LSTM-Driven Smart Home System: A Study of Temperature and Humidity Prediction and Energy Management

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Abstract. Smart home systems (SHS) have gained significant popularity due to their inherent convenience. Using Internet of Things (IoT) technology, SHS can automatically adapt indoor environments according to user needs. However, most existing SHS rely on preset configurations and lack the ability to predict environmental changes, while also exhibiting shortcomings in energy management such as the ability to seamlessly transition between solar and natural gas. In response to these challenges, this paper introduces a SHS built on Long Short-Term Memory (LSTM) network models. By using publicly available datasets from the Kaggle platform for training and validation purposes, the LSTM model demonstrates exceptional performance in the tasks of temperature and humidity prediction as well as energy switching operation. It exhibits high accuracy and holds great potential for practical implementation within SHS applications. The research not only addresses the shortcomings of traditional SHS in environmental prediction and energy management by introducing the LSTM model but also provides an important theoretical foundation for future advancements in SHS. The results indicate that the LSTM model is capable of making precise predictions in intricate environmental conditions, optimizing energy utilization efficiency and promoting the development of smarter, energy-saving home systems.

Keywords: SHS, LSTM, Temperature Prediction, Humidity Prediction, Energy Management

1 Introduction

As the economy develops, people's pursuit of a higher quality of life intensifies, making smart home system (SHS) increasingly popular due to their significant convenience. IoT technology is widely used in SHS. Through artificial intelligence, machine learning, and other related IoT technologies, SHS can automatically regulate home temperature and humidity using devices like air conditioners and humidifiers, based on user needs [1]. However, current SHS relatively rely on user presets, making it difficult to adjust settings optimally by predicting future environmental changes. Furthermore, many homes use multiple energy sources like solar and gas, and solar energy efficiency decreases considerably in poor weather. Without timely switching to natural gas, there can be insufficient energy supply. Existing systems find it challenging to manage energy switching based on environmental changes, which may lead to decreased system efficiency and user satisfaction.

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To address the shortcomings of current SHS in environmental prediction and energy management, this paper aims to develop an SHS based on a deep learning model. The system will automatically adjust air conditioners, heaters, and humidifiers by predicting indoor temperature and humidity to cater to varying user needs. Additionally, the system will integrate weather data to enable intelligent switching between solar energy and natural gas, aiming to enhance energy use efficiency and user comfort while maintaining stable system operation. These improvements are expected to provide innovative solutions and methodologies for optimizing and advancing future SHS.

2 Model selection

This section describes the process of deep model selection. Three common deep learning models will be compared, and finally the most suitable model will be selected.

In SHS, temperature and humidity data and weather conditions are related to time series. These data have time dependency, so this paper has to choose a deep learning model that is appropriate for processing time series. Recurrent Neural Network (RNN)is a common model to handle time series data, but in practice, RNN is prone to the problems of gradient vanishing and gradient explosion when dealing with long time series, so RNN is not appropriate to handle long time series like temperature or humidity [2]. In contrast, Long Short-Term Memory Network (LSTM) addresses the shortcomings in the processing of long sequences in RNNs by introducing a gating mechanism, which allows it to perform better in processing time-series data with long time dependencies. Although Gated Recurrent Unit is computationally efficient, the prediction accuracy may not be as good as LSTM due to the simplified structure [3]. Therefore, in order to meet the requirement of SHS for high accuracy prediction, we finally chose LSTM model.

Next, this paper will introduce the basic model of the LSTM as well as the input layer, output layer, and loss function of the system.

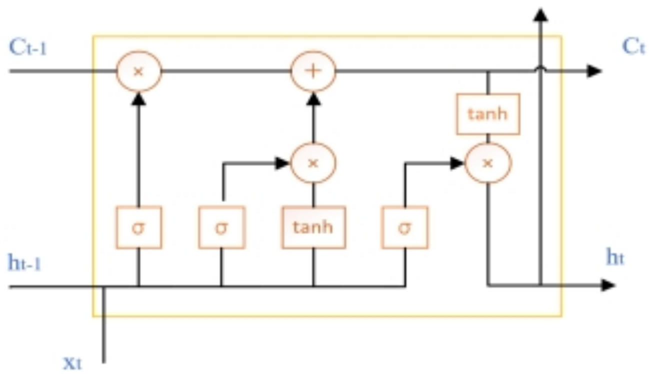

Fig. 1. The structure of single LSTM unit.

The LSTM cell consists of three key gates including the input gate, forget gate, and output gate (Figure1). The forward computation process is outlined as follows:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad (1)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (2)$$

$$\widetilde{c_t} = \tan h(W_c[h_{t-1}, x_t] + b_c) \quad (3)$$

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tilde{c}_t \quad (4)$$

$$o_t = \sigma(W_0[c_t, h_{t-1}, x_t] + b_0) \quad (5)$$

$$h_t = o_t \cdot \tan h(c_t) \quad (6)$$

Where $W_f, W_{c,} W_i$ are the weight matrix determined by the gradient descent method, b_f, b_c, b_i are biased. h_{t-1} is the previous hidden layer state, h_t is the current state, x_t is the input in the current state. And c_t, c_{t-1}, $\widetilde{c_t}$ represents the current cell state value, the previous cell state value, and the updated value of the current cell state. The forget gate determines whether to retain or discard information from the prior memory cell. The input gate adds new information to the cell state, while the output gate regulates whether the information is passed to the next layer [4].

To effectively predict indoor environmental changes and facilitate intelligent energy source switching, this paper utilizes multi-dimensional time series data as inputs to the LSTM model's input layer. These inputs include indoor temperature and humidity, along with external weather data such as weather conditions and cloud coverage. By incorporating these diverse data points, the system can accurately capture environmental changes over time, enabling more precise decision-making. This method enables LSTM models to grasp time-varying environmental information to make better predictions and decisions. In the network's output layer, the results from the LSTM layer are transformed into concrete predictions. The predictions generated by the output layer include future indoor temperature and humidity values, which are used to automatically adjust air conditioners, heaters, and humidifiers. In addition, the output layer generates decisions about energy switching, determining whether switching between solar and natural gas is required.

In this system, it is necessary to fulfill two prediction tasks, one is the regression prediction of temperature and humidity, and the other is the categorization decision for energy switching. Due to the different nature of these two tasks, the study uses two different loss functions to optimize the model. For temperature and humidity prediction, which is a regression task, the model generates continuous outputs. The goal of this kind of task is to make our predicted temperature and humidity close to the real values. And the mean square error (MSE) calculates the squared average of the difference between the predicted and true values. By squaring operation, MSE is more sensitive to larger errors, which is important for SHS because more accurate prediction results are needed for the regulation of devices such as air conditioners humidifiers to increase the comfort of the environment and the user's experience. Therefore, we used MSE as a loss function [5]. The MSE is calculated using the following formula:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 + \lambda \sum_{j=1}^{m} w_j^2 \quad (7)$$

Where y_i is the true temperature or humidity value at time step i, whereas $\hat{y}_i$ is the predicted value of the model and n denotes the total number of time steps.

As for the energy switching task belongs to the categorical labeling, the model output is to choose solar energy or natural gas. And the cross-entropy loss function (CELF) can effectively handle the dichotomous task since it effectively quantifies the discrepancy between the model's output probability distribution and the true categories, it enhances the model's classification decision-making capabilities [6]. In the energy switching task, the CELF helps the model to make optimal decisions based on the input environmental characteristics by clearly distinguishing between different energy choices, thus ensuring that the system chooses the most appropriate form of energy under different conditions. Therefore, the author adopts the CELF. For the binary classification task, the CELF is expressed as follows:

$$\mathrm{Cross-EntropyLoss} = -\frac{1}{n}\sum_{i=1}^{n}\left[y_i \log(\hat{P}_i) + (1-y_i)\log(1-\hat{P}_i)\right] \tag{8}$$

Where y_i is the true category of the ith sample (0 for natural gas, 1 for solar), $\widehat{P}_i$ is the probability that the model predicts that the sample belongs to category 1 (i.e., solar).

3 Data preparation and model training

3.1 Dataset description

In the LSTM model for indoor temperature and humidity prediction, the author uses a dataset that records temperature and humidity data inside a 73 square meter apartment. This dataset covers a wide range of influences such as air conditioning usage, open windows and ventilation, and indoor activities, which together contribute to changes in indoor temperature and humidity [7]. By analyzing this data, the SHS can better predict the changes in temperature and humidity and automatically adjust the air conditioner and humidifier to ensure the comfort of the indoor environment.

For the LSTM model of energy switching, the author uses a dataset that records daily weather information for the world's capitals, covering key meteorological features including weather condition descriptions and cloud cover from August 29, 2023 [8]. These features directly influence the energy usage strategies of SHS under different weather conditions. Weather condition descriptions provide detailed textual descriptions of the daily weather, such as sunny, cloudy, and rainy. These descriptions directly affect the solar power generation capacity. Cloudiness is another key feature that directly affects the power generation efficiency of solar panels. Higher cloudiness reduces the efficiency of solar energy, so the system may rely more on natural gas in high cloudiness weather. By comprehensively analyzing these characteristics, the SHS can make real-time decisions about energy switching, optimize energy use, and improve the user's living comfort.

3.2 Data preprocessing

In this study, the input data contains numerical features such as temperature, humidity, and cloudiness. Since the numerical ranges of these features vary widely, it may lead to instability in the training process. In contrast, Min-Max normalization can reduce the numerical differences between features by scaling the data to a fixed range of [0, 1], preventing certain features from having an excessive impact on the model [9]. Therefore, we used the Min-Max normalization method for the dataset. For the energy switching dataset, as it contains textual descriptions, we need to convert it to a numerical format for the model to process, and we used One-Hot Encoding to convert each category to a binary vector to enable the model to accurately learn and process this information [10]. In order to achieve accurate prediction of energy switching by the model, we first set up labels for different energy use cases based on weather conditions and cloud requirements. The specific labels are shown in Table 1, through which the model can accurately learn and predict the type of energy that should be selected under different weather conditions, so as to optimize energy usage.

Table 1. Energy Source Selection Criteria Based on Weather Conditions.

Weather Condition	Cloud Requirement	Energy Source
Sunny, Clear, Partly cloudy	No	Solar Energy
Light drizzle, Patchy rain nearby, Light rain	below 20%	Solar Energy
Moderate rain, Heavy rain, Fog/Mist	No	Natural Gas
Overcast	No	Natural Gas
Light rain, Moderate rain, Thunderstorm	No	Natural Gas
Cloudy	Over 70%	Natural Gas

3.3 LSTM-Based temperature and humidity prediction model

This research used a sliding window technique with 16 time steps to construct the samples, in order to exploit not only less but all historic information available from each of one individual sample when desired outputs are temperature and humidity features at the next time step. The dataset was split into two parts, 80% of the sample for training and the remaining 20% to test our model. A two-layer LSTM model was developed, with 100 units in the first layer and 50 units in the second. To mitigate overfitting, a Dropout layer with a rate of 0.2 was applied after each LSTM layer [11]. The output layer consists of a fully connected layer with two nodes, used to predict temperature and humidity. The model employs MSE as the loss function and the Adam optimizer is used for optimization. Additionally, early stopping was implemented to further prevent overfitting [12].

To validate the model's effectiveness and predictive capability, we recorded the training loss and validation loss variations, as shown in Figure 2, and compared the predicted temperature and humidity values against actual measurements, as shown in Figure 3 and 4.

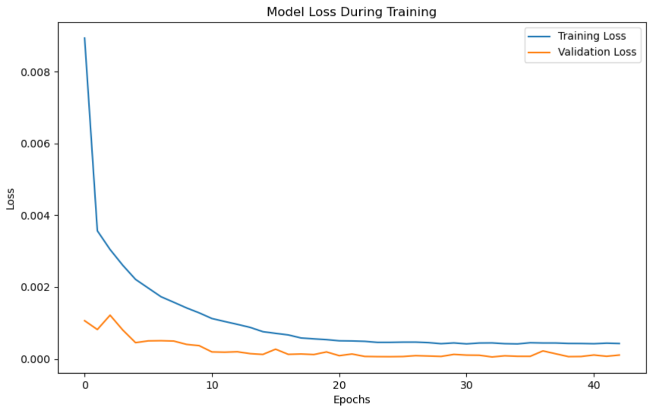

Fig. 2. Model Loss During Training.

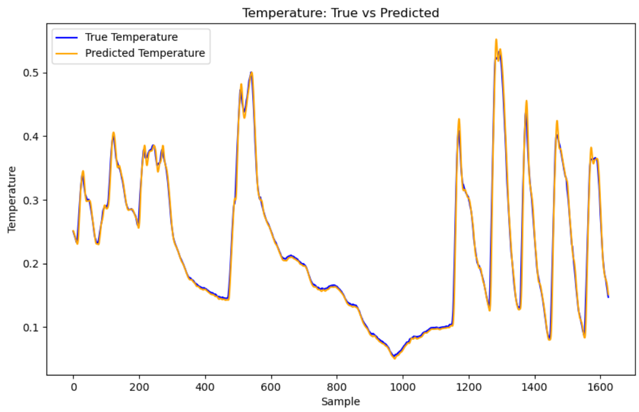

Fig. 3. Comparison of actual and predicted values for temperature.

Figures 2, 3 and 4 depict the model's overall performance in predicting temperature and humidity. The gradual decrease of the loss curve shows the model's effective optimization. In the prediction plots, the model's output values closely align with actual observations, confirming the model's accuracy. These results show that the LSTM model exhibits excellent performance in time series prediction for both temperature and humidity, providing highly accurate predictions.

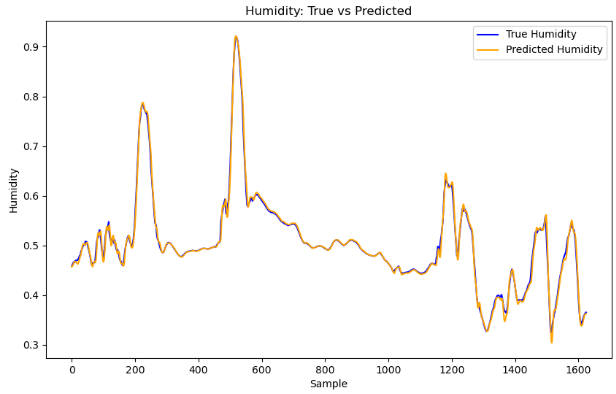

Fig. 4. Comparison of actual and predicted values for humidity.

3.4 LSTM-Based energy switching prediction model

Like the previous section, the authors divided the dataset into a two sets, the training set and the test set, where 80% is for training data and 20% is for test data. We designed an LSTM model with 256 units and added an additional two fully connected layers, one of which has 128 layers and the other has 64 layers. After each layer, a dropout layer was added with a dropout rate of 0.2 to protect against overfitting. The model employs CELF as the loss function and is optimized using the Adam optimizer. To monitor the loss on the validation set and adjust the training process accordingly, this paper introduces a learning rate scheduler and an early stopping method.

For the assessment of the performance of the designed model in the energy switching task, we recorded the training loss, training accuracy during training, and the validation loss and validation accuracy at the end of training cycle, which are shown in Figure 5 and 6.

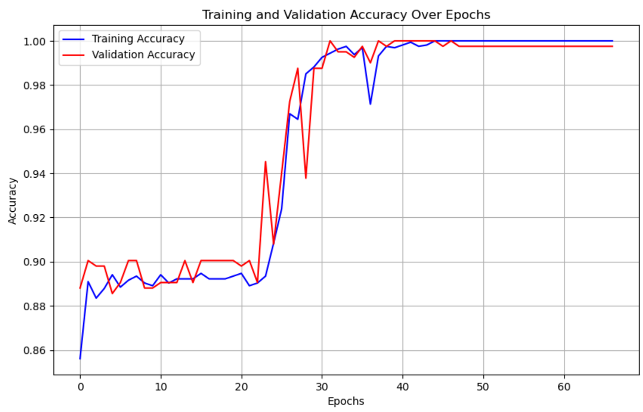

Fig. 5. Model Training and Validation Accuracy Over Epochs.

Figures 5 and 6 depict how the accuracy and loss of the model varies with the number of epochs on the training set during training and the number of epochs on the validation set at the end of each epoch. The graph on the left shows that as the epochs increase, the accuracy of the model on both the training and validation sets increases and stabilizes, eventually reaching nearly 100% accuracy, demonstrating that the model can make more accurate decisions. The graph on the right side shows that both the training loss and the validation loss decrease rapidly and tend to zero. It shows that the prediction error of the model has been effectively controlled. Taken together, these curves show that the model has good generalization ability in the energy switching task, and is able to meet the demand of accurately predicting energy switching under different weather conditions in SHS, improving the efficiency and stability of energy management in SHS.

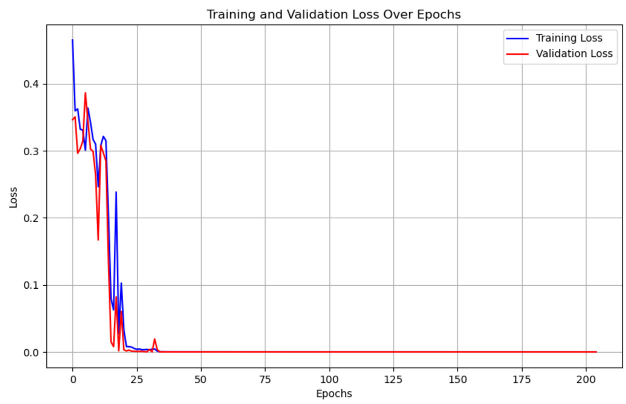

Fig. 6. Model Training and Validation Loss Over Epochs.

In addition, to more accurately assess the performance of the model we designed for the smart home energy switching task, this study performed a 10-fold cross-validation and recorded F1 Score, TPR, FPR, and Accuracy [13-14]. These metrics more comprehensively reflect the performance of our model in terms of classification, which is depicted in Figure 7.

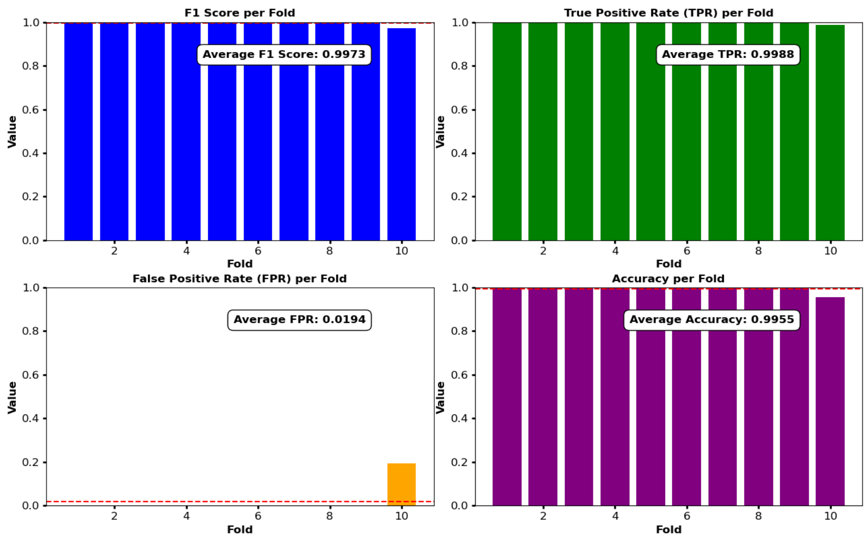

Fig. 7. Cross-Validation Metrics per Fold.

Figure 7 shows that the model's F1 score, TPR, and accuracy are all close to 1, while the FPR is very close to 0. These metrics further demonstrate the model's robustness across different data splits, proving its consistency and generalizability, and highlighting the accuracy and reliability of our model in the smart home energy switching task, ensuring stable system operation.

4 Conclusion

An LSTM-based SHS is introduced in this paper, and it will predict how the indoor temperature, humidity, or weather effects can be anticipated so that automatic adjustments for air conditioners, heaters, humidifiers, and energy sources switching like solar and natural gas can be switched. Through deep learning, the system overcomes limitations in environmental change prediction, and energy management ingrained within conventional SHS. The results validate the excellent performance of the LSTM model for the temperature and humidity prediction and energy switching tasks under different weather conditions should be satisfied to guarantee system operation stability and user comfort. This study serves as an essential theoretical reference and a significant aid for SHS optimization, proving that LSTM is capable of making accurate predictions with good energy management in complex environments.

Nevertheless, the study in this paper still has some limitations. First, the model structure relying on temperature, humidity, and weather has relatively high prediction accuracy but ignores other influencing factors such as air quality or user behavior. Future work should introduce more environmental parameters into the model to make it more comprehensive and accurate. In addition, only one LSTM model was implemented for prediction in this paper, and although it achieves high accuracy, future work can try to combine multiple learning-based models, like combining LSTM with convolutional neural networks, and also introduce reinforcement learning strategies for better performance and robustness of prediction results Finally, energy management strategies, especially energy switching strategies in multi-energy systems, can be further optimized to ensure efficient and stable energy supply in complex and changing environments. These improvements will help facilitate the development of SHS to better meet the future demands of people living smart and comfortable lives.

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