

**GROUP 5**

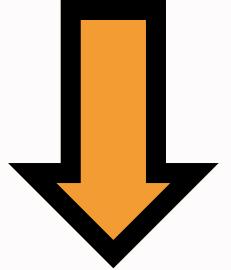
AI เพื่อการประเมินวัสดุและวิเคราะห์ปัญหา  
งาน Construction Call

# **CO-NA-LY-SIS** (construction + analysis)

**AI for object recognition and problem analysis  
in Construction Call**



**7-11 convenience stores serve 12.6 million  
daily customers**

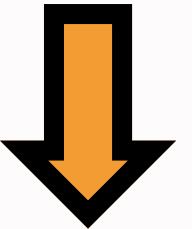


**increased of maintenance needs.**





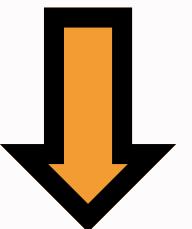
**Boonchuay (ບຸນຈູາຍ) application was  
created**



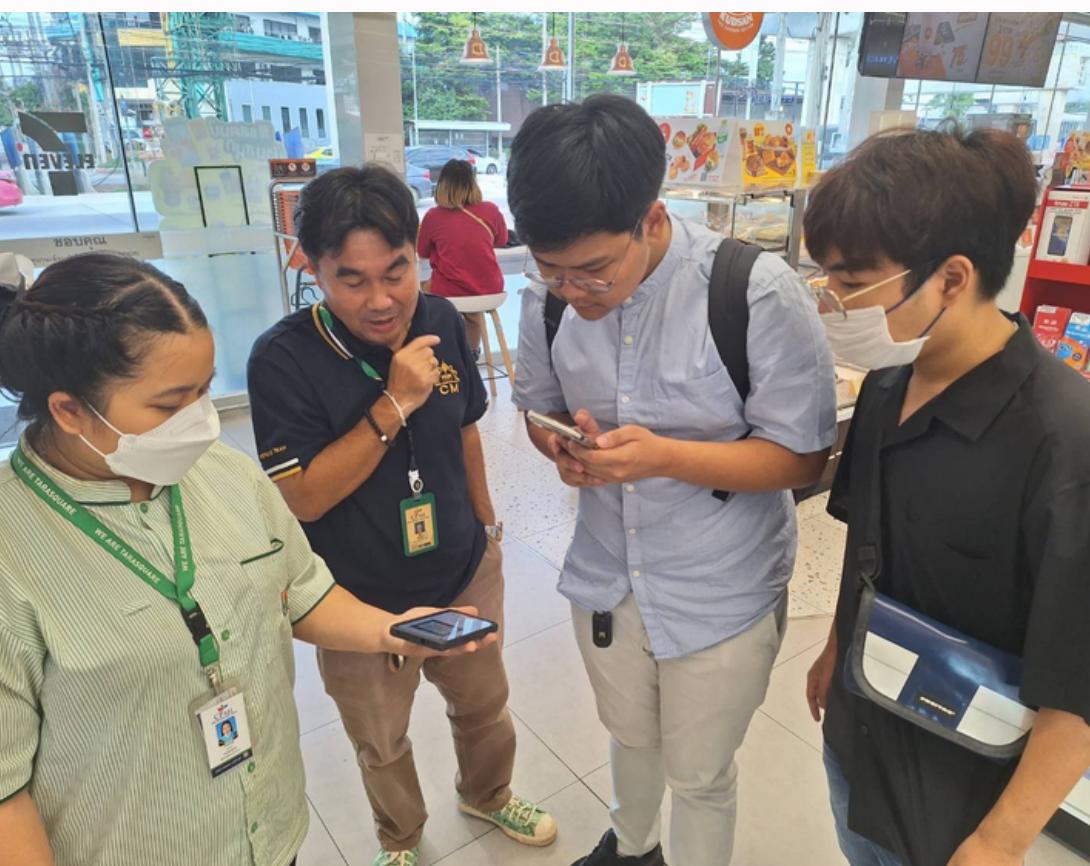
**for reporting damage**



**Menu/Button-Based Chatbot**



- **Conducting on-site surveys**
- **to see the actual product types**
- **and observing the actual use of the Boonchuay application by employees**

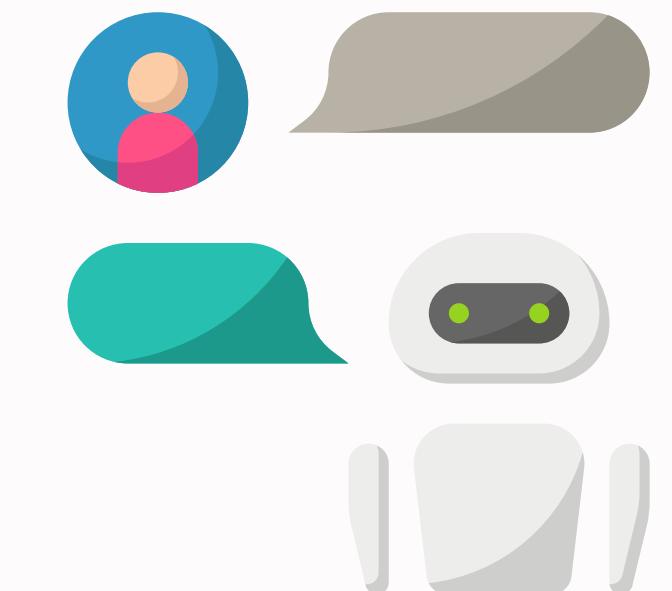




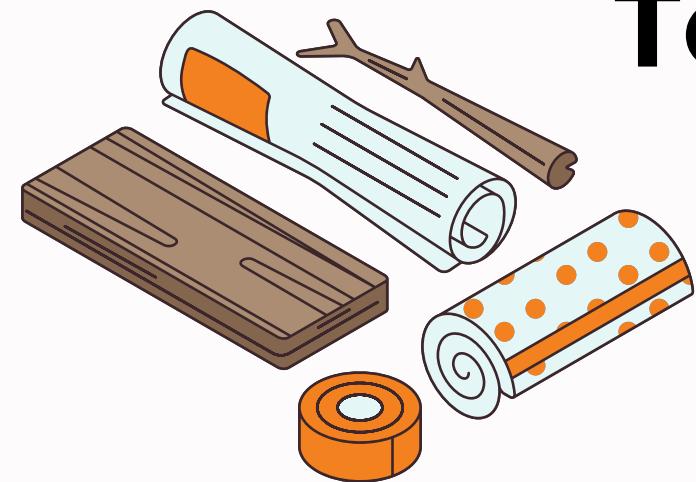
- **real footage of How 7-11's employees use 'บุญช่วย' application**
- **up to 94 product types which employees have to select**

=

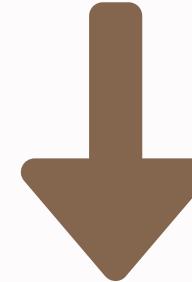
**confusion**



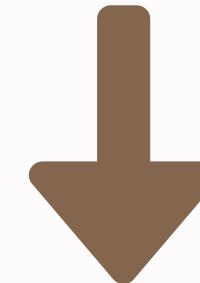
# PAIN POINT



Too many **categories of materials** and  
Too many **causes of damage**.



**confusion among the employees.**

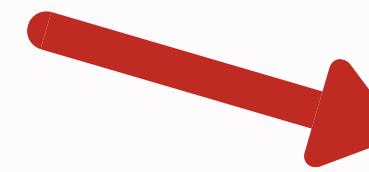


**Misreported types of materials**

**No Automate  
system**

**Increased expenses  
of the salary from  
25 employees**

**Increase travel cost  
almost 600,000 Baht  
every month**



**Approximately  
7,000,000  
Baht per year is lost  
due to human error**

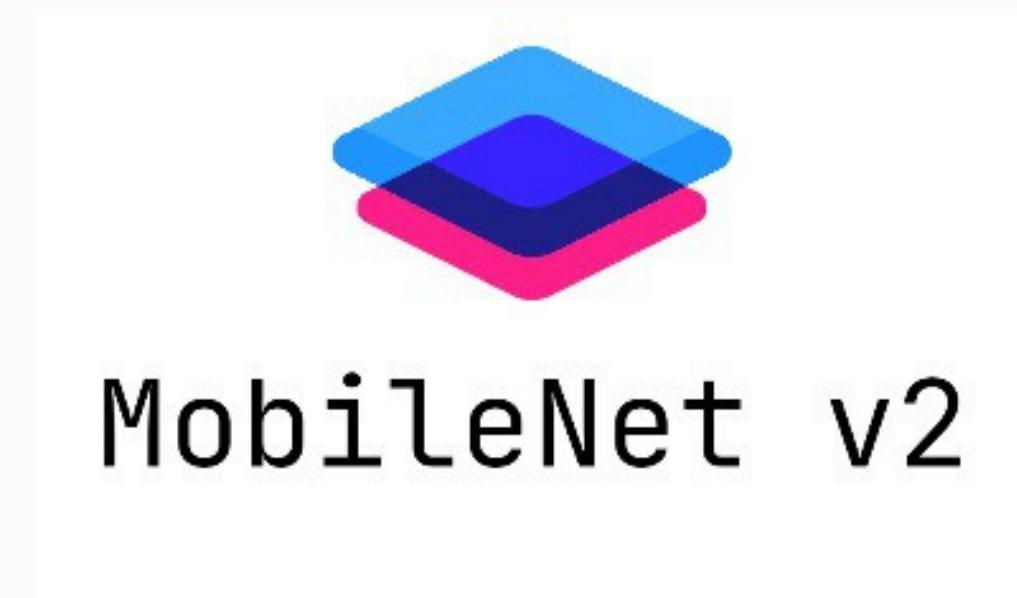


# No more misreporting product types

Because we are

# CO-NA-LY-SIS

with



# STARTING WITH DOOR AND FLOOR

# WHY WE CHOOSE DOOR AND FLOOR?

8308 misreported product types per year



723 incorrect calls from floor and door

11% from total

353 calls per year

370 calls per year

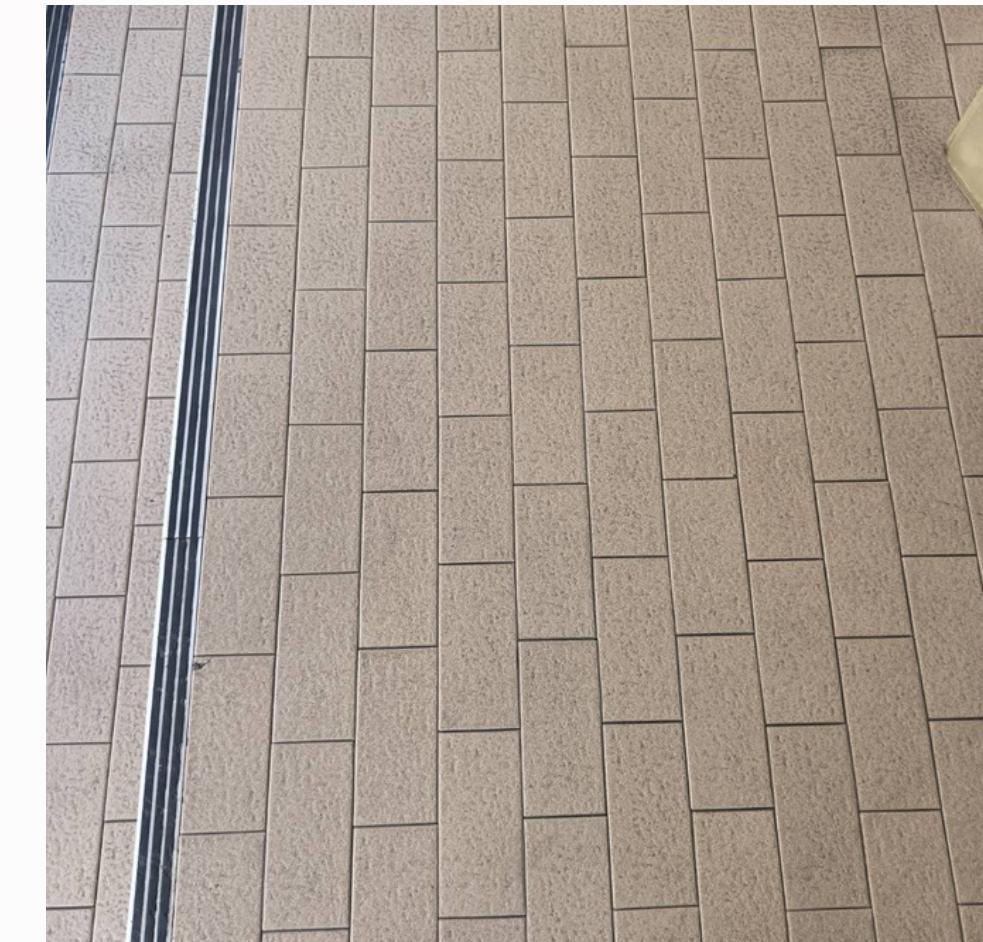
# PROJECT DETAIL-TYPE FLOOR



Back Area



Selling Area



Front Area

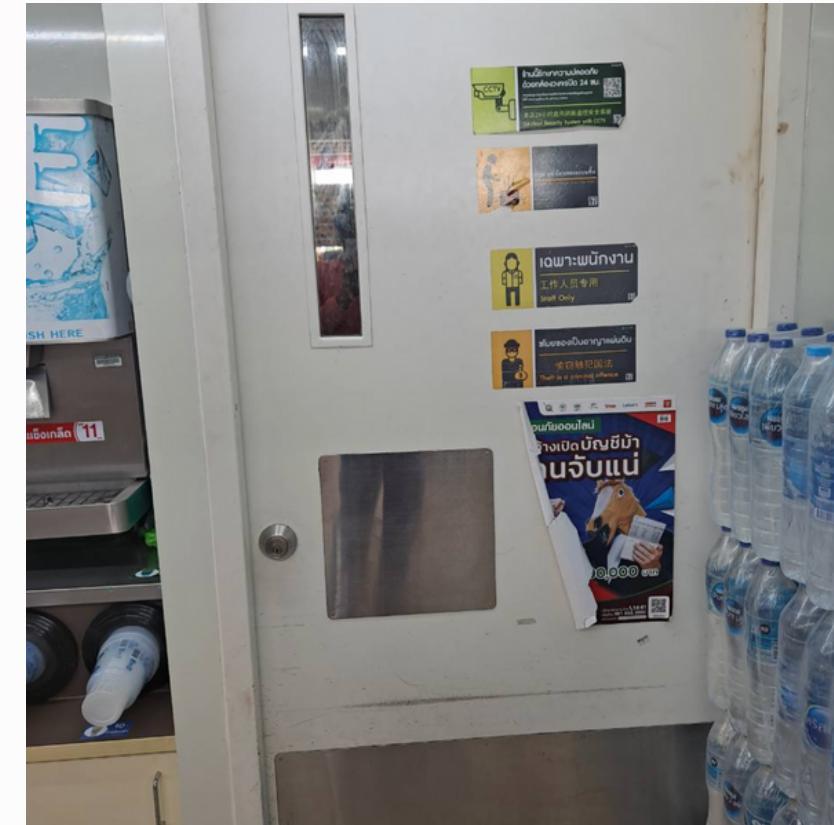
# PROJECT DETAILS- TYPES OF DOOR



Front Door



Emergency  
Door



Back Door



Toilet Door

# OBJECTIVES

01

Reduce the cost of incorrect calls for materials by implementing an AI model



02

Automate the "Construction calling" process for every 7-Eleven branch to further reduce the monthly maintenance costs.



03

Enhancing overall job efficiency by reducing downtime caused by human errors.



04

Increasing the monthly repair volume due to faster and more accurate work



# PROJECT DETAIL

Taking picture onsite or from gallery



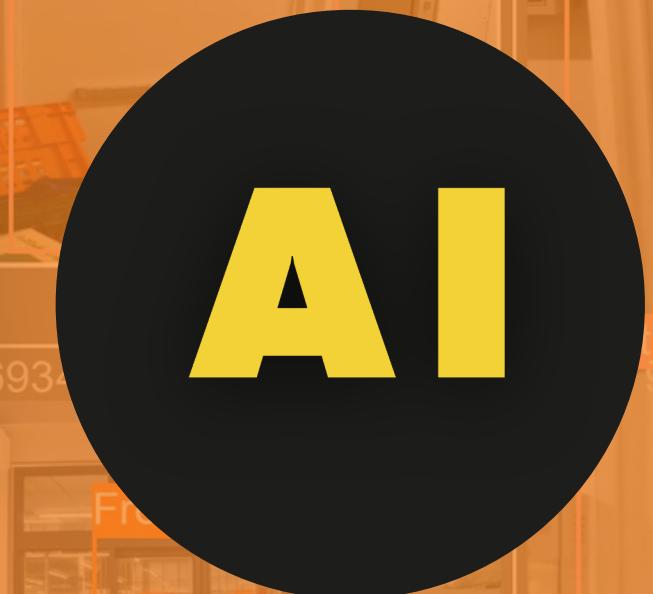
AI system predict cracks in tiles and broken doors



Collect data and send report result to user



# MAKING THE AI

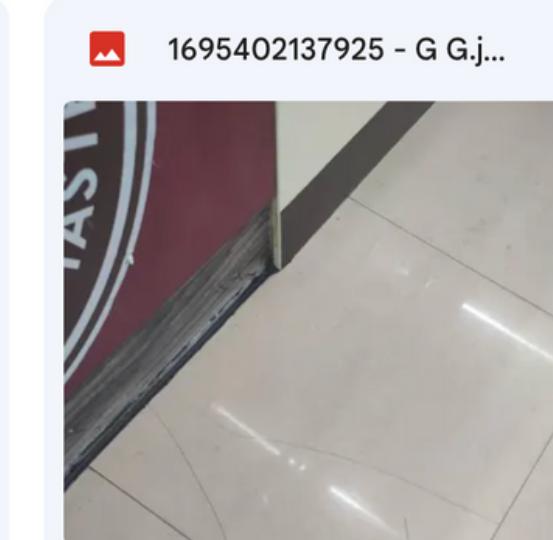
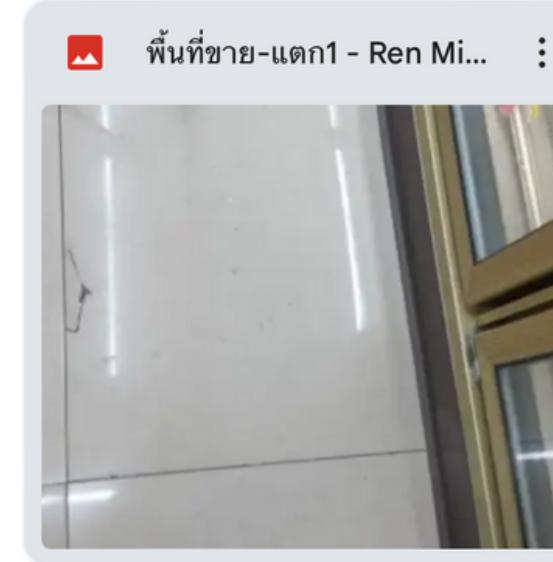


# DATA COLLECTING

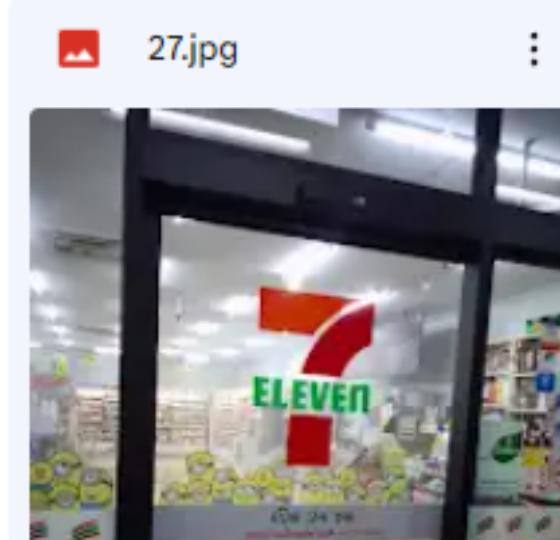
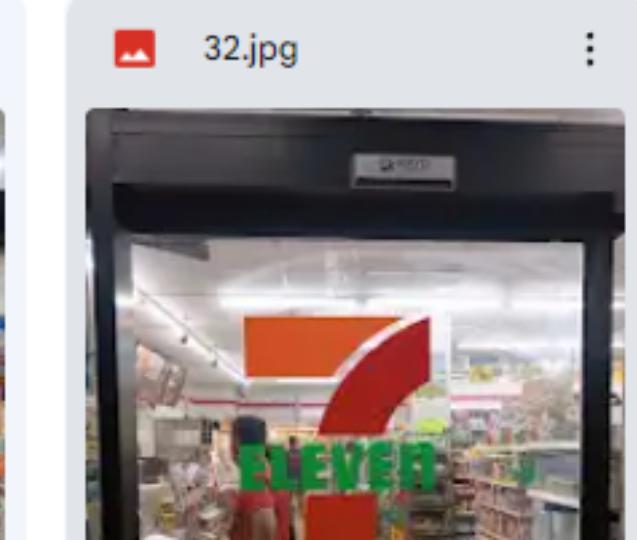
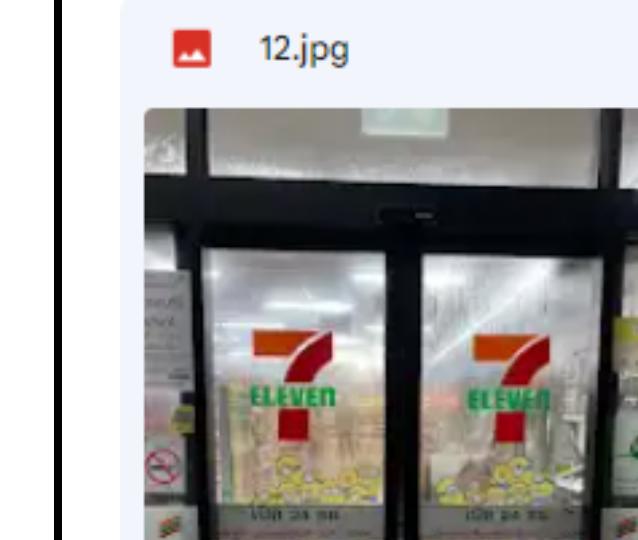
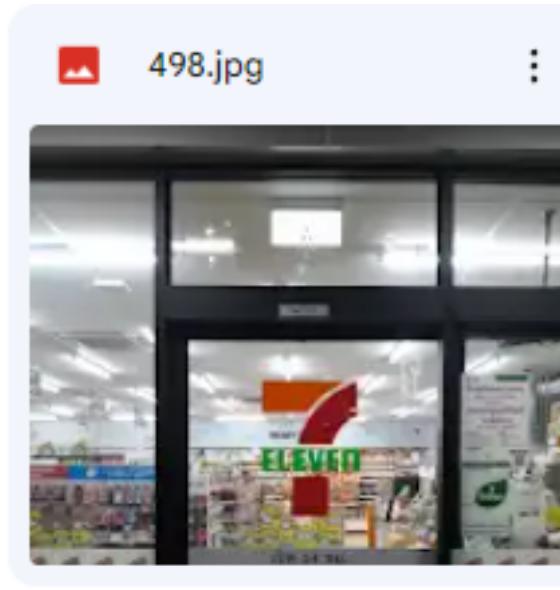
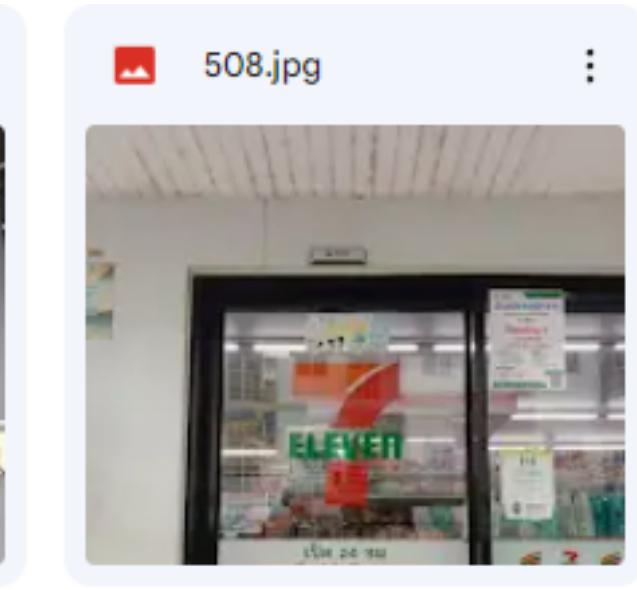
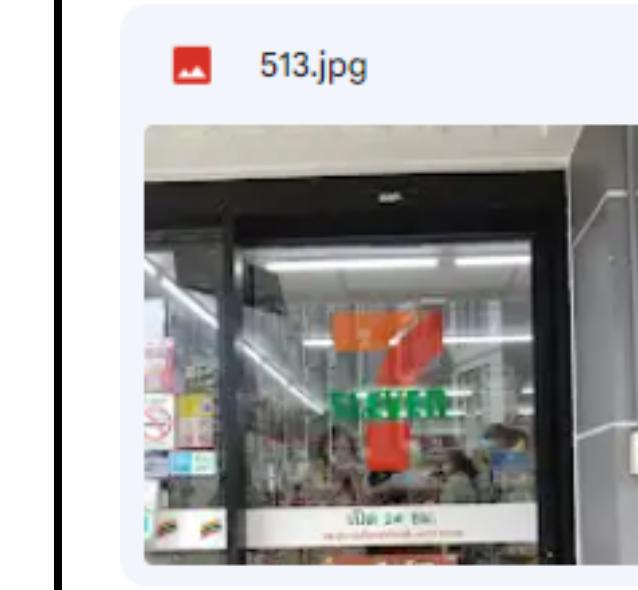


- Receiving data of door and tile from BU and upload to cloud.
- Since we have **2 different types of material**, we decided to split model in to **2 models**.

## Dataset 1 - FLOOR



## Dataset 2 - DOOR



# DATA COLLECTING

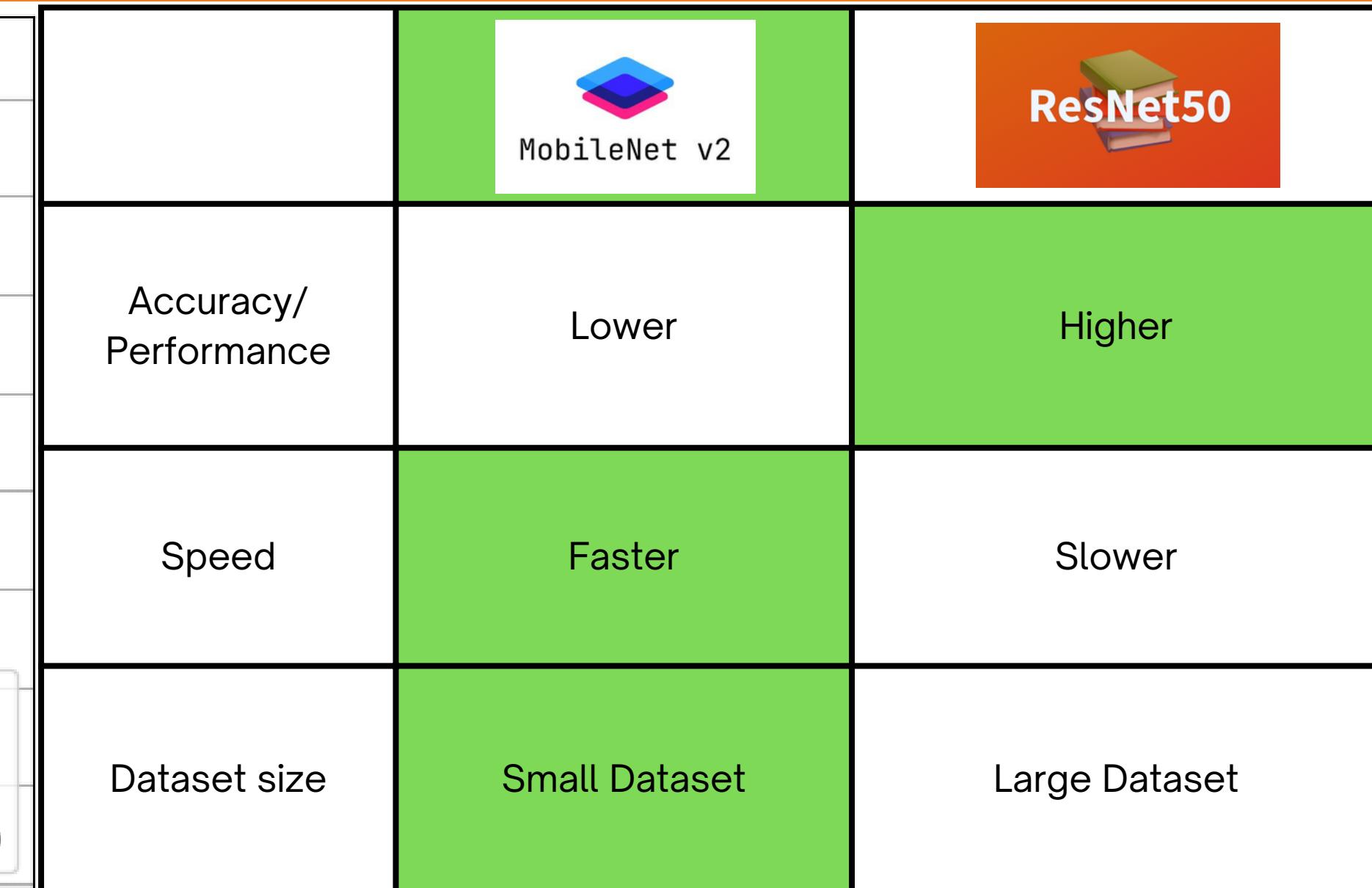
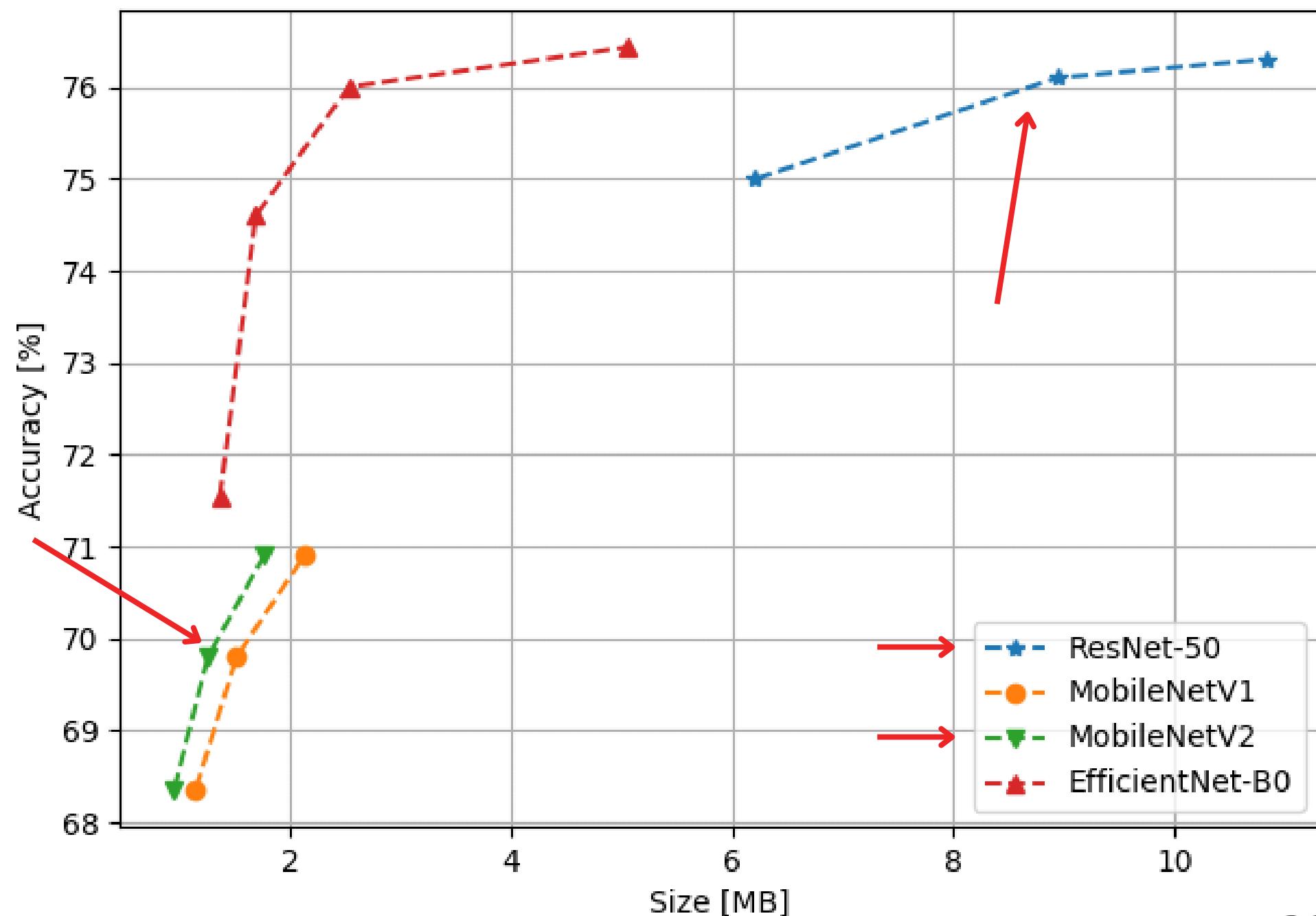
- Select **pictures** that Tile / Door is the **majority** in the pictures for training AI



Cleansing tile dataset

Cleansing door dataset

# CHOOSING MODEL - IMAGE CLASSIFICATION



| Network           | Top 1       | Params      | MAdds       | CPU         |
|-------------------|-------------|-------------|-------------|-------------|
| MobileNetV1       | 70.6        | 4.2M        | 575M        | 113ms       |
| ShuffleNet (1.5)  | 71.5        | <b>3.4M</b> | 292M        | -           |
| ShuffleNet (x2)   | 73.7        | 5.4M        | 524M        | -           |
| NasNet-A          | 74.0        | 5.3M        | 564M        | 183ms       |
| MobileNetV2       | <b>72.0</b> | <b>3.4M</b> | <b>300M</b> | <b>75ms</b> |
| MobileNetV2 (1.4) | 74.7        | 6.9M        | 585M        | 143ms       |

| Model        | No weight decay (%)  | Weight decay (%)            | Norm-bias (%)               |
|--------------|----------------------|-----------------------------|-----------------------------|
| ResNet       | 93.40 ( $\pm 0.04$ ) | 94.76 ( $\pm 0.03$ )        | <b>94.99</b> ( $\pm 0.05$ ) |
| DenseNet     | 90.78 ( $\pm 0.08$ ) | 92.26 ( $\pm 0.06$ )        | <b>92.46</b> ( $\pm 0.04$ ) |
| MobileNetV2  | 92.84 ( $\pm 0.05$ ) | <b>93.64</b> ( $\pm 0.05$ ) | <b>93.64</b> ( $\pm 0.03$ ) |
| ResNet Fixup | 10.00 ( $\pm 0.00$ ) | 91.42 ( $\pm 0.04$ )        | <b>91.55</b> ( $\pm 0.07$ ) |
| MLP          | 58.88 ( $\pm 0.10$ ) | 58.95 ( $\pm 0.07$ )        | <b>59.13</b> ( $\pm 0.09$ ) |

# CHOOSING MODEL - OBJ. DETECT

|   | YOLOv5<br>(Y <sub>s</sub> ) | Faster R-CNN<br>with MVGG16 | YOLOR-<br>P6    |
|---|-----------------------------|-----------------------------|-----------------|
| Training (batch size, epochs, learning rate)          | (16, 1200, 0.0032)          | (2, 100, 0.0001)            | (8, 1200, 0.01) |
| Training Loss   | 0.020                       | 0.136                       | 0.0170          |
| mAP@0.5-0.95  | 58.9%                       | 45.4%                       | 43.2%           |
| Inference speed:<br>Image resolution<br>(1774 × 2365) | 0.009 s                     | 0.047 s                     | 0.03 s          |
| Inference speed:<br>Image resolution<br>(204 × 170)   | 0.009 s                     | 0.052 s                     | 0.03 s          |
| Model Size (MB)                                       | 14.8                        | 134.5                       | 291.8           |

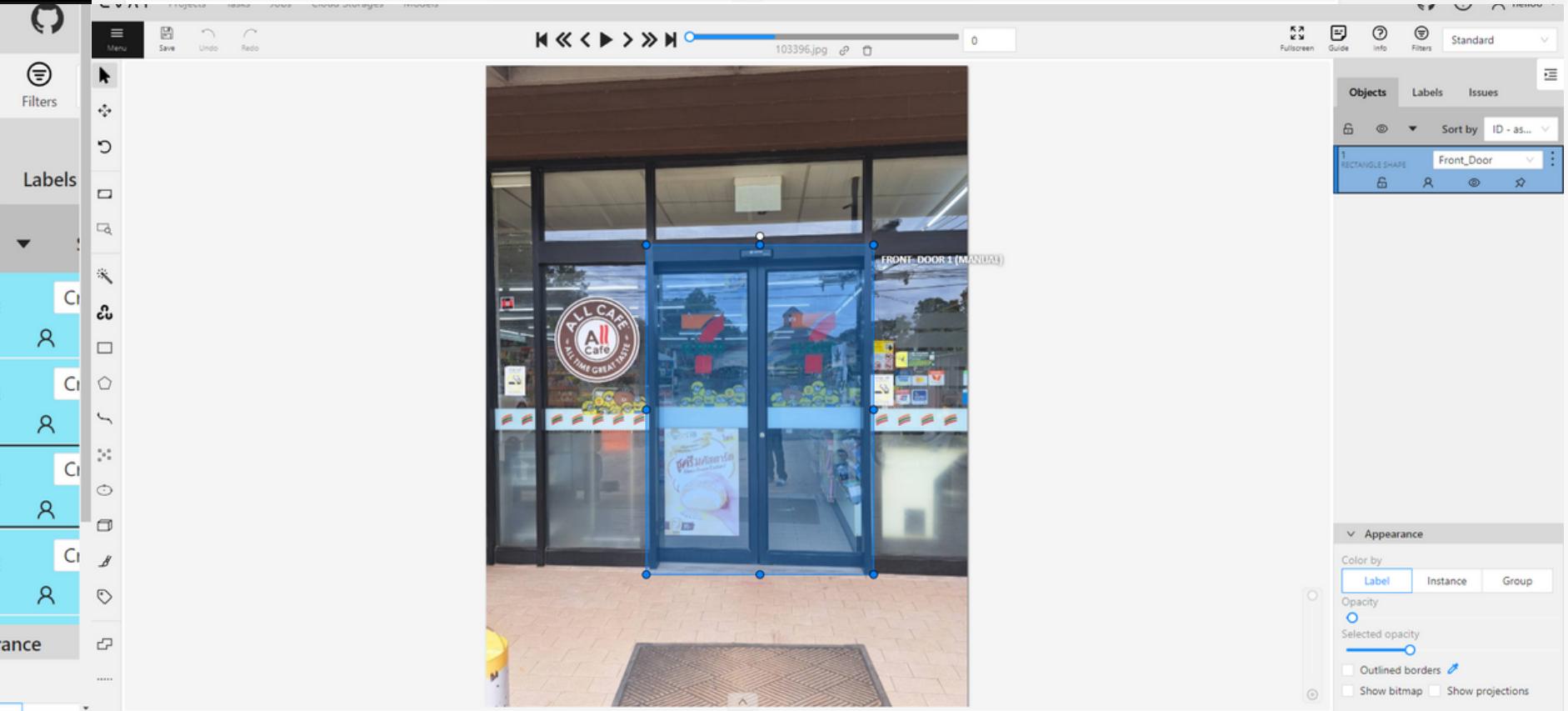
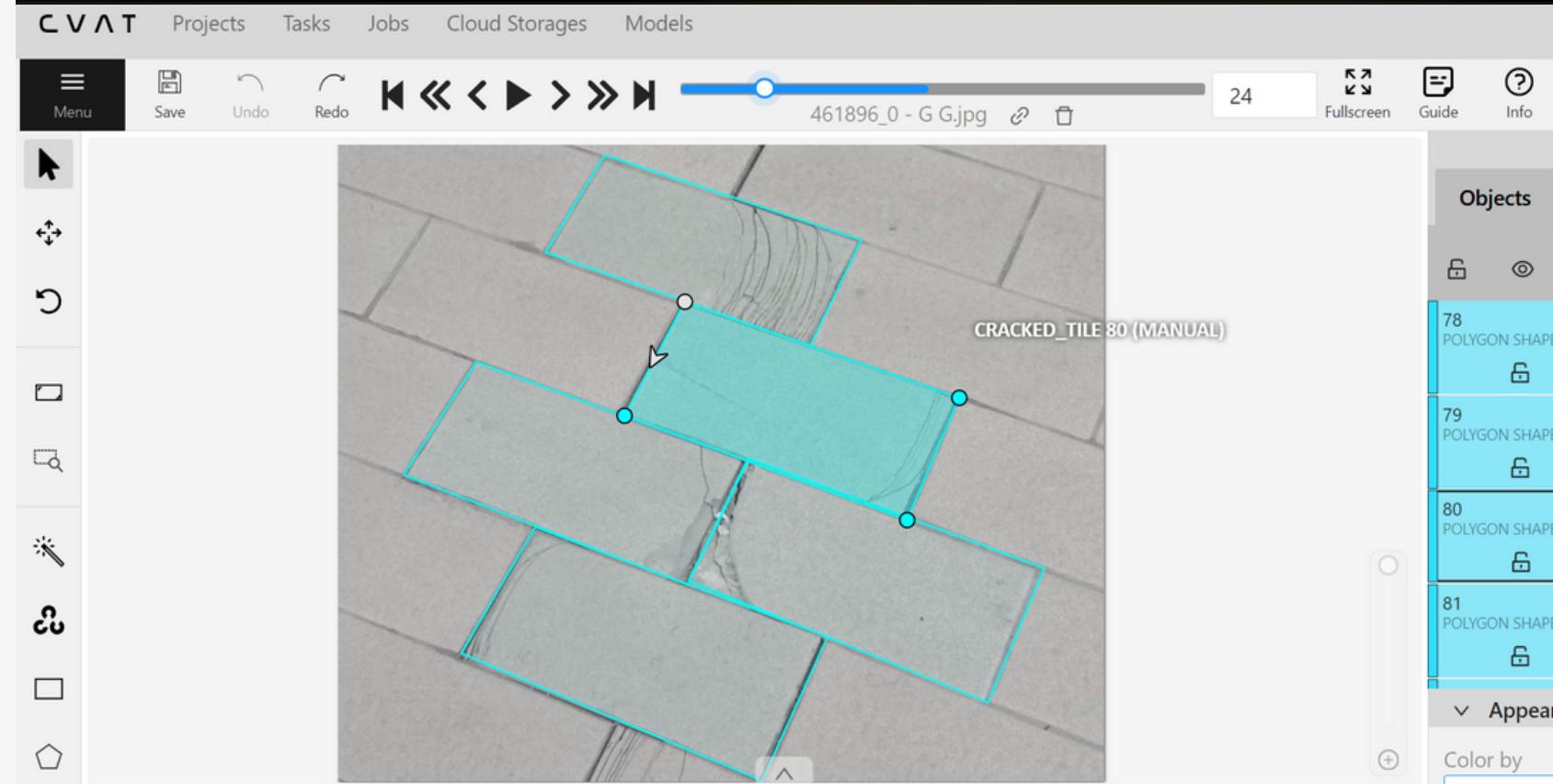
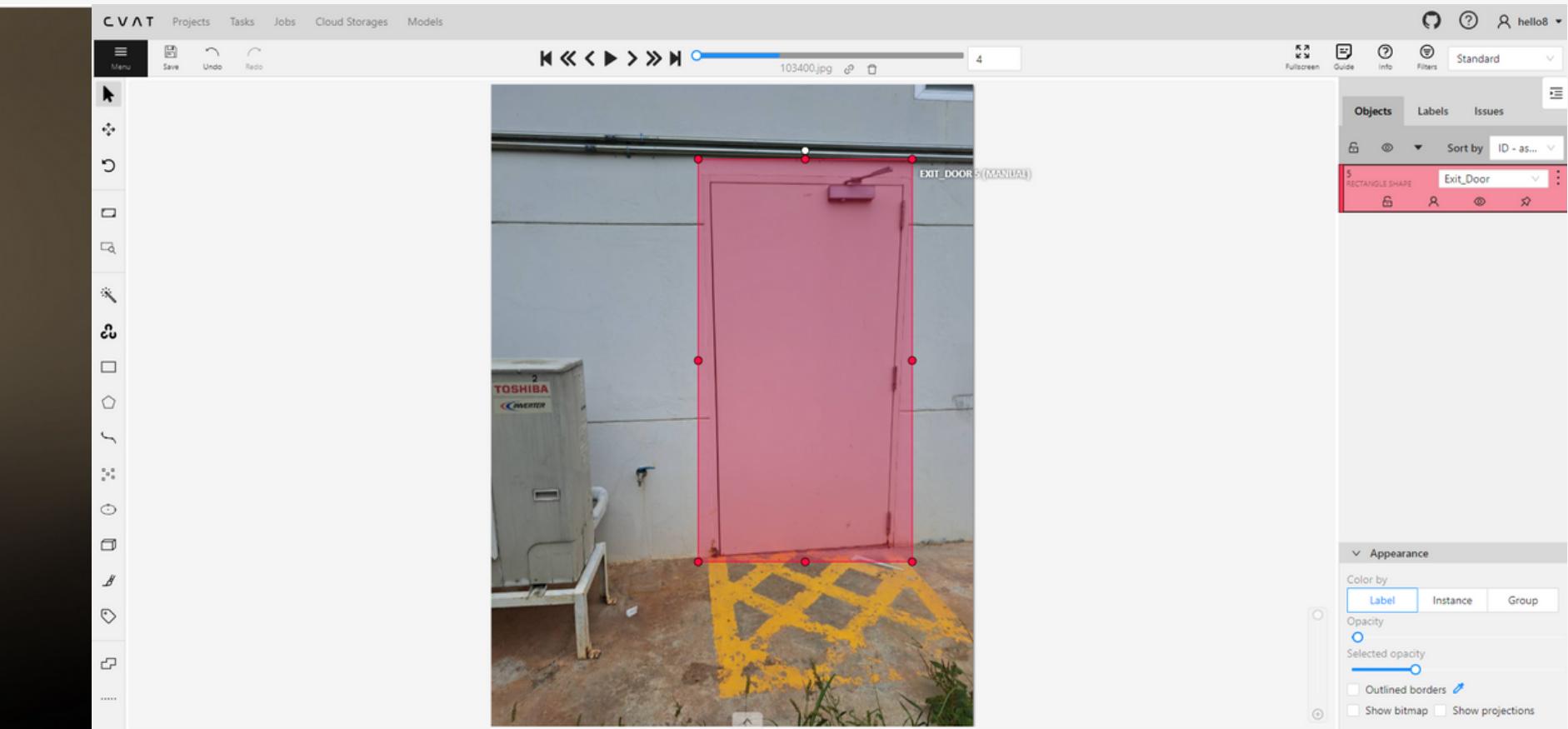
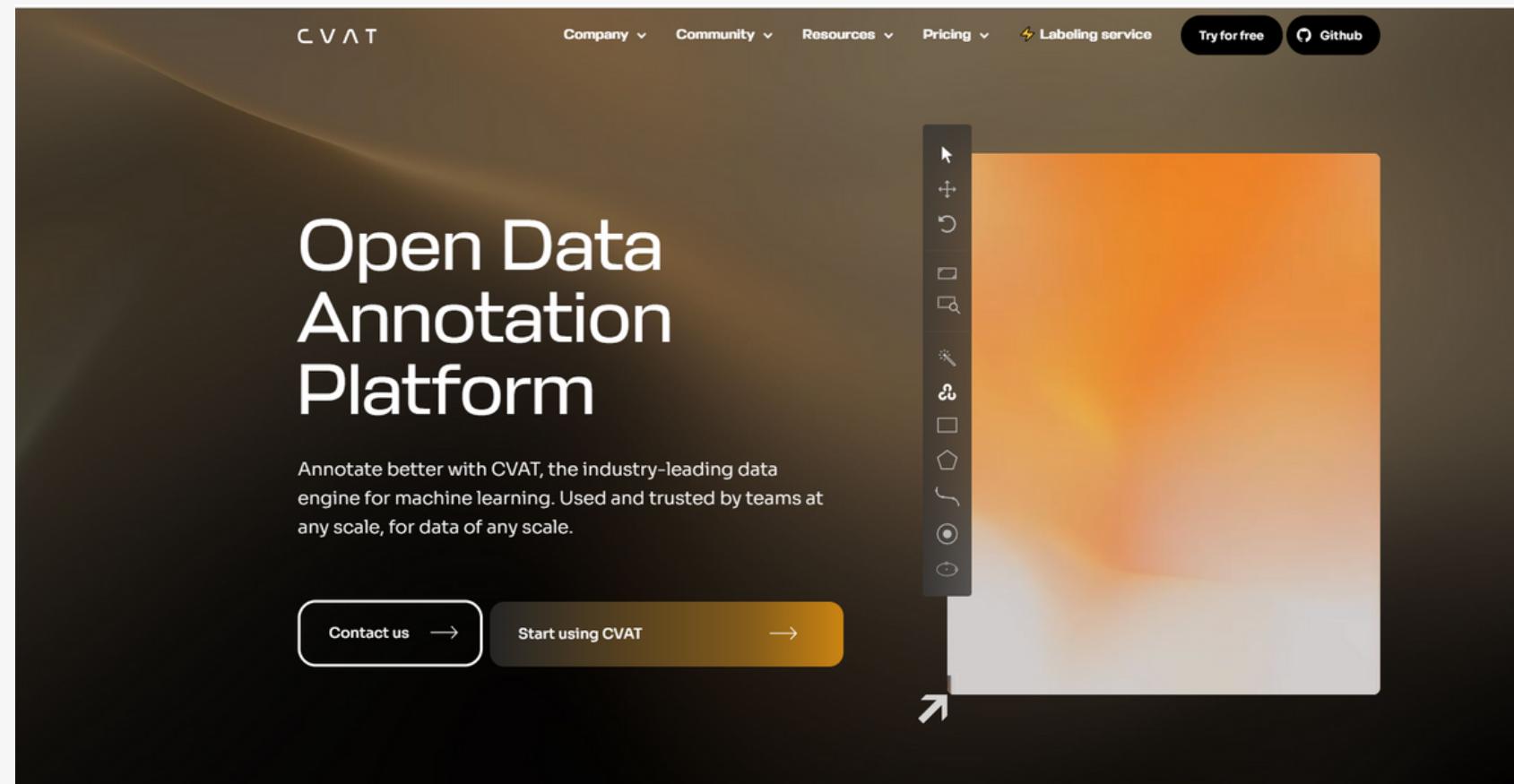
|                          | YOLOV5                               | YOLOV8 ( Nano )                      | FASTER RCNN         |
|--------------------------|--------------------------------------|--------------------------------------|---------------------|
| Performance ( mAP @0.5 ) | 0.59                                 | 0.787                                | 0.55                |
| Speed                    | Faster                               | Fastest                              | Slowest             |
| Dataset Size             | Small dataset ( Require Annotation ) | Small dataset ( Require Annotation ) | Medium - Large data |

**Object Detection Performance Comparison  
(YOLOv8 vs YOLOv5)**

| Model Size | YOLOv5 | YOLOv8 | Difference |
|------------|--------|--------|------------|
| Nano       | 28     | 37.3   | +33.21%    |
| Small      | 37.4   | 44.9   | +20.05%    |
| Medium     | 45.4   | 50.2   | +10.57%    |
| Large      | 49     | 52.9   | +7.96%     |
| Xtra Large | 50.7   | 53.9   | +6.31%     |

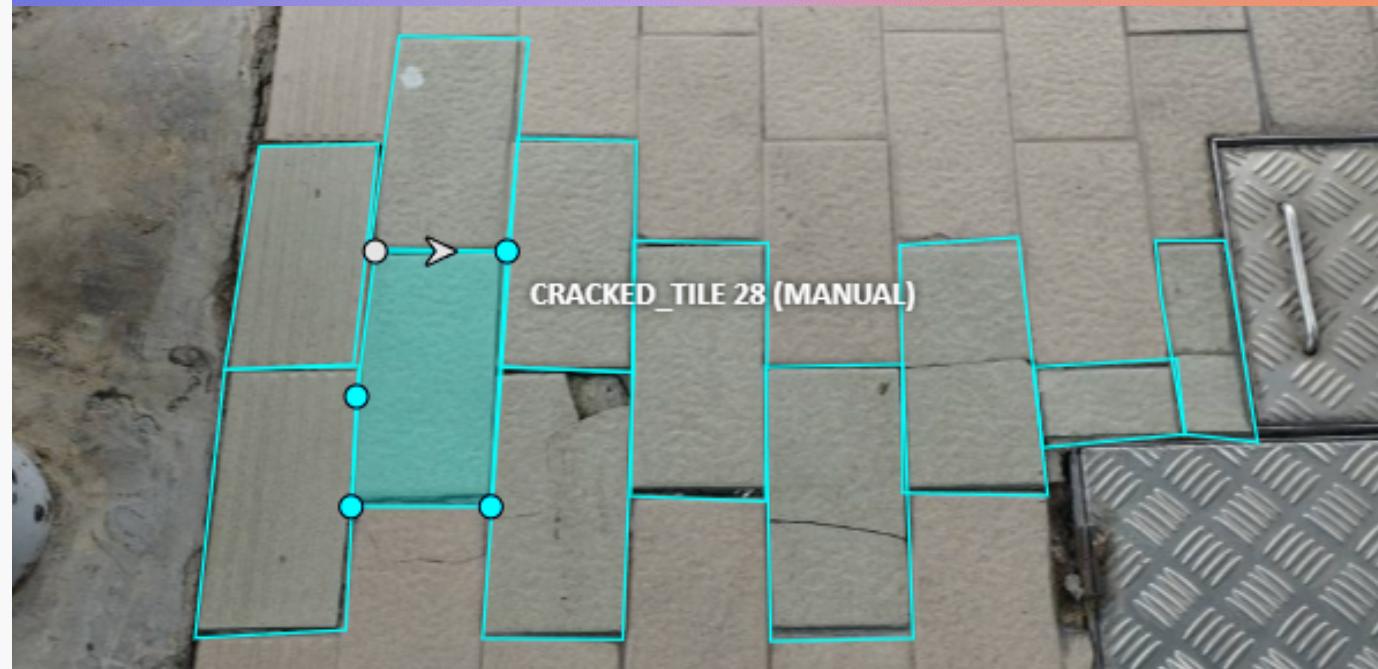
\*Image Size = 640

# DATA ANNOTATION FOR YOLOV8



# TRAINING MODEL FOR FLOOR

Train model by **YoloV8** for cracks detect



Train model **MobileNetV2** for classify location



```
26/26 [=====] - 11s 421ms/step - loss: 0.0517 - accuracy:  
Epoch 93/100  
26/26 [=====] - 11s 422ms/step - loss: 0.0463 - accuracy:  
Epoch 94/100  
26/26 [=====] - 11s 425ms/step - loss: 0.0533 - accuracy:  
Epoch 95/100  
26/26 [=====] - 11s 419ms/step - loss: 0.0694 - accuracy:  
Epoch 96/100  
26/26 [=====] - 11s 419ms/step - loss: 0.0680 - accuracy:  
Epoch 97/100  
26/26 [=====] - 11s 413ms/step - loss: 0.0599 - accuracy:  
Epoch 98/100  
26/26 [=====] - 11s 418ms/step - loss: 0.0590 - accuracy:  
Epoch 99/100  
26/26 [=====] - 11s 431ms/step - loss: 0.0491 - accuracy:  
Epoch 100/100  
26/26 [=====] - 11s 409ms/step - loss: 0.0550 - accuracy:
```

# RESULT FLOOR

Correct Accuracy

98.33%

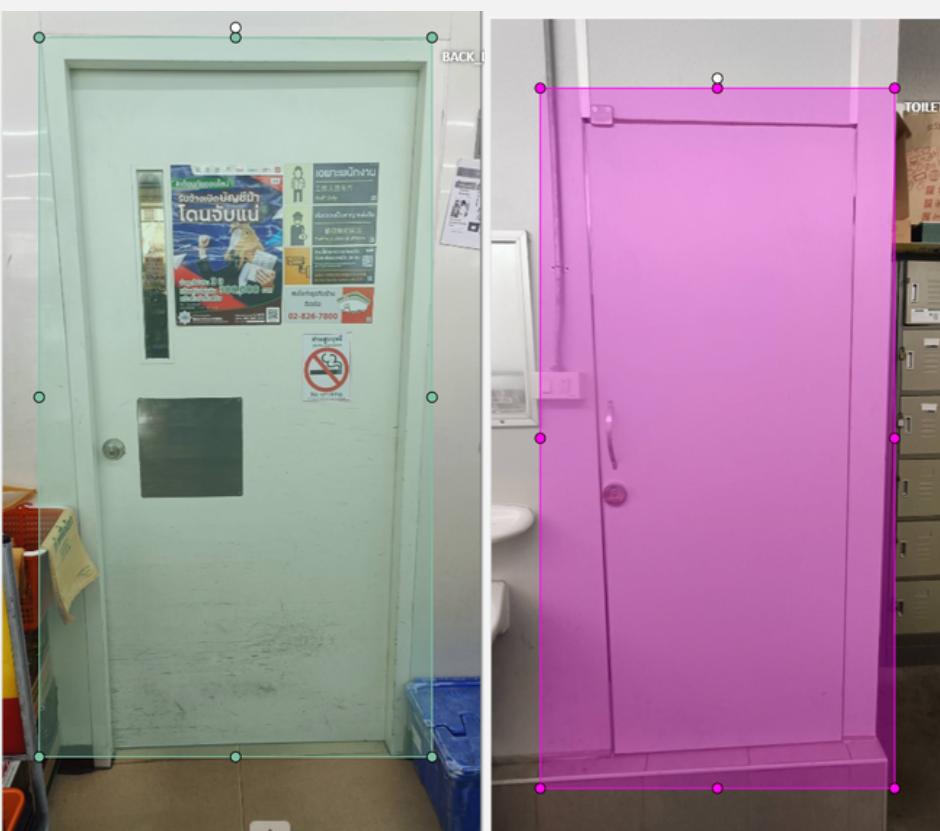
Predicted Class: Selling Area  
Confidence: 0.94



# TRAINING MODEL FOR DOOR



Train model by Yolov8n -  
200 epoch



```
import os  
  
from ultralytics import YOLO  
  
# Load a model  
model = YOLO("yolov8n.yaml") # build a new model from scratch  
  
# Use the model  
results = model.train(data=os.path.join(ROOT_DIR, "scratch.yml"), epochs=200, pretrained = T
```

# RESULT DOOR

## Correct Accuracy

# 98.83%



# Impacts / Gain Point

| types of Construction call | Amount of Calls | Correct calls | Incorrect calls | Cost for closed/opened calls | Traveling cost (Baht) | Total (Baht) |
|----------------------------|-----------------|---------------|-----------------|------------------------------|-----------------------|--------------|
| Floor                      | 4,410           | 4,057         | 353             | 24,710                       | 353,000               | 377,710      |
| Door                       | 4,621           | 4,251         | 370             | 25,900                       | 370,000               | 395,900      |

- **Reduce** cost more than **700,000** Baht per year
- **Reduce** the incorrect calls more than **700** calls per year

# Future goals

| types of Construction call | Amount of Calls | Correct calls | Incorrect calls | Cost for closed/opened calls | Traveling cost (Baht) | Total (Baht) |
|----------------------------|-----------------|---------------|-----------------|------------------------------|-----------------------|--------------|
| 94 types                   | 81,752          | 75,212        | 6,540           | 457,800                      | 6,540,000             | 6,997,800    |

- More Type 2 Types → 94 Types
- Reduce cost 6,997,80 Baht → By 98%
- Develop model to handle other type of material
- Integrate the AI with BoonChuay (Application chatbot)

# Our Team

**Pawaris panyasombat**

**Pichaporn Ruamkonthong**

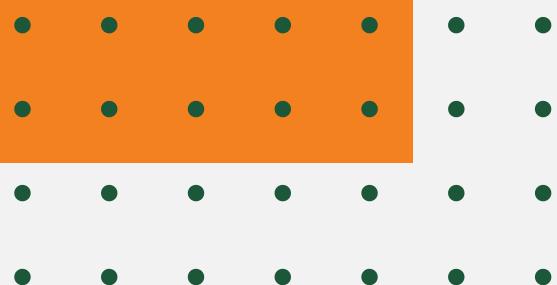
**Thanavin Denkavin**

**Bhumipat Ngamphueak**

## Mentors

**T.K. GearWalker**

**Polakrit Krajaisri**



# Business Unit

คุณ ชา� กิติกรณ์ รองผู้จัดการทั่วไปส่วนงาน Store Construction Management (PTT+BU)

คุณ ศศิธร อุดศร เจ้าหน้าที่

คุณ เจริญ ทรัพย์สมบูรณ์ ผู้จัดการฝ่าย

คุณ นรเดช ชื่นวิภาสกุล เจ้าหน้าที่อาวุโส

คุณ จตุพร สุทธิการ วิศวกรอาวุโส

คุณ พัชระ รมย์มาลี วิศวกรอาวุโส

คุณ เมรี ทองสาดี เจ้าหน้าที่อาวุโส

คุณ นงนุช คงมานะ เจ้าหน้าที่อาวุโส

คุณ ธนากร เกิดฤทธิ์ เจ้าหน้าที่อาวุโส

คุณ ผสันต์สุข ประทุมพวง เจ้าหน้าที่

คุณ ธนาดา ตันภูมิ เจ้าหน้าที่อาวุโส

คุณ กมลภา ประทุมกรพย์ เจ้าหน้าที่

คุณ รัชชัย ชัยกุหลาบ ผู้จัดการฝ่าย

คุณ กัญญาเวร์ เตชะศรินทร์ ผู้จัดการฝ่าย

คุณ ฐานกร เพ็ชรเกิด เจ้าหน้าที่

คุณ สุนิสา มีสังฆะ เจ้าหน้าที่

คุณ อมรรัตน์ ปัญญาปฏิพักษ์ วิศวกรอาวุโส

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# THANK YOU