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Exploring the State of Art Existing Deep Learning Based Advanced Weather Forecasting Systems: A Systematic Review

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The average person who evaluates the changes occurring in the status of the atmosphere nowadays views weather forecasting as an essential and vital procedure in daily life. Moreover, for many industries including mining, aviation, agriculture and energy production, weather forecasting is essential because it facilitates decision-making and reduces the risks associated with extreme weather occurrences. For effective weather decisions, making an accurate prediction of environmental factors is a must. Previously, various weather systems have been reported that were based on conventional statistical forecasting techniques; however, it was not effective on nonlinear data patterns because it worked on a linear correlation structure between forecasts and historical data. With technological advances, machine learning-based forecasting techniques are found to be a better solution to mapping nonlinear patterns in data than linear statistical conventional modelling approaches, which consequently leads to better decision-making in relation to weather prediction. In this article it has been explored that all those weather forecasting system devised based on deep learning techniques. This review has summarized the detailed analysis of the adopted techniques; dataset employed and obtained performance of the systems in the reviewed articles. The analysis presented in the articles for weather forecasting system will helps the working professional to choose the suitable technique for their current problem in the similar context.

Keywords: Weather Forecasting, Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), Big Data Analytics, Numerical Weather Prediction (NWP), Automated Weather Forecasting System, Meteorological Data.

1. Introduction

The proper functioning of several businesses, such as agriculture, aviation, marine transportation, and energy generation, depends on accurate weather forecasting. Accurate weather forecasts may help farmers choose when to sow, water, and harvest their crops, increasing agricultural yields and lowering the chance of weather-related crop damage. More sustainable farming methods and increased food security result from this.

Precise weather forecasts are essential for flight planning in aviation, since they guarantee both crew and passenger safety. These forecasts are essential for pilots and air traffic controllers to avoid hazardous weather situations including thunderstorms, turbulence, and ice that might endanger flight safety. This leads to less fuel being used, more effective flying paths, and fewer delays (Salman et al. 2015) [1].

Accurate weather forecasting is also very beneficial to maritime traffic. Weather forecasts are used by shipping firms to create safer and more effective routes, steering clear of hazardous situations like storms and high waves. This reduces the possibility of expensive mishaps and delays in addition to safeguarding the lives of the crew and cargo.

Weather forecasts are crucial to the energy generation industry, especially for renewable energy sources like solar and wind power, which maximize energy output. Accurate forecasts of solar radiation levels and wind speeds help energy businesses better balance supply and demand, improving grid stability and lowering dependency on fossil fuels.

Numerical weather prediction (NWP) models are the cornerstone of conventional weather forecasting. These models mimic and forecast atmospheric behaviors by utilizing intricate mathematical formulas and information obtained from ocean-atmosphere interactions. The dynamic and chaotic character of weather systems presents inherent hurdles to the accuracy and dependability of NWP models, even with notable breakthroughs in this domain.

Furthermore, advancements in solar energy prediction, projected to play a larger role in the power grid, are anticipated to result in $455 million in savings for utility companies by 2040 (Haupt et al. 2014) [2]. The meteorological community faces an enviable problem: how to deal with a huge influx of mesoscale weather information, rapid improvements in numerical modeling and data assimilation, and extraordinary enhancements in our ability to communicate graphical information and data to individuals at nearly any location (Mass et al.2011) [3]. Significant cost reductions can also be achieved through enhanced forecasting in other sustainable computational domains. Therefore, researchers and professionals like meteorologists are working tiredly to forecast the weather with any required accuracy. Optimality, the same become the objective of the present research too.

Traditional computational intelligence techniques felt out of place when it came to producing precise weather forecasts in the big data era that has now arrived for weather forecasting; hence, artificial intelligence or machine learning has been proposed to be implemented (Gao & Chiu, 2012) [4].

Meteorological satellites are used by countries to swiftly transmit weather observations and revisions in today's rapid communications network, producing amazingly accurate forecasts (Emies & Knoche 2009) [5]. The volume of data is expanding rapidly relative to computational capacity, and there are various definitions of big data. According to theories, big data requires new technological architectures, data analysis methods, and tools to create valuable resources for businesses and uncover hidden insights through analytics value (Katal et al., 2014; Weyn et al., 2021) [6][7].

Because of the characteristics of big data, existing infrastructure and conventional methods are inadequate for managing it. Therefore, there is a need for tools capable of processing and storing vast quantities of data, along with new approaches and methodologies specifically designed for big data analytics (Rahmani et al) [8].

Artificial intelligence (AI) and associated data science techniques have been created to manage vast amounts of data across various domains. Integrating AI methods with a scientific Understanding the environment can greatly improve the precision of predicting various factors. This approach builds upon conventional Model Output Statistics (MOS) methods (Glahn & Lowry, 1972) [9], which generate stochastic, nominal, and causal predictions based on output from Numerical Weather Prediction (NWP) models.

AI methods employed in environmental sciences include Artificial Neural Networks (ANNs), decision models, evolutionary algorithms, imprecise logic, and principal component analysis (Allen et al., 2007) [10]. Clustering was utilized for classification of rainfall areas (Baldwin et al., 2005) [11]. Further clustering was employed for radar-echo classification mapping (Lakshmanan & Smith, 2010) [12], It was further used for storm track detection, and also was applied to radar image segmentation (Manross et al.) (Henry et al., 2021) [13][14].

Furthermore, because AI-driven models are flexible and can learn from real-time data, they are excellent at handling unexpected disasters and abrupt weather changes. When fresh information becomes available, these models iteratively update and improve their forecasts, increasing their efficacy under changing meteorological circumstances. Because of this flexibility, meteorologists and emergency personnel may quickly modify plans and distribute resources in response to changing weather patterns and new threats.

Essentially, using AI and ML to weather forecasting improves operational effectiveness while fortifying society's resistance to hazards associated with climate change. Through increased precision, predictability, and flexibility in weather predictions, these technologies are vital for reducing the effects of extreme weather, promoting sustainable growth, and strengthening worldwide readiness for disasters.

Even with major improvements, there are still a number of difficulties with weather forecasting. These include the standardization of meteorological data from various sources, the integration of hybrid models that integrate AI/ML with traditional Numerical Weather Prediction (NWP) methodologies, and the improvement of computer performance to handle the challenges of large-scale data processing. To tackle these obstacles, interdisciplinary cooperation, continuous investigation, and significant expenditures on state-of-the-art technology are necessary.

The major problem is developing hybrid models that combine classic NWP techniques with AI/ML. While AI/ML methods are highly effective in identifying patterns and managing intricate data linkages, classical NWP models are necessary for modeling atmospheric physical processes. When these methods are seamlessly integrated, prediction accuracy and dependability may be improved across a range of weather phenomena and timescales (Henry et al., 2021) [14].

Furthermore, because meteorological data comes in a variety of forms, sizes, and sources, standardizing it still presents a major challenge. Improving data consistency and quality requires standardizing data standards and harmonizing data from satellite imaging, climate models, and ground-based observations. This standardization provides more comprehensive and trustworthy research, enhancing prediction accuracy and enabling decision makers in weather-sensitive businesses.

Enhancing computational efficiency is also essential for managing the growing amount and complexity of meteorological data. Increased computer power allows for faster data processing, model simulation, and real-time forecasting. It also makes weather forecasts timelier and more accessible for stakeholders and the general public (Kapucu, N. 2008) [15].

It will need consistent work in research, technological development, and cooperation both inside and beyond the meteorological community to overcome these obstacles. The working professionals and researchers can improve the dependability and accessibility of weather forecasts by tackling these challenges. As a result, society gains from improved risk management techniques, more informed financial planning choices, and the encouragement of efficient environmental stewardship measures in response to weather-related effects and climatic unpredictability. Customer needs and perceptions are changing at rapid pace. For organizations to survive, aligning to these changes with agility will be of paramount importance. Accurate forecasts will play a vital role to support the managers for correct decision making (Yerpude et al., 2017) [16].

Due to incorporation of AI and machine learning, accurate weather forecasting has become more accessible. Previously exclusive to national meteorological organizations, advanced forecasting systems are now affordable for small enterprises and municipal governments. At the local level, this democratization encourages creativity and adaptability, allowing for proactive remedies to weather-related issues like heatwaves, snowstorms, and droughts.

For instance, the energy sector uses weather predictions to balance supply and demand; the aviation sector uses them to determine the optimum flight paths; the marine sector uses them to assure safe navigation; and the agriculture sector uses them to schedule planting and harvesting. Weather forecasting has enormous economic ramifications and has the ability to reduce the negative impacts of severe weather, perhaps saving millions of dollars.

Traditionally, the cornerstone of weather forecasting has been Numerical weather prediction (NWP) models forecast weather patterns by utilizing statistical techniques and information from ocean-atmosphere interactions. These models use complex mathematical equations to describe the physical processes controlling the atmosphere. The environment's high degree of dynamic and chaos poses challenges for these traditional methodologies, even with their increasing use and accuracy improvements.

The accuracy and stability of traditional NWP models are limited by factors such air turbulence, sudden changes in the weather, and the nonlinear nature of atmospheric events. The inherently unpredictable character of the weather system highlights the need for increasingly sophisticated and accurate forecasting techniques.

In order to visualise the impact of AI and ML on the performance improvement of weather forecasting systems, the present article explored the report research work. This review of reported work aims to provide an extensive evaluation of the current level of AI and ML applications in weather forecasting.

2. Literature review on related work

A number of forecasting models have been created by academics for time series forecasting in a variety of sectors, including power production, finance, agriculture, and industry. All these models or techniques use historical time series data primarily for prediction. Forecasting techniques based on historical data may be broadly divided into two categories: statistical techniques were used to construct the first, while learning approaches were used to generate the second. For forecasting purposes, statistical techniques including the ARIMA model, multiple regressions, and exponential smoothing were employed.

When combined, these models are known as time series models for forecasting. These traditional estimators for worldwide predictions are the ARIMA approaches, which have been used in several data-driven forecasting applications by academics. However, artificial intelligence (AI) models, also known as soft computing approaches, predict outcomes more rapidly and with less processing than these statistical time series models when compared to statistical techniques like ARIMA techniques. They use a variety of techniques to provide forecasts about solar energy. Among the techniques employed are deep learning (DL) frameworks, fuzzy logic (FL), genetic algorithms (GA), probabilistic models, and optimization techniques. These methods are further divided into four groups: DL techniques, ML techniques, and artificial intelligence techniques. An all-AI based model has been shown to be a beneficial tool for forecasting, and these approaches are employed when nonlinear data analysis and forecasting are involved in the problem. All of these models use the data as inputs to get the desired results, including:

Gore and Gawali (2023) [17] analysed the weather forecasting using machine learning algorithms. For the research data has been provided by The Indian Metrological Department (IMD) in Pune, Maharashtra, India. Using machine learning techniques, author have developed a forecasting system for the Marathwada region. In terms of mean and highest temperatures, average and least temperature, entirety month of rainfall, substantial precipitation in the month, the number of rainy days, average wind speed, average station and sea level pressure, and relative humidity, author have obtained overall accuracy values of 1.83, 1.95, 1.89, 2.66, 32.16, 11.91, 2.24, 1.69, 1.43, 1.62, and 9.37, respectively.

Singh and Rawat (2023) [18] also employed machine learning model such as Boost, Random Forest and SVM for weather forecasting. The dataset has been collected from IMD India for predicting temperature in Visakhapatnam. Random Forest and SVM found to be performed somewhat better on a number of metrics.

(Abdulla et al., 2022) [19] Investigated how meteorological feature can be predicted using deep learning model with Long-Short-Term-Memory (LSTM). LSTM model is extended for univariate and multivariate problems, followed by a comparison. The experimental results show that the prediction error is 45% reduced compared to baseline models, when adaptive learning was used based on a bidirectional LSTM model. In addition, the results also indicate that by using only univariant model, author can use less features for learning which subsequently decreases time as well as memory usage of model construction and maintenance.

Makala et al. (2021) [20] employed ARIMA and SVM for the price prediction of gold. The analysis was done on daily data taken from the World Gold Council spanning 1979 to 2019.

Both models were trained using data up to 2014; the remaining data is used for validation. Using the performance assessment tools of RMSE and MAPE, the study's findings demonstrate that ARIMA, RMSE, and MAPE resulted in 36.18 and 2897, respectively. But as compared to ARIMA, SVM performed well with RMSE of 0.028 and MAPE of 2.5. Schultz et al (2021) [21] found the recent excitement surrounding artificial intelligence that reignited enthusiasm for using AI techniques that have been effective in the domains of robotics, strategic games, image identification, voice recognition, and other application areas. But also found little evidence to suggest that by integrating big data mining and neural networks into the weather forecasting workflow, prediction.

Latif et al (2023) [22] evaluates the LSTM and ARIMA models' ability to predict Bitcoin prices. This study demonstrates that even with ARIMA's sophistication, LSTM can consistently anticipate fluctuations in the price of Bitcoin.

ArunKumar et al. (2021) [23] conducted an analysis for comparison, as numerous machine learning and deep learning models were published in the scientific literature to predict COVID-19, but no thorough analysis comparing statistical and deep learning models has been done. To predict the trends of the COVID-19, GRU, LSTM, ARIMA, and SARIMA models were trained, tested, and optimized. LSTM and GRU outperformed statistical ARIMA and SARIMA models

In this work, author has proposed a review on AI techniques for weather forecasting that can fully replace the existing numerical weather models and data assimilation systems. This topic includes an examination of cutting-edge machine learning theories and how they relate to meteorological data and its relevant statistical features. Menculini et al. (2021) [24] compared When LSTM and ARIMA for predictions actual historical prices. During the given time period, the LSTM model was able to predict both the direction and the value of Bit coin values, while ARIMA could only follow the trend of the prices. This study demonstrates that even with ARIMA's sophistication, LSTM can consistently anticipate fluctuations in the price of Bitcoin.

Singh et al. (2020) [25] forecast of confirmed SARS-CoV-2 infections in the most impacted nations using ARIMA and LS-SVM. The findings showed that the LS-SVM model outperformed the ARIMA model in terms of accuracy and also pointed to a sharp increase in SARS-CoV-2 confirmed instances across all of the countries included in the analysis.

Atique et al. (2020) [26] forecast daily solar energy generation using ARIMA and machine learning techniques on time series data. In experimentation, the superior performance of SVM in this field of work demonstrates the promise of machine learning based methodologies compared to the ARIMA model. Tiwari et al. (2020) [27] used SVM and ARIMA modeling techniques to analyze continuous one-year ambient noise data. To train the model, a case study of every commercial location is used. Tenfold cross-validation has been utilized in SVM to determine the ideal value of the hyper-parameters (γ, ε, and C). An alternative method for simulating ambient noise levels during the day and night is the Box-Jerkin ARIMA methodology. A number of statistical measures, including R2, MSE, RMSE, and MAPE, were employed to evaluate the performance of the suggested models. The SVM model has been found to perform better than ARIMA models. Zhang et al. (2020) [28] computed standard precipitation evapotranspiration index (SPEI) using ARIMA, WNN, and SVM models. For this temperature and precipitation data gathered from seven meteorological stations in the research area between 1979 and 2016, the was used. The R2 and NSE values of the WNN model were 0.837 and 0.831, respectively; those of the SVM model were 0.833 and 0.827, respectively which were best to ARIMA model.

Alim et al (2020) [29] compared the efficacy of the XGBoost and ARIMA model for forecasting the incidence of brucellosis. The human brucellosis data from January 2008 to June 2018 comprised the training set,July 2018 to June 2019 made up the test set. Alternatively, the test set yielded the XGBoost model's MAE, RSME, and MAPE was 249.307, 280.645, and 7.643, while the ARIMA were 529.406, 586.059, and 17.676 respectively. Ai Amin et al. (2020) [30] utilize electrical load forecasting to contrast the forecasting performance of the ARIMA and SVM models. Following the comparison, it was discovered that SVM outperforms ARIMA for non-linear patterns, whereas ARIMA performs better when approximating linear types of loads based on MAPE and MSE scores. Liu et al. (2020) [31] compared three models such as EEMD-ARIMA, EEMD-BP, and EEMD-SVM using the hourly urban water consumption dataset for times series prediction. As per the findings The EEMD-ARIMA, EEMD-BP, EEMD-SVM, ARIMA, BP, and SVM have mean absolute percentage errors (MAPE) of 5.2036, 1.4460, 1.3424, 5.7891, 4.3857, and 3.8470%, respectively.

Chattopadhyay et al (2020) [32] used deep learning model to weather forecasting. The author has suggested using capsule neural networks, or CapsNets in this work to weather forecast. CapsNets had learned on huge mid tropospheric circulation patterns (Z500) labelled 0–4 based on the presence and geographic location of surface high temperatures over America multiple days in advance, utilizing information from a large-ensemble fully coupled Planet model. Only using Z500, the training networks had accuracy (recalls) of 69–45% (77–48%) or 62-41% (73–47%) when predicting the existence or location of cold or heat waves 1–5 days in advance.

Jakaria et al (2020) [33] developed machine learning-based intelligent weather prediction system. give a method for predicting the weather that makes use of past data from several weather stations to train basic machine learning models. This method can quickly produce predictions that are useful for predicting specific weather conditions in the near future. The evaluation findings demonstrate that the models' accuracy is sufficient to be employed in conjunction with the most advanced methods currently available.

Suresha et al (2020) [34] used Shannon Airport meteorological dataset's variables for cloud cover, sky visibility, the humidity level, and sun shine duration to test multiple linear regression was to forecast rain. The model found to be performed well on given dataset.

Diez and Del (2020) [35] analyzed the effectiveness of eight machine learning and statistical techniques for long-term daily precipitation prediction in a semi-arid climate that are influenced by atmospheric synoptic patterns. The research's findings show that the chosen hyperparameters have a significant impact on how well most machine learning models function. It is discovered that neural networks operate best at predicting the occurrence and severity of rainfall. Verma et al (2020) [36] develops an interactive weather prediction system that may be used to forecast weather information for a variety of locations, including residences, businesses, stadiums, and agricultural settings. The system makes use of an LDR light level sensor and a DHT11 temperature and humidity sensor. The artificial intelligence environment is set up using a logistic regression model. The system gives 84% accuracy.

Coulibaly et al (2020) [37] devised rule-driven machine learning for information extraction from meteorological data. Using this approach, variable such as latent as well as sensible heat flux, air humidity and temperature, the speed and direction of the wind, rain, global radiation, etc was tested and results was found effective in the domain. Mansfield et al (2020) [38] educate societal adaptation and mitigation actions, as it is essential to comprehend and estimate regional climate change under various scenarios of anthropogenic emissions. For this machine learning has been applied and found effective. Stirnberg et al (2020) [39] tested the air quality using machine learning the implementation of a machine learning model advances the knowledge of the factors that contribute to near-ground PM10 and our ability to infer PM10 using satellite AOD. Hourly PM10 concentrations are connected to meteorological, land cover, and satellite-based AOD parameters. The overall R^2 of 0.77 has been achieved.

Lv et al (2020) [40] extend the one-step forecasting model for HFRS by presenting a multistep prediction technique based on XGBoost. The data was gathered on the occurrence of HFRS in mainland China between 2004 and 2018. To create the yearly ARIMA model and XGBoost model, the information from 2004 to 2017 were split into training sets. The prediction performance was tested using the 2018 data. Fang et al (2020) [41] compared XGBoost model and ARIMA model to see which was better at predicting the occurrence of COVID-19 in the United States. The training and validation sets' MAPE scores for the XGBoost model (4.046% and 7.892%) were both very good. Noorunnahar et al (2020) [42] utilized XGBoost model and ARIMA model for rice production prediction. In contrast, the XGBoost algorithm's test set's MAPE value (5.38%) was less than the ARIMA model's (7.23%), suggesting that XGBoost outperforms ARIMA when estimating Bangladesh's yearly rice production. Zhang et al (2020) [43] performed sales volume time series forecast with XGBoost. Priyadarshini et al (2020) [44] analyzed time data and identifying anomalies to create reliable smart homes. Here ARIMA model worked well. Makridakis et al (2020) [45] presents the data used and their features, as well as the competition's background, organization, and implementations. As such, it facilitates their understanding by acting as an introduction to the outcomes of the two forecasting tasks. Hoang et al (2020) [46] employed neural network LSTM to practice predicting weather conditions using various combinations of meteorological factors, including temperature, precipitation, humidity, wind speed, and pressure, in the context of modern technology. The model gains 64% accuracy. Fallucchi et al (2020) [47] presents an experimental development of a machine learning time series analysis related to the paroxysmal meteorological occurrence known as a "cloudburst," which is characterized by a highly concentrated, severe storm that occurs within a few hours and is much localized.

Namini et al (2020) [48] demonstrate comparison and behavioral analysis between LSTM and BiLSTM models. The goal is to investigate the extent to which adding more data layers for training could help adjust the involved parameters. The findings demonstrate that BiLSTM-based modeling, which incorporates extra data training, provides more accurate predictions than standard LSTM-based models. Paliari et al (2020) [49] focuses on modeling and predicting general time series gathered from many open datasets through the training and implementation of contemporary machine learning algorithms, such as Deep Neural Network techniques. In order to forecast how particular economic and social phenomena would change over time, a specific focus on these phenomena informed the selection of the data utilized in the experiments. The comparison of the previously described prediction methods and their optimization to increase accuracy remain the primary and ultimate objectives. Kalimuthu et al (2020) [50] demonstrate projects use machine learning, one of the most modern advances in crop prediction, to assist beginning farmers in planting appropriate crops. A supervised learning algorithm called Naive Bayes suggests how to do it. Here, the crop seed data are gathered at the ideal conditions—temperature, humidity, and moisture content—to ensure the crops grow successfully. The model achieved 97% accuracy. Kirbas et al (2020) [51] verified models for the COVID-19 instances from Denmark, France, the United Kingdom, Finland, Switzerland, and Turkey were created using the LSTM, ARIMA and NARNN) techniques. The most accurate model was chosen using six model performance metrics (MSE, PSNR, RMSE, NRMSE, MAPE, and SMAPE). The study's initial phase's findings indicated that LSTM was the most accurate model.

Nguyen et al. (2019) [52] forecast the final price of Bitcoin the following day, algorithms for machine learning and (ARIMA) model was used in this work. Subsequently, author introduces hybrid techniques that combine machine learning and ARIMA to enhance Bitcoin price prediction. The findings of the experiment demonstrated that hybrid approaches have higher prediction accuracy when using RMSE and MAPE. Yamak et al. (2019) [53] attempted to make a time series forecast by contrasting three distinct machine learning models. Our time series data collection will be the price dataset for Bitcoin, from which we will get our predictions. The outcomes demonstrate that the ARIMA model outperformed regression models based on deep learning in terms of performance. For both MAPE and RMSE, ARIMA yields the greatest results, at 2.76% and 302.53, respectively. Nevertheless, the Gated Recurrent Unit (GRU) outperformed the LSTM, with corresponding MAPE and RMSE of 3.97% and 381.34.

Hua (2019) [54] compared the forecasting accuracy of the value of bitcoin in US dollars using two distinct models: the ARIMA model and LSTM network. Pycurl obtains real-time pricing information from Bitfine. TensorFlow and Keras are used to implement the LSTM model. In this study, the ARIMA model is primarily utilized to offer a traditional comparison of time series forecasting. As anticipated, it is capable of making efficient predictions limited to short time intervals, with a time period-dependent consequence. The LSTM could perform better with more essential time for training the model, particularly when using a CPU. Singh et al (2019) [55] goal to create a weather forecasting system that may be utilized in remote locations. Weather conditions are predicted using machine learning and data analytics techniques like random forest categorization. This study develops a portable, low-cost weather forecast system.

Anjali et al (2019) [56] employed three machine learning models MLR, ANN, and SVM for temperature prediction via comparative study of meteorological data gathered from Central Kerala between 2007 and 2015. Compared to ANN and SVM, MLR is a more accurate model for temperature prediction, as seen by the error metrics and the CC. Ratra and Kumar (2019) [57] developed a simulated framework using data analysis and machine learning techniques to predict various climate conditions. Kim et al (2019) [58] devised links reported weather forecasts with undisclosed weather variables through a two-step modeling procedure. The empirical findings demonstrate that, regardless of the specific machine learning algorithms used, this strategy outperforms a base approach by significant margins. The R-squared value of 70.5% in the test data indicates that the random forest regression technique outperforms all other algorithms in solving this particular problem. Four variables are produced by the intermediate modeling procedure, and the post-analysis gives these variables a high priority. The developed model makes accurate forecasts up to one day in advance. Muszynski et al (2019) [59] provided optimized technique that uses machine learning and topological data analysis to identify atmospheric rivers (ARs) in climate data. Rhanoui et al (2019) [60] provide a predictive strategy that utilizes and contrasts the Deep Learning Recurrent LSTM model and the Machine Learning ARIMA model. Because of its capacity to infer non-linear relationships from data, the LSTM model performs better than the ARIMA model, as demonstrated by both the application and the comparison analysis. Oswal (2019) [61] compared the different assessment criteria of these machine learning model and show how reliable they are in predicting rainfall through weather data analysis. De Saa et al (2019) [62] evaluates deep learning methods and the ARIMA model for temperature forecasting. Limited convolutional layers are used in the deep learning model to derive spatial features, and LSTM layers are used to extract temporal features. Szeged, Hungary's hourly temperature data collection is used to test both of these models. The experimental findings showed that the deep learning model outperformed the conventional ARIMA methodology. Zhou et al (2019) [63] used a web traffic dataset for forecasting performance comparisons utilizing several evaluation metrics. ARIMA and LSTM were used. Using the most recent techniques, both models produced results that were comparable, with LSTM marginally outperforming its classical equivalent in the TSF challenge. Azari et al (2019) [64] demonstrate the Cellular traffic prediction and classification using ARIMA and LSTM and LSTM performed better over ARIMA in this application. Shafin (2019) [65] attempted to determine the trend of Bangladesh's annual average temperature as well as the average temperature by season using many machine learning methods. Machine learning techniques like Linear Regression, Polynomial Regression, Isotonic Regression, and Support Vector Regressor were employed in the experiment. The training dataset is most accurately predicted by the Isotonic Regression algorithm, whereas the future average temperature is most accurately predicted by the Polynomial and Support Vector Regressors.

Yovan (2019) [66] use the K means clustering strategy has a faster calculation time than the other clustering models for rainfall and Storm Prediction. The findings show that compared to the other method currently in use, the K-means clustering tool conducts clustering more quickly.

Ransom et al. (2019) [67] evaluate statistical and machine learning techniques for integrating weather and soil conditions into maize nitrogen recommendations. The RM approach was the best machine learning algorithm for modifying N recommendation tools (r2 rose between 0.72 and 0.84 and the RMSE dropped between 41 and 94 kg N ha^{-1}).

Deb et al. (2019) [68] suggested method enables to determine a relationship between changing weather parameters and the degree of traffic congestion. The city of Mumbai, India's Uber Movement traffic data was incorporated into many machine learning algorithms that had already been evaluated. After comparing the outcomes of the various machine learning algorithms, we were able to determine that, with an accuracy of 85%, logistic regression performs the best when applied to the Uber data that was gathered.

An enhanced rainfall forecast model using wavelet transform and seasonal ANN was suggested by Tran et al (2019) [69]. The authors also looked into other approaches for forecasting monthly precipitation.

In a comparison of market forecasting models utilizing ANN, Medina et al (2019) [70] found that neural networks gave results that were more reliable than those from other techniques.

Author in Weyn et al (2019) [71] without explicating the information from the physical phenomena, has proposed a simple weather prediction models based on the deep convolutional neural networks (CNNs). The proposed CNN model had trained on historical data of weather. The proposed system has anticipated one or two basic meteorological fields on a Northern Hemisphere grid. The proposed CNNs has been trained on only 500-hPa geopotential height outperform persistence, climatology, and the dynamics-based barotropic vorticity model at forecast lead times up to 3 days. However, the model had fall short of an operational full-physics weather prediction model.

Further it has been notable that the CNN model has been capable to foresee large changes in the strength of weather systems, as opposed to the barotropic vorticity equation, the basic dynamical equation that only uses data from 500 hPa. The CNN predictions have been slightly enhanced by adding input data with a thickness of 700–300 hPa. Our most effective CNN is capable of predicting realistic meteorological states with lead times of 14 days and does a decent job of reflecting the seasonality and annual variations of 500-hPa heights. Only using Z500, the training networks had accuracy (recalls) of 69–45% (77–48%) or 62-41% (73–47%) when predicting the existence or location of cold or heat waves 1–5 days in advance.

Naveen and Mohan (2019) [72] has described an ensemble weather predictive model that iteratively forecasts six important meteorological variables with a six-hour temporal resolution using the Deep Learning Weather Prediction (DLWP) models. Convolutional neural networks (CNNs) on a cube-globe grid had used in this operationally effective approach to provide global predictions. The experiment was performed on a one GPU, the trained model had generated a 320-member collection of six-week forecasts at 1.4° resolution in about three minutes. I

Further in order to construct a collection of 32 DLWP models with slightly different learned weights, the CNN training has been randomized. The DLWP model suggests total column water vapour but not rainfall, and it provides a reliable 4.5-day probabilistic forecast of Hurricane Irma. In a one-year unrestricted simulation, it not only simulates mid-latitude weather systems but also randomly produces tropical cyclones.

The ensembles' mean RMSE sustains accuracy in regard to climatology after 2 weeks when averaged worldwide and over a 2-test set, with anomalous correlation coefficients staying above 0.6 through six days.

As to regulate load and amplitude, transform wind energy into electricity, and securely link wind energy to the grid, effective wind-power prediction can improve a wind power system's ability to react to the volatility of wind energy.

Further Yin et al. (2019) [73] proposed wind power prediction model. Author has utilized a hybrid data decomposition method, where EMD is first used to breakdown the signal. IMF1 is then further broken down using VMD.

Similarly, a study on several weather prediction models using decision trees, support vector machines, and ANN was conducted by Kunjumon et al (2018) [74]. In their study of machine learning-based weather forecasts and related issues, Naveen and Mohan (2018) [72] covered a range of weather prediction application areas. Sher et al (2018) [75] developed wavelet neural network-based prediction models. An evolutionary approach with many objectives is used to train the wavelet neural network. The choice of mother wavelet and decomposition levels determines how accurately the wavelet-based decomposition technique can de-noise signals.

In order to predict wind speed, various research has recently been conducted using EMD-based models. The most effective and improved data decomposition model for information denoising and nonlinear and discontinuous time series analysis is called EEMD (Ensemble Empirical Mode Decomposition).

Using MapReduce and machine learning algorithms, Reddy and Babu (2017) [76] investigated various big data weather forecasting models. The authors also discussed the drawbacks and problems of big data weather prediction, particularly predicting rainfall.

3. Types of model analysis for weather forecasting

In weather forecasting, the use of machine learning (ML) and artificial intelligence (AI) techniques has transformed the industry. Large-scale meteorological data generated by weather stations, satellites, and smart devices, together with advances in computer technology, have propelled these developments. Machine learning algorithms have demonstrated promising results in identifying intricate patterns in meteorological data that conventional models would overlook [78][79] [84].

Large datasets may be processed by these algorithms, which can also identify intricate patterns and forecast outcomes quickly and accurately. Weather forecasting has undergone a dramatic paradigm change with the integration of AI and ML, switching from conventional, deterministic models to data-driven, probabilistic techniques. This change signals the beginning of a new era in meteorological sciences that will allow for more accurate and consistent weather forecasts.

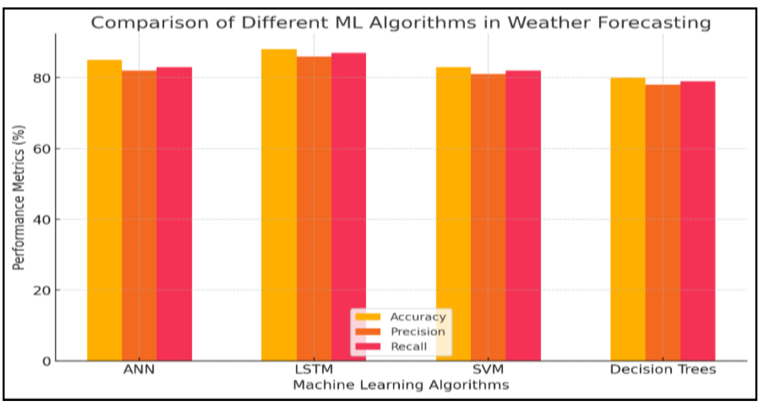

Figure 1: Comparison of Different ML Algorithms in Weather Forecasting

This paper is reviewing many machine learning techniques in the context of weather forecasting, and also weighed the benefits and drawbacks of AI or ML models such as Artificial Neural Networks (ANNs), Long Short-Term Memory (LSTM) networks, Support Vector Machines (SVM), and Decision Trees [80][81].

Artificial Neural Networks (ANNs) are designed to mimic the way the human brain is structured. They are particularly good at recognizing patterns and solving nonlinear issues, which makes them suitable for identifying complex links in meteorological data. Because they can store information over long periods of time, a kind of recurrent neural network called an LSTM network is particularly helpful for time series forecasting, improving forecasts of sequential weather patterns. While Decision Trees give interpretable models that offer clear insights into crucial weather factors, Support Vector Machines (SVMs) are preferred because to their resilience in handling high-dimensional data and classification jobs [82][83].

Moreover, there are several benefits and difficulties associated with combining these machine learning methods with weather forecasting. Because of their ability to recognize patterns, artificial neural networks (ANNs) may identify minute correlations in meteorological data, increasing the precision of forecasts for phenomena like temperature swings and storm patterns. Long-term forecasting and climate modelling benefit from the use of LSTM networks because they can capture temporal relationships, improving predictions over longer time periods.

SVMs are very good at categorizing weather occurrences and differentiating across weather patterns, which makes them useful for accurate classification and forecasting jobs in meteorology. These methods have advantages, but they also have drawbacks: For training and optimization, ANNs need a lot of computer power and knowledge, whereas LSTM networks could have trouble processing noisy or erratic data patterns. Large-scale meteorological datasets might cause scalability problems for SVMs, which perform well in high-dimensional environments, while Decision Trees, although intuitive, run the risk of oversimplifying complicated weather occurrences.

Because Artificial Neural Networks (ANNs) mimic the structure of the human brain, they are particularly good at pattern recognition and nonlinear problem solving. They are useful for identifying minute connections in weather patterns because they are skilled at capturing complex linkages within meteorological data. Recurrent Long Short-Term Memory (LSTM) neural networks are very useful for weather forecasting because of their long retention and use times. This ability enhances their ability to predict time-dependent phenomena, such as temperature trends and precipitation patterns.

Decision trees give models that are simple to grasp and comprehend, giving valuable insights into important meteorological factors. They make it easy to see the decision-making processes involved in weather prediction with their hierarchical structure. Support Vector Machines (SVMs), on the other hand, are excellent at categorization jobs and work well with high-dimensional meteorological data. Their ability to classify and distinguish between distinct weather patterns allows them to contribute to the development of more precise and trustworthy weather forecasts.

When these machine learning methods are used with big meteorological datasets, they have a lot to offer. They improve the accuracy and timeliness of weather forecasts by analyzing and assessing large amounts of data. When it comes to understanding and categorizing meteorological data, Decision Trees and SVMs offer clarity and robustness, while ANNs and LSTM networks deepen the analysis by catching intricate trends across time. When combined, these methods give meteorologists the ability to produce forecasts that enhance public safety, boost economic efficiency, and aid in crucial decision-making for weather-dependent businesses.

The analysis's other main area of interest is the smooth transition between deep learning analytics and weather forecasting. Increasing prediction accuracy requires utilizing a wide range of data sources and contemporary data processing methods. Weather monitoring equipment generates vast volumes of data, therefore sophisticated analytics methods are required for effective handling, processing, and evaluation. Utilizing the deep learning technology is crucial for merging information from many sources, such satellite imagery, climate models, and ground-based observations, into extensive databases. By greatly enhancing the forecasting models' dependability and resilience, this integration enables meteorologists to provide predictions that are more accurate and consistent.

This integrated approach is critical to the use of AI and ML technology in meteorological applications. These tools can find hidden patterns and connections in meteorological data that traditional approaches might miss by utilizing deep learning analytics. The ability of ANNs and LSTM networks to analyze vast amounts of data and capture intricate temporal relationships improves the forecasting power of weather models. When combined with large data, decision trees and support vector machines (SVMs) offer reliable frameworks for for precisely analysing and categorizing meteorological occurrences.

This research also explores the challenges involved in deep learning - driven weather prediction. To overcome these obstacles, strong algorithms that can efficiently handle the enormous amount of meteorological data must be developed. As part of this, high processing speeds must be maintained in order to handle real-time data streams quickly and precisely. In addition, one major challenge is the heterogeneous nature of meteorological data, which comes from many sources, scales, and formats. To fully utilize this broad data landscape in decision support systems and predictive modelling, standardization and harmonization are crucial.

It is imperative to solve these difficulties in their whole in order to integrate the deep learning analytics into weather forecasting. In addition to controlling data velocity and volume, efficient algorithms also need to preserve data consistency and quality across many sources. High processing speeds are essential in real-time forecasting scenarios where quick data analysis may make the difference between prospective threats and effective early warnings. This necessitates using cutting-edge computing strategies like parallel processing to efficiently maximize computational resources and speed up data analysis.

In order to maximize computer resources and accelerate data analysis, it is imperative to leverage parallel processing techniques in order to design efficient algorithms that can handle large amounts of meteorological data. The ability to compute simultaneously across several processors or cores is known as parallel processing, and it greatly improves the speed and effectiveness of data handling in applications related to weather forecasting. Meteorologists may increase the precision and timeliness of weather forecasts by streamlining data analysis procedures and making the most of these computing capabilities.

By carefully examining these problems, this study seeks to determine workable answers and potential areas for further investigation. The intricacies of weather forecasting based on large data need novel methods for algorithm development and computer optimization. This entails optimizing algorithms to manage heterogeneous data, expanding processing power to accommodate real-time data streams, and guaranteeing consistent and reliable data from a variety of sources.

Understanding and methodically addressing these challenges is essential to maximizing the advantages of AI and ML in weather forecasting. Meteorologists may improve prediction accuracy, fortify early warning systems, and facilitate well-informed decision-making in weather-sensitive businesses by growing algorithmic skills and computing efficiency. In addition to optimizing the application of AI and ML technologies, this proactive strategy also supports their usefulness in strengthening societal resilience to weather-related risks and difficulties.

When AI and ML technologies are combined, weather forecasting might benefit greatly. Improved forecast accuracy not only lowers economic losses but also improves public safety by improving preparedness for extreme weather occurrences. In order to provide prompt preventative measures that shield communities, infrastructure, and livelihoods from the effects of severe weather conditions, early warning systems depend on accurate and fast weather predictions. Forecasts that are precise enough to be used in advance enable decision-makers to take preventative actions, such making preparations for evacuation and allocating resources, which reduce risks and increase readiness.

Furthermore, by streamlining their operations with more accurate forecasts, weather-dependent companies stand to gain. The energy industry is better able to control changes in supply and demand, allocating resources optimally and reducing interruptions. In order to prevent weather-related delays and dangers, aviation businesses can enhance flight planning and scheduling, guaranteeing passenger safety and operational effectiveness. The agricultural industry may improve crop management techniques to maximize yields and minimize losses from unfavourable weather.

Accurate weather forecasts, for instance, have the power to completely transform a variety of industries. Accurate projections help businesses in the energy sector keep a careful balance between supply and demand. Companies are able to improve resource allocation, minimize inefficiencies, and alleviate costs associated with abrupt changes in weather conditions by forecasting weather patterns that affect energy production and consumption.

Analogously, accurate weather forecasts enable airlines to maximize flight patterns and timetables in the aviation industry. Airlines can increase passenger safety, reduce aircraft interruptions, and boost operational efficiency by avoiding bad weather and circumstances. This not only helps the airline sector but also improves traveller satisfaction generally and lessens the environmental effects of fuel usage.

Furthermore, precise projections are essential for farmers to efficiently organize their operations in agriculture. Farmers can plan planting dates, irrigation schedules, and crop protection strategies by forecasting weather patterns. This proactive strategy maximizes yields, ensures food security, and reduces agricultural losses brought on by unfavourable weather conditions. Thus, improved weather forecasting encourages sustainable farming methods and increases the resilience of the world's food supply.

These developments highlight how improved weather forecasting helps society as a whole. Accurate projections support sustainable development objectives by boosting resilience and economic efficiency in important industries. By offering prompt alerts and facilitating proactive steps to reduce the hazards connected to climate change and extreme weather occurrences, they enhance readiness for disasters. In the end, accurate weather forecasting is essential for developing adaptive strategies, boosting environmental sustainability globally, and boosting climate resilience.

Table 1: Analysis of Model's types of reviewed articles

S.No.	Authors	Models	Dataset
1.	Gore and Gawali [17]	Autocorrelation and Linear Regression	IMD Pune
2.	Singh and Rawat [18]	XGboost, Random Forest and SVM	IMD Pune
3.	Abdulla et al., [19]	Adaptive Deep Learning Models (LSTM)	Historical Weather Data
4.	Latif et al.,[22]	ARIMA and LSTM	Bit coin
5.	Makala et al., [20]	ARIMA and SVM	Price prediction of gold
6.	Weyn et al., [7]	Deep Learning	Climate Data
7.	ArunKumar et al., [23]	LSTM and GRU ARIMA and SARIMA	COVID-19 cases
8.	Kim et al., [77]	Neural network	El Niño forecasts
9.	Menculini et al., [24]	ARIMA and LSTM	Food prices
10.	Singh et al., [25]	ARIMA and SVM	COVID-19
11.	Atique et al., [26]	ARIMA, ANN and SVM	Solar energy
12.	Tiwari et al., [27]	ARIMA and SVM	Noise levels
13.	Zhang et al., [28]	ARIMA, WNN and SVM	Drought forecasting
14.	Alim et al., [29]	ARIMA and XGBoost	Infected patients
15.	Al Amin et al., [30]	ARIMA and SVM	Electrical load
16.	Liu et al., [31]	ARIMA, BP and SVM	Water usage
17.	Chattopadhyay et al., [32]	CapsNets	Weather prediction
18.	Jakaria et al., [33]	Ridge Regression SVR, MLPR, and Extra-Tree Regression (ETR).	Weather prediction

19.	Suresha et al., [34]	Multiple Linear Regression	Weather forecasting
20.	Diez and Del [35]	8 regression and machine learning methods	Rain forecasting
21.	Verma et al., [36]	Logistic regression model	Weather forecasting
22.	Coulibaly et al., [37]	Data mining	Weather forecasting
23.	Mansfield et al., [38]	Regression	Weather forecasting
24.	Stirnberg et al., [39]	Gradient Boosted Regression Trees	Air quality
25.	Lv et al., [40]	ARIMA, XG Boost	Infectious disease prediction
26.	Fang et al., [41]	XG Boost	COVID-19 patients' data
27.	Noorunnahar et al., [42]	ARIMA, XG Boost	Rice production
28.	Zhang et al., [43]	ARIMA, XG Boost and LSTM	Retail sales dataset
29.	Priyadarshini et al., [44]	ARIMA, SARIMA, and LSTM	Load forecast
30.	Makridakis et al., [45]	Multiple model	Retail unit sales
31.	Hoang et al., [46]	LSTM model	Weather prediction
32.	Fallucchi et al., [47]	Machine learning	Weather Series Analysis
33.	Namini et al., [48]	LSTM BiLSTM	Stock indices
34.	Paliari et al., [49]	ARIMA, LSTM and XGBoost	Stock indices
35.	Kalimuthu et al., [50]	Naive Bayes	Weather forecasting
36.	Kirbas et al., [51]	ARIMA, LSTM and NARNN	COVID-19 cases
37.	Nguyen et al., [52]	ARIMA, LSTM and CNN	Bit coin
38.	Yamak et al., [53]	ARIMA, LSTM and GRU	Bit coin
39.	Hua [54]	ARIMA, LSTM	Bit coin
40.	Singh et al., [55]	Random forest	Weather forecast
41.	Anjali et al., [56]	MLR, SVM and ANN	Temperature prediction
42.	Ratra and Kumar [57]	Random Forest Regression and Logistic Regression	Weather Prediction
43.	Kim et al., [58]	Random forest regression	Weather Prediction
44.	Muszynski et al., [59]	SVM	Climate data
45.	Rhanoui et al., [60]	LSTM and ARIMA	Financial budget
46.	Oswal [61]	Logistic Regression, Decision Tree, KNN, AdaBoost and Gradient Boosting	Rainfall Prediction
47.	De Saa et al., [62]	LSTM and ARIMA	Temperature prediction
48.	Zhou et al., [63]	LSTM and ARIMA	Web traffic
49.	Azari et al., [64]	LSTM and ARIMA	Cellular traffic prediction
50.	Shafin [65]	Linear Regression, Polynomial Regression, Isotonic Regression, and Support Vector Regressor	Weather prediction
51.	Ransom et al., [67]	Random forest	Weather and soil prediction
52.	Deb et al., [68]	Logistic regression	Weather prediction

4. Analysis of performance matrixes

In order to evaluate the performance of the proposed ANN model on the given dataset of the following testing parameters have been chosen.

1. Coefficient of determination
2. MSE

3. RMSE
4. Precision
5. Recall
6. F1 score
7. Accuracy

4.1 Coefficient of determination

In case of forecasting the result of an event, the coefficient of determination being a statistical measurement looks at how variations in one variable may be explained by differences in a second variable.

The Coefficient of determination has been representing by the equation 1.

$$R^2 = 1 - \frac{RSS}{TSS} \tag{1}$$

Where RSS means to sum of squares of residuals

and TSS = total sum of squares

4.2 MSE

MSE is an abbreviation for Mean Squared Error. It basically lets you know how closely a regression line resembles a set of data points for the given dataset. In actuality, being a risk function, it corresponds to the squared error loss's expected value. The average, more particularly the mean, of errors squared from data related to a function is used to determine the mean square error. The MSE has been representing by the equation 2.

$$MSE = 1/n \sum_{i=1}^{n} (y_i - y^{\wedge}{}_i)^2 \quad (2)$$

4.3 RMSE

The model’s error in predicting quantitative data has been measured using the Root Mean Square Error (RMSE). The RMSE is representing in equation 3.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(y_i - y^{\wedge}{}_i)^2}{n}} \quad (3)$$

An implementation of a CNN network can be tested employing performance measures such as precision, recall, F1-score, and support, which are calculated after the training of network.

4.4 Precision

It is defined as the ratio of accurately positive observations was predicted to the total number of correctly observations predicted.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{4}$$

4.5 Recall

It is defining the ratio of true positive observations predicted to all of yes observations in the original class.

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive+False Negative}} \quad (5)$$

4.6 F1score

It is result of average (in weighted) of Recall and Precision. This rating is based on into account both false positives and false negatives.

$$\text{F1 Score} = \frac{2}{\text{Recall}^{-1}+\text{Precision}^{-1}} \quad (6)$$

Or

$$\text{F1 Score} = 2\frac{\text{Recall X Precision}}{\text{Recall+ Precision}}$$

(7)

Or

$$\text{F1 Score} = \frac{\text{True Positive}}{\text{True Positive}+\frac{1}{2}(\text{False Positive+False Negative})} \quad (8)$$

4.7 Accuracy is defining as the ratio of correct predicted instances or samples to all instances

$$\text{Accuracy} = \frac{\text{True Positive+True Negative}}{\text{True Positive+True Negative+False Postive+False Nagative}} \quad (9)$$

The performance metrics analysis of various reviewed papers is described in the table 2.

Table 2: Analysis of performance metrics of reviewed articles

S.No.	Authors	Metrics	Results
1.	Gore and Gawali [17]	Accuracy	Effective
2.	Singh and Rawat [18]	Several	Random Forest and SVM found to be performed somewhat better on a number of metrics
3.	Abdulla et al., [19]	RMSE	RMSE decreases from 0.864 to 0.593.
4.	Latif et al.,[22]	Accuracy	LSTM = 99.73%
5.	Makala et al., [20]	RMSE and MAPE	a 2.5 MAPE and an RMSE of 0.028.
6.	Weyn et al., [7]	RMSE	Deep Learning is suitable for the application
7.	ArunKumar et al., [23]	RMSE	LSTM outperformed other model
8.	Kim et al., [77]	Correlation coefficient	The Nino3.4 index prediction and associated temporal classification showed increases in the correlation coefficient of 5.8% and 13%, respectively.
9.	Menculini et al., [24]	Accuracy	LSTM outperformed ARIMA
10.	Singh et al., [25]	RMSE, MAE and MSE	LS-SVM outperformed
11.	Atique et al., [26]	MAPE	SVM outperformed
12.	Tiwari et al., [27]	RMSE, R2 and MSE	SVM outperformed
13.	Zhang et al., [28]	NSE, R2 and MSE	The WNN model's R2 and NSE values are 0.837 and 0.831.

14.	Alim et al., [29]	MAE, RAME	For the XGBoost model, the MAE, RSME, and MAPE are 249.307, 280.645, and 7.643, in that order.
15.	Al Amin et al., [30]	MSE and MAPE	SVM outperforms ARIMA
16.	Liu et al., [31]	Numerous	EEMD-ARIMA's MAPE is 5.2036; EEMD-BP is 1.4460; EEMD-SVM is 1.3424; ARIMA is 5.7891; BP is 4.3857; and SVM is 3.8470.
17.	Chattopadhyay et al., [32]	Accuracies and recalls	CapsNets outperform
18.	Jakaria et al., [33]	RSME	ML performed well on data
19.	Suresha et al., [34]	RSE and R2	0.4096
20.	Diez and Del [35]	Accuracy	Neural networks perform best
21.	Verma et al., [36]	Accuracy	84%
22.	Coulibaly et al., [37]	------	Effective
23.	Mansfield et al., [38]	RMSE	Effective
24.	Stirnberg et al., [39]	R2	0.77
25.	Lv et al., [40]	MASE, MAPE, MPE, MAE	MAE= 132.055 and 173.403
26.	Fang et al., [41]	MASE, MAPE, MPE, MAE	MAPE= 4.046% and 7.892%
27.	Noorunnahar et al., [42]	MSP	XG Boost outperform ARIMA
28.	Zhang et al., [43]	MAE, RSME	XG Boost outperform existing model
29.	Priyadarshini et al., [44]	MAE, RSME	ARIMA outperform other model
30.	Makridakis et al., [45]	Accuracy	Promising
31.	Hoang et al., [46]	Accuracy	64%
32.	Fallucchi et al., [47]	Accuracy	Promising
33.	Namini et al., [48]	RMSE	BiLSTM outperformed LSTM
34.	Paliari et al., [49]	MAE	LSTM outperformed other
35.	Kalimuthu et al., [50]	Accuracy	97%
36.	Kirbas et al., [51]	MSE, RMSE	LSTM outperformed other
37.	Nguyen et al., [52]	RMSE	Hybrid approaches have higher prediction accuracy
38.	Yamak et al., [53]	RMSE	Gated Recurrent Unit (GRU) outperformed the LSTM, with corresponding MAPE and RMSE of 3.97% and 381.34.
39.	Hua [54]	Time efficiency	LSTM perform better
40.	Singh et al., [55]	Accuracy	87.90%
41.	Anjali et al., [56]	RMSE, MSE	MLR is a more precise over other
42.	Ratra and Kumar [57]	F1, recall, precision	Logistic Regression performed better
43.	Kim et al., [58]	R2	70.5%
44.	Muszynski et al., [59]	Accuracy	90%
45.	Rhanoui et al., [60]	MSE	LSTMs outperformed other models
46.	Oswal [61]	Accuracy	Decision Tree= 91%
47.	De Saa et al., [62]	MSE	LSTMs outperformed other models
48.	Zhou et al., [63]	MSE	LSTMs outperformed other models
49.	Azari et al., [64]	MSE	LSTMs outperformed other models
50.	Shafin [65]	MSE, RMSE and R2	Isotonic Regression algorithm outperformed other models
51.	Ransom et al., [67]	Accuracy	Promising
52.	Deb et al., [68]	Accuracy	85%

The above table 2 analysis of different performance metrics has done and results are shown. This matrix used by meteorologists and various agencies to check the performance of various models using MSE (Mean Square error), RMSE (Root Mean Square Error, accuracy, Correlation Coefficient etc.

5. Conclusion

Weather forecasting has benefited greatly from the application of Artificial Intelligence (AI) and Machine Learning (ML), outperforming conventional Numerical Weather Prediction (NWP) models in terms of accuracy and dependability of predictions. These developments result from AI and ML's capacity to analyse enormous volumes of detailed meteorological data and find subtle patterns that conventional models could miss. In the field of meteorological sciences, this shift from deterministic models to data-driven probabilistic techniques represents a critical turning point.

Because AI and ML technologies make it possible to analyze intricate linkages and nonlinear processes in the atmosphere, weather forecasting has undergone a revolution. By identifying minute patterns and complex connections in meteorological data, they have increased prediction accuracy and reliability, improving disaster preparedness and public safety. The precision and anticipation of severe weather alerts have significantly improved, enabling communities to better plan and get ready for crises and lessen the damage that extreme weather events due to people and their property.

Weather forecasting powered by AI has advantages for a number of sectors. Precise weather forecasts in the energy sector allow for the best possible supply and demand balancing, which minimizes operational interruptions and inefficiencies. Improved flight planning and scheduling improves the aviation sector by increasing passenger safety and operational effectiveness and reducing environmental impact. In a similar vein, the agricultural industry can maximize yields and guarantee food security by making knowledgeable decisions about planting, irrigation, and crop protection. This proactive strategy strengthens the resilience of the world food supply and encourages sustainable farming methods.

But there are still difficulties. To properly utilize AI in weather forecasting, challenges including heterogeneity in data and the requirement for more effective algorithms must be resolved. Better data assimilation methods and increasingly complex AI models must be created as a result. In real-time forecasting scenarios, where quick data analysis may distinguish between possible hazards and useful early warnings, high processing speeds are crucial. To maximize computer resources and speed up data analysis, it is essential to use cutting-edge computing techniques like parallel processing.

Resolving these issues is crucial to raising the accuracy and efficiency of weather predictions even more. Improving algorithmic power and computational effectiveness will maximize the use of AI and ML technologies while reinforcing their usefulness in enhancing societal resilience to weather-related hazards and difficulties. Significant economic gains will result from these developments, which will also enhance public safety by better planning for catastrophic weather events, promote sustainable development, and strengthen climate resilience.

In conclusion, by boosting resilience and economic efficiency across important industries, the incorporation of AI and ML into weather forecasting is a revolutionary advance that supports sustainable development goals. AI-driven weather forecasting plays a critical role in catastrophe planning by enabling pre-emptive actions and delivering early alarms, eventually boosting environmental sustainability and global climate resilience.

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