MACHINE LEARNING BASED UNDERSTANDING OF FACTORS AFFECTING CLIMATE CHANGE

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ABSTRACT

Recent all-round advancements in machine learning, as a subfield of artificial intelligence, have begun a new era of data-driven decision-making approaches in climate prediction, introducing transformative techniques that not only help to deliver high-accuracy forecasts but also quantify the inherent uncertainty associated with atmospheric outcomes. Building upon this theme, our research paper focuses on using advanced algorithms such as ensemble learning, probabilistic models which will be useful for dual purposes - for capturing climate dynamics and for providing robust estimates of uncertainty events. Together, these approaches pave the way for more engaging and accurate predictions across temporal and spatial scales. Furthermore, the proposed solutions have significant potentials to enhance climate risk assessment and inform policy decisions in the context of global warming and sustainable development, for making more accurate and timely decisions compared to traditional time-consuming procedures, enabling scalable solutions for real-world climate adaptions and mitigating challenges.

Keywords-Climate Prediction, Machine Learning, Global Warming, Accuracy

INTRODUCTION

Artificial Intelligence is a paradigm that enables machines and computers to perform complex tasks and problems associated with human intelligence. In today's modern era, AI is rapidly evolving in numerous fields like education, agriculture, healthcare, transportation, business, industry and so on. It is the revolutionizer which absolutely has changed the way of our thinking, working and managing. [2]

In sectors like healthcare, AI can find out diseases so efficiently and effectively by matching different symptoms with the actual disease, in agriculture IoT- based drone technology can be incorporated to automate the irrigation and monitoring process of the fields, in education automatic assigning of grades, focusing upon students' individual feedback, speech-to-text conversion, voice commands, image recognition all these are responsible for making the education system more versatile and more meaningful.[3]

Weather, associated with climate are those to which our lives got intricately attached. From going to workplace to our clothing choice, in every rhythm of our lives, weather and climate are the two main foundational structures. Farmers have to rely on certain weather conditions for irrigation, planting and harvesting purpose,[21] the transportation industry is fully reliant on specific weather conditions, leading to flight cancellation and delay of vessel services. On the other hand, climate is another invisible dictator of our societal plays.From determin- ing the actual agricultural production with reference to a particular place to economic sustainability to the entire blueprint for human settlement and sur- vival, it completely dictates where cities can flourish, how populations must adapt and lastly how natural ecosystems and biodiversity can grow up.

The long-term change in weather conditions, typically averaged over 10-15 years for a broader range of area, is termed 'climate' and 'climate change' refers to the significant changes in the average or mean climate conditions due to some natural or artificial means.It can be caused by different kinds of natural factors like changes in the earth's orbit, tilt, axis, plate tectonics and volcanic eruptions and changes in the strength of the sun.On the other, if we consider artificial means and human activities, it covers the ever- growing industrializa- tion and population growth, the greenhouse gas emissions, global warming and increasing sea level, deforestation, fossil fuel burning and the list will never be completed.[7] As a result, long-term changes in global meteorological fac- tors such as temperature, precipitation and wind speed can be reflected in the earth's ecological system on a global scale.[22] So in today's world, global cli- mate change is one of the most burning environmental issues, which results in unexpected changes in weather events, biodiversity loss and profound changes in global economics and social changes.[15]

So foreknowledge on climate has become an indispensable tool, helping societies to mitigate risks, optimizing resources and overall improve the sustainability and viability of our communities.From boosting agricultural yields to make the ability to anticipate the impacts of extreme weather events, climate predic- tion has drastically changed our way of thinking, working and decision-making. But that long-term climate change leads to an inability to accurately predict the patterns of the climate and gives rise to what is known as "weather uncer- tainty". Weather itself is most volatile, and weather prediction is one of the most complex and time-consuming processes, where that newcomer "weather uncer- tainty" has made that process more cumbersome and hectic.The up-growing effect of weather uncertainty is not only becoming a reason for widespread dis- ruption of weather events but also becoming a primary driver of worldwide instability.[10],[12]

As a result, the topic of climate prediction has become so popular in re- cent years, and the use of machine learning in the fields of climate prediction is on trend now.General Circulation Models(GCM) have been used for a long time.[13]. Various in- depth analysis of Earth's climate dynamics by combining several oceanic, terrestrial and atmospheric phenomena had been approached for that method, but local fluctuations and different regional characteristics couldn’t be fully represented in that, specifying its spatial constraints. Traditional techniques based on large datasets having underlying complex physical, chemical , biological interactions used a large amount of computational resources, and these models usually required an extremely high accuracy of the initial conditions and parameters of the model. Numerical Weather Prediction (NWP)is another type of traditional predictive model which can predict future weather changes on a large basis through numeric calculations with respect to oceanic conditions and current atmospheric state.

In recent years, AI and machine learning genres have become the most de- manding and explorative in the fields of climate prediction, finding out complex underlying patterns and developing data-driven strategies for climate change mitigation and adaptation.[1], [4]. AI is fundamentally restructuring climate forecasting, implementing real-world strategies for everything from crop plan- ning to national disaster response with blistering speed and accuracy.

This project leverages AI not just to predict future climate scenarios but to fundamentally understand and forecast the uncertainty within our weather. This approach provides a clear provision for long-term climate policy while enabling more multidisciplinary, risk-aware decisions for immediate weather-dependent operations.[16]

Related Work

By 1963, the research paper ”Deterministic non-periodic flow”, written by Lorenz, had dramatically altered the perception of weather prediction, which was followed by a long duration of time. In that, Lorenz had shown that the solution of a simple set of non-linear equations can be altered at any time based on the initial perspectives, and after a certain period of time, there is no single predictive solution of those non-linear equations. He compared the atmosphere to a regime-like structure which is a factor of prediction up to a certain period, and after that, it can be changed randomly or disruptively.

The renowned Numeric Weather Prediction (NWP) had multidimensional approaches to give a conclusion about the final prediction where distinct com- ponents analyze complex patterns of solar variations, wind speed. It is a syn- chronization of different types of interconnected models which dissect the atmo- sphere into three-dimensional space and solve some of the complex equations by physics. Specialized models in NWP, known as ”Radiative Transfer Schemes”, calculate how solar energy is absorbed. Modern NWP models take two sides of convention: data assimilation and ensemble. In data assimilation, real-world data gathering is to be done by assembling satellite data, weather balloons, ground data to create the best possible initial state of the atmosphere, and in an ensemble, multiple models with slightly different behavior and initial condi- tions are to be executed to produce a more optimized, robust and generalized output.

In recent decades, machine learning-based prediction methods are so on de- mand (Bochenek and Ustrnul, 2022; Kashinath et al., 2021; Yu et al.,2021) [12].Machine Learning-based prediction generally refers to nowcasting immediate storms by analyzing patterns, forecast according to meteorological elements at a certain period of time for up to two weeks by learning complex physics, and predicting climate by self-learning and improving.Post-hoc experiments are to be used to interpret the predictability of the models which are already trained without changing the underlying models (Deng et al., 2024; Fu et al., 2021; Wang et al., 2020). This type of experiment can be done on three perspectives: perturbation-based methods, game theory based methods and gradient-based methods.

In that era of machine learning and artificial intelligence, big data analy- sis has become the engine of modern innovation.It is useful for storing a huge amount of data, from neatly structured tabular formats to semi-structured files and completely unstructured raw data like images and texts collected from social media.The actual magic happens when that analyzed data is used to uncover underlying patterns, trends, relationships to extract meaningful insights which can give fuels to data processing techniques, power intelligent systems and bring rebel breakthroughs across the world of technology.By using tools like HADOOP working upon that technology, data coming from diverse sources from satellite imagery, ground-based sensors to ocean buoys and historical weather data of a wide range of types, can be processed with enormous speed and efficiency. Underlying hidden patterns can be exploited, which wasn't be possible before by using only machine learning algorithms, and it leads to more accurate fore- casts of temperature changes, precipitation patterns and frequency of extreme weather patterns, which can also be helpful for policymakers to understand the potential consequences of their decisions and develop targeted mitigation strategies.

The invention of Artificial Neural Network has become a most significant turning point in the waves of Artificial Intelligence andMachine Learning by incorporating the capability of mimicking the intricate structure of the human brain. Artificial Neural Network is capable of detecting complex patterns, non- linear relationships in vast datasets by adjusting the strength of the connections between neurons. Likewise in climate prediction, NN is adaptable to learn from historical climate data, including various variables representing temperature, humidity, wind speed and can make predictions for future climate conditions with its immense inference speed and rapid analysis by that NN can give a range of possible outcomes and quantify uncertainty in a prediction, named as

”Ensemble Forecast”.Researchers like French et al. (1992) used NN to predict two-dimensional rainfall patterns, McCann (1992) tried to forecast the likelihood of significant thunderstorms. Another subdomain under NN, refers to ”Convolu- tional Neural Network”, is responsible for processing and analyzing data having grid-like topology like images, which incorporates some special mathematical operations called ”convolution” to automatically and hierarchically learn fea- tures from the input data.By training on satellite imagery and other spatial climate data, CNN learns to extract the patterns of historical hurricanes, atmo- spheric rivers, and other extreme weather conditions, which helps earlier and more efficient warnings to prepare against any upcoming harsh situations. Shietal. showed a CNN capable of real-time 1080p super-resolution on a single GPU.Another scientist Heikkila¨ et al., performed ”Dynamic Downscaling”, the process for converting large-scale predictions into high-resolution forecasts for specific localities by finding implicit relationships between the coarse GCM output and fine-grained historical weather data, which is essentially helpful for adaptation planning and impact assessment.

METHODOLOGY

The primary objective of that study was to develop a machine learning frame- work capable of generating probabilistic weather predictions and quantifying the uncertainty in short-term weather predictions.

Dataset Description

That analysis took place using the ”Climate Change: Earth Surface Temper- ature Data” dataset from Kaggle.com, which is publicly available collection of temperature data, the result of long-term data cleaning, processing and analyz- ing climate trends, originally curated by the ”Berkeley Earth Surface Temper- ature project”.This dataset focuses on comprising global average land temper- ature by state and country basis.There are five datasets encompassing Global Land Temperatures By Country, Global Average Land Temperature by State, Global Land Temperatures By State, Global Land Temperatures By Major City, Global Land Temperatures By City spanning from 1750 to 2015.

Data Preprocessing

Feature Extraction through Geographical Knowledge Altitude

To understand about climate, we need to know the crucial impact of al- titude. Altitude refers to the height of a location above sea level. With the increasing altitude, the temperature generally decreases. This phenomenon is known as Environmental Lapse Rate (average drop of about 0.65°C to 0.7°C per 100 metres). From the data, we found 3448 unique cities across all the countries. Based on this, we manually made a column named as Altitude (height from sea level) using city, country, latitude and longitude.The altitude values were taken from Google Earth and Wikipedia.

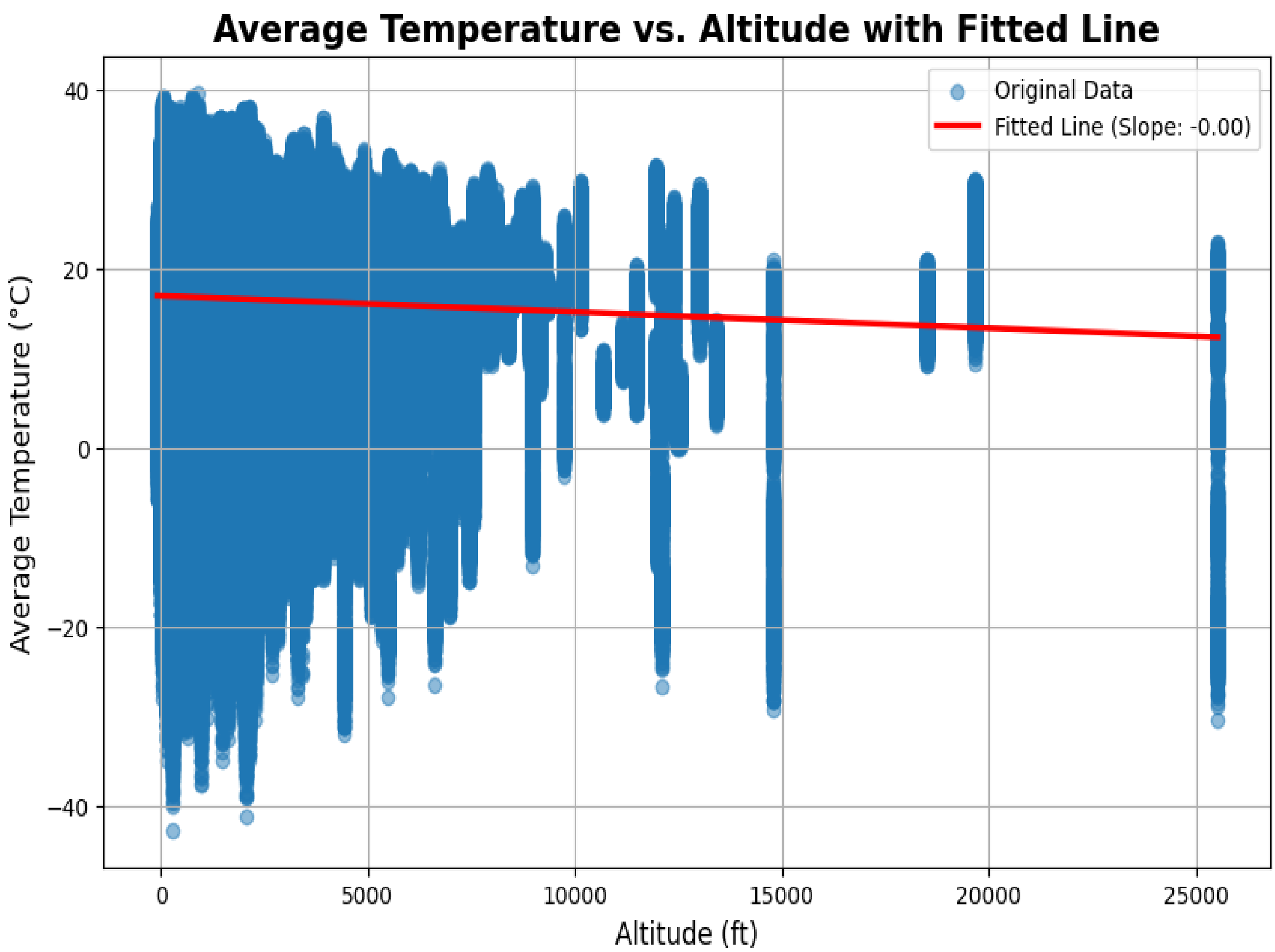
Date

As our data is in range from the year 1748 to 2013, we converted this to feature, means from the first date it will count as 1, then 2 and so on.

Latitude and Longitude

Latitude is the distance of north and south of the equator (line connecting all the points at equal distance between the North and South Poles).At higher latitudes, the Sun's rays are less direct.So, the farther an area is from the equator,

Figure 1 Average Temperature vs. Altitude



The lower of its temperature.At the poles, the Sun's rays are least direct.Most of the area is covered with ice and snow, which reflects a lot of sunlight.Here, temperature is lowest. Longitude itself does not directly affect climate, but it plays an indirect role in climate patterns through its influence on time zones, solar radiation, and ocean currents.

In our data, the latitude and longitude were written as strings with 'N'/'S' for latitude or 'E'/'W' for longitude (i.e. "45.67N" or "123.45W").We converted these into numeric signs, i.e. for Northern and Eastern it is positive (+) sign and for Southern and Western it is negative (-) sign.

Mapping the weather uncertainty to class level

In climate change, the uncertainty is not a regular event, it does not occur in a consistent or repetitive way.It may differ from what it is supposed to be. Artificial Intelligence (AI)

Future Scope

Advanced Modeling Techniques

By applying Deep Learning frameworks like Long Short Term Memory(LSTMs) and Gated Recurrent Unit(GRU) are very much competent and reliable to time-series analysis and capture complex dependencies which cannot be fully modeled by classifiers.

Data Enrichment and Feature Engineering

By using more informative and compact dataset including satellite imagery, atmospheric aerosol data, El Niño–Southern Oscillation (ENSO) can be more instructive to the model's predictive capability and performance.

Model Interpretability and Explainability (XAI)

Using Explainable AI (XAI) techniques such as SHAP (SHapley Additive exPla- nations) and LIME (Local Interpretable Model-agnostic Explanations) would be effective for identifying key meteorological drivers of uncertainty, which will be helpful for transforming the "black box" into valuable model insights.

Real World Deployment and Generalization

Finally, the model's generalizability should be tested on different geographical regions with diverse climate patterns to develop an operational, real-time early warning system which can be used by policymakers and data scientists for strategic decision making.

CONCLUSION

From the vast amount of data, we find out the altitude of each unique country and handle it manually. The date feature is transformed into a continuous numerical feature to capture temporal progression. By converting latitude and longitude into numerical values, we make their direct effects understandable. By applying all these techniques in our analysis, we obtain the best possible results.

This study is proof of successful application of machine learning framework in predicting uncertain weather events and the novelty lies in the methodology of that experiment where we have binarized the target metric by its 80th per- centile for creating an effective environment for identifying the notable periods of significant and most powerful climate instability.

This study acts as an interface between the world of reaction and the world of prediction by acting as the foundational base for early-risk detector, resource allocator for competing with climate-sensitive issues and a crucial component in developing more effective climate mitigation strategies.By presenting that proof of concept as the base, more future explorative research should be conducted on this domain, such as deep learning models like LSTMs to capture the temporal dependencies more preciously, the use of model interpretability techniques like ”SHAP” to unlock the ”Black Box” to gain deeper scientific insights.

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