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Weather Forecasting: A Systematic Review Using AI Approaches

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Abstract: *The global climate is in a perpetual state of rapid transformation, and the need for precise weather predictions has become increasingly paramount in contemporary society. From agriculture and business to transportation and everyday commutes, we heavily depend on accurate weather forecasts to facilitate seamless operations in various aspects of our lives. For ensuring uninterrupted mobility and the smooth functioning of daily routines accuracy of prediction is essential.Impacts of weather forecasting is huge in daily life activities so; scholarly genre is taking great interest in this field. Large amounts ofdata from multiple sources, such as satellites, weather stations, radar and historical records is complex task to predict. Artificial Intelligence (AI) brought tremendous impacts to process its various techniques and results are highly satisfied. The main benefits of AI inweather forecasting are its ability to process huge amounts of data fastly and accurately. Through this literature review, a good number of research papers are studied and illustrated the performance of distinct modals of artificial intelligence. Papers revels the modals performance based on different attributes as per regions, range & duration. AI is playing pivotal role to predict huge data of different time intervals in short time. The transformative prospective of AI in weather forecasting deceits in its ability to provide more consistent and accurate predictions.As the technology endures to advance, we can believe to see even more refined accuracy rates in weather forecasting systems inthe coming time. This study is summarizing artificial approaches those are effective andstill be used to attain higher accuracy.*

Keywords: Weather Forecasting, Machine learning, Data Mining, Deep Learning, Climatic Attribute

I. INTRODUCTION

Weather is an integral part of our daily lives, influencing our decisions, activities, and overall well-being. From planning outdoor events to determining our clothing choices, weather conditions hold significant importance. Accurate anticipation of weather patterns has emerged as a pivotal element in contemporary society, empowering individuals, businesses, and governments to make well-informed decisions and undertake suitable actions in response to dynamic weather conditions. [1]. As a result, the need for effective weather forecasting systems has grown substantially. Weather forecasting is a complex scientific discipline that involves the analysis of vast amounts of data and the application of sophisticated mathematical models. Traditionally, meteorologists have relied on observations from weather stations, weather balloons, and satellites to understand atmospheric conditions and make predictions. However, with advancements in technology, including the use of supercomputers, advanced algorithms, and improved data collection methods, weather forecasting has significantly evolved in recent years [2].

The fundamental goal of weather forecasting is to furnish precise and timely predictions for diverse meteorological parameters, including temperature, precipitation, wind speed, and atmospheric pressure. These forecasts play a crucial role in numerous sectors such as agriculture, aviation, energy, transportation, and emergency management. For instance, farmers depend on weather predictions to strategize irrigation, crop protection, and harvesting activities, while airlines utilize them to optimize flight routes, mitigate turbulence, and ensure the safety of passengers. Similarly, energy companies depend on accurate forecasts to manage power generation and distribution, while emergency management agencies utilize them to prepare for severe weather events and mitigate their impact. Despite significant advancements, weather forecasting still faces several challenges [3]. The atmosphere is a complex and chaotic system, making it inherently difficult to predict with absolute certainty. Factors such as climate change, topographical variations, and atmospheric phenomena further contribute to the complexity of weather patterns. Consequently, forecast errors and uncertainties persist, affecting the reliability and usability of predictions. This systematic review aims to comprehensively evaluate the state-of-the-art in weather forecasting, focusing on the need for accurate and timely predictions. By examining the existing literature, research methodologies, and technological advancements, this review seeks to identify the strengths, limitations, and potential areas for improvement within the field [4]. Additionally, it will explore emerging technologies, such as machine learning, data assimilation, and ensemble forecasting, which hold promise for enhancing forecast accuracy and reducing uncertainties. Ultimately, the findings of this systematic review will provide valuable insights into the current state of weather forecasting, shedding light on its importance and the challenges it faces. It will serve as a foundation for future research and developmentefforts aimed at improving weather forecasting systems, ensuring they meet the evolving needs of society. By striving for more accurate and timely predictions, we can enhance our preparedness, mitigate risks, and make better-informed decisions in the face of changing weather conditions [5].

Deep learning techniques leverage layered neural networks to identify and extract meaningful patterns from datasets.

In the realm of Big Data, neural networks with deep architectures exhibit proficient capabilities in extracting high-level abstract features. Various models for weather forecasting, leveraging deep learning, have emerged, demonstrating effective prediction of weather conditions. This paper aims to provide a comprehensive examination of weather forecasting models incorporating diverse techniques and methodologies employed by researchers [6]. The salient features of the paper include:

(1) A meticulous evaluation of assorted weather forecasting models.

(2) Examination of crucial hyper-parameters employed in forecasting models.

(3) An exact classification of weather forecasting models.

(4) Investigation of distinct parameters based on different techniques

(5) Serving as a reference for burgeoning researchers keen on weather forecasting, presenting insights into distinct techniques and accessible distinct database

(6) Deliberation on potential future research directions within this domain.

The paper's structure follows a systematic progression. Section 2 offers a thorough overview of relevant surveys, while Section 3 provides insights into the motivation driving the proposed work. Section 4 delves into the specifics of the proposed framework, introducing a comprehensive weather forecasting framework, followed by the classification of weather forecasting models in Section 5. Scrutiny of the results is undertaken in Section 6, and Section 7 engages in a concise discussion on challenges and outlines potential future directions. Finally, Section 8 brings the paper to a conclusion.

II. RELATED SURVEY

A complete study of weather conditions determining includes a complex investigation of different procedures, mechanical progressions, and interdisciplinary methodologies pointed toward improving the precision and dependability of expectations. Mathematical Climate Expectation (NWP) remains at the front line, with continuous examinations concerning state of the art mathematical models, reenactment strategies, and the combination of outfit gauging to address vulnerabilities. The overview dives into the basic space of information digestion, assessing strategies that actually consolidate observational information from different sources, like satellites and radar, into estimating models. Moreover, the thriving impact of AI, including brain organizations and profound learning calculations, is under a magnifying glass for its groundbreaking effect on design acknowledgment, highlight extraction, and model alignment in weather conditions estimating. Remote detecting innovations, like LiDAR and Doppler radar, assume a critical part, adding to a comprehension of climatic circumstances [7]. The examination additionally inspects the expectation and moderation of outrageous climate occasions, considering the effect of environmental change on their recurrence and force. Simultaneously, the job of hydrological and environment models in both present moment and long haul environment conjectures is evaluated. Check and approval techniques, continuous observing, and correspondence methodologies are painstakingly contemplated to work on the viable relevance of anticipating frameworks [8]. In an effort to push the boundaries of predictive power, research is broadening its scope to include new technologies like quantum computing and advanced data analytics. Finally, this comprehensive study includes the social and economic effects of weather forecasting, such as disaster preparedness, agriculture, transportation, and public safety. This study features the dynamic and developing nature of weather conditions estimating, mirroring the business' proceeded with progress and advancement. In this segment, we audit a few examinations connected with weather conditions gauging, dive into enormous information studies investigating research bearings [13], and break down different profound learning structures reasonable for large information handling to address difficulties and future patterns [9].

Saima et al. [10] investigates the advantages and disadvantages of various weather forecasting models, including statistical, artificial intelligence, and hybrid models. Nagaraja et al. [11] presents a survey zeroing in explicitly on prescient models created for wind energy, determined to distinguish solid models that shed light on wind conduct. Machine learning forecasters, deep learning forecasters, and hybrid models are all examined by Liu et al. [12] in their focus on wind speed forecasting models. AI forecasters for weather conditions guaging incorporate counterfeit brain organizations, support vector machines, and outrageous learning machines. Profound learning forecasters incorporate autoencoders, repetitive brain organizations, and long-transient memory organizations, which are especially valuable for time series gauging. Kunjumon et al [13] direct a concentrate on prescient models in view of counterfeit brain organizations, support vector machines and choice trees. Naveen and Mohan [14] investigate different application areas of weather conditions anticipating, concentrate on weather conditions determining models utilizing AI methods, and address weather conditions estimating points. Using Map Reduce and machine learning, Reddy and Babu [15] examined big data weather forecasting models, focusing on the limitations and issues of big data weather forecasting, particularly rainfall forecasting. Tran-Anh et al. [16] investigate a variety of approaches for monthly rainfall and propose an improved rainfall forecasting model based on seasonal artificial neural networks (ANNs) and wavelet transforms. Tarade and Katti [17] direct a complete investigation of wind speed estimating frameworks in view of ARIMA, ANN and polynomial bend fitting. At last, Kulkarni et al. [18] research the viability of various factual methodologies in foreseeing wind speed.

Experimental results have confirmed the generation of reliable outcomes in wind speed prediction through the superior performance of ARIMA being surpassed by extrapolation using periodic curve fitting and Artificial Neural Networks (ANN). In a comparative study of demand forecasting models, consistent and enhanced accuracy is observed with the utilization of ANN in comparison to other methodologies, as determined by the investigation conducted by Medina et al. [19]. The impact of neural networks in post-processing ensemble weather prediction models, with a specific focus on temperature prediction in Germany, is explored by Rasp and Lerch [20]. An extensive survey on various time series prediction models utilizing Long Short-Term Memory (LSTM) and ARIMA is undertaken by Siami-Namini et al. [21]. A comprehensive review of energy forecasting models, summarizing current research trends and highlighting publicly available datasets for energy forecasting research, is provided by Hong et al. [22]. The proposed framework in this study facilitates a precise classification of diverse weather forecasting models. State-of-the-art models are not only presented but challenges and future directions are also discussed. This framework represents a distinct approach to surveying existing weather forecasting models, primarily classifying them based on the employed methodology. The survey further categorizes models based on the specific weather parameter to be predicted and provides details on available open datasets for experimentation. The motivation behind this innovative survey approach is elaborated upon in the subsequent section [23].

The following table summarizes key information from various research articles related to air quality forecasting, weather forecasting, renewable energy systems, wind speed prediction, crop health assessment, smart grid weather prediction, and temperature forecasting. Each row corresponds to a different study, providing details on the author, solution approach/method, advantages, limitations, and research gaps identified. Insights of distinct papers such as deep learning algorithms for air quality forecasting, highlighting their applications and drawbacks, with a research gap in the description of certain algorithms and low accuracy levels. Similarly, paper explores smart grid weather prediction using quantum technologies, noting the model's potential limitations in reliability for different regions and suggesting the use of larger datasets for improved accuracy. Each study contributes unique insights and addresses specific gaps in the respective fields, showcasing the diverse approaches and challenges in weather-related research

Table 1: The brief summarized review of some other related research work

S.N	Author	Solution Approach/ Method	Advantages	Limitations	Research Gap
1.	Shahiba H et. al [24]	In this article, EBWF prediction system is used for various stations of Indian airport.	Proposed model outperforms Random Forest ,KNN,GBDT & NBB models.	By using big data theory only less amount of data can be predicted.	Comparison of Correlation coefficient (CC), Index Agreement (IA), and NashSutcliffe Efficiency Coefficient (NSE) could be improved
2.	Wu et. al. [25]	In this article, various deep learning algorithms used in air quality forecasting are summarized and discussed, along with their theoretical underpinnings, hyper parameters, applications, and drawbacks.	Interested researchersmay find deep learning applications in time series air quality predictions useful.	Description of many algorithms is missing and also the accuracy level is low.	A small data set has been used to check the accuracy of air quality. Different time series algothirms can be used to measure air quality.
3.	Jeseena et. al.[23]	This study offers a comprehensive analysis of various methods for weather forecasting, along with some publicly accessible datasets.	This study offers a thorough taxonomy of weather forecasting models and explores probable future avenues for this field of study.	The key shortcoming identified by the evaluation of the existing systems was the absence of a stability assessment of the weather forecasting models.	Weather forecasting attitubutes such as ozone, dew point & precipitation have been measured less by distinct algorithms like DNN, RNN, and SDAE & LSTM.
4.	Meenal et. al[26]	This paper describes current and emerging weather predicting strategies for smart grid renewable energy systems, such as solar and wind forecasts.	Physical, statistical, AI, ML, and DL models were discussed.	Being no -informed about the mechanics of the atmosphere.	The atmospheric conditions depend upon seven layers so research gap is huge. There is possibility to bring out more accurate prediction of renewable energy system. Air motions obey Newton's laws of dynamics can be considered too.

5.	Liu et. al [4]	In the WPD-CNN, LSTM-CNN model, the original wind speed time series is decomposed into sub-layers.	The proposed model outperforms the other eight models in forecasting 1D wind speed time series over the range of one to three steps, and it is robust and effective at doing so.	Accuracy level is low.	Dimensionality of wind speed time series over the range can be improved. Few more steps are possible to decompose sub layers using CNN & LSTM.
6.	Rubini et. al[28]	This survey aims to determine crop health and help farmers, who depend on agriculture for revenue, survive.	This survey focused on deep learning as a pioneering technology that may be used in any field to tackle complex input-output interactions.	Huge dimension and high redundant features	Agriculture is dominant area in weather forecasting. There is research gap to collect reliable and big data related to crop health.
7.	Safari et. al [29]	This study discusses smart grid weather prediction, regular approaches, and quantum technologies in ladders.	Quantum technology and Quantum Neural Networks (QNN) can be used with other techniques to create accurate,ultrafast models.	Quantum technologies and smart grid weather prediction have been investigated.	Used model may not be reliable for other regions and broaden range. So large data set can be taken for more accuracy and implemented over large range.
8.	Jakaria et. al[30]	We provide a method for weather forecasting that involves the utilization of historical data from several weather stations in order to train basic machine learning models that can generate meaningful forecasts in a short time.	The models' accuracy is good enough to employ with state-of-the-art approaches, according to the examination.	Traditional weather predictions use big, complicated physics models that use long-term atmospheric conditions.	Hourly temperature of two months' details could be converted to minutes. Few more sensors for training data can be taken and there are good chances to implement deep learning algorithms.

9.	Ramesh et. al[31]	This study forecasted seven- day high and low temperatures based on the previous two days' weather.	However, functional regression was found to have a high bias and a low variance, whereas linear regression had the opposite properties.	If the forecast were instead based upon the weather of the preceding four or five days, the bias of the functional regression model may likely be minimized.	Emission of different gases can be measured more accurately by considering linear regression and principal regression.
10.	Schultz et. al[32]	We investigate whether DL can substitute for numerical weather models and data assimilation techniques.	The question of whether or not DL can take the place of numerical weather models and data assimilation approaches is discussed.	In general, meteorological DL needs benchmark datasets with baseline scores and software frameworks that make it easy to pick a meteorological problem and try out multiple solutions.	Using of deep learning algorithms for real time will enhance the assimilation of data henceforth more accurate results are possible.
11.	Campbell et. al[33]	We use a straightforward time series approach to model and forecast the daily average temperature in cities across the United States, and we investigate whether or not this approach is relevant to participants in the weather derivatives market.	Time series modeling exposes conditional mean and variance dynamics in daily average temperature and discrepancies in temperature distributions and surprises.	Weather derivatives may benefit from more research on time series forecasting methods.	Time series data can be used for unstructured data and data set for real time limitation can be enriched. We can enhance the range of region and variance dynamics can be enhanced too.
12.	Tian et. al [34]	We propose a new technique that emphasizes both long- term and short-term memory (LSTM)	For the purpose of demonstrating the efficiency of our approach, we use Caltrans PeMS data and our own traffic flow data.	flow of traffic despite the fact that some variables in the data are missing	Building the causal links between weather parameters and more system indicators can be used.
13.	Lin Chen et. al [35]	Our art formats weather forecasts. Long-term climate change will affect future generations.	Information and statistics analysis algorithms incorporate a woody area for weather	Staff discrepancies and inequality, accurate weather prediction	The loss in performance of the optimally controlled can be improved by LSTM & regression algorithm.

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			Forecasting.		
14.	Gehrmann et. al [36]	Compares research on mission learning and deep learning methods to optimize prediction and precision.	This study examines weather forecasting techniques.	Choosing the best technique to improve performance is a difficult issue.	Comparison of distinct algorithms to seek optimization is still unrevealed.
15.	Mehta al.[37]	The system forecasts weather for a given timeframe. Variables are used to describe the weather.	Only important attributes are employed in weather forecasting. Location strongly influences character qualities. Existing weather conditions are used to fit a model	Fluctuations are Investigated using machine learning and extrapolation. This system uses linear and logistic regression.	Weather condition is very much fluctuating and real time prediction is still tedious task for researchers. Large time frame and variables by observing few more attributes can be enhanced so far.

III. MOTIVATION

Motivation for the development and advancement of weather forecasting systems stems from the quest to enhance predictive accuracy and reliability across three distinct categories based on the employed model or methodology: statistical models, Artificial Intelligence (AI) models, and hybrid models. In the realm of statistical models, the motivation lies in leveraging historical weather data to discern patterns and trends, allowing for short-term predictions. These models, such as linear regression, emphasize the statistical connection between variables and aim to establish precise relationships through data analysis. The motivation for pursuing statistical models is rooted in their simplicity, interpretability, and the ability to capture linear dependencies within meteorological data [38]. Then again, the ascent of Man-made reasoning (artificial intelligence) models, driven by the progressions in AI and profound learning, has given another outskirt to weather conditions determining. The inspiration driving utilizing simulated intelligence models lies in their ability to deal with complex, non-direct connections inside meteorological information. AI calculations, including choice trees, support vector machines, and brain organizations, can observe complicated designs, working with both present moment and long haul forecasts. The inspiration for embracing simulated intelligence models is grounded in their versatility to advancing information structures, considering further developed determining precision by catching nuanced conditions that conventional factual models could disregard.

Half and half models, coordinating both measurable and simulated intelligence strategies, address a combination of the smartest possible situation. The inspiration for creating mixture models lies in tending to the impediments of individual methodologies. By joining the interpretability of factual models with the complicated example acknowledgment capacities of artificial intelligence, crossover models plan to give more thorough and exact weather conditions gauges. The inspiration is established chasing collaborations, where the qualities of every philosophy make up for the shortcomings of the other, bringing about a more vigorous and versatile gauging framework fit for dealing with different meteorological difficulties. Generally, the inspiration for weather conditions determining frameworks across these three classes mirrors a pledge to nonstop improvement, driven by the craving to saddle the qualities of various techniques. The overarching objective is to push the boundaries of accuracy in weather predictions, thereby enhancing our capacity to anticipate and mitigate the impact of changing weather patterns on various aspects of society. This can be accomplished through the synergistic power of hybrid models, the simplicity of statistical models, the complexity-handling capabilities of AI models, or both [39].

IV. PREDICTION MODEL FOR WEATHER FORECASTING

Advanced prediction models that make use of the capabilities of machine learning algorithms have emerged as a result of the paradigm shift in the field of weather forecasting brought about by the development of artificial intelligence (AI). These computer based intelligence driven models for weather conditions determining address a spearheading approach, tackling the force of immense datasets, unpredictable examples, and computational ability to upgrade the exactness and unwavering quality of expectations. Through the incorporation of refined calculations, for example, brain organizations and profound learning designs, these models show an uncommon capacity to observe mind boggling connections inside barometrical information, prompting more nuanced and exact figures. The prescient ability of simulated intelligence models reaches out past conventional techniques, as they independently adjust to advancing examples and progressively change their boundaries because of ongoing information inputs. Besides, these models add to a more profound comprehension of intricate meteorological peculiarities, offering important experiences into environment elements and adding to the continuous talk on environmental change. As AI continues to evolve, the prediction models for weather forecasting stand at the forefront, exemplifying the transformative potential of cutting-edge technologies in unraveling the complexities of the atmosphere and ushering in a new era of informed decision-making in various sectors reliant on accurate weather predictions.

The schematic representation of a meteorological forecasting model is delineated in Figure 1. The systematic stages within the meteorological prediction framework encompass the procurement of data, preprocessing of data, selection and other required steps for research paper. Progresses in technologies such as the Internet of Things (IOT), Wireless Sensor Networks, and Cloud Computing have precipitated the accessibility of meteorological data in varied formats and substantial magnitudes Juneja, A et. al [40]. This data, comprised of both pertinent and extraneous information, is frequently lacking a defined structure. Following the acquisition of data, the subsequent phase involves preprocessing to eradicate irrelevant and absent values, yielding refined data. Data pre-processing includes crucial steps such as data cleaning, data integration, data reduction, and data transformation. These techniques aim to enhance the quality of input data; as high-quality input data invariably contributes to quality output during the training process. Data cleaning methods specifically target noise, missing values, and inconsistencies in the data. Real-world data commonly exhibit missing values, necessitating imputation using techniques like mean values, especially since many forecasting algorithms do not support data with missing values [41].

The data integration process consolidates data from various sources into a coherent data store, while data reduction techniques minimize data size through aggregation, elimination of redundant features, or clustering. In the data transformation step, normalization or standardization techniques are employed to convert the data into a suitable form for processing [42]. These transformation techniques not only enhance the accuracy and efficiency of mining algorithms but also reduce model training time.

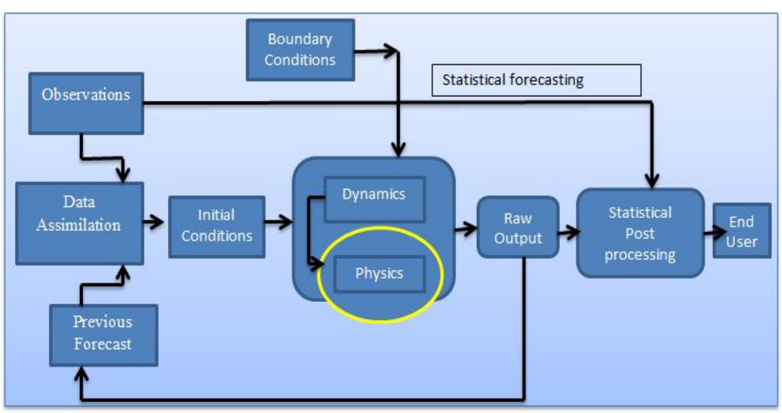

Figure 1: Physical model for weather prediction

These pre-processing techniques are often used in conjunction. After data pre-processing, an appropriate forecasting model is selected, trained, and tested using datasets. Effective forecasting of weather information is achieved through the use of suitable algorithms. Model selection and training constitute a crucial step in any forecasting system, where knowledge about various forecasting models aids researchers in choosing a model tailored to the application domain

The fundamental system of this presentation is given by the "Forecast chain" that diagrams all the key advances important to deliver a climatic figure for an end client. The current (or past) condition of the climate characterized at each model network point. Getting these underlying conditions isn't inconsequential on the grounds that the issue is horribly underdetermined. Perceptions of direct model amounts like temperature are inadequate in reality, just accessible from surface stations, unpredictable climate swell risings and along airplane flight tracks. Satellites give worldwide inclusion in great transient and spatial goals however just takes roundabout estimations. To take care of this issue, perceptions are joined with past model figures in a procedure called "information absorption" Great beginning conditions are fundamental for climate estimates. Thus, at most operational demonstrating focuses these days a bigger number of individuals are working right now on the improvement of the physical model. For atmosphere forecasts, it is additionally critical to determine limit conditions, for instance ozone depleting substance outflows. Since anticipating these contains a great deal of vulnerability, models are generally run with a few discharge pathways to acquire a scope of arrangements [43].

The issue of acquiring great beginning and limit conditions is a key test in climatic displaying. In the papers introduced here, be that as it may, information digestion just assumes an auxiliary job. P1–3 utilizes admired arrangements, while P4 utilizes information from an operational predictions framework that incorporates cutting edge information osmosis techniques. Having acquired introductory and limit conditions, it is conceivable to run the environmental model and produce a figure. Be that as it may, the crude model yield is once in a while utilized straightforwardly by end clients since it regularly has orderly mistakes. Hence an entire field of research manages the post processing of environmental predictions [44].

The physical model: In this model, the environment is the principle segment of each determining framework. Such a model attempts to estimate the physical procedures overseeing the advancement of the climatic state as precisely as could be expected under the circumstances. The model is comprised of two center segments, called, to some degree discretionarily, " physics "and" dynamics science" in air science language. The elements understand the Navier-Stokes conditions, which oversee the progression of air, on a three-dimensional lattice utilizing limited differencing plans [45]. It very well may be seen as a capacity that maps the model state starting with one-time stage then $y_{t+1}=H(y_t)$,Where y is the model state vector that contains every single model variable, for example temperature, winds and weight, at ea ch model matrix point. Since the atmosphere has an exceedingly no uniform angle proportion, a lot more extensive than tall, the even framework dispersing Δx is a few times the vertical network dividing Δz. The discrete time step Δt is coupled to the spatial network by the CFL condition, Here CFL is referred as the Courant–Friedrichs–Lewy [47].$w\Delta t\ \Delta z + u\Delta t\ \Delta x \leq C_{max}$. Where Cmax must be not exactly a specific worth (that relies upon the time venturing plan) to guarantee a steady time reconciliation. Note that quick waves are normally taken care of by a different joining plan. The coupling of the time venture to the lattice separating implies that multiplying the even goals builds the computational expense by a factor of 24. Since computational assets are constrained, an exchange off between incorporation time, the topographical model degree and the model goals must be made.Numerous physical procedures happen on scales littler than the network spacing's of current barometrical models, for instance fierce blending, radioactive warming and cooling and most cloud forms . These sub grid forms, in any case, are vitally critical to the development of the environment and their impact on the settled scales must be approximated. These approximations are classified "parameterization". The absolute arrangement of all parameterizations is known as the "material science" of a barometrical model. A parameterization P predicts the impact of a sub grid procedure on the settled scales Δx_{sg} as an element of the settled state and parameterization explicit parameters θ that can incorporate tuning parameters or outer forcing [46]:$\Delta x_{sg} = P(x, \theta)\ \Delta t$. The absolute model at that point is a mix of the settled shift in weather conditions D and the sub grid material science P: $x_{t+1} = D(x_t + \Delta x_{sg})$ or $D(x_t) + \Delta x_{sg}$.The request for physics and dynamics science varies from model to demonstrate. Discovering great approximations of sub grid forms ends up being troublesome. Hence, parameterizations are the significant wellspring of vulnerability in the present climatic prototypes.

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V. CATEGORIZATION OF WEATHER FORECASTING MODELS

Weather forecasting models undergo categorization based on several crucial factors, forming a comprehensive framework to understand their functionality. The classification considers elements such as the number of variables involved, forecasted time steps, methodology, prediction horizon, and the specific parameter being predicted. Models are classified as either univariate or multivariate, depending on whether they rely on a single variable or multiple variables for forecasting. For instance, a temperature prediction model incorporating various environmental factors is considered multivariate, while a model relying on a single variable is termed univariate.

Further categorization involves distinguishing between single-step and multistep models, where single-step models forecast a singular observation in the future, while multistep models predict multiple time steps ahead. The temporal scale of weather forecasting spans four categories: very short-term, short-term, medium-term, and long-term, with shorter-range forecasts generally exhibiting higher accuracy. Deterministic and probabilistic methods constitute another classification, with deterministic models providing precise forecasts for specific locations, while probabilistic models offer probabilities of weather events. This survey primarily focuses on deterministic forecasting models, further dividing them into statistical models, Artificial Intelligence models, and hybrid models.

Additionally, models can be specialized based on the parameter being predicted, such as temperature prediction models, wind speed prediction models, rainfall prediction models, dew point prediction models, among others. Recognizing the significant impact of weather on social and economic activities, accurate predictions play a pivotal role in preventing adverse events. Numerous methods have been proposed over the years to achieve this goal, and the subsequent section delves into the various categories of weather forecasting models, shedding light on their diverse characteristics and applications

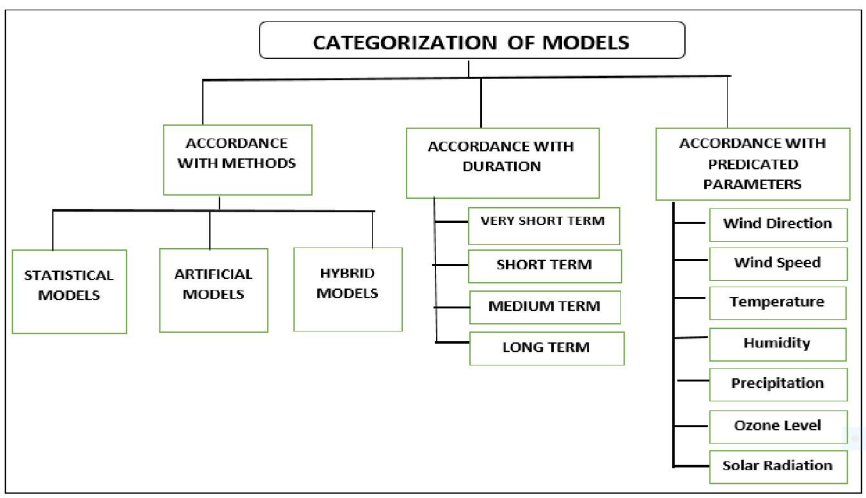

Figure 2: Categorization of Weather Forecasting Models

1. CATAGORIZATION ACCORDANCE WITH METHODOLOGY USED

Categorizing models based on forecasting methodology involves grouping them into statistical models, Artificial Intelligence models, and hybrid models.

1.1 STATISTICAL MODELS

Statistical models play an indispensable role in weather forecasting, especially in the realm of short-term predictions, leveraging historical weather data for insightful insights. Straight relapse, a noticeable measurable displaying method, lays out a direct connection among reliant and free factors, working with exact expectations with insignificant blunder. With regards to straightforward direct relapse, which focuses on two consistent factors, an inclination drop improvement calculation is utilized to limit expectation blunders [47]. Broadening this procedure, different direct relapse thinks about more than one free factor, accordingly expanding the prescient abilities of the model. The statistical models ARMA, ARIMA, multiple regression, and VAR are all widely used in weather forecasting. While VAR is useful for forecasting a vector of time series, it is especially useful for predicting interrelated variables, while ARIMA is adept at handling time-series data and can predict future observations .Multi-variable polynomial regression (MPR) rainfall prediction models have been the subject of numerous studies, exemplified by the works of Zaw and Naing [48]. These studies have demonstrated how well MPR performs in comparison to multiple linear regression models. Moreover, research led by Kavasseri and Seetharaman [49] and Erdem and Shi [50] has introduced breeze speed and power expectation models conveying partial ARIMA, ARMA, disintegrated ARMA, VAR, and confined VAR, highlighting the flexibility of factual models in tending to a range of estimating difficulties. Important are the headways in half breed models, exemplified by the proposition by Khashei and Bijari [51], which coordinate direct ARIMA and nonlinear fake brain organization (ANN) models, exhibiting upgraded adequacy in accomplishing better anticipating precision analyzed than traditional individual models These mechanical steps highlight the significant meaning of measurable models in refining and lifting the capacities of weather conditions estimating frameworks.

1.2 ARTIFICIAL INTELLIGENCE MODELS

The advancement of Artificial Intelligence has spurred the emergence of intelligent forecasting models. These models have demonstrated robustness and effectiveness when compared to statistical models. Artificial Intelligence models excel in handling non-linear datasets and showcase superior forecasting performance. Within this category, these models are further divided into machine learning predictors and deep learning predictors [52].

1.3 HYBRID MODELS

Hybrid models in the realm of weather forecasting represent a cutting-edge approach that amalgamates the strengths of various modeling techniques to enhance the overall accuracy and reliability of predictions. These hybrid models synergistically blend traditional statistical methods with advanced artificial intelligence (AI) and machine learning algorithms, providing a comprehensive framework to capture the complex and dynamic nature of atmospheric phenomena. By integrating the strengths of different models, hybrid approaches aim to overcome individual model limitations and improve the overall forecasting performance]. In the context of weather forecasting, hybrid models often combine statistical models, such as autoregressive integrated moving average (ARIMA) or exponential smoothing, with sophisticated machine learning algorithms like artificial neural networks (ANNs), support vector machines (SVMs), or deep learning architectures. This combination allows for a more robust analysis of historical weather patterns, taking into account both linear trends and non-linear relationships that may exist in the data. One notable advantage of hybrid models is their ability to handle diverse types of meteorological data, including temperature, humidity, wind speed, and atmospheric pressure, among others. The incorporation of multiple data sources contributes to a more comprehensive understanding of the atmospheric conditions, enabling the model to make more informed and accurate predictions. Moreover, hybrid models often demonstrate improved performance in capturing abrupt changes or non-stationary patterns in weather data, a challenge often faced by purely statistical or machine learning models [53].

Hybrid models, integrating both machine learning (ML) and deep learning (DL) techniques, represent a cutting-edge approach in weather forecasting, combining the strengths of diverse algorithms to enhance prediction accuracy. These models leverage the versatility of ML algorithms, such as decision trees, support vector machines, and random forests, along with the intricate pattern recognition capabilities of DL, typically implemented through artificial neural networks (ANNs). The synergy of these techniques enables the exploitation of complex relationships within meteorological data, capturing both linear and non-linear dependencies. For instance, a hybrid model may involve combining the temporal sequence analysis of recurrent neural networks (RNNs) with the hierarchical feature learning of convolutional neural networks (CNNs), providing a robust framework for capturing both short-term fluctuations and long-term trends in weather patterns [54].

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One notable example of a hybrid model for weather forecasting involves the integration of autoregressive integrated moving average (ARIMA), a traditional time series analysis method, with recurrent neural networks (RNNs). ARIMA is adept at capturing temporal dependencies, while RNNs excel in learning sequential patterns. By fusing these techniques, the hybrid model achieves a more comprehensive understanding of the underlying dynamics in meteorological data, resulting in improved forecasting accuracy. Additionally, advancements in hybrid models include the incorporation of long short-term memory (LSTM) networks, a type of recurrent neural network designed to capture long-term dependencies, further enhancing the model's ability to discern subtle and prolonged weather patterns [55].

Research in this field continues to explore novel combinations of ML and DL algorithms, adapting to the evolving complexities of meteorological data. Hybrid models hold promise not only in refining short-term weather predictions but also in addressing the challenges associated with long-term climate forecasting. As technological advancements continue, the integration of machine learning and deep learning approaches in hybrid models is poised to play a pivotal role in pushing the boundaries of weather forecasting accuracy and reliability.

2. CLASSIFICATION BASED ON PREDICTED PARAMETERS

Forecasting models can be grouped into various categories depending on the specific parameter they aim to predict. These categories include temperature prediction models, wind speed prediction models, rainfall prediction models, dew point prediction models, and others. Each prediction model focuses on forecasting a particular parameter based on historical observation. The prediction of weather forecasting based on temperature constitutes a critical aspect of meteorological modeling, influencing a myriad of human activities, from agriculture and energy consumption to public safety and infrastructure planning. Various sophisticated models are employed to forecast temperature trends, taking into account an array of factors that contribute to the complex thermal dynamics of the atmosphere. Meteorologists use both univariate and multivariate models, considering variables such as humidity, atmospheric pressure, wind patterns, and geographical features to enhance the accuracy of temperature predictions. Time plays a crucial role in these forecasts, with models categorizing predictions into very short-term, short-term, medium-term, and long-term, each addressing distinct time horizons. The utilization of deterministic models, which provide precise temperature forecasts for specific locations, and probabilistic models, which offer the likelihood of temperature-related events, showcases the versatility of forecasting approaches [56].

The advent of advanced technologies has facilitated the integration of statistical models, Artificial Intelligence (AI) models, and hybrid models in predicting temperature patterns. Statistical models, grounded in historical data and mathematical relationships, analyze past temperature trends to extrapolate future conditions. AI models, such as machine learning algorithms and neural networks, exhibit a capacity to discern intricate patterns in temperature data, enabling more nuanced and adaptive predictions. Hybrid models, combining the strengths of statistical and AI methodologies, aim to overcome the limitations of individual approaches, offering a comprehensive understanding of temperature dynamics. Specialized temperature prediction models further refine forecasting precision, addressing specific climatic phenomena like heatwaves, cold spells, or seasonal variations. The significance of accurate temperature forecasts extends beyond meteorological curiosity; it directly influences sectors like agriculture, where planting and harvesting decisions hinge on temperature predictions, and energy management, where heating and cooling demands are contingent on anticipated temperature variations. The continuous refinement and innovation in temperature prediction models underscore the commitment to improving our understanding of atmospheric processes, ultimately enhancing our ability to anticipate and adapt to the ever-changing dynamics of temperature-driven weather patterns. Similarly, Forecasting models tailored for predicting wind speed play a pivotal role in addressing the diverse applications that heavily rely on accurate wind speed predictions. This predictive capability holds significant implications for various sectors, including power generation, agriculture, industry, naval systems, and marine activities [57].

The intricate dynamics of wind speed are influenced by the movement of air from high pressure to low pressure areas. The fundamental principle underlying wind behavior is the differential in atmospheric air pressure, where air moves from regions of higher pressure to those of lower pressure. This movement, driven by pressure differences, ultimately dictates the speed of the wind. The relationship between pressure and wind speed is such that greater pressure disparities result in higher wind speeds. Moreover, understanding the variation in atmospheric air pressure with altitude is crucial in these models. The weight exerted by the air on the Earth's surface changes with altitude, introducing an additional layer of complexity to the prediction models. Accurate predictions of wind speed and direction are imperative for optimizing wind energy generation, planning agricultural activities, ensuring the safety and efficiency of industrial operations, guiding naval systems, and facilitating maritime activities. As such, advancements in wind speed prediction models contribute significantly to enhancing our ability to harness the power of the wind across various sectors, promoting sustainability and informed decision-making [58].

The prediction of weather forecasting based on atmospheric pressure is intricately tied to the fundamental principle that atmospheric pressure decreases with increasing altitude. This essential relationship serves as a key indicator for meteorologists in anticipating and understanding changes in weather patterns. As air ascends in the Earth's atmosphere, the decreasing atmospheric pressure corresponds to alterations in temperature and humidity levels.

Additionally, the concept of dew point, denoting the temperature at which air becomes saturated with moisture and dew forms, plays a pivotal role in weather prediction. The amount of water vapor in the air is directly linked to the dew point, with higher levels indicating increased humidity. Understanding the dew point is particularly significant for regions with varying climatic conditions, as it influences the growth of vegetation. In desert ecosystems, where water availability is limited, the dew point becomes crucial for the survival and growth of plants adapted to arid conditions. Similarly, areas experiencing moderate rainfall benefit from a higher dew point, supporting the flourishing of diverse plant life. This intricate interplay between atmospheric pressure, dew point, and water vapor levels underscores the importance of considering these factors in the prediction of weather forecasting, contributing to a more comprehensive understanding of the dynamic and interconnected nature of Earth's atmospheric conditions. The quantity of moisture present in the lower atmosphere, known as humidity, holds immense significance in various aspects of weather forecasting and agricultural practices [59].

Humidity serves as a critical factor influencing leaf growth, photosynthesis, and pollination, all of which directly impact the overall economic yield of crops. Maintaining an optimal level of humidity is essential for the physiological processes of plants, ensuring their healthy development and productivity [96]. Adequate humidity supports the expansion of leaves, facilitating efficient photosynthesis, the fundamental process through which plants convert sunlight into energy. Moreover, humidity plays a pivotal role in the pollination process, influencing the success of fertilization and subsequent crop yields. Weather forecasting models that take into account the dynamics of humidity in the lower atmosphere provide valuable insights for farmers and agricultural planners, enabling them to make informed decisions about irrigation, crop selection, and other agricultural practices. By understanding and predicting humidity levels, weather forecasting contributes to the sustainable management of agricultural resources, fostering optimal conditions for plant growth and enhancing overall economic outcomes in the realm of agriculture. Ozone, a hazardous pollutant in the lower atmosphere, affects plants, humans, and other organisms. The ability to predict and control ozone concentrations is crucial in mitigating the adverse impacts of tropospheric ozone on human health and the environment within the realm of weather forecasting. Tropospheric ozone, a significant component of air pollution, is known for its detrimental effects on respiratory health and the overall well-being of ecosystems. Predicting ozone concentrations involves intricate analyses of atmospheric conditions, emission sources, and meteorological factors, providing essential information for anticipating periods of heightened ozone levels [98]. This predictive capability empowers authorities to implement timely measures such as air quality alerts and emission controls, minimizing exposure risks and safeguarding public health. Furthermore, the integration of ozone concentration predictions into weather forecasting models allows for a more comprehensive understanding of atmospheric dynamics, enhancing the accuracy of weather predictions and contributing to informed decision-making. By exercising control measures based on these predictions, policymakers and environmental agencies can proactively address and alleviate the environmental and health impacts associated with elevated tropospheric ozone levels, fostering a more resilient and sustainable approach to weather-related challenges [60].

Quantitative rainfall, referring to the measurable amount of rainfall received over a specific period in a designated area, stands as a critical parameter for the development of weather forecasting models. Predicting rainfall is of paramount importance, especially for sectors like agriculture and flood monitoring systems, where accurate forecasts can significantly impact decision-making processes. Agricultural practices heavily rely on precise rainfall predictions to plan planting schedules, manage irrigation, and optimize resource utilization. In regions where agriculture is a primary economic activity, having reliable quantitative rainfall forecasts enables farmers to make informed choices that contribute to crop health and yield. Additionally, accurate predictions of rainfall play a crucial role in flood monitoring systems, helping authorities and communities prepare for potential inundations and take preventive measures to mitigate the impact of excessive rainfall. Therefore, the development of forecasting models that can reliably predict quantitative rainfall serves as a cornerstone in ensuring the resilience of agricultural practices and enhancing overall preparedness for weather-related challenges [61].

Weather forecasting based on the parameter of precipitation is crucial for agricultural planning and decision-making. Precipitation, whether in the form of frozen water or liquid, plays an integral role in shaping the agricultural landscape. The amount and timing of precipitation directly impact various agricultural activities, influencing critical decisions related to irrigation, spraying, and harvesting. Adequate precipitation is essential for crop growth, ensuring a sufficient water supply to nourish plants and support their development. Farmers rely on accurate precipitation forecasts to determine when and how much irrigation is necessary, optimizing water usage and resource management. Additionally, precipitation forecasts guide decisions regarding the timing of pesticide and fertilizer application, as well as the ideal periods for planting and harvesting crops. In regions where water resources are limited, precise predictions of precipitation become even more crucial for farmers to plan and adapt their agricultural practices effectively. Overall, the accurate forecasting of precipitation is indispensable for farmers and agricultural stakeholders, enabling them to make informed decisions that contribute to sustainable and productive farming practices].

3. COMPARATIVE ANALYSIS OF VARIOUS ALGORITHMS

In the dynamic realm of weather forecasting, the scrutiny and comparison of various algorithms based on time series data play a pivotal role in elevating prediction accuracy and refining model performance. Meteorologists and researchers strategically leverage an array of algorithms, including the autoregressive integrated moving average (ARIMA), long short-term memory (LSTM) networks, support vector machines (SVM), and artificial neural networks (ANN), to meticulously analyze historical weather data and make predictions about future patterns [105]. The assessment and comparison of these algorithms revolve around their proficiency in capturing temporal dependencies, navigating non-linear relationships inherent in weather phenomena, and adapting to the ever-changing dynamics of weather conditions [62].

As researchers delve into the nuanced intricacies of algorithmic performance, they employ established statistical metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the coefficient of determination (R-squared). These metrics serve as quantitative benchmarks, offering a standardized means of evaluating the accuracy and efficacy of predictions generated by different algorithms. By systematically comparing these metrics, meteorologists gain valuable insights into the algorithms' relative strengths and limitations, enabling them to make informed decisions about which approach best aligns with the unique demands of specific forecasting tasks [63].

Recognizing the distinctive capabilities and constraints of each algorithm in handling time series data is paramount. A nuanced understanding of these intricacies empowers researchers to make judicious choices when selecting the most suitable algorithm for a given forecasting scenario. This discerning approach not only contributes to immediate improvements in weather prediction capabilities but also fosters ongoing advancements in the field as researchers refine their methodologies and algorithms based on empirical evidence and emerging insights.

Table 2: Need, Performance & computational requirements of unsupervised algorithms used in weather forecasting

Algorithm	Advantages	Limitations	Data Requirements	Interpretability	Computational Requirements
Neural Networks	Captures complex relationships, feature extraction	Requires large amounts of labeled training data	High-quality labeled data	Challenging for black-box models	High
Support VectorMachines	Effective for small to medium-sized datasets	May struggle with non-linear relationships	Well-structured and labeled data	Interpretable	Moderate to high
Random Forests	Handles non- linear relationships, robust	Limited interpretability	Structured and labeled data	Feature importance analysis	Moderate to high
K-Nearest Neighbors	Simple implementation, adaptable to newdata	Sensitive to irrelevant features	Structured and labeled data	Intuitive	Low to moderate
Gaussian Processes	Flexible and non-parametric	Computationally intensive	Well- calibrated labeled data	Interpretation	High
Hidden Markov Models	Captures temporal dependencies	May struggle with complex non-linear patterns	Sequential and labeled data	Interpretation	Moderate to high
Autoregressive Models	Capturestime-dependent patterns	Assumes linear relationships	Sequential and labeled data	Interpretable	Low to moderate

Illustrated table provides a general overview, and the performance and suitability of algorithms can vary depending on the specific time series characteristics, forecasting objectives, available data, and computational resources. Interpretability may also differ among algorithms, with some offering more transparency than others. It's important to select the most appropriate algorithm based on the specific requirements and constraints of the forecasting task.

VI. FUTURE SCOPE AND CHALLENGES FOR WEATHER FORECASTING

Weather forecasting is a skill that requires observing and processing a large amount of data. That data can be short, medium and long according to need of forecasting. It is complicated and often hard to do. Weather systems can be as small, brief thunderstorms with a diameter of a few miles that last a few hours to large rain and snow storms with a diameter of a thousand miles that last for days. We can measure different attributes of weather such as precipitation, dew point, snow hailing, ozone layers, wind speed, wind direction, humidity, temperature, air pressure, temperature of ozone layer, wind gust intensity, precipitation rates, solar radiation, relative humidity etc.

The future of weather prediction holds promising avenues for improvement and innovation based on recent research findings. Deep learning algorithms, particularly in air quality forecasting, present opportunities for advancements, although challenges such as missing algorithm descriptions and low accuracy levels. Weather forecasting models are evolving with a comprehensive analysis of various methods, including deep neural networks (DNN), recurrent neural networks (RNN), and stacked denoising autoencoders (SDAE). Strategies for predicting renewable energy systems, especially in the smart grid, require a deeper understanding of atmospheric mechanics and consideration of Newton's laws of dynamics. Advanced models like the WPD-CNN, LSTM-CNN, are demonstrating effectiveness in wind speed time series forecasting, although improvements in accuracy and dimensionality are still necessary. Agriculture, a dominant area in weather forecasting, demands the collection of reliable big data to detect crop health issues early. Quantum technologies, such as Quantum Neural Networks (QNN), show promise in creating accurate and ultrafast smart grid weather prediction models, although regional reliability and broader range application need attention. Machine learning models utilizing historical data from multiple weather stations are proving accurate and could be further enhanced with additional sensors and the implementation of deep learning algorithms. Research on forecasting high and low temperatures highlights the importance of considering longer weather patterns for minimizing biases in functional regression models. Deep learning's potential to substitute for numerical weather models and data assimilation techniques suggests a shift towards more accurate real-time predictions. Time series forecasting methods, especially for weather derivatives, offer room for enhancement, emphasizing the need for enriched datasets and improved variance dynamics. Innovative techniques like long-term and short-term memory (LSTM) models showcase potential in capturing the dynamics of weather parameters and system indicators, signaling a future where causal links are explored. As climate change affects future generations, incorporating woody areas and addressing staff discrepancies through LSTM and regression algorithms becomes critical for accurate weather prediction. Overall, the future of weather prediction lies in addressing current limitations, embracing diverse technologies, and leveraging advanced algorithms to enhance accuracy and reliability across various domains.

VII. CONCLUSION

In the context of global warming, the uncertainty surrounding climate changes and their impact on vital factors such as agriculture necessitates proactive measures. Having insights into upcoming weather conditions becomes crucial for making informed decisions. Accuracy in weather forecasting is of utmost importance and holds significant economic benefits. The relevance of weather forecasting and monitoring has increased, especially with the advancements in technology. Modern techniques, including machine learning and data science algorithms, contribute substantially to accurate predictions. This study highlights the practical use and application of weather forecasting technology, envisioning its role in developing prediction tools and websites. weather forecasting is one of the major fields for researchers. This is the field which includes human daily routines, agriculture and crop production, harvesting, sowing, weeding, aviation, water Conveyance, fisheries, irrigation, hydro power projects, armed jobs, natural adversities, loading of food grains, security of livestock, food production, nautical and sea nourishment and individual comfort zones are all greatly influenced by the weather. Planning for the present and the future involves a lot of forecasting techniques over short range, medium range and large range. Distinct sort of models has been proposed according to horizontal and vertical distance of atmosphere. Attributes such as dew points, wind speed, humidity, temperature, air pressure, temperature of ozone layer, wind direction, wind gust intensity, precipitation rates, solar radiation
, relative humidity etc. have been measured by using mentioned technologies of ancient methods and contemporary methods including machine learning and deep learning. Depending upon results has been shown in different papers. Therefore, there are other factors that could have a significant impact on the forecasting result can be considered in mind to bring out more accurate result using reliable and real data set using appropriate hybrid models.

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