Accelerated Temperature Prediction in an IoT Enabled Scaled Home

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Abstract

Testbed development for smart homes is a timely and expensive process. By using a scaled model home in an isolated environment as a testbed, we are able to perform accelerated experiments on smart homes under various scenarios. Temperature and humidity data were collected from the model home, which conducts various realistic simulations under diverse climatic conditions. This data was used to train machine learning algorithms to predict changes in temperature and humidity within the home with the eventual goal of developing an intelligent agent that can internally regulate humidity and temperature in a more financially and environmentally conscious manner.

Implementation

This project expands on works by Ling et al. [1], Burns et al. [2], and Mendula et al. [3].

- Raspberry Pis are small, highly efficient computers; HATs are expansion boards that connect to the Pi's set of 40 GPIO pins.
- Two Raspberry Pis are used for data collection. One of them includes a Pi HAT and acts as an actuator for the changing of motor states.
- The scaled home is contained in a greenhouse, creating an isolated environment that provides more control to perform experiments.

Methods

With goals of realism and climatic diversity in mind, Figure 1 shows the cities we chose to emulate during a specific month of the year.

We used a scaling formula to keep temperature and humidity within an achievable and controllable range for our environment (70°-80°F). These values can be scaled back to represent their real-world values:

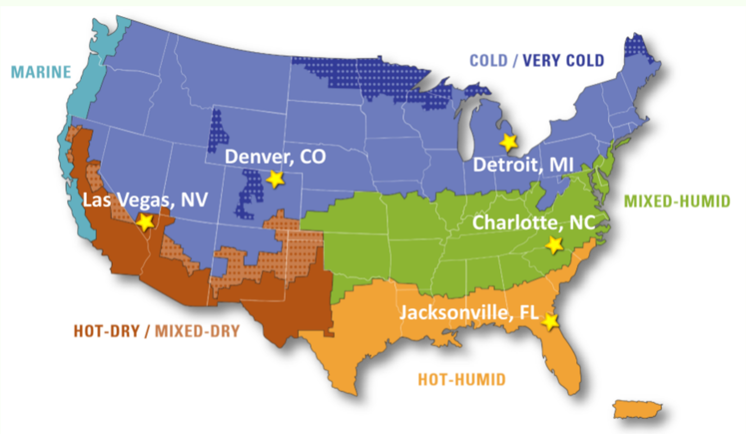

Figure 1. A map of the chosen locations [4].

$$SH_{Temp} = \frac{target_{City} - min_{City}}{max_{City} - min_{City}} \times (max_{SH} - min_{SH}) + min_{SH}$$

Simulation Development:

- We created three types of simulations that model the movements of one to three people inside the house.
- Each city has its own version of the three simulations, giving us a total of 15 baseline simulations for five cities.
- Due to repeated trials, we have a total of 20 simulations to analyze.

FOR MORE DETAILED INFORMATION SCAN THIS CODE

Experimental Setup

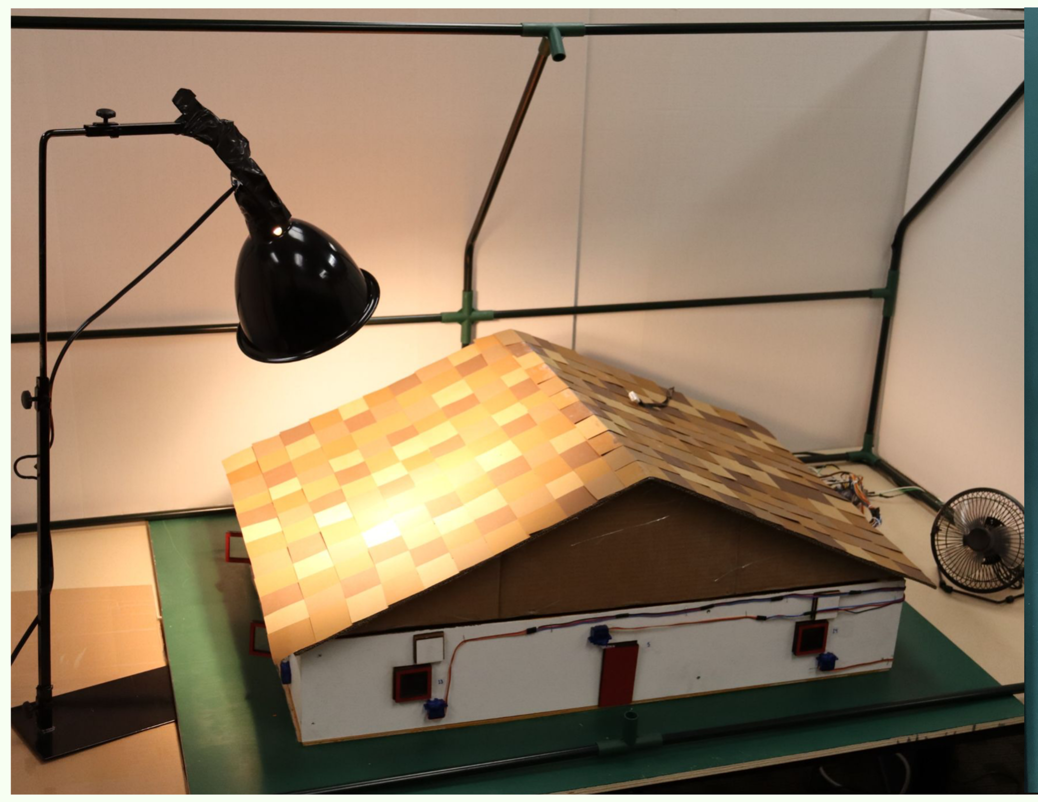

Figure 2. External view of the testbed.

Figure 3. Internal view.

Results

Temperature and humidity were predicted using three different algorithms: Long Short Term Memory (**LSTM**), k-nearest neighbors (**KNN**), and **Random Forest**. Each algorithm ran with two different versions of the data: one with and one without time as an additional input variable. Total of the 20 simulations split into two groups: 15 for training and 5 for testing.

Algorithm Performance Evaluation

	LSTM		KNN		Random Forest	
	w/o Time	With Time	w/o Time	With Time	w/o Time	With Time
RMSE↓	**0.60**	0.64	0.99	1.01	0.75	0.75
MAE↓	**0.42**	0.44	0.69	0.73	0.54	0.54
R2 Score↑	**0.90**	0.89	0.72	0.69	0.84	0.84

Figure 4. Accuracy comparison of the three algorithms trained.

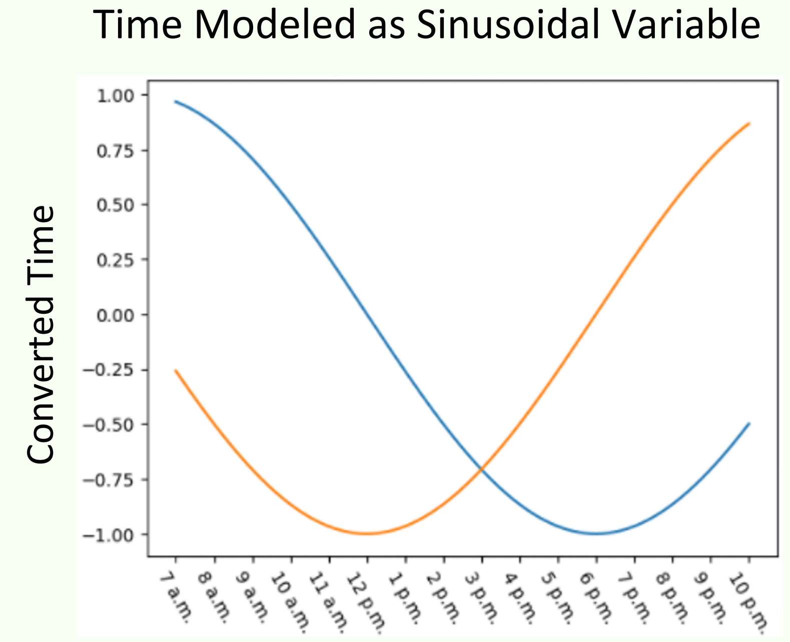

Figure 5. Cyclic representation of time used as an input variable.

- The cyclic pattern of a day can be represented by sine and cosine functions.
- LSTM and KNN performed comparably, and RF performed the same when time was not given as input.
- This shows machine learning algorithms can capture time relation from the given previous sequences.

Results (Cont.)

Figure 6 shows the Prediction vs Actual plots of best performing algorithms. Grid search on parameters was applied to find the best parameters for each algorithm.

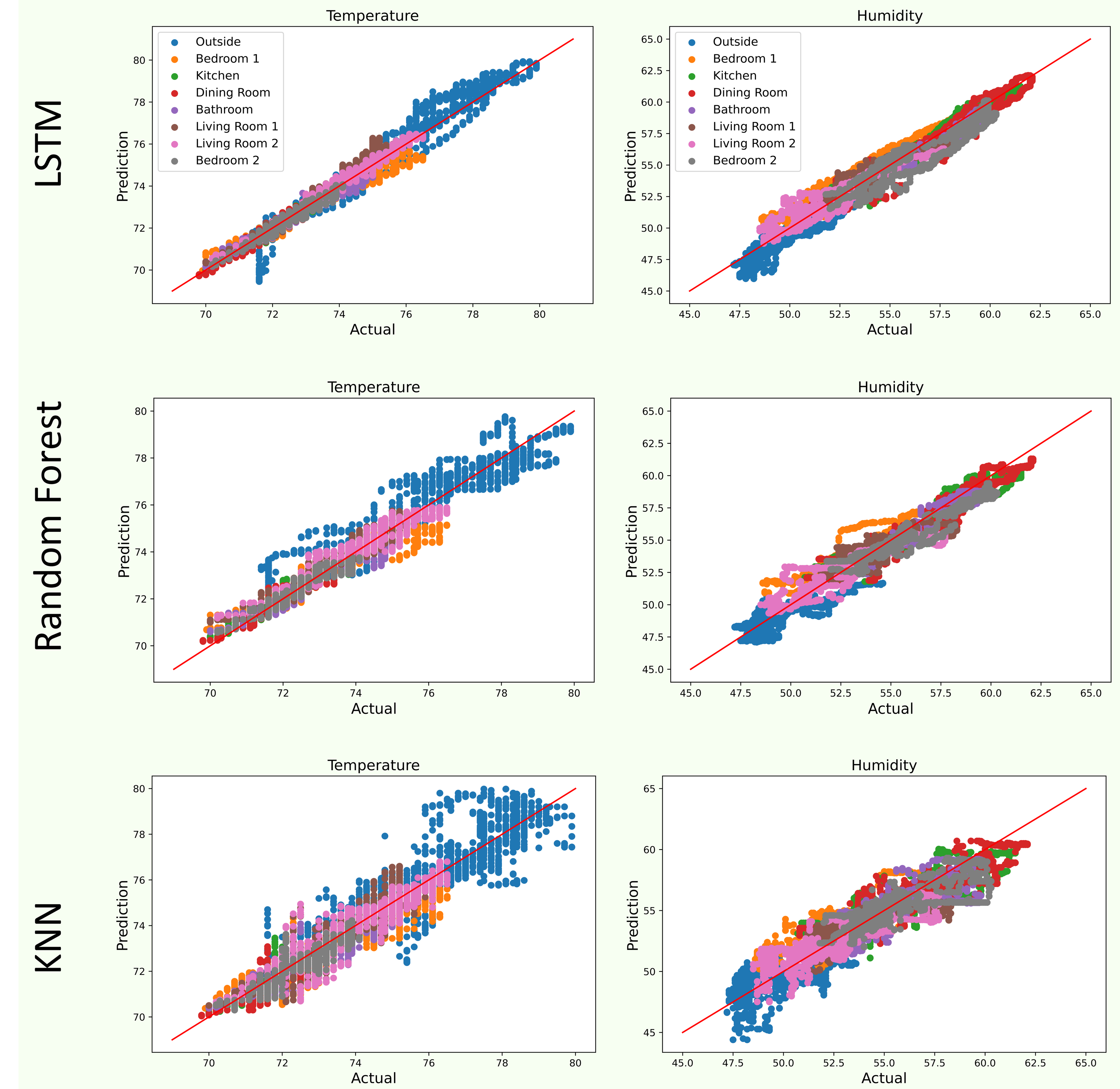

Figure 6. Performance evaluation of ML algorithms.

Conclusion and Future Work

- LSTM, KNN, and Random Forest all performed well on both datasets.
- Excluding time as a variable only slightly improved the performance of LSTM and KNN while leaving Random Forest unchanged.
- Overall, LSTM had the most accurate predictions.
- Proposed future work includes:
  - Collecting more data focused on humidity
  - Mapping collected data back to real world measurements
  - Developing an intelligent agent that is able to change internal temperature and humidity by altering the state of the home

Acknowledgements

The support for this work was provided by the National Science Foundation REU program under Award No. 1852002. Any opinions, findings, and conclusions and recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

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