Indoor Occupancy Prediction using an IoT Platform

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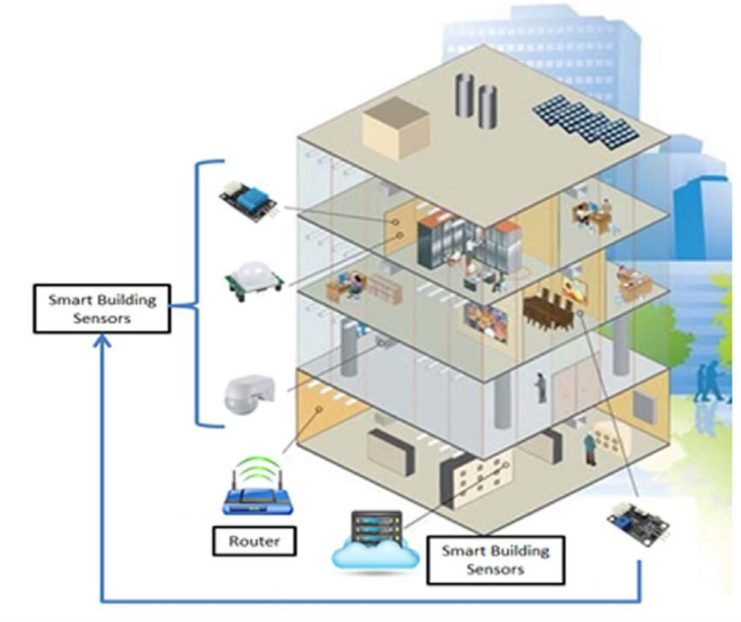
Motivation

- Building Information Management (BIM):
  - 65% of Canada energy in operation.
  - Contribute to 17% of greenhouse gas emission.
- IoT platforms:
  - Open source platforms versus commercial platforms.
  - Current platforms collect times series data OR event-triggered data.
  - Create an interoperable and non-intrusive sensing environment.
- Occupancy Detection Models:
  - Current models are focused on using simulated data and mathematical models.
  - Need for data-driven models.

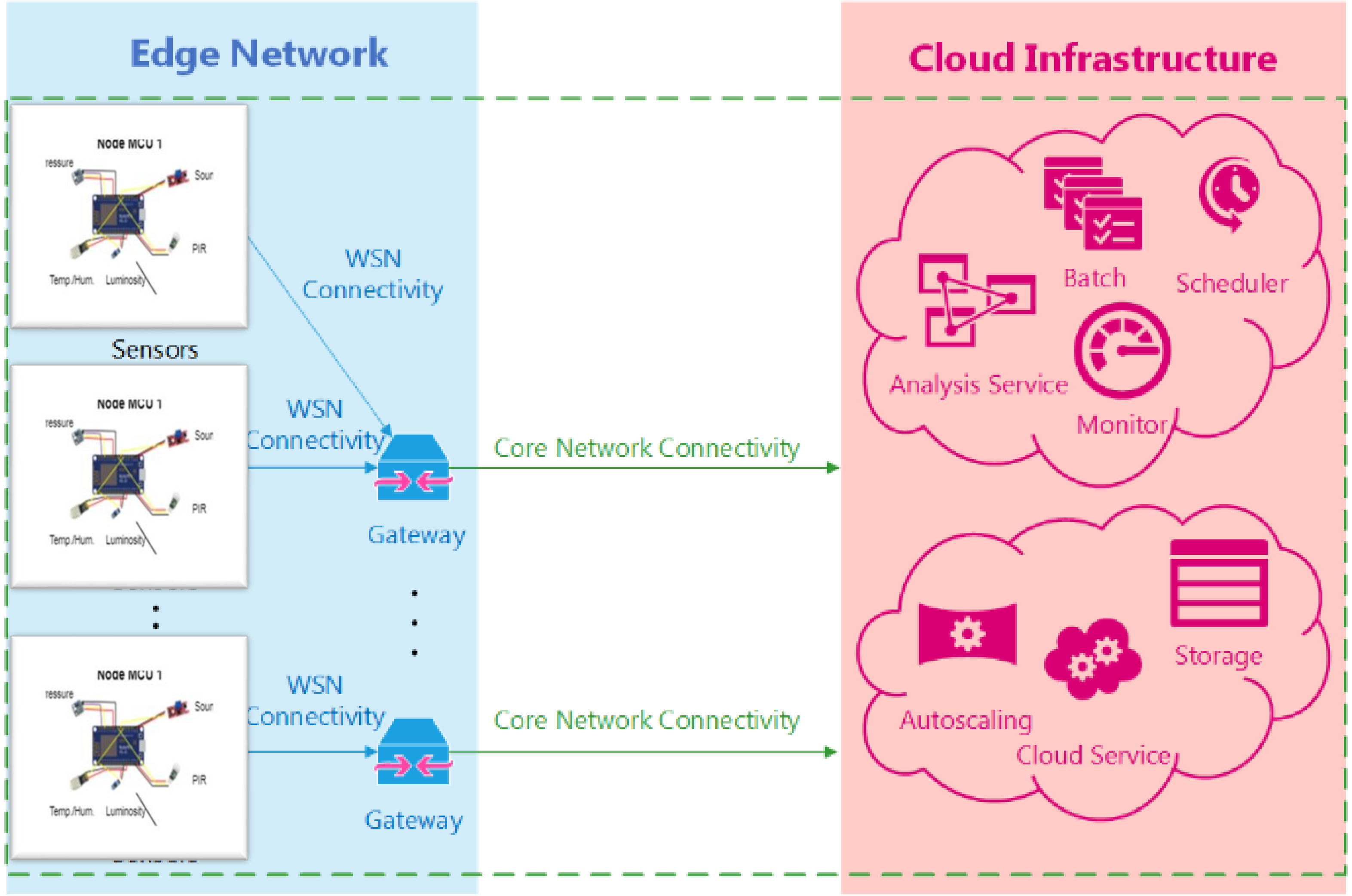


Plageras (2017)

Research Objectives

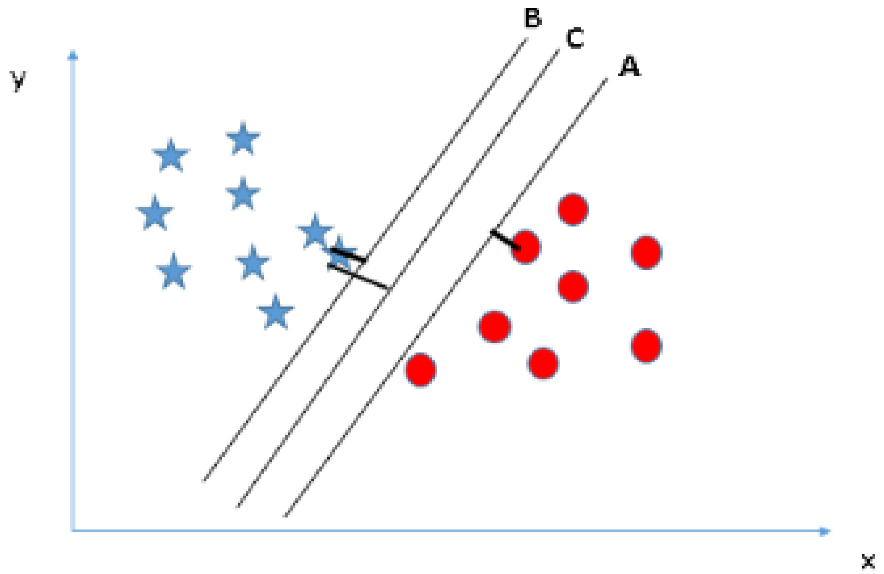
- Develop an open source IoT platform that can efficiently collect time series and event based raw data.
- Implement non-intrusive sensing units.
- Apply SVM to predict occupancy.
- Evaluate our SVM model using a real-world data driven experiment.

Proposed IoT Platform

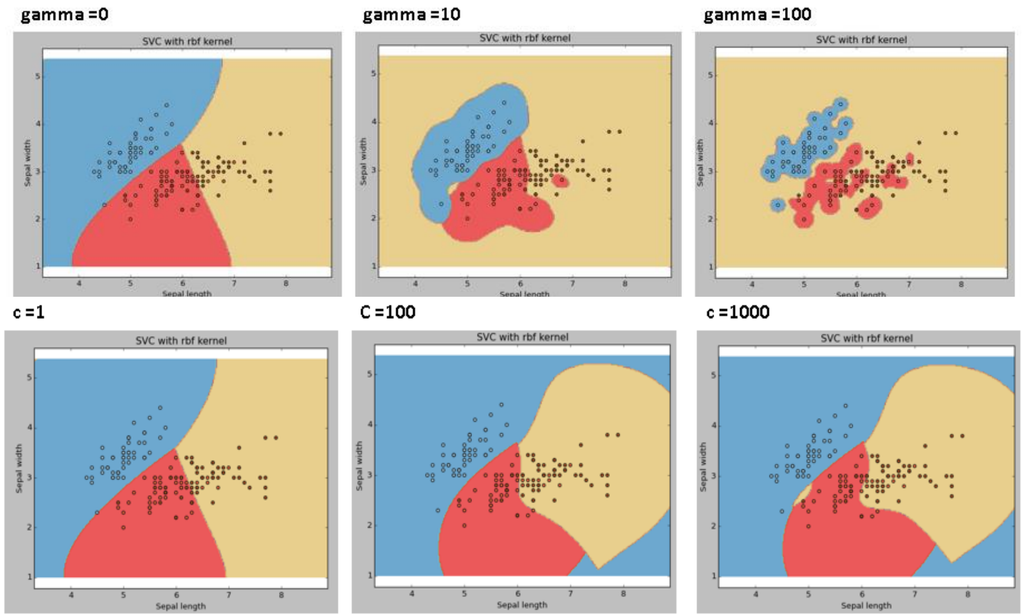


Proposed Occupancy Prediction Model using of SVM

- Separates objects by maximizing the margins.
  - Classifies objects by distance from hyper-plane .
- The parameters Kernel, Gamma and C.



Source: https://www.analyticsvidhya.com/blog/2017/09/understaing-support-vector-machine-example-code/



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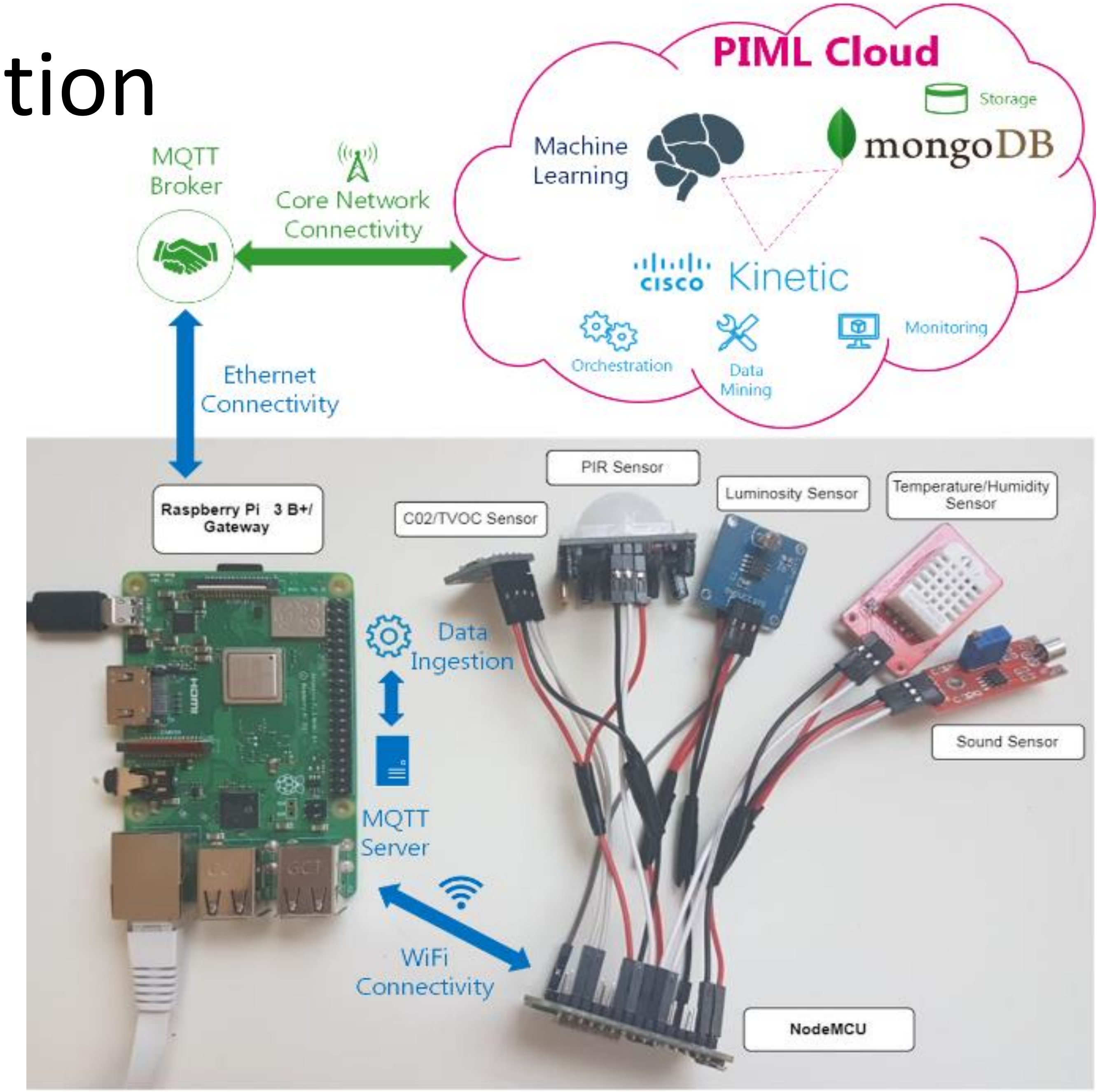
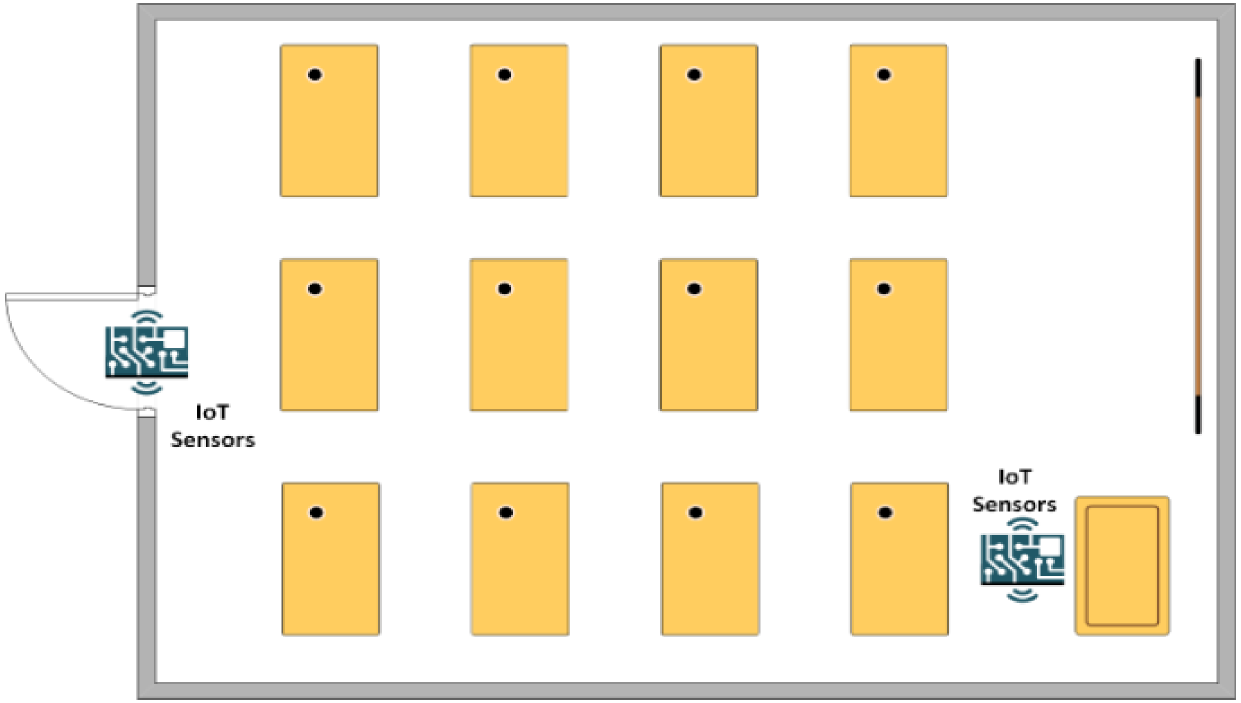
Implementation



Experiment

- Windowless classroom room with a projector, lecture podium and 12 desks.
- Two NodeMCUs were deployed.
- Collected entry/exit events and prologue occupancy.
- Collected time series data from all sensors.
- The duration of the experiment was 13 days.



Pre-processing and Analytical Tasks

- Summarization tasks:
  - Averages of Observations.
  - Standard deviations.
  - Max. and Minimum values.
- Annotation tasks:
  - Convert all categorical data into numerical data.
  - Occupancy status labels were created based on event-triggered data.
- Training tasks:
  - Applied a Grid search to optimize parameters.
  - 80% of the data was used to train the SVM model.

Results

- Overall accuracy of the SVM prediction was 96%.
- Key parameters: Precision, Recall and F-1 score.
- Misclassified values are reflected by False Negatives and False positives.

	Precision	Recall	F1 Score	Support
Free	0.99	0.97	0.98	40353
Occupied	0.87	0.95	0.91	9186
Micro Average	0.96	0.96	0.96	49539
Macro Average	0.93	0.96	0.94	49539
Weighted Average	0.97	0.96	0.96	49539

CONFUSION MATRIX RESULTS.

	Free	Occupied
Free	TP = 39002	FN = 1351
Occupied	FP = 474	TN = 8712

Conclusions

- Deployed an open source IoT platform capable of integrating non-intrusive sensing and a SVM model for predicting indoor occupancy in buildings.
- Indoor IoT platforms are key for collecting non-intrusive sensing data to understand occupancy patterns toward reducing energy emissions.

Conclusions

- The results presented achieved 96% prediction accuracy.
- Retained the privacy of all occupants.
- This experiment provided useful insights for:
  - Threshold tuning of sensors.
  - Parameter adjustments to optimize the SVM algorithm.

Future Research

- Improve the threshold adjustments according to different rooms: C02 and TVOC.
- Determine the best location for sensors when scaling up.
- Develop an automated method for labeling the occupancy status for training the SVM model.
- Introduce the time dimension to our SVM model occupancy.

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