Ubiquitous and Mobile Computing
CS 528: *Group 1 Presentation*

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FluSense: Harnessing Syndromic Signals of Influenza-Like Illness from Hospital Waiting Room Crowd with Contactless Sensing System

Introduction

- **Severity of Influenza and Other Cold Diseases**
  - Discusses the serious nature and public health impact of influenza and cold diseases.
- **Limitations of Current Flu Monitoring Methods**
  - Highlights over-reliance on clinical report data, leading to delayed outbreak responses.
- **Proposing Non-Contact Monitoring Techniques**
  - Suggests using non-contact techniques for more timely and accurate disease monitoring.

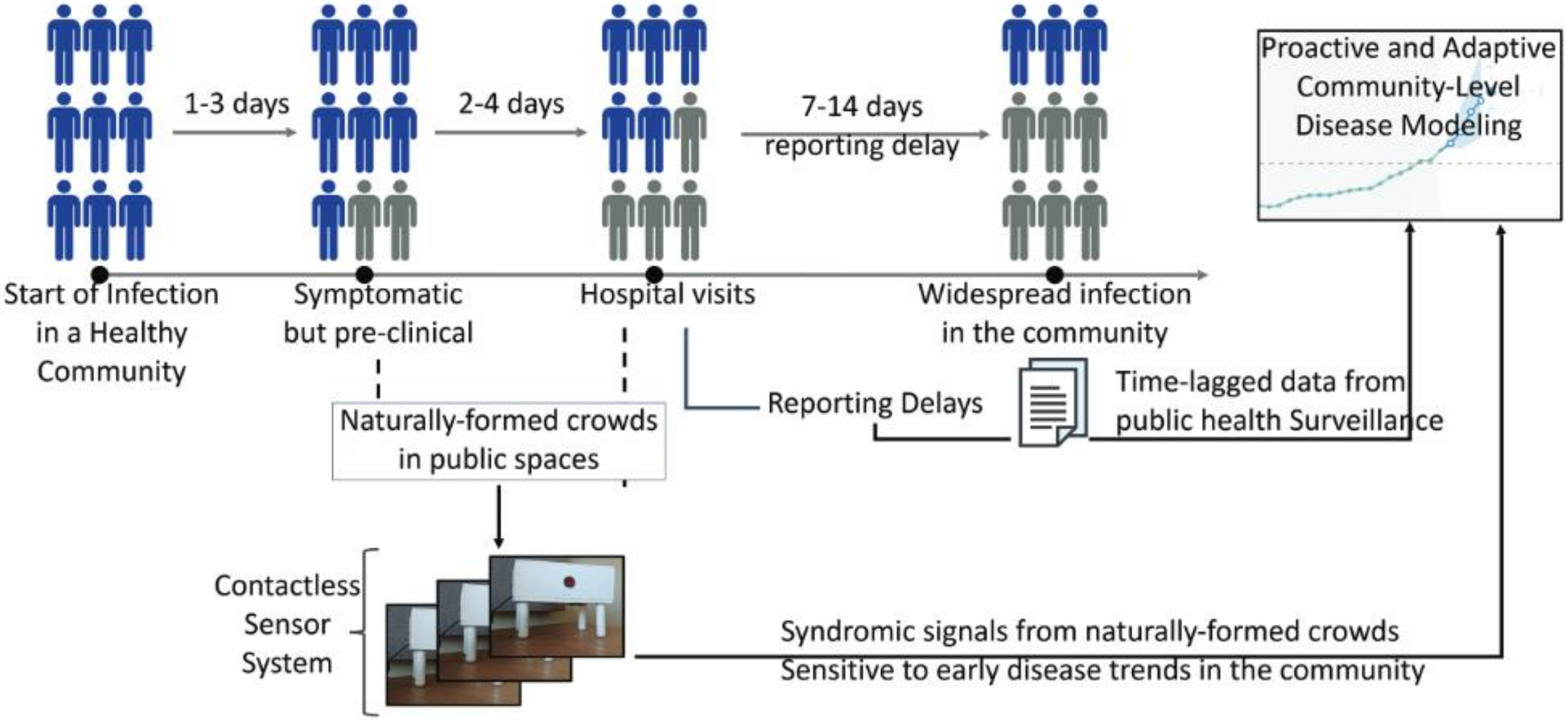
Related Work

- **Prior work mostly looked at other ways - tech and social media**
- **FluBreaks: Early Epidemic Detection from Google Flu Trends (2012)**
  - **https://www.jmir.org/2012/5/e125**
  - Done at the Regional Level
  - Does not track low internet use populations

- **Twitter Catches The Flu: Detecting Influenza Epidemics using Twitter (2011)**
  - https://aclanthology.org/D11-1145.pdf
- **Flu Detector - Tracking Epidemics on Twitter (2010)**
  - https://link.springer.com/chapter/10.1007/978-3-642-15939-8_42

State of the Art Medical

- **Strengths and Limitations**
- **Combining Multiple Data Sources**



Flusense: a contactless sensing platform

- device with sensors
  - Microphone Array - coughing
  - Thermal Camera - sensing people
- All data collected will be processed in real-time for the privacy

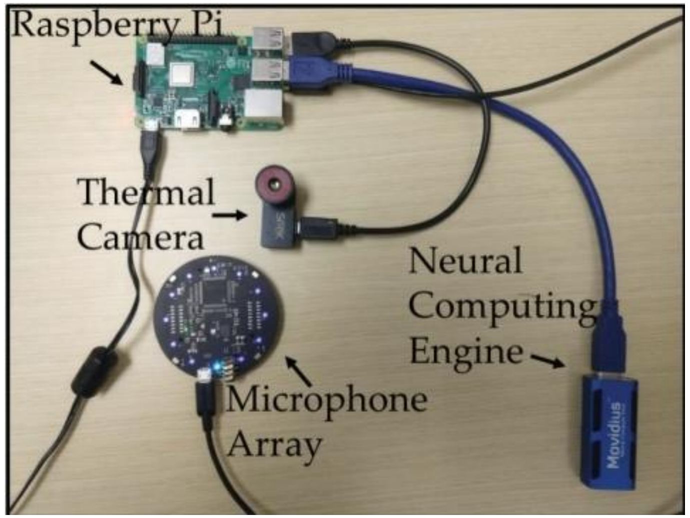
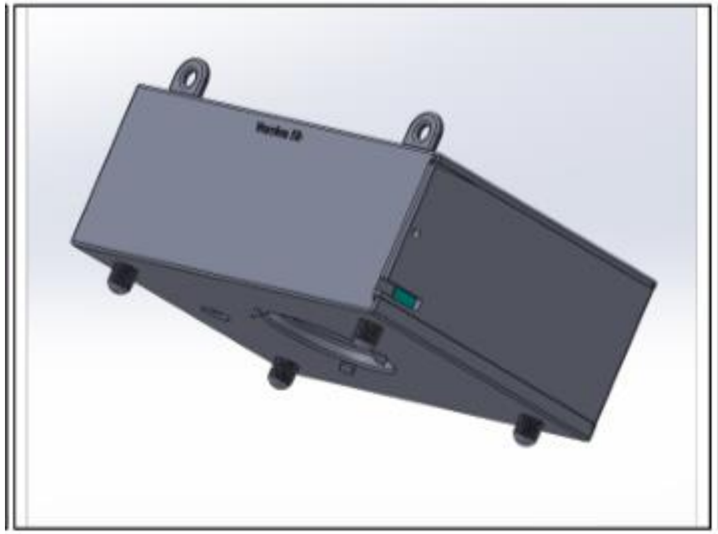


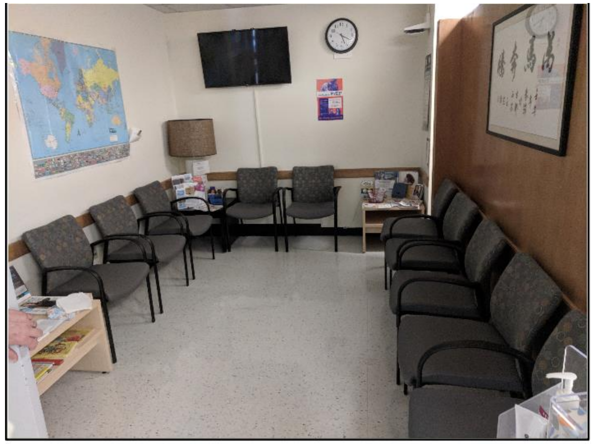
Illustration of electronic components

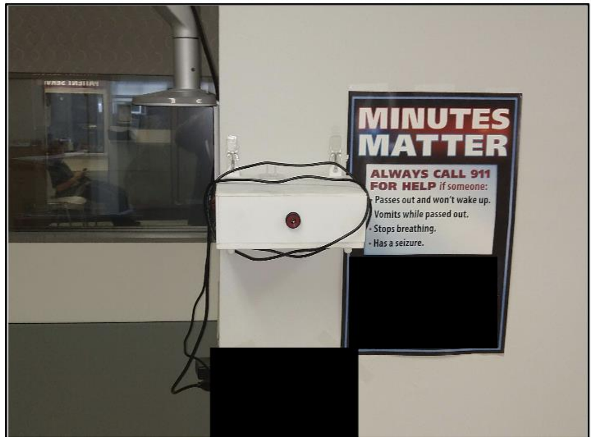

the 3D mechanical design of the sensor box/enclosure


the deployed Flu Sense platform

Data Collection in a Clinical Setting

- From December 2018 to July 2019 (**Seven Months**).
- **Four** public waiting areas within the university health service
- **Data Type (for Evaluation)**
  - The daily patient count (Extract ground-truth patient count data from clinic records)
  - The total number of flu tests ordered per day (influenza-like-illness cases)
  - The total count of positive flu test cases per day (diagnosed influenza cases)





Cough Recognition Algorithms for Public Spaces

- Data Source:
  - Google Audioset, ESTI, DEMAND, and TIMIT

Audio Annotations:

- The Google Audioset, consisting of partially annotated YouTube clips, was manually annotated for 45,550 seconds by two human raters, tagging speech, cough, sneeze, sniffle, gasp, silence, and background noise.
- Other datasets come with some form of annotation

Augmentation Techniques

- **Volume Augmentation**: Varying the volume of audio data to simulate different distances.
- **Background Noise Augmentation**: Adding various background noises to create a robust dataset for different environmental conditions.
- **Room Impulse Response Augmentation**: Utilizing the Aachen room impulse response dataset to ensure effectiveness in diverse acoustic environments.
- **Combined Augmentation**: Applying combinations of the above methods to ensure realistic technical challenges in the dataset.

Modeling

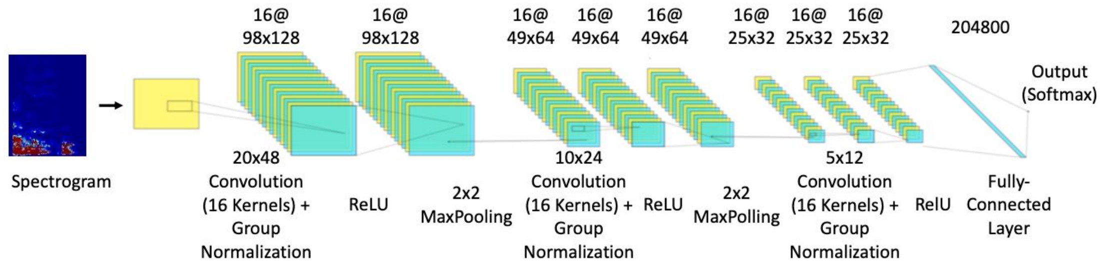
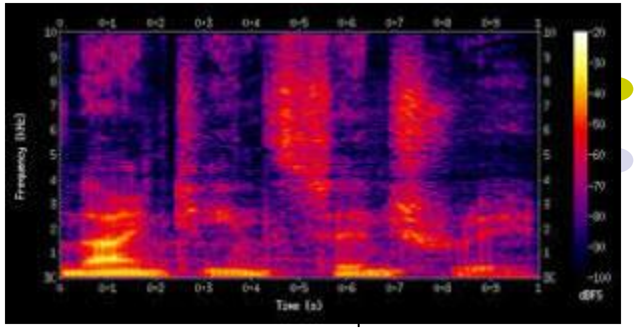


Fig. 4. illustrates the architecture of the CNN-based cough recognition algorithm.



Data Partitioning: Audio data were split into 80% for training, 10% for validation, and 10% for testing.

Model Building: A CNN-based architecture, optimized for resource-constrained settings, was used. The cough and speech recognition models were developed using spectrograms converted from one-second audio snippets.

Performance in Different Conditions: The models were tested under various conditions like no background noise, with speech, and with hospital noise. The best-performing model achieved an F1 score of 87.0% under all augmentations.

Adaptation and Validation with Real-World Data

- **Evaluating Cough Model**: 2,500 audio snippets from FluSense platforms were sampled and manually labeled to validate the cough model. This validation led to improvements in the model's precision, recall, and F1 score.
- **Variability in Different Settings**: The model's performance was assessed across different waiting areas and conditions, showing reasonable accuracy and adaptability to different acoustic environments.

Detecting People

- Data Collection
  - Thermal Images: A total of 359,789 thermal images were collected from FluSense units.
- Crowd Estimation Modeling
  - Model Frameworks: Two different model frameworks were considered - Single Shot Detector and Faster-RCNN.
  - Transfer Learning: The models, initially pre-trained on the COCO dataset, underwent transfer learning with the collected thermal images.

Performance Evaluation

- **Evaluation Metrics**: Metrics like mean Average Precision (mAP), Log Average Missing Rate (LAMR), and Root Mean Squared Error (RMSE) were used.
- **Model Efficiency**: The transfer-learned models, especially the Faster-RCNN, showed significant performance improvements compared to the baseline models.

Creating the FluSense Model

- Track performance vs actual reported cases
- Tracked various combinations of features
- Picked best features
  - TAC - total number of coughing seconds
  - CSR - Cough to speech Ratio
  - CBYT - Cough By People Time

		Leave-One-Day-Out-Cross-Validation			
		Total Test		Total Positive	
Model	Feature	ρ	RMSE	ρ	RMSE
Baseline	Baseline = [dayType, isHoliday]	0.42	5.02	0.19	2.28
Linear Regression	Baseline + top 3	0.53	4.58	0.33	2.07
Gradient Boosted Tree	Baseline + top 3	0.58	4.44	0.45	2.01
Random Forest	Baseline + top 3	0.65	4.28	0.61	1.68
Random Forest	Baseline + tac	0.59	4.34	0.40	2.00
Random Forest	Baseline + csr	0.58	4.39	0.38	2.03
Random Forest	Baseline + cbypt	0.56	4.44	0.36	2.05

Location Matters

- Model performed very well in scenarios with significant flu activity (pediatric and walk-in)

- No statistical relationship in locations with scheduled appointments (Checkup and Women's Clinic)

Waiting area	*IRR*	*p-value*	95% CI	
Walk-in 1	1.00024	<0.001	1.0014	1.0033
Walk-in 2	1.00297	<0.001	1.0016	1.0043
Checkup	1.014	0.055	0.99968	1.029
Pediatric	1.0193	0.003	1.0064	1.032
Womenś clinic	1.0071	0.354	0.9922	1.022

Discussion

- **Conclusion**
  - Provide a novel and useful method to inform seasonal influenza surveillance and forecasting
- **Limitations**
  - Limitation of the computation power/ memory/ power requirements
  - Without applying other thermal cameras with higher-resolution
  - Not optimize the locations for deployment of sensor boxes
  - Deployment scenario is only in the university hospital
- **Possible future work**
  - Consider optimizing deployment locations
  - Implement across various space-time settings with protecting public privacy

References

- **Article**:
  Forsad Al Hossain, Andrew A. Lover, George A. Corey, Nicholas G. Reich, and Tauhidur Rahman. 2021. FluSense: Harnessing Syndromic Signals of Influenza-Like Illness from Hospital Waiting Room Crowd with Contactless Sensing System. GetMobile: Mobile Comp. and Comm. 25, 2 (June 2021), 27–32. https://doi.org/10.1145/3486880.3486889
- **Paper**:
  Forsad Al Hossain, Andrew A. Lover, George A. Corey, Nicholas G. Reich, and Tauhidur Rahman. 2020. FluSense: A Contactless Syndromic Surveillance Platform for Influenza-Like Illness in Hospital Waiting Areas. Proc. ACM Interact. Mob. Wearable Ubiquitous Technol. 4, 1, Article 1 (March 2020), 28 pages. https://doi.org/10.1145/3381014