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NEW WEATHER FORECASTING APPLICATIONS

تطبيقات جديدة للتنبؤ بالطقس

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Abstract

Most state-of-the-art approaches for weather and climate modelling are based on physics informed numerical models of the atmosphere. These approaches aim to model the non-linear dynamics and complex interactions between multiple variables, which are challenging to approximate. Additionally, many such numerical models are computationally intensive, especially when modelling the atmospheric phenomenon at a fine-grained spatial and temporal resolution. Recent data-driven approaches based on machine learning instead aim to directly solve a downstream forecasting or projection task by learning a data-driven functional mapping using deep neural networks. However, these networks are trained using curated and homogeneous climate datasets for specific spatiotemporal tasks, and thus lack the generality of numerical models. In this research, the data available on Google for research objectives was used in two different algorithms through neural networks (ANN) and by controlling the design of these networks and training them hard, with the aim of obtaining results with a high degree of accuracy for weather forecasting for a period of up to 365 days in the first proposed model of neural networks and in case of the second algorithm the weather forecasted period is of up to four years (1460 days). All the facilities available in the fifty most used and downloaded weather forecasting applications from Google have been added to the proposed applications so that they are also available for usability through the two proposed models. The degree of accuracy obtained is high for the proposed two algorithms.

ملخص

تعتمد معظم الأساليب الحديثة لنمذجة الطقس والمناخ على نماذج رقمية مستنيرة للفيزياء للغلاف الجوي. تهدف هذه الأساليب إلى نمذجة الديناميكيات غير الخطية والتفاعلات المعقدة بين المتغيرات المتعددة ، والتي يصعب تقريبها. بالإضافة إلى ذلك ، فإن العديد من هذه النماذج العددية مكثفة ومعقدة من الناحية الحسابية ، خاصة عند نمذجة ظاهرة الغلاف الجوي بدقة مكانية وزمنية دقيقة. بدلاً من ذلك ، تهدف الأساليب الحديثة القائمة على البيانات القائمة على التعلم الآلي إلى حل مهمة التنبؤ أو الإسقاط النهائية مباشرة من خلال تعلم رسم خرائط وظيفية تعتمد على البيانات باستخدام الشبكات العصبية العميقة. ومع ذلك ، يتم تدريب هذه الشبكات باستخدام مجموعات بيانات مناخية منسقة ومتجانسة لمهام زمنية مكانية محددة ، وبالتالي تفتقر إلى عمومية النماذج العددية. في هذا البحث تم استخدام البيانات المتاحة علي جوجل بغرض الاستخدام البحثي بطريقتين مختلفتين من خلال الشبكات العصبية (ANN) ومن خلال التحكم في تصميم هذه الشبكات وتدريبها تدريب شاق وذلك بهدف الحصول علي نتائج ذات درجة دقة عالية وذلك للتنبئ بدرجات الطقس لمدة تبدا تصل الي ٣٦٥ يوم في مقترح النموذج الاول للشبكات العصبية ولمدة اخري تصل اربع سنوات (١٤٦٠ يوم) في مقترح النموذج الثاني. تم اضافة جميع الامكانيات المتاحة في اكثر خمسين تطبيقا استخداما وتحميلا من موقع جوجل لكي تكوم متاحة الاستخدام ايضا من خلال النموذجين المقترحين

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Introduction

Weather have serious impacts on life, both human and animal, in the short term. Natural disasters such as hurricanes and tornadoes result from certain weather pattern combinations and can injure or kill thousands of people depending on their scope. These disasters often do lasting damage to cities and ecosystems as well. Because of this, being able to predict and understand weather patterns is a very useful skill when preparing for disaster. The weather of any given region is important because it has a considerable impact on the water, sunlight and temperature of an ecosystem, according to the University of Illinois. These factors play a serious role by influencing the types of plant and animal wildlife that can survive in the area. Certain weather patterns can also cause dangerous storms and natural disasters. Variation in long-term weather patterns and tendencies can result in certain regions getting more or less water or sunlight than other areas. All living things require water, but because some organisms require more than others. The weather in an ecosystem determines what types of living things are best suited to live there. This principle also holds true for amounts of sunlight. The intensity and duration of sunlight in an area determines whether or not it can sustain different species of plant life. The weather of any given region is important because it has a considerable impact on the water, sunlight and temperature of an ecosystem. These factors play a serious role by influencing the types of plant and animal wildlife that can survive in the area. Certain weather patterns can also cause dangerous storms and natural disasters. Variation in long-term weather patterns and tendencies can result in certain regions getting more or less water or sunlight than other areas. All living things require water, but because some organisms require more than others. The weather in an ecosystem determines what types of living things are best suited to live there. This principle also holds true for amounts of sunlight. The intensity and duration of sunlight in an area determines whether or not it can sustain different species of plant life. The changing weather has been profoundly affecting people’s lives since the beginning of mankind. Weather conditions play a crucial and important role in production and economic industries such as transportation, tourism, agriculture and energy. Therefore, reliable and efficient weather forecasting is of great economic, scientific and social significance. The weather forecasting tasks deserves extensive attention. Meteorological parameters, such as temperature, humidity, visibility, and precipitation, can provide strong and powerful support and time series historical information for researchers to analyse the variation trends and tendency of weather conditions. For the past few decades, Numerical Weather Prediction (NWP) is the widely used traditional method, which utilizes physical models to simulate and predict meteorological dynamics in the atmosphere or on the Earth’s surface. How- ¨ ever, the prediction of NWP may not be more accurate enough due to the uncertainty of the initial conditions of the differential equation, especially in complex atmospheric processes. In addition, NWP has highly requirements on computing power. In recent years, meteorological researchers have achieved considerable breakthroughs, achievements, and successes in introducing data-driven approaches, most prominently deep learning methods, to the task of weather forecasting. Data-driven approaches and models exploit the time series historical meteorological observation data aggregated over years to model patterns to learn the input-output mapping. In the task of time series forecasting, Transformers have shown great modelling ability for long-term dependencies and interactions in sequential data benefiting from the self-attention mechanism. In the more challenging task of spatio-temporal forecasting, the classical Convolutional Neural Networks (CNNs) which work well on regular grid data in Euclidean domain have been greatly challenged to handle this problem due to the irregular sampling of most spatio-temporal data. The Graph Neural Networks (GNNs), which have already been extensively applied to traffic forecasting, yield effective and efficient performance by e connections among them as graph nodes and edges, respectively. However, studies focusing on the field of meteorology are relatively scarce, while the demand for weather forecasting is increasing dramatically. For data-centric deep learning method, the performance of the model heavily depends on the quality of the available training data. High-quality benchmark datasets can serve as “catalysts” for quantitative comparison between different algorithms and promote constructive competition. In the field of meteorological science, reanalysis dataset cannot ensure the authenticity of the data. Remote sensing dataset cannot reliably reflect complexities of near-surface weather conditions. Fusion dataset cannot guarantee real-time performance. Inadequacies of existing datasets also include diversity of meteorological factors and applicable tasks. In this work, we present a new benchmark dataset. This data set is the available dataset exist on google website available for usability in research prospective. In this aspect we use two data sets for the current research one of them is used for building an algorithm for forecasting weather for 365 days and the other dataset is used for the second algorithm for forecasting weather for 1460 days (four years). The dataset used in the presented analysis for the first algorithm is available on the link https://power.larc.nasa.gov/data-access-viewer/ . this data set is considered for ten years for the study for the first algorithm. Figure 1. Present an image of the starting of data set and the end of the data set for this model. The dataset used in our analysis for the second algorithm is available on this link https://power.larc.nasa.gov/data-access-viewer/ . The second Figure 2. presents a sample of this dataset. The used dataset consists of 7305 records of data temperatures recorded daily for twenty years starts from first day of January 2003 till first of January of 2023.

1	01-01-13	14.18	5.91	6.98	3.84	9.05	19.3	13.73	2.99	240.19	62.56	1	1	2013
2	01-02-13	15.53	5.34	6.91	3.92	10.87	20.19	14.74	2.62	278.69	77.31	2	1	2013
3	01-03-13	16.94	3.62	5.86	2.32	12.98	20.89	16.06	1.83	272.19	75.25	3	1	2013
4	01-04-13	15.96	4.27	7.24	0.37	12.52	19.39	15.1	2.24	268.06	72.56	4	1	2013
5	01-05-13	14.45	8.55	10.27	6.62	11.62	17.27	14.17	4.45	269.25	73.62	5	1	2013
6	01-06-13	14.1	12.7	17.33	8.66	10.99	17.21	14.14	7.53	249.44	69.12	6	1	2013

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3649	12/28/2022	17.22	2.33	3.8	0.31	13.34	21.1	16.66	1.28	227.62	64.94	28	12	2022
3650	12/29/2022	16.92	3.59	6.48	1.2	11.9	21.93	16.45	1.74	229.75	73.75	29	12	2022
3651	12/30/2022	17.64	6.28	7.27	5.61	14.15	21.13	17.01	3.05	202.94	78.19	30	12	2022
3652	12/31/2022	16.87	6.56	7.53	5.24	12.85	20.88	16.15	3.28	37.81	71.69	31	12	2022
3653	01-01-23	17.39	7.38	8.03	6.05	14.79	19.99	16.68	3.75	21.81	71.12	1	1	2023

Figure 1. Sample of the used dataset in the current research.

01-01-03	15.245	10.42	20.07	-263.5	14.63	11.36	8.33	14.38	1	1	2003
02-01-03	14.395	9.11	19.68	-262.58	14.67	10.67	7.15	14.19	2	1	2003
03-01-03	15.9	12.69	19.11	-266.72	15.81	13.37	11.44	15.31	3	1	2003
04-01-03	15.965	11.63	20.3	-264.49	15.47	11.94	8.69	15.2	4	1	2003
05-01-03	16.34	10.28	22.4	-261.02	15.32	10.42	5.76	15.08	5	1	2003

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28-12-22	17.22	13.34	21.1	-265.39	15.99	13.19	9.73	16.66	28	12	2022
29-12-22	16.915	11.9	21.93	-263.13	16.94	13.9	11.35	16.45	29	12	2022
30-12-22	17.64	14.15	21.13	-266.17	17.34	14.96	12.91	17.01	30	12	2022
31-12-22	16.865	12.85	20.88	-265.12	16.48	13.41	10.67	16.15	31	12	2022
01-01-23	17.39	14.79	19.99	-267.94	17.08	13.95	11.23	16.68	1	1	2023

Figure 2. Sample of the used dataset in the current research for the second algorithm.

Literature Survey

Forecast of future weather is one of the dominant concerns in today's era. Several techniques that have been used to forecast future weather are statistical analysis, machine learning, and deep learning techniques. Forecast of weather can assist in the decision-making process for the prevention of disasters. While forecasting weekly weather can help people, decide and manage their activities and recreational programs it can also help Smart management programs. The accuracy of the Short term ambient forecast conditions is particularly conducive to the development of forecast management strategies. Munulty proposed an operational weather forecasting approach within the central region for a national weather service [1]. This model focusses on the primary central region warm season weather producer, the thunderstorm. some of the unique aspects of central region thunderstorms are highlighted. The model in this research is focused to answer four questions. Will thunderstorms occur that will affect the area of forecast responsibility considered? If thunderstorms develop, will these thunderstorms reach serve intensity? If these thunderstorms reach serve intensity, what types of serve phenomena are likely with these storms? If thunderstorms occur, what storm type is most likely to be observed? A neural network-based algorithm for predicting the temperature is presented by Baboo and Shereef [2]. The Neural Networks package supports different types of training or learning algorithms. One such algorithm is Back Propagation Neural Network (BPN) technique. The main advantage of the BPN neural network method is that it can fairly approximate a large class of functions. This method is more efficient than numerical differentiation. The simple meaning of this term is that the proposed model has potential to capture the complex relationships between many factors that contribute to certain temperature. The proposed idea is tested using the real time dataset. The results are compared with practical working of meteorological department and these results confirm that the model have the potential for successful application to temperature forecasting. The analyse of data mining techniques in forecasting weather is presented by Mandale and. Jadhawar [3]. The model is carried out using Artificial Neural Network and Decision Tree Algorithms and meteorological data collected in specific time. The performance of these algorithms was compared using standard performance metrics, and the algorithm which gave the best results used to generate classification rules for the mean weather variables. The results show that given enough case data mining techniques can be used for weather forecasting. Holmstrom et al [4] explore an application to weather forecasting to potentially generate more accurate weather forecasts for large periods of time. The scope of this model was restricted to forecasting the maximum temperature and the minimum temperature for seven days, given weather data for the past two days. A linear regression model and a variation on a functional regression model were used, with the latter able to capture trends in the weather. Both of the proposed models were outperformed by professional weather forecasting services, although the discrepancy between these models and the professional ones diminished rapidly for forecasts of later days, and perhaps for even longer time scales. The linear regression model outperformed the functional regression model, suggesting that two days were too short for the latter to capture significant weather trends. Biswas et al [5] introduce a classifier approach for prediction of weather condition and show how Naive Bayes and Chi square algorithm can be utilized for classification purpose. This system is a web application with effective graphical User Interface. User will login to the system. User will enter some information such as current outlook, temperature, humidity and wind condition. The system will take this parameter and predict weather after analysing the input information with the information in database. Consequently, two basic functions to be specific classification (training) and prediction (testing) will be performed. The outcomes demonstrated that these data mining procedures can be sufficient for weather forecasting. Segarra et al [6] proposed a methodology for quantifying the impact of the error generated by the weather forecast in the building's indoor climate conditions and energy demand. The objective is to estimate the error introduced by the weather forecast in the load forecasting to have more precise predicted data. The methodology employed site-specific, near-future forecast weather data obtained through online open access Application Programming Interfaces (APIs). The weather forecast providers supply forecasts up to 10 days ahead of key weather parameters such as outdoor temperature, relative humidity, wind speed and wind direction. This approach uses calibrated Energy Plus models to foresee the errors in the indoor thermal behaviour and energy demand caused by the increasing day-ahead weather forecasts. A case study investigated the impact of using up to 7-day weather forecasts on mean indoor temperature and energy demand predictions in a building located. The main novel concepts in this paper are: first, the characterization of the weather forecast error for a specific weather data provider and location and its effect in the building's load prediction. The error is calculated based on recorded hourly data so the results are provided on an hourly basis, avoiding the cancel out effect when a wider period of time is analysed. The second is the classification and analysis of the data hour-by-hour to provide an estimate error for each hour of the day generating a map of hourly errors. This application becomes necessary when the building takes part in the day-ahead programs such as demand response or flexibility strategies, where the predicted hourly load must be provided to the grid in advance. The methodology developed in this paper can be extrapolated to any weather forecast provider, location or building. Machine Learning in Heliophysics and Space Weather Forecasting model is proposed by Nita et al [7]. Their objective was to discuss critical developments and prospects of the application of machine and/or deep learning techniques for data analysis, modelling and forecasting in Heliophysics, and to shape a strategy for further developments in the field. Data Verification and Benchmark Datasets are used in the current proposed model. Also Model verification and cross-comparison between observations and laboratory plasma experiment are held. The verification of data and models is considered for the verification of the model performance. A Real-time weather forecasting and analysis has been proposed by Yada et al [8] using the parameters temperature and humidity. In this model correlation analysis is used as a key for prediction in an ARIMA (Auto-Regressive Integrated Moving Average) Model. In the past, old physical prediction models that were not much appropriate for the forecast due to the random nature of weather over a long period. In the presented scenario, techniques like Machine learning, IoT, ANN are more robust in prediction with more accurately and for a longer period. But these things are limited to machines, to make a more advancement by making machine think like a human, so that natural intelligence of human can govern over the machine and for prediction in a much realistic way. new class of problems using Cognitive computing (CC) is used. it deals with complex problems same way as human tackle the unknown problems. The purpose of the constructed model is to analyse weather forecasting using different computing techniques and design a more efficient prediction model using cognitive computing. A new, optimized method for deriving NUCAPS level 2 horizontally and vertically gridded products is described by Berndt et al [9]. This work represents the development of approaches to better synthesize remote sensing observations that ultimately increase the availability and usability of NUCAPS observations. This approach, known as "Gridded NUCAPS", was developed to more effectively visualize NUCAPS observations to aid in the quick identification of thermodynamic spatial gradients. Gridded NUCAPS development was based on operations-to-research feedback and is now part of the operational National Weather Service display system. In this model, the discussion of how Gridded NUCAPS was designed, how relevant atmospheric fields are derived, its operational application in pre-convective weather forecasting, and several emerging applications that expand the utility of NUCAPS for monitoring phenomena such as fire weather, the Saharan Air Layer, and stratospheric air intrusions. Promising results are obtained. Two data-driven models for long-term weather conditions forecasting to support operation and maintenance (O&M) decision-making process were introduced by Pandit et al [10]. The approaches are long short-term memory network, abbreviated as LSTM, and Markov chain. An LSTM is an artificial recurrent neural network, capable of learning longterm dependencies within a sequence of data and is typically used to avoid the long-term dependency problem. While, Markov is another data-driven stochastic model, which assumes that, the future states depend only on the current states, not on the events that occurred before. The readily available weather FINO3 datasets are used to train and validate the performance of these models. A performance comparison between these weather forecasted models would be carried out to determine which approach is most accurate and suitable for improving offshore wind turbine availability and support maintenance activities. The entire study outlines the weakness and strength associated with proposed models in relations to offshore wind farms operational activities. The weather forecasting device proposed Bindhu [11] utilizes the weather pi board to measure the changes in the atmosphere and process them using the raspberry pi processor and conveys the information to the server utilizing the 4G modem, the proposed method seems to be provide an accurate measurement of weather forecasting and this tested by implementing the proposed method over the delta districts of India and observing the results using the Think speak. The proposed method utilizes the sensors to monitor the weather changes and engages the raspberry pi to process the information gathered and convey it to the end user. The proposed system was tested by implementing it in the Indian delta districts and the accuracy, precision and flexibility in the forecasting was evinced by the data output observed over and done with the Think speak Web. an inclusive survey and methods based on Machine Learning, and Deep Learning Techniques used to predict weather is introduced by Bhawsar [12]. Climate guesses are made by social occasion quantitative data about the current status of the environment at a given spot and utilizing meteorology to considered project to present how the climate will change. With scientific advancements, a lot of research is going on weather gauging utilizing Data mining, deep learning, machine learning has been done. However, there was a lack of surveys available on the present status of exploration and application. The proposed model offers a survey of weather forecasting using various techniques. Also summarizing the key concepts and focusing on the existing work on weather forecasting, its types, and its applications. To conclude, how deep learning, data mining, and machine learning algorithms were employed in weather forecasting is exceptionally important to guarantee future exploration will focus destined for success, accordingly improving the performance of weather predictions. A forecast model for high-resolution numeric weather data using both input weather data and observations by providing a novel deep learning architecture is introduced by Tekin et al [13]. The problem is designed as spatiotemporal prediction. The model is composed of Convolutional Long-short Term Memory, and Convolutional Neural Network units with encoder-decoder structure. This design enhances the short long term performance and interpretability with an attention and a context matcher mechanism. We perform experiments are done for high-scale, real-life, benchmark numerical weather dataset, ERA5 hourly data on pressure levels, and forecast the temperature. The results show significant improvements in capturing both spatial and temporal correlations with attention matrices focusing on different parts of the input series. The model obtains the best validation and the best test score among the baseline models, including ConvLSTM forecasting network and U-Net. Qualitative and quantitative results and show that the model forecasts 10 time steps with 3-hour frequency with an average of 2 degrees' error. The analyse the use of various data mining techniques in forecasting maximum temperature, rainfall and wind speed is presented and reviewed by Pandey et al [14]. This review is very useful, since it brings a better understanding of the field of analysis, and this is an important role in this paper. From the review it can be concluded that this field invites a great deal of interest by researchers. One of the idea that were identified during this research is related with the combined use of various climatic issues. An ANN and Convolutional Neural Networks (CNNs) models are applied in weather forecasting by Kareem et al [15]. The prediction technique relies solely upon learning previous input values from intervals in order to forecast future values. The Convolutional Neural Networks (CNNs) are a form of deep learning technique that can help classify, recognize, and predict trends in climate change and environmental data. However, due to the inherent difficulties of obtained results, which are often independently identified, non-stationary, and unstable CNN algorithms should be built and tested with each dataset and system separately. The presented CNN model's forecasting efficiency was compared to some state-of-the-art ANN algorithms. The analysis shows that weather prediction applications become more efficient when using ANN algorithms because it is really easy to put into practice. An algorithm for recalibration data size into 3 data sets for weather forecasting and personalized medicine demand is presented by Kumar et al [16]. In this model the proposed approach is validated with multiclass calibration experiments on CIFAR-10 and ImageNet, where it obtained a 35% lower calibration error than histogram binning and, unlike scaling methods, guarantees on true calibration. In these experiments, also estimate the calibration error and ECE more accurately than the commonly used plugin estimators. In this algorithm all these methods are implemented in a Python library. A significantly-improved data-driven global weather forecasting framework using a deep convolutional neural network (CNN) to forecast several basic atmospheric variables on a global grid is presented by Weyn et al [17]. New developments in this framework include an offline volume-conservative mapping to a cubed sphere grid, improvements to the CNN architecture, and the minimization of the loss function over multiple steps in a prediction sequence. The cubed-sphere remapping minimizes the distortion on the cube faces on which convolution operations are performed and provides natural boundary conditions for padding in the CNN. The improved model produces weather forecasts that are indefinitely stable and produce realistic weather patterns at lead times of several weeks and longer. For short to medium-range forecasting, proposed model significantly outperforms persistence, climatology, and a coarse-resolution dynamical numerical weather prediction (NWP) model. A mixed model that uses only a subset of the original weather trajectories combined with a post-processing step using deep neural networks is proposed by Grönquist et al [18] for systems that are associated with a high computational cost and often involve statistical post-processing steps to inexpensively improve their raw prediction qualities. This model enables to account for non-linear relationships that are not captured by current numerical models or post-processing methods. Applied to global data, our mixed models achieve a relative improvement in ensemble forecast skill (CRPS) of over 14%. Furthermore, the model demonstrates that the improvement is larger for extreme weather events on select case studies. The proposed model can use fewer trajectories to achieve comparable results to the full ensemble. By using fewer trajectories, the computational costs of an ensemble prediction system can be reduced, allowing it to run at higher resolution and produce more accurate forecasts. A compared multilayer perceptron (MLP), long short-term memory (LSTM), and gated recurrent unit (GRU) with the proposed new hybrid models, including CNN-LSTM and CNN-GRU is presented by Eyob Wegayehu and Muluneh [19]. One-step daily streamflow in different agro climatic conditions, rolling time windows, and a range of variable input combinations has been simulated. -e analysis used daily multivariate and multisite time series data collected from Awash River Basin (Borkena watershed: Ethiopia) and Tiber River Basin (Upper Tiber River Basin: Italy) stations is presented. In the proposed algorithm, -e datasets were subjected to rigorous quality control processes. Consequently, it rolled to a different time lag to remove noise in the time series and further split into training and testing datasets using a ratio of 80: 20, respectively. Finally, the results showed that integrating the GRU layer with the convolutional layer and using monthly rolled average daily input time series could substantially improve the simulation of streamflow time series. A deterministic neural network weather forecasting system is structured by Scher and Messori [20], into an ensemble forecasting system. Four methods to generate the ensemble: random initial perturbations, retraining of the neural network, use of random dropout in the network, and the creation of initial perturbations with singular vector decomposition are applied. The latter method is widely used in numerical weather prediction models, but is yet to be tested on neural networks. The ensemble mean forecasts obtained from these four approaches all beat the unperturbed neural network forecasts, with the retraining method yielding the highest improvement. However, the skill of the neural network forecasts is systematically lower than that of state-of-the-art numerical weather prediction models. Two of these methods perturb initial conditions (one with random perturbations, one with perturbations based on the SVD technique). The third method retrains the neural network, creating a slightly different neural network each time, and the fourth methods uses dropout in the network to generate an ensemble. Deep Attention Unistream Multistream (DAUM) networks that investigate different types of input representations (i.e. tensorial unistream vs. multistream) as well as the incorporation of the attention mechanism is presented through an algorithm by Abdellaoui and Mehrkanoon [21]. In particular, adding a self-attention block within the models increases the overall forecasting performance. Furthermore, visualization techniques such as occlusion analysis and score maximization are used to give an additional insight on the most important features and cities for predicting a particular target feature of target cities under consideration. In this study, a self-attention mechanism proved to be beneficial to these models since it consistently improved the results. From the analysis of the experimental results, it has been shown that a multi-stream input representation is globally more suitable for this task. Due to the recent development of deep learning techniques applied to satellite imagery, weather forecasting that uses remote sensing data has also been the subject of major progress. This concept has been used in a proposed model by Fernandez et al [22]. This model investigates multiple steps ahead frame prediction for coastal sea elements in the Netherlands using U-Net based architectures. Hourly data from the Copernicus observation programme spanned over a period of 2 years has been used to train the models and make the forecasting, including seasonal predictions. The applied technique proposes a variation of the U-Net architecture and further extend this novel model using residual connections, parallel convolutions and asymmetric convolutions in order to introduce three additional architectures. In particular, it shows that the architecture equipped with parallel and asymmetric convolutions as well as skip connections outperforms the other three discussed models. Numerical weather forecasting on high-resolution physical models consume hours of computations on supercomputers and application of deep learning and machine learning methods in forecasting revealed new solutions in this area. This idea is considered in the presented model structured by Tekin et al [23]. In this model, forecast high-resolution numeric weather data using both input weather data and observations by providing a novel deep learning architecture is structured. the problem is formulated as spatiotemporal prediction. The proposed model is composed of convolutional Long-short Term Memory, and Convolutional Neural Network units with encoder-decoder structure. The short long term performance is enhanced and interpretability with an attention and a context matcher mechanism. Experiments on high-scale, real-life, benchmark numerical weather dataset, ERA5 hourly data on pressure levels, and forecast the temperature. The results show significant improvements in capturing both spatial and temporal correlations with attention matrices focusing on different parts of the input series. Newly proposed graph neural network architectures are repetitively evaluated on standard tasks such as traffic or weather forecasting. This idea is presented through the technique proposed by Rozemberczki et al [24]. In this research, the Chickenpox Cases in Hungary dataset as a new dataset for comparing graph neural network architectures. The proposed time series analysis and forecasting experiments demonstrate that the Chickenpox Cases in Hungary dataset is adequate for comparing the predictive performance and forecasting capabilities of novel recurrent graph neural network architectures. The presented exploratory analysis highlighted the unique statistical characteristics of the dataset which make predicting the weekly number of cases a challenging task. The forecasting capabilities of the state-of-the-art recurrent graph neural networks is evaluated. The research findings demonstrate that the current design of graph neural networks is moderately well suited for solving this task. Chattopadhyay et al [25] proposed a model of 3 components to integrate with data-driven weather prediction (DDWP), in order to improve the physical consistency and forecast accuracy. y. The first element is a deep spatial transformer added to the latent space of the U-NETs to preserve a property called equivariance, which is related to correctly capturing rotations and scaling of features in spatio-temporal data. The second elemnt is a data-assimilation (DA) algorithm to ingest noisy observations and improve the initial conditions for next forecasts. The last element is a multi-time-step algorithm, which combines forecasts from DDWP models with different time steps through DA, improving the accuracy of forecasts at short intervals. The proposed elements reduce the average error rendered in forecasting results and are flexible and can be used in a variety of DDWP setups. The novel approach using a neural network is presented by Clare et al [26] to predict full probability density functions at each point in space and time rather than a single output value, for producing a probabilistic weather forecast. This enables the calculation of both uncertainty and skill metrics for the neural network predictions, and overcomes the common difficulty of inferring uncertainty from these predictions. This approach is data-driven and the neural network is trained on the Weather Bench dataset (processed ERA5 data) to forecast geopotential and temperature 3 and 5 days ahead. In this model data exploration leads to the identification of the most important input variables, which are also found to agree with physical reasoning, thereby validating of this approach. In order to increase computational efficiency further, each neural network is trained on a small subset of these variables. The outputs are then combined through a stacked neural network; the first time such a technique has been applied to weather data. This approach is found to be more accurate than some numerical weather prediction models and as accurate as more complex alternative neural networks, with the added benefit of providing key probabilistic information necessary for making informed weather forecasts. An optimistic online learning algorithms that require no parameter tuning and have optimal regret guarantees under delayed feedback is developed by Flasapohler et al [27]. The algorithms—DORM, DORM+, and AdaHedgeD—arise from a novel reduction of delayed online learning to optimistic online learning that reveals how optimistic hints can mitigate the regret penalty caused by delay. The proposed algorithm pair this delay-as-optimism perspective with a new analysis of optimistic learning that exposes its robustness to hinting errors and a new meta-algorithm for learning effective hinting strategies in the presence of delay. It is concluded by benchmarking that the proposed algorithms on four sub-seasonal climate forecasting tasks, demonstrating low regret relative to state-of-the-art forecasting models. Several deep learning models to classify the states (dry, moist, wet, icy, snowy, slushy) are developed and implemented by Jahin and Krutsylo [28]. Depending upon the best model, the Proposed weather forecast app will predict the state taking the Ta, Tsurf, Height, Speed, Water, etc. into consideration. In the presented technique, the crucial part was to define a safety metric which is the product of the accident rates based on friction and the accident rates based on states. A regressor tool is developed that will predict the safety metric depending upon the state obtained from the classifier and the friction obtained from the sensor data. A pathfinding algorithm has been designed using the sensor data, open street map data, weather data. A proposed model by He et al [29] in which Sub-seasonal climate forecasting (SSF) is the prediction of key climate variables such as temperature and precipitation on the 2-week to 2-month time horizon in considered. Skillful SSF would have substantial societal value in areas such as agricultural productivity, hydrology and water resource management, and emergency planning for extreme events such as droughts and wildfires. Despite its societal importance, SSF has stayed a challenging problem compared to both short-term weather forecasting and long-term seasonal forecasting. Recent studies have shown the potential of machine learning (ML) models to advance SSF. In this model, for the first time, a fine-grained comparison of a suite of modern ML models with start-of-the-art physics-based dynamical models from the Sub-Seasonal Experiment (SubX) project for SSF is performed. Additionally, we explore mechanisms to enhance the ML models by using forecasts from dynamical models. Finally, the suitably incorporating dynamical model forecasts as inputs to ML models can substantially improve the forecasting performance of the ML models. Espeholt et al [30] introduce a model in which twelve-hour precipitation forecasts using large context neural networks. In this research a neural network that is capable of large-scale precipitation forecasting up to twelve hours ahead has been presented and, starting from the same atmospheric state, the model achieves greater skill than the state-of-the-art physics-based models HRRR and HREF that currently operate in the Continental United States. Interpretability analyses reinforce the observation that the model learns to emulate advanced physics principles. These results represent a substantial step towards establishing a new paradigm of efficient forecasting with neural networks. Promising results are attained. Wegayehu, E., and Muluneh, F., [31] introduce a new model in which Stacked Long Short-Term Memory (S-LSTM), Bidirectional Long Short-Term Memory (Bi-LSTM), and Gated Recurrent Unit (GRU) with the classical Multilayer Perceptron (MLP) network for one-step daily streamflow forecasting were compared. The analysis used daily time series data collected from Borkena (in Awash river basin) and Gummera (in Abay river basin) streamflow stations. All data sets passed through rigorous quality control processes, and null values were filled using linear interpolation. A partial autocorrelation was also applied to select the appropriate time lag for input series generation. Then, the data is split into training and testing datasets using a ratio of 80: 20, respectively. Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and coefficient of determination (R2) were used to evaluate the performance of the proposed models. Finally, the findings are summarized in model variability, lag time variability, and time series characteristic themes. As a result, time series characteristics (climatic variability) had a more significant impact on streamflow forecasting performance than input lagged time steps and deep learning model architecture variations. weather forecasting is of great importance in science, business, and society. The best performing data-driven models for weather prediction tasks rely on recurrent or convolutional neural networks, where some of which incorporate attention mechanisms. Bilgin et al [32] introduced a novel model based on Transformer architecture for weather forecasting. The proposed Tensorial Encoder Transformer (TENT) model is equipped with tensorial attention and thus it exploits the spatiotemporal structure of weather data by processing it in multidimensional tensorial format. The model shows that compared to the classical encoder transformer, 3D convolutional neural networks, LSTM, and Convolutional LSTM, the proposed TENT model can better learn the underlying complex pattern of the weather data for the studied temperature prediction task. Experiments on two real-life weather datasets are performed. The datasets consist of historical measurements from weather stations in the USA, Canada and Europe. The first dataset contains hourly measurements of weather attributes for 30 cities in the USA and Canada from October 2012 to November 2017. The second dataset contains daily measurements of weather attributes of 18 cities across Europe from May 2005 to April 2020. Two attention scores are introduced based on the obtained tonsorial attention and are visualized in order to shed light on the decision-making process of our model and provide insight knowledge on the most important cities for the target cities. A Shifts Dataset for evaluation of uncertainty estimates and robustness to distributional shift has been proposed by Malinin [33]. The dataset, which has been collected from industrial sources and services, is composed of three tasks, with each corresponding to a particular data modality: tabular weather prediction, machine translation, and self-driving car (SDC) vehicle motion prediction. All of these data modalities and tasks are affected by real, "in-the-wild" distributional shifts and pose interesting challenges with respect to uncertainty estimation. In this work a description of the dataset and baseline results for all tasks is presented. A report provides a description of the methodology used in the IEEE-CIS 3rd Technical Challenge was proposed by Bean [34]. For the forecast, a quantile regression forest approach using the solar variables provided by the Bureau of Meteorology of Australia (BOM) and many of the weather variables from the European Centre for Medium-Range Weather Forecasting (ECMWF) was used. Groups of buildings and all of the solar instances were trained together as they were observed to be closely correlated over time. Other variables used included Fourier values based on hour of day and day of year, and binary variables for combinations of days of the week were implemented. The start dates for the time series were carefully tuned based on first phase and cleaning and thresholding was used to reduce the observed error rate for each time series. For the optimization, a four-step approach was used using the presented forecast technique developed. First, a mixed-integer program (MIP) was solved for the recurring and recurring plus once-off activities, then each of these was extended using a mixed-integer quadratic program (MIQP). A promising results are attained. FourCastNet, short for Fourier ForeCasting Neural Network, is a global data-driven weather forecasting model that provides accurate short to medium-range global predictions at 0.25◦ resolution was presented by Pathak et al [35]. FourCastNet accurately forecasts high-resolution, fast-timescale variables such as the surface wind speed, precipitation, and atmospheric water vapour. It has important implications for planning wind energy resources, predicting extreme weather events such as tropical cyclones, extra-tropical cyclones, and atmospheric rivers. FourCastNet matches the forecasting accuracy of the ECMWF Integrated Forecasting System (IFS), a state-of-the-art Numerical Weather Prediction (NWP) model, at short lead times for large-scale variables, while outperforming IFS for small-scale variables, including precipitation. FourCastNet generates a week-long forecast in less than 2 seconds, orders of magnitude faster than IFS. The speed of FourCastNet enables the creation of rapid and inexpensive large-ensemble forecasts with thousands of ensemble-members for improving probabilistic forecasting. In this article, how data-driven deep learning models such as FourCastNet are a valuable addition to the meteorology toolkit to aid and augment NWP models are presented and discussed. WeatherBench is a benchmark dataset for medium-range weather forecasting of geopotential, temperature and precipitation, consisting of preprocessed data, predefined evaluation metrics and a number of baseline models. WeatherBench Probability extends this to probabilistic forecasting by adding a set of established probabilistic verification metrics (continuous ranked probability score, spread-skill ratio and rank histograms) and a state-of-the-art operational baseline using the ECWMF IFS ensemble forecast. A model using the above features is presented by Garg et al [36] to enhance the weather forecasts. In addition, three different probabilistic machine learning methods—Monte Carlo dropout, parametric prediction and categorical prediction, are tested through which the probability distribution is discretized. the plain Monte Carlo dropout severely underestimates uncertainty. The parametric and categorical models both produce fairly reliable forecasts of similar quality. The parametric models have fewer degrees of freedom while the categorical model is more flexible when it comes to predicting non-Gaussian distributions. None of the models are able to match the skill of the operational IFS model. One of the new founds is That the benchmark will enable other researchers to evaluate their probabilistic approaches. A deep-learning-based algorithms to learn the statistical properties of an ensemble prediction system, is introduced by Brecht and Bihlo [37]. The ensemble spread, given only the deterministic control forecast. Thus, once trained, the costly ensemble prediction system will not be needed anymore to obtain future ensemble forecasts, and the statistical properties of the ensemble can be derived from a single deterministic forecast. The classical pix2pix architecture to a three-dimensional model and also experiment with a shared latent space encoder–decoder model is adapted and trained them against several years of operational (ensemble) weather forecasts for the 500 hPa geopotential height. The results demonstrate that the trained models indeed allow obtaining a highly accurate ensemble spread from the control forecast only. A convolutional variational autoencoder-based stochastic data-driven model that is introduced by Chattopadhyay et al [38]. In this model pre-trained on an imperfect climate model simulation from a 2-layer quasi-geostrophic flow and retrained, using transfer learning, on a small number of noisy observations from a perfect simulation. This re-trained model then performs stochastic forecasting with a noisy initial condition sampled from the perfect simulation. The ensemble-based stochastic data-driven model outperforms a baseline deterministic encoder-decoder-based convolutional model is shown in terms of short-term skills while remaining stable for long-term climate simulations yielding accurate climatology. General an enhancement has achieved. Post-processing ensemble prediction systems can improve the reliability of weather forecasting, especially for extreme event prediction. In recent years, different machine learning models have been developed to improve the quality of weather post-processing. However, these models require a comprehensive dataset of weather simulations to produce high-accuracy results, which comes at a high computational cost to generate. Ashkboos et al [39] introduced a model for weather forecasting considering the previous features. The proposed model introduces the ENS-10 dataset, consisting of ten ensemble members spanning 20 years (1998–2017). The ensemble members are generated by perturbing numerical weather simulations to capture the chaotic behaviour of the Earth. To represent the three-dimensional state of the atmosphere, ENS-10 provides the most relevant atmospheric variables at 11 distinct pressure levels and the surface at 0.5° resolution for forecast lead times T=0, 24, and 48 hours (two data points per week). The ENS-10 prediction correction task is used for improving the forecast quality at a 48-hour lead time through ensemble post-processing. The introduced technique is promising in its results. To improve the security and reliability of wind energy production, short-term forecasting has become of utmost importance. This feature is considered in the proposed model introduced by Bensten et al [40]. The study focuses on multi-step spatio-temporal wind speed forecasting for the Norwegian continental shelf. In particular, the study considers 14 offshore measurement stations and aims to leverage spatial dependencies through the relative physical location of different stations to improve local wind forecasts and simultaneously output different forecasts for each of the 14 locations. The multi-step forecasting models produce either 10-minute, 1- or 4-hour forecasts, with 10- minute resolution, meaning that the models produce more informative time series for predicted future trends. A graph neural network (GNN) architecture was used to extract spatial dependencies, with different update functions to learn temporal correlations. These update functions were implemented using different neural network architectures. Various alterations have been proposed to better facilitate time series forecasting, of which this study focused on the Informer, LogSparse Transformer and Autoformer. By comparing against spatio-temporal Long ShortTerm Memory (LSTM) and Multi-Layer Perceptron (MLP) models, the study showed that the models using the altered Transformer architectures as update functions in GNNs were able to outperform these. Deep learning-based weather forecasting has made stunning progress, from various backbone studies using CNN, RNN, and Transformer to training strategies using weather observations datasets with auxiliary inputs. All of this progress has contributed to the field of weather forecasting; however, many elements and complex structures of deep learning models prevent from reaching physical interpretations. Seo et al [41] proposes a SImple baseline with a spatiotemporal context Aggregation Network (SIANet) that achieved state-of-the-art in 4 parts of 5 benchmarks of W4C'22 benchmark dataset. This simple but efficient structure uses only satellite images and CNNs in an end-to-end fashion without using a multi-model ensemble or fine-tuning. This simplicity of SIANet can be used as a solid baseline that can be easily applied in weather forecasting using deep learning. The model shows that SIANet can achieve state-of-the-art on various benchmark test sets using only satellite images and without multi-model ensemble and fine-tuning. Based on the attained promising results SIANet will become a solid baseline that solves the problem that existing deep learning-based weather forecasting models are not utilized due to their complexity.

Weather forecasting centres currently rely on statistical post processing methods to minimize forecast error. This improves skill but can lead to predictions that violate physical principles or disregard dependencies between variables, which can be problematic for downstream applications and for the trustworthiness of post processing models, especially when they are based on new machine learning approaches. Building on recent advances in physics-informed machine learning, Zanetta et al [42] propose to achieve physical consistency in deep learning-based post processing models by integrating meteorological expertise in the form of analytic equations. Applied to the post-processing of surface weather in Switzerland, the proposed model proved that constraining a neural network to enforce thermodynamic state equations yields physically-consistent predictions of temperature and humidity without compromising performance. This technique approach is especially advantageous when data is scarce, and our findings suggest that incorporating domain expertise into post processing models allows to optimize weather forecast information while satisfying application-specific requirements. Based on the data characteristics of urban weather conditions, a deep learning network was designed to forecast urban weather conditions, and its feasibility was proved by experiments by Chen et al [43]. In view of the non-stationary and seasonal fluctuation of the time series of daily weather conditions in Shenzhen from 2015 to 2019, empirical mode decomposition (EMD) was used to carry out the stationary processing for the daily minimum humidity, minimum pressure, maximum temperature, maximum pressure, maximum wind speed and minimum temperature. The decomposed components, residual sequence and original sequence was reconstructed according to the degree of relevance. On this basis, a long short-term memory (LSTM) neural network for the Shenzhen daily weather forecast was used, using the advantages of the LSTM model in time-series data processing, using the grid search algorithm to find the optimal combination of the above parameters and combining with the gradient descent optimization algorithm to find optimal weights and bias, so as to improve the prediction accuracy of Shenzhen weather characteristics. The experimental results show that our design of the EMD-LSTM model has higher forecasting precision and efficiency than traditional models, which provides new ideas for the weather forecast. Weather and climate forecasting relies on numerical simulation with complex physical models and is both expensive in computation and demanding on domain expertise. With the explosive growth of spatiotemporal Earth observation data in the past decade, data-driven models that apply Deep Learning (DL) are demonstrating impressive potential for various weather and climate forecasting tasks. The Transformer as an emerging DL architecture, despite its broad success in other domains, has limited adoption in this area. Gao et al [44] propose Earth former, a space-time Transformer for Earth system forecasting. Earth former is based on a generic, flexible and efficient space-time attention block, named Cuboid Attention. The idea is to decompose the data into cuboids and apply cuboid-level self-attention in parallel. These cuboids are further connected with a collection of global vectors. We conduct experiments on the MovingMNIST dataset and a newly proposed chaotic N-body MNIST dataset to verify the effectiveness of cuboid attention and figure out the best design of Earth former. Experiments on two real-world benchmarks about precipitation now casting and El Niño/Southern Oscillation (ENSO) forecasting show that Earth former achieves state-of-the-art performance. Brandstetter et al [45] presents the first usage of multivector representations together with Clifford convolutions and Clifford Fourier transforms in the context of deep learning. The resulting Clifford neural layers are universally applicable and will find direct use in the areas of fluid dynamics, weather forecasting, and the modelling of physical systems in general. We empirically evaluate the benefit of Clifford neural layers by replacing convolution and Fourier operations in common neural PDE surrogates by their Clifford counterparts on 2D Navier-Stokes and weather modelling tasks, as well as 3D Maxwell equations. For similar parameter count, Clifford neural layers consistently improve generalization capabilities of the tested neural Partial differential equations (PDEs) surrogate. Nguyen et al [46] introduced ClimaX, a flexible and generalizable deep learning model for weather and climate science that can be trained using heterogeneous datasets spanning different variables, spatio-temporal coverage, and physical groundings. ClimaX extends the Transformer architecture with novel encoding and aggregation blocks that allow effective use of available compute while maintaining general utility. ClimaX is pre-trained with a self-supervised learning objective on climate datasets derived from CMIP6. The pre-trained ClimaX can then be fine-tuned to address a breadth of climate and weather tasks, including those that involve atmospheric variables and spatio-temporal scales unseen during pretraining. Compared to existing data-driven baselines, the proposed technique shows that this generality in ClimaX results in superior performance on benchmarks for weather forecasting and climate projections, even when pretrained at lower resolutions and compute budgets. Weather forecasting is one of the cornerstones of meteorological work. Zhu et al [47] present a new benchmark dataset named Weather2K, which aims to make up for the deficiencies of existing weather forecasting datasets in terms of real-time, reliability, and diversity, as well as the key bottleneck of data quality. In this aspects and to be specific, Weather2K is featured from the following aspects: 1) Reliable and real-time data. The data is hourly collected from 2,130 ground weather stations covering an area of 6 million square kilometres. 2) Multivariate meteorological variables. 20 meteorological factors and 3 constants for position information are provided with a length of 40,896 time steps. 3) Applicable to diverse tasks. A set of baseline tests is conducted on time series forecasting and spatio-temporal forecasting. Weather2K is the first attempt to tackle weather forecasting task by taking full advantage of the strengths of observation data from ground weather stations. Based on Weather2K, Meteorological Factors based Multi-Graph Convolution Network (MFMGCN), was proposed which can effectively construct the intrinsic correlation among geographic locations based on meteorological factors. Sufficient experiments show that MFMGCN improves both the forecasting performance and temporal robustness. Weather2K seems to be significantly motivate researchers to develop efficient and accurate algorithms to advance the task of weather forecasting.

Model Feature for Weather

Most state-of-the-art approaches for weather and climate modelling are based on physics informed numerical models of the atmosphere. These approaches aim to model the non-linear dynamics and complex interactions between multiple variables, which are challenging to approximate. Additionally, many such numerical models are computationally intensive, especially when modelling the atmospheric phenomenon at a fine-grained spatial and temporal resolution. Recent data-driven approaches based on machine learning instead aim to directly solve a downstream forecasting or projection task by learning a data-driven functional mapping using deep neural networks. However, these networks are trained using curated and homogeneous climate datasets for specific spatiotemporal tasks, and thus lack the generality of numerical models. The problem of forecasting weather has been scientifically studied for centuries due to its high impact on human lives, transportation, food production and energy management, among others. In this research the introduced weather applications named by **Weather 365 and weather 1460** is mainly presented based on the research study and analysis for the most popular weather forecasting applications exist on google. The research studied the highest 50 downloaded weather forecasting applications based on the recorded downloads for each weather forecasting application. The main features for each application are considered in the new proposed weather forecasting application. Table 1. presents the 50 weather forecasting applications. In this table the downloads for two different dates have been recorded and presented in the table. Also the star rating for each weather forecasting application has been recorded at each recorded date. In this table some applications have been removed by their owners. The study of these 50 weather forecasting applications and the services that they can provide to the users from the weather forecasting application itself shows that these services varies from one application to another. However, all the features that can be provided by all applications are twenty features but these twenty features cannot be provided by only one application from the 50 weather forecasting applications. Also the minimum number of features that can be provided by only one application was found by just only three features while the maximum number of features that can be provided by only one of the studied weather forecasting applications is 18 features. In the current study the proposed new weather forecasting application named by **weather 365** and **weather 1460** will provide all the recorded features found in the studied 50 weather forecasting applications. Adding all these features for the proposed weather application **weather 365** and **weather 1460** make it of a privilege advantage over all the considered studied applications as it will be seen in the coming sections. Table 2. lists the main features recorded in the 50 studied and considered weather forecasting applications Part (a), part (b) and part (c). In table (2) the avla weather forecasting application is the one that has the least number of features (three features) that are presented in the table. Also Accu weather forecasting application is the one of the maximum number of features in the recorded studied weather forecasting applications. These eighteen features are presented in the table. Also in this table meteoblue and ventusky weather forecasting applications are providing the same features through their construction designs and hence they are listed in the same row (22) of the table. These two applications are considered in the current study as they registered as of the highest 50 downloadable weather forecasting applications.

Table 1. the downloads for the highest weather forecasting applications at two different dates.

s.n	data history	17/3/2023	9/5/2023		
	Application name	Downloads in millions	Ratings 1-5	Downloads in millions	Ratings 1-5
1	Acc Weather	100+	4.4	100+	4.3
2	xiaomi Weather	1000+	4.5	1000+	4.5
3	arab weather	1 +	4.2	1 +	4.2
4	weather(macropinch)	10 +	4.5	10 +	4.5
5	clime radar live weather	10 +	4.1	10 +	4.2
6	today weather	1 +	4.7	1 +	4.7
7	forecast (weather by z apps)	1 +	4.7	1 +	4.8
8	the weather channel	100+	4.7	100+	4.7
9	weather forecast & widget&radar	10+	4.7	10+	4.8
10	weawow	5+	4.9	5+	4.9
11	weather&radar	50+	4.5	50+	4.3
12	weatherBug	10+	4.6	5+	4.6
13	the weather now	1+	4.4	1+	4.4
14	weather mate(m8)	.5+	4.6	.5+	4.4
15	live weather by apalon	10+	4.5	10+	4.5
16	windy.app&windy	10+	4.7	5+	4.7
17	overdrob	1+	4.6	1+	4.6
18	daily weather	100+	4.6	100+	4.7
19	Weather live	1+	4.7	1+	4.8
20	weather network	10+	4.4	10+	4.4
21	yowindow	10+	4.7	10+	4.7
22	meteoblue	1+	4.6	1+	4.6
23	ventusky	1+	4.4	1+	4.4
24	Foreca	1+	4.6	1+	4.6
25	wunderground	10+	4.7	10+	4.7
26	weather forecat by bacha	5+	4.7	50+	4.7
27	(yahoo)weather	10+	4.6	10+	4.6
28	what a weather	.1+	4.5	.1+	4.4
29	Air visual	5+	4.5	5+	4.5
30	warn wetter	1+	4.3	1+	4.4
31	wind finder	5+	4.7	5+	4.7
32	met office	1+	4.3	1+	4.3
33	netatmo	.5+	4.4	.5+	4.4
34	Met eum	1+	4.5	1+	4.7
35	weather home	10+	4.2	10+	4.2
36	msn	1+	3.9	1+	4
37	vremenar	.01+	4.3	.01+	Review is removed
38	yr	5+	4.2	5+	4.3
39	Mobile weather	1+	4.4	1+	Review is removed
40	avia weather	.1+	4.6	.1+	4.6
41	carrot	.5+	3	.5+	2
42	weather morocast	10+	4.4	10+	4.4
43	rain viewer	1+	4.3	1+	4.3
44	google weather	4300+	4.6	4400+	4.7
45	daily weather by shalltry	50+	4.7	100+	4.7
46	weather xl by exovoid	10+	4.5	10+	4.5
47	weather 24	10+	4.4	10+	4.5
48	1 weather	100+	4.4	100+	4.5
49	weather widget	50+	4.6	50+	4.6
50	rain alert	.5+	4.4	.5+	Review is removed

Table 2. lists the main features recorded in the 50 studied and considered weather forecasting applications. Part (a).

s.n	feature / app	Weather data now	current location	Find me anywhere in the world	Clothing recommendations	health recommendations	Road and transportation recommendations	Life and sports recommendations	Weather forecast for the next 24 hours	Weather forecast for the next 4 days	Weather forecast for the next 7 days	Weather forecast for the next 14 days	Weather forecast for the next 30days	Weather forecast for the next 45 days	Weather forecast for 6 months	Subscribe by email	Weather heat maps around the world	Send weather alerts	Switch weather units	Analysis of weather indicators in more than one different unit	News related to the weather	Total
1	Accu weather	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes		yes	yes	yes	yes	yes		18
2	xiaomi Weather	yes	yes	yes					yes	yes	yes	yes						yes	yes			9
3	taqs alearab	yes	yes	yes	yes	yes	yes	yes	yes	yes		yes				yes	yes	yes		yes	yes	15
4	ahwal altaqs (macropinch)	yes	yes	yes					yes	yes	yes								yes			7
5	radar altaqs almubashir	yes	yes	yes						yes	yes					yes	yes		yes			8
6	Today weather	yes	yes	yes		yes			yes	yes	yes								yes	yes		9
7	forecast (weather by z apps)	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes				yes	yes	yes	yes			15
8	The weather channel	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes					yes		yes	yes		14
9	alnashrat aljawiyat wal raadar	yes	yes	yes		yes	yes		yes	yes	yes						yes		yes	yes		11
10	weawow	yes	yes	yes					yes	yes	yes					yes	yes	yes	yes	yes		11
11	Weather & radar	yes	yes	yes					yes	yes	yes					yes	yes		yes	yes		10
12	Weather Bug	yes	yes	yes				yes	yes	yes						yes			yes			8
13	The weather now	yes	yes	yes					yes								yes	yes				6
14	Geometric weather(m8)	yes	yes	yes						yes	yes								yes	yes		7
15	live weather by apalon	yes	yes	yes	yes		yes		yes	yes		yes			yes	yes			yes	yes		12
16	windy.app&windy	yes	yes	yes					yes								yes					5
17	over drop	yes	yes	yes					yes	yes	yes					yes	yes		yes	yes		10
18	daily weather	yes	yes	yes	yes	yes	yes	yes	yes	yes		yes		yes		yes		yes	yes			14
19	Weather live	yes	yes	yes		yes		yes	yes		yes	yes	yes							yes		10
20	weather network	yes	yes	yes			yes	yes	yes				yes			yes	yes	yes				10
21	yowindow	yes	yes	yes							yes			yes			yes			yes		7
22	ventusky and meteoblue	yes	yes	yes					yes	yes					yes		yes	yes	yes			9
23	forecast	yes	yes	yes					yes	yes	yes	yes				yes	yes	yes	yes	yes		12
24	wunderground	yes	yes	yes		yes		yes	yes	yes	yes	yes					yes		yes	yes		12

Table 2. lists the main features recorded in the 50 studied and considered weather forecasting applications. Part (b) cont.

25	weather forecast by bacha	yes	yes	yes				yes									yes	yes	yes			7
26	weather(yahoo)	yes	yes	yes														yes				4
27	what a weather	yes	yes	yes					yes	yes		yes	yes	yes	yes				yes		yes	11
28	Air visual	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes					yes	yes	yes	yes	yes		15
29	warn wetter	yes	yes	yes												yes	yes	yes			yes	7
30	wind finder	yes	yes	yes						yes	yes					yes	yes	yes	yes	yes		10
31	met office	yes	yes	yes				yes	yes	yes	yes	yes					yes				yes	10
32	netatmo	yes	yes	yes													yes					4
33	Met eum	yes	yes	yes					ye	yes	yes	yes				yes	yes		yes	yes		11
34	weather home	yes	yes	yes			yes		yes	yes	yes						yes	yes	yes	yes	yes	12
35	msn ALtaqs	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes						yes	yes		yes	14
36	vremenar	yes	yes	yes													yes					4
37	yr	yes	yes	yes					yes	yes	yes					yes	yes	yes	yes	yes		11
38	Mobile weather	yes	yes	yes					yes	yes	yes							yes	yes	yes		9
39	avia weather	yes	yes	yes																		3
40	carrot	yes	yes							yes						yes		yes	yes			6
41	weather morocast	yes	yes	yes			yes			yes	yes	yes					yes		yes	yes		10
42	rain viewer	yes	yes	yes													yes					4
43	Google weather	yes	yes	yes					yes	yes	yes								yes			7
44	daily weather by shalltry	yes	yes	yes					yes	yes				yes		yes	yes	yes	yes			10
45	altaqs xl by exovoid	yes	yes	yes															yes			4
46	weather24	yes	yes	yes					yes	yes		yes			yes	yes	yes					9
47	1 weather	yes	yes	yes					yes	yes		yes			yes	yes	yes	yes	yes	yes		12

48	weather widget	yes	yes	yes						yes	yes	yes										6
Table 2. lists the main features recorded in the 50 studied and considered weather forecasting applications. Part (c) cont.																						
49	rain alert	yes	yes	yes					yes	yes	yes	yes					yes		yes			9
51	our app	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	under construction	yes	yes	yes	yes	20
Total without our app.		50	50	49	8	11	12	13	35	37	28	19	4	5	6	21	33	23	35	23	6	20

The Algorithms Features

The proposed algorithms for the two weather forecasting applications having the same features and methodology. In this methodology we use pandas as open source tool start with where it is a fast, powerful, flexible and easy to use open source data analysis and manipulation tool, built on top of the Python programming language. Then NeuralProphet is used because it changes the way time series modelling and forecasting can be done as it supports for auto-regression and covariates; it has an automatic selection of training related hyperparameters; also it has fourier term seasonality at different periods such as yearly, daily, weekly, hourly; it is an efficient in piecewise linear trend with optional automatic changepoint detection; plotting for forecast components, model coefficients and final predictions; support for global modelling; lagged and future regressors; sparsity of coefficients through regularization; and user-friendly and powerful Python package. After using Neural prophet, Matplotlib is used where it is Visualization tool with Python and is a comprehensive library for creating static, animated, and interactive visualizations in Python. Matplotlib makes easy things easy and hard things possible. Also it has a creative publication quality plots. It makes interactive figures that can zoom, pan, update and customize visual style and layout. Also it can export to many file formats and can be embed in JupyterLab and Graphical User Interfaces and use as a rich array of third-party packages built on Matplotlib. Last Pickle in Python is primarily used in serializing and deserializing a Python object structure in other words, it's the process of converting a Python object into a byte stream to store it in a file/database, maintain program state across sessions, or transport data over the network. The pickled byte stream can be used to re-create the original object hierarchy by unpickling the stream. This whole process is similar to object serialization in Java or .Net. pathing through the above described algorithm using the second dataset link in which the data used for twenty years a sample data results and figures attained will be presented as follows:

Read in Data and Process Dates

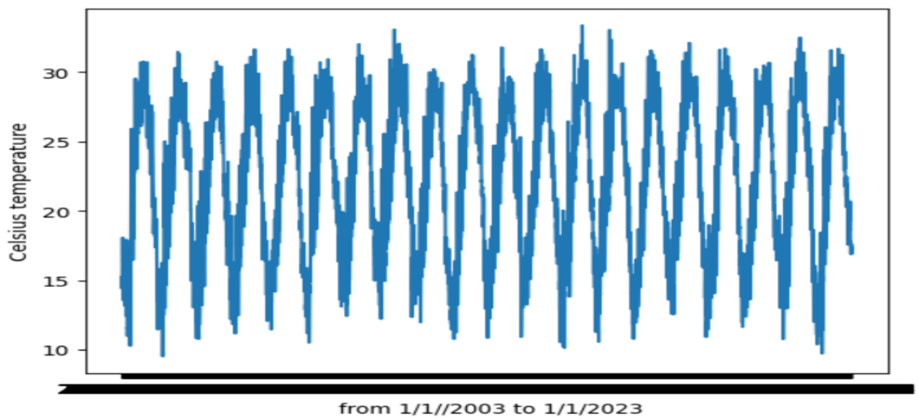
The results of this step

	YEAR	MO	DY	T2M	T2MDEW	T2MWET	TS	T2M_RANGE	T2M_MAX	T2M_MIN	avg	date	forecating
0	2003	1	1	14.38	8.33	11.36	14.63	-263.50	20.07	10.42	15.245	2003-01-01	NaN
1	2003	1	2	14.19	7.15	10.67	14.67	-262.58	19.68	9.11	14.395	2003-01-02	NaN
2	2003	1	3	15.31	11.44	13.37	15.81	-266.72	19.11	12.69	15.900	2003-01-03	NaN
3	2003	1	4	15.20	8.69	11.94	15.47	-264.49	20.30	11.63	15.965	2003-01-04	NaN
4	2003	1	5	15.08	5.76	10.42	15.32	-261.02	22.40	10.28	16.340	2003-01-05	NaN

```
In [67]: df.columns

Out[67]: Index(['YEAR', 'MO', 'DY', 'T2M', 'T2MDEW', 'T2MWET', 'TS', 'T2M_RANGE',
        'T2M_MAX', 'T2M_MIN', 'avg', 'date', 'forecating'],
       dtype='object')
```

```
Out[68]: YEAR            int64
         MO              int64
         DY              int64
         T2M           float64
         T2MDEW        float64
         T2MWET        float64
         TS            float64
         T2M_RANGE     float64
         T2M_MAX       float64
         T2M_MIN       float64
         avg           float64
         date           object
         forecating    float64
         dtype: object
```



Train Model

Training the neural network model on the data of 20 weather years and passing it on 10,000 deep learning layers with adjusting the weights of the neural network to obtain the highest prediction the following data will obtained.

accuracy

Forecasting

The prediction results were from 2023 to 2026 with an accuracy of 0.15 and the number of days was 1460, starting from 1/1/2023 to 12/31/2026.

beginning of the table

```
forecast.head()
```

Predicting DataLoader 0: 100% 2/2 [00:00<00:00, 222.95it/s]

Out[87]:

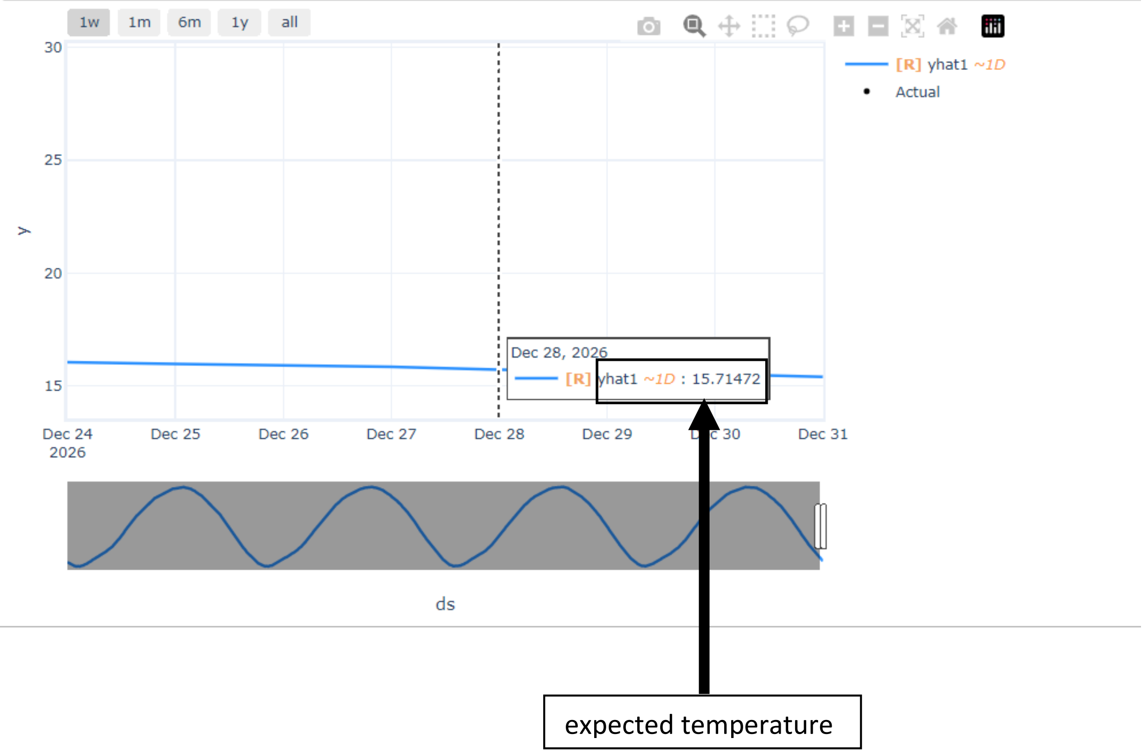
	ds	y	yhat1	trend	season_yearly	season_weekly
0	2023-01-02	None	15.193560	22.196365	-7.015715	0.012909
1	2023-01-03	None	15.132182	22.196430	-7.091733	0.027483
2	2023-01-04	None	15.004835	22.196497	-7.164419	-0.027242
3	2023-01-05	None	14.917093	22.196564	-7.233664	-0.045806
4	2023-01-06	None	14.875750	22.196629	-7.299354	-0.021524

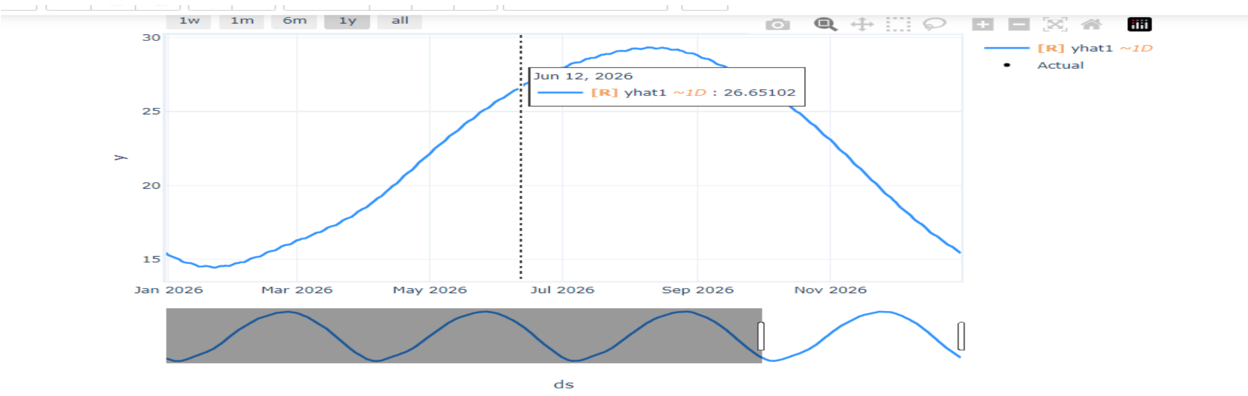
The rows at the end of the forecast table

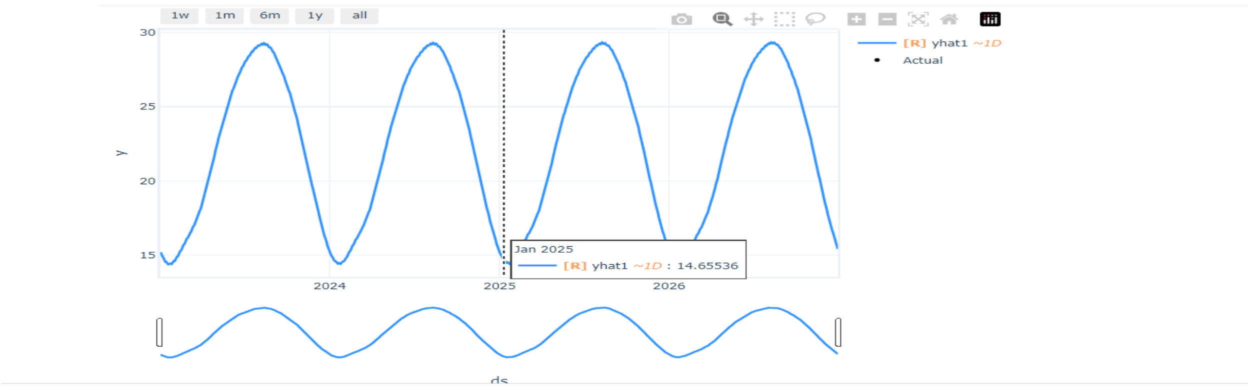
In [89]:
```
forecast.tail()
```

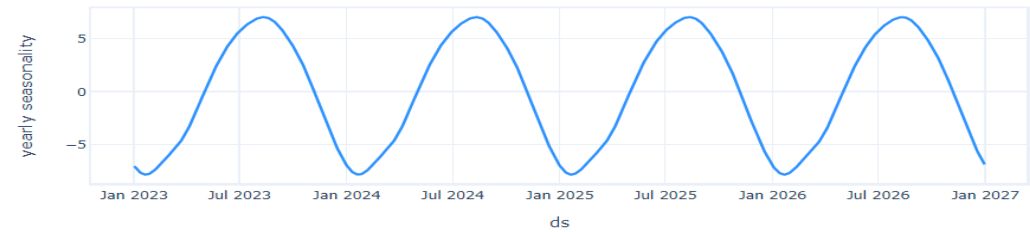
Out[89]:

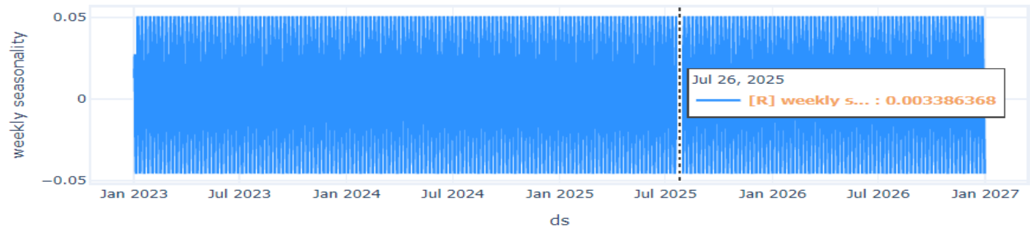
	ds	y	yhat1	trend	season_yearly	season_weekly
1455	2026-12-27	None	15.846045	22.291557	-6.496305	0.050793
1456	2026-12-28	None	15.714723	22.291622	-6.589809	0.012909
1457	2026-12-29	None	15.638472	22.291687	-6.680700	0.027483
1458	2026-12-30	None	15.495655	22.291754	-6.768856	-0.027242
1459	2026-12-31	None	15.391855	22.291819	-6.854158	-0.045806











Read in Data and Process Dates for the first dataset link (365)

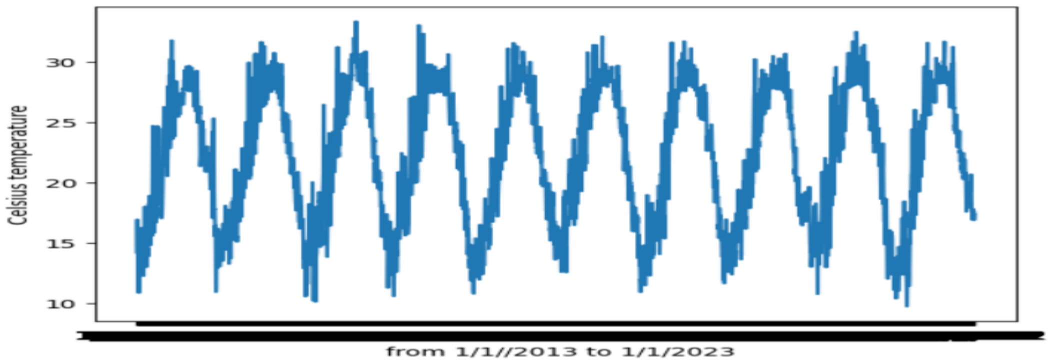
The results of this step

	YEAR	MO	DY	RH2M	WD50M	WS2M	T2M	T2M_MAX	T2M_MIN	WS50M_MIN	WS50M_MAX	WS50M	avg	date	The number of days
0	2013	1	1	62.56	240.19	2.99	13.73	19.30	9.05	3.84	6.98	5.91	14.18	1/1/2013	1
1	2013	1	2	77.31	278.69	2.62	14.74	20.19	10.87	3.92	6.91	5.34	15.53	1/2/2013	2
2	2013	1	3	75.25	272.19	1.83	16.06	20.89	12.98	2.32	5.86	3.62	16.94	1/3/2013	3
3	2013	1	4	72.56	268.06	2.24	15.10	19.39	12.52	0.37	7.24	4.27	15.96	1/4/2013	4
4	2013	1	5	73.62	269.25	4.45	14.17	17.27	11.62	6.62	10.27	8.55	14.45	1/5/2013	5

-
-
-
-

	YEAR	MO	DY	RH2M	WD50M	WS2M	T2M	T2M_MAX	T2M_MIN	WS50M_MIN	WS50M_MAX	WS50M	avg	date	The number of days
3648	2022	12	28	64.94	227.62	1.28	16.66	21.10	13.34	0.31	3.80	2.33	17.22	12/28/2022	3649
3649	2022	12	29	73.75	229.75	1.74	16.45	21.93	11.90	1.20	6.48	3.59	16.92	12/29/2022	3650
3650	2022	12	30	78.19	202.94	3.05	17.01	21.13	14.15	5.61	7.27	6.28	17.64	12/30/2022	3651
3651	2022	12	31	71.69	37.81	3.28	16.15	20.88	12.85	5.24	7.53	6.56	16.87	12/31/2022	3652
3652	2023	1	1	71.12	21.81	3.75	16.68	19.99	14.79	6.05	8.03	7.38	17.39	1/1/2023	3653

```
YEAR                                int64
MO                                  int64
DY                                  int64
RH2M                              float64
WD50M                             float64
WS2M                              float64
T2M                               float64
T2M_MAX                           float64
T2M_MIN                           float64
WS50M_MIN                         float64
WS50M_MAX                         float64
WS50M                             float64
avg                               float64
date                       datetime64[ns]
The number of days                  int64
dtype: object
```



Train Model

Training the neural network model on the data of 11 weather years and passing it on 10,000 deep learning layers with adjusting the weights of the neural network to obtain the highest prediction accuracy

```
Epoch 10000: 100% ████████ 10000/10000 [00:00<00:00, 34917.33it/s, loss=0.00273, v_num=12, MAE=.5, RMSE=1.730, Loss=0.00287, RegLoss=0.000]
```

The number of layers of deep learning

Error percentage in degrees Celsius

Forecasting

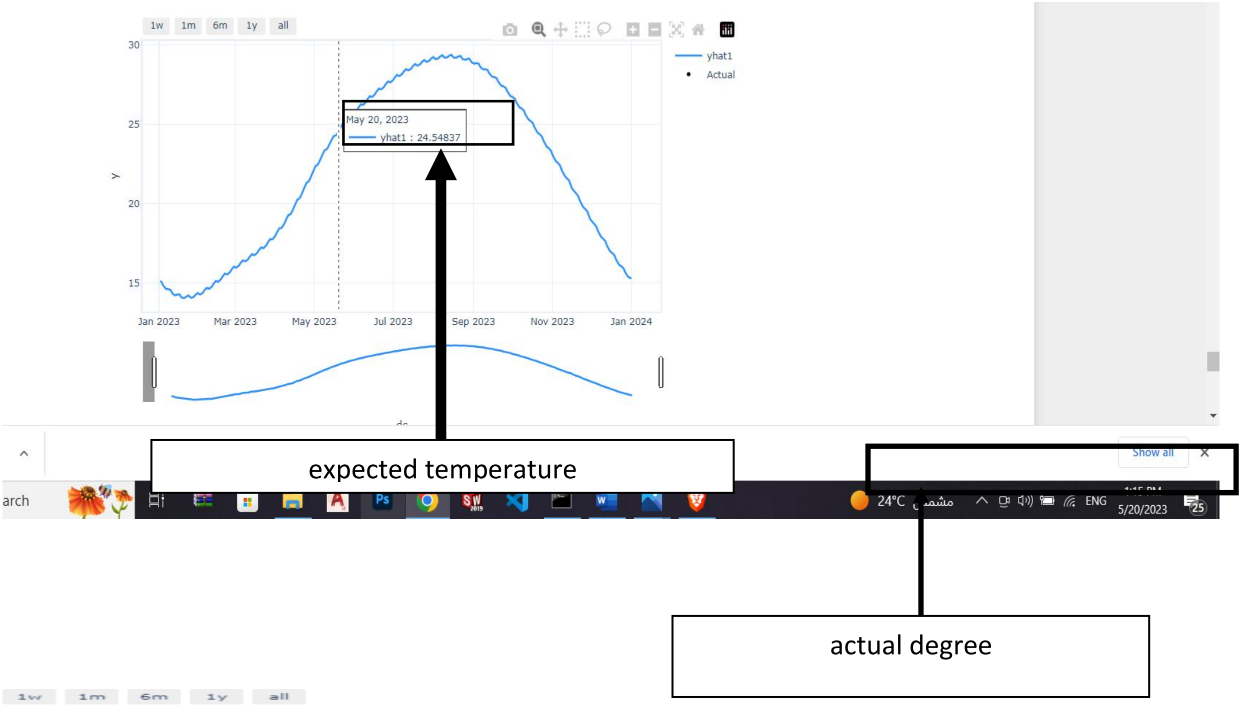
The forecast results were from 1/2/2013 to 1/1/2023, the number of days is 365, and the error percentage is plus or minus 0.5 Celsius beginning of the table

yhat1 is the expectation

1	01-01-13	14.18	5.91	6.98	3.84	9.05	19.3	13.73	2.99	240.19	62.56	1	1	2013
2	01-02-13	15.53	5.34	6.91	3.92	10.87	20.19	14.74	2.62	278.69	77.31	2	1	2013
3	01-03-13	16.94	3.62	5.86	2.32	12.98	20.89	16.06	1.83	272.19	75.25	3	1	2013
4	01-04-13	15.96	4.27	7.24	0.37	12.52	19.39	15.1	2.24	268.06	72.56	4	1	2013
5	01-05-13	14.45	8.55	10.27	6.62	11.62	17.27	14.17	4.45	269.25	73.62	5	1	2013

The rows at the end of the forecast table

3649	12/28/2022	17.22	2.33	3.8	0.31	13.34	21.1	16.66	1.28	227.62	64.94	28	12	2022
3650	12/29/2022	16.92	3.59	6.48	1.2	11.9	21.93	16.45	1.74	229.75	73.75	29	12	2022
3651	12/30/2022	17.64	6.28	7.27	5.61	14.15	21.13	17.01	3.05	202.94	78.19	30	12	2022
3652	12/31/2022	16.87	6.56	7.53	5.24	12.85	20.88	16.15	3.28	37.81	71.69	31	12	2022
3653	01-01-23	17.39	7.38	8.03	6.05	14.79	19.99	16.68	3.75	21.81	71.12	1	1	2023



Sample comparison between forecasted values and actual data

real weather	Our weather forecast	date
15	14.72	5/1/2023
14.8	14.5	5/2/2023
16.7	16.23	5/3/2023
18.8	18.43	5/4/2023
23.1	22.63	5/5/2023

Conclusion

Weather forecasting is a long standing scientific challenge with direct social and economic impact. The task is suitable for deep neural networks due to vast amounts of continuously collected data and a rich spatial and temporal structure that presents long range dependencies. In this paper two weather forecasting applications have been presented based on the study for the highest 50 downloadable weather applications exist on google website. The proposed applications are designed such that they provide all the facilities founded in the studied applications which makes them superior than the studied applications. Also the maximum duration can be forecasted by any one of the 50 application was for six months while the duration forecasted by one of the proposed application is 365 days while the can provide forecasting over 1460 days and these forecasting durations are more powerful and superior than any one of the studied 50 applications. Also one of the strongest feature for the proposed algorithms is that they can integrated to many life and beneficial applications for human beings.

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