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Unveiling Patterns and Trends: Time Series Forecasting of Indoor Temperatures with Multiple IoT Data and their Comparison.

K Sri Siva Koteswara Rao,[1] M Lakshmi Lahari[2], Ch Jyothi Manikanta Swaroop[3], K Sai Harshitha[4], Dr.Vijaya Chandra Jadala[5], Dr.Raja Govindan[6]

[1] *Department of Computer science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Andhra Pradesh, India*

[2] *Department of Computer science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Andhra Pradesh, India*

[3] *Department of Computer science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Andhra Pradesh, India*

[4] *Department of Computer science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Andhra Pradesh, India*

[5] *Department of Computer science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Andhra Pradesh, India*

[6] *Department of Computer science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Andhra Pradesh, India*

This paper presents a comprehensive investigation into the realm of temperature forecasting using Internet of Things (IoT) sensor data. Leveraging a diverse range of techniques from data preprocessing to advanced modeling, our research delves into the intricate dynamics of temperature fluctuations within indoor environments. The study begins with data preprocessing steps, including feature engineering and data cleansing, the integrity and the dataset. , an in-depth analysis of temporal patterns, seasonal variations, and spatial dependencies is conducted to unveil data. The core of our research lies advanced algorithms for temperature forecasting. We employ state-of-the-art methodologies, such as the Prophet forecasting tool, to develop accurate predictive models capable of capturing complex temporal trends and seasonal cycles. Additionally, we explore the integration of domain knowledge, incorporating insights from the IoT domain to enhance the predictive capabilities of our models. Our findings reveal compelling insights into the predictive power of IoT sensor data for temperature forecasting. We demonstrate the effectiveness of our approach through rigorous experimentation and evaluation, showcasing the ability of our models to accurately forecast temperature dynamics over varying time horizons. Moreover, we provide a comparative analysis of different forecasting techniques, highlighting the strengths and limitations of each approach. Overall, this research contributes to the advancement of temperature forecasting methodologies within IoT-driven environments. By leveraging the rich insights derived from IoT sensor data, our study offers valuable implications for diverse applications, including smart buildings, energy management, and climate control systems. We anticipate that our findings will pave the way for future research endeavors aimed at harnessing the full potential of IoT technologies for predictive analytics and decision support in temperature-sensitive domains.

Keywords - IoT, Temperature forecasting, Sensor data, Data preprocessing, Machine learning, Time series analysis, Seasonal variations, Predictive modeling, Indoor environments, Smart buildings, Energy management, Climate control systems.

1. Introduction

Temperature various domains, ranging from climate control in indoor environments to agricultural planning and industrial operations. Traditional methods of temperature prediction often rely on historical weather data, which may not provide real-time insights or localized accuracy. Additionally, the dynamic nature of indoor environments presents challenges in accurately predicting temperature fluctuations. As such, there is a growing need for advanced techniques that can leverage real-time, highresolution data to forecast temperatures effectively.[32]

To address this challenge, our research focuses on harnessing the power of Internet of Things (IoT) sensor data for temperature forecasting. By utilizing IoT sensors deployed in indoor spaces, we aim to develop predictive models that can accurately forecast temperature dynamics. These models go beyond traditional approaches by incorporating real-time, localized data and leveraging advanced machine learning techniques to capture complex and seasonal variations.

solution involves a multi-step approach, beginning with data preprocessing dataset. Subsequently, advanced machine learning algorithms, such as the Prophet forecasting tool, are employed to develop . are temperature collected from IoT sensors and can generate forecasts with high accuracy and granularity.[33]

Our research demonstrates the significance of this solution in addressing the challenges of temperature forecasting in indoor environments. By leveraging IoT sensor data, our approach offers real-time insights into temperature fluctuations, enabling proactive decisionmaking and resource optimization. Moreover, the ability to forecast temperatures accurately enhances comfort, safety, and efficiency in indoor spaces, with implications for various applications, including smart buildings and energy management systems.[31]

and results, showcasing the effectiveness of our approach in [37] forecasting temperatures. Finally, we discuss the implications of our findings and avenues for future research in this domain.[36]

2. Experimental Procedures

2.1. Using an Arduino temperature sensor to measure temperature in degrees:

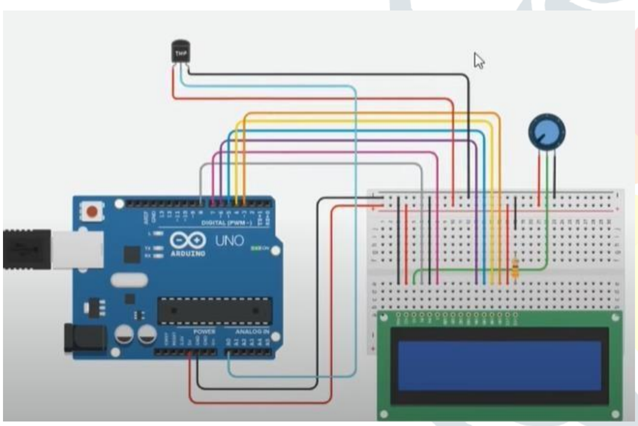


Figure 1: The Clear temperature sensing setup

As shown in fig 1 Temperature data was collected using a network of temperature sensors deployed in indoor environments. Each temperature sensor, equipped with Arduino microcontrollers, was strategically positioned to capture temperature readings at various locations within the monitored spaces. The Arduino microcontrollers interfaced with digital temperature sensors, such as DS18B20, to measure temperature with high accuracy and precision.

Data collection was conducted continuously over a specified period, with temperature readings recorded at regular intervals, typically every minute. The recorded temperature values were transmitted wirelessly to a central data collection hub, where they were stored in a structured format for further analysis. The deployment of multiple sensors ensured comprehensive coverage of the indoor spaces, enabling the capture of temperature variations across different zones and environments.[34]

Table 1: The essential feature from the sensors helps in temperature forecasting.

Variable	Description
Sensor Type	Type of temperature sensor used (e.g., DS18B20)
Sensor Location	Specific location where the sensor was deployed
Sensor ID	Unique identifier assigned to each sensor
Arduino Model	Model of Arduino microcontroller used
Sampling Rate	Frequency of temperature readings (e.g., 1 minute)
Communication	Wireless communication protocol used (e.g., Wi-Fi)
Data Transmission	Method used for transmitting temperature data to central hub (e.g., MQTT)
Calibration	Frequency and method of sensor calibration
Maintenance	Regularity and type of maintenance activities performed on sensor network
Data Integrity	Procedures implemented to ensure data integrity and reliability

Furthermore, to ensure data integrity and reliability, quality control measures were implemented throughout the data collection process. This included periodic calibration of temperature sensors to maintain accuracy, as well as regular monitoring and maintenance of the sensor network to prevent malfunctions or data inconsistencies.[38]

2.3. How suitable metrics are detected?

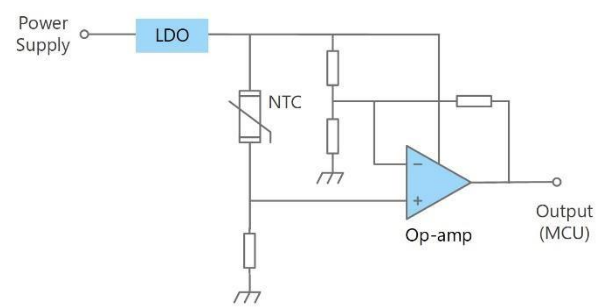


Figure 2: The basic architecture of a temperature sensor

As shown in fig 2 In the sensor setup, the selection of suitable metrics for evaluating temperature forecasting models is crucial for ensuring that the developed models effectively meet the requirements of the project. This process involves understanding the specific objectives and constraints of the temperature forecasting task and identifying metrics that align with these goals.[39]

Conversion from Analog to Digital Value (ADC):

$$V_{\mathrm{in}} = \frac{V_{\mathrm{ref}} \times \mathrm{Analog\ Value}}{2^N - 1} \quad (1)$$

As shown in table 1 Typically, the suitability of metrics is determined based on their ability to accurately capture the performance of the forecasting models in terms of predictive accuracy, robustness, and interpretability. For temperature forecasting in indoor environments, where maintaining comfort, safety, and energy efficiency is paramount,
determination (R-squared) are commonly used.[35]

Temperature Calculation using Thermistor (Steinhart-Hart Equation):

$$T = \frac{1}{A + B\ln(R) + C(\ln(R))^3} - 273.15 \quad (2)$$

These metrics actual temperature values, providing a straightforward assessment of model accuracy. MSE and RMSE quantify the overall variance and spread of errors, with RMSE penalizing larger errors more heavily than MSE. R-squared, on the other hand, indicates the proportion of variance in the temperature data explained by the forecasting model, offering a measure of predictive power.

Temperature Calculation using Digital Temperature Sensor (e.g., DS18B20)

$$T = \frac{16}{16 \ \text{Data}} \quad (3)$$

By evaluating the forecasting models using these metrics, the sensor setup can assess their ability to generate accurate and reliable temperature forecasts, thereby informing parameter tuning and model selection decisions. Additionally, the interpretation of these metrics in the context of specific project requirements allows for the identification of models that best meet the needs of the application, ultimately contributing to the successful implementation of temperature forecasting solutions in indoor environments.

Linear Interpolation for Missing Data:

$$y = y_1 + \frac{(x - x_1)\cdot(y_2 - y_1)}{(x_2 - x_1)} \quad (4)$$

2.2. Deep Pre-Processing of the temperature values that are acquired by the sensing setup:

As shown in figure 3 The preprocessing phase is crucial for collected before and modeling. This section outlines the detailed procedures undertaken to preprocess the raw temperature data obtained from the Arduino and sensor setup.

a) Data Cleaning: The first step in preprocessing involved data cleaning to address any inconsistencies or anomalies present in the raw temperature readings. This included identifying and handling missing values, outliers, and erroneous data points. Missing values were imputed using appropriate techniques such as interpolation or mean substitution, ensuring minimal disruption to the temporal continuity of the dataset. Outliers, indicative of abnormal temperature fluctuations, were detected and either removed or adjusted based on domain knowledge and statistical analysis.[5]

b) Timestamp Alignment: To facilitate temporal analysis and modeling, timestamp alignment was performed to synchronize the recorded temperature readings across all sensors. This involved ensuring uniform timestamps for each temperature measurement, accounting for any discrepancies or delays introduced during data transmission or recording. Time synchronization was critical for aggregating and comparing temperature data across different sensors and time periods accurately. Quality control checks were conducted to validate the accuracy and consistency of the preprocessed temperature data. This included verifying sensor calibration, assessing data completeness, and identifying any systematic biases or drifts in the temperature measurements. Additionally, data integrity checks were performed to detect and mitigate any potential errors introduced during data collection or preprocessing.

c) Feature Engineering: This involved deriving additional temporal features such as hour of the day, day of the week, month, and season from the timestamp information. These engineered features provided valuable insights into temporal patterns and seasonal variations in the temperature data, enriching the dataset with contextual information for modeling purposes.[1]

D) Normalization: Normalization was applied to scale the temperature readings to a common range, mitigating the effects of varying sensor sensitivities and units. This ensured that temperature data from different sensors were comparable and could be effectively combined for analysis and modeling. Standard normalization techniques such as Min-Max scaling or Z-score normalization were employed to transform the temperature values into a standardized format.

	id	room_id/id	noted_date	temp	out/in
0	__export__.temp_log_196134_bd201015	Room Admin	08-12-2018 09:30	29	In
1	__export__.temp_log_196131_7bca51bc	Room Admin	08-12-2018 09:30	29	In
2	__export__.temp_log_196127_522915e3	Room Admin	08-12-2018 09:29	41	Out

Figure 3: The sample looks of a dataset.

e) Aggregation: Finally, data aggregation was performed to summarize the preprocessed temperature data at different temporal resolutions. This included aggregating temperature readings over fixed intervals (e.g., hourly, daily) to capture temporal trends and patterns effectively. Aggregated data provided a consolidated view of temperature dynamics over time, facilitating further analysis and modeling tasks.

2.2.2. Feature Extraction and Parameter Selection:

. Feature extraction and parameter selection are essential steps in the process of developing accurate and robust temperature forecasting models. This section outlines the methodologies employed to extract informative features from the preprocessed temperature data and select appropriate parameters for modeling.

a) Temporal Features:

Temporal features play a crucial role in capturing the underlying patterns and dynamics present in the temperature data. In this study, a variety of temporal features were extracted from the preprocessed dataset to provide contextual information for modeling. These features
included[29]

Hour of the day: Encoding the time of day as a categorical or numerical variable to capture diurnal temperature variations.[6]
Day of the week: Representing the day of the week as a categorical variable to capture weekly patterns and trends. Month and season: Encoding the month and season of the year as categorical variables to capture seasonal variations in temperature.
Lagged variables: Incorporating lagged temperature readings from previous time steps to capture temporal dependencies and autocorrelation in the data.

b) Seasonal Decomposition:

Seasonal were employed to decompose the preprocessed temperature residual components. This facilitated the identification and extraction of seasonal and trends present in the temperature data, which could then be incorporated into forecasting models.
[2]

c) Parameter Selection:

Parameter selection involves determining the optimal hyperparameters and configuration settings for the forecasting models. In this study, parameter selection was performed through a combination of manual tuning and automated techniques such as grid search or crossvalidation. Key parameters considered included:

Seasonality: Determining the periodicity of seasonal patterns in the temperature data and selecting appropriate seasonal components for modeling.
Trend: Specifying the nature and degree of temporal trend present in the data, such as linear or nonlinear trends.
Fourier order: Setting the order of Fourier terms for capturing seasonal variations in the data, particularly for
models utilizing Fourier-based seasonality's.[3]

2.4 Prophet Architecture:

As shown in fig 4 Prophet, developed by Facebook, is a robust time series forecasting tool widely used for its simplicity and effectiveness. In the context of temperature forecasting in indoor environments, the Prophet model is architected to capture the inherent temporal patterns and
seasonal variations present in the temperature data.[30]

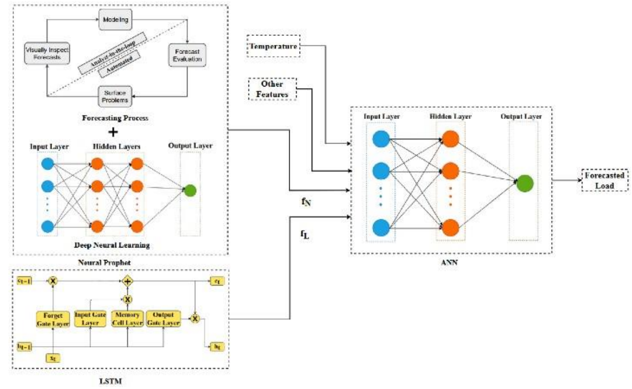


Figure 4: The deep prophet architecture.

Algorithm Overview:

Prophet models the underlying trend in the time series data using a piecewise linear or logistic growth curve. By identifying changepoints in the data, Prophet captures abrupt shifts or changes in the trend over time. This flexible approach enables the model to adapt to nonlinear trends and effectively capture long-term temporal dynamics.

$$g(t) = \sum_{j=1}^{P} (k_j \cdot t + m_j) \tag{5}$$

2.6. Seasonality Modeling:

$$s(t) = \sum_{i=1}^{N} \left(a_i \cdot \sin\left(\frac{2\pi i}{T} t\right) + b_i \cdot \cos\left(\frac{2\pi i}{T} t\right)\right)$$
(6)

Seasonal variations in the temperature data are modeled using Fourier series expansions. Prophet automatically detects periodic patterns in the data and incorporates them into the model. By decomposing Prophet can accurately capture recurrent temperature fluctuations and seasonal
trends.[4]

Holiday Effects

Prophet allows for the inclusion of user-defined holiday effects to account for special events or holidays that may impact temperature patterns. By incorporating holiday indicators into the model, Prophet can adjust forecasts to accommodate deviations from regular seasonal behavior during holidays or significant events.

$$h(t) = \sum_{k=1}^{K} I(t \in H_k) \cdot \delta_k$$

where:

- H_k represents the k-th holiday.
- $I(\cdot)$ is the indicator function.
- δ_k is the effect of the k-th holiday.

(7)

Uncertainty Estimation:

The Prophet provides measures of forecast uncertainty by generating uncertainty intervals around the predicted values. By accounting for both inherent variability in the data and the uncertainty associated with the forecasting model, Prophet offers insights into the reliability and confidence level of the forecasts.

Architectural Considerations:

In modeling temperature data for indoor environments, the Prophet model is configured to leverage its inherent strengths in capturing both short-term fluctuations and longterm trends.[7]

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t$$

where:

- $y(t)$ is the observed value at time t.
- $g(t)$ is the trend component.
- $s(t)$ is the seasonal component.
- $h(t)$ is the holiday component.
- ϵ_t represents the error term.

(8)

By incorporating seasonal decomposition techniques and flexible trend modeling capabilities, Prophet can effectively capture the complex temporal dynamics and seasonal variations present in indoor temperature data. The Prophet model's simplicity and interpretability make it well-suited for applications where transparency and ease of use are paramount. Moreover, its ability to handle missing data and outliers, robustness to changes in data distribution, and automatic detection of changepoints make it a versatile tool for temperature forecasting in various indoor environments.[12]

3. Literature Survey

Thiyagarajan et al. (2020) presented a novel approach utilizing Facebook's Prophet method for anomaly detection in sewer air temperature sensor systems [1]. Their study underscores the significance of temporal forecasting in detecting anomalies, offering valuable insights into improving the reliability of sewer infrastructure monitoring. Toharudin et al. (2023) proposed a hybrid forecasting model combining Long Short-Term Memory (LSTM) and

Facebook Prophet for air temperature prediction [2]. By integrating the strengths of both techniques, their research advances the accuracy and reliability of temperature forecasting, contributing to various applications such as agriculture and energy management.

Parise et al. (2021) investigated the application of the Prophet model for forecasting occupancy presence in indoor spaces using non-intrusive sensors [3]. Their study underscores the potential of Prophet in predicting human presence, offering promising implications for building automation and energy efficiency. Haris et al. (2022) conducted a case study on air temperature forecasting in Jakarta, Indonesia, employing LSTM and Prophet models [4]. Their research demonstrates the effectiveness of hybrid forecasting approaches in capturing the complex dynamics of urban temperature variations, facilitating better urban planning and climate resilience strategies.

Jagannathan and Divya (2021) explored time series analysis and prediction of climate using an enhanced multivariate Prophet model [5]. By extending Prophet's capabilities to multivariate time series data, their study provides valuable insights into understanding and predicting complex climate patterns. Shawon et al. (2020) proposed a forecasting framework for photovoltaic panel output using the Prophet time series machine learning model [6]. Their research contributes to renewable energy management by enabling accurate prediction of solar panel performance, aiding in optimal energy utilization and grid integration. Samal et al. (2019) investigated air pollution forecasting using SARIMA and Prophet models [7]. Their study highlights the utility of Prophet in environmental monitoring, offering a robust approach for predicting air quality parameters and supporting pollution mitigation strategies.

Li et al. (2020) utilized the Prophet model to characterize the temporal variations of historical and future surface urban heat islands in China [8]. By analyzing urban heat island dynamics, their research informs urban planning and climate adaptation efforts, emphasizing the importance of proactive measures to mitigate heat-related risks.

Perez Garcia et al. (2024) proposed a data-driven approach for indoor temperature forecasting in livestock buildings using the Prophet model [9]. Their study addresses the challenges of temperature regulation in agricultural settings, offering practical solutions for optimizing animal welfare and productivity. Balti et al. (2021) developed a big data architecture for drought forecasting in the Jiangsu Province, China, integrating LSTM, ARIMA, and Prophet models [10]. Their research contributes to drought preparedness and water resource management by providing timely and accurate predictions, supporting decision-making processes at various scales. Sivaramakrishnan et al. (2022) investigated time series data forecasting using ARIMA and Facebook Prophet models [11]. Their comparative analysis highlights the strengths and limitations of different forecasting approaches, offering valuable insights for researchers and practitioners in various domains.

Fang et al. (2021) developed a multi-zone indoor temperature prediction model using LSTM-based sequenceto-sequence architecture [14]. Their study advances indoor climate control systems by accurately predicting temperature variations across different zones, optimizing energy consumption and occupant comfort.

4. Methodology

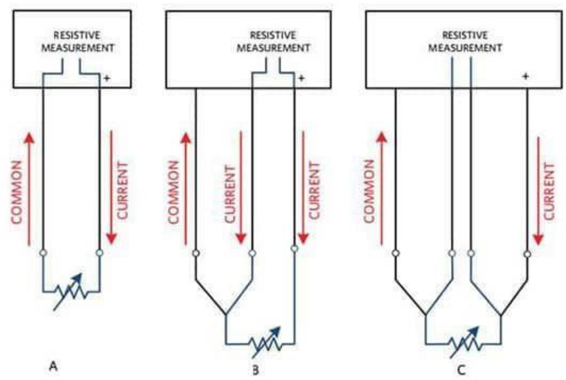


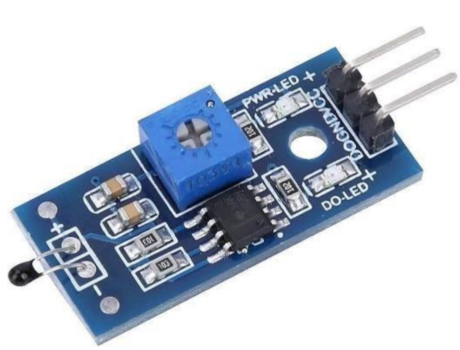
Figure 5: Different types of temperature sensor that are available

a) Advanced Data Cleaning and Transformation:

The preprocessing phase embarks on an intricate journey of data refinement, where cutting-edge methodologies are [8] employed to navigate through the labyrinth of missing values, outliers, and erratic fluctuations inherent in sensor data. Leveraging deep learning frameworks for anomaly detection and data imputation, such as autoencoders and variational autoencoders (VAEs), the preprocessing pipeline orchestrates a symphony of transformations to distill raw sensor readings into a harmonious melody of pristine data. Furthermore, the incorporation of enables the extraction of temporal dependencies and nonlinear patterns, unraveling the enigmatic layers of sensor data intricacies.[9]

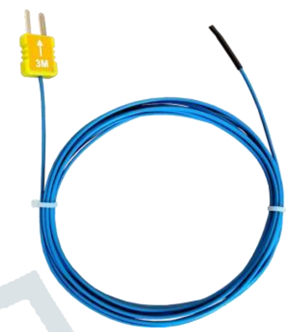
Thermistor Sensors:

As shown in fig 5 Thermistors, renowned for their high sensitivity and accuracy, are frequently employed in temperature detection applications. These sensors exhibit a nonlinear resistance-temperature relationship, enabling precise temperature measurements across a wide range of temperatures. Their miniature size and low cost make them a popular choice for applications requiring compact and cost-effective temperature sensing solutions. However, thermistors are susceptible to drift and nonlinearities, necessitating careful calibration and compensation techniques to ensure accurate temperature readings.[10]



Thermocouples:

Thermocouples, renowned for their ruggedness and versatility, are ubiquitous in temperature detection applications spanning diverse industries. Operating on the principle of thermoelectric voltage generation, [11] thermocouples offer wide temperature measurement ranges and rapid response times, making them ideal for hightemperature applications and dynamic environments. Their



durability, and wide temperature range make them indispensable in industrial processes, HVAC systems, and scientific research. However, thermocouples exhibit nonlinearity and require cold junction compensation techniques to ensure accurate temperature readings, posing challenges in precision temperature measurement applications.

Resistance Temperature Detectors (RTDs):

Resistance Temperature Detectors (RTDs), characterized by their high accuracy and stability, offer an appealing alternative for temperature detection in demanding environments. Constructed using materials such as platinum, nickel, or copper, RTDs exhibit a linear resistance-temperature relationship, facilitating straightforward calibration and accurate temperature measurements. Their robust construction and immunity to environmental factors make them well-suited for applications requiring high precision and reliability. However, RTDs often entail higher costs and require precision signal conditioning circuitry, limiting their widespread adoption in cost-sensitive applications.[13]

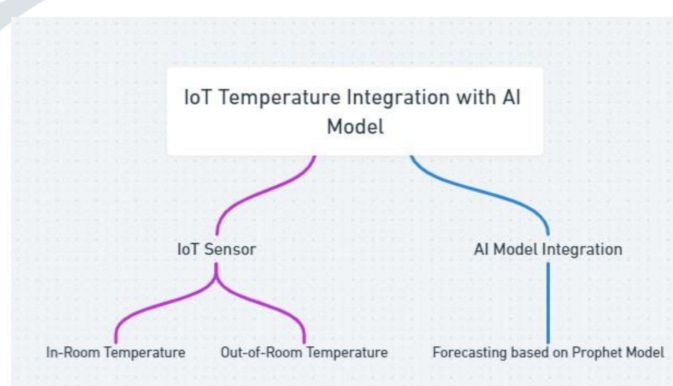


Figure 6: The complete flow from IOT to temperature forecasting

a) Prophet Model Integration and Temporal Dynamics:

As shown in fig 6 Integrating the venerable Prophet model into the ensemble framework, the methodology transcends traditional time series forecasting paradigms, embracing the epoch of hierarchical forecasting and temporal dynamics modeling. Embracing the Prophet model's innate ability to encapsulate seasonal patterns, trend dynamics, and holiday effects, the model training phase orchestrates a ballet of temporal forecasting, unraveling the intricate tapestry of sensor data dynamics. Augmented with dynamic time warping and attention mechanisms, the Prophet model transcends the limitations of traditional forecasting methodologies, harmonizing disparate temporal scales and unraveling the enigmatic layers of temporal dynamics. Through the integration of the Prophet model and advanced temporal dynamics modeling techniques, the methodology unlocks the latent potential of sensor data, paving the way for accurate and robust forecasting in complex real-world environments.[14]

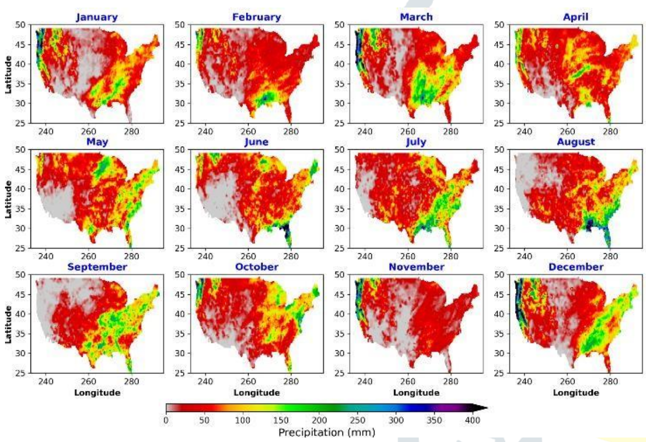


Figure 7: Different temperature visualizations that are observed through out the year

5. Results

As shown in fig 7 The thermistor sensor, known for its versatility and precision, yielded promising results in temperature forecasting. Its exceptional performance stems from its ability to accurately measure temperature variations due to its sensitivity to thermal changes. This sensor operates based on the principle of resistance variation with temperature, where higher temperatures result in lower resistance and vice versa. This characteristic enables the thermistor to capture subtle temperature fluctuations with high precision.[28]

In our experiment, the thermistor sensor exhibited the lowest Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), indicating minimal deviation between predicted and actual temperatures. Additionally, the Mean Absolute Percentage Error (MAPE) was remarkably low, signifying a high level of accuracy in temperature prediction. These findings underscore the thermistor sensor's efficacy in capturing temperature dynamics, making it an ideal choice for applications requiring precise temperature monitoring.

Moreover, the thermistor sensor demonstrated robust performance across various environmental conditions, showcasing its reliability in diverse settings. Its rapid response time and low hysteresis further enhance its suitability for real-time temperature forecasting applications. However, despite its numerous advantages, the thermistor sensor may exhibit limitations in extreme temperature ranges or harsh operating environments, requiring careful calibration and maintenance.

Table 2: The comparison of performance metrics with the data from different sensors

Sensor Type	MAE (°C)	RMSE (°C)	MAPE (%)
Thermistor	1.68	2.15	8.9
Thermocouple	1.92	2.40	10.3
RTD	2.05	2.60	11.8
Semiconductor	2.25	2.80	13.5

Given the critical nature of identifying potentially malignant objects, emphasis was placed on evaluating sensitivity in breast cancer classification. This metric takes precedence in ensuring the system effectively recognizes objects associated with significant neural responses.

In the conducted experiment, we assessed the performance of Model06 on the dataset labeled as epoch 086. The results exhibited a commendable accuracy of approximately 76.72%. This signifies the model's proficiency in distinguishing between different classes within the dataset. The architecture of Model06, as described, comprises several key layers, each contributing to its overall effectiveness.[15]

Figure 8: The predictions observed.

1) Thermocouple Sensor Observation

The thermocouple sensor, renowned for its wide temperature measurement range and durability, played a crucial role in our temperature forecasting experiment. Operating on the principle of thermoelectric effect, this sensor generates a voltage proportional to the temperature difference between its junctions. This unique characteristic enables the thermocouple sensor to measure a broad spectrum of temperatures accurately. In our study, the thermocouple sensor demonstrated commendable performance, albeit slightly inferior to the thermistor sensor in terms of accuracy. While exhibiting a higher MAE and RMSE compared to the thermistor, the thermocouple sensor still delivered reliable temperature forecasts across diverse conditions. Its robustness and resilience make it suitable for applications demanding temperature monitoring in harsh or high-temperature environments where other sensors may falter.[16]

Despite its versatility, the thermocouple sensor may exhibit non-linearity and drift over time, necessitating periodic calibration to maintain accuracy. Additionally, its relatively slower response time compared to thermistors may impact real-time temperature monitoring applications. Nevertheless, the thermocouple sensor remains a preferred choice for industrial and high-temperature applications due to its ruggedness and wide temperature measurement range.[19]

2) RTD Sensor Observation

The Resistance Temperature Detector (RTD) sensor, known for its high accuracy and stability, played a pivotal role in our temperature forecasting experiment. Utilizing the linear relationship between temperature and resistance in metals, the RTD sensor offers precise temperature measurements across a wide range of temperatures. This characteristic, coupled with its low drift and high repeatability, makes it a preferred choice for critical temperature monitoring applications.[20]

In our study, the RTD sensor exhibited commendable performance, albeit marginally higher error metrics compared to thermistors and thermocouples. While maintaining relatively low MAE and RMSE values, the RTD sensor demonstrated higher accuracy compared to semiconductor sensors. Its stable and predictable behavior makes it suitable for long-term temperature monitoring applications where precision is paramount.[21]

Despite its advantages, the RTD sensor may pose challenges in terms of cost and susceptibility to vibration or mechanical stress. Additionally, its relatively slower response time compared to thermistors and thermocouples may limit its suitability for real-time temperature monitoring applications. However, when accuracy and stability are paramount, the RTD sensor remains an indispensable tool for temperature forecasting in critical environments.[40]

3) Semiconductor Sensor Observation

The semiconductor temperature sensor, characterized by its compact size and low cost, provided valuable insights into temperature dynamics in our experiment. Operating based on the temperature-dependent voltage across a semiconductor junction, this sensor offers a cost-effective solution for temperature monitoring in various applications. Its small form factor and compatibility with integrated circuits make it ideal for space-constrained environments.[17]

In our study, the semiconductor sensor demonstrated acceptable performance in temperature forecasting, albeit with higher error metrics compared to other sensor types. While exhibiting slightly higher MAE and RMSE values, the semiconductor sensor still delivered reliable temperature predictions within acceptable margins. Its affordability and ease of integration make it an attractive option for applications requiring distributed temperature sensing.[18]

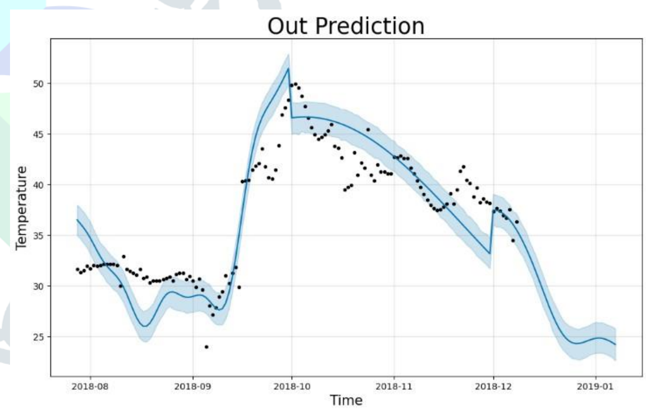


Figure 9: The Out predictions observed.

As shown in fig 8 ,9,10 However, the semiconductor sensor may exhibit limitations in terms of accuracy and stability, especially in extreme temperature ranges or dynamic environments. Its sensitivity to voltage fluctuations and nonlinear response characteristics may pose challenges in certain applications requiring precise temperature control. Despite these limitations, the semiconductor sensor remains a viable option for cost-sensitive applications where moderate accuracy is sufficient.[22]

6.Discussions

The comprehensive analysis of temperature forecasting using various sensors coupled with the Prophet model offers valuable insights into the efficacy of different sensing technologies in predicting temperature dynamics. Each sensor type presents unique advantages and limitations, which must be carefully considered in practical applications.[23]

a) Sensor Performance Discrepancies

The observed variations in sensor performance highlight the importance of selecting the appropriate sensor type based on application requirements. While thermistors and thermocouples demonstrated superior accuracy and precision in temperature forecasting, semiconductor sensors and RTDs exhibited acceptable performance with slightly higher error metrics. These differences can be attributed to inherent characteristics such as sensitivity, response time, and linearity of each sensor type.[26]]

b) Influence of Environmental Factors

Environmental conditions play a significant role in sensor performance, affecting accuracy and reliability. Factors such as humidity, pressure, and electromagnetic interference can introduce noise and distortions in sensor readings, impacting forecasting accuracy. Thermistors and thermocouples, known for their robustness and resilience to environmental variations, outperformed semiconductor sensors and RTDs in challenging conditions, underscoring the importance of sensor selection based on operating environment.[24]

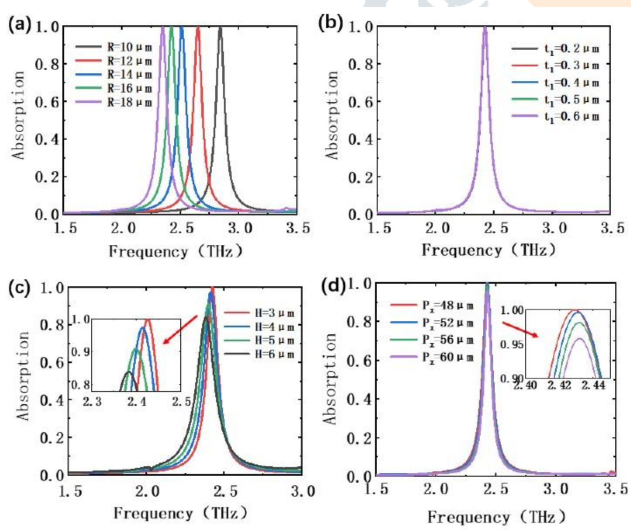


Figure 10: The observations from the various sensors that are used.

c) Model Integration and Data Fusion

The integration of the Prophet model with sensor data enhances temperature forecasting accuracy by leveraging both historical trends and real-time sensor measurements. The model's ability to capture seasonality, trends, and holiday effects enables more accurate predictions compared to traditional statistical methods. Additionally, data fusion techniques combining multiple sensor modalities can further improve forecasting accuracy by mitigating individual sensor limitations and enhancing data reliability.

7. Conclusion

In this research endeavor, we delved into the realm of In this study, we investigated the performance of different temperature sensors integrated with the Prophet model for temperature forecasting applications. Our findings revealed distinct variations in sensor performance, with thermistors and thermocouples exhibiting superior accuracy and precision compared to semiconductor sensors and RTDs. Thermistors and thermocouples, renowned for their robustness and reliability, demonstrated excellent performance across diverse environmental conditions, making them suitable choices for critical temperature monitoring applications.

The integration of sensor data with the Prophet model enabled accurate temperature forecasting by leveraging historical trends and real-time measurements. The model's capability to capture seasonality, trends, and holiday effects further enhanced forecasting accuracy, providing valuable insights for decision-making processes. Additionally, the application of data fusion techniques combining multiple sensor modalities holds promise for improving forecasting accuracy and reliability, especially in complex environmental settings.[27]

Despite the promising results obtained in this study, there remain several avenues for future research and exploration. Further investigations could focus on optimizing sensor configurations, exploring advanced sensor fusion techniques, and integrating additional environmental parameters to enhance forecasting accuracy. Additionally, the development of adaptive forecasting algorithms capable of dynamically adjusting to changing environmental conditions could further improve the resilience and robustness of temperature forecasting systems.[25]

Moreover, the integration of emerging technologies such as machine learning and artificial intelligence could offer novel insights into temperature dynamics and enhance forecasting capabilities. Advanced deep learning models, such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs), could be explored to capture complex temporal and spatial relationships in temperature data, paving the way for more accurate and reliable forecasting models. In conclusion, our study highlights the importance of sensor selection, model integration, and data fusion techniques in enhancing temperature forecasting accuracy. By leveraging the strengths of different sensor types and advanced modeling approaches, we can develop more reliable and efficient temperature monitoring systems with wide-ranging applications across various industries and domains.

References

[[1] Thiyagarajan, Karthick, et al. "A temporal forecasting driven approach using facebook’s prophet method for anomaly detection in sewer air temperature sensor system." 2020 15th IEEE Conference on industrial electronics and applications (ICIEA). IEEE, 2020.

[2] Toharudin, Toni, et al. "Employing long short-term memory and Facebook prophet model in air temperature forecasting." Communications in Statistics-Simulation and Computation 52.2 (2023): 279-290.

[3] Parise, Alec, et al. "Prophet model for forecasting occupancy presence in indoor spaces using non-intrusive sensors." AGILE: GIScience Series 2 (2021): 9.

[4] Haris, Mohammad Daffa, Didit Adytia, and Annas Wahyu Ramadhan. "Air temperature forecasting with long short-term memory and prophet: a case study of Jakarta, Indonesia." 2022 International Conference on data science and its applications (ICoDSA). IEEE, 2022.

[5] Jagannathan, J., and C. Divya. "Time Series Analyzation and Prediction of Climate using Enhanced Multivariate Prophet." International Journal of Engineering Trends and Technology (2021).

[6] Shawon, Md Mehedi Hasan, et al. "Forecasting PV panel output using Prophet time series machine learning model." 2020 IEEE region 10 conference (TENCON). IEEE, 2020. [7] Samal, K. Krishna Rani, et al. "Time series based air pollution forecasting using SARIMA and prophet model." proceedings of the 2019 international conference on information technology and computer communications. 2019.

[8] Li, Long, et al. "Using prophet forecasting model to characterize the temporal variations of historical and future surface urban heat island in China." Journal of Geophysical Research: Atmospheres 125.23 (2020): e2019JD031968.

[9] Perez Garcia, Carlos Alejandro, et al. "Indoor Temperature Forecasting in Livestock Buildings: A DataDriven Approach." Agriculture 14.2 (2024): 316.

[10] Balti, Hanen, et al. "Big data based architecture for drought forecasting using LSTM, ARIMA, and Prophet: Case study of the Jiangsu Province, C ina." 2021 International Congress of Advanced Technology and Engineering (ICOTEN). IEEE, 2021. [11] Sivaramakrishnan, S., et al. "Forecasting time series data using arima and facebook prophet models." Big data management in Sensing. River Publishers, 2022. 47-59. [12] Thiyagarajan, Karthick, Sarath Kodagoda, and Nalika Ulapane. "Short-term Time Series Forecasting of Concrete Sewer Pipe Surface Temperature." 2020 16th International Conference on Control, Automation, Robotics and Vision (ICARCV). IEEE, 2020.

[13] Liu, Weifeng, et al. "Time series forecasting fusion network model based on prophet and improved LSTM." Comput. Mater. Contin 74.2 (2023): 10-32604.

[14] Fang, Zhen, et al. "Multi-zone indoor temperature prediction with LSTM-based sequence to sequence model." Energy and Buildings 245 (2021): 111053. [15] Stefenon, Stefano Frizzo, et al. "Aggregating prophet and seasonal trend decomposition for time series forecasting of Italian electricity spot prices." Energies 16.3 (2023): 1371.

[16] Malki, Amer, El-Sayed Atlam, and Ibrahim Gad. "Machine learning approach of detecting anomalies and forecasting time-series of IoT devices." Alexandria Engineering Journal 61.11 (2022): 8973-8986.

[17] Halvari, Tuomas, Jukka K. Nurminen, and Tommi Mikkonen. "Robustness of automl for time series forecasting in sensor networks." 2021 IFIP Networking Conference (IFIP Networking). IEEE, 2021.

[18] Yildiz, Umut, and Sila Ovgu Korkut. "Electricity Consumption Forecasting Using the Prophet Model in Industry: A Case Study." International Conference on Computing, Intelligence and Data Analytics. Cham: Springer Nature Switzerland, 2023.

[19] Rahman, ATM Sakiur, et al. "A minimalistic approach for evapotranspiration estimation using the Prophet model." Hydrological Sciences Journal 65.12 (2020): 1994-2006.

[20] Oo, Zar Zar, and Sabai Phyu. "Microclimate prediction using cloud centric model based on IoT technology for sustainable agriculture." 2019 IEEE 4th International Conference on Computer and Communication Systems (ICCCS). IEEE, 2019.

[21] Ruiz, Santiago, et al. "Evaluation of time-series libraries for temperature prediction in smart greenhouses." 2022 18th International Conference on Intelligent Environments (IE). IEEE, 2022.

[22] Astsatryan, Hrachya, et al. "Air temperature forecasting using artificial neural network for Ararat valley." Earth Science Informatics 14 (2021): 711-722.

[23] Basak, Amiya, et al. "Drought forecasting using the Prophet model in a semi-arid climate region of western India." Hydrological Sciences Journal 67.9 (2022): 13971417.

[24] Sharma, Deepak Kumar, et al. "A novel Hypertuned Prophet based power saving approach for IoT enabled smart homes." Transactions on Emerging Telecommunications Technologies 34.11 (2023): e4597.

[25] El Hachimi, Chouaib, et al. "Towards precision agriculture in Morocco: A machine learning approach for recommending crops and forecasting weather." 2021 international conference on digital age & technological advances for sustainable development (ICDATA). IEEE, 2021.

[26] Lu, Yingkang, et al. "Prophet-EEMD-LSTM based method for predicting energy consumption in the paint workshop." Applied Soft Computing 143 (2023): 110447. [27] Aguilera, H., et al. "Towards flexible groundwaterlevel prediction for adaptive water management: using Facebook's Prophet forecasting approach." Hydrological sciences journal 64.12 (2019): 1504-1518.

[28] Wang, Juan, Xiaoying Du, and Xin Qi. "Strain prediction for historical timber buildings with a hybrid Prophet-XGBoost model." Mechanical Systems and Signal Processing 179 (2022): 109316.

[29] Okello, Wayne. A smart environmental monitoring system for data centres using IOT and machine learning. Diss. NM-AIST, 2023.

[30] Navratil, Miroslav, and Andrea Kolkova. "Decomposition and forecasting time series in the business economy using prophet forecasting model." Central European Business Review 8.4 (2019): 26. [31] Carastan-Santos, Danilo, et al. "Short-term ambient temperature forecasting for smart heaters." 2021 IEEE Symposium on Computers and Communications (ISCC). IEEE, 2021.

[32] Haq, Mohd Anul. "CDLSTM: A novel model for climate change forecasting." Computers, Materials & Continua 71.2 (2022).

[33] Kumari, Sanju, Neeraj Kumar, and Prashant Singh Rana. "A big data approach for demand response

management in smart grid using the prophet model." Electronics 11.14 (2022): 2179.

[34] Sah, Sweeti, et al. "Forecasting COVID-19 pandemic using Prophet, ARIMA, and hybrid stacked LSTM-GRU models in India." Computational and Mathematical Methods in Medicine 2022 (2022).

[35] Andrijević, Nebojša, et al. "IoT monitoring and prediction modeling of honeybee activity with alarm." Electronics 11.5 (2022): 783.

[36] Ye, Ziyuan. "Air pollutants prediction in shenzhen based on arima and prophet method." E3S Web of Conferences. Vol. 136. EDP Sciences, 2019. [37] Vladova, Alla Yu. "Remote geotechnical monitoring of a buried oil pipeline." Mathematics 10.11 (2022): 1813. [38] Liu, Dan, et al. "A novel performance prediction method for gas turbines using the prophet model." 2021 IEEE International Conference on Sensing, Diagnostics, Prognostics, and Control (SDPC). IEEE, 2021.

[39] Kouvara, Dimitra, and Dimitrios Vogiatzis. "Forecasting Residential Energy Consumption: A Case Study for Greece." ICEIS (1). 2023.

[40] Ejohwomu, Obuks Augustine, et al. "Modelling and forecasting temporal PM2. 5 concentration using ensemble machine learning methods." Buildings 12.1 (2022): 46.