Weather Forecasting Using Machine Learning

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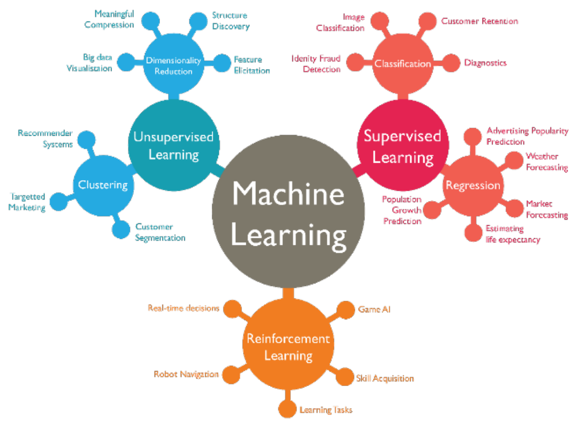
Abstract: Recent research has shown that forecasts produced by physics-based models operating in operational centers may be rivaled by those produced by global deep-learning weather prediction models. It's unclear whether these models' lowest forecast error stems from pattern matching or from the incorporation of atmospheric dynamics. The answer to this question will determine how valuable these models are as tools for basic research. We provide a novel neural network-based method that simultaneously produces forecasts for every location and lead time. Unlike many post-processing approaches, our method loosens the distributional assumption by using normalizing flows as flexible parametric distribution estimators. This enables us to analytically anticipate shifting forecast distributions with precision. The present expansion of deep learning appeal in Earth sciences may be attributed to its capacity to build completely data-driven models of complex processes inside the Earth system. Deep learning-based weather prediction (DLWP) models have advanced significantly in the previous few years, achieving forecast skills comparable to well-established numerical weather prediction (NWP) models at a much reduced processing cost. To train DLWP models with several million parameters that are reliable, accurate, and tractable, the model architecture has to include suitable inductive biases that contain structural assumptions about the data and modeled processes. When these biases are carefully chosen, learning occurs more quickly and better generalization to previously unknown content is achieved. Inductive biases are critical to successful DLWP models, but they are often omitted from discussions and their impact on model performance is not well understood. We further explore five key design elements in this analysis: input data, forecasting objective, loss components, layered deep learning architecture design, and optimization strategies. We analyze the inductive biases of the latest DLWP models. We present the connection between the choices taken in each of the five design elements and the underlying structural presumptions.

Keywords: - **Deep Learning Weather Prediction, Neural Networks, Forecasting Models, Atmospheric Dynamics, Data-Driven Approaches**

INTRODUCTION

The most used method for weather forecasting is numerical weather prediction, or NWP. Starting with the best assessment of the Earth System's present condition, partial differential equations are numerically integrated to provide a weather prediction. The early works include the notion that the physical rules of thermodynamics and fluid dynamics may be utilized to forecast the condition of the atmosphere. A weather prediction in a standard NWP framework is the outcome of a deductive inference: a deterministic forecast is derived from the best possible initial conditions by optimally combining earth system observations and short-range forecasts through data assimilation. This is done by applying the laws of physics. Nevertheless, there are limitations to our capacity to precisely understand the starting circumstances and solve the equations numerically. Because of this, ensemble forecasting is used to take into consideration uncertainty in the forecasting model as well as the beginning circumstances. The ensemble prediction that is produced then forms the foundation for probabilistic forecasting. The idealized gas law, the first rule of thermodynamics, mass and momentum conservation, and the Navier-Stokes equations regulating fluid dynamics are all combined in numerical weather prediction, or NWP. The end product is a set of partial differential equations that are nonlinear and describe the physical processes taking place in the atmosphere. In order to provide weather predictions, the set of equations is numerically integrated in time on discretized, three-dimensional grid structures, assuming beginning circumstances that precisely represent the state of the atmosphere. Modern operational NWP models span a broad variety of geographical and temporal forecast scales, including global seasonal scales, mid-term weekly scales, and local, sub-hourly kilometer-scales. In all instances, however, our ability to forecast the weather in advance is severely limited by the intrinsic nonlinearities of atmospheric dynamics. Different NWP models function differently depending on a variety of design decisions, the two most important of which are the modeling of sub grid processes and the assimilation of data.

Machine Learning: The most widely used method for forecasting the future or categorizing data to assist individuals in making important choices is machine learning. In order for machine learning algorithms to learn from previous experiences and evaluate historical data, they are trained over instances or examples. As a result, it can recognize patterns as it repeatedly trains over the instances, enabling it to forecast future events. The fundamental building block of machine learning algorithms is data. By training these machine learning algorithms on previous data, we are able to generate new data. Generative Adversarial Networks, for instance, are a sophisticated kind of machine learning that can produce more photos by learning from past photographs. This also applies to text and voice synthesis. As a result, data science applications now have a plethora of new possibilities thanks to machine learning. Math, statistics, and computer science are all combined in machine learning. Using statistics is crucial for deriving conclusions from the data. The development of machine learning models may benefit from mathematics, while algorithm implementation ultimately requires computer science. Still, modeling alone is insufficient. For the model to provide you correct results, you must also properly optimize and modify it. To get the best outcome, optimization approaches need adjusting the hyper parameters. Both the globe and people's wants and demands are changing in the modern day. In addition, the digital revolution is entering its fourth industrial revolution. We need computational algorithms that can churn the data and deliver us findings that would be advantageous to us in a number of ways if we are to extract meaningful insights from this data and learn from the way that people and the system interact with the data. A number of sectors, including manufacturing, finance, healthcare, and medicine, have been completely transformed by machine learning. As a result, machine learning is becoming a crucial component of contemporary industry.



Pandas: Pandas is a well-liked Python data science library, and for good reason—among many other things, it provides strong, expressive, and adaptable data structures that facilitate data manipulation and analysis. One such structure is the Data Frame. Wes McKinney created the sophisticated data manipulation program known as Pandas. The Data Frame is its primary data structure, and it is based on the Numpy package. Tabular data may be stored and managed using Data Frames with rows representing observations and columns representing variables. Since Pandas is based on the NumPy package, a large portion of Num Py's structure is either duplicated or utilized in Pandas. Pandas data is often used to feed Sci Py statistical analysis, Mat plotlib graphing routines, and Scikit-learn machine learning algorithms.

Numpy: Numpy is the core library for scientific computing in Python. It provides a high-performance multidimensional array object, and tools for working with these arrays. If you are already familiar with MATLAB, you might find this tutorial useful to get started with Numpy. A num py array is a grid of values, all of the same type, and is indexed by a tuple of nonnegative integers. The number of dimensions is the rank of the array; the shape of an array is a tuple of integers giving the size of the array along each dimension. Num Py is, just like Sci Py, Scikit-Learn, Pandas, etc. one of the packages that you just canâ€™t miss when youâ€™re learning data science, mainly because this library provides you with an array data structure that holds some benefits over Python lists, such as: being more compact, faster access in reading and writing items, being more convenient and more efficient.is the core library for scientific computing in Python. It provides a high-performance multidimensional array object, and tools for working with these arrays. If you are already familiar with MATLAB, you might find this tutorial useful to get started with Numpy. A numpy array is a grid of values, all of the same type, and is indexed by a tuple of nonnegative integers. The number of dimensions is the rank of the array; the shape of an array is a tuple of integers giving the size of the array along each dimension. Num Py is, just like Sci Py, Scikit-Learn, Pandas, etc.

LITERATURE SURVEY

Chuang Zhang[1]: Weather Visibility Prediction Based on Multimodal Fusion

In this research they have proposed Road, sailing, and aircraft traffic are all impacted by visibility. Predicting visibility is important for managing life and productivity. The variables that impact meteorological visibility are more complex than those that affect weather forecast, which is based only on atmospheric parameters. One example of such a factor is air pollution from industrial exhaust emissions. On the other hand, the majority of the visibility prediction used today is derived from a numerical process akin to weather prediction. In this research, we suggested a multimodal fusion approach for constructing a weather visibility forecast system. A multimodal fusion visibility prediction system was constructed using an emission detection technique and an advanced numerical prediction model. To train the fusion model for numerical prediction, we used LightGBM and XGBoost, the most sophisticated regression approach. We suggest adding the outcome of an estimate based on Landsat-8 satellite pictures to help with the forecast by estimating factory emission using the conventional detector in the satellite image. Our numerical prediction model is more accurate than other existing methods, as demonstrated by testing it using atmosphere data from various meteorological observation stations in the Beijing, Tianjin, and Hebei region between 2002 and 2018. The accuracy of our visibility prediction system is further enhanced after fusing it with an emission detection method.

Nazzareno Pierdicca[2]: **Excess Path Delays From Sentinel Interferometry to improve Weather Forecasts**

In this study they have suggested In addition to providing precise monitoring of earth surface deformation, a synthetic aperture radar may provide high horizontal resolution troposphere data, such as total path delay and columnar water vapor. The radar inter fero grams may be post processed and properly inter fero metrically processed to accomplish this. The tropospheric products' fine and unparalleled horizontal resolution may provide information that would otherwise be impossible to include into numerical weather prediction models, which are steadily improving their resolving power. Several tips on the best ways to handle the processing, along with a new way to convert multipass differential interferometry results to absolute tropospheric columnar values, are presented. The suggested goods and techniques are evaluated using actual Sentinel-1 data. The purpose of the experiment is to assess the obtained information's correctness and how it affects the ability to forecast the weather for two Italian meteorological events. The study's primary focus is on the potential for using geosynchronous platform interferometric products to supplement the high resolution of SAR sensors with the frequent return needed for meteorological applications.

Wenying Zhang[3]: Weather Prediction with Multiclass Support Vector Machines in the fault detection system

In this research they have suggested Many photovoltaic (PV) businesses install weather sensors to keep an eye on the condition of their PV power system since the efficiency of PV electricity is directly correlated with the weather. With the advancement of soft measuring technologies, the expensive and outmoded instrumental approach is rendered unnecessary. In this research, a new approach based on partial meteorological data and PV power data is proposed for weather prediction. Instead than using a meteorological equipment, this approach infers the kinds of weather via data analysis. By using support vector machines (SVM) and comparing the actual and forecasted weather, a more accurate defect detection may be achieved. A direct Support Vector Machine (SVM) is used to create the weather prediction model and train multiclass predictors. While Support Vector Machines (SVM) are a viable option for classification, the outcomes of the classification process are contingent upon the selection of the soft margin coefficient, the kernel type, and the kernel parameters. In this study, the particle swarm optimization (PSO) technique is used to improve these parameters in the hopes of achieving accurate prediction results. Based on prediction findings, this approach is both practical and efficient.

Jianyuan Wang[4]: MetroEye: A Weather-Aware System for Real-Time Metro Passenger Flow Prediction

In this system, have proposed Predicting passenger movement in real time is crucial for managing and designing subway networks. The majority of prediction algorithms now in use simply take into account the amount of passenger flow; they do not take into account the impact of external elements like as temperature, air quality, and weather. This study proposes MetroEye, a systematic framework for weather-aware real-time passenger flow forecast. Both an online and an offline system are included in the framework. The offline system uses a conditional random field (CRF) model to determine how passenger flow volume and meteorological variables relate to one another. The model's higher forecast accuracy, particularly in big stations, is shown by the experimental findings. Effective techniques for simulating the volume of passenger movement in real time are offered by the online system. Beijing Urban Rail Transit Control Center has chosen MetroEye due to its high practicality in monitoring the passenger flow status of the Beijing subway system.

Yaseen Essa [5]: Deep Learning Prediction of Thunderstorm Severity Using Remote Sensing Weather Data

In this system, have suggested In South Africa, lightning is the most serious weather-related fatality and one of the main causes of power outages. Regretfully, quantitative lightning prediction continues to be difficult for risk management. In this work, we use meteorological data from remote sensing to assess the accuracy of several LSTM neural network model variations on thunderstorm severity. These variations of the LSTM model include ConvLSTM, CNN-LSTM, and LSTM-FC. Processing is aided by the spatiotemporal feature recognition of the CNN-LSTM and ConvLSTM models. The information used is a combination of weather-feature data from the network of weather stations run by the SAWS and lightning detection network (LDN) data from the SALDN. We predict the intensity of thunderstorms in North-Eastern South Africa every hour between December 2013 and March 2016, based on the frequency of lightning strikes. On data collected between July 2008 and November 2013, models were trained. All models tested on mean absolute error (MAE flashes.hr1) instead of mean square error (MSE). Additionally, we changed the models according to the input datasets—SALDN+SAWS, SAWS-alone, and SALDN just. Of the LSTM model variations (LSTM-FC MAE=67; ConvLSTM MAE=86), we discovered that the CNN-LSTM model (MAE=51) performed the best. Upon comparing models across input datasets, we discovered that SALDN alone (MAE=59) performed better than both SAWS and SALDN+SAWS (SAWS MAE=74; SAWS+SALDN MAE=70). We find that, when compared to ConvLSTM and LSTM-FC models, CNN-LSTM models perform better in terms of prediction accuracy; however, input data must be taken into account.

METHODOLOGY

The methodology encompasses data collection and preprocessing, where the existing system gathers performance data for the Low GloSea6 model, while the proposed system incorporates the most recent data with linear interpolation and time series forecasting. Data division involves splitting into training and testing sets, with the proposed system utilizing a moving window algorithm. Model architecture includes the existing system's two-stage approach and the proposed system's introduction of a spatial feature attention module in the decoder, enhancing performance through a feedforward neural network. Evaluation metrics focus on accuracy in predicting optimal parameters and temperature values, with the proposed system emphasizing minimizing error rates in execution time prediction. Experimental validation involves executing the Low GloSea6 model with different parameter combinations for the existing system, while the proposed system undergoes validation using recent data with iterative optimization and fine-tuning, addressing I/O load issues and improving hardware and software characteristics. The comparative analysis highlights the proposed spatial feature attention module's efficiency in enhancing overall system performance, providing a comprehensive and systematic approach to model optimization.

EXISTING SYSTEM

Numerical weather prediction models, which use weather observation data, such as temperature and humidity, are the main tool used in weather forecasting. For weather forecasting, the UK-based GloSea6 numerical weather prediction model has been used by the Korea Meteorological Administration (KMA). Supercomputers are necessary to run these models for research reasons in addition to using them for real-time weather predictions. However, many researchers have had trouble executing the models because of the restricted supercomputer resources. at order to solve this problem, the KMA created the Low GloSea6 low-resolution model. Although Low GloSea6 can operate on small and medium-sized servers at research facilities, it still consumes a lot of computer resources, particularly in the I/O load. Model I/O optimization is crucial because I/O load may lead to performance deterioration for models with heavy data I/O; nevertheless, user trial-and-error optimization is ineffective. In order to improve the hardware and software characteristics of the Low GloSea6 research environment, this work provides a machine learning-based method. There were two stages in the current procedure. Initially, Low GloSea6 internal parameters and hardware platform parameters were obtained by gathering performance data under different settings using profiling tools. Secondly, the acquired data was used to build a machine learning model that identified the ideal hardware platform parameters and Low GloSea6 internal parameters for fresh study settings. When compared to the actual parameter combinations, the machine-learning model demonstrated a high degree of accuracy in its successful prediction of the ideal combinations of parameters in various research situations. With an error rate of just 16% when compared to the actual execution time, the projected model execution time, in particular, based on the parameter combination, demonstrated a noteworthy result.

PROPOSED SYSTEM

Since the experiment was conducted using the most recent data, some preprocessing processes were incorporated to accurately represent the performance of the model. Using linear interpolation in the forward direction, the missing values in the data were imputed. Using prior values as a starting point, linear interpolation calculates the missing values in ascending order. In time series forecasting, smoothing data using a simple moving average and a suitable window length is a useful approach since it eliminates noise and random changes from the data while taking into account time-varying weather. The training set and testing set of the data are divided into proportions of 0.7 and 0.2, respectively. The moving window algorithm is used to process the training and test sets in order to produce the input and output sequences. Temperature values are included in the output sequence, and characteristics are contained in the input sequence. Because it immediately aligns with the output feature, the spatial feature attention module is created in the decoder parallel to the temporal layer to collect spatial feature correlations while attending the most relevant time steps. Using a feed forward neural network, spatial feature embedding’s are separately created and fed into the spatial feature attention module. In order to allocate weights in the model, the feedforward neural network that computes spatial feature embedding’s performs a series of calculations that include concatenating input feature data from the prior hidden state of the decoder with the soft-max activation function.

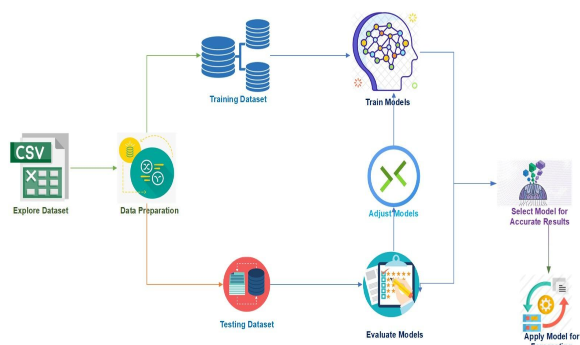


Fig: Architecture Flow Diagram

Exploratory Data Analysis: Exploratory Data Analysis (EDA) is a data mining technique that involves evaluating datasets to highlight their key features, often using visual aids. Before beginning the modeling work, EDA is used to examine what the data can tell us. Determining significant features of the data from a spreadsheet or a column of numbers is a difficult task. Analyzing simple statistics to get insights may be tiresome, monotonous, and/or intimidating. In the context of data analytics, exploratory data analysis is often referred to as a qualitative rather than a quantitative examination. This implies that it entails approaching a dataset's intrinsic characteristics using a curiosity-driven approach. It typically doesn't try to determine the substance of a dataset using cold measurements or inferences. Single-variable analysis One of the most basic types of data analysis is univariate analysis. One variable's (or one data column's) distribution is examined at a time. Although it's not required, univariate analysis often makes use of visual aids including tables, pie charts, histograms, and bar charts. Multivariate analysis examines the link between two or more variables by examining their distribution. Most multivariate studies (bivariate analyses) compare two variables simultaneously. Sometimes, however, three or more factors are involved. In any case, doing univariate analysis on every variable prior to performing a multivariate EDA is a smart idea. A multivariate visualization may be made using any plot or graph that has two or more data points.

Feature Analysis: In order to model a collection of data, feature selection reduces the dimensionality of the data by choosing a subset of features (predictor variables) with the highest predictive potential. Using feature selection, one can: Avoid modeling with an excessive amount of features, which are more prone to rote memorizing certain training instances, in order to prevent overfitting. Minimize the size of the model to improve computing efficiency with high-dimensional data or to get it ready for embedded deployment, where memory can be scarce. Reduce the number of characteristics used to increase interpretability; this may assist find the ones that influence model behavior. There are several popular methods for selecting features; we will find the best method based on our dataset. Change the feature set iteratively to maximize performance or minimize loss: Stepwise regression iteratively increases or decreases features until prediction accuracy is no longer improved. It works with methods for either extended linear regression or linear regression. Comparably, a feature set is accumulated by successive feature selection until accuracy, or a customized performance metric, no longer improves. Sort characteristics according to their inherent qualities: These techniques approximate a feature ranking, which may then be used to choose the characteristics that rank highest. Minimal redundancy By minimizing mutual information between features and response variable and maximizing mutual information between features themselves, maximum relevance (MRMR) features are identified. Similar techniques To evaluate the relevance of a feature, rank the characteristics based on Laplacian scores or perform a statistical test to see whether a particular feature is independent of response.

Weather Forecasting: The dataset is divided into training, testing, and validation portions at the ratios of 7:2:1. 30% of the dataset is used as the training dataset, which is used to build the model; 10% is used as the validation dataset, which is used to configure the model; and 20% is used as the testing dataset, which is used to see how the model functions with fresh data. The three levels of a neural network model are typically input, hidden, and output. To improve nonlinear capacity, the layers are made up of networked neurons with nonlinear switching activation functions. The data is first obtained by the input layer, which then forwards it to a hidden layer for processing before returning the findings to the output layer. The output layer is now used to display results. But given the limitations, it is anticipated that lengthy unofficial chains of computational operations will be needed to train a neural network. The neural network topology employed in this research has two dropout levels and three dense layers. In contrast, the DNN consists of three dropout layers and five dense layers. Precision of Classification An accurate labeling of a data instance by a model is measured by its classification accuracy. This is measured using a variety of measures, including recall, precision, and overall accuracy (OA).

RESULT ANALYSIS

	Frequency	Signal Strength	Bandwidth	Temperature	Humidity	Wind Speed	Precipitation	CPU Usage	Memory Usage	WiFi Strength	System Load
0	120000000	-44	50000	24	47	7	10.900476	25.0	28.3	-77	4.300781
1	160000000	-97	1000000	27	39	16	46.467472	0.0	28.3	-57	4.300781
2	90000000	-87	500000	40	58	7	0.899704	100.0	28.3	-20	4.300781
3	160000000	-29	100000	28	50	8	20.771250	25.0	28.3	-38	4.300781
4	70000000	-26	10000	22	78	16	47.174738	0.0	28.3	-43	4.300781
...	...	...	...	...	...	...	...	...	...	...	...
164155	160000000	-63	200000	31	44	7	29.016592	0.0	30.6	-95	4.391113
164156	120000000	-15	10000	28	30	3	31.336959	0.0	30.6	-20	4.391113
164157	160000000	-97	10000	25	30	17	5.665096	0.0	30.6	-72	4.391113
164158	120000000	-29	500000	28	41	12	30.577004	0.0	30.6	-91	4.391113
164159	70000000	-68	100000	23	78	10	6.747127	0.0	30.6	-58	4.391113

FIGURE 1. Kaggle Dataset

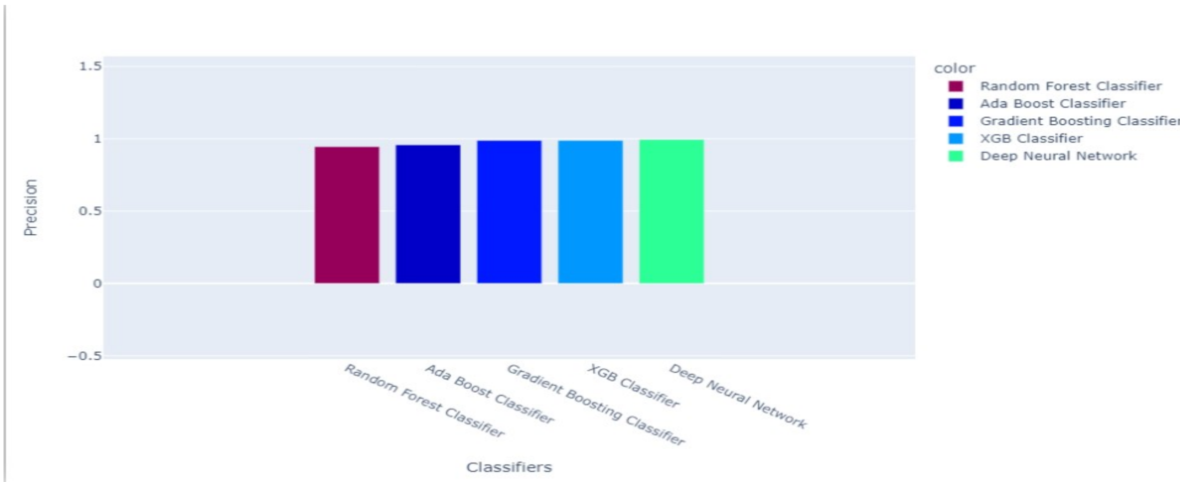


Fig2. Precision based on different algorithm

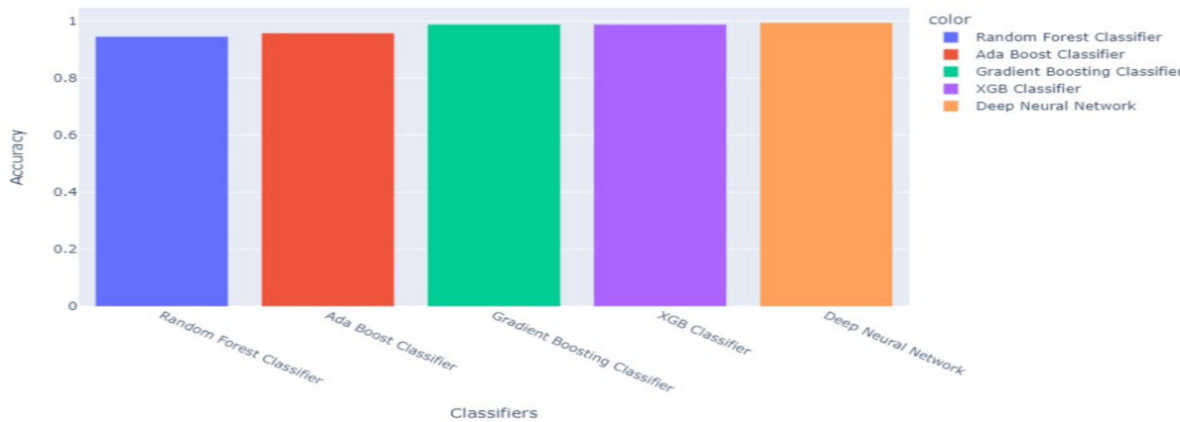


Fig 3. Accuracy level based on different algorithm

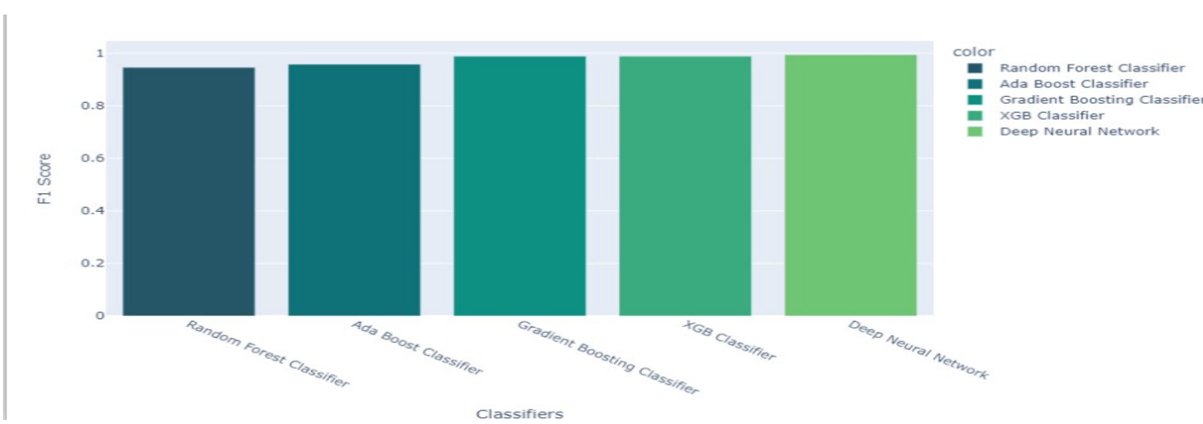


Fig 4. Evolution Metric in binary and multi-class classification

CONCLUSION

The prediction of weather conditions using science, technology, and physics principles for a specific place and time is known as weather forecasting. Understanding the science of atmospheric processes and projecting future atmospheric states are made possible by the quantitative data that is provided by meteorological features, such as temperature, humidity, wind speed, precipitation, and atmospheric pressure, that are collected over a period of time at a given location. Weather forecasting aids in the planning of future weather conditions and their impact on our daily activities. In order to forecast a single output feature, we presented our new model in this research. It has an inbuilt spatial feature attention mechanism that allows us to capture long-term dependencies and spatial feature correlations of multivariate input time series. When abrupt changes in input sequences are seen, the spatial feature attention mechanism is able to understand the quantitative mutual effect of input features on target feature, leading to correct predictions. Simultaneous changes detected in successively linked weather variables may be used to determine the size of a weather feature shift. The weight of each geographic feature's effect from numerous weather variables on the target variable may be ascertained by using multivariate weather variables to predict a single target weather characteristic.

FUTURE WORK

In terms of prospective improvements, the suggests looking at the roles of regularization and normalization fashion in this research, since they were used extremely effectively by other challenge participants but did not provide any clear gains in the model under investigation.

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