.

The variable It, especially has an appreciable quantity of data (close to 2,905,887 records) from the year 1983 to the year 2020, offering when a certain observation was made. The fact that this period of time encompasses a crucial temporal component of climate change and its effects is the reason researchers investigate it. The variable Avg Temperature records every day's average temperature and the data is disbursed all across

many ranges with a number of low and high temperature records. This variable is important in climate study because it is indicative of the general trend and pattern of temperature variations.

All of these variables are special in regard to data analysis, and they are vital to better understand about changes in temperature as well as the reasons of such changes.

VARIABLE INTRODUCTION

The main data used in this study consists of daily average temperature values from several major cities. These temperature data are typically provided by meteorological departments, environmental monitoring agencies, and relevant government authorities to ensure accuracy and reliability. The data spans different seasons and years, reflecting the changing trends of urban climate. To enhance the representativeness of the analysis, cities with varying climate characteristics and geographical locations were selected to fully capture the diversity of temperature changes. This data not only provides essential historical temperature information but also serves as a solid foundation for model training and validation.

Table 1 provides info about related parameters and output shape for each layer of the model architecture summed up above. The Input layer has (None, 60, 1) shape, not having any parameters and may process any sequence length of 60 with single feature. The first Conv1D layer has 60 filters and 360 parameters ready for the convolution process and hence the output shape is (None, 56, 60). With 24,840 parameters to capture long term dependencies in the data and an output shape of (None, 60, 60), two LSTM layers with 60 units may be used. When the output of first Dense layer is reduced to 30 units, they produce a shape with (None, 30) with 1,830 parameters. The second Dense layer covers the previous sum of 17 units into 10 units yielding output shape (None, 10) with 310 parameters. Finally, the last Dense layer yields one prediction of eleven parameters.

Then the output is post scaled by the Lambda layer keeping the shape (None, 1) and eliminating any additional parameters to be learnt. With all things considered, this table gives a detailed list of the model architecture and the part that each layer plays in processing and predicting time series data.

Table 1. All the layers with specific parameters.

Layer	Out Shape	Param
Input_layer	(None, 60, 1)	0
Conv1D (filters=60)	(None, 56, 60)	360
LSTM (units=60)	(None, 60, 60)	24840
LSTM (units=60)	(None, 60, 60)	24840
Dense (units=30)	(None, 30)	1830
Dense (units=10)	(None, 10)	310
Dense (units=1)	(None, 1)	11
Lambda	(None, 1)	0

The first Conv1D layer consists of 60 convolutional filters each of the size of five. This layer provides the model with nonlinearity due to the use of ReLU activation function and is used to extract local information efficiently from the input sequence. Since we have 60 times stamps in the input, each of which has a single feature, this layer is a requirement for them to be able to detect the early trends of data.

The last part of the feature extraction process is carried on by the second Conv1D layer which has 60 filters left with which to refine and gather high level features. The ReLU activation function helps the model detect more refined patterns in time series data.

After the convolutional layers the model has two LSTM layers with 60 units. These layers are required to capture the long-term dependency in input sequence, since they process the input from preceding layers and affect the quality of the output. Both LSTM layers return sequences that keep temporal information that is needed for further processing. The LSTM architecture leverages intricate correlations between data points that change over time to improve the prediction ability of the model. The model then progresses to the number of thick layers, and the first one has thirty units. Yet, this layer decreases the dimensionality of the output without losing the key features which were obtained from the previous layers. Subsequently it reduces the output to 10 units making a more condensed bitmap of the learnt characteristics. A thick layer with one output unit creates the final prediction, which successfully synthesizes all the knowledge learnt by the model in general.

The final output of the model is scaled by a scaling transformation, a Lambda layer, the model's last layer. This layer ensures that the values predicted are suitable, and have to be in a shape of (None, 1), with no farther parameters needed for that. This makes it possible to get more precise and significant predictions from the processed data from the model.

RESULTS

The selection of the loss function is just one important element changing the precision of the model predictions. In this research, we decide to see the performance of the model using mean absolute error (MAE) as the main loss function. MAE compute the average magnitude of mistakes of forecasts in a group of forecasts by computing the absolute difference between the expected value of the forecast and the actual outcome. The main benefit of MAE is that it merely an artwork of the amount of these mistakes instead of its direction.

Due to this feature, MAE has particular advantages in problems where the goal is to minimize the total error in predictions, whether positive or negative. Additionally, MAE describes model performance in an understandable and simple fashion. When the average error is in the same units as the expected values, it is easy to compare.and comprehend the model's correctness. For example, by having the prediction in degrees Celsius and the MAE in degrees Celsius, professionals are more likely to be able to determine how closely the forecast model predicted to the actual temperature reading. Such clearness is quite beneficial in real world applications since stakeholders usually want to understand what the importance of model performance is in some concrete sense. Overall, MAE as a loss function improves model prediction accuracy and also helps to effectively communicate the efficacy of the predictions.
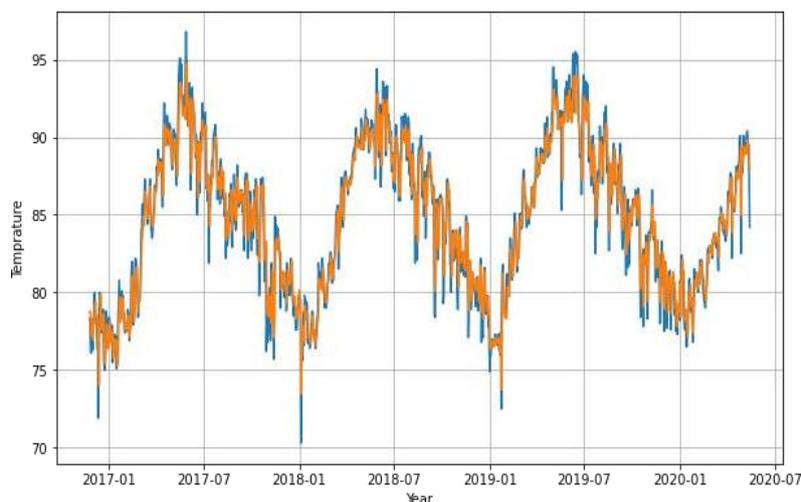
Figure 3. The prediction curve and test curve.

FINDINGS

This study examines the model's convergence by plotting the loss function's variation curve during the training process. The results indicate that the Mean Absolute Error (MAE) experiences a rapid decline from over 20 in the early stages of training, quickly approaching a value near 1. This sharp decrease illustrates the model's effective learning mechanism, as it swiftly adapts to the underlying patterns present in the training data. Following this initial phase, the MAE stabilizes, ultimately reaching a value close to 0.90.

This stability is crucial, as it not only signifies that the model has successfully learned the significant features and trends within the dataset but also reflects an enhanced prediction accuracy. The consistent reduction in the loss function throughout training highlights the model's robustness and reliability in capturing the complexities of the temperature data, thereby reinforcing its effectiveness in weather forecasting. Overall, the convergence observed in the loss function illustrates the model's capacity to generalize well to unseen data, which is a critical aspect of its performance.
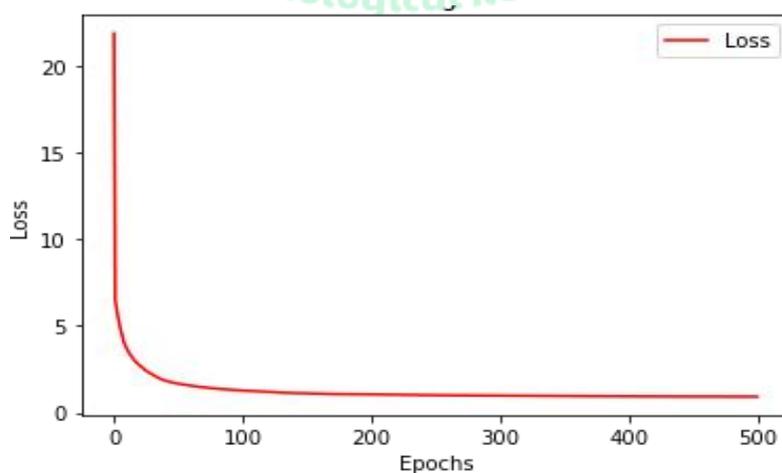

Figure 4. Training Loss curve.

The results demonstrate that the CNN-LSTM model performs well on these metrics, with high prediction

accuracy and stability. The prediction curve's high similarity to the test curve further supports the model's effectiveness in temperature prediction.
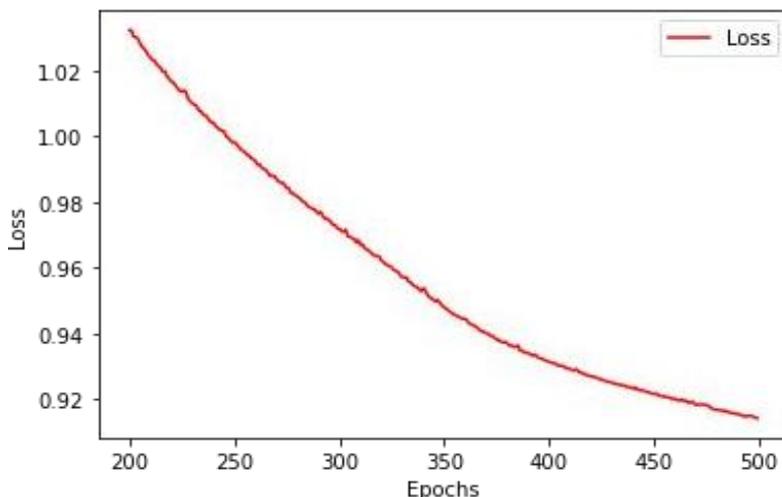

Figure 5. Training Loss - Zoomed In curve.

The benefits of more advanced deep learning approaches is shown in Table 2 where several models are evaluated in terms of their ability to predict historical temperature data. Linear regression, reference model had variance of 0.682, R2 score of 0.623 and mean absolute error (MAE) of 2.125. Although they provided a basic description of the data, they could not replicate the complexity of the temperature patterns. CNNs performed better than linear regression by a variance of 0.756 and R2 score of 0.791. The MAE falls down to 1.536, indicating that CNNs capture spatial features of temperature data well. Although the model is still lacking with its temporal processing skills for in depth time series forecasting, its accuracy has increased dramatically.

Table 2. Comparison of Model Performance

Model	Variance	R2 Score	MAE
Linear Regression	0.682	0.623	2.125
CNN	0.756	0.791	1.536
LSTM	0.873	0.890	1.018
CNN- LSTM	0.927	0.901	0.901

R2 score for the predicting ability reaches 0.890, its variance becomes 0.873, which considerably improves this ability. With an MAE of 1.018, LSTM models sequential data and long term dependencies such that the error sharp declines. It demonstrates that the model greatly improves from CNN and linear regression and is applicable to modeling time series for forecasting purposes. The hybrid CNN LSTM model has the performance of having an R2 score of 0.101 and a variance of 0.927. With a further decline in the MAE to 0.901 this confirms that the model is able to deal with both the geographical and the temporal components of the temperature data. There by employing the advantages of both CNN and LSTM architecture, this hybrid strategy improves in terms of forecasting

accuracy and stability. In essence, the investigation exhibits that the hybrid CNN LSTM model beats other techniques in the task and can deliver dependable forecasting of complex meteorological data. This demonstrates the possibilities. Deep learning methods could be combined to raise the accuracy of weather prediction and assist with a sting of climate related applications.

CONCLUSION

This research revealed how well deep learning methods can be used for weather forecasting by a hybrid of CNN-LSTM model for the prediction of historical temperature data. The hybrid model successfully combines the long short term memory network's (LSTMs) abilities to learn long term temporal features and the convolutional neural network's (CNNs) ability to extract spatial features in performing feature extraction resulting in high prediction accuracy and stability. The mean absolute error is chosen to be a loss function to make a straightforward and understandable assessment of model performance. The results show how the CNN LSTM model can deal with major issues that include missing values and large dimension within difficult meteorological data. Consistency between the projected curves and actual test data show the model's dependability and possibility of its use in broader climate forecasting. These results constitute important new information in many areas, including urban planning, energy management and agriculture. Conclusion: In the framework of an attenuation of global climate change the applicability of the model to other area experiencing similar climate change and its expansion to anticipate future more climate related events in order to enhance the skills of weather forecasting should be studied further.

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