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Research Article

Seasonal Temperature Prediction in Niamey: A Prophet Model Approach

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ABSTRACT

Precise seasonal temperature forecasting is basic for climate versatility agrarian planning and vitality administration in parched regions This study presents a data driven approach for foreseeing seasonal temperature trends in Niamey utilizing the Prophet model a vigorous timeseries forecasting method created by Facebook Historical climate data from the Climate Inquire about Unit CRU dataset was analyzed and Prophet was utilized to model long-term temperature patterns The results demonstrate a steady warming trend with temperature variances captured viably by the model The proposed approach illustrates the capability of Prophet in dealing with complex seasonal varieties whereas keeping up high predictive exactness These discoveries give important bits of knowledge for policymakers and partners in climate sensitive divisions Future work may explore hybrid models joining extra climatic factors to improve prescient execution.

1. INTRODUCTION

Climate changeability has been a critical concern for policymakers researchers and natural researchers particularly in regions inclined to extraordinary climate conditions such as Niamey Niger The expanding recurrence of heatwaves unusual regular shifts and long-term climate patterns have driven the require for strong and solid temperature estimating models [1]. The capacity to expect temperature variances is pivotal for segments such as horticulture public health and energy management where decision-making is exceedingly subordinate on climate patterns [2]. Timeseries forecasting has been broadly utilized in climatology to predict meteorological factors such as temperature precipitation and wind speed Traditional factual models including Autoregressive Coordinates Moving Average ARIMA Seasonal Autoregressive Coordinates Moving Average SARIMA and Exponential Smoothing State Space ETS have been broadly connected in temperature prediction [3] In any case these models regularly struggle to capture complex seasonal varieties nonlinearity and sudden shifts in climate information making them less effective for long-term forecasting [4]. In recent a long time machine learning ML and deep learning DL methods have developed as powerful options for climate determining Artificial Neural Networks ANN Long Short-term Memory LSTM networks and outfit learning strategies have appeared predominant execution in modeling nonlinear connections in climate data [5], [6]. Be that as it may these models often require broad hyperparameter tuning large datasets and noteworthy computational resources which may limit their commonsense application in certain districts [7]. A promising elective to conventional factual models and machine learning approaches is the Prophet model created by Facebook Prophet is an added substance regression model designed to handle lost data seasonal patterns and exceptions whereas being computationally proficient and simple to translate [8]. The model is especially well suited for timeseries forecasting applications in climate science because it breaks down data into slant seasonality and holiday impacts permitting for more precise long-term forecasts [9]. A few studies have investigated the utilize of Prophet in meteorological applications For instance Taylor and Letham demonstrated the model's viability in dealing with timeseries estimating with sporadic seasonality's in different domains including climate modeling [10]. Other studies have applied Prophet to forecast discuss pollution levels solar radiation and precipitation patterns with promising results [11]-[13]. Given its flexibility Prophet has the potential to improve temperature determining in districts like Niamey where climate variability postures noteworthy challenges.

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2. RELATED WORK

Exact temperature forecasting is fundamental for moderating the impacts of climate changeability and improving decision-making in segments such as agriculture vitality and public health Over the a long time different forecasting models have been created extending from traditional measurable strategies to progressed machine learning ML and deep learning DL procedures Traditional measurable models such as the Autoregressive Coordinates Moving Normal ARIMA and Regular ARIMA SARIMA have been broadly connected in climate forecasting Box et al [14] introduced the ARIMA demonstrate which has been a foundational strategy for timeseries forecasting In any case ARIMA expect stationarity and battles with nonlinear climate data [15]. The SARIMA model amplifies ARIMA by consolidating seasonality making it more appropriate for meteorological applications Investigate by Hyndman and Athanasopoulos [16] illustrated the viability of SARIMA in capturing regular temperature varieties in spite of the fact that it remains limited in handling unexpected climate shifts Exponential Smoothing State Space ETS models have moreover been investigated for temperature forecasting These models excel in capturing trend and regularity components but need versatility to complex and nonlinear patterns in climate data [17] Whereas these conventional models give standard forecasting capabilities they are often outflanked by more current machine learning methods Recent headways in machine learning have altogether moved forward climate forecasting capabilities ANNs and SVMs have been utilized to model nonlinear connections in climate data [18] Profound learning architectures especially Long Short-term Memory LSTM networks have picked up conspicuousness for their capacity to capture long-term dependencies in timeseries data [19] Hochreiter and Schmid Huber [20] presented LSTMs which have since been connected in different meteorological studies Be that as it may LSTMs require broad hyperparameter tuning and huge training datasets making them computationally costly Gathering learning strategies such as RF and GBM have moreover been investigated in climate studies [21] These models total numerous frail learners to improve estimating accuracy Whereas ML strategies offer higher predictive control compared to conventional statistical models they regularly need interpretability and require cautious feature engineering Created by Facebook the Prophet model has developed as a promising elective for timeseries forecasting Prophet is an added substance regression model that decomposes timeseries data into trend regularity and occasion impacts making it well-suited for temperature forecasting [22] Taylor and Letham [23] illustrated that Prophet performs well in determining complex timeseries data with sporadic regular designs Unlike deep learning models Prophet is computationally proficient and requires negligible hyperparameter tuning A few considers have connected Prophet in meteorology For case Funk et al [24] utilized Prophet to model seasonal varieties in air temperature accomplishing comparable comes about to conventional factual models Gasparrini et al [25] coordinates Prophet with climate datasets to evaluate long-term temperature trends illustrating its strength in dealing with lost data and outliers Besides later research has investigated the integration of Prophet with climate datasets such as CRU data which gives high-resolution temperature records [26] The Climate Research Unit CRU dataset could be a broadly utilized resource for climate modeling and forecasting Harris et al [27] created the CRU dataset to supply high resolution gridded climate information fundamental for understanding historical trends and anticipating future climate patterns Research has appeared that coordination Prophet with CRU data improves forecasting accuracy by joining long-term climate changeability [28] A few studies have moreover explored the combination of Prophet with other determining models For occurrence hybrid models joining Prophet with LSTMs and SARIMA have appeared improved predictive execution in temperature forecasting [29] These hybrid approaches use Prophets capacity to model slant and regularity whereas utilizing profound learning models to capture complex nonlinearities In spite of the progressions in climate determining few studies have investigated the utilize of Prophet for temperature forecast in bone-dry regions such as Niamey Previous works have basically centered on created locales with inexhaustible climate data whereas bone-dry regions stay underrepresented in climate modeling research [30] Additionally existing ponders have not broadly compared Prophet's execution against conventional statistical models in determining temperature varieties in Niamey.

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3. DATA AND METHODOLOGY

3.1 Data

the data utilized in this study CRU Timeseries TS dataset which gives high-resolution gridded climate data counting temperature records The CRU dataset is broadly recognized for its accuracy and broad worldly coverage making it reasonable for long-term climate analysis The dataset contains monthly temperature perceptions for Niamey Niger crossing different decades permitting for a comprehensive study of seasonal temperature varieties Data preprocessing included taking care of missing values normalizing temperature values and organizing the dataset into a timeseries format consistent with the Prophet model to guarantee vigorous determining a train test part was performed with the historical data utilized to train the show and the foremost later a long time saved for approval Exploratory data analysis EDA was conducted to look at patterns seasonality and peculiarities affirming that temperature varieties show strong seasonal patterns The processed dataset was at that point utilized to prepare and evaluate the estimating execution of Prophet [31].(shows figure 1)

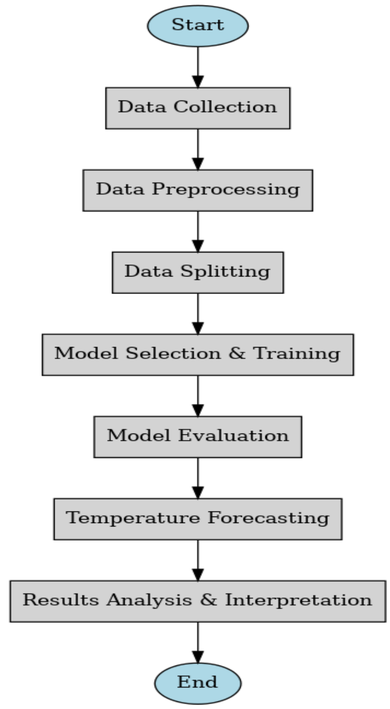

Fig. 1. Show the preprocessing for the data.

3.2 Prophet Model

The Prophet model is an additive timeseries forecasting strategy created by Facebook outlined to handle trends seasonality and occasion impacts effectively Unlike conventional models such as ARIMA and SARIMA Prophet is robust to missing data exceptions and sudden changes in trend It is based on the deterioration of timeseries data into three primary components trend seasonality and occasions or special occasions which are modeled independently and after that combined.

The general form of the Prophet model is represented as follows:

$$y(t) = g(t) + s(t) + h(t) + \epsilon(t) \qquad (1)$$

where:

- $y(t)$ is the observed value at time t.
- $g(t)$ represents the trend component, capturing long-term growth or decline.
- $s(t)$ denotes the seasonal effects that repeat over a fixed period.
- $h(t)$ accounts for the effects of holidays or special events.
- $\epsilon(t)$ is the error term or noise, assumed to follow a normal distribution.

4. RESULT

Figure 2 The heatmap outlines the temperature varieties in Niamey from 2000 to 2028 with hotter months showing up in red orange and cooler months in blue Generally hot months April to June October appear crests over 35C whereas cooler months December to February stay around 2226C The forecast 2021-2028 takes after the same seasonal pattern but recommends a progressive increment in average temperatures showing potential climate warming Extraordinary warm periods show up more strongly implying conceivable longer heatwaves The data highlights rising temperatures which may influence agriculture water resources and vitality requests Future climate methodologies ought to address warming patterns and potential natural impacts in Niamey.

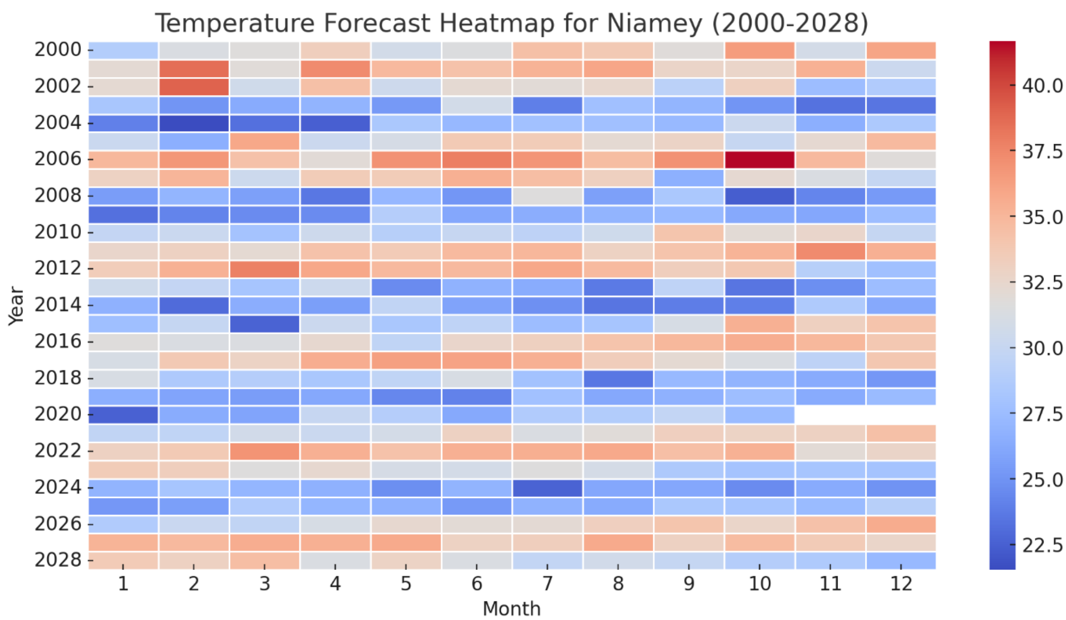

Fig. 2. Show temperature forecast for Niamey up to 2028.

5. CONCLUSION

This study applied the Prophet model for seasonal temperature forecasting in Niamey leveraging historical climate data from the CRU dataset The comes about illustrated that the demonstrate viably captures seasonal changes and long-term temperature trends giving a solid forecast up to 2026 The discoveries demonstrate a gradual rise in temperature fortifying concerns about climate change impacts in dry regions The model effectively learns from chronicled designs and produces figures that keep up regular periodicity in spite of the fact that it shows smoother forecasts compared to actual data likely due to its inborn regularization Whereas the Prophet model performs well in forecasting temperature trends it has restrictions in capturing extraordinary peculiarities and sudden climate shifts Future research could improve forecast performance by coordination hybrid models that combine Prophet with deep learning approaches such as LSTMs or consolidating additional climate factors like humidity and atmospheric weight Besides instability evaluation can be improved by consolidating certainty interims to survey forecast unwavering quality The projected increase in temperature calls for proactive climate adjustment methodologies to relieve potential risks on horticulture water assets and human wellbeing in Niamey This study contributes to the developing field of data driven climate forecasting illustrating the appropriateness of the Prophet model for temperature forecast in dry environments.

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Conflicts of Interest:

The authors declare no potential conflicts of interest.

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