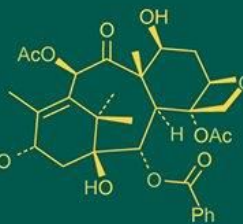
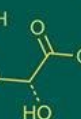
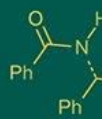


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Applications of machine learning in climate science: Weather prediction and environmental monitoring

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Abstract

The application of machine learning (ML) in climate science is rapidly changing how weather and the environment are measured and predicted. While operating optimally, conventional climate models bear the issues related to the non-linear nature of many natural systems and the presence of high-dimensional data. Here, ML offers a solution to these limitations as it allows a system to assess the dataset's patterns, improve the prediction's reliability, and lower the cost of computations. Neural networks, support vector machines (SVMs), ensemble models, and reinforcement learning enabled short-term and precise long-term predictions of weather and its quantification, including hurricanes, droughts, and floods. Other areas that benefit from ML include monitoring the environment by tracking forest loss, air quality, the water temperature of the ocean, and the level of hazardous emissions into the atmosphere. Extension with the Numerical Weather Prediction models enhances the accuracy of the forecast. There are problems with data quality, the computational expense required, and proper interpretability, but there are solutions involving resource sustainability, renewable energy predictions, and ecological surveys. This paper demonstrates how ML can revolutionize climate science and facilitate climate change mitigation and adaptation worldwide.

Keywords: Artificial intelligence, meteorology, forecasting, environment, artificial neural network, supervised learning, global warming, hazing, resilience, ecology

1. Introduction

1.1 Brief on Machine Learning For Climate Scientists

These diagnostics are inherent in the conventional climate models that have been a foundation of climate studies for quite a long time, characterized by the use of fundamental physical laws and numerical approaches describing the behaviour of the atmospheric layer. These models have been instrumental in studying our planet's weather, climatic oscillations and general secular climate characteristics. However, the models face severe difficulties due to the nature of climate systems, which are inherently complex and characterized by nonlinearity. At multiple fronts within the climate system, such as the atmosphere's chemistry and oceanic currents, the number of exerted processes and back-interactions defines a daunting complexity that might not be fully encompassed through conventional approaches^[10]. On the contrary, machine learning (ML) is acknowledged as a valuable tool that extends the active arsenal of data-driven methodologies in the context of climate models. Decision and prediction-making is another area where ML algorithms perform exceptionally, as they can extract hitherto unknown correlations and relationships within a vast data set that may not be detected in usual statistical modelling. Temperature patterns, for instance, picked by ML models from historical data allow the algorithm to identify complicated patterns that are otherwise hard coded into the programming, and these include fine details of the interactions and effects that can help in the accurate prediction of climate change^[11].

Moreover, the application of machine learning in climate modelling yields the benefit of enhanced prediction performance. Similar to decision-making with very vast sets of data, ML algorithms can help predict complexities in climate models by flagging correlations and variations. For example, neural networks can better describe spontaneous features of atmospheric processes, thus improving the accuracy of weather predictions and climatological scenarios. Moreover, climate simulations are expensive, and ML models help to minimize their computational costs. Most traditional climate models are highly complex structures that can be computationally procedure intensive and require extensive processing

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time in high simulation resolution ^[5]. The ML models can approximate these calculations in a much shorter time. They, therefore, can offer a prediction in a relatively shorter time while not heaving much from the accurate simulations. Such efficiency allows analysis and decisions simultaneously, which is critical for accurate time-based weather forecasting and climate change and its associated risks. Machine learning algorithms in finance enable the identification of anomalies by approximating computationally heavy models, which means that many scenarios can be quickly tested. This capability is beneficial when deciding on the possible consequences of climate interventions or modifying forecasts concerning recent data. Namely, it plays the role of a force multiplier, amplifying the capabilities of conventional climate models and allowing for a more efficient study of the climate systems' characteristics ^[13].

1.2 Processing Vast Environmental Data

Recently, we have been witnessing a flood of data that spawns hundreds of devices such as satellites, ground sensors, and weather stations. These instruments amass various affordances of the environment, including temperature, humidity, wind velocity, and atmosphere composition. One key aspect about this data is that it is big and high dimensional, which is a blessing and a curse for climatologists. A vast amount of new data arises constantly, and in such a case, the most suitable approach is using machine learning techniques to handle and analyze this volume of data. The algorithms inherent in the ML approach work well with high-dimensional data and can process large volumes of information containing many indicators and characteristics. This capability is critical when analyzing multi-parametric climate data in which interrelated functions are non-linear ^[9].

Some data analysis models help to combine linked data drawn from other channels, thus widening the range of collected information. For example, satellite imagery may be combined with ground-based sensors to improve the assessment of certain environmental variables. In addition, various stages show that ML algorithms can address issues on how data resolution, sampling rates, and units are standardized or fused. Due to their ability to go through vast amounts of data, ML algorithms are helpful in revealing features that should help Climate Science progress. It can distinguish relations or patterns that tend to be indiscernible, employing several statistical approaches simply because of the vast quantities of data. For example, by using ML, it is possible to identify preconditions for climate changes, ascertain climate features correlated with certain weather conditions, or define the impact of different variables on climate events. Consequently, applying ML in big data is advantageous for immediate surveillance and prediction ^[11]. Due to the constant stream of data from many sensors and satellites, the projections and analyses from ML models can be made quickly. This real-time processing is essential for timely weather, disaster warnings, and environmental analysis. Moreover, ML algorithms enhance the creation of a foretelling system, which estimates the upcoming climate using past and present climates as samples. These models enable the improvement of long-term climate prognoses and potential future situations with the help of learning from previous patterns. Altogether, using machine learning in climate science offers to combat the issues associated with

the contemporary world's vast and complicated environmental data sets. In fact, from the view of the data we mentioned above, ML offers all the money to cope with high dimensional data, integrate multiple data sources, and derive knowledge to improve our capability of anticipating climate and environmental change ^[5].

2. Weather Prediction Applications

2.1 Machine Learning Techniques for Forecasting Weather Patterns

2.1.1 Neural Networks

Neural networks remain a crucial approach to machine learning methods in weather prediction. These are numerical methods based on the neuronal structure of the human brain designed to learn, analyze and work with high and non-linear data content. Neural networks are linked layers of neurons, or input/output data points, which can discover data features through training. When dealing with weather prediction forecasts, neural networks compute and forecast different climatic parameters, including temperature, relative humidity, wind velocity and pressure. These networks also have the advantage of learning from historical weather data in a way that goes beyond what conventional statistics can find. For instance, a neural network can be trained with meteorological data of the past several decades to forecast the temperatures of a day by identifying how one or the other combination of conditions leads to specific temperatures. Weather prediction is essential, so people always require the accuracy that neural networks can from large data sets with many variables. It can quickly assimilate information from satellite pictures, ground reports, and atmospheric profiles and offers complete forecasts. In addition, improving deep learning models - a branch of neural networks composed of more than one hidden layer - expands these models' ability to find more detailed patterns in output features of the weather data feedstock and, step by step, increase the reliability of predictions ^[19].

2.1.2 Support Vector Machines (SVMs)

A Support Vector Machine (SVM) is a group of supervised learning methods used for classification and regression analysis. They work to locate the best hyperplane that can effectively distinguish between different data classes with the most significant possible distance between them. For categorical weather events, SVMs are helpful in weather forecasting since they do not require a linear boundary between classes, and they're fortified for high-dimension data. SVMs are well suited to predicting discrete weather events like storms, rain or no rain, clear skies, etc. For example, the SVM can be trained to distinguish between "Rainy Day" and "Not Rainy Day" by analyzing atmospheric characteristics such as humidity, pressure and temperature. Thus, reconsidering the examples of the weather defined by the mentioned categories, the SVM extracts the factors that usually predict each weather type. Regarding overfitting the strength of SVMs, they can handle non-linear relationships by using kernel functions that map the input space to a higher dimension where all the inputs can be separated linearly. SVMs usually work on a principle that linearly separates data in the input space, but this feature enables SVMs to work with non-linearly separable weather patterns. Furthermore, it was found that SVMs have a lower risk of overfitting the data, making it appropriate for

predicting other data points not included in the training data set [5].

2.1.3 Ensemble Models

An ensemble is a machine learning model that integrates the feedforward predictions of individual models to enhance the general prognosis. The simple notion is that even though specific models can have a certain level of bias or weakness, bringing their results together will somewhat suppress all such weaknesses. Probabilistic output forms are typical ensemble models and indispensable in weather forecasting. By performing combinations of models, each trained from different portions of data or trained by various algorithms; ensemble methods observe more extensive ranges of climate possibilities. For instance, an ensemble model might use the output of multiple neural networks and or SVM models to make a probability estimate for precipitation. This enhances the reliability of forecasts and, at the same time, minimizes the probabilities of building models which may contain high variability relative to the best model [8].

Nested-ensemble models benefit different complex and non-linear systems like the atmosphere, where slight input variation produces significant output variations. They assist forecasters in evaluating the possibilities of weather outcomes, and this aspect is determinative when deploying, planning, and executing in agriculture, aviation, or the disaster preparedness industry.

2.2 Improving Short-Term and Long-Term Forecasts

Machine learning is essential in improving short-term and long-term weather predictions, using the ability of the models to work with and analyze a large amount of data.

2.2.1 Short-Term Forecasts

In the short-term forecast, which may take several hours, up to 3-7 days, ML models analyze real-time data to forecast near-term changes in the weather. It is important to note that these models take feeds from the current observations in the form of satellite images, radar, weather stations and sensors to change the prediction results with the latest information available. Due to the ML algorithms' speed, accuracy, and efficiency, they can deal with the constant data feed and make instantaneous predictions. For example, they can predict the growth and migration of thunderstorms with the help of current data from radars or meteorological data on the state of the atmosphere. They can forecast short-term changes, such as temperature fluctuations or wind changes, crucial for activities like flying or organizing outdoor events. Short-term forecast accuracy contributes positively to saving lives and minimizing inconvenience due to nasty weather conditions [17].

2.2.2 Long-Term Forecasts

Therefore, long-term Forecasting entails the study of climate characteristics at higher intervals, which may be in weeks, months and even years. Long-term forecasts are incorporated using the ML models to determine patterns and relations from historical climate information related to future conditions [23]. These models can sense signals of phenomena like El Niño or La Niña that favour substantial shifts in global climate. To overlay sea surface temperatures, atmospheric pressure indices, past weather data, etc, through the multivariate database, the advanced scientific accomplishment of ML algorithms in seasonal Forecasting

is invaluable. Such predictions prove helpful, especially in areas like agriculture, where people can predict how many months it will rain or be cold, to enable people to prepare by undertaking serious planting when it is raining or too cold. Also, long-term temperature predictions enable climatic predictions and allow policymakers to make future climatic predictions [8].

2.3 Predicting Extreme Weather Events

One of the most significant challenges of climate science involves predicting extreme events, which is another skill that is well done through machine learning. By applying analytical machine learning tools, the precision of such predictions is improved, including potential indicators of dangerous weather.

2.3.1 Hurricanes and Cyclones

Tropical storms modelled through their formation, future trajectories, and intensity are forecast using machine learning models supported by ocean temperatures, atmospheric characteristics, and past storm patterns. These models can point towards environmental conditions that foster hurricanes, including sea surface temperatures greater than predetermined values and low vertical wind shear. From the previous history of hurricane movements and their strength, the ML can enhance the projection of a storm's movement and possible landing places. The information is crucial for warning, responding to catastrophes, and deploying disaster management strategies. Enhanced intensity predictions assist the government in making necessary preparations in case of storms and other disasters.

2.3.2 Tornadoes

Forecasting tornadoes is problematic since these atmospheric vortices form from a cloud and are short-lived. Finally, based on the implemented machine learning algorithms, meteorological conditions such as instability, wind shear, and other factors that predict tornado formation are evaluated. It is possible to extract signatures that point to tornadoes from radar signals and use the data on the environmental parameters. These predictions come in handy in providing early and accurate information on possible tornadoes, thus saving lives by offering the community more time in search of safety from these storms. Improvements in hurricane forecasts with the help of ML are also used to study the formation mechanism of these tornadoes, which could also contribute to more advanced prediction of tornado conditions [17].

2.3.3 Precipitation Patterns

Data mining methods examine moisture patterns, pressure systems and temperature gradients to forecast major storms and possible flooding occurrences. Due to the ability of the various ML models to map the different relationships and dependencies among different meteorological variables, the models can produce more accurate results regarding the intensity and duration of precipitation. Flood hazard mitigation and managing water-scarce resources, agriculture and water supply are some areas where heavy rain forecasts are significant. ML models can predict the areas prone to flash floods or long-term flooding, thus assisting the authorities in issuing a warning or even preventing it." These forecasts help in infrastructure development and

managing the emergency services, minimizing storms' social-economic effects ^[31].

2.4 Integration with Numerical Weather Prediction (NWP) Models

Combining machine learning with conventional Numerical Weather Prediction (NWP) is an innovation in weather predicting. This combination effectively capitalizes on the strengths of both approaches to improve their expectations and reliability.

2.4.1 Enhanced Performance

NWP models are supported by machine learning models, which fix some of the biases and enhance the resolution of the forecasts. These problems stem from NWP models addressing complex physical equations describing atmospheric physics and are liable to systematic errors produced by approximation techniques. These biases could be learnt through the difference of the actual data from the outputs obtained from the NWP and subsequent modification of the forecasts. For instance, if an NWP model usually produces low-temperature values in some regions under specific circumstances, an ML model can recognize this problem and adjust the follow-up ones. Such synergy leads to more accurate forecasts, especially for temperature parameters, amount of rain, and wind rate. The following diagram gives an instance of this type of integration and points to an intelligent agricultural system with weather forecast and environmental condition monitoring and the ML system to support better decision-making of farming fields ^[15]. This system retrieves data from environmental perceivers, including the soil's pH,

temperature and humidity, and combines it with online weather alerts from external web services. Besides, a control unit processes the data and sends it from the cloud to apply machine learning algorithms like Random Forest to predict appropriate crops. These predictions are freely available on mobiles and web browsers to assist farmers in making the right decisions. Here, health information embodied in sensor data is integrated with weather forecasts and machine learning analysis following the principle of improving the estimates using ML combined with NWP. This example shows that data and forecasts enhance agricultural results in the same way that ML-corrected NWP models generate superior predictions in conventional meteorology ^[33].

2.4.2 Data Assimilation

Data assimilation provides a way of incorporating observational data into the models to correct forecast initialization and forecast itself. This risk should be estimated using the following inputs: Incorporating machine learning yields into NWP models improves the outcome. By using the latest data to refine estimates of atmospheric variables, the ML models assist the NWP models in beginning with a better representation of the current state of the atmosphere. This is particularly effective when the observations are limited or when frequent update is required, such as during extreme weather conditions. ML and NWP models can handle real-time data and obtain the necessary information to provide more frequent forecast updates. The result is a more dynamic and efficient way of generating real-time forecasts, which may help change fast weather patterns.

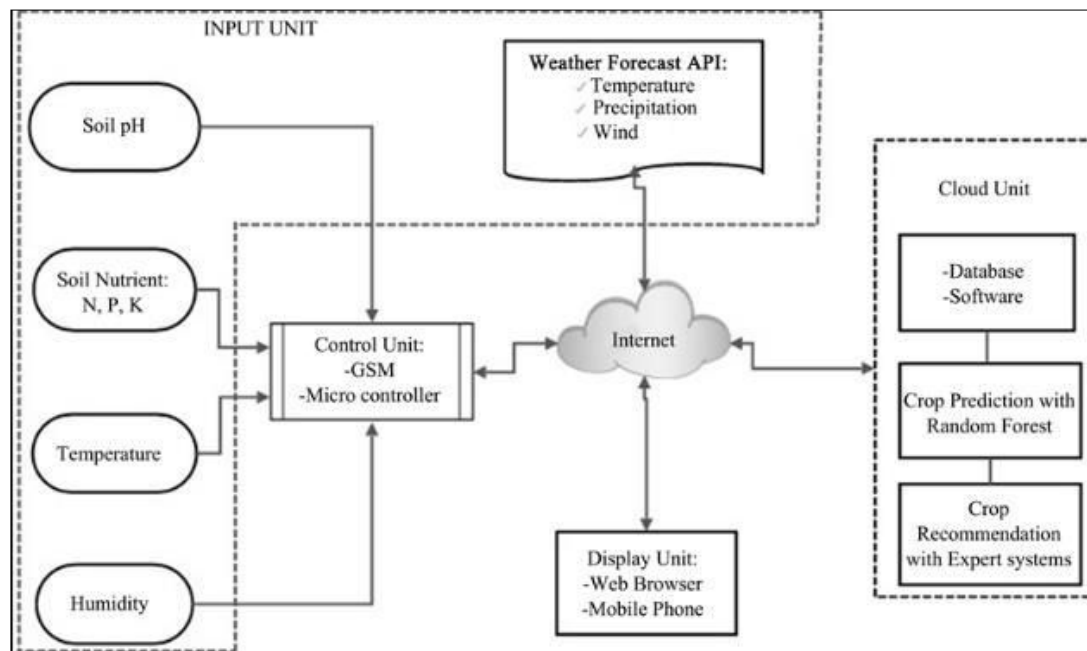


Fig 1: Architecture of IoT-Based Smart Agriculture System with Crop Prediction and Recommendation Framework

Therefore, using machine learning approaches in weather prediction improves the prospects of weather forecasts, the general and specific short-term and long-term outcome prediction, the prediction of spectacular weather conditions, and unity with the usual NWP models. These reflect the improvement of meteorological data, which is crucial for protecting life, resources and revenue and understanding the outcome of climate fluctuations ^[2].

3. Environmental Monitoring Applications

3.1 Tracking and Monitoring Environmental Changes

3.1.1 Deforestation

The models are used to identify changes in forest cover with the help of satellite images. These models identify land use types and differentiate between forested and deforested areas. The ability to collect large amounts of data from satellite imagery means that by applying conventions in

machine learning, one can monitor forests in real time and discover illegitimate logging activities and unauthorized conversion of forests. In this regard, timely data helps the relevant authorities quell further loss of forests through timely intervention and better manage the remaining forests. Applying this approach helps improve the quality of conserving species diversity and stabilizing the balance between species ^[32].

3.1.2 Air Quality

As an air quality forecasting system, the machine learning algorithms predict the amounts of Pollutant Standard Index (PSI) values containing particulate matter (PM2.5) and ozone. The ML models can accurately predict pollution levels by introducing data from air quality sensors, meteorological data, and emission data into an algorithm. This prediction is required in health impact assessments because they inform the public on days that air quality is terrible. Policymakers and environmental agencies can use such data to devise policies and implement measures such as emission standards and encouraging the use of environmentally friendly transport.

3.1.3 Ocean Temperatures

It is precisely with the help of machine learning that we can track the ocean's temperature, which is crucial for climate change. For example, when one examines sea surface temperature records, the occurrence of El Niño or La Niña can be studied using Statistics and Machine Learning models. Thus, these models enable us to understand climate fluctuations by outlining aberrations and trends in sea temperature. Also, ML algorithms forecast alterations to the marine environment, including coral bleaching and species distribution. Marine conservation, fisheries management, and understanding the health state of the aquatic ecosystems require this information significantly.

3.2 Early Warning Systems for Natural Disasters

3.2.1 Droughts

Machine learning models improve watering deficiency using seasonal climatic data such as rainfall deficits, residual soil moisture, temperature deviations, and other data to enhance drought prediction. By specifying the relationships between precipitation variables and the development of drought circumstances, the ML algorithms help determine when and where droughts will appear. Such an ability makes it easier for governments as well as other organizations to undertake measures aimed at ensuring that there is sufficient water in appropriate concentrations as well as to ensure that farming activities are planned around such equal and scarce resources for countries all through in supporting and helping affected communities to cope with the impacts of droughts ^[13].

3.2.2 Wildfires

Wildfire risk prediction evaluates characteristics like fire weeds dryness, climate or weather conditions, elevation, and anthropogenic impact. This data is then fed into machine learning models that detect zones with the risk of being affected by wildfires. These models help firefighting agencies and emergency services to determine the potential wildfire risks and allocate their resources to prevent and prepare the public in the best way possible. It is almost

impossible to avoid wildfire occurrences, but early detection and prediction reduce losses on properties and the environment and loss of lives.

3.2.3 Floods

The machine learning models that reconstruct the river flow and rainfall-runoff approaches enhance the flood prediction. Weather sensors, hydrological data, and data on land use, therefore, enable the ML algorithms to predict floods better. They assist in giving alerts on impending disasters and are helpful in evacuation and putting in place barriers to floods. Flood forecasting plays a core role in disaster preparedness and minimizes the cost and sociology of floods on the people.

3.3 Real-Time Monitoring of Greenhouse Gas Emissions

Machine learning accelerates the objective monitoring and measurement of greenhouse gas emissions generated by industries and naturally produced. Based on data collected through sensors and satellites, ML algorithms bring out the particulars of emissions of gases such as carbon dioxide and methane. This online monitoring is essential for emissions management, providing necessary information to policymakers on the current emissions levels and the impacts of measures put in place. High-quality emission information can support governmental and organizational decisions, help to set reasonable emission goals, and improve policies for meeting climate goals. Applying this aspect of ML makes it easy to monitor the contributions and shenanigans of those involved in dealing with the issue of climate change.

4. Key Machine Learning Techniques Used

4.1 Deep Learning Models for Spatiotemporal Data Analysis

Convolutional Neural Networks (CNNs) extract spatial features from the data on grid-like structures, such as images. It is used most frequently to interpret satellite images to analyze weather and observe and track the physical changes in land and ocean usage patterns. Due to the ability of CNNs to analyze visual information, they provide solutions for pattern recognition and abnormalities in environmental properties, making climate modelling and prediction more accurate ^[3].

Recurrent Neural Networks (RNNs) which learn temporal structures associated with sequential information that is adequate to reason time series data in weather prediction and climatic patterns. RNNs analyze a sequence of one or more data points, or parameters, to determine how climate variables change with time, for instance, daily temperatures. This capability can significantly improve expectations of forthcoming weather by relying on previous records.

4.2 Transfer Learning

When using ground-bottom knowledge to get better results in another related problem, one practice is referred to as transfer learning. In climate science, we can fine-tune our models on large external databases to compensate for lack of data. Another advantage is that by training on existing models of climate trends worldwide, researchers can apply them locally, making the results more accurate without spending a lot of time collecting fresh data.

4.3 Reinforcement Learning

Reinforcement learning is a type of learning that emphasizes policy learning through experimentation with the environment. In complex systems such as climate models, it enhances decision-making processes. For instance, reinforcement learning algorithms can shift some aspects of climate models regarding correcting their continual errors or controlling resources according to the given environment.

5. Challenges in Applying ML to Climate Science

5.1 Data Quality Issues

Data quality is a significant issue in climate science because, for example, upwelling measurements have not been standardized across platforms and time, can be significantly affected by calibration problems and thus may introduce significant errors into data time series. Moreover, the missed information during the records themselves interrupts the modelling and decreases the accuracy of the prognosis. Solving these concerns is a crucial prerequisite for solidifying data preprocessing pipelines and relying more on data validation.

5.2 Limited Availability of Labeled Data

Numerous machine learning techniques use labelled databases, but there is little data on some environmental variables. Obtaining labelled data is usually challenging and time-consuming because it involves experts' help, and the whole process is costly. This limitation is daunting for supervised learning applications in climate science since the approaches may need to be either replaced by unsupervised learning or enhanced with data augmentation [34].

5.3 Need for Explainable ML Models

As for sophisticated models such as deep neural networks, it is hard to determine how they make their decisions. This opacity can negatively affect stakeholder trust as decision-makers need to be confident in adopting ML-based predictions for which they need a clear understanding. Coordination between IT, operational, and policy-making requirements can only be achieved in line with the development of explainable AI models.

5.4 Computational Demands of Large-Scale Models

When large data sets of climate information are used to train machine learning models, sizeable computational and storage resources are called for. This makes them less accessible and scalable, mainly when dealing with expanding data amounts. Qualified resources require intensive system resources, which makes them less dependent on handling expanding data amounts. Solving this problem requires fine-tuning algorithms and high computing environments such as cloud environments and high-performance cluster computation.

5.5 Integrating Heterogeneous Datasets

The Volunteered Geographic Information data from satellites, sensors, and models in different formats and resolutions has led to data fusion issues. Uniform implementation measures are essential to regenerative integration and cooperation, challenging unifying diverse models. Solving these problems requires setting standard procedures and designing complex data analysis procedures.

6. Opportunities and Future Directions

6.1 Improving Sustainability Efforts

Through machine learning tools, the utilization of natural resources can be managed, thus predicting the supplies and demands. They offer knowledge based on relevant facts in formulating environmental policies and standards that guide the world.

6.2 Developing Predictive Frameworks for Climate Change Adaptation

Applying the analysis results, ML models help identify areas and industries that may become most exposed to the effects of climate change, thereby applying adaptation measures where these are required most. They are a tool for scenario building by depicting the possible consequences of various climate prognoses to help develop more sustainable long-term plans and avoid damaging climate change repercussions [19].

6.3 Renewable Energy Forecasting

As for the ML models, they predict the capability of generating energy from renewable sources such as the sun and wind to assist with grid supervision and organizational planning. They also reduce the efficiency of energy storage systems maintenance and loading and enable integration of renewable energy into presently existing power systems, hence making minimal use of fossil fuels.

6.4 Biodiversity Monitoring

Species distribution models help to forecast the change of species' habitats with the help of machine learning due to climate change. These predictions help in the formulation of conservation measures, helping in the identification of endangered species and ecosystems to protect and support the balance of ecosystems. Without balance, species die out [25].

7. Case Studies and Real-World Implementations

7.1 Weather Forecasting Applications

The ML models forecast storms' intensification and movement path in storm tracking. These applications improve warning systems and give earlier and more precise alarms that help in case of emergencies and disasters. Improved forecasts can help decide where to allocate or evacuate in a disaster [32-43].

7.2 Environmental Initiatives

Air quality monitoring systems utilize real-time data analysis driven by ML algorithms to determine the likely pollution levels in the given area and emission source probing. It helps regulatory agencies to monitor pollution sources and to prevent exposure to hazardous pollutants by airing alerts to the general public.

7.3 Collaborative Efforts

Part of the climate services of governmental organizations such as the National Oceanic and Atmospheric Administration (NOAA) is based on machine learning to broaden its abilities to analyze and predict patterns. Scholars at research organizations design new ML approaches to be explicitly used for climate models, providing new scientific findings. IBM and Microsoft are among the computer

technology corporations that have initiated a joint program, such as AI for Earth, implementing new technologies for environmental inquiries and interdisciplinary teamwork^[27].

8. Conclusion

The application of modern and sophisticated computing tools, such as ML, in climatology has changed how weather forecasts and environmental monitoring are performed. It enhances the basic climate models by creating more features, fine-tuning the prediction, and reducing the need for complex computations. These capabilities enhance the ability to produce short-range and long-range forecasts, climate prediction, and climate variation monitoring in real-time, such as air quality and ocean temperatures, the rates of deforestation, and the levels of greenhouse gas emissions. Integration between ML and Numerical Weather Prediction (NWP) models improves the accuracy of future weather forecasts mainly from the same family of models Accurate Models; applications are the Neural Network model, Support Vector Machine model, Ensemble model, and Reinforcement Learning model, among which provide practical solutions to dynamic climatic conditions. However, a few limitations are present, including how to develop high-quality datasets, how much computational complexity is needed, and how to create an interpretable and transparent model for trusting stakeholders. However, there is still much work to be done to achieve the potential of ML for furthering sustainability, Forecasting renewable power production, and adapting to climate change patterns. In the future, climate science will build upon the cooperation of academic and research institutions and governmental and industrial organizations to design high-powered and integrative ML architectures for more responsible climate management and policy. Therefore, machine learning is a helpful approach to intervening in the challenges posed by climate science. In the future, the primary goal of ML will be to contribute to the world's solutions to climate change, improve disaster prevention and management, and make practical use of resources for the development of a sound future that the world needs.

9. References

1. Abbot J, Marohasy J. The application of machine learning for evaluating anthropogenic versus natural climate change. *GeoResJ*. 2017;14:36-46. <https://doi.org/10.1016/j.grj.2017.08.001>.
2. Barque M, *et al*. Improving wind power prediction with retraining machine learning algorithms. In: Proceedings of the 2018 International Workshop on Big Data and Information Security (IWBIS), Jakarta, Indonesia, 12-13 May. 2018:43-48. <https://doi.org/10.1109/IWBIS.2018.8471696>.
3. Belochitski A, Krasnopolsky V. Stable emulation of model physics in a GCM using a neural network. *arXiv*; c2021. Available at: <https://arxiv.org/abs/2103.07028>.
4. Bochenek B, *et al*. Day-ahead wind power forecasting in Poland based on numerical weather prediction. *Energies*. 2021;14(7):2164. <https://doi.org/10.3390/en14072164>.
5. Bodini N, *et al*. Can machine learning improve the representation of turbulent kinetic energy dissipation in complex terrain? *Geosci Model Dev*. 2020;13(9):4271-4285. <https://doi.org/10.5194/gmd-13-4271-2020>.
6. Cho D, *et al*. Comparative assessment of bias correction methods for extreme air temperature forecasts. *Earth Space Sci*. 2020;7(7). <https://doi.org/10.1029/2019EA000740>.
7. Davenport FV, Diffenbaugh NS. Using machine learning to analyze physical causes of climate change: A case study of U.S. Midwest extreme precipitation. *Geophys Res Lett*. 2021;48. <https://doi.org/10.1029/2021GL093787>.
8. Dhall D, Kaur R, Juneja M. Machine learning: A review of the algorithms and its applications. In: Singh PK, Kar AK, Singh Y, Kolekar MH, Tanwar S, editors. *Lecture Notes in Electrical Engineering. Proceedings of the ICRIC, Jammu, India, 8-9 March 2019*. Cham: Springer; c2020. p. 47-63. https://doi.org/10.1007/978-3-030-24051-5_5.
9. Donadio L, Fang J, Porté-Agel F. Numerical weather prediction and artificial neural network coupling for wind energy forecast. *Energies*. 2021;14(2):338. <https://doi.org/10.3390/en14020338>.
10. Dong W, Yang Q, Fang X. Multi-step ahead wind power generation prediction based on hybrid machine learning techniques. *Energies*. 2018;11(8):1975. <https://doi.org/10.3390/en11081975>.
11. Fang Y, *et al*. Classification of Northeast China cold vortex activity paths in early summer based on K-means clustering and their climate impact. *Adv Atmos Sci*. 2021;38:400-412. <https://doi.org/10.1007/s00376-020-0111-y>.
12. Fradkov AL. Early history of machine learning. *IFAC-PapersOnLine*. 2020;53:1385-1390. <https://doi.org/10.1016/j.ifacol.2020.12.589>.
13. Gómez JL, *et al*. Photovoltaic power prediction using artificial neural networks and numerical weather data. *Sustainability*. 2020;12(24):10295. <https://doi.org/10.3390/su122410295>.
14. Harder P, *et al*. Emulating aerosol microphysics with machine learning. *Machine learning in Earth sciences*; c2020.
15. Huang L, *et al*. Solar radiation prediction using different machine learning algorithms and implications for extreme climate events. *Front Earth Sci*. 2021;9:202. <https://doi.org/10.3389/feart.2021.601452>.
16. Iverson LR, Prasad AM, Liaw A. New machine learning tools for predictive vegetation mapping after climate change. In: Smithers R, editor. *Landscape Ecology of Trees and Forests. Proceedings of the 12th Annual IALE (UK) Conference, Cirencester, UK, 21-24 June*. Piastany: IALE; c2004. p. 317-320.
17. Kim D, Hur J. Short-term probabilistic forecasting of wind energy resources using the enhanced ensemble method. *Energy*. 2018;157:211-226. <https://doi.org/10.1016/j.energy.2018.04.092>.
18. Kirkwood C, *et al*. A framework for probabilistic weather forecast post-processing across models using machine learning. *Philos Trans A Math Phys Eng Sci*. 2021;379(2194):20200099. <https://doi.org/10.1098/rsta.2020.0099>.
19. Kosovic B, *et al*. A comprehensive wind power forecasting system integrating artificial intelligence and numerical weather prediction. *Energies*. 2020;13(6):1372. <https://doi.org/10.3390/en13061372>.

20. Ma Y-J, Zhai M-Y. A dual-step integrated machine learning model for 24h-ahead wind energy generation prediction. *Appl Sci.* 2019;9(10):2125. <https://doi.org/10.3390/app9102125>.
21. Mahesh B. Machine learning algorithms—a review. *Int J Sci Res*; c2019.
22. Mathe J, *et al.* PVNet: A LRCN architecture for spatio-temporal photovoltaic power forecasting from numerical weather prediction. *arXiv*; c2020. Available at: <https://arxiv.org/abs/1902.01453>.
23. Mellit A. An overview on machine learning and deep learning applications for photovoltaic forecasting. In: Hajji B, *et al.*, editors. *Proceedings of the 2nd International Conference on Electronic Engineering and Renewable Energy Systems*, Saidia, Morocco, 13-15 April 2020. Singapore: Springer; c2020. p. 55-68. https://doi.org/10.1007/978-981-15-2329-8_6.
24. R Core Team. R: A language and environment for statistical computing. Vienna: R Foundation for Statistical Computing; c2017. Available at: <https://www.R-project.org/> [Accessed 17 Dec 2021].
25. Safdar EA, Safdar NA, Khan PA. A survey to assess knowledge attitude practice of people towards vitamin D. *Acta Tradit Med.* 2023;2(01):27-34. <https://doi.org/10.5281/zenodo.8282626>.
26. Khambalkar PA, Yadav SS, Sadawarti MJ, Shivansh. Innovative use of algae for carbon sequestration and renewable energy generation. *Environ Rep*; c2023. <https://doi.org/10.51470/ER.2023.5.2.10>.
27. Kotyal K. Circular agriculture: Sustainable farming practices for zero waste. *Environ Rep*; c2023. <https://doi.org/10.51470/ER.2023.5.1.08>.
28. Seifert A, Rasp S. Potential and limitations of machine learning for modeling warm-rain cloud processes. *J Adv Model Earth Syst.* 2020;12(6). <https://doi.org/10.1029/2020MS002301>.
29. Sagar S. Greening the tech industry: Evaluating the environmental impact of e-waste recycling technologies. *Environ Rep*; c2023. <https://doi.org/10.51470/ER.2023.5.1.05>.
30. Silge J, Robinson D. tidytext: Text mining and analysis using tidy data principles in R. *J Open Source Softw.* 2016;1(37):37. <https://doi.org/10.21105/joss.00037>.
31. Singh A, Thakur N, Sharma A. A review of supervised machine learning algorithms. In: *Proceedings of the 3rd International Conference on Computing for Sustainable Global Development (INDIACom)*, New Delhi, India, 16-18 March. 2016:1310-1315.
32. Singh AK, Yadav SS, Joshi E, Khambalkar PA. Sustainable groundwater management, addressing depletion through advanced technology and policy. *Environ Rep*; c2022. <https://doi.org/10.51470/ER.2022.4.1.01>.
33. Theocharides S, *et al.* Day-ahead forecasting of solar power output using gradient boosting machines. In: *Proceedings of the 2018 IEEE 7th World Conference on Photovoltaic Energy Conversion (WCPEC)*, Waikoloa, HI, USA; c2018. p. 2371-2375. <https://doi.org/10.1109/PVSC.2018.8547715>.
34. Ramesh S. The role of nature-based solutions in climate change adaptation and mitigation. *Environ Rep*; c2019. <https://doi.org/10.51470/ER.2019.1.1.01>.
35. Theocharides S, *et al.* Day-ahead photovoltaic power production forecasting methodology based on machine learning and statistical post-processing. *Appl Energy.* 2020;268:115023. <https://doi.org/10.1016/j.apenergy.2020.115023>.
36. Tripathi S, Srinivas VV, Nanjundiah RS. Downscaling of precipitation for climate change scenarios: A support vector machine approach. *J Hydrol.* 2006;330:621-640. <https://doi.org/10.1016/j.jhydrol.2006.04.030>.
37. Walsh E, *et al.* Using machine learning to produce a very high-resolution land-cover map for Ireland. *Adv Sci Res.* 2021;18:65-87. <https://doi.org/10.5194/asr-18-65-2021>.
38. Wang Y, *et al.* A GPU-accelerated radiation transfer model using the lattice Boltzmann method. *Atmosphere.* 2021;12(10):1316. <https://doi.org/10.3390/atmos12101316>.
39. Wu Y-K, *et al.* Probabilistic wind power forecasting using weather ensemble models. *IEEE Trans Ind Appl.* 2018;54(6):5609-5620. <https://doi.org/10.1109/TIA.2018.2864417>.
40. VijayKumar R. Biochar in soil restoration: A comprehensive review on enhancing soil health and carbon sequestration. *Environ Rep*; c2019. <https://doi.org/10.51470/ER.2019.1.1.05>.
41. Safdar EA, Tabassum R, Khan PA, Safdar NA. Cross sectional retrospective study on mifepristone and misoprostol combination vs misoprostol alone for induction of labour in management of IUFD. *Acta Pharma Rep*; c2023.
42. Zong L, *et al.* Large-scale synoptic drivers of co-occurring summertime ozone and PM2.5 pollution in eastern China. *Atmos Chem Phys.* 2021;21:9105-9124. <https://doi.org/10.5194/acp-21-9105-2021>.
43. Safdar NA, Nikhat EAS, Fatima SJ. Cross-sectional study to assess the knowledge, attitude, and behavior of women suffering from PCOS and their effect on the skin. *Acta Tradit Med.* 2023;2(01):19-26.