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A Comprehensive Review of Artificial Intelligence and Machine Learning to Overcome Globalwarming Impacts

Sajjad Sohail[1], Sharjeel Tariq[2] , M. Junaid Arshad[3]
[1,2,3]Department of Computer Science, University of Engineering and Technology, Lahore
[1]sajjadjutt987@gmail.com, [2]2022mscs225@student.uet.edu.pk

***Abstract*— Advances in technology have transformed the way we understand and respond to weather patterns, leading to significant improvements in forecasting and climate change mitigation. Historically, weather prediction played a crucial role in agriculture and human migration, but it has faced numerous challenges due to data ambiguity and the limitations of traditional numerical weather prediction (NWP) models. However, with the emergence of machine learning (ML), deep learning (DL), and the Internet of Things (IoT), new opportunities for more accurate and timely weather predictions have arisen. These advancements hold the potential to protect crops, alert farmers to adverse conditions, and contribute to climate change mitigation strategies. Machine learning and artificial intelligence (AI) methods have been integrated into weather forecasting to enhance prediction accuracy. Techniques such as neural networks, motion detection, and computer vision are applied to analyze vast datasets, providing more precise environmental monitoring. Innovations in IoT, along with machine learning models, offer the ability to detect changes in weather conditions in real-time, leading to more responsive forecasting. In this comprehensive review, we explore various deep learning, machine learning, and IoT-based approaches that are employed to improve weather prediction and analyze their comparative effectiveness. By examining these advanced methods, we aim to highlight their role in combating the impacts of global warming and supporting sustainable practices. The review also underscores how AI and ML techniques contribute to mitigating the consequences of climate change, enabling a proactive approach to safeguarding the environment and addressing global challenges.**

***Index Terms*— Machine Learning, Deep Learning, Weather Prediction, Weather Forecast, IoT, Python and Artificial Neural Network**

I. Introduction

WEATHER forecasting involves predicting future weather conditions using principles from physics, mathematical models, statistical analysis, and geographic information such as latitude. Since ancient times, humans have adapted to their environment by forecasting the weather to prepare for various conditions. Weather elements like humidity, precipitation, temperature, and wind can significantly impact our daily lives, and adjusting to these elements is crucial for well-being.

Advancements in technology, such as Internet of Things (IoT) sensors, have simplified the process of monitoring and reacting to weather changes. For example, solar panels can capture and store energy during sunny days, which can then be used to power wind turbines and other equipment, ultimately benefiting agricultural practices. This integration of technology and weather forecasting allows for more efficient and sustainable ways to manage environmental changes.

Machine learning is a branch of artificial intelligence that focuses on developing systems that can learn and evolve from experience, without the need for explicit programming. This self-improving capability offers a more reliable alternative to traditional human-based processes, which are prone to errors. In weather forecasting, machine learning algorithms analyze historical data to make future predictions, with ensemble learning emerging as a popular technique for climate and weather forecasting [1]. This approach relies on large datasets instead of physical processes, enabling the system to detect patterns and predict weather conditions with greater accuracy.

Weather forecasting has a wide range of applications, from agriculture and tourism to aviation and disaster preparedness. However, it also faces challenges, such as handling massive amounts of weather data and building robust predictive models that can identify and use underlying structural trends [2]. The explosion of weather observation data and advancements in information and computer technology over the past decade have motivated researchers to explore innovative methods for weather prediction.

As global warming and climate change continue to impact our planet, the need for accurate weather forecasting has become more critical to mitigate risks and respond to climate-related disasters. Artificial intelligence and machine learning provide powerful tools to analyze vast datasets and make predictions that can help address these challenges. Between 2000 and 2012, the world saw approximately $1.7 trillion in economic losses and nearly 2.9 billion people affected by climate-related events, underscoring the importance of improved weather forecasting in reducing the impact of global warming and other climatic shift [21].

II. Related Work

A. *Challenges in Weather Forecasting*

In the last decade, numerous significant efforts have addressed weather forecasting challenges through statistical modeling, including machine learning techniques, with promising outcomes. These initiatives have employed both manual and automated learning approaches. Weather forecasting data generally comprise high-dimensional time series collected from weather stations across different geographic regions.

Several research studies have explored various neural network models to enhance weather forecasting accuracy. For example, Recurrent Neural Network (RNN) models have been used to predict annual runoff in specific regions. Chen and Hwang'[l] research introduces a fuzzy time series model for temperature prediction, utilizing historical data translated into linguistic values for analysis. In another study, researchers found that a collection of artificial neural networks (ANNs) could effectively learn weather patterns by leveraging ANN features to statistically downscale rainfall forecasts. Additionally, a separate study proposed a chaotic oscillatory-based neural network to analyze Light Detection and Ranging (LIDAR) data for weather-related insights.

B. *Recurrent Neural Network*

Recurrent neural networks, or RNNs, are a specialized form of artificial neural networks designed for processing time series data and sequences. A distinct type of RNN is the Elman network, which can have multiple hidden layers. Each hidden layer receives its weights from the layer preceding it, starting with the initial layer that connects to the input. This structure allows information to flow not only forward but also back to earlier layers, creating a form of recurrence.

Elman networks use activation functions, which can vary but typically exhibit continuity and the ability to reach defined output values. The recurrent aspect of these networks allows for context preservation across time steps; specifically, the delay between the input of a previous hidden layer (at time \(t - 1 \)) and the current input (at time \(t \)) creates a dynamic where past information informs current processing. This recurrent connection inherently involves a feedback loop, allowing the network to adjust and accommodate potential noise or interference in the input data. Consequently, RNNs are particularly useful for tasks requiring temporal context, like sequence prediction and time-dependent pattern recognition.

C. *Data Collections*

The ENSO (El Niño Southern Oscillation) dataset contains key environmental indicators used to study climate patterns and weather fluctuations. This dataset includes various components such as wind patterns, the Southern Oscillation Index, sea surface temperature measurements, and data on outgoing longwave radiation. These elements are crucial for understanding the complex dynamics of ENSO, a climate phenomenon with significant impacts on global weather patterns.

Several international organizations are responsible for collecting and disseminating this data, with the National Weather Service's Center for Environmental Prediction Climate, part of NOAA (National Oceanic and Atmospheric Administration), being one of the leading providers. This dataset is used by researchers and meteorologists worldwide to predict weather trends, monitor climate change, and study the broader effects of ENSO on global weather systems.

D. *Convolution Network (CN)*

Convolutional network (CN) models and similar architectures are inspired by biological systems, reflecting aspects of how the human brain processes information. According to B.1 & Heryadi [4], a deep CN architecture typically consists of multiple stages. In CN applications using color images as input, the feature map domain is usually a 2D array that represents one of the color channels of the input image. For audio data, feature maps are often structured as 1D arrays, while for video or volumetric images, the feature map domain can be a 3D array. This flexibility allows convolutional networks to process various types of data effectively, adapting to the specific requirements of each input format. The multi-stage structure of CN models facilitates hierarchical feature extraction, with each stage learning increasingly complex representations from the input data.

III. Literature Review

Traditionally, future weather states are forecasted by integrating the governing partial differential equations (PDEs) that represent the current weather conditions. This method has long been the foundation of weather prediction. These nonlinear PDEs encapsulate the atmospheric processes related to motion, heat, radiation, and chemistry. To obtain numerical solutions to these PDEs, spatial and temporal discretization techniques are applied.

Numerical Weather Prediction (NWP) models use these equations to predict a range of meteorological variables, such as temperature, wind speed, precipitation, and sea level pressure. The process generally involves several key steps:

Data Collection: Gathering datasets from remote sensing sources, such as satellites and weather stations.

Data Preprocessing: Using a data assimilation system to clean and refine the raw datasets, ensuring they meet quality control standards.

Modeling and Prediction: Feeding the processed data into machine learning models to generate precise weather forecasts.

Data Visualization: Displaying the results in a comprehensible format for further analysis and interpretation.

These steps constitute a generalized approach to numerical weather prediction, integrating traditional meteorological techniques with modern data processing and machine learning to enhance forecast accuracy and reliability.

A. *Machine Learning and Deep Learning Techniques*

DLWP, or Data-Driven Long-term Weather Prediction, represents an approach that relies on data-centric methodologies. Instead of traditional physics-based numerical weather prediction models, DLWP employs deep neural networks (DNNs) to analyze large-scale datasets. These DNN models are designed to uncover underlying patterns, relationships, and correlations within the data, allowing them to capture the dynamics of weather phenomena.

By feeding original datasets into DNN models, DLWP aims to derive meaningful insights into weather changes from vast amounts of meteorological data. The effectiveness of this approach depends on the choice of neural network architecture, which can vary based on the specific characteristics of the meteorological data. Some models might excel at capturing temporal patterns, while others are better suited for spatial correlations.

The exploration of the most suitable DNN models for various data types is a key aspect of this approach. Researchers assess different architectures to determine which ones are most effective for specific weather-related tasks. This investigation involves considering unique meteorological data features, such as time series trends, spatial patterns, and multi-dimensionality, to optimize the performance and accuracy of weather prediction.

DLWP's data-driven nature provides an alternative to conventional weather forecasting methods, leveraging the computational power of deep learning to improve the precision and reliability of weather predictions. The ongoing research in this area focuses on identifying the most appropriate models for each dataset and refining the techniques to enhance predictive capabilities.

B. Multi-layered datasets

Temperature data at a specific location and moment can be represented by a four-dimensional array, with real-type values, structured as form t (longitude, latitude, level, time). This multidimensional representation allows for a detailed analysis of temperature across various geographic and temporal scales.

Meteorological data, derived from in-situ observations and model simulations, often exhibit multi-resolution and multidimensional characteristics, ranging from one-dimensional to four-dimensional arrays. The complexity of these datasets can pose significant challenges in terms of processing and analysis.

Autoencoders, a type of neural network, are commonly used to reduce dimensionality in complex datasets. These models are particularly well-suited for handling high-dimensional, real-type data, offering a way to compress and simplify information while preserving key features. In meteorology, autoencoders and their variants play an important role in processing large-scale, complex datasets, enabling more efficient data analysis and supporting a range of applications, from weather forecasting to climate research. Their ability to reduce dimensionality helps address computational challenges while maintaining the essential structure and information contained in the original data.

C. Satellite photography datasets

Remote sensing data, like images from meteorological satellites, currently generate hundreds of gigabytes of information each day. This data is vital for weather forecasting, especially when identifying extreme weather conditions. Convolutional Neural Networks (CNNs) are a subset of deep neural networks designed for feature representation in image processing tasks. They are particularly effective in handling large-scale image data due to their structure, which involves sharing convolutional kernel weights among neurons and applying pooling functions to reduce the number of hyperparameters in each hidden layer. This design helps to minimize the risk of overfitting and avoid falling into local optima during training.

Because of these characteristics, CNNs have become widely used in weather forecasting applications, where they excel at processing complex satellite imagery to detect patterns and anomalies. Their ability to recognize features within images makes them ideal for analyzing weather-related data and identifying extreme weather events. By leveraging CNNs, meteorologists can improve the accuracy of weather forecasts and enhance early warning systems for severe weather, ultimately contributing to better disaster preparedness and public safety.

D. Fully Driven Hybrid Architectures

Meteorological data exhibit both geographical and temporal structures, suggesting that data-driven weather prediction can be formulated as a sequence problem to capture spatial and temporal elements in weather datasets. To address this, hybrid architectures are used, combining different deep learning techniques to process complex meteorological data effectively. These architectures aim to harness the strengths of different models to improve weather forecasting accuracy and efficiency.

E. Current Weather and Predicted Weather

Lee, G. H. presents a Convolutional LSTM (ConvLSTM) network designed for precipitation nowcasting, where convolutional operations are applied in both input-to-state and state-to-state transitions. This architecture incorporates a prediction network and an encoding network. Unlike traditional fully connected LSTMs, ConvLSTM leverages convolutional structures to encode spatiotemporal relationships in meteorological data, enhancing weather forecast accuracy. Although ConvLSTM's structure doesn't inherently rely on specific locations, the Trajectory-Gated Recurrent Unit (TrajGRU) is proposed to account for location-based variations in natural motion and transformations. TrajGRU dynamically creates a local neighborhood set for each position and timestamp using the current input and previous state, allowing it to capture complex spatiotemporal correlations in meteorological data.

F. Upcoming Weather Disaster Prediction

Weather disaster prediction, such as forecasting extreme weather events, has similarities to flood disaster prediction because both rely on analyzing datasets with analogous patterns. The overlap in data characteristics allows for cross-application of predictive models, enabling disaster preparedness and mitigation. By identifying commonalities between these different datasets, researchers can apply similar techniques to predict and manage the risks associated with weather-related disasters.

IV. METHODOLOGY

Various machine learning models are used for weather prediction. Among them, several key structures and architectures have emerged:

Core Deep Neural Network (DNN) Models: These include basic architectures such as Autoencoders, Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) networks. These foundational models are utilized to analyze and predict weather patterns.

Fully Data-Driven Hybrid Architectures: These models are built on fundamental DNN structures and aim to capture more intricate temporal and spatial characteristics. They combine various DNN approaches to address the complexities of weather data.

Combined Data-Driven and Theory-Guided Models: These architectures merge data-driven approaches with traditional Numerical Weather Prediction (NWP) methodologies, blending the flexibility of deep learning with theoretical underpinnings. This hybrid approach seeks to enhance the predictive power of weather models.

1) Upgrading DNN Models with Theoretical Information

Traditional mathematical models in weather prediction rely on foundational theoretical principles, including Newton's second law of motion, the law of conservation of mass, the first law of thermodynamics, the ideal gas law, and hydrostatic equilibrium. These principles underpin Numerical Weather Prediction (NWP) models, allowing them to simultaneously capture the spatial-temporal dynamics of various meteorological components and consider the interactions among different weather-related variables. As a result, traditional models can simulate many critical aspects of observed weather and climate [6].

In contrast, data-driven Deep Neural Network (DNN) models can sometimes struggle to capture the complex causality inherent in weather and climate systems because they primarily rely on empirical data. This can lead to challenges when modeling the entire intricate framework of climate and weather without understanding the underlying principles.

One approach to enhance DNN models is to incorporate scientific prior knowledge as constraints during training. This integration can help ensure physical consistency and improve the interpretability of DNN-based models. By embedding theoretical information into DNN models, it's possible to bridge the gap between purely data-driven approaches and traditional theoretical models, creating a more robust and reliable framework for weather prediction. This hybrid approach can lead to more accurate forecasts and a deeper understanding of the causal relationships in meteorological and climate systems.

2) Approaches to Integrate LSTM Autoencoders with Weather Prediction Models

Based on the Long Short-Term Memory (LSTM) Autoencoder approach [7], Wang et al. [8] frame the problem of weather forecasting as an end-to-end deep learning (DL) challenge and propose an efficient data fusion system. This system learns from historical weather data while integrating prior information from Numerical Weather Prediction (NWP), allowing it to predict a range of meteorological variables. Using a unique loss function based on negative log-probability error, this approach enables both single-value forecasting and uncertainty estimation. This innovative method merges DNN with traditional NWP to create a more effective weather forecasting system.

To address real-time series forecasting, the authors of [9] designed a neural network architecture to predict meteorological conditions, focusing on a multi-layer perceptron neural network. Leveraging the European Centre for Medium-Range Weather Forecasts (ECMWF) data collection and specific sensor parameters, this architecture provides real-time, high-precision outputs. This design is instrumental in delivering accurate weather forecasts and allows for more effective handling of complex time-series data. By combining deep learning models like LSTM Autoencoders with NWP, these approaches offer a promising path for improving weather forecasting. Integrating data-driven methods with established numerical weather prediction techniques creates a hybrid system capable of predicting meteorological conditions with greater accuracy and reliability. This fusion of approaches is particularly useful for handling uncertainty in weather forecasts and delivering real-time results.

3) Refining Results of DNN with Theoretical Constraints

Grover et al. propose a hybrid architecture designed to capture the spatial-temporal relationships among meteorological variables. This architecture is built upon three key components:

i. Base-Up Predictors: A group of base-up predictors for each weather characteristic, trained using accurate data. This approach helps to capture the essential trends and patterns within the data.
ii. Physical Constraints: The outputs of these predictors are constrained by physical laws to ensure spatial smoothness. This component introduces theoretical knowledge, grounding the predictions in known physical principles, thereby increasing the model's reliability.
iii. Deep Belief Network (DBN): The final section consists of a hierarchical deep belief network (DBN), which comprises layers of stacked Restricted Boltzmann Machines (RBM). This component models the joint statistical relationships among different meteorological variables, providing a higher-level view of the data structure.

By combining these three components, this hybrid approach allows for better refinement of predictive models, accommodating spatial relationships and physical constraints. The inclusion of DBN provides the advantage of capturing longer-range conditions across space, enhancing the model's ability to generalize and make more accurate predictions for large-scale phenomena.

This refined architecture improves upon traditional data-driven models by integrating domain-specific knowledge and statistical modeling techniques. By incorporating physical constraints and high-level joint relationships, this approach ensures that the resulting predictions align with known meteorological principles, thereby contributing to more robust and reliable weather forecasting.

4) Machine Learning-driven mathematical model development

The computational demands of Numerical Weather Prediction (NWP) have grown significantly due to the increasing volume of meteorological data and the ongoing push for higher model resolutions. These rising computational requirements have created challenges for traditional NWP methods, potentially leading to bottlenecks and decreased efficiency.

Deep Neural Network (DNN) models offer an alternative approach by "learning" system behaviors through data-driven techniques, eliminating the need to solve complex partial differential equations (PDEs). This ability to model weather-related processes quickly and efficiently can help overcome some of the limitations of traditional NWP.

A trained DNN can serve as a substitute for a specific module or process within NWP models, either improving the accuracy or the computational feasibility of the overall system. By replicating specific cycles or components, DNNs can offer a more streamlined and adaptive approach to weather prediction, reducing the burden on computational resources while maintaining or enhancing forecast accuracy.

5) Convolutional Neural Networks and Artificial Neural Networks

Artificial neural networks fundamentally consist of a series of nonlinear functions applied to input data, resulting in one or more output variables. Convolutional Neural Networks (CNNs) represent a specialized subset of artificial neural networks that are extensively used in deep learning applications. They gained significant recognition in 2012 for their breakthrough performance, especially in image recognition tasks, and have since become a leading approach in several fields, including weather forecasting and meteorological analysis.

When dealing with meteorological data presented on regular 2-D grids, standard CNN architectures developed for image recognition tasks can be directly applied. This is because the spatial structure of weather data aligns well with the design of CNNs, which excel at capturing spatial patterns and features. Unlike other approaches, such as multi-linear regression, CNNs do not require dimensionality reduction, making them particularly well-suited for processing complex meteorological data.

The ability to apply CNNs directly to meteorological data provides a significant advantage in weather forecasting, allowing researchers to leverage advanced deep learning techniques to analyze and predict weather patterns with greater accuracy and efficiency. This direct application underscores the flexibility and robustness of CNNs in handling various types of data, supporting their growing popularity in the field of meteorology and beyond.

6) Weather Pattern Segmentation

Recent studies have shown that the accuracy and propagation of medium-range weather forecasts over Europe depend on initial meteorological conditions in the Euro-Atlantic region. Researchers examined four weather patterns identified through k-means clustering of the first ten Empirical Orthogonal Functions (EOFs) of the 500hPa geopotential height field. These patterns resemble well-known atmospheric configurations, such as NAO+, NAO-, Atlantic Ridge, and Blocking streams. This raises the question of whether these weather patterns can be used as indicators of forecast reliability.

To investigate, researchers computed the average spread for each of the four weather patterns based on their training data. They then used this information to gauge the likely consistency of forecasts by measuring how far each pattern's spread was from current weather conditions. For each test day, forecasts were made by comparing the calculated mean distance to the current weather conditions, providing insights into forecast consistency.

7) Results

This section presents the outcomes of our machine learning (ML) approach. We begin by examining the discrepancy between the expected and actual model spread. Next, we assess how well our forecasts can distinguish days with significant errors from those with more accurate assumptions. We evaluate the effectiveness of our approach relative to the time spent preparing the dataset.

Following this, we measure the performance of our method against traditional techniques as outlined in the "Methodologies" section. This comparison allows us to gauge the improvement our ML strategy offers over conventional approaches. By covering these elements, we aim to provide a comprehensive overview of the strengths and limitations of our ML-based forecasting system.

8) Diagnosing Forecast Errors

To illustrate the usability advantage of analyzing correlations (e.g., "uncertainty predictions with a correlation of X or higher with model spread are preferred"), we examine how well our uncertainty forecasts distinguish between days with high and low forecast errors. This approach involves assessing the relationship between spread (forecast uncertainty given by ensemble models) and the actual forecast skill (measured by error).

While scatterplots of spread versus error offer a basic view, they can be misleading due to the reported inverse correlation between consistency and forecast error. To mitigate this, forecasts are grouped into "bins" based on their spread, with each bin containing about 300 data points. This technique helps smooth out noise and makes interpreting trends easier, though there can be some leveling off at the higher and lower percentiles.

A robust measure of forecast uncertainty is indicated by a consistent increase in average error with rising predicted uncertainty. Our analysis shows that the network trained on spread largely exhibits this characteristic, with a minor dip in the middle range and some leveling at high uncertainty. The network trained on error displays a similar pattern, suggesting that both approaches are effective at indicating forecast uncertainty. Overall, these findings align with prior results indicating that both training methods yield comparable performance in forecasting uncertainty, validating their use as reliable indicators of weather forecast uncertainty.

9) Comparing with Standard Reference Methods

To gauge the effectiveness of our method and understand its performance across various scenarios, we compare our results with those from the benchmark methods detailed in Section 3.2. We examine the correlation between predicted uncertainties from our models and the GEFS forecast ensemble spread for lead days 3 to 6. Additionally, we assess the F1 score to evaluate the accuracy in classifying forecast errors. Figure 11 illustrates the outcomes of this analysis.

Overall, our approach significantly outperforms a broad range of other methods across various lead times, both in terms of its correlation with forecast spread and its ability to describe forecast error [11]. The nearest neighbor method demonstrates a weak to moderate correlation with the ensemble spread for days 3 and 4 but shows no significant correlation on days 5 and 6. The local method exhibits consistent, albeit low, correlation across all lead times except day 6. Clustering techniques perform poorly for short lead times but improve at day 6, approaching the skill of our spread-trained neural network. Overall, the baseline methods perform well, but our approach consistently demonstrates superior skill, especially in terms of correlation and forecast error correction.

V. Final Results

A) Outcomes of Experiments under Low-Moisture Conditions

In 2012, a widespread drought in the United States led to a significant reduction in corn yields, dropping by about 22.5%. To understand how this drought impacted the accuracy of yield forecasts, we used six artificial intelligence models to predict corn yields, utilizing a spatiotemporal coordinate database.

The actual and predicted corn yields for the study period were analyzed, with red dots representing data from the exceptionally dry 2012 season and black dots indicating all other years. The Deep Neural Network (DNN) model displayed the most accurate results, with minimal deviation from the ideal 1:1 line. In contrast, the other five models exhibited greater variability and slight judgment errors, indicating that they struggled to adapt to the extreme drought conditions in 2012.

The DNN model, however, managed to provide predictions that closely aligned with actual yield statistics, suggesting it effectively avoided overfitting and handled exceptions well. The accompanying figure illustrates both the actual and predicted corn yields, highlighting the errors in predictions from the leave-one-year-out blind tests conducted for 2006-2015. While 2012's corn yields were lower due to the drought, the DNN model's prediction accuracy remained consistent with results from other, more typical years.

B) Data from Experiments Conducted During Heatwaves

We conducted sensitivity tests to assess how well six AI models could predict crop yields during varying durations of heatwaves. These tests helped gauge the models' accuracy when subjected to heatwaves lasting between three and fifteen days. Using six different AI models, we computed the accuracy metrics for predicting corn yields under these heatwave conditions.

The accuracy of the other five models decreased over time. The DNN model showed a mean absolute error (MAE) of 0.781 tons per hectare for heatwaves longer than five days, whereas the other models exhibited MAE values ranging from 1.068 to 1.352 tons per hectare. The DNN model's root mean square error (RMSE) was 1.033 tons per hectare, while the RMSE for the other models ranged from 1.345 to 1.776 tons per hectare, indicating a 30-72% improvement in precision by the DNN model. This indicates that the DNN model effectively handled varying heatwave conditions.

C) Weather Event Typology

To evaluate the proposed weather event classification model, we used the Los Angeles weather history dataset and the J48 implementation of C4.5, employing various cross-validation methods like 5-fold, 10-fold, and 20-fold, as well as random splits, such as 50-50, 60%-40%, and 70%-30%. We compared the performance of the C4.5 classifier against a classic learning algorithm, Naive Bayes, and presented the results in [14].

Each experiment was run multiple times with different random seeds, averaging results over 20 experimental runs. To assess the performance, we computed metrics like accuracy, precision, recall, and F-score for each weather event class. Higher values for these metrics indicate better performance in classifying weather events.

D) Limited information

Traditional weather prediction models rely heavily on data from radiosonde imaging. However, the number of radio stations worldwide has decreased in recent years. Advanced countries are investing more in launching satellites than deploying weather balloons. While satellite data is globally abundant, data integration specialists still face challenges in effectively processing this information for use in weather models. Additionally, critical atmospheric variables, especially those over the oceans, remain challenging to capture. As a result, the accuracy of weather prediction models depends significantly on the quality and completeness of their source data.

E) Anticipating Rainfall Over the Coming Days

This study examines time-series data from five major UK cities to evaluate three different LSTM-based neural network architectures for predicting 8-hour precipitation volumes. Specifically, it compares models based on LSTM Networks, Stacked-LSTM Networks, and Bidirectional-LSTM Networks with an XGBoost decision tree algorithm and a model derived from AutoML. The experimental procedure is as follows:

Build an XGBoost model for each of the five datasets as a baseline, with a limited hyperparameter search to determine optimal values.

Use an AutoML tool to evaluate various regression algorithms, selecting the best-performing model for each dataset.

Construct two models based on LSTM Networks and one model based on Stacked-LSTM Networks, with non-comprehensive hyperparameter tuning for each dataset.

Identify the best-performing model from the previous step and construct two Stacked-LSTM models and one Bidirectional-LSTM model.

The performance of these algorithms can be influenced by various design choices, including the values of parameters and hyperparameters. Although each dataset underwent a non-comprehensive hyperparameter tuning process, it was outside the scope of this study to identify the optimal values for each precipitation forecasting model's parameters and hyperparameters.

F) Support Vector Machine (SVM)

Support vector machines (SVMs), rooted in the Vapnik-Chernoverkis theory, are widely utilized for prediction, classification, and regression analysis due to their ability to address non-linear problems effectively. Unlike many other machine learning models, SVMs can operate as comprehensive classifiers and handle instances with limited training data. Here's a summary of how SVMs operate and their predictive capabilities:

Data Processing: The initial step involves adjusting the data to fit the SVM structure. If the input contains categorical attributes, it must be converted to numerical format. Additionally, data scaling is crucial to streamline computation and enhance performance.

Kernel Selection: The SVM's flexibility comes from its various kernel functions, such as linear, polynomial, sigmoid, and radial basis function (RBF). RBF is particularly effective for mapping data to higher-dimensional spaces, allowing SVMs to address complex non-linear relationships.

Avoiding Overfitting: To prevent overfitting, cross-validation and penalty parameters are used. The choice of kernel also plays a role in managing overfitting risks. Linear kernels are preferred when the dataset has a high number of features.

Applications: SVMs have proven reliable in predicting energy consumption, with RBF being the typical choice for energy forecasting. In scenarios with a high number of features, linear kernels might be more suitable. SVMs' versatility and robustness make them a preferred choice for various prediction tasks, such as predicting hourly cooling loads or analyzing relationships between different data points.

Overall, SVMs' ability to address non-linear problems with robustness and flexibility has made them a popular choice for various machine learning applications.

G) Integrated Machine Learning Model

Gartner's 2016 Hype Cycle (Forni and Meulen, 2016) identified that AI technology had peaked in terms of inflated expectations. Given the complexity and extensive testing involved, hybrid AI methods have become more popular. For instance, Greenery et al. (2012) combined traditional analysis with AI techniques to improve the classification and prediction of various compounds. Similarly, Voyant et al. (2017) suggested that a hybrid approach outperforms single predictors for solar radiation forecasting. Marasco and Kontokosta (2016) found that AI technology could rapidly assess energy efficiency when regulatory records decline. Cramer et al. (2017) suggested that AI-based frameworks could help predict rainfall.

In a world of rapidly growing data, the most successful tools will be those that can manage large volumes of information while providing quick responses. Thus, a hybrid AI approach is considered the next major development in the field. By combining different AI techniques, hybrid methods can leverage the strengths of each while minimizing weaknesses. According to Wang et al., hybrid AI can be classified into two types: heterogeneous models that blend different foundational models and homogeneous models that use similar underlying structures (Hao et al., 2018; Wang et al., 2017).

VI. CONCLUSION

Our study examined whether AI techniques could estimate weather conditions and forecast uncertainty based on errors and dispersions from past ensemble predictions. Using a convolutional neural network trained on either the errors from past deterministic weather forecasts or the ensemble spread from earlier group predictions, we found that it is possible to assign a scalar value of reliability or forecast uncertainty to a new climate field. The results suggest that our AI-based approach can effectively indicate forecast uncertainty.

The dataset used, GEFS reforecast v2, is consistently updated, making our approach applicable to operational settings. While our method doesn't perform as well as ensemble spread when predicting forecast errors, it generally surpasses two other methods cited in literature—classification by weather type and persistence in phase space—at lead times up to six days.

However, this approach has a significant limitation: the reliance on past forecast data to train the model. Training takes about 30 minutes with two NVidia K80 GPUs, while inference (feeding an input field to predict uncertainty) requires only seconds, making this method much more cost-effective than running a full ensemble NWP model. In operational settings, the network can be retrained daily to incorporate new data and ensure optimal performance. This approach could be used to gauge the reliability of forecast models and help decide the number of ensemble runs needed, thus improving resource allocation in weather forecasting.

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