Weather Forecasting & Analysis Using Hindu Calendar (Lunisolar Calendar)

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Abstract:- This paper investigates the unique temporal insights offered by Vedic Hindu calendars, classified as lunisolar, which inherently accommodate both solar and lunar motions. While contemporary time series analysis predominantly relies on Gregorian (solar) calendars, this study explores the potential advantages of incorporating Hindu calendars. Focusing on the intricate influences of the Sun and Moon on natural phenomena, the research underscores the crucial role of time series analysis in day-to-day applications. The study delves into weather prediction, specifically examining the correlation between paksha (lunar fortnights) and weeks. Through logical and experimental analyses, the paper not only highlights the inherent capabilities of Hindu calendars but also presents a multidimensional approach to weather forecasting by integrating their temporal insights. This research contributes to the ongoing exploration of ancient calendrical systems for contemporary scientific applications.

Keywords:- *Lunisolar Calendar, Hindu Calendar, Time Series Analysis, Weather Prediction, Correlation Analysis, and Temperature Forecasting.*

I. INTRODUCTION

Weather prediction, a formidable challenge, necessitates a robust foundation of historical data to discern patterns governing atmospheric conditions. Over the centuries, extensive datasets encompassing temperature, pressure, humidity, and diverse meteorological parameters have facilitated the construction of various prediction models. Despite the strides made, existing models exhibit occasional inaccuracies, revealing the need for precision in optimization strategies.

This paper diverges from conventional methodologies by embracing a unique perspective rooted in the Hindu calendar, extending its lens to the temporal divisions governing months. Focusing on the Indian region, specifically Bengaluru, we embark on a comparative analysis between the Gregorian and Hindu calendars. This study seeks to unravel nuanced insights within the intricacies of Hindu calendrical divisions, offering an alternative framework for understanding weather patterns.

Within the confines of this research, we channel our exploration towards the precision of weather predictions based on the Hindu calendar. By synthesizing observations and data encompassing both calendar systems, we endeavor to discern novel revelations and patterns that may elude conventional meteorological approaches.

The following sections meticulously outline the methodology employed, data sources utilized, and the nuanced findings garnered through this distinctive interplay between ancient Hindu calendrical wisdom and contemporary meteorological analytics. Through this interdisciplinary approach, we strive to contribute to the evolving discourse on weather prediction methodologies, opening avenues for fresh perspectives.

II. LITERATURE REVIEW

A. Overview of Existing Calendar Systems

The Gregorian calendar, instituted by Pope Gregory XIII in 1582, stands as the globally accepted solar calendar, featuring a year of 365 days and introducing a leap year every four years. Its introduction aimed to rectify inaccuracies in the preceding Julian calendar. In contrast, the Hebrew calendar, a lunisolar system vital to Jewish tradition, integrates lunar months with adjustments for the solar year through a periodic leap month. This ensures alignment with seasonal events, particularly significant for festivals like Passover. Meanwhile, the Hindu calendar, deeply embedded in Hindu culture, operates as a lunisolar calendar, incorporating lunar months and periodically adding an intercalary month to sync with the solar year. This calendar, rich in religious and cultural significance, guides the timing of festivals, ceremonies, and agricultural activities in Hindu communities, offering a unique perspective on timekeeping and celestial observation..

B. Limitations of Commonly Used Solar Calendars

Leap Year Complexity: Common solar calendars, including the Gregorian, introduce leap years to account for the extra fraction of a day in Earth's orbit around the Sun. While this adjustment is necessary, it adds a layer of complexity to the calendar system.

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Cultural Misalignment: Solar calendars may not align seamlessly with cultural or religious practices globally. The timing of significant events for different communities may not be accurately represented, leading to potential cultural dissonance.

Lack of Lunar Consideration: Solar calendars often neglect lunar influences, focusing primarily on Earth's orbit around the Sun. This oversight can impact the representation of lunar phases, which holds significance in various cultural and religious contexts.

Seasonal Drift: Over extended periods, there's a potential for seasonal drift in solar calendars. This means that the timing of seasons may gradually shift, impacting the precision of seasonal timing in the long term.

Understanding these limitations is crucial for evaluating alternative calendar systems that may better suit specific cultural, religious, or practical requirements.

C. Advantages and Features of Hindu calendars

The Hindu calendar system boasts several advantages that contribute to its significance and relevance. Firstly, its lunisolar nature provides a unique flexibility by incorporating both solar and lunar elements. This allows for a more nuanced representation of celestial events and their impact on Earth. The calendar's alignment with cultural and religious practices ensures accurate timing of festivals and rituals, enhancing its cultural resonance. Additionally, the Hindu calendar's observance of natural phenomena, influenced by the Sun and the Moon, proves advantageous for applications such as weather prediction. The system's potential for time series analysis further underscores its utility in contemporary fields like data science. In embracing both solar and lunar aspects, the Hindu calendar presents a comprehensive and inclusive approach to timekeeping, offering a holistic understanding of time that extends beyond mere chronological measurement. These attributes collectively position the Hindu calendar as a valuable and versatile temporal framework.

III. METHODOLOGY

The methodology employed in this study involved a meticulous fusion of two key datasets spanning a decade, encompassing prokerala panchang data from 2012 to 2022 and temperature records for Bengaluru over the same period. The prokerala panchang dataset provided a rich array of parameters such as day, weekday, tithi, nakshatram, yogam, and karanam, while the temperature dataset included daily minimum, maximum, and average temperatures. The methodology comprised essential steps like data preprocessing to address missing values and ensure alignment, followed by a detailed Exploratory Data Analysis (EDA) to unravel intricate correlations among various variables. The EDA delved into relationships within thithi days, weekdays, and months, unveiling patterns and insights that set the foundation for subsequent analysis.

The comprehensive approach laid the groundwork for the subsequent steps in the methodology, providing a robust foundation for meaningful insights.

A. Data Collection

We collected the data from prokerala panchang, where we got the data of panchang. The collected csv file contained data of 10 years from 2012 to 2022. Along with this file, we obtained the temperature dataset of Bengaluru of 10 years from 2012 to 2022. While the panchang data has columns like day, weekday, tithi, nakshatram, yogam, karanam etc., the temperature dataset has minimum, maximum and average daily temperatures of Bengaluru. We used these data files to do timeseries forecasting, analysis and predictions.

B. Data Preprocessing

- The code begins by loading two datasets, 'panchang_data.csv' and Bangalore temperature file into DataFrames (df and temp, respectively). Initial examination of df involves concatenating selected columns into a new DataFrame df2 and extracting the day from the 'Day' column, stored in a new column 'day'. Subsequently, a subset of rows is selected to create df3..
- Simultaneously, temperature data for Bangalore is loaded from the temperature data file. Relevant rows are selected based on date and the index is reset for better handling. The two datasets (df3 and temp) are then combined using the 'Date' column to create a new DataFrame data..
- The time series data preparation involves cleaning the 'Tithi' column in df3 by removing time information and unnecessary text. A new column 'panchang' is created in df3 by combining selected columns. Simultaneously, the temperature data is extracted from data into a new DataFrame d. To facilitate time series modeling, the temperature data is normalized using Min-Max scaling. The time series data is then split into training and testing sets.

IV. EXPLORATORY DATA ANALYSIS (EDA)

Exploratory Data Analysis is a crucial phase in understanding the characteristics and patterns present in the dataset. Here's how EDA is performed on the prepared dataset:

A. Time Series Plot

The first step involves visualizing the time series data to discern patterns in temperature over the entire observation period. A line plot is generated to showcase the trends in normalized temperature over time.

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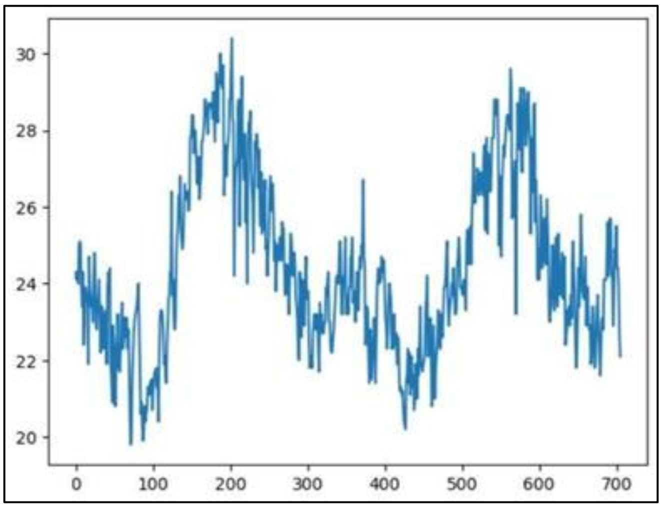

Fig 1: Time-Series Line Graph of Temperature in Bengaluru

Further analysis involves understanding the correlation between Panchang elements and temperature.” We performed two correlations here which are Tithi-based and Day-based.

B. Tithi-Based Correlation

In this segment of the analysis, a Tithi-specific correlation study is conducted. The 'Tithi' column is processed to create a new DataFrame, 'new_df,' where each Tithi is associated with its corresponding temperature values. This transformation allows for a granular examination of how individual Tithis relate to temperature fluctuations. The newly created 'new_df' is organized with each row representing a specific Tithi, and columns containing temperature values for that Tithi across different time points.

A correlation matrix is then computed based on this transformed data. The matrix provides a numerical representation of the relationship strength between each pair of Tithis. Visualizing this correlation matrix through a heatmap allows for an intuitive interpretation of patterns. High positive correlations are depicted by warmer colors, indicating a simultaneous increase or decrease in temperature with specific Tithis. Conversely, cooler colors signify low or negative correlations, suggesting an inverse relationship.

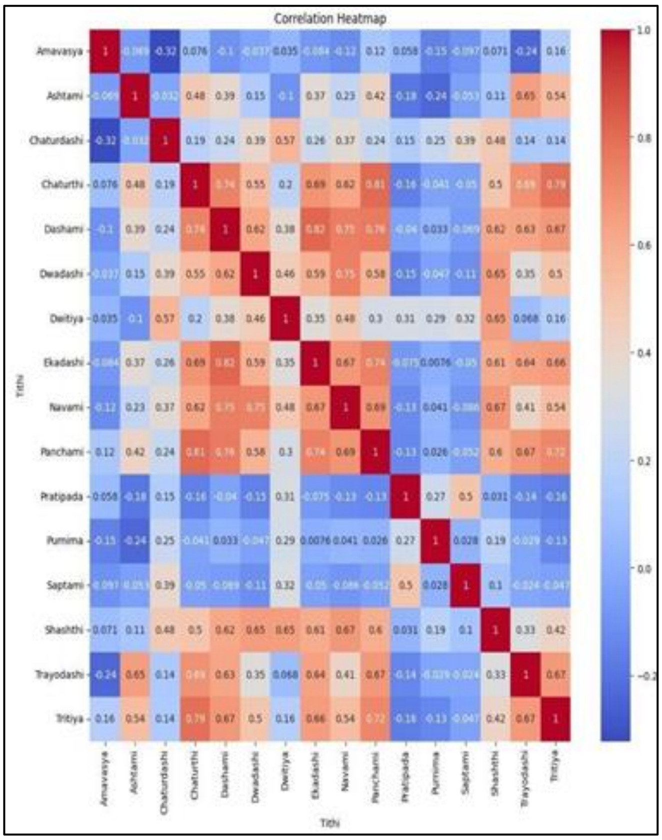

Fig 2: Correlation Hear-Map of Tithis

- The investigation focused on understanding the interrelation among various Tithis in the Hindu calendar within a one-year dataset. Unlike the conventional Gregorian calendar, where dates are largely independent, each Tithi in the Hindu calendar demonstrated a noticeable degree of correlation with others. The heatmap analysis revealed predominantly negative correlations among Tithis.

For instance, a compelling observation emerged from the heatmap – Chaturdashi and Amavasya exhibited a notably strong negative correlation. This implies that a rise in temperature during Chaturdashi may coincide with a decrease in temperature during Amavasya. Conversely, Ekadashi and Panchami displayed a high positive correlation. In practical terms, a temperature increase during Ekadashi might correspond to an elevated temperature during Panchami. This nuanced understanding of Tithi correlations provides valuable insights into potential temperature patterns, contributing to the broader comprehension of climatic influences dictated by the Hindu calendar.

C. Day-Based Correlation:

In a parallel exploration, the dataset is transformed to investigate temperature patterns based on the day of the week. Similar to the Tithi-based analysis, a correlation matrix is computed, with each row representing a specific day of the week and columns containing temperature values for that day across different time points. The resulting heatmap visually represents the correlation strengths between days and temperature.

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These correlation analyses provide valuable insights into the potential influence of specific Tithis and days of the week on temperature variations. Identifying patterns in these correlations contributes to a nuanced understanding of how Hindu calendar elements may play a role in shaping temperature trends. The heatmaps serve as powerful visual tools to communicate these intricate relationships, paving the way for informed interpretations and discussions in subsequent sections of the analysis.

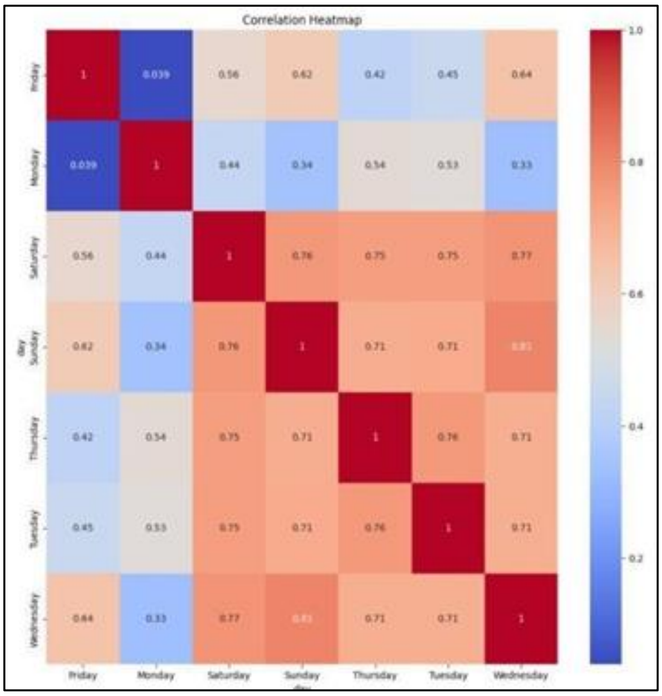

Fig 3: Correlation Hear-Map of Days(Vaara)

- The investigation extended to the correlation patterns among weekdays, offering insights into their interrelationships within the dataset. In contrast to the Thithi days, weekdays displayed a prevalence of positive correlations. Notably, Sunday and Wednesday exhibited a notably high positive correlation, implying that elevated temperatures on Wednesdays might correspond to higher temperatures on subsequent Sundays.
- Conversely, Monday and Friday stood out with a marked negative correlation compared to other weekdays. This suggests an inverse relationship, indicating that if temperatures are higher on a Monday, they are likely to be lower on a subsequent Friday, and vice versa. These intricate correlations among weekdays contribute to a nuanced understanding of how specific days of the week may influence temperature dynamics in the studied region.

D. Month-Based Correlation

The analysis delved into exploring correlations among different months in the Hindu calendar, shedding light on potential patterns and relationships. Each month's dataset was scrutinized to discern how temperature fluctuations correlate across the Hindu calendar months.

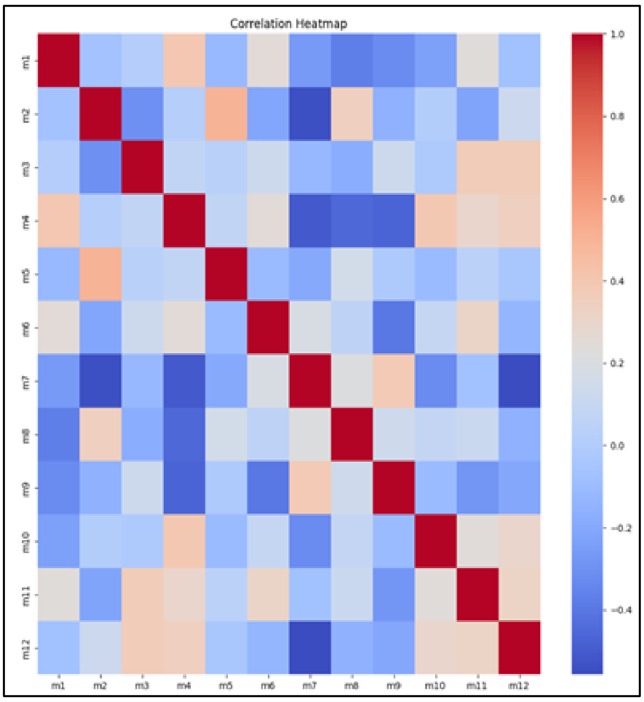

Fig 4: Correlation Hear-Map of Months in Hindu Calender

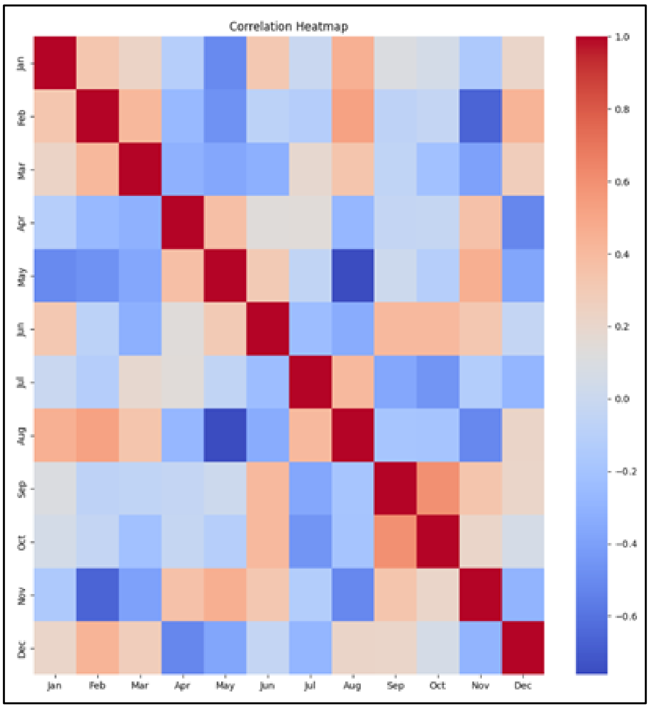

Fig 5: Correlation Hear-Map of Months in Gregorian Calender

In the extensive exploration of temperature variations over the course of a year, a meticulous examination of correlations between months in both the Hindu and Gregorian calendars was conducted. Focusing on the year 2019 in the Gregorian calendar and Vikram Samvat 2077 (March 2019 - March 2020) in the Hindu calendar, intriguing patterns emerged.

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The analysis underscored a notable distinction between the two calendars. In the Hindu calendar, months exhibited a higher degree of correlation, predominantly characterized by strong negative correlations. This cohesiveness within the Hindu calendar months suggests a potential facilitation of forecasting analyses due to the consistent 30-day duration of each month.

Contrastingly, the Gregorian calendar presented a challenging landscape for correlation analysis. The absence of pronounced positive or negative correlations between months implies a greater degree of variability. Moreover, the irregular days in each month added complexity to the analysis, necessitating the use of interpolation and correlation functions to standardize each month to a 30-day format.

In essence, the study accentuates the contrasting correlation dynamics between Hindu and Gregorian calendar months, with potential implications for the predictability and analysis of temperature patterns.

V. WEATHER PREDICITON &HINDU CALENDAR

We built two modesl in order to predict the temperature and compare the results in both the Hindu Calendar and the Gregorian Calendar. The code implements two distinct prediction models: one based on a Long Short-Term Memory (LSTM) neural network and another using a simple time series forecasting approach.

A. LSTM Neural Network Model

The LSTM model is constructed using TensorFlow and Keras. It comprises multiple LSTM layers with decreasing units, followed by a dense layer for predicting temperature values. The model is compiled with the mean squared error loss function and the Adam optimizer. Training is performed over 30 epochs, using a batch size of 64. The LSTM architecture enables the network to capture temporal dependencies in the data, crucial for time series prediction. Both training and testing predictions are visualized and compared with actual temperature values.

We used the model to predict the temperature for the years Vikram Smavat 2076-2077 of Hindu Calendar, which translates to 2019 March to 2020 March in Gregorain Calendar. We obtained the loss function of about 0.01.

The LSTM model is chosen for its proficiency in handling time-series data, making it well-suited for the intricate temporal patterns present in the temperature dataset. Its capability to capture long-term dependencies and remember past information aligns with the complex nature of temperature variations over extended periods.

Given that weather conditions often exhibit subtle and prolonged changes influenced by various factors, the LSTM model's ability to discern these patterns makes it a valuable tool for accurate temperature predictions.

The prediction graph is shown below:

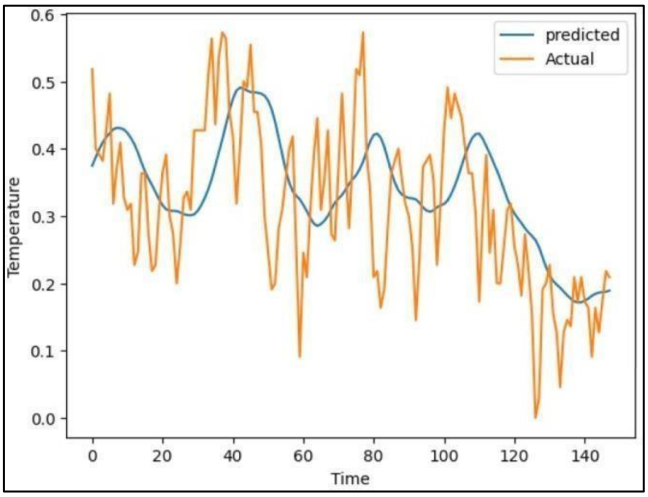

Fig 6: Temperature Prediction of a Gregorian Calendar Year (2019 – 2020)

B. Time Series Forecasting Model

The second approach involves a simpler time series forecasting model. The temperature data is preprocessed and scaled using MinMaxScaler. A time step of 14 days is chosen, and the dataset is divided into training and testing sets. The model architecture includes LSTM layers with decreasing units, followed by a dense layer. Similar to the LSTM model, it is compiled with mean squared error loss and the Adam optimizer. The model is trained for 30 epochs with a batch size of 64. The predictions are then inverse-transformed to obtain temperature values, and the results are compared with the actual temperature values.

These models aim to capture and leverage the temporal patterns in the dataset to make accurate temperature predictions. The LSTM model, in particular, excels at learning long-term dependencies in sequential data, making it well-suited for time series forecasting tasks. The models' performance can be assessed through visual inspection of predicted versus actual temperature plots and quantitative measures like mean squared error or other relevant metrics.

The predictions are made for the same time period mentioned before. The loss function obtained here is 0.01.

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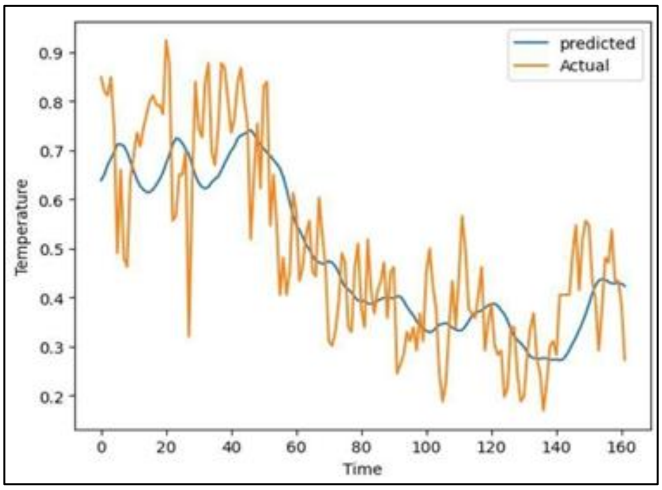

Fig 7: Temperature Prediction of a Hindu Calendar Year (Vikram Smavat 2076-2077)

VI. RESULTS

On comparing the predictions of temperature using both Hindu and Gregorian Calendars, it is observed that in the Hindu Calendar approach, the temperature variation has shown an identifiable pattern. The prediction model performed well and followed the actual trend in a better way. Also, as the pattern is more clear and predcitable in this case, we can get more insights and better results from the models built on Lunisolar calendar approach like the Hindu Calendar. Considering the Gregorain Calendar approach, it shows rapid change in the temperature over the time and could not follow a predictable pattern. As the prediction model did not do much better in this model, it is well done in the previous case. So, we can get some initial insights that following the lunisolar approach yeilds better observation of patterns in the temperature over the time rather than the solar or lunar approaches alone. The more better the patterns we observe, the more accurate and better results we obtain. With our analysis and predictions, we found that the lunisolar approach in predicting the temperature stands out better than the other approaches.

VII. CONCLUSION

In conclusion, the comparative analysis of temperature predictions using both Hindu and Gregorian Calendars reveals distinctive patterns and performance disparities. The Hindu Calendar approach, rooted in the lunisolar system, showcases a commendable ability to capture and predict temperature variations with a discernible pattern. The predictive model aligned well with the actual trends, indicating the effectiveness of the lunisolar calendar in providing valuable insights into temperature fluctuations over time.

On the contrary, the Gregorian Calendar approach struggled to exhibit a clear and predictable pattern in temperature variations. The model's performance fell short, highlighting the limitations of relying solely on a solar calendar for temperature predictions. This stark difference in predictive outcomes underscores the potential superiority of the lunisolar approach, as exemplified by the Hindu Calendar, in understanding and forecasting temperature changes.

For future work, the focus could shift towards refining and expanding the lunisolar calendar-based prediction models. Exploring additional features or incorporating advanced machine learning techniques could enhance the accuracy of temperature predictions. Furthermore, extending the analysis to different geographical regions or incorporating more granular data could provide a comprehensive understanding of lunisolar calendar applications in diverse contexts. The findings suggest a promising avenue for leveraging lunisolar calendars in weather prediction, encouraging further exploration and refinement of predictive models based on these ancient timekeeping systems.

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