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Weather Forecasting Models Based on Deep Learning Techniques: A Survey

Ammar Younus Mahmood [1] , Asst. Prof. Dr. Khalid Mohammed Saffer [2] , Asst. Prof. Dr Alaa Jalal Abdullah [3] , Asst. Prof. Dr. Bashar Talib AL-Nuaimi [4]

Abstract

Weather forecasting is inherently complex; however, scientists are endeavoring to leverage the latest computational technologies to enhance its accuracy. By using huge amounts of data, scientists hope to be able to predict potential weather patterns as accurately as possible. If their efforts succeed, meteorologists may be able to predict major events for years or even decades to come. This could provide tremendous potential to save the lives of many people from severe weather conditions such as hurricanes, droughts, and floods. Many different methods and algorithms for deep learning and machine learning have been used to predict weather, including RNN, LSTM, GRU, RN-Net, the CRNN model, and BLSTM-GRU, and machine learning algorithms including ANN, SVM, Random Forest (RF), and K-Nearest Neighbor. . In this survey, we will briefly summarize the methods used to build models to predict climate change.

Keywords: LSTM, GRU, RNN, Deep Learning, Weather forecasting

Affiliation of Authors

[1, 2, 3, 4] College of Science, University of Diyala, Iraq, Diyala,

[1]scicompms222309@uodiyala.edu.iq
[2] dr.khaledmoh@uodiyala.edu.iq
[3] alaajalal@uodiyala.edu.iq
[4] alnuaimi_bashar@uodiyala.edu.iq

[1] **Corresponding Author**

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نماذج التنبؤ بالطقس المبنية على تقنيات التعلم العميق: دراسة استقصائية

عمار يونس محمود [1] ، خالد محمد صفر [2] ، الاء جلال عبد الله [3] ، بشار طالب النعيمي [4]

المستخلص

إن التنبؤ بالطقس أمر صعب للغاية، لكن العلماء يحاولون استخدام أحدث تقنيات الكمبيوتر لجعل العملية أكثر دقة. وباستخدام كميات هائلة من البيانات، يأمل العلماء أن يتمكنوا من التنبؤ بأنماط الطقس المحتملة بأكبر قدر ممكن من الدقة. وإذا نجحت جهودهم، فقد يتمكن علماء الأرصاد الجوية من التنبؤ بالأحداث الكبرى لسنوات أو حتى لعقود قادمة. ويمكن أن يوفر هذا إمكانات هائلة لإنقاذ حياة العديد من الأشخاص من الظروف المناخية القاسية مثل الأعاصير والجفاف والفيضانات. تم استخدام العديد من الأساليب والخوارزميات المختلفة للتعلم العميق والتعلم الآلي للتنبؤ بالطقس، بما في ذلك RNN وLSTM وGRU وRN-Net ونموذج CRNN وBLSTM-GRU، وخوارزميات التعلم الآلي بما في ذلك ANN وSVM و(RF) Random Forest، وK-أقرب جار. . في هذا الاستطلاع، سنلخص بإيجاز الطرق المستخدمة لبناء نماذج للتنبؤ بتغير المناخ.

الكلمات المفتاحية: LSTM، GRU، RNN، التعلم العميق، التنبؤ بالطقس

انتساب الباحثين

[1] كلية العلوم، جامعة ديالى، العراق، ديالى،

[1]scicompms222309@uodiyala.edu.iq
[2] dr.khaledmoh@uodiyala.edu.iq
[3] alaajalal@uodiyala.edu.iq
[4] alnuaimi_bashar@uodiyala.edu.iq

[1] **المؤلف المراسل**

معلومات البحث
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1. Introduction

The climatic conditions that have a direct relationship to the life of organisms on the surface of the Earth, such as temperature, humidity, wind, and rain, have a profound impact on many aspects of human life[1]. Natural factors that affect the Earth, including the sun, wind, snow, rain, deserts, oceans, savannas, forests, and man-made factors, all contribute to the global climate[2]. Figure (1 describes the overall structure of a weather prediction model. The weather prediction framework has multiple steps: data collection, model selection, training, data preprocessing, results visualization, and model evaluation. Meteorological and climate data have become easily accessible and available to all researchers thanks to the rapid development of modern technology and new applications like Internet of Things, wireless sensors, and cloud computing [3]. Because of deep learning's strength, adaptability, and seamless feature extraction from time series, machine learning has a bright future ahead of it. Deep learning has produced excellent results with high accuracy[4]. "Deep learning" is a subset of machine learning that combines deep architectures and supervised or unsupervised learning techniques to automatically build hierarchical representations. Artificial neural networks are used in deep learning to extract intelligence from massive datasets. Large data can be processed more precisely with deep learning techniques. Deep learning algorithms are well-suited for handling time-series data and often achieve higher prediction accuracy because they can effectively capture temporal patterns and timestamp-related information. In addition, deep neural networks consist of several layers during which the data is processed through non-linear equations. Figure (1) describes a deep neural network containing four hidden layers, where the outputs of the first layer become the inputs to the next layer, and so on.

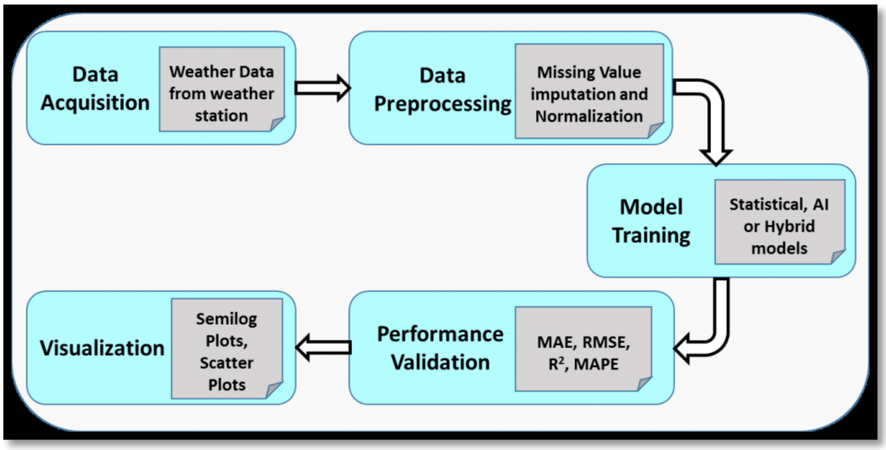

Figure (1): The layout of the Weather Forecasting Model [5]

Numerous factors are considered when classifying weather forecasting systems into different categories. The parameters include the number of variables to be forecasted, the number of time steps to be anticipated, the prediction horizon, the methodology, and the number of variables involved [6]. Figure (2) shows the complete structure of deep networks for predicting the different variables explained previously

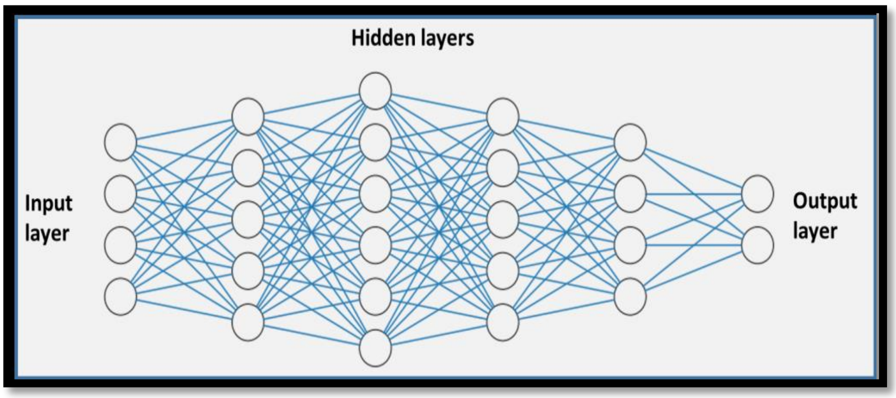

Figure (2): Structure of a deep neural network [5]

Depending on how many variables are included in the forecasting process, the forecasting models can be either univariate or multivariate. For example, multivariate forecasting is a style of forecasting temperature is anticipated using multiple environmental inputs. A multivariate model predicts the outcome based on multiple parameters, while a univariate model relies on just one variable [7].

The deterministic forecasting models can also be categorized into statistical, artificial intelligence, and hybrid models. There are various types of forecasting models, such as those that anticipate temperature, wind speed, rainfall, dew point, and more [8], based on the parameter to be forecasted, as shown in figure (3). By precisely forecasting meteorological conditions, can be avoided in social and economic operations. A number of approaches have been proposed in the resent years to address this goal.

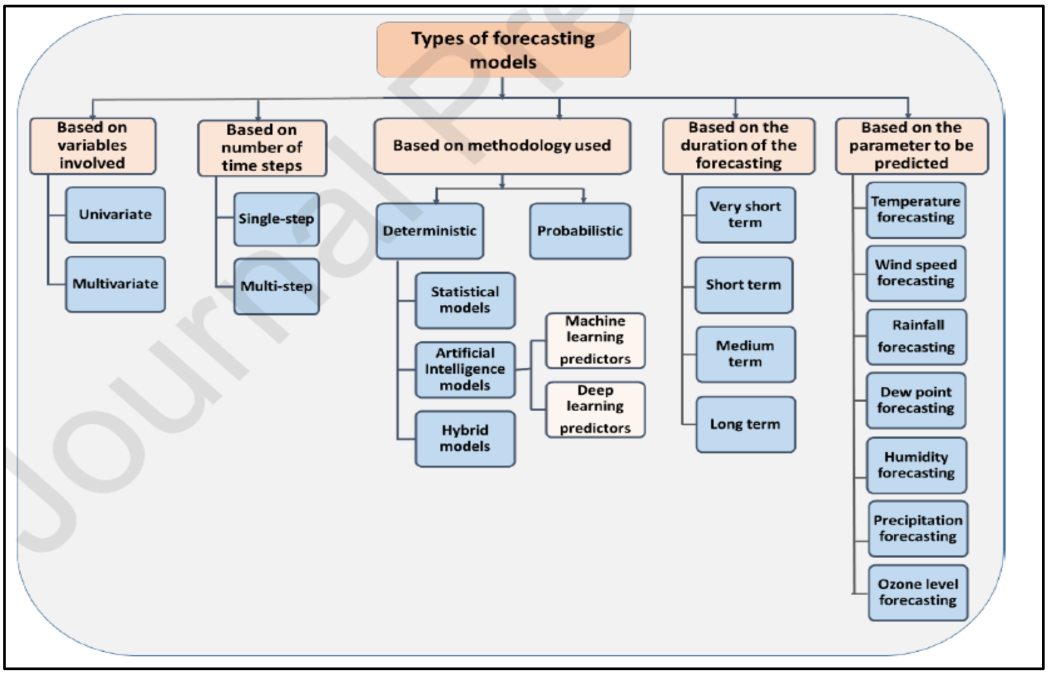

Figure (3): Classification of forecasting models [5]

Many studies have examined weather forecasting using deep learning techniques [9]. The researchers were able to predict rainfall in Southeast China by using the RN-Net model. RN-Net is a deep neural network with two inputs and two encoders. By integrating radar data and precipitation spatiotemporal properties, RN-Net provides a more suitable foundation for forecasting and delivers highly accurate predictions in both space and time. Still, there is potential for improvement in RN-Net's accuracy for rainfall intensity nowcasting [14,15,17,18, 20]. Only summer and autumn statistics are available for Southeast China because of data limitations. To provide more meteorological spatiotemporal information for forecasting, researchers are therefore working to expand the dataset's size and spatial coverage [10]. This work proposes a 128-neuron long short-term memory (LSTM) model for rainfall prediction in Jimma, Western Oromia, Ethiopia, and presents deep learning techniques for rainfall prediction. Numerous meteorological factors were taken into consideration, such as rainfall, wind speed, solar radiation, relative humidity, tmax, and tmin. It was also compared with a number of machine learning models.

Promising results indicate that the proposed methodology may accurately predict average rainfall (mm) with 99.72% accuracy. Because of this, the LSTM-based rainfall forecasting model can be used in a range of situations where rainfall prediction is necessary, including smart agriculture. [11] proposed a technique that uses historical temperature data and an artificial neural network to anticipate temperature changes. In particular, the researchers created a convolutional recurrent neural network (CRNN) model, which consists of an RNN and a convolutional neural network (CNN) component. The model can use neural networks to learn from historical data the temporal and spatial relationships between temperature changes. The researchers used daily temperature values for the Chinese mainland from 1952 to 2018 to assess the proposed CRNN model. The results show that the developed model can forecast temperature changes with an approximate 0.907°C error. [12] In this work, researchers in Thimphu, Bhutan's Simtokha district, used deep learning models to forecast rainfall. This work proposed the BLSTM-GRU model, which was compared against LSTM, GRU, and 1-D CNN, three additional deep learning models. The Bhutan Meteorological Department provided the data used in this work, which covered the years 1997 through 2017. With an MSE score of 0.007, an improved correlation value of 0.93, and an R2 score of 0.87, the suggested model BLSTM-GRU beat other models, whereas the performance of LSTM, GRU, and 1-D CNN is roughly similar, with LSTM outperforming to a greater extent.

2. Deep learning predictors

Deep learning is a subset of machine learning that combines deep architectures with supervised or unsupervised learning techniques to automatically learn hierarchical representations of data. It utilizes artificial neural networks to extract meaningful patterns and insights from large-scale datasets[13]. Because deep learning algorithms can learn the temporal dependence found in time series data, they are more dependable for time series prediction [14]. In its techniques for predicting properties, deep learning relies on deep neural networks, whose structures in turn contain several layers, some of which are hidden, in which the data passes through non-linear processing stages, where the outputs of one layer are inputs to the next layer. [15]. Deep learning has become widely known in many applications and specializations because it has proven to be highly reliable in the accuracy of its outputs. These applications include time series forecasting, speech recognition, climate prediction, genomics, and other applications. [16].

2.1 Recurrent neural networks (RNNs)

Recurrent neural networks (RNNs) are neural networks designed primarily to analyze sequential data, like time series, speech recognition, natural language processing, and weather forecasting. The basic equations of Recurrent Neural Networks (RNNs) serve as a foundational model that provides a rational path toward eventually arriving at the LSTM system structure.[17]. The basic idea is to connect hidden units in neural networks to themselves repeatedly with a time delay [18]. This is because the hidden units are able to feed their inputs back to themselves after learning certain features and representations. This can be understood as providing the network with dynamic memory. The concept of weight sharing is applicable here, just as it is in CNNs. Several stages of the input process can employ the same filter. This enables RNNs to be trained with sequences of varying lengths. What's more, it applies to sequence lengths that weren't seen during training. Figure (4) shows the general structure of the (unregistered) RNN.

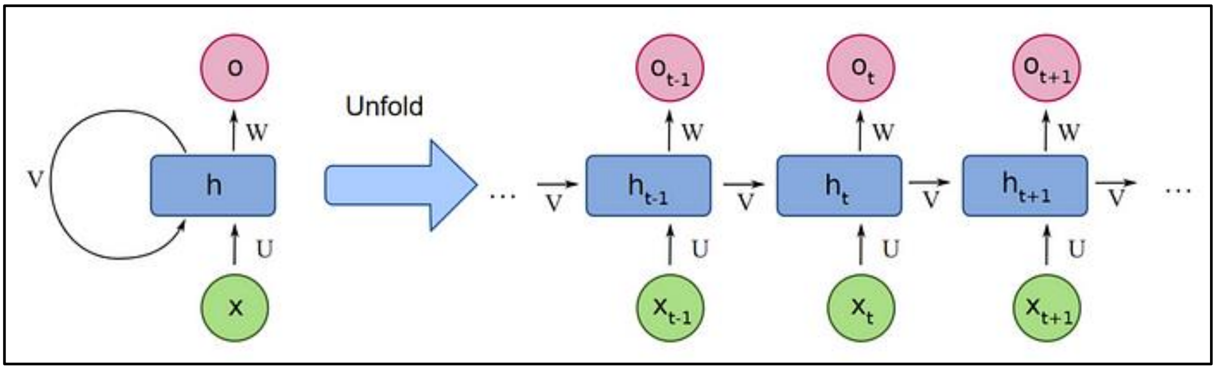

Figure (4): Structure of the RNN

2.2 Long Short-term Memory (LSTM)

Neural Network for Long Short-Term Memory. LSTM introduces a new state unit *C* and stores information in a control unit outside of the RNN's usual flow, in contrast to an RNN's single hidden layer [19]. The RNN's hidden state is split into two halves by the LSTM: working memory (*ht*) and memory cells (*ct*). The memory cell is responsible for preserving the sequential features. The memory of the previous sequence is controlled by the forgetting gate f. The output is the working memory (ht), and the output gate (o) determines what has to be recorded to the current memory (ct). The input gate I controls the current input xt and the fraction of the current state information ht -1 that will be written to the memory cells. To simultaneously calculate the current input (xt) and the previous state information (ht -1), non-linear activation uses linear combination [20]. The LSTM architecture can be defined as follows, Figure (5).

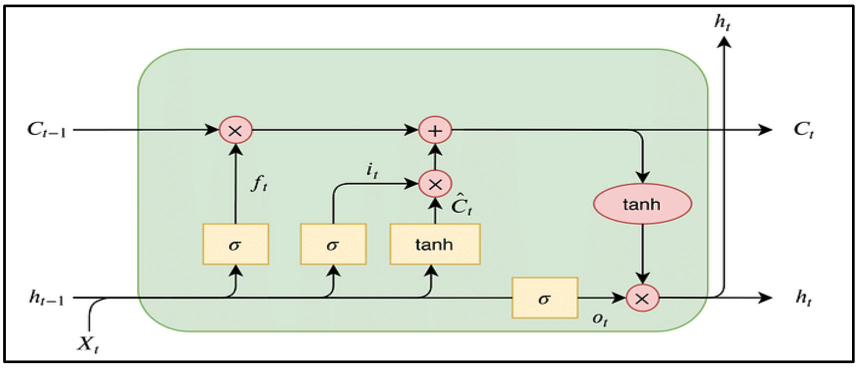

Figure (5): LSTM architecture

2.3 Gated Recurrent Units (GRU)

In many cases, the GRU model performs similarly to the LSTM model. In comparison to the LSTM model, the GRU model has fewer gates. Furthermore, the GRU outperforms the LSTM and does a better job of handling small data sets than it does. The vanishing gradient problem affects RNNs. An update and reset gate were included in the architecture of GRU in order to address this issue [12]. The GRU, in contrast to the LSTM, does not have a dedicated output gate but instead uses an update and reset gate to tackle the vanishing gradient problem of a standard RNN [21] [22]. The reset gate is the initial gate in the GRU model. The data from the prior moment (h_{t-1}) and the present moment (x_t) are multiplied by to obtain a linear transformation using the reset gate's weight matrix.as in Figure (6).

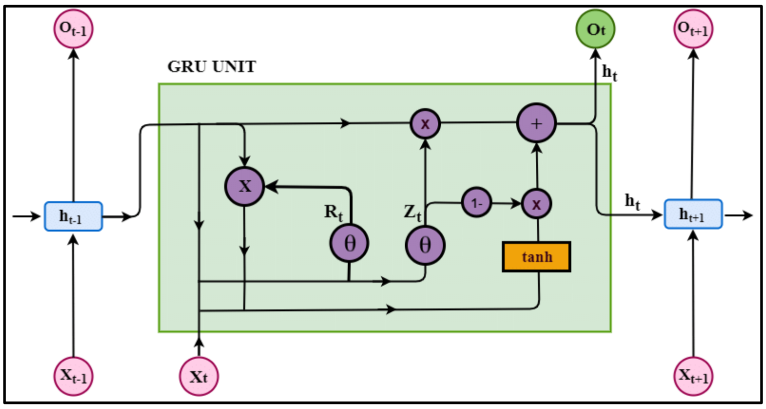

Figure (6): GRU architecture

3. Conclusion

The many methods and approaches for weather prediction are explained in this study. Deep learning algorithm produces more accurate weather forecasts in light of the findings. Time constraints pose challenges for both supervised and unsupervised algorithms when it comes to learning and verification. The advancement of deep learning methods and big data technology has made it possible to anticipate the climate and forecast the weather with accuracy and efficiency. The primary criteria used to categorize weather forecasting models are the methodology used and the weather parameter to be forecasted. All of the current models just assess how accurate the predictions are. In the realm of weather prediction, deep architecture neural networks and hybrid models have shown promise recently. The survey offers the most recent weather forecasting models, as well as information on their difficulties, publicly accessible datasets, and potential future study areas.

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