Online-Journals.org

iJIM International Journal of Interactive Mobile Technologies

iJIM | eISSN: 1865-7923 | Vol. 17 No. 21 (2023) | OPEN ACCESS

https://doi.org/10.3991/ijim.v17i21.44143

PAPER

Comparison of Predictive Algorithms for IoT Smart Agriculture Sensor Data

Jakup Fondaj[1](✉), **Mentor Hamiti**[1], **Samedin Krrabaj**[2], **Xhemal Zenuni**[1], **Jaumin Ajdari**[1]

[1]South East European University, Tetovo, North Macedonia

[2]University "Ukshin Hoti", Prizren, Kosovo

jf13459@seeu.edu.mk

ABSTRACT

This paper compares predictive algorithms for smart agriculture sensor data in Internet of Things (IoT) applications. The main objective of IoT in agriculture is to improve productivity and reduce production costs using advanced technology and artificial intelligence. In this study, we compared various predictive algorithms for analyzing IoT smart agriculture sensor data. Specifically, we evaluated the performance of NeuralProphet, Random Forest Regression, SARIMA, and Artificial Neural Networks (ANN) by KERAS algorithms on a dataset containing temperature, humidity, and soil moisture data. The dataset was collected using IoT sensors in a smart agriculture system. The results showed that Random Forest Regression, Seasonal ARIMA, and Artificial Neural Networks by KERAS algorithms outperformed NeuralProphet algorithm in terms of accuracy and computational efficiency.

KEYWORDS

NeuralProphet, Random Forest Regression, SARIMA, Artificial Neural Networks (ANN) by KERAS, Internet of Things (IoT), smart agriculture sensor data, artificial intelligence (AI)

1 INTRODUCTION

Computing power has reached a state where many can predict future results using a sample of data for whatever objective they want to achieve. Humans have historically been trying to forecast weather and climate in the future.

Using artificial intelligence and a sample of data containing temperatures from past dates, we can predict temperatures for future dates. Temperature is usually affected by different weather phenomena such as humidity and pressure, but historically, temperatures have yearly trends that can be used to get an idea of future temperatures.

The sample data has been measured using IoT sensors in Libelium Smart Agriculture modules, which measure air temperature, air humidity, air pressure, and soil moisture.

Fondaj, J., Hamiti, M., Krrabaj, S., Zenuni, X., Ajdari, J. (2023). Comparison of Predictive Algorithms for IoT Smart Agriculture Sensor Data. *International Journal of Interactive Mobile Technologies (iJIM)*, 17(21), pp. 65–78. https://doi.org/10.3991/ijim.v17i21.44143

Article submitted 2023-08-21. Revision uploaded 2023-09-15. Final acceptance 2023-09-17.

Different algorithms have been used to get predictions, and some of them returned similar results. In this paper, we are going to compare the results predicted by four different algorithms: NeuralProphet [12], Random Forest Regression [11], SARIMA [10], and Artificial Neural Networks (ANN) [13] by KERAS.

The aim of this paper is to compare results from four different AI prediction algorithms that return similar results. Most of these algorithms use step predictions, which are based on the assumption that every temperature measurement is based on the previous measurement. Temperature samples for these algorithms have been measured hourly by IoT sensors for five years. A sample this large can be used to train models to show a near-accurate prediction of future temperatures. Models are going to be trained for many cycles so they can show as accurate results as possible. Once results have been produced, they will be compared with each other to find differences between them, comparing their visualizations and errors.

The following in the second section presents the related work for this topic. The third section presents the methodology we used for this research. The fourth part presents the results of the research. Last are the conclusion and future works.

2 RELATED WORKS

This study [1] introduces an innovative Internet of Things (IoT) framework for agriculture, enabling real-time data collection and predictive analysis. By integrating sensors to monitor soil conditions and crop health, farmers receive actionable insights for optimized decision-making and resource allocation, revolutionizing traditional farming methods.

The research [2] presents a wireless sensor network (WSN) framework for smart agriculture. It employs IoT technology to track soil conditions, temperature, and moisture, enabling real-time data analysis for informed decision-making by farmers. This work showcases IoT's potential to enhance sustainable resource management and crop yield.

The research [3] introduces an IoT-centered irrigation system that employs predictive algorithms. Through the real-time collection of data and the utilization of predictive models, this system adeptly orchestrates irrigation schedules to optimize water consumption. This endeavor enhances smart agriculture by enhancing resource allocation and bolstering crop yield through the synergy of IoT and predictive algorithms.

This paper [4] introduces IoT-enabled climate prediction for Smart Farming 4.0, employing IoT sensors and LSTM algorithms. The system forecasts climate patterns, aiding proactive decision-making in agriculture. It advances precision farming by mitigating adverse climatic conditions, enhancing crop yield, and managing resources.

Exploring IoT in precision farming, the authors [5] highlight its potential to revolutionize agriculture. By utilizing IoT devices for real-time monitoring and data-driven decisions, precision farming becomes sustainable and high-yield. This work contributes to agricultural technology's transformative impact on resource-efficient practices.

This research [6] employs IoT-based WSN and deep learning (DL) for evapotranspiration modeling in irrigation scheduling. The specialized DL technique optimizes water management. By utilizing IoT and advanced DL, the study enhances agriculture, achieving optimal water utilization and crop yield.

Investigating predictive analytics for IoT-enabled smart homes, the paper [7] optimizes energy consumption for sustainable urban development. Leveraging IoT technology and predictive modeling, it promotes efficient energy management in smart homes, aligning with eco-friendly urban planning.

This study [8] introduces a blockchain and smart contract framework for managing drones and IoT sensors in agriculture. It enhances transparency, traceability, and security in farm operations, contributing to precision agriculture and sustainable practices.

The paper [9] presents a hybrid classifier for analyzing sensor data in climate-smart agriculture systems. This approach combines classification techniques to interpret complex data, advancing precision farming and resource optimization.

A comparison of machine learning (ML) algorithms for crop yield prediction using sensor data in precision agriculture. The study [16] assesses algorithms like decision trees, random forest, and gradient boosting, highlighting their varying performance based on sensor data type.

This study [17] employs ML algorithms and deep learning to distinguish stars and galaxies from astronomical images. The authors explore accurate classification using machine learning, contributing to advancements in astrophysics and data science.

The paper [18] evaluates ML algorithms for soil moisture prediction using IoT sensor data. Algorithms such as random forest and artificial neural networks perform well, enhancing precision agriculture and efficient water management.

This research [19] compares ML algorithms for predicting fruit yield using sensor data. ANNs demonstrate high performance, contributing to smart agriculture's transformative potential.

The study [20] assesses ML algorithms for crop yield prediction using IoT sensor data. Algorithms such as gradient-boosting excel, enhance precision agriculture practices for optimal resource utilization.

This paper [21] evaluates ML algorithms for soil moisture prediction in precision agriculture. Gradient boosting and ANNs outperform other algorithms, contributing to efficient water management and crop yield optimization.

This study [24] explores IoT-based surveillance systems with enhanced security features. The integration of IoT devices and cloud technology enables real-time data analysis and response, emphasizing secure application development.

The research [25] focuses on classifying stars and galaxies using ML algorithms and DL techniques. It offers insights into accurate classification based on unique characteristics, advancing astrophysics and data science.

3 RESEARCH METHODOLOGY

From our previous research [26] we chose four algorithms to use for the prediction of whether conditions as "NeuralProphet [12], Random Forest Regression [11], SARIMA [10], and ANN [13] facilitated by the KERAS framework" [26].

To compare the results, we get from the four predictive algorithms we use in this research, we employ metrics such as "mean absolute error (MAE)" [15], "root mean squared error (RMSE)" [22], and "mean squared error (MSE)" [23].

The datasets, henceforth referred to as samples, encompass hourly temperature readings spanning from January 1, 2017, to December 31, 2021. Utilizing these data points, our endeavor entails forecasting temperatures for the entire year 2022. Instances of sensor data gaps have been mitigated by substituting them with specific values to maintain dataset continuity. It is important to mention that before using the dataset, we have done data preprocessing in order to remove unnecessary data and missing data. The data are time-series and seasonality data saved in CSV format. We use Python [27] to do the experiments and Plotly [27] in the library for visualization of results.

3.1 NeuralProphet

NeuralProphet [12] stands as an "ANN-derived time-series model," drawing inspiration from both Facebook Prophet and AR-Net. Constructed upon Python's PyTorch framework, it finds utility in making predictions for various time-series phenomena, including temperature forecasts [22]. Figure 1 presents the main concept behind the ANN model.

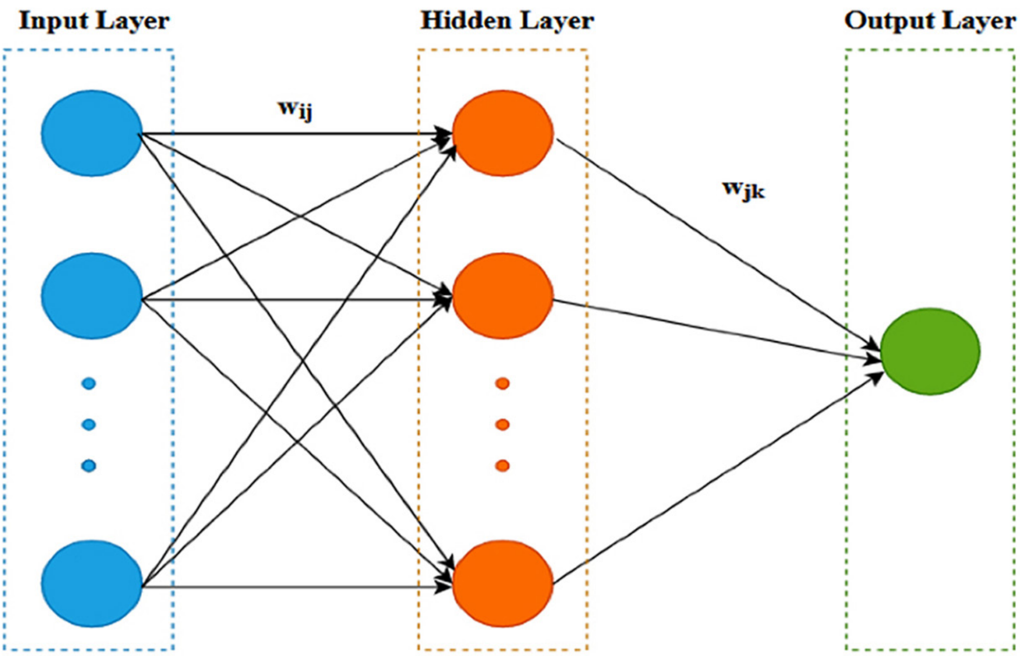

Fig. 1. The main concept behind the artificial neural network model [12]

This model will be employed to predict forthcoming temperature values based on historical temperature data.

Once our dataset is prepared and refined, it is inputted into the NeuralProphet model. Subsequently, the model undergoes training for 5000 epochs, resulting in a MAE of approximately 4.1 degrees after the specified period. Figure 2 presents the process of temperature prediction using NeuralProphet.

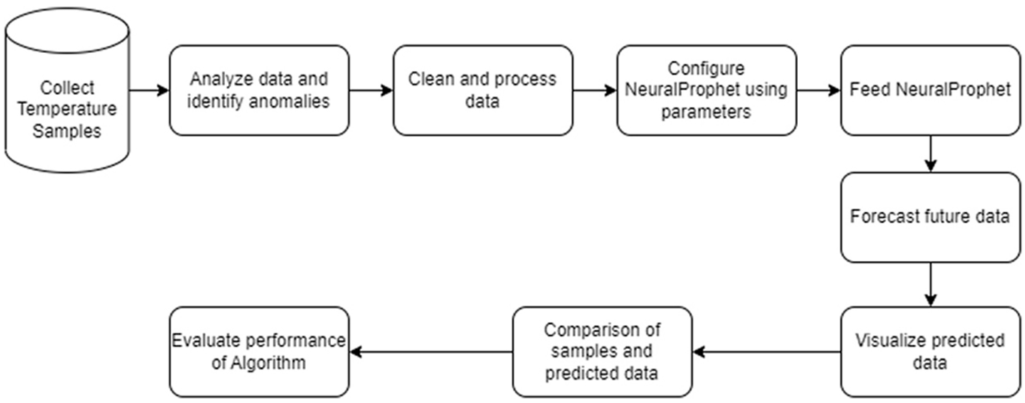

Fig. 2. Process of temperature prediction using NeuralProphet [12]

3.2 Random Forest Regression

The Random Forest [11] methodology is applicable for making predictions in time-series contexts. To utilize Random Forest for forecasting, a transformation of the dataset into a supervised learning scenario is necessary. Within this context, Random Forest Regression stands as a supervised learning technique, employing the concept of "ensemble learning." This approach involves the amalgamation of predictions generated by numerous machine learning algorithms to yield more precise forecasts than those produced by a single model. The structure or the Random Forest algorithm is presented in Figure 3.

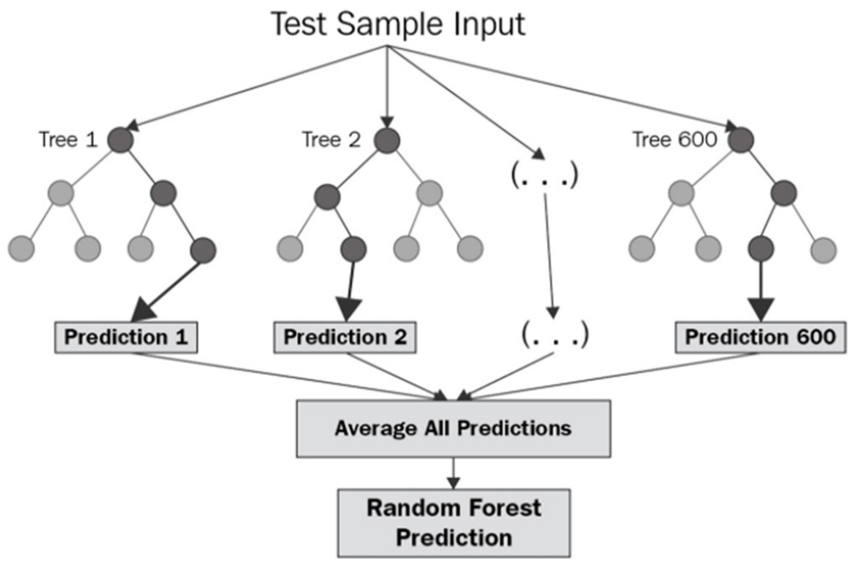

Fig. 3. Random Forest algorithms' structure [11]

After our dataset has undergone cleansing and preprocessing, it will undergo a transformation into a supervised learning format. Subsequently, this transformed data will be divided into training and testing subsets. Following this partitioning, the model will be trained on the training data and then tested on separate testing data. This evaluation will yield both predictions and a MAE, which was observed to be approximately 5.8 degrees.

Subsequently, a comparative analysis will be conducted, aligning the predicted data against the actual data to verify the accuracy of the algorithm's performance. This step ensures confirmation that the algorithm has successfully fulfilled its intended task.

3.3 SARIMA

ARIMA [14], which stands for "Autoregressive Integrated Moving Average" [14], holds a prominent position as a well-recognized and extensively employed technique for predicting time-series data involving varying quantities. Introducing seasonality into ARIMA leads to the creation of SARIMA [10], denoting "Seasonal Autoregressive Integrated Moving Average." This augmented approach becomes particularly advantageous for making predictions in time-series data that encompass both seasonal patterns and underlying trends.

$$SARIMA\ (p,d,q)\ (P,D,Q)_m \tag{1}$$

In the provided function, the variable 'p' signifies the count of autoregressive terms, 'd' denotes the number of nonseasonal differences required to achieve stationarity, and 'q' represents the quantity of lagged forecast errors in the predictive equation. Additionally, 'P,' 'D,' and 'Q' are introduced for handling the seasonal aspect of the time series.

The forecasting procedure employed by SARIMA follows an order of 1, 1, 1. When the dataset is loaded, it is fit into a SARIMAX model. The prediction of temperature is executed using a 1-step prediction model, wherein today's temperature is estimated based on the previous day's reading, and this process is repeated sequentially. This modeling approach yields an RMSE of merely 2.5 degrees. This outcome is satisfactory, considering the multitude of external variables influencing air temperature.

After fitting the model, we initiate non-dynamic predictions. This strategy ensures that only one-step-ahead forecasts are generated, implying that predictions at each instance are formed using the complete historical data up to that point.

Our prediction results in a MSE value of just 2.1 degrees, which is notably low and falls within acceptable bounds.

3.4 ANN by KERAS

According to [13], ANN is a computational model inspired by the structure and functioning of the human brain's neural networks. It's a machine-learning approach that attempts to mimic the way biological neurons communicate and process information. KERAS is an open-source high-level neural network API written in Python. It provides a user-friendly interface for building, training, and deploying ANNs. The concept of how the ANN algorithm works is presented in Figure 4.

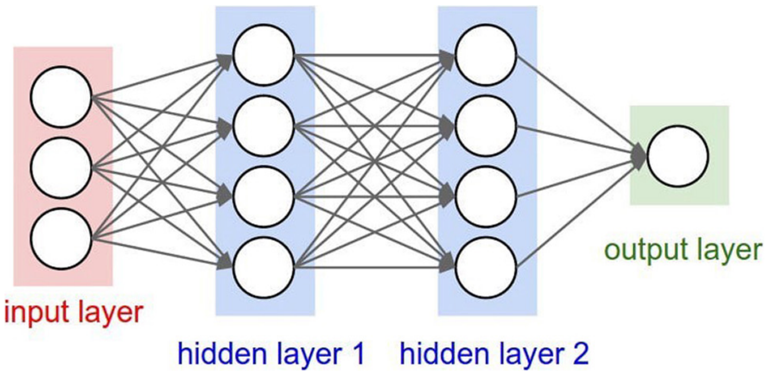

Fig. 4. Artificial neural network concept [13]

Our approach involves allocating 70% of the dataset for training the algorithm, while the remaining 30% is utilized for testing its outcomes. After the dataset is loaded and undergoes preprocessing, it is divided into a 70/30 ratio for the specific purposes of training and testing.

The trained model adopts the Keras dense layer, featuring interconnected neurons, and integrates batch normalization to optimize the training of deep neurons. This ensures alignment between inputs and outputs according to their intended patterns. Additionally, the rectified linear unit (ReLU) is employed, functioning as a tensor to process inputs and generate refined outputs [13].

Once the model is prepared, the dataset undergoes 100 epochs of model execution. However, at around 60 epochs, the prediction process halts as it has been executed sufficiently and its loss has reached a minimal level. This observation indicates the model's commendable efficiency in its operations.

Implementing Keras' ANN [13] in this algorithm yields a MAE [15] value of 4.5 degrees, showcasing the accuracy of the predictions made by the model.

4 PERFORMANCE MEASUREMENT OF PREDICTIVE ALGORITHMS

These initial findings serve as the basis for a comprehensive evaluation of the effectiveness of each algorithm, encompassing key metrics such as MAE [15], RMSE [22], and MSE [23] for forecasting both air temperature and air humidity.

Presented in the table below are the outcomes derived from utilizing four distinct algorithms for prediction:

Table 1. Comparison of predictive algorithms

	NeuralProphet	RFR	SARIMA	ANN by KERAS
Mean Squared Error (MSE)	24.0°C^2	38.1°C^2	4.4°C^2	33.6°C^2
Root Mean Squared Error (RMSE)	4.9°C	6.2°C	2.1°C	5.8°C
Mean Absolute Error (MAE)	4.1°C	5.8°C	2.0°C	5.5°C

From the result, we get we can conclude that SARIMA shows better results because of low MAE, RMSE, and MSE which means the result from the prediction is close to the real values.

5 RESULT AND DISCUSSION

After conducting confident runs for each algorithm, the prediction outcomes exhibit a remarkable similarity. This similarity arises from the shared utilization of the daily assumption concept across all algorithms. Notably, Random Forest Regression [11], Seasonal ARIMA [10], and ANN by Keras [13] have produced highly similar results, emphasizing a step-by-step predictive approach. In contrast, NeuralProphet [12] has focused more on capturing the underlying data trend, resulting in smoother temperature transitions throughout the year.

Importantly, it should be noted that our dataset initially contained numerous erroneous values. These discrepancies were rectified by substituting specific values to ensure the dataset's continuity, preventing any gaps that could impact the training and testing of our models. This adjustment had a notable influence on most models, as they occasionally converged toward the frequently occurring corrected value during their training phases. The missing values happened because the sensors didn't work correctly.

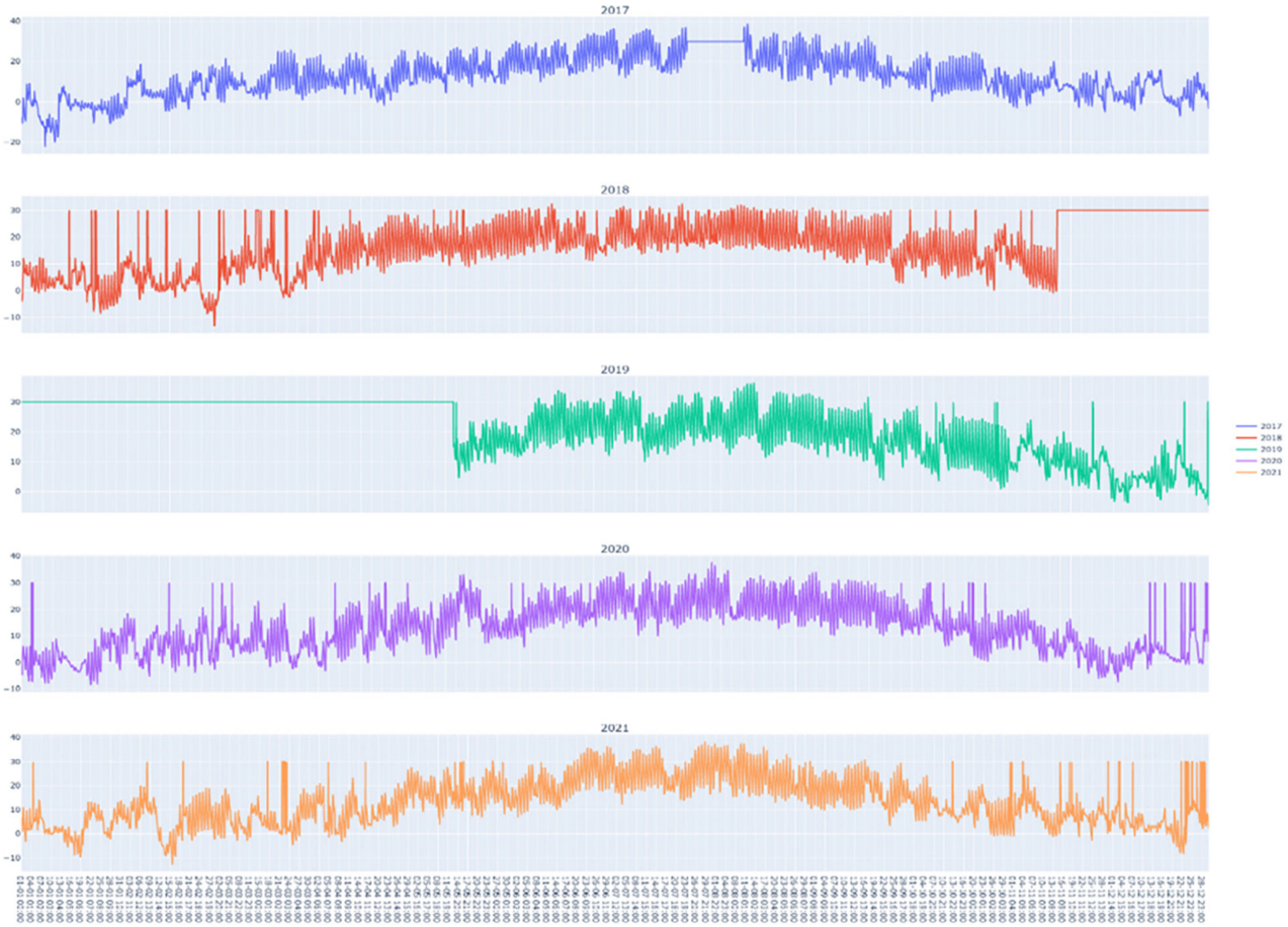

Fig. 5. Dataset visualization

5.1 Sample data (Dataset)

Illustrated in Figure 5, our dataset spans five complete years, encompassing temperature recordings from the commencement of 2017 to the conclusion of 2021. These temperature measurements were gathered through the utilization of IoT sensors. A distinct pattern within the dataset emerges, which is characterized by numerous instances of “peaks” or “flat lines” at the 30-degree mark. These instances correspond to artificially “corrected” values intended to rectify erroneous sensor readings.

Nevertheless, discernible patterns become evident upon visual examination. During the winter months, temperatures predominantly hover around 0 degrees or even dip into negative territory. Genuinely accurate temperature readings exhibit a high level of consistency and proximity. The transition to spring is marked by temperature fluctuations, a phenomenon attributed to the inherent variability of this season, which encompasses a diverse range of weather conditions, including sunshine, rain, and cloudiness.

As summer arrives, temperatures once again exhibit a significant level of consistency. Summers in Kosovo are characterized by their warmth and sunniness, punctuated by infrequent temperature drops. Akin to the spring, the autumn season displays erratic temperature variations, alternating between warm days and chilly nights.

The identifiable patterns suggest the feasibility of employing seasonality-based algorithms for prediction, yielding substantial and realistic forecasts.

5.2 NeuralProphet

Implementing the NeuralProphet algorithm on our dataset yields a notably "smooth" outcome. This is predominantly attributed to NeuralProphet's emphasis on capturing data trends as opposed to prioritizing step-by-step predictions. In Figure 6 below, we present the result we get from the prediction for the 2022 temperature based on five years of previous data.

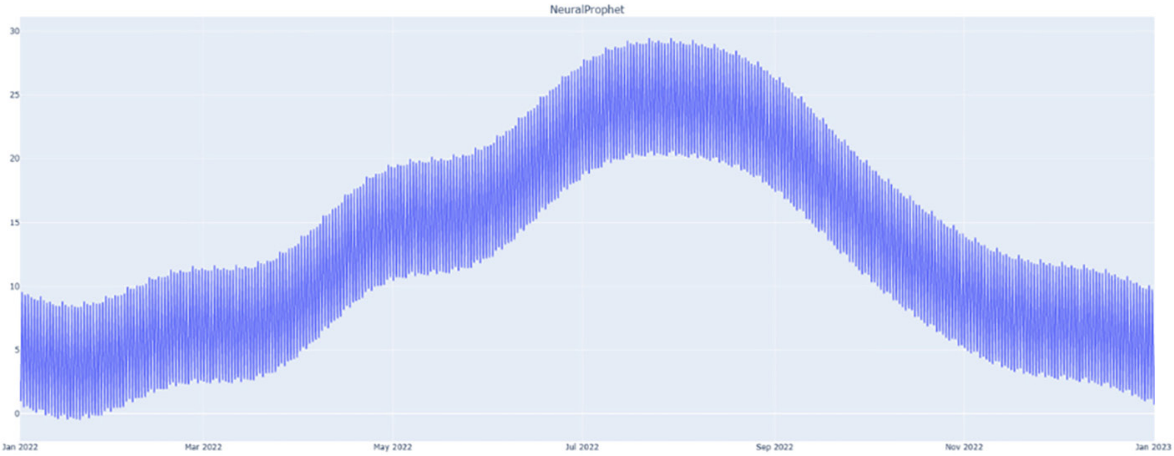

Fig. 6. NeuralProphet prediction result visualization

It continues to offer a comprehensible prediction, portraying chilly winters, variable temperatures in spring, scorching summers, and declining temperatures during autumn.

A noteworthy observation from NeuralProphet is its emphasis on capturing hourly temperature fluctuations, showcasing a substantial divergence of approximately 10 degrees between daytime peak warmth and nighttime lowest temperatures.

5.3 Random Forest Regression

In contrast to NeuralProphet's trend-centric approach, Random Forest Regression places its emphasis on step-wise predictions, resulting in outcomes with more pronounced fluctuations, akin to the patterns observed in our dataset visualizations. Figure 7 presents the result we get from the Random Forest Regression predictive algorithm for 2022 temperature based on five years of previous data.

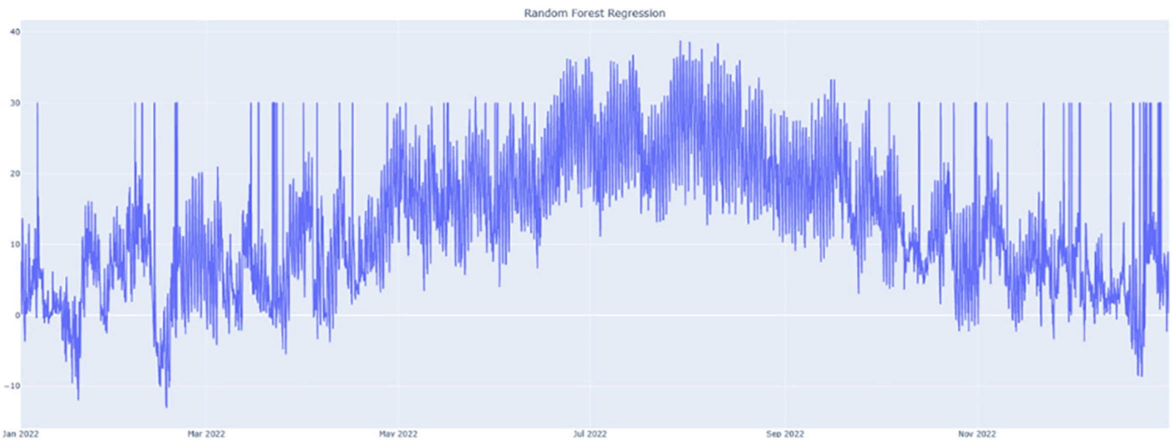

Fig. 7. Random Forest Regression prediction result visualization

A prominent observation is the presence of irregular 30-degree spikes and anomalies in the temperature measurements within the datasets. However, despite these irregularities, the generated forecast closely resembles typical annual temperature patterns. This suggests that step-wise predictions can provide valuable insights into future temperature trends.

5.4 SARIMA

Similar to Random Forest Regression, SARIMA produces a forecast that closely aligns with the dataset. Unlike NeuralProphet, it doesn't emphasize trends. Furthermore, in contrast to Random Forest Regression, SARIMA exhibits reduced volatility in response to anomalies. Figure 8 presents the result we get from the SARIMA predictive algorithm for the 2022 temperature based on five years of previous data.

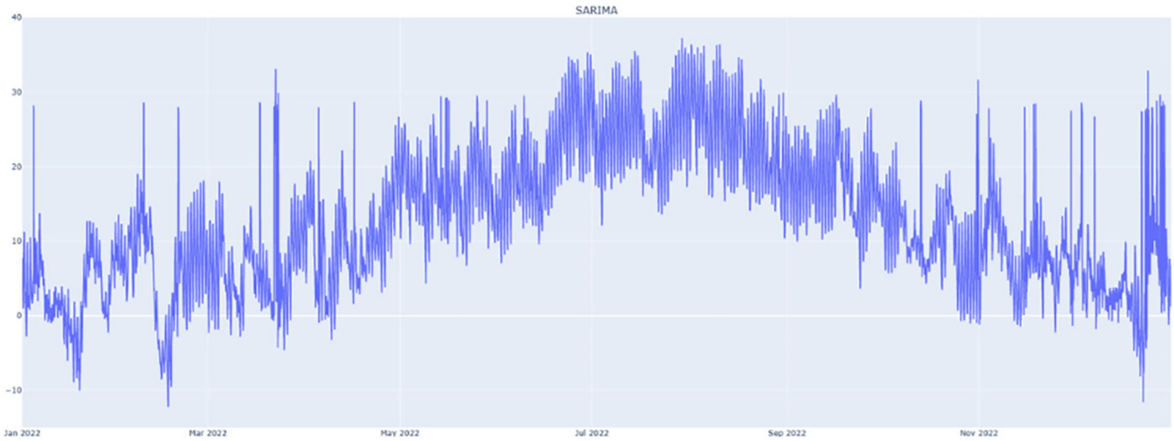

Fig. 8. SARIMA prediction result visualization

The distinction between daytime and nighttime temperatures appears to be less pronounced compared to Random Forest Regression, rendering it a more realistic portrayal. Additionally, SARIMA demonstrates greater resilience towards anomalies, depicting temperatures in proximity to 30 degrees rather than precisely at 30 degrees during anomaly spikes.

5.5 ANN by keras

The forecasts generated by the Keras ANN exhibit a smoother representation compared to other predictions, with fewer pronounced fluctuations. The Keras-based ANN algorithm places greater emphasis on actual temperature patterns than anomalies. The visualization closely resembles our datasets, although the algorithm is influenced by anomalies, leading to slightly elevated temperatures in response. Figure 9 presents the result we get from the ANN predictive algorithm for 2022 temperature based on five years of previous data.

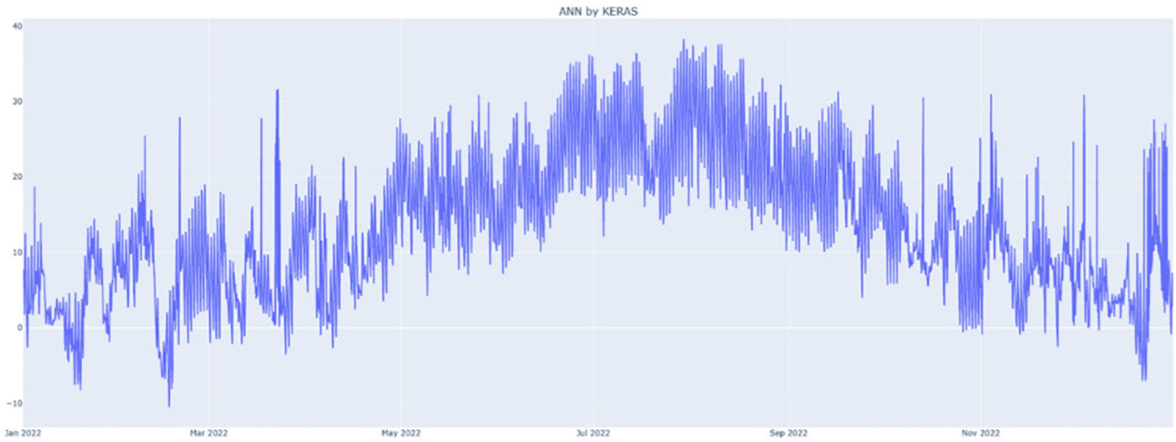

Fig. 9. ANN by Keras prediction result visualization

The disparity between nighttime and daytime temperatures is more pronounced in this algorithm compared to others. However, taking into account the seasonal patterns, this approach can yield predictions quite akin to actual measurements.

Displayed in Figure 10 is the outcome of predictions using all four algorithms, highlighting that NeuralProphet yields the least favorable results, while the remaining three algorithms exhibit notable success.

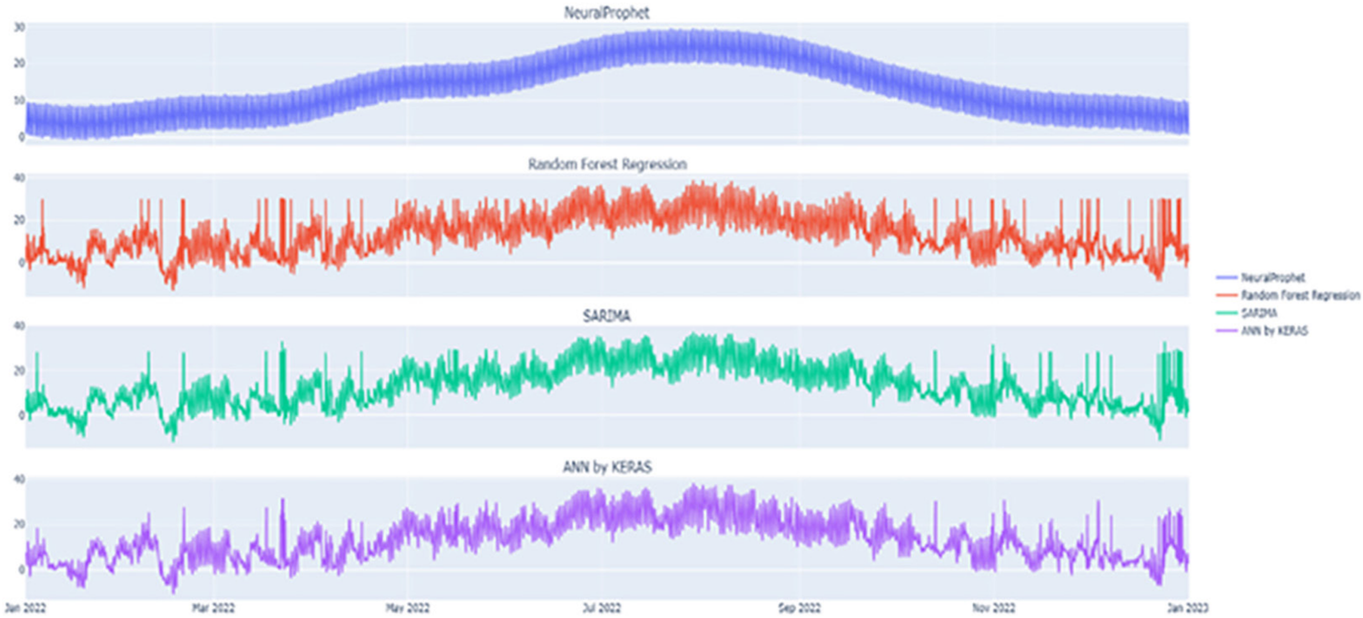

Fig. 10. The result from the prediction of our four predictive algorithms NeuralProphet, Random Forest Regression, SARIMA and ANN

6 CONCLUSION AND FUTURE WORKS

Temperature forecasting requires predictive algorithms that not only capture seasonal patterns but also incorporate step-wise predictions to track trend changes. Illustrated in Figure 10 are the prediction outcomes from all algorithms, showcasing the distinctions between the results.

A reliable prediction shouldn't portray a smooth temperature curve, as this doesn't align with real-world conditions. A seamlessly smooth curve suggests a reliance on trends rather than accounting for daily fluctuations in data.

Predictive models such as Random Forest Regression, Seasonal ARIMA, and ANNs by Keras exhibit the highest levels of success in temperature forecasting, yielding errors within the 2 to 5-degree range. Considering the multitude of factors influencing temperature, this level of error is relatively low.

The presence of anomalies within the dataset significantly impacts predictions, resulting in sudden spikes in temperatures. Algorithms attempt to mitigate this effect by predicting temperatures close to the anomaly, but inaccuracies remain apparent, particularly during colder seasons.

The models demonstrate errors spanning between 2 and 5° Celsius, indicating a relatively modest margin of error given the complex interplay of variables affecting temperature. Nevertheless, it's essential to acknowledge that anomalies present in the datasets have influenced the predictive outcomes, leading to occasional disparities across different seasons.

Temperature predictions in smart agriculture have numerous practical implications, ranging from resource optimization and crop management to climate change adaptation. These applications can lead to increased agricultural productivity, reduced environmental impact, and improved sustainability in farming practices.

Future endeavors will involve comparing predicted temperatures with actual measurements for the corresponding year. The impact of anomalies on predictions will also be a focus of forthcoming research. Additionally, efforts will be directed toward assessing the computational efficiency of these algorithms. The most important aspect of our research in the future is to propose a model that will show the best time to do grape harvesting and sterilization in the Kosovo region in order to increase grape quality and quantity.

7 REFERENCES

[1] A. Alaa, E. Mai, M. Nada, S. Loa'a, A. Nada, A. Yomna, M. Darweesh, and F. Mohamed, "Smart IoT monitoring system for agriculture with predictive analysis," in *8th International Conference on Modern Circuits and Systems Technologies (MOCAST)*, Thessaloniki, Greece, 2019, pp. 1–4. https://doi.org/10.1109/MOCAST.2019.8741794

[2] L. Al-Tarawneh, A. Mehyar, S. E. Alasasaf, and M. Al-Mariat, "Environmental tracking system using IoT based WSN: Smart agriculture," in *4th IEEE Middle East and North Africa COMMunications Conference (MENACOMM)*, Amman, Jordan, 2022, pp. 147–152. https://doi.org/10.1109/MENACOMM57252.2022.9998269

[3] R. Madhumathi, T. Arumuganathan, R. Shruthi, and R. Sneha Iyer, "Intelligent time-based irrigation system using predictive algorithms and internet of things," in *International Conference on Data Science, Agents & Artificial Intelligence (ICDSAAI)*, Chennai, India, 2022, 2022, pp. 1–6. https://doi.org/10.1109/ICDSAAI55433.2022.10028945

[4] D. S. Anindya, M. Yuliana, and M. Z. Samsono Hadi, "IoT based climate prediction system using long short-term memory (LSTM) algorithm as part of smart farming 4.0," in *International Electronics Symposium (IES), Surabaya, Indonesia*, 2022, pp. 255–260. https://doi.org/10.1109/IES55876.2022.9888486

[5] A. Songruk, S. Arunrungrusmi, K. Tunlasakun, S. Suwannakhum, N. Mungkungline, W. Poonthong, and T. Yuji, "Application of internet of thing (IoT) for precision farming," in *16th International Conference on Signal-Image Technology & Internet-Based Systems (SITIS)*, Dijon, France, 2022, pp. 417–420. https://doi.org/10.1109/SITIS57111.2022.00069

[6] G. Sharma, Pulkit, H. Sharma, S. Jain, and N. Kumar, "Modeling evapotranspiration in IoT based WSN for irrigation scheduling: An optimized DL approach," *GLOBECOM 2022–2022 IEEE Global Communications Conference*, Rio de Janeiro, Brazil, 2022, pp. 1948–1953. https://doi.org/10.1109/GLOBECOM48099.2022.10001423

[7] Mohammad Shorfuzzaman and M. Shamim Hossain, "Predictive analytics of energy usage by IoT-Based smart home appliances for green urban development," *ACM Trans. Internet Technol.*, vol. 22, no. 2, 2022. https://doi.org/10.1145/3426970

[8] R. Chinnaiyan and S. Balachandar, "Reliable administration framework of drones and IoT sensors in agriculture farmstead using blockchain and smart contracts," in *Proceedings of the 2020 2nd International Conference on Big Data Engineering and Technology (BDET 2020)*, Association for Computing Machinery, New York, NY, USA, 2020, pp. 106–111. https://doi.org/10.1145/3378904.3378918

[9] Ankur Pandey, Piyush Tiwary, Sudhir Kumar, and Sajal K. Das, "A hybrid classifier approach to multivariate sensor data for climate smart agriculture cyber-physical systems," in *Proceedings of the 20th International Conference on Distributed Computing and Networking (ICDCN '19)*, Association for Computing Machinery, New York, NY, USA, pp. 337–341, 2019. https://doi.org/10.1145/3288599.3288621

[10] SARIMA. https://github.com/imkhoa99/Time-Series-Analysis-and-Weather-Forecast-/blob/master/Time_Series_Project.ipynb. [Accessed on: 12.11.2022].

[11] Random Forest Regression. https://machinelearningmastery.com/random-forest-for-time-series-forecasting/. [Accessed on: 12.12.2022].

[12] Neural Prophet. https://www.section.io/engineering-education/building-a-time-series-weather-forecasting-application-in-python/. [Accessed on: 05.10.2022].

[13] KERAS. https://github.com/MTxSouza/TemperaturePrediction-TimeSeries. [Accessed on: 02.11.2022].

[14] ARIMA. https://www.machinelearningplus.com/time-series/arima-model-time-series-forecasting-python/. [Accessed on: 12.11.2022].

[15] F. Saba, N. Ahmed, U. Khan, A. Waheed, M. Rafiq, and S. Mohyud-Din, "A comprehensive review of mean absolute error (MAE) for time series forecasting," *Applied Sciences*, vol. 8, no. 9, p. 1549, 2018. https://doi.org/10.3390/app8091549

[16] E. Elbasi, C. Zaki, A. E. Topcu, W. Abdelbaki, A. I. Zreikat, E. Cina, A. Shdefat, and L. Saker, "Crop prediction model using machine learning algorithms," *Applied Sciences*, vol. 13, no. 16, p. 9288, 2023. https://doi.org/10.3390/app13169288

[17] N. Poornima and M. Murugan, "Natural disaster resilience approach (NDRA) to online social networks," *J. Ambient. Intell. Human Comput.*, vol. 12, pp. 5651–5678, 2021. https://doi.org/10.1007/s12652-020-02644-1

[18] Boxiong Yang, Faizan Ali, Ping Yin, Tao Yang, Ying Yu, Shelei Li, and Xiaofei Liu, "Approaches for exploration of improving multi-slice mapping via forwarding intersection based on images of UAV oblique photogrammetry," *Computers & Electrical Engineering*, vol. 92, p. 107135, 2021. https://doi.org/10.1016/j.compeleceng.2021.107135

[19] X. Bai, Z. Li, W. Li, Y. Zhao, M. Li, H. Chen, S. Wei, Y. Jiang, G. Yang, and X. Zhu, "Comparison of machine-learning and CASA models for predicting apple fruit yields from time-series planet imageries," *Remote Sensing*, vol. 13, no. 16, p. 3073, 2021. https://doi.org/10.3390/rs13163073

[20] Kumar Gaurav, Gaurav Arun, and D. Nautiyal, "A comparative study of machine learning algorithms for crop yield prediction using IoT sensor data," *International Journal of Electronics, Communications and Electrical Engineering*, vol. 7, no. 4, pp. 18–23, 2021. https://doi.org/10.46703/ijeee.v7i4.579

[21] D. Fernández, E. Adermann, M. Pizzolato, R. Pechenkin, C. G. Rodríguez, and A. Taravat, "Comparative analysis of machine learning algorithms for soil erosion modelling based on remotely sensed data," *Remote Sensing*, vol. 15, no. 2, p. 482, 2023. https://doi.org/10.3390/rs15020482

[22] Galit Shmueli, Peter C. Bruce, Peter Gedeck, and Nitin R. Patel, *Data Mining for Business Analytics: Concepts, Techniques, and Applications in Python*. New Jersey: Wiley, 2019.

[23] Gareth James, Daniela Witten, Trevor Hastie, and Robert Tibshirani, "An introduction to statistical learning: With applications in R," *Springer*, 2013. https://doi.org/10.1007/978-1-4614-7138-7

[24] Ioannis Adamopoulos, Aristidis Ilias, Christos Makris, and Yannis C. Stamatiou, "Intelligent surveillance systems on the internet of things based on secure applications with the IBM cloud platform," *International Journal on Information Technologies and Security*, vol. 15, no. 2, pp. 59–74, 2023. https://doi.org/10.59035/XVRS3592

[25] Amit Sadanand Savyanavar, Nikhil Mhala, and Shiv H. Sutar, "Star-Galaxy classification using machine learning algorithms and deep learning," *International Journal on Information Technologies and Security*, vol. 15, no. 2, pp. 87–96, 2023. https://doi.org/10.59035/VVLR5284

[26] J. Fondaj, M. Hamiti, S. Krrabaj, J. Ajdari, and X. Zenuni, "A prediction model of smart agriculture based on IoT sensor data: A systematic literature review," in *12th Mediterranean Conference on Embedded Computing (MECO)*, Budva, Montenegro, 2023, pp. 1–8. https://doi.org/10.1109/MECO58584.2023.10154965

[27] Plotly library, https://plotly.com/python/. [Accessed on: 17.07.2023].

8 AUTHORS

Jakup Fondaj, South East European University, Tetovo, North Macedonia (E-mail: jf13459@seeu.edu.mk).

Mentor Hamiti, South East European University, Tetovo, North Macedonia.

Samedin Krrabaj, University "Ukshin Hoti", Prizren, Kosovo.

Xhemal Zenuni, South East European University, Tetovo, North Macedonia.

Jaumin Ajdari, South East European University, Tetovo, North Macedonia.