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Carlos Alejandro Reyes Pérez , Miguel Enrique Iglesias Martínez * , Jose Guerra Carmenate , Humberto Michinel Álvarez , Eduardo Balvis , Fernando Giménez Palomares , Pedro Fernández de Cordoba

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Real-Time Indoor Air Quality Analysis Using Recurrent Neural Networks: A Case Study of Environmental Variables

Carlos A. Reyes Pérez [1], Miguel E. Iglesias-Martínez [1,2,*], Jose Guerra-Carmenate [1], Humberto Michinel Álvarez [2], Eduardo Balvis [3], Fernando Giménez Palomares [1] and Pedro Fernández de Córdoba [1]

[1] Grupo de Modelización Interdisciplinar, InterTech, Instituto Universitario de Matemática Pura y Aplicada, Universitat Politècnica de València, Camino de Vera, s/n, 46022 València, Spain
[2] Grupo de Ingeniería Física, Escuela de Ingeniería Aeronáutica y del Espacio, Universidad de Vigo, Edif. Manuel Martínez Risco, Campus de As Lagoas, 32004 Ourense, Spain
[3] Departamento de Ingeniería de Sistemas y Automática, Escuela Superior de Ingeniería Informática, Universidade de Vigo, Edificio Politécnico s/n, 32004 Ourense, Spain
* Correspondence: miigmar@upv.es

Abstract: In the pursuit of energy efficiency and reduced environmental impact, adequate ventilation in enclosed spaces is essential. This study presents a hybrid neural network model designed for real-time monitoring and prediction of environmental variables. The system comprises two phases: An IoT hardware-software platform for data acquisition and decision-making, and a hybrid model combining short-term memory and convolutional recurrent structures. The results are promising and hold potential for integration into parallel processing AI architectures.

Keywords: neural network; air quality; environment

1. Introduction

The primary source of CO_2 in non-industrial indoor environments is human metabolism, resulting in higher concentrations compared to outdoor spaces [1,2]. It has been established that exposure to concentrations exceeding 1000 ppm can adversely affect human cognitive abilities [3]. Additionally, CO_2 levels are closely linked to ventilation efficiency [4] and the risk of indoor airborne infections [5]. Due to these critical implications, CO_2 concentration is frequently employed as an indicator of indoor air quality.

Presently, a wide range of devices is available for measuring indoor CO_2 levels, with some capable of monitoring additional parameters such as relative humidity and temperature. These devices can be categorized into two groups: those that exclusively display real-time measurements, often via a screen, and those that offer data storage capabilities. Devices in the first group often include audible and visual alarms; nevertheless, they lack the capacity for generating historical records of measured variables. Devices in the second group allow for the storage of acquired data, typically through cloud servers managed by the manufacturing or marketing company [6,7].

In many cases, the acquisition of data for indoor air quality and environmental variables lacks the ability for total, unique, and personalized control, leading to limitations in understanding and responding to the data effectively. Additionally, data storage often comes with an extra cost, making long-term monitoring challenging.

Continuous monitoring over an extended period, ideally spanning several weeks, is essential for gaining a deeper insight into usage patterns, occupancy profiles, contamination types (background or localized), periodicity, and the potential for space improvement [8–10].

In situations where thermal and humidity comfort is inadequate, it becomes necessary to assess and adjust the air conditioning system, control and regulation mechanisms, the need for humidification or dehumidification, and even calculate the required water vapor adjustments to achieve specific comfort conditions. This process enables the selection of appropriate devices or systems for this purpose. Monitoring CO_2 concentration and temperature is instrumental in evaluating the efficiency of ventilation systems and programming their regulation based on CO_2 levels [3,11,12]. By addressing these aspects, this research aims to provide valuable insights and solutions for enhancing indoor air quality and environmental conditions in enclosed spaces.

1.1. Related Works

Over the past decade, significant advancements have been made in the field of weather prediction, driven by the application of advanced machine learning techniques. When it comes to analyzing time series datasets, such as signals and text, Long Short-Term Memory (LSTM) neural networks have emerged as a prominent choice [13]. LSTM addresses a common challenge faced by Recurrent Neural Networks (RNN), which is the vanishing gradient problem, by incorporating memory cells and gating mechanisms. This unique architecture empowers LSTMs to effectively capture long-term dependencies within time series data, making them well-suited for tasks involving temporal patterns [14].

Empirical evidence has demonstrated that LSTM architectures often outperform alternative machine learning models in terms of accuracy, particularly when dealing with numerical values.

Artificial Neural Networks (ANN) are intricate systems composed of interconnected processing units that operate in parallel. While ANNs have demonstrated excellent performance in applications like Optical Character Recognition (OCR), their superiority over traditional statistical pattern classifiers remains inconclusive [15].

In ANN systems, the initial stage involves processing real-number input signals. The connections, often referred to as edges, link artificial neurons to their respective outputs and are determined by non-linear functions applied to the sum of their inputs. These edges have adjustable weights that evolve iteratively during the learning process, directly influencing the strength of the signal. For a signal to propagate from one layer to another within the ANN, it must surpass a predefined threshold. Typically, ANNs incorporate multiple layers to facilitate various transformations of input signals. After traversing these layers iteratively, the output layer produces the final results [16].

Numerous previous studies have explored various ANN architectures [17], applied LSTM for weather forecasting [14], and developed simulation models to predict rainfall [18], all of which have contributed to improved modeling efficiency. Additionally, research has been conducted to harness LSTM for greenhouse climate modeling, with a focus on forecasting the impact of six climate factors: temperature, light, humidity, CO_2 concentration, soil temperature, and soil moisture, on crop growth. To capture climate variations, a sliding time window approach was adopted to record minute-by-minute changes in environmental conditions. This model was evaluated using datasets comprising three different types of vegetables and demonstrated commendable accuracy when compared to alternative models. Notably, it exhibited robustness and optimal performance within a fixed 5-minute time window. However, the model's performance gradually declined as the window size was increased [19].

In previous research [20,21], LSTM-based models have been successfully employed for a range of applications, including the prediction of Point of Interest (POI) categories and the hourly daily irradiance forecast. The solar prediction technique introduced in these studies, which combines LSTM with weather data, considers the interdependence of hours throughout the day. Results have demonstrated that this novel approach exhibits reduced overfitting and superior generalization capabilities compared to traditional backpropagation algorithms (BPNN). Specifically, the proposed algorithm led to a remarkable 42.9 percent reduction in Root Mean Squared Error (RMSE) in comparison to BPNN [22].

Furthermore, in the context of meteorological applications involving time series data prediction, both LSTM and Transudative LSTM (T-LSTM) models were leveraged. These models were applied to regression problems using a quadratic cost function. The studies also explored two weighting strategies based on the cosine similarity test between test and training samples. Experiments were conducted under varying climatic conditions over two distinct one-year periods. The results revealed that T-LSTM outperformed LSTM in the prediction task [23].

Likewise, a statistical model for predicting weather variables near Indonesian airports, employing both single-layer and multi-layer LSTM models, was developed [24]. The main objective was to assess the impact of intermediate weather variables on prediction accuracy. The proposed model builds upon the standard LSTM architecture by integrating intermediate variable signals into the LSTM memory block. In this approach, visibility serves as a predictor, while pressure, humidity, temperature, and dew point function as independent variables.

In this model, the initial layer comprises separate LSTM models based on location, and the second layer takes the hidden states of the first LSTM layer as input. Experimental results clearly indicate that the inclusion of spatial information from the dataset significantly enhances the prediction performance of the stacked LSTM-based model [25].

The combination of LSTM [26,27] and CNN [28,29] network architectures has found applications in various research fields, including accident prediction, energy consumption forecasting in households, and stock market analysis [30–32]. For instance, accident prediction and energy consumption forecasting models, described in [33,34], are based on the CNN-LSTM architecture.

In contrast, an opposite LSTM-CNN architecture was employed for stock market applications as demonstrated in [35]. Similarly, a recent study on CO_2 emissions [36] introduced a CNN-LSTM architecture for multivariate and single-step analysis, using a sliding window of three values and a one-step horizon. These studies often rely on large volumes of simulated data for training, given the limited availability of actual data.

It is important to note that both [35] and [36] focused on single-step forecasts into the future and utilized exogenous variables as inputs, increasing the complexity of the architectures.

However, the architectures discussed in these previous works primarily addressed short-term predictions, and their focus was not on behavioral predictions for high-frequency time series. This study proposes a hybrid model with variations in processing layers designed specifically for high-frequency forecasting. The main contributions of this work are as follows:

- Proposal of a hybrid LSTM-CNN architecture for forecasting 48 steps into the future for high-frequency time series. The baseline sampling time was 30 minutes.
- The proposal is based on univariate analysis of the environmental variables studied.
- Unlike other models, our architecture does not use a pooling layer to prevent the loss of information in the network.

The work has been organized as follows: Section 3 presents the theoretical foundations of the research, as well as the validation metrics used. Section 4 describes the experimental process and the data acquisition for the development of the work. Section 5 summarizes the obtained results. Finally, the conclusions of the research and the references consulted are provided.

2. Basic foundations of the proposed model

This section describes the theoretical foundations of the proposed architecture, which is based on the combination of a model that utilizes long short-term memory and convolution layers for forecasting environmental variables, specifically Carbon Dioxide and Temperature. The description of the long-term memory network architecture that applies to an input sequence for each element involves a convolution layer, which is described as follows:

$$y_i = g\left(\sum_{j=0}^{F-1} w_j x_{(i \times S)+j} + b\right) \tag{1}$$

where:

- y_i is the output value at position i in the convolutional layer.
- x is the input signal to the convolutional layer.

- w_j is the filter value at position j.
- b is the bias value of the layer.
- S is the step or stride used to move the filter along the input signal.
- F is the filter dimension.
- g is the activation function applied to the weighted sum of input values and filter weights.

A graphical representation of the proposed recurrent neural network architecture and the sequential input-output data process is shown in Figure 1.

Both neural networks have identical architectures, which include an Input layer, three LSTM layers with 32 units each, a Convolutional layer with 128 units, and a Dense layer with 48 neurons. The Dropout regularization method is applied to the LSTM layers with a value of 0.5. This method probabilistically excludes input connections from activation and weight updates during training, with the goal of reducing overfitting and enhancing model performance.

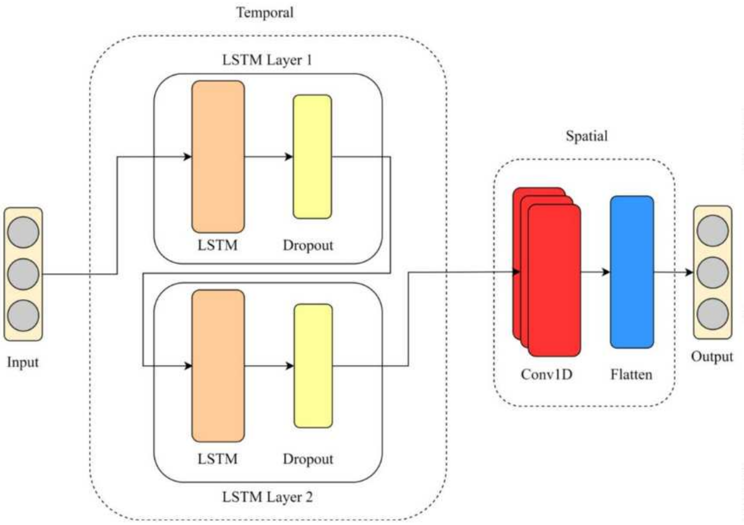


Figure 1. Architecture of the LSTM-CNN Neural Network used.

Figure 2 illustrates the final layer of the network, which is a Dense layer responsible for processing the information generated by the LSTM and Convolutional layers and producing the model's outputs. Each network forecast is calculated by applying the activation function, in this case, a linear activation function. This function operates on the sum of weights (w) and inputs (a), to which the bias (b) is added.

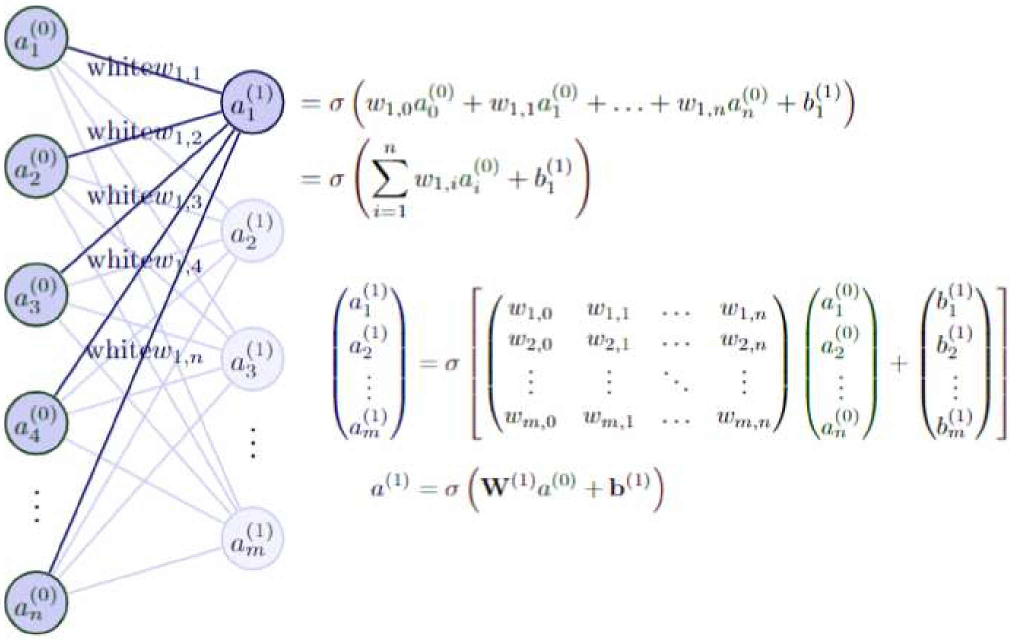


Figure 2. Final layer operations of the proposed architecture.

2.1. Hardware and experimental descriptions

The device developed for monitoring ventilation and thermal comfort, known as the 'AirQ-Monitor,' comprises the following fundamental hardware elements:

- 1x SoC ESP32 (integrated into the PCB): serves as the main system processor.
- 1x SCD30 sensor: a module for sensing the concentration of CO_2, temperature, and humidity.
- 1x TFT 2.4" touch screen: used for equipment display and configuration interface.
- Plastic chassis (derived from a generic model).

Figure 3 illustrates the system architecture, depicting multiple AirQ-Monitor devices connected to a server. The system is powered by a 5-volt source through a micro USB connector. Since all components operate at 3.3 volts, a voltage regulator is employed to reduce the voltage to this level. The ESP32 communicates with the SCD30 module through an I2C bus at a frequency of 100kHz. For controlling and displaying measurements on the screen, as well as handling other graphical elements, one of the SPI interfaces of the SoC is utilized. The touch panel, which enables user interaction with the device, operates in an analog manner and does not use any specific bus or standard protocol. Additionally, the collected data are transmitted to a cloud IoT server via a WiFi network. Figure 3 provides a block diagram that visually represents the composition of the device.

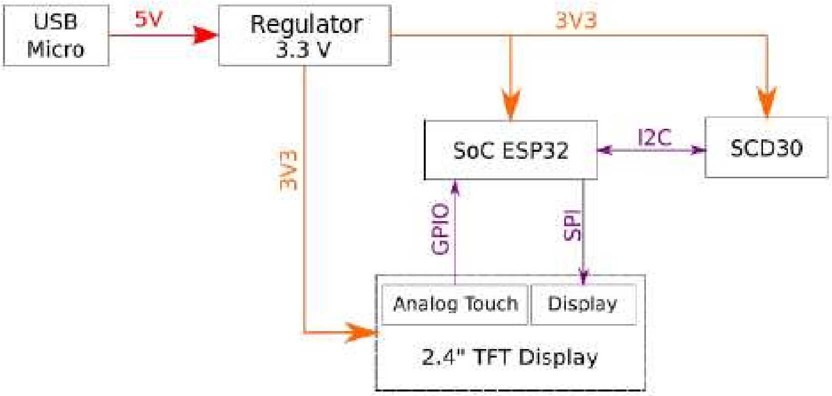


Figure 3. Block diagram of the developed device.

Data processing has been performed using the TensorFlow framework. The data used to train the network was collected from devices installed on the campus of the Universitat Politècnica de Valencia in Spain. Data have been collected from various locations since March 2022. Eighty percent of the data was utilized for training the model, while the remaining 20% was used for evaluation.

2.2. Server and model deployment

As an additional aspect of this research, the proposed model has been implemented on a real-time server. The development of the real-time server processing utilized the 'Flask' framework. The server is hosted on a cloud computing machine and offers several accessible endpoints. Below, we describe some characteristics of these processes:

- Results: Provides the most current forecast values.
- Input: Displays the input values used to generate the most recent forecasts.
- Real: Presents the forecasted values that correspond to the previous input, allowing for a comparison between the model's estimates and the actual values (from the last input)

Figure 4 illustrates the system architecture after receiving data from the Thingsboard cloud, which was used in the experiment.

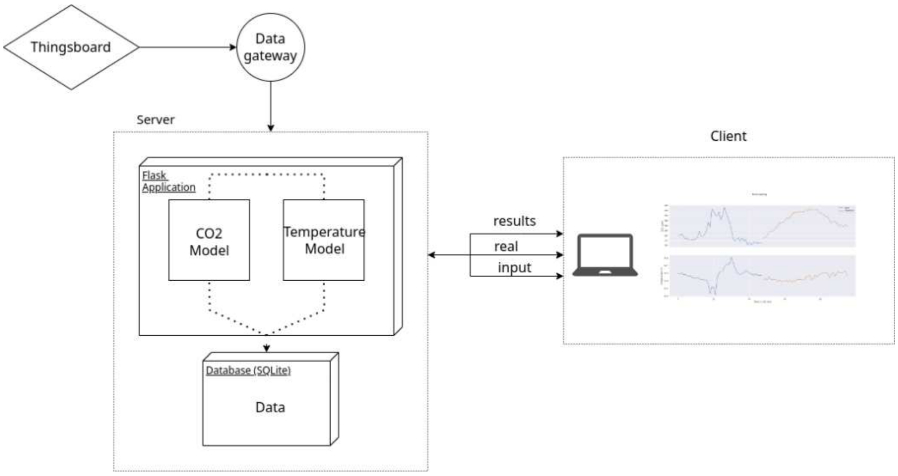


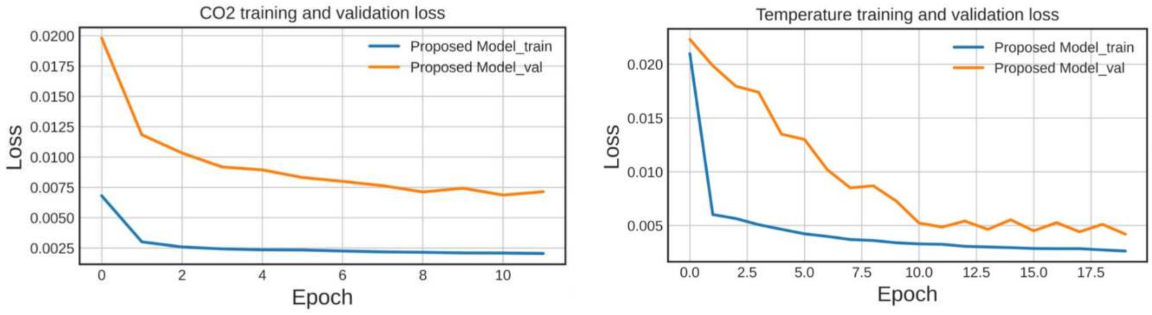
Figure 4 Real time general systems architecture.

A Python-based data gateway handles the regular and automatic communication between the Thingsboard platform and the server. The server hosts the models for CO_2 and temperature, which process incoming information and generate forecasts. Data related to the input, forecasts, and timestamps are stored in a SQLite database for future use. Clients can request information from the server through endpoints such as 'result,' 'real,' and 'input,' enabling the presentation of results in a suitable format for decision-making.

3. Results and discussion

For the implementation of the proposed model, a 48-step sliding window is used, which is equivalent to one day (24 hours). The data is sampled at a frequency of every 30 minutes, and the model generates forecasts with a horizon of 48 steps, also equivalent to one day with the same sampling frequency. The objective is to provide a reliable 24-hour forecast for both CO_2 and temperature, based solely on their behavior in the preceding 24 hours.

Figures 5 and 6 display the results obtained during the model training process for the variables CO_2 and temperature, respectively.



(**a**) (**b**)

Figure 5. Training models: (**a**) CO_2 model training (**b**) Temperature model training.

As part of the analysis of CO_2 samples acquired by the developed device, we processed over 200.000 samples, each acquired at a 60-second interval. However, for the prediction task, the model operated with a 30-minute interval between samples, allowing us to evaluate its performance across various temporal horizons. The data for processing were acquired from the platform of the developed ventilation monitoring system, Thingsboard. In Figure 7, you can observe a screenshot of the cloud visualization platform and the data obtained from the sensors.

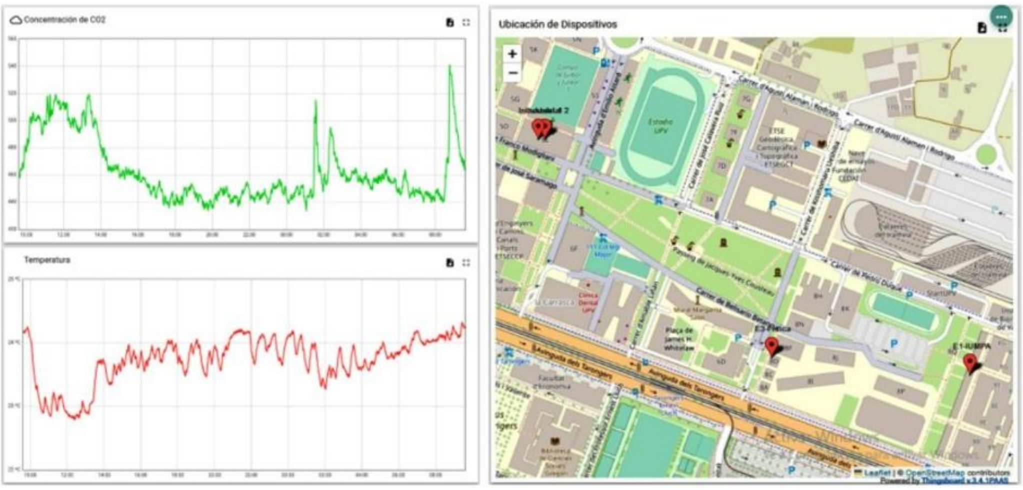


Figure 6. Screenshot of the cloud visualization platform and the obtained data from the sensors.

Initially, the proposed model is trained using all the acquired data. The process of running the trained model unfolds as follows: Every 30 minutes, a dataset frame is automatically sent from the cloud (Thingsboard) to the server, updating the information related to the behavior of CO_2 and temperature during the previous 24 hours. Subsequently, the model predicts the behavior of CO_2 and temperature for the next 24 hours. Figures 8 and 9, respectively, provide screenshots of the obtained results using a sliding window and a 24-hour temporal horizon. It's important to note that the results displayed in Figures 8 and 9 are continuously updated as the server processes incoming samples. This process operates in real-time.

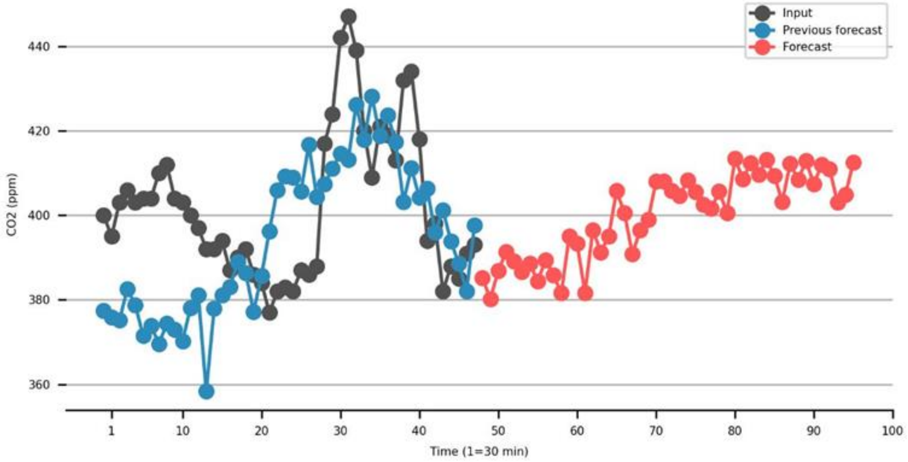


Figure 7. Screenshot of the obtained results of the proposed CO_2 model using the hybrid LSTM-CNN architecture.

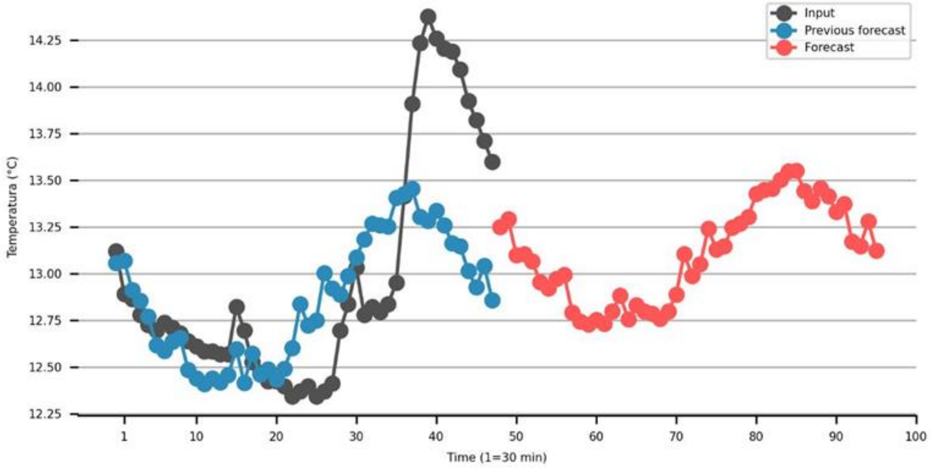
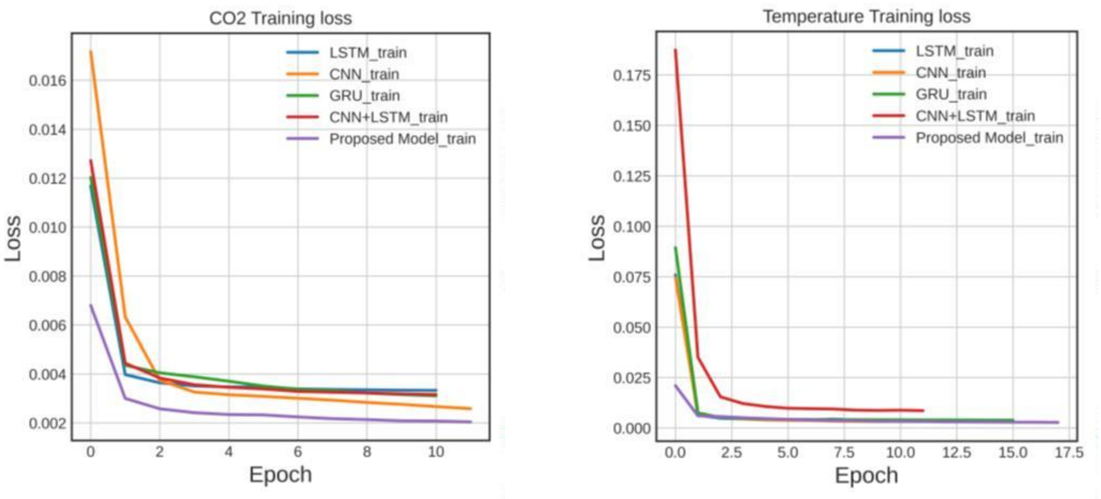


Figure 8. Screenshot of the Results Obtained from the Hybrid LSTM-CNN Architecture-Based Temperature Model.



(**a**) (**b**)

Figure 9. Training models comparison: (**a**) CO_2 training loss (**b**) Temperature training loss.

After evaluating the model, an error value of 13.8160 ppm was obtained for the 24-hour forecasts of CO_2, and 0.4623 °C for temperature.

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Additionally, Table 1 displays the metrics obtained during the model's training evaluation. These metrics provide insights into the efficiency and accuracy of the proposed model for real-time prediction of environmental variables.

Table 1. Metrics of the model during its evaluation.

Metrics	Carbon Dioxide	Temperature
MAE	13.3925	0.6062
RMSE	19.268	0.880
MAPE	3.2690	5.3623

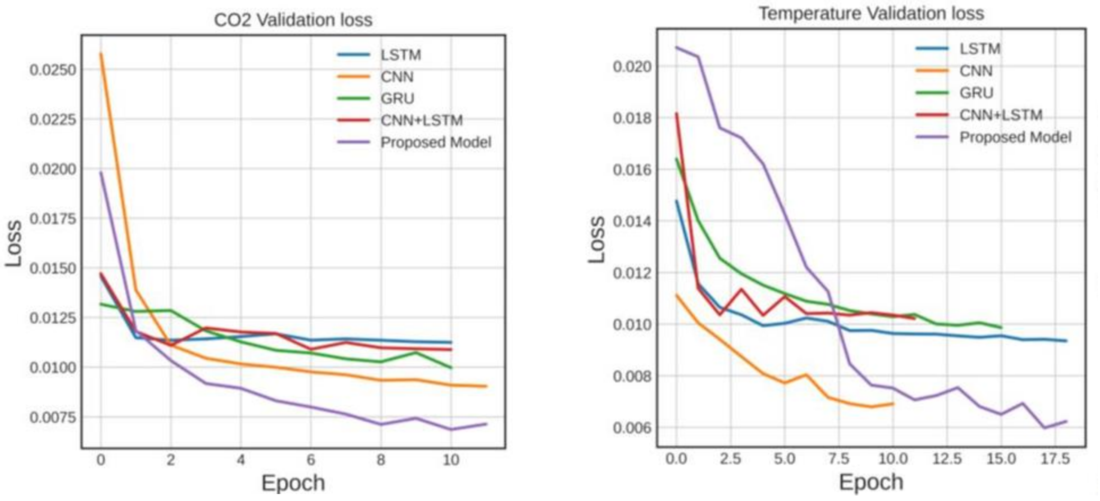
4. Discussion: Comparison with other methods

In order to verify the effectiveness of the proposed architecture in this work, we conduct a comparative analysis with other models from previous research. The comparison includes the following architectures: Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), Gated Recurrent Unit (GRU), and two hybrid variants of the LSTM and CNN architectures.

The models used for the comparative study were trained on the same Carbon Dioxide and Temperature data obtained from Universitat Politècnica de València. The Early-Stopping method is applied to prevent overfitting.

Figure 10 illustrates that for both the carbon dioxide and temperature models, the error minimization curve during training exhibits a shallower slope in the proposed model compared to the other evaluated architectures.

On the other hand, in Figure 10, in terms of validation loss metrics, the proposed model demonstrates superior performance and lower errors. While temperature initially exhibits a high error and slower convergence, its error minimization is also more significant compared to other methods.



(**a**) (**b**)

Figure 10. Validation models comparison: (**a**) CO_2 validation loss (**b**) Temperature validation loss.

The results demonstrate that the architecture proposed in this work, utilizing a hybrid model with modifications in the pooling layer structure, yields superior CO_2 and temperature data forecasts. Table 2 summarizes the obtained results in terms of validation losses, quantifying the total number of errors in the validation set.

Table 2. Validation loss of the proposed model compared to others models.

Model	CO_2 validation loss	Temperature validation loss
LSTM	0.01124	0.00934
GRU	0.00996	0.00986
CNN	0.00903	0.00690
CNN+LSTM	0.01088	0.01021
Proposed Model	0.00712	0.00622

5. Conclusions

This study has presented the outcomes of predictive analysis involving CO_2 and temperature values using a novel hybrid neural network architecture. The developed predictive model for high-frequency time series aims to assess the behavior of these variables and their potential impact on indoor spaces' occupant performance when ventilation levels are insufficient. The novelty of our model lies in its omission of the pooling layer to prevent information loss within the network. Notably, we achieved favorable results up to 48 time steps into the future with a 30-minute sampling interval.

Our model operates in real-time by synchronizing with a cloud-based data server, ensuring continuous learning and enhancing forecasting performance. Furthermore, the proposed architecture offers optimization flexibility concerning data window size and the prediction time horizon. These findings highlight the model's potential for improving indoor air quality and supporting decision-making for maintaining optimal environmental conditions.

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