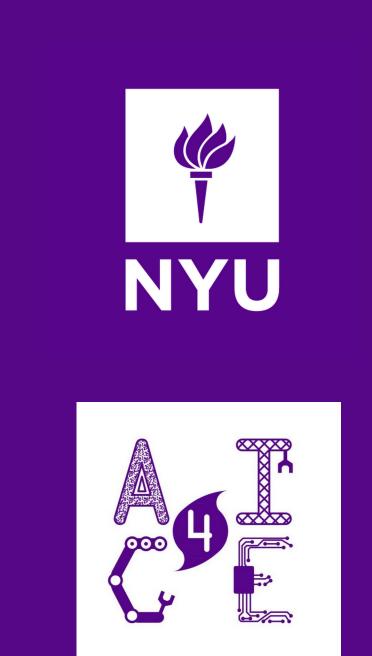
# **Abstract**

In collaboration with the New York State Office of Technology and Innovation (NYCOTI), we present a low-power, privacy-centric pedestrian monitoring solution, leveraging the ESP32S3 IoT board. This system deploys the YOLO v3 detection model and a SORT Tracking algorithm, transmitting data via LoRaWAN frequencies to AWS IoT for visualization on a dashboard. Our solution aids in effective urban planning and real-time decision-making and contributes to smart city initiatives and edge-based machine learning.

# Leveraging Low-Power Computer Vision for Pedestrian Counting in New York City



### Introduction

Existing pedestrian counters, such as MetroCount, Eco-Counter, and Trafsys, utilize outdated infra-red technology, protocols with high power consumption, or technologies that violate privacy through video recording. We propose a pedestrian counter that is low in power consumption, cost-effective, and accurate, capable of scaling with urban areas including cities, parks, and tourist destinations.

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# Methodology

Our system comprises four main components:

- 1. A small ESP32S3 IoT board, custom-fitted with a camera and a YOLOv3 detection model made by Seeed Studio.
- 2. SORT tracker algorithm, coupled with a people counter algorithm.
- 3. A LORaWAN setup, which includes a lora module (RFM95W), a gateway, and uses the services of The Things Network (TTN), a global collaborative Internet of Things ecosystem that creates networks, devices and solutions using LoRaWAN.
- 4. An AWS IoT Cloud setup (Amazon Web Services Internet of Things) to process data ingestion and create relevant visualizations for the stakeholders involved.

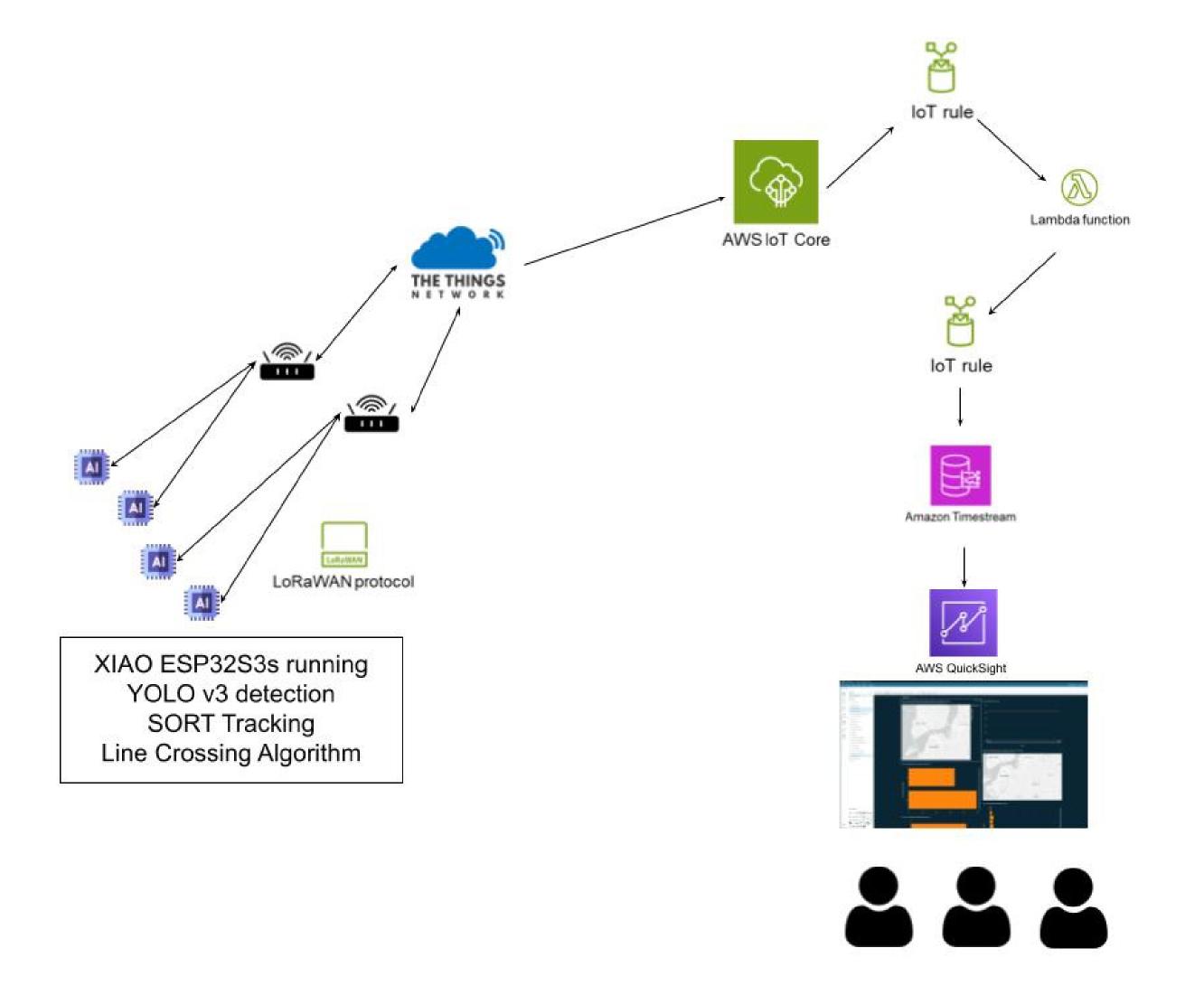
The people-counting algorithm can be further dissected into three primary components:

- 1. Camera frame capture paired with a pruned, quantized iteration of YOLOv3. This model has been specifically trained to detect only humans.
- 2. People counter logic, which integrates three lines with slopes 0,  $\infty$ , and 1, each passing through the center of a 240x240 frame.
- 3. The SORT Tracker, which is bifurcated into the Kalman filter and the Hungarian Algorithm. With the assumption of a linear velocity model, the Kalman filter predicts the position of detections in the current frame based on the previous frame's data. Subsequently, the Hungarian algorithm assigns IDs to these predictions based on the detections found in the current frame.

For tracking purposes, we maintain a record of an object's last position using a hashmap. When the center point of an object previously tracked shifts its position from behind one of the three lines to a position ahead of it, a count is registered. We then determine and transmit the highest count among all three lines using the LORaWAN protocol.

### Architecture

Pedestrian counts computed on the ESP32S3 are relayed to the lora module via physical GPIO connections. Once at the lora module, the data is transmitted using the LORaWAN protocol and captured by a gateway situated within a 1.3-mile radius. Afterward, this data is forwarded to TTN. Utilizing the MQTT protocol, TTN then sends the data to AWS IoT. Here, a pipeline is established to ingest data from all ESP32S3 deployments, aggregate it, and timestamp it with the assistance of services like AWS Lambda, IoT Rule, and Amazon TimeStream. Upon completion of ingestion, a comprehensive dashboard is crafted in AWS QuickSight, showcasing various charts to provide a thorough analysis for stakeholders.



# **Results and Analysis**

The primary focus of analysis of our research were on the low power constraint and the accuracy of our people counter.

To test the accuracy of the people counter, we investigated the performance of our hardware setup and algorithm in three types of urban outdoor settings where such a counter could be deployed: a park, a plaza, and a shaded walkway. We recorded counts from the set for 1.5 to 2 minutes and manually counted the pedestrians captured in the frame. Here are our results:



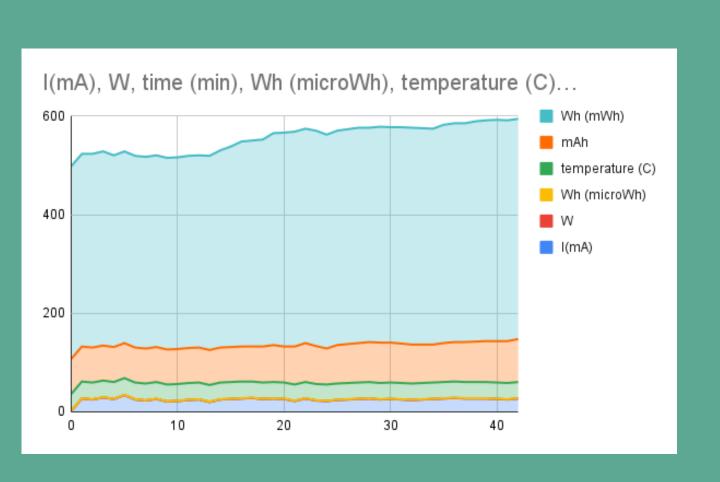
Average Accuracy = 48%

In our experiments, we observed that the frame rate of our camera was notably slow, leading to poor tracking. A pedestrian might be detected in one frame but would disappear in the subsequent one as they exited the camera's field of view.

We also made an observation about distance: pedestrians walking closer to the camera proved harder to track as they exited the frame rapidly, while those further away weren't detected at all. At approximately 7 feet, we found an optimal distance where every pedestrian was detected, tracked, and counted successfully.

This underscored for us the importance of the camera's positioning to achieve the correct field of view and ensure tracking accuracy.

To assess power consumption, we measured various electrical values for the board, including wattage, current, voltage, temperature, and timestamp. These measurements were taken while executing tasks like camera frame capture, YOLO detection, SORT tracking, line counting, and LOrA transmission. After recording values for an hour, our estimates suggest that a 10,000 mAh battery operating at 3.7V can power the board for roughly 86 hours. This duration aligns well with the operational requirements of our partner, NYC OTI/



# Conclusion

Our project emphasizes the implementation of a low-power, computer vision-based people counter as an alternative to counters reliant on high-power technology. We've achieved an average accuracy of 48% in urban spaces like parks, plazas, and walkways. Future improvements will center on integrating a higher frame-rate camera to enhance the accuracy of our counter, while still managing power consumption efficiently.

### Citations

- bit.ly/45eoZVp
  - bit.ly/3OnydYrbit.ly/3KrrD20

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