COMPARATIVE ANALYSIS OF MACHINE LEARNING TECHNIQUES FOR FORECASTING WEATHER: A CASE STUDY

Jorge Díaz-Ramírez, Ximena Badilla-Torrico, Fabian Santiago Muñoz, Miguel Pinto Bernabé and Ernie Quenaya-Quenaya

SUMMARY

Climate change is here and is a reality in the world; therefore, studying this phenomenon based on its relationship with meteorological parameters is the first step to making informed decisions. With this in mind, the objective of this work was to conduct a comparative analysis of machine learning techniques used in weather forecasting to evaluate their accuracy in weather forecasting in a localized area, Iquique. The methodology used was exploratory, and the design was experimental based on Knowledge Discovery in Databases (KDD). The Transformer network and Arima in distant horizons gave better performance, indicating that Machine Learning techniques, particularly Deep Learning, can contribute to and complement classic weather forecasting techniques. Understanding the contribution of classic techniques such as Machine Learning in climate forecasting opens a range of possibilities to be further investigated.

Introduction

In the climate change phenomenon, human activities have contributed to the exacerbation of the greenhouse effect, resulting in global warming (Cravero *et al.*, 2021; Vessuri, 2023). This pressing issue affects not only current generations but also future ones (Naciones Unidas ONU, 2019). As the UN Intergovernmental Group of Experts on Climate Change highlights, Greenhouse Gases (GHG) have a direct relationship with global average temperature, with GHG concentrations and global temperature rising since the Industrial Revolution (Naciones Unidas ONU, 2019). Thus, understanding the connections between meteorological parameters and climate forecasting is crucial, particularly for specific regions. For the above, the objective of this research was to conduct a comparative analysis of Machine Learning techniques to evaluate their performance and understand their contribution to climate forecasting in the city of Iquique.

This research focused on Iquique because it is a Chilean coastal city with a desert climate that experiences diverse weather conditions due to its location. Our study aims to assess the performance of Machine Learning (ML) techniques, specifically Deep Learning (DL), in climate forecasting for Iquique. It is important to note that the General Directorate of Civil Aeronautics (GDCA) weather station at the Diego Aracena Airport is 45km south of Iquique. On average, we found that the temperature is 5.9 degrees higher, and the relative humidity is 20.27% lower. The pressure is 3.46 hectopascals (hPa) higher within the city compared to the GDCA weather station. When comparing our data collected within the city to the data from the meteorological station, we observe significant differences in the measurements, as illustrated in Figure 1.

The contribution of this research to this field, on the one hand, involves conducting a comparative analysis of various ML techniques to evaluate their performance and understand their potential impact on climate forecasting in Iquique. We collected data using three Raspberry devices located in different parts of the city to measure meteorological parameters of interest. On the other hand, the citizens of Iquique will have an online platform with precise measurements of what happens in the city related to temperature, humidity, and atmospheric pressure.

The structure of the article is as follows: First, works related to the field of climate prediction are presented, focusing on forecasts based on large data sets and techniques based on artificial neural networks proposed in the scientific literature. The methodology used in this research is described, the data collection and preparation, the Machine Learning techniques applied, the experiments carried out to evaluate different approaches and configurations, the analysis of the results obtained, and the metrics used to evaluate the performance of the proposed models in the context of the climatic prediction in Iquique are

KEYWORDS / Deep Learning / Forecasting / Machine Learning / Transformer / Weather /
Received: 12/11/2023. Accepted: 05/10/2024.

Jorge Díaz-Ramírez (Corresponding author). Graduated in Computer Engineering, Universidad de Tarapacá, Chile. Master's degree in Information Technology, Universidad Técnica Federico Santa María, Chile. Certificate in Intelligence Systems for Competitiveness, Pontificia Universidad Católica (UC), Chile. PhD student in Engineering Science, UC, Chile. Assistant Professor, Universidad de Tarapacá, Iquique, Chile. Address: Avenida Luis Emilio Recabarren 2477, Iquique, Tarapacá, Chile. e-mail: jdiazr@academicos.uta.cl.

Ximena Badilla-Torrico. Graduated in Computer Engineering and Industrial Engineering, Universidad Central, Chile. Master's degree in Administration (MBA), Universidad de Chile, Chile. Professor, Universidad de Tarapacá, Chile.

Fabian Santiago Muñoz. Master's degree in Education. PhD student in Computer Science, Euskal Herriko Unibertsitatea, Viscaya, Spain. Professor, Universidad de Tarapacá, Chile.

Miguel Pinto Bernabé. Civil Engineer in Computer Science, Universidad de Tarapacá, Chile. Master's degree in Software Engineering, Universidad de Tarapacá, Chile.

Ernie Quenaya-Quenaya. Student of Civil Engineering in Computer Science, Universidad de Tarapacá, Chile. Freelance programmer, Chile.

ANÁLISIS COMPARATIVO DE TÉCNICAS DE APRENDIZAJE AUTOMÁTICO PARA LA PREVISIÓN METEOROLÓGICA: ESTUDIO DE UN CASO PRÁCTICO

Jorge Díaz-Ramírez, Ximena Badilla-Torrico, Fabian Santiago Muñoz, Miguel Pinto Bernabé y Ernie Quenaya-Quenaya

RESUMEN

El cambio climático es una realidad en el mundo; por lo tanto, estudiar este fenómeno basándose en su relación con los parámetros meteorológicos es el primer paso para tomar decisiones informadas. Con esto en mente, el objetivo de este trabajo consistió en realizar un análisis comparativo de técnicas de aprendizaje automático utilizadas en la predicción del tiempo para evaluar su precisión en la predicción meteorológica en una zona localizada, Iquique. La metodología utilizada fue exploratoria, y el diseño fue experimental basado en el Descubrimiento de Conocimiento en Bases de Datos (KDD). La red Transformer y Arima en horizontes distantes mostraron un mejor rendimiento, indicando que las técnicas de Aprendizaje Automático, en particular el Aprendizaje Profundo, pueden contribuir y complementar las técnicas clásicas de predicción del tiempo. Comprender la contribución de técnicas clásicas como el Aprendizaje Automático en la predicción climática abre un abanico de posibilidades para ser investigadas más a fondo.

ANÁLISE COMPARATIVA DE TÉCNICAS DE APRENDIZADO DE MÁQUINA PARA PREVISÃO DO TEMPO: UM ESTUDO DE CASO

Jorge Díaz-Ramírez, Ximena Badilla-Torrico, Fabian Santiago Muñoz, Miguel Pinto Bernabé e Ernie Quenaya-Quenaya

RESUMO

A mudança climática é uma realidade no mundo; portanto, estudar este fenômeno com base em sua relação com os parâmetros meteorológicos é o primeiro passo para tomar decisões informadas. Com isso em mente, o objetivo deste trabalho foi realizar uma análise comparativa das técnicas de aprendizado de máquina utilizadas na previsão do tempo para avaliar sua precisão na previsão do tempo em uma área localizada, Iquique. A metodologia utilizada foi exploratória, e o desenho foi experimental baseado na Descoberta de Conhecimento em Bases de Dados (KDD). A rede Transformer e Arima em horizontes distantes apresentaram melhor desempenho, indicando que as técnicas de Aprendizado de Máquina, particularmente o Aprendizado Profundo, podem contribuir e complementar as técnicas clássicas de previsão do tempo. Entender a contribuição de técnicas clássicas como o Aprendizado de Máquina na previsão climática abre uma gama de possibilidades para serem investigadas mais a fundo.

detailed. Finally, the conclusions are presented, highlighting the key findings of the study and discussing the implications for the field of climate prediction. In addition, possible directions do offer for future research and development in this area.

Related Works

Weather forecasting research has grown significantly due to its profound impact on our daily lives and various industries (Lee *et al*., 2020; Parashar and Johri, 2021). Predicting climate parameters like temperature, precipitation, pressure, wind, and humidity, is a dynamic and complex challenge due to the ever-changing environmental conditions (Molina *et al*., 2023; Naveen and Mohan, 2019). The key to improving forecasting accuracy lies in the choice of predictive techniques. In particular, Machine Learning (ML) techniques have been increasingly utilized for both long-term predictions using autoregressive integrated moving average (ARIMA) methods and short-term predictions using Artificial Neural Networks (ANNs)

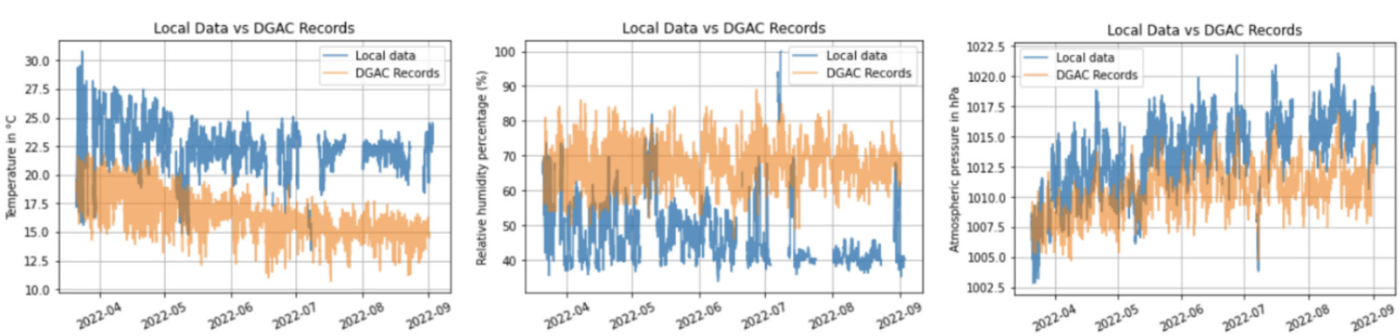

Figure 1. Comparison of values of climatic variables from Local and DGAC records. The first graph represents the temperature, the second the relative humidity, and the third the atmospheric pressure. Source: Own elaboration.

(Bochenek and Ustrnul, 2022; Lee *et al*., 2020).

This research breaks new ground by conducting a comparative analysis of various ML techniques to assess their efficacy and potential impact on climate forecasting, specifically on Iquique. The process involved collecting data through three Raspberry Pi devices installed in different city areas to measure critical meteorological parameters (Bernatin *et al*., 2022; Sunehra, 2019). Consequently, not only will the citizens of Iquique have an online platform offering precise measurements of temperature, humidity, and atmospheric pressure, but they will also gain better insights into the local climate trends (Corburn *et al*., 2022).

Historically, weather forecasting has been considered a science and technology-based prediction of atmospheric states. To model the non-linearity of climate elements, ANNs have proven useful, with deep learning (DL) approaches further enhancing the capability to address the non-linearity of meteorological parameters (Abdalla *et al*., 2021; Ren *et al*., 2021). One widely used algorithm for weather forecasting is the Random Forest. Mainly used for predicting weather based on past forecasts, it is valued for its accuracy when working with large data sets and its flexibility to be used separately for each classification (Krocak *et al*., 2023; Dhamodaran *et al*., 2020; Tyralis *et al*., 2019). However, it is worth mentioning that every technique has its limitations. For instance, problems of gradient vanishing and exploding in Recurrent Neural Networks (RNNs) and the constraints of convolutional filters in Convolutional Neural Networks (CNNs) can limit the effectiveness of these methods in modeling long-term and intricate relationships in sequential data (Torres *et al*., 2020; Wu *et al*., 2020). A refined version of RNN is Long-short-term memory techniques (LSTM). These can address the gradient vanishing problem, allowing for more effective predictions than conventional RNNs (Lee *et al*., 2020). The LSTM predictor performs excellently in hourly temperature prediction (Haque *et al*., 2021; Hou *et al*., 2022; Qi and Guo, 2020). Moreover, the DL Transformer architecture is a promising alternative for modeling time series that are complex and dynamic, as it can process the entire data stream using self-attention mechanisms to learn dependencies (Ang, 2023; Vaswani *et al*., 2017; Wu *et al*., 2020). In assessing the accuracy of the predictions, the Mean Square Error (MSE) has emerged as one of the most utilized evaluation indices, along with horizons to measure returns over time (Nandi *et al*., 2022; Parashar and Johri, 2021). This research expands on these methods, providing a practical solution that harnesses ML techniques' power to increase climate forecasting precision.

Methodology

The type of research carried out was exploratory. In turn, the research design was quantitative experimental, obtaining the data of the meteorological parameters through the Raspberry Pi devices. Various ML techniques were applied to these datasets, thus obtaining the performance results of each algorithm. Subsequently, the techniques that obtained the best results were selected. With the selected techniques, an exploratory analysis of the meteorological parameters (such as temperature, pressure, and humidity) was carried out, as well as the weather forecast based on these variables. The software interface used for these purposes was a web application developed with Angular (Angular, 2022), NodeJS (Open JS Fundation, 2022), an Apache2 web server (The Apache Software Foundation, 2022) and a Mysql database (Oracle, 2022).

Figure 2 illustrates the research process based on Knowledge Discovery in Databases (KDD) that we employed (Fayyad *et al*., 1996). Initially, the data collected from the Raspberry Pi devices were stored in a centralized database. Selection of data for the project was the next step, and we based our criteria on the relevance to our objective, consistency of the measurements, and completeness of the records.

Data

As shown in Figure 2, the data was obtained from the Raspberry Pi 4 (model B with 8GB of RAM) at different points in the city of Iquique. Due to budget constraints, the number of devices implemented was three. They were strategically placed in the city's northern, central, and south-central areas to account for possible differences in the measurements. Each of these three Raspberry Pi devices collects temperature, pressure, and humidity data. The data capture periodicity was every 5 seconds, including variables such as 'Id', the unique identifier for the query; 'Remote_Id', the identifier of the Raspberry; 'Ambient_Temperature (Ts)', referring to the ambient temperature; 'Air_Pressure (QFE)', which is the air pressure; 'Humidity (HR)', indicating the ambient humidity; 'Created', the initial time and date of the capture; and 'ServerDate', the time and date in the database. Due to connection limitations, the data capture codes were executed every 72 hours, restarting this process at that time. The data capture process for the training of the predictive techniques began on August 4, 2021, and ended on September 1, 2022. The sensors captured 4,940,511 records since their start-up; however, only 40,892 records were used

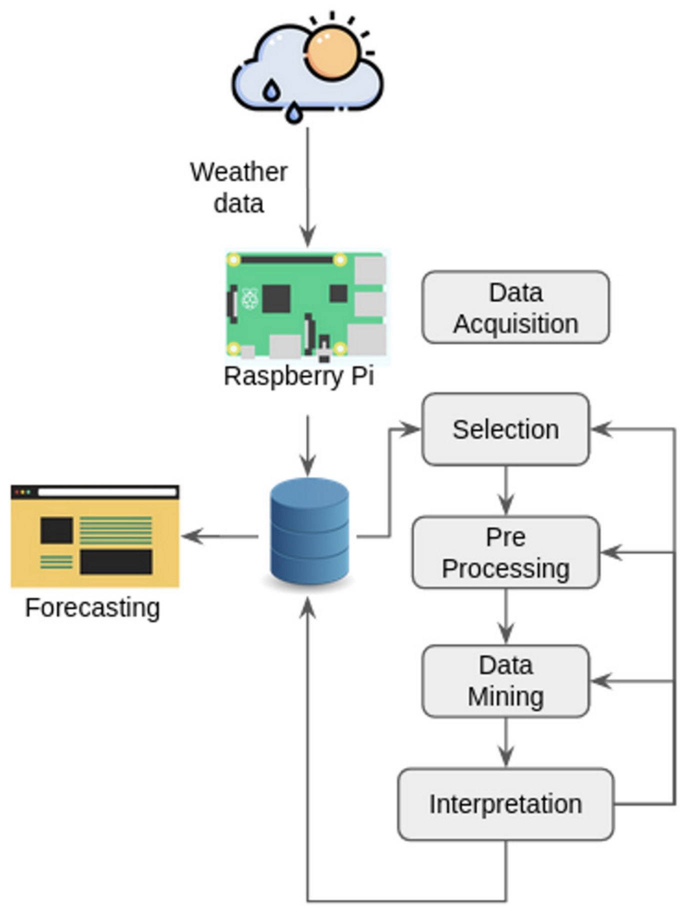

Figure 2. Overall Process based on Knowledge Discovery in Databases (KDD). Source: Own elaboration.

for training the models. First, the decrease in the number of records is mainly due to the low significance of the raw data (captured every 5 seconds) for studying the behavior of climatic variables. For example, the environmental temperature varies significantly (more than one degree) in steps of 1 hour. Secondly, without the previous point, the models become notoriously slow and less predictively effective since they are victims of the vanishing gradient problem due to the high data density per hour without significant selection. These ideas motivate improving the records' interpolation and integrating data from the GDCA, which are tested hourly and add to downtime. The Raspberry will continue to capture data for the web platform at https://clima.uta.cl/. In addition, the information was not captured due to electricity, internet, or device connection problems; these records, with the data disseminated by the GDCA, are imputed.

Techniques

The studied techniques describe how the training data associates features (characteristics) and labels (predictions). Also, a multivariable technique identifies multiple input variables to define multiple output variables (Concato *et al*., 1993). These techniques are known as MIMO (Multiple Input, Multiple Output), and combinations of input variables (input) predict values of output variables (output). At the same time, another important concept is that of *Autoregression* (Jayagopal *et al*., 2022). This concept corresponds to a technique that describes multiple past m states of a variable used to define the current or future state of the same variable. These are called *Autoregressive*, and one of their advantages is the ability to generate forecasts long periods into the future by 'walking' over their predictions.

Experiments

Several experiments, with the final data set, were carried out to analyze the contribution provided by statistical techniques and Machine Learning in climate forecasting. The techniques had general parameters, such as 100 epochs, MSE loss function, and Adam optimizer.

AutoRegressive Integrated Moving Average (ARIMA): This technique uses a statistical machine learning (Hewage *et al*., 2021), which uses variations and regressions of statistical data to find patterns in a prediction (Jayagopal *et al*., 2022). These techniques are univariable and require that the perceived periodicity of the time series to be studied be indicated as a minimum. Most climatic variables draw 24-hour cycles corresponding to one day, so for each variable with these characteristics, an ARIMA technique is built. One of the outstanding features of ARIMA is that it is possible to make 'bulk' predictions with only a fixed future value of the time series (an arbitrary future date) depending entirely on the last steps that the technique is creating. In these, the variance decreases over time, and the predictions converge on the average of the variables. In data preparation, local records, grouped by an hour (72 records) in the last three days, were selected, and linear interpolation to construct the technique was used.

Deep Neural Network (DNN): On the contrary, ML techniques do not consume a bulk of their past states as features but relate sets of datetimes with, for example, a specific temperature, building a mapping of the type 'Variable is proportional to Moment (past or future)'. Consequently, the training 'moment to value variable' assignments generalize better. For this reason, time features such as hour, day, and month, which are independent and therefore do not require consuming their predictions, are converted from the new inputs to the technique. Unlike ARIMA, a DNN can have a multivariable output and precisely control the neural network's internal behavior, such as the number of layers and the way of activation. However, it requires an enormous amount of meaningful and consistent data (Díaz–Vico *et al*., 2017). In data preparation, DNN uses large and consistent data grouped by an hour (to increase relevance), and an additional selection of external data is made (to increase "story"). Likewise, external data from the GDCA, corresponding to 2019 and 2020, are used to impute the records without data. The parameter settings for the DNN were Adam Optimizer, the activation function of ReLu, and 100 training epochs.

Random Forest (RF): This technique arises from the need to unite the ideas explored in previous techniques; that is, the predictions generated by this technique consider the history of the variables (annual cycles) and records of previous hours (Meng and Zhu, 2023). Furthermore, the existing relationship can detect the cyclical behavior of climatic variables through Hours(H), Days(D), and Months(M); in turn, the prediction considers the temperature that precedes it. For data selection, local data is used together with GDCA data (2 years) grouped by an hour; both are joined by data integration (join & replace).

Long Short-Term Memory (LSTM): This technique uses the forecast through the detection of natural cycles in climatic variables (as in DNN) and, in turn, considers the previous values of these same variables in 24 hours (as ARIMA). The advantage of this technique is that it has more information to establish a single forecast since it will consume a table of 24 rows and six columns to generate three forecasts, one for each climate variable (van Nooten *et al*., 2023). Data selection and integration were identical to the previous techniques, adding data normalization, a requirement for working with neural networks. In addition, using a time series generator, a windows system was implemented. The implementation of a LSTM layer is essential. Strictly speaking, the layer is a LSTMcell + RNN (Recurrent Neural Network) structure. In other words, it consists of a series of LSTM neurons connected sequentially as an RNN. The network configuration considered 100 epochs for training, Adam optimizer, and LeakyReLu activation function.

Transformer network: The last technique corresponds to a Transformer network (Vaswani *et al*., 2017), which uses attention algorithms to detect patterns and trends in the data. Developed initially for Natural Language Processing (NLP) topics, their ability to consume sequential data and create new sequences based on them makes them helpful in generating climate forecasts (Lim *et al*., 2021). Again how the technique consumes data changes. This time it will be mapped in the sequence-by-sequence (seq2seq) way, where each sequence consists of a 24*5 array of attributes. The sliding window mechanism used for LSTM is maintained, but now, because the algorithm demands more control over the windowing system, it is implemented manually (without using libraries). Data selection was similar to previously studied techniques. In addition, the sequential data, to provide information about the position of the data in the sequence, was encoded. In this way, instead of decomposing time into its characteristics (hour, day, month), important time cycles (one day, one year) are encoded by sine functions. Additionally, the record date is traditionally normalized and decomposed using a sliding window system. The code is implemented based on (Ntakouris, 2021), with 100 epochs for training and Adam's optimizer.

Analysis and Results

AutoRegressive Integrated Moving Average (ARIMA)

ARIMA is, by its inherent design, primarily assessed through autonomy tests. This is because the model's internal mechanisms perform autoregressive processes to project forecasts into future periods. It leverages historical data to predict future points by learning and understanding patterns and trends in the time-series data. As can be seen in Figure 3, the results garnered by the ARIMA model largely mirror the behavior of the input variables provided. This indicates that the model has effectively learned the inherent structure and characteristics of the time-series data, resulting in predictions that closely align with the underlying patterns and trends of the given variables. This adherence to the original data dynamics showcases the proficiency of ARIMA in making reasonably accurate forecasts far into the future.

Deep Neural Network (DNN)

One notable advantage of the DNN technique is its ability to generate forecasts for near and distant future periods. It accomplishes this without a dependency on past values or relationships, meaning that the model generates its predictions at a relatively low computational cost while preserving climatic variables' seasonality. This characteristic makes it an efficient tool for weather forecasting where temporal patterns play a significant role. However, the technique also comes with certain disadvantages. One of the main drawbacks is that it needs to utilize new information as input in the forecasting process. This limitation means that it cannot leverage the most recent data to improve its predictions, thus making the application of an autonomy test impossible. As depicted in Figure 4, the DNN technique produces results that largely mirror the behavior of the variables in the test data set. This suggests a high level of accuracy in approximating the patterns and trends inherent in the data. However, it is essential to note that the predictions exhibit signal behavior, implying that they reflect a mathematical model's output rather than directly mimicking the natural phenomena they are meant to forecast. This underscores the need for careful interpretation of the results and additional validation against real-world observations.

Random Forest (RF)

As depicted in Figure 5, we observe a comparative analysis of the Random Forest model's prediction against the actual values and historical data. This visualization is an insightful resource to evaluate the model's performance in approximating the time-series data. The Random Forest model, a robust machine learning algorithm renowned for its accuracy, is particularly adept at managing complex datasets with multiple input variables, such as those encountered in weather forecasting. Its inherent design allows it to handle non-linearity and interactions between variables, which is essential in modeling climatic elements' multifaceted nature. In this comparison, the

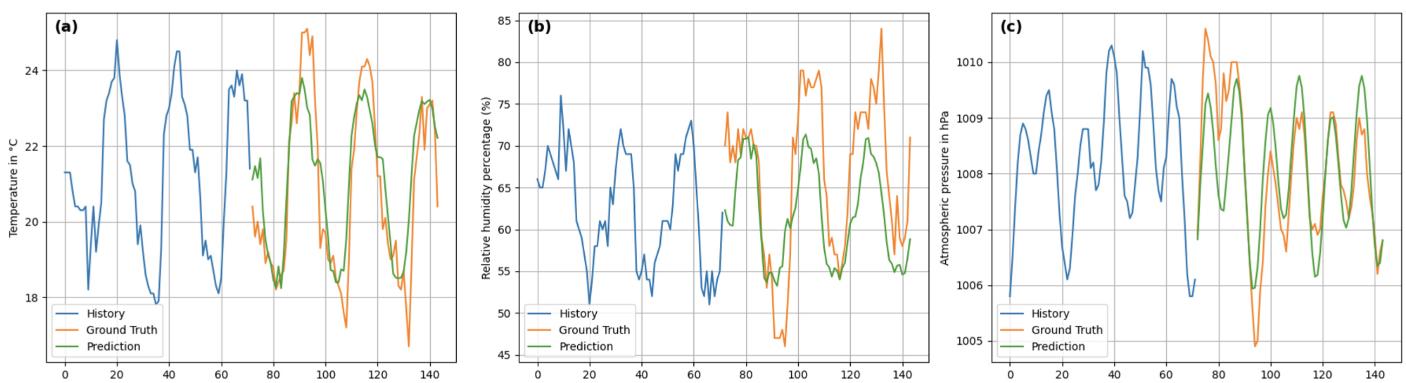

Figure 3. Results of model ARIMA with History, Ground Truth, and Predictions data. The (a) graph represents the temperature prediction, the (b) graph represents the relative humidity prediction, and (c) graph represents the atmospheric pressure prediction. Source: Own elaboration.

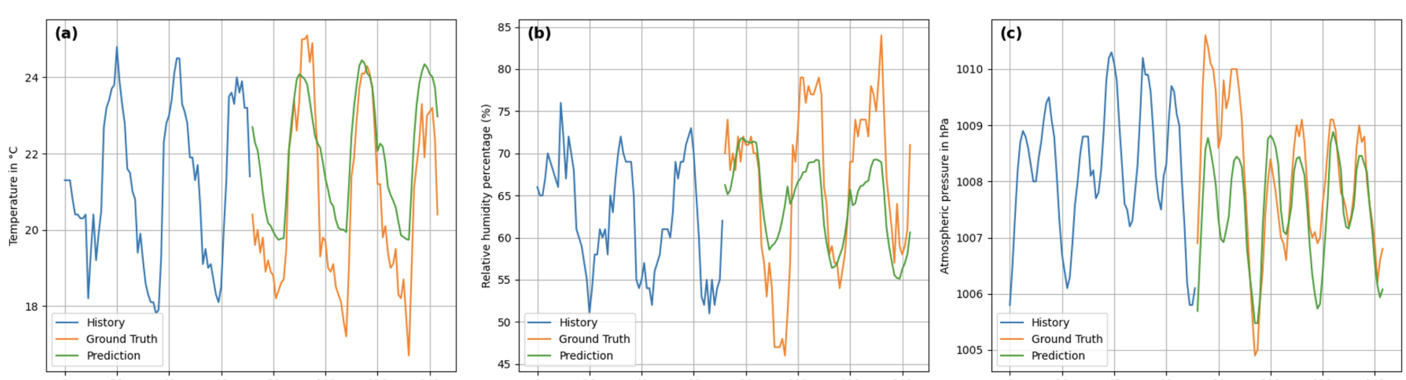

Figure 4. Results of model DNN with History, Ground Truth, and Predictions data. The (a) graph represents the temperature prediction, the (b) graph represents the relative humidity prediction, and (c) graph represents the atmospheric pressure prediction. Source: Own elaboration.

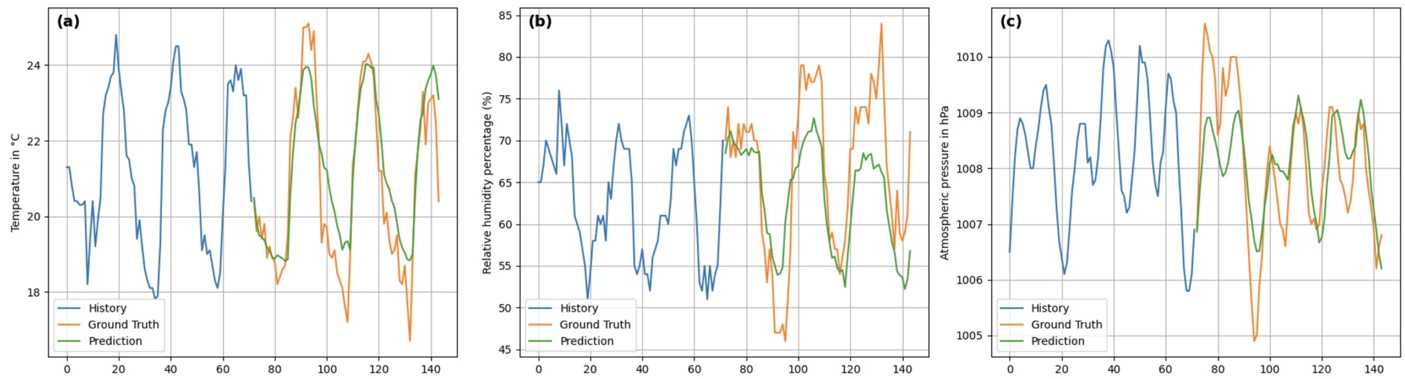

Figure 5. Results of model RF with History, Ground Truth, and Predictions data. The (a) graph represents the temperature prediction, the (b) graph represents the relative humidity prediction, and (c) graph represents the atmospheric pressure prediction. Source: Own elaboration.

Random Forest model's predictions align impressively with the actual observed values, signaling high predictive accuracy. The ability of the model to mirror the primary trends and seasonality in the climate data becomes evident, indicating its successful capture of the underlying patterns and dynamics of the climate system. The juxtaposition of predicted and actual values with historical data validates the accuracy and reliability of the Random Forest model in weather forecasting. It also accentuates that the predictions resemble the actual values, reflecting the model's robust predictive capabilities. Through this figure, we can appreciate the Random Forest model's strength as a climate forecasting tool. At the same time, it is crucial to acknowledge its limitations and the ongoing need for model refinement and validation against actual climatic phenomena.

Long Short-Term Memory (LSTM)

Figure 6 clearly illustrates the performance of LSTM model across different weather parameters. The LSTM model is known for its ability to process long data sequences while effectively handling problems like vanishing or exploding gradients. This makes it an ideal choice for complex forecasting tasks like weather prediction. In the case of temperature and pressure, as depicted in the figure, the LSTM model exhibits a significant degree of accuracy. The predictions mirror the actual data behavior, demonstrating the model's robustness and efficacy in handling these specific climatic elements. The LSTM's ability to recognize and learn from long-term dependencies in the data allows it to capture and predict the intricate patterns within these parameters. However, when it comes to humidity, there is a notable increase in variability in the model's predictions compared to actual values. This could be attributed to humidity's inherently complex and nonlinear nature as a climatic factor, which might require more intricate model architectures or additional feature engineering. It is crucial to note that while the LSTM model has shown promising results in weather forecasting, the results underline the importance of ongoing model tuning and evaluation. The LSTM model's strength lies in its ability to learn from long data sequences, making it particularly suitable for time-series problems like weather forecasting. However, as the variation in humidity prediction suggests, the model might need further refinement or additional data to capture better and predict complex climatic elements.

Transformer network

Figure 7 visually represents the Transformer model's performance in predicting various weather parameters. The Transformer, a state-of-the-art model designed to process sequence data, has significantly impacted fields where sequence

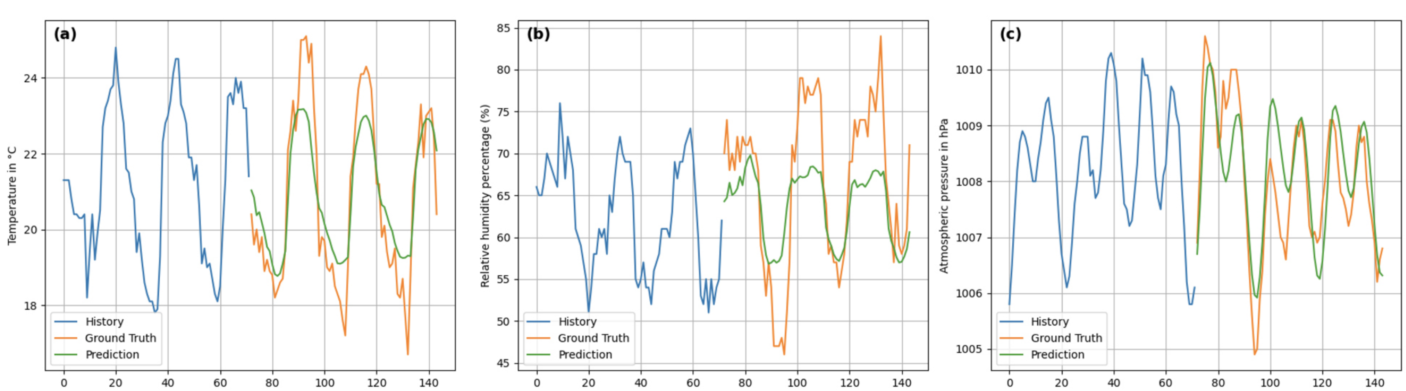

Figure 6. Results of model LSTM with History, Ground Truth, and Predictions data. The (a) graph represents the temperature prediction, the (b) graph represents the relative humidity prediction, and (c) graph represents the atmospheric pressure prediction. Source: Own elaboration.

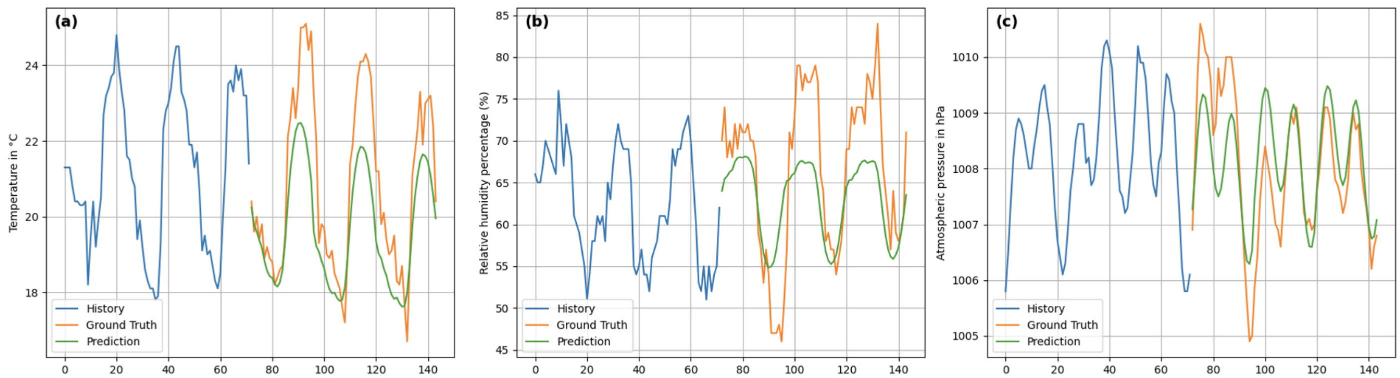

Figure 7. Results of model Transformer with History, Ground Truth, and Predictions data. The (a) graph represents the temperature prediction, the (b) graph represents the relative humidity prediction, and (c) graph represents the atmospheric pressure prediction. Source: Own elaboration.

prediction is critical, including natural language processing and, as demonstrated here, weather forecasting. The model's semi-autoregressive nature allows it to make predictions that closely align with the actual values for the temperature and pressure variables. This accuracy can be attributed to the Transformer's unique architectural features, including self-attention mechanisms and position encoding, which effectively capture dependencies in sequential data, even over long ranges. Consequently, the model excels in tasks where understanding long-term patterns is crucial.

However, when it comes to predicting humidity, some discrepancies appear between the predicted and the actual values. Despite maintaining the same overall structure, the extremes of the prediction curve deviate from the real data curve. This divergence may result from the complex interactions and nonlinear relationships that often characterize humidity. It is important to remember that while the Transformer model shows strong predictive capabilities, these results indicate the need for ongoing model optimization. Particularly with complex environmental data like humidity, further tuning and potentially more complex model architectures may be required to improve prediction accuracy. Despite these challenges, the Transformer model's ability to effectively capture and predict patterns in sequence data makes it a valuable tool in weather forecasting.

Performance metric

The performance metrics utilized in this study include the Mean Average Error (MAE), Mean Square Error (MSE), and Mean Absolute Percentage Error (MAPE), along with horizons, defined as the number of tests (Nandi *et al*, 2022). Figure 8 illustrates the evaluation results for each technique against the same test data set, presenting average error metrics across different horizons. The figure provides a comparative analysis of the modeling techniques, with two models distinctly outperforming the others: ARIMA and the Transformer network. The Deep Neural Network (DNN) exhibits stable results across all metrics—MSE, MAE, and MAPE—demonstrating its consistent performance. In contrast, LSTM and Random Forest (RF) display higher variability in their results, potentially attributed to their reliance on the underlying data and their sensitivity to specific data characteristics. For instance, LSTM's memory capability can lead to varying results with certain types of time-series data. As depicted in the sub-figure (a), ARIMA consistently outperforms all other techniques in terms of the MSE metric, up until horizon 80, where the Transformer network matches its performance. The Transformer's MSE stabilizes and remains constant, indicating its robustness over longer horizons. Moreover, a notable crossover event occurs around horizon 70, as seen in sub-figure (b), where the

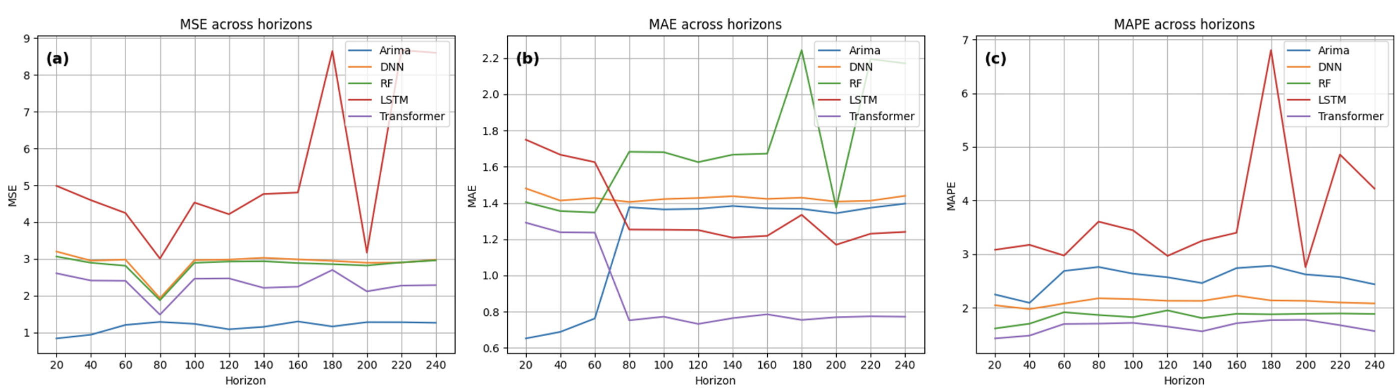

Figure 8. Error Metrics Analysis of Machine Learning Models. Evaluating MSE in (a), MAE in (b) and MAPE in (c) across different horizons. Source: Own elaboration.

Transformer network reduces its MAE, maintaining this lower error rate until the final horizon. Regarding MAPE, sub-figure (c) illustrates the Transformer network's superior performance over ARIMA across time.

This overall analysis verifies the complementary roles of traditional machine learning techniques like ARIMA and advanced deep learning models like Transformer in climate forecasting. It underscores the need for a diversified approach to weather prediction models to leverage the unique strengths of different techniques for improved accuracy and reliability.

Conclusions

The investigation underscores the intricate relationships among temperature, humidity, and pressure in weather forecasting, reaffirming their significant roles in understanding climatic patterns and variations. Traditional techniques like ARIMA and modern Machine Learning and Deep Learning methodologies—specifically the Transformer network—were leveraged to predict weather patterns in a localized context. This comparative analysis offered insights into the relative performance of these models in predicting climatic changes. Contrary to a broad assumption in the field, this research found that neural networks could yield compelling results even without vast amounts of data, underscoring the potential of these networks for climate variable forecasting. This is a notable departure from prevalent literature and suggests promising avenues for future investigations on efficient data utilization.

In the context of measurement metrics, this study found that a suite of techniques could be utilized to elucidate the relationship between forecast and actual values. The average absolute error provided a tangible measure of model performance among them. With its attention mechanism, the Transformer network showed a distinct edge over other models and ARIMA, especially across larger horizons.

The potential applications and contributions of these findings are manifold. For the residents of Iquique, accurate and reliable weather forecasting could support better decision-making, for example, agricultural planning. Furthermore, through this research, was developed an online platform offering precise and located measurements of temperature, humidity, and atmospheric pressure within the city. This platform, powered by the data collected from strategically placed Raspberry Pi devices, provides real-time and localized weather updates to the citizens of Iquique, promoting accessibility and awareness of climatic conditions. Moreover, it can aid in implementing energy-efficient measures in households and industries based on weather predictions, contributing to broader sustainability goals. The contribution of this research extends beyond the practical benefits to the residents of Iquique. It also involves conducting a comprehensive comparative analysis of various Machine Learning techniques, evaluating their performance, and understanding their potential impact on climate forecasting. This endeavor provides valuable insights for the scientific community and contributes significantly to the ongoing discourse on applying Machine Learning and Deep Learning in climatology. This research showcases a comprehensive comparison of traditional and advanced forecasting models, offering a reference point for future studies in this field. It emphasizes the growing relevance of Deep Learning in climate studies and the potential to improve such models further. As such, the contributions of this research are both practical, in the form of an accessible weather forecasting platform, and academic, through the enhancement of understanding and knowledge in this critical field. The research could explore applying these models to other climatic variables and different geographical contexts in future directions. The performance of these models across varying data scales and quality would be another avenue to investigate. Furthermore, given the promising results of the Transformer network, a more granular examination of its structure and working mechanisms might shed light on opportunities for optimization and improved performance.

In conclusion, this study highlights the power of leveraging diverse techniques for weather forecasting. It contributes to the ongoing discourse on utilizing Machine Learning and Deep Learning in climate studies. It adds to this domain's growing body of knowledge and presents a robust groundwork for future explorations.

DATA AVAILABILITY STATEMENT

The source codes and data associated with this project are available at https://github.com/jdiazram/clima-uta and on the web platform https://clima.uta.cl.

ACKNOWLEDGMENTS

The authors would like to thank the contribution of the Universidad de Tarapacá with the UTA-MAYOR N°6726-20 project and Eduardo Dávalos for his contribution to the creation of the project website.

REFERENCES

Abdalla AM, Ghaith IH, Tamimi AA (2021). Deep Learning Weather Forecasting Techniques: Literature Survey. *International Conference on Information Technology, ICIT 2021 - Proceedings*, Amman, Jordan. pp. 622–626. https://doi.org/10.1109/ICIT52682.2021.9491774

Ang S (2023) Precipitation Forecasting Using Transformer: A Comparative Study with Unet. *Highlights in Science, Engineering and Technology 39*: 627–632. https://doi.org/10.54097/hset.v39i.6613

Angular (2022). *Angular*. https://angular.io/

Bernatin T, Sriram JVS, Tejas Sai P, Nisha SA, Revathy, Jayapriya J (2022) Climatic Data Acquisition using Sensor Interfaced Raspberry System. *6th International Conference on Intelligent Computing and Control Systems (ICICCS)*, Madurai, India, 2022, pp. 406-409. https://doi.org/10.1109/ICICCS53718.2022.9788322

Bochenek B, Ustrnul Z (2022) Machine Learning in Weather Prediction and Climate Analyses - Applications and Perspectives. *Atmosphere 13*: 180. https://doi.org/10.3390/atmos13020180

Concato J, Feinstein AR, Holford TR (1993) The risk of determining risk with multivariable models. *Annals of Internal Medicine 118*: 201–210.

Corburn J, Njoroge P, Weru J, Musya M (2022) Urban Climate Justice, Human Health, and Citizen Science in Nairobi's *Informal Settlements. Urban Science 6*: 36. https://doi.org/10.3390/urbansci6020036

Cravero AL, Sepulveda S, Muñoz L (2021) Big Data Architectures for the Climate Change Analysis: A Systematic Mapping Study. *IEEE Latin America Transactions 18*: 1793–1806. https://latamt.ieeer9.org/index.php/transactions/article/view/3623

Dhamodaran S, Krishna Chaitanya Varma Ch, Dwarakanath RC (2020) Weather Prediction Model Using Random Forest Algorithm and GIS Data Model. *Innovative Data Communication Technologies and Application*. Springer International Publishing. pp. 306–311.

Díaz–Vico D, Torres–Barrán A, Omari A, Dorronsoro JR (2017) Deep Neural Networks for Wind and Solar Energy Prediction. *Neural Processing Letters 46*: 829–844. https://doi.org/10.1007/s11063-017-9613-7

Fayyad U, Piatetsky-Shapiro G, Smyth P (1996). From Data Mining to Knowledge Discovery in Databases. *AI Magazine 17*: 37. https://doi.org/10.1609/aimag.v17i3.1230

Haque E, Tabassum S, Hossain E (2021). A Comparative Analysis of Deep Neural Networks for Hourly Temperature Forecasting. *IEEE Access 9*: 160646–160660. https://doi.org/10.1109/ACCESS.2021.3131533

Hewage P, Trovati M, Pereira E, Behera A (2021) Deep learning-based effective fine-grained weather forecasting model. *Pattern Analysis and Applications 24*: 343–366. https://doi.org/10.1007/s10044-020-00898-1

Hou J, Wang Y, Zhou J, Tian Q (2022). Prediction of hourly air temperature based on CNN–LSTM. *Geomatics, Natural Hazards and Risk, 13*: 1962–1986. https://doi.org/10.1080/19475705.2022.2102942

Jayagopal P, Muthukumaran V, Koti MS, Kumar SS, Rajendran S, Mathivanan SK (2022). Weather-based maize yield forecast in Saudi Arabia using statistical analysis and machine learning. *Acta Geophysica 70*: 2901–2916. https://doi.org/10.1007/s11600-022-00854-z

Krocak MJ, Ripberger JT, Ernst S, Silva C, Jenkins-Smith H, Bitterman A (2023) Public Information Priorities across Weather Hazards and Time Scales. *Bulletin of the American Meteorological Society 104*: E768–E780. https://doi.org/https://doi.org/10.1175/BAMS-D-22-0190.1

Lee S, Lee YS, Son Y (2020) Forecasting daily temperatures with different time interval data using deep neural networks. *Applied Sciences (Switzerland) 10*: 1609. https://doi.org/10.3390/app10051609

Lim B, Arık SÖ, Loeff N, Pfister T (2021). Temporal Fusion Transformers for interpretable multi-horizon time series forecasting. *International Journal of Forecasting 37*: 1748–1764. https://doi.org/https://doi.org/10.1016/j.ijforecast.2021.03.012

Meng L, Zhu L (2023) Statistical Modeling of Monthly and Seasonal Michigan Snowfall Based on Machine Learning: A Multiscale Approach. *Artificial Intelligence for the Earth Systems 2*: e230016. https://doi.org/https://doi.org/10.1175/AIES-D-23-0016.1

Molina MJ, O'Brien TA, Anderson G, Ashfaq M, Bennett KE, Collins WD, Dagon K, Restrepo JM, Ullrich PA (2023) A Review of Recent and Emerging Machine Learning Applications for Climate Variability and Weather Phenomena. *Artificial Intelligence for the Earth Systems 2*: 220086. https://doi.org/https://doi.org/10.1175/AIES-D-22-0086.1

Naciones Unidas ONU (2019) *Cambio climático*. https://www.un.org/es/global-issues/climate-change.

Nandi A, De A, Mallick A, Middya AI, Roy S (2022) Attention based long-term air temperature forecasting network: ALTF Net. *Knowledge-Based Systems 252*: 109442. https://doi.org/10.1016/J.KNOSYS.2022.109442

Naveen L, Mohan HS (2019) Atmospheric weather prediction using various machine learning techniques: A survey. *Proceedings of the 3rd International Conference on Computing Methodologies and Communication (ICCMC).* Erode, India. pp. 422–428. https://doi.org/10.1109/ICCMC.2019.8819643

Ntakouris T (2021) *Timeseries classification with a Transformer model*. https://keras.io/examples/timeseries/timeseries_transformer_classification/

Open JS Fundation (2022) *Node.js*. https://nodejs.org/en/

Oracle (2022). *MySQL*. https://www.mysql.com/

Parashar N, Johri P (2021) Short-Term Temperature and Rainfall Prediction at Local and Global Spatial Scale: A Review. *International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE).* Greater Noida, India. pp. 742-746.

Qi Y, Guo C (2020) Deep Learning-based Hourly Temperature Prediction: A Case Study of Mega-cites in North China. In Proceedings of the 3rd International Conference on Big Data Technologies (ICBDT '20). *ACM International Conference Proceeding Series*, New York, NY, USA. pp. 93–96. https://doi.org/10.1145/3422713.3422718

Ren X, Li X, Ren K, Song J, Xu Z, Deng K, Wang X (2021) Deep Learning-Based Weather Prediction: A Survey. *Big Data Research 23*: 100178. https://doi.org/https://doi.org/10.1016/j.bdr.2020.100178

Sunehra D (2019). Raspberry Pi Based Pollution and Climate Monitoring System using Internet of Things. *International Journal of Advanced Research in Engineering and Technology (IJARET) 10*: 44–54.

The Apache Software Foundation (2022) *Welcome! - The Apache HTTP Server Project*. https://httpd.apache.org/

Torres J, Hadjout D, Sebaa A, Martínez-Álvarez F, Troncoso A (2020) Deep Learning for Time Series Forecasting: A Survey. *Big Data 9*. https://doi.org/10.1089/big.2020.0159

Tyralis H, Papacharalampous G, Langousis A (2019) A Brief Review of Random Forests for Water Scientists and Practitioners and Their Recent History in Water Resources. *Water 11*: 910. https://doi.org/10.3390/w11050910

van Nooten CC, Schreurs K, Wijnands JS, Leijnse H, Schmeits M, Whan K, Shapovalova Y (2023) Improving Precipitation Nowcasting for High-Intensity Events Using Deep Generative Models with Balanced Loss and Temperature Data: A Case Study in the Netherlands. *Artificial Intelligence for the Earth Systems 2*: e230017. https://doi.org/https://doi.org/10.1175/AIES-D-23-0017.1

Vaswani A, Shazeer N, Parmar N, Uszkoreit J, Jones L, Gomez AN, Kaiser L, Polosukhin I (2017) *Attention Is All You Need*. https://doi.org/10.48550/arxiv.1706.03762

Vessuri H (2023) ¿Catástrofe Climática? *Interciencia 48*: 125.

Wu N, Green B, Ben X, O'Banion S (2020). *Deep Transformer Models for Time Series Forecasting: The Influenza Prevalence Case*. http://arxiv.org/abs/2001.08317.