Building Function Classification

Team: Functional on Caffeine

Aryan Agrawal | Veena Vadakkathmana Ramadas | Tatva Agarwal

Problem Statement

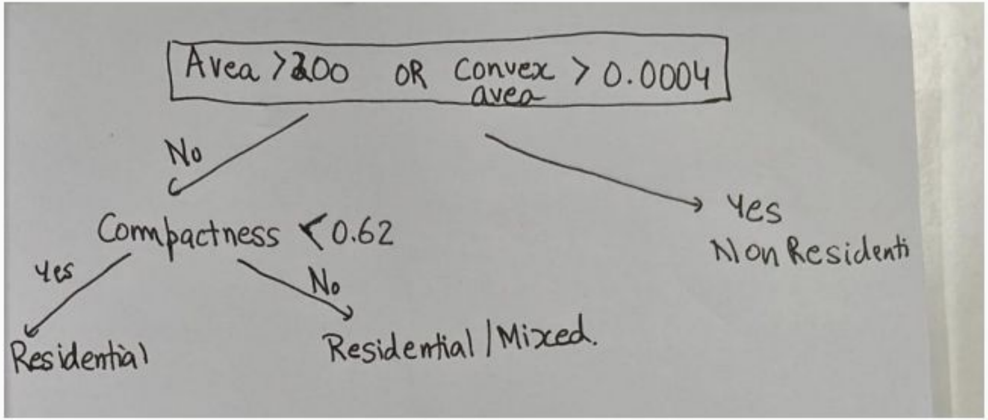
- OSM currently has marked only 0.6% of building tags and out of them several are marked incorrectly
- Marking the building is important for
  - Disaster Management and Response
  - Energy Consumption Estimation
- A decision tree was made using various spatial and non-spatial attributes

Subproblem Scope

- The problem statement has been scoped down to 6 major areas in Hyderabad so as to cover a wide variety of buildings:
  - Telecom Nagar ↣ 60 ground truth points
  - HiTech City ↣ 54 ground truth points
  - Badangpet ↣ 20 ground truth points
  - Ramachandrapuram ↣ 132 ground truth points
  - Madhur Nagar ↣ 31 points
  - Sainikpuri ↣ 83 points

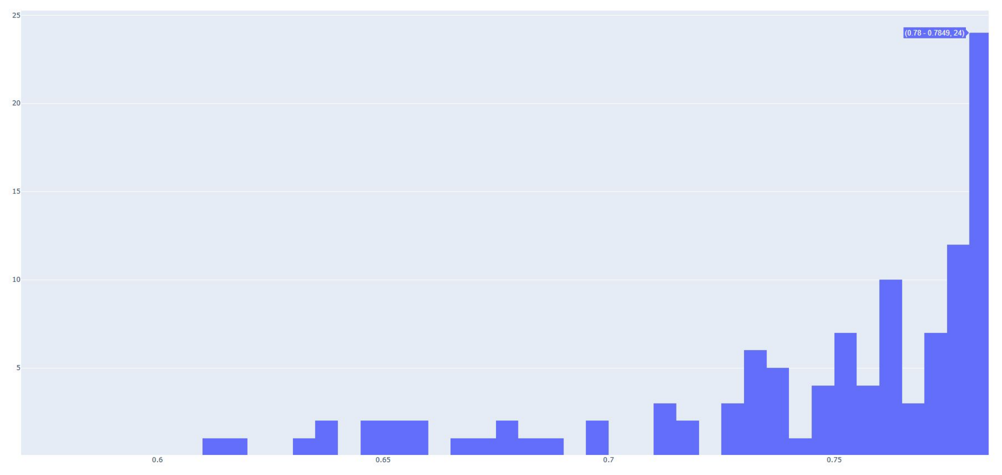
Mid-Eval -> Now

Until now, the manual decision tree is the following; having ~85% accuracy on the small subset of ground truth data collected



Compactness

- Both residential and commercial developers often choose rectangular forms for economic reasons, regardless of function. The Use of Basic Shapes in Residential and Home Architecture | Blog | Bill Whittaker (source)
- Poor space usage. Most land plots are rectangular, so if there are circular properties there is a lot of space that's not utilized at all. And the inside becomes difficult to furnish efficiently. What are the disadvantages of skyscrapers with round floor plates? : r/architecture (source)



Mixed

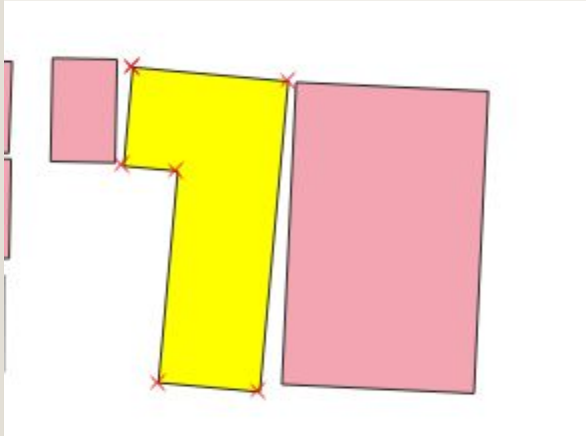
Initial Hypothesis:

- If compactness less than a threshold then it cannot be mixed as choosing that building would be a waste of space for the business.

Results

Our hypothesis is true as we can see from the histogram:

- No mixed building has compactness < 0.62



Mixed building with low compactness

<u>Possible rule in decision based classifier:</u>

if compactness < 0.62:
    Non-residential / residential
Else:
    Non-residential / residential / mixed

This good as its a shallow rule only rules out 1

96%

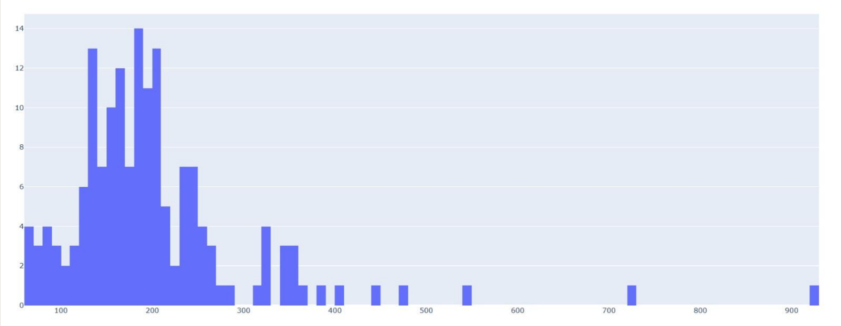
Area

➔ Building footprint areas are a good indicator for identifying between Residential and Non-Residential Buildings because most residential properties like Family houses and Duplexes are for personal living built on small private plots.

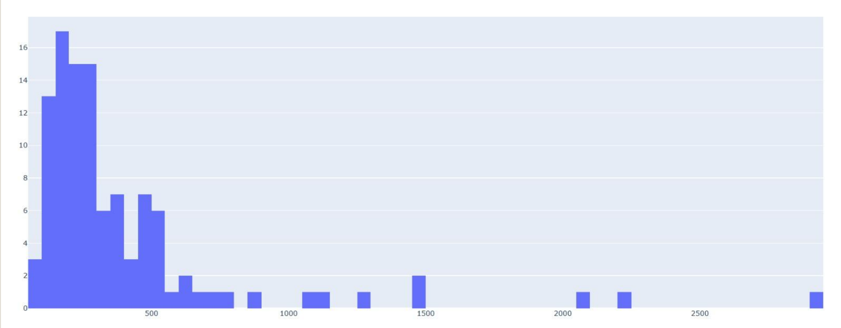
Initial Hypothesis:

➔ While most commercial and non-residential buildings are built on larger plots since they need larger spaces. This makes them a logical choice for use in a decision tree.

➔ Apartments, Bunglows, Penthouses often fall as an outlier, because even though they are residential, they have high footprint area, In such cases, we need to use other geometric features, or spatial neighbourhood relation like in a colony most houses will have small regular sized plots.



residential

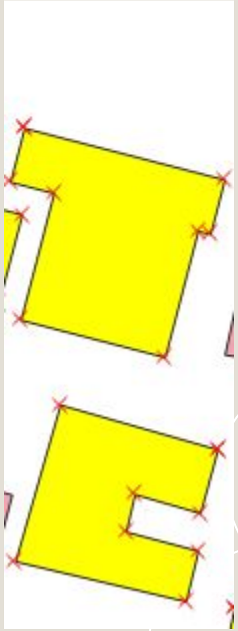


non-residential

Results

Our hypothesis is true as we can see from the histogram:

- Most of the buildings above 200 m^2 are non-residential buildings



2 Apartments with area>250m^2

75%

Possible rule in decision based classifier:

    if area > 200:
        Non-residential
    Else:
        Non-residential / residential / mixed

Nearest Neighbour Distance

- ➔ We calculated a spatial feature called Nearest Neighbour DIstance which calculates the distance between two neighbouring polygons (buildings) not having a road in between.
- ➔ Used a PyQGIS Script to perform the computation.
- ➔ This can be used as a useful metric to classify between residential and non-residential buildings since most residential buildings are made on regularly spaced plots and have lower distance between them. While non-residential commercial spaces can have varied distance to their neighbouring buildings due to zoning laws, parking spaces etc.
- ➔ We consider 15m to be the threshold from edge to edge of each building, greater than that are classified as non-residentials

In our limited dataset, we do not see a clear demarcation in the values, but on a larger scale, such a trend will appear (study done in Afghanistan supports this fact)

Warren C. Jochem, Tomas J. Bird, Andrew J. Tatem, Identifying residential neighbourhood types from settlement points in a machine learning approach,
Computers, Environment and Urban Systems, Volume 69, 2018, Pages 104-113, ISSN 0198-9715, https://doi.org/10.1016/j.compenvurbsys.2018.01.004.

Transit Distance

Initial Hypothesis:

- Residential buildings should be nearer to bus stops, train stations, metro, etc.
- This makes sense as people will build such stations near residential homes so that more people use public transport for easier accessibility to other places

- This hypothesis was not supported by our data as we found out that even non-residential and mixed buildings were close enough to these stations
- Non-residential and commercial buildings also need easy access to such stops

Slenderness

- Slenderness is the height of a building/sqrt(area)

- Initial Hypothesis:
- We can notice the following extremes for slenderness:
    - either very high (large height, compact area ↠ apartments)
    - or very low values (low height, huge area ↠ godowns and large non-residential area)
- This means that we can say high values are residential, low-medium values and residential/mixed and the ones medium-height and very low are non-residential

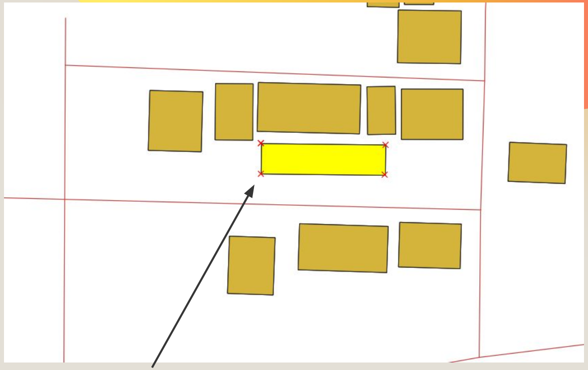
- We were unable to test the hypothesis as we were unable to process and spatially join google 2.5D data with our Openstreetmap data.

Elongation Aspect Ratio

- Elongation Aspect Ratio is a geometric feature derived by the formula
  ElongationAR = MaxSide / MinSide (of the building bounding box)
- It specifies how elongated / disproportionate a building is in its length and width

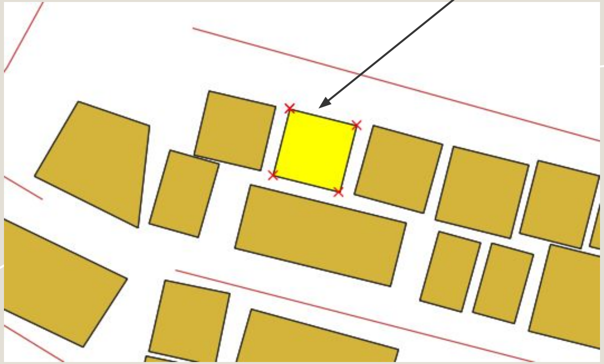
Initial Hypothesis

- This serves as a good feature since most residential buildings are compact and rectangular, this leads to their elongation being in the range of 1.5 - 2.
- Whereas most non-residential buildings fulfill a purpose which need long spans or linear layouts (e.g. train stations, malls, shopping complexes etc). These types of buildings have an elongation more than 5 or around 1 (for very compact buildings like stadiums etc).



This building is residential but has elongation as 4.08

This building is non-residential but has elongation as 1.016



Why not convex hull area?

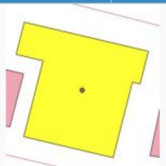
This study investigated the performance of 20 shape indices, 2 of which are new, and proper shape index–classification scheme pairs to characterise BF shape complexity in GIS. For this purpose, three shape complexity categories were defined for BFs. Benchmark data was then constructed based on the perceptual shape interpretation by human experts. Eighteen selected indices were automatically computed in GIS. These indices were then statistically assessed with histograms, correlation matrix, and boxplots. Accordingly, four indices were found appropriate. In addition, two new indices were proposed and statistically found sufficient. Three categories of simple, moderate, and complex BFs were identified with each pair of the indices and the classification schemes in GIS. In this context, four classification schemes were used. Concerning the indices, *ERI* showed the highest performance than the others, followed by *CNV*, *RI*, and *REC* in a descending order. Among the classification schemes, *Ccs* had the highest performance. To sum up, it is recommended to employ the aforementioned indices and *Ccs* with the derived custom ranges to characterise absolute shape complexity while the other
schemes can preferably be used in local regions where the identification
ape complexity is often more important.
performance of the indices as shape complexity increases indicates the
e sophisticated shape analysis and recognition methods. In addition, the
formance of shape indices, and the classification methods used in machine
data mining can be investigated for BF shape characterisation.

Convex Hull Area

Accuracy: 81% accuracy

	resident/mixed gtruth	Non-resident gtruth
resident/mixed predicted	122	26
Non-resident predicted	7	20

prediction	grnd_truth
non-residential	residential



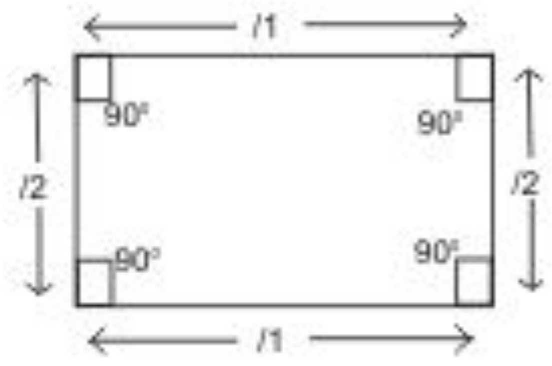
Convex hull can be a good indicator for classifying buildings as residential/mixed or non-residential because a larger convex hull usually means that area is more spread out. Therefore, the non-residential areas will have cover bigger and more irregular areas than typical resident plots.

Edge cases for this can include weirdly shaped buildings which can also be residential.

Basaraner, Melih & Cetinkaya, Sinan. (2017). Performance of shape indices and classification schemes for characterising perceptual shape complexity of building footprints in GIS. International Journal of Geographical Information Science. 1-26. 10.1080/13658816.2017.1346257.

Equivalent Rectangular Index

- Non-residential and mixed types will tend to have more irregular shape than residential buildings
- This can be attributed to the fact that
  - Non-residential buildings are more likely to be irregular in shape
  - Also, in the Indian context, people tend to follow vastu shastra which says that 1:2 is an ideal ratio for residential buildings

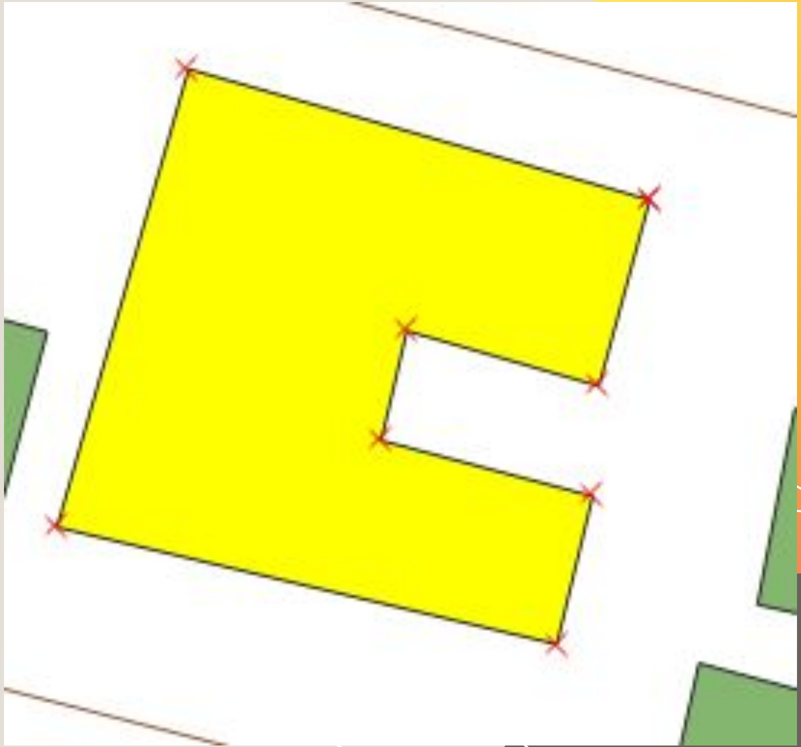


Rectangular plot is auspicious in the ratio of 1:2 and if the length is facing North and breadth is facing West then the inmates reap rich benefits from the plot in terms of health, wealth and prosperity.

Results

Hypothesis comes out to be true

- Residential buildings have ERI values that tend towards 1
- Non-residential and mixed buildings have values which are much lesser than 1



Possible rule in decision based classifier:

```
if eri < 0.9
        non-residential/mixed
else
        non-residential/mixed/residential
```

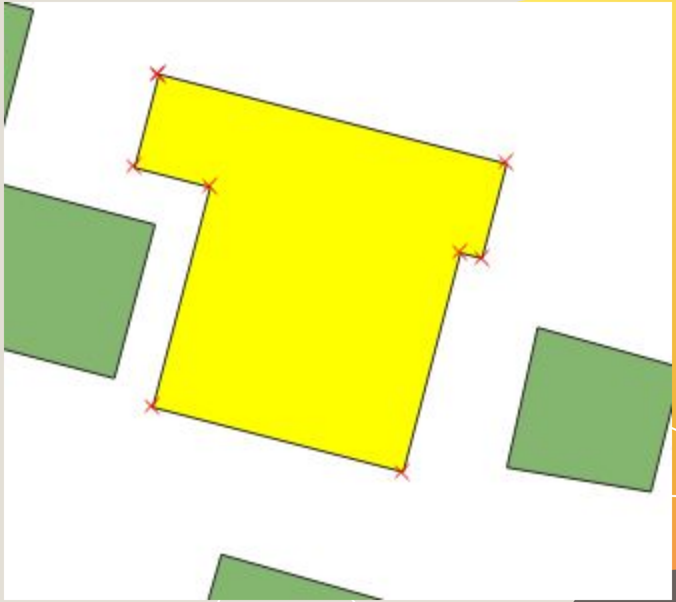
Corner Count

Initial Hypothesis

- Residential buildings are more likely to be square/rectangular in shape and hence the number of corners will be equal to 4
- If the number of corners of the building is greater than 4, it is most likely a mixed building (residential with extension) or a non-residential building with complex geometry

Results

Our hypothesis is mostly true:
- The buildings which have more than 4 corners are non-residential or mixed
- If a building has 4 corners, it can be either of the three types

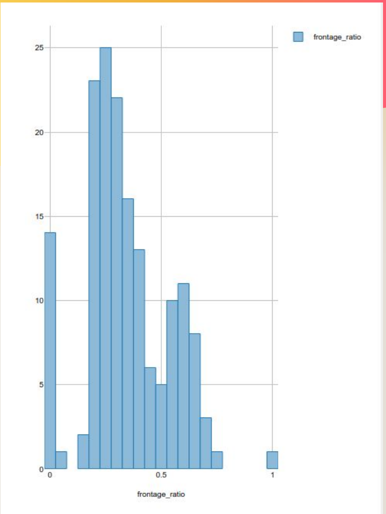


Possible rule in decision based classifier:

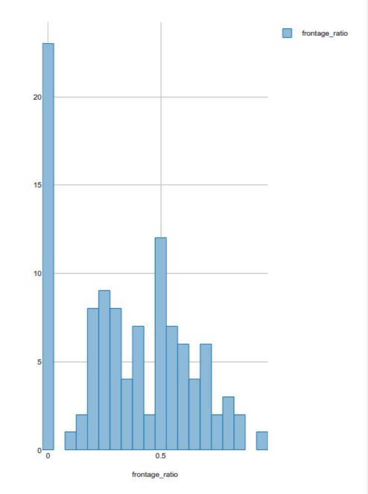
```
if corner_count > 4:
        non-residential/mixed
else
        non-residential/mixed/residential
```

Frontage Ratio

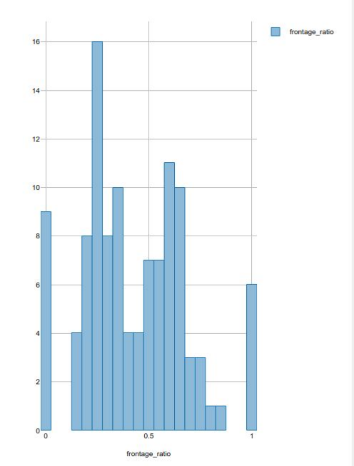
- Gives us the ratio of the street facing perimeter with the actual perimeter
- Non-residential buildings usually have large perimeter so even though they have one or two edges facing the street, the overall ratio will come out to be small
- Residential buildings with small perimeter or corner side buildings will have high frontage ratio



Residential

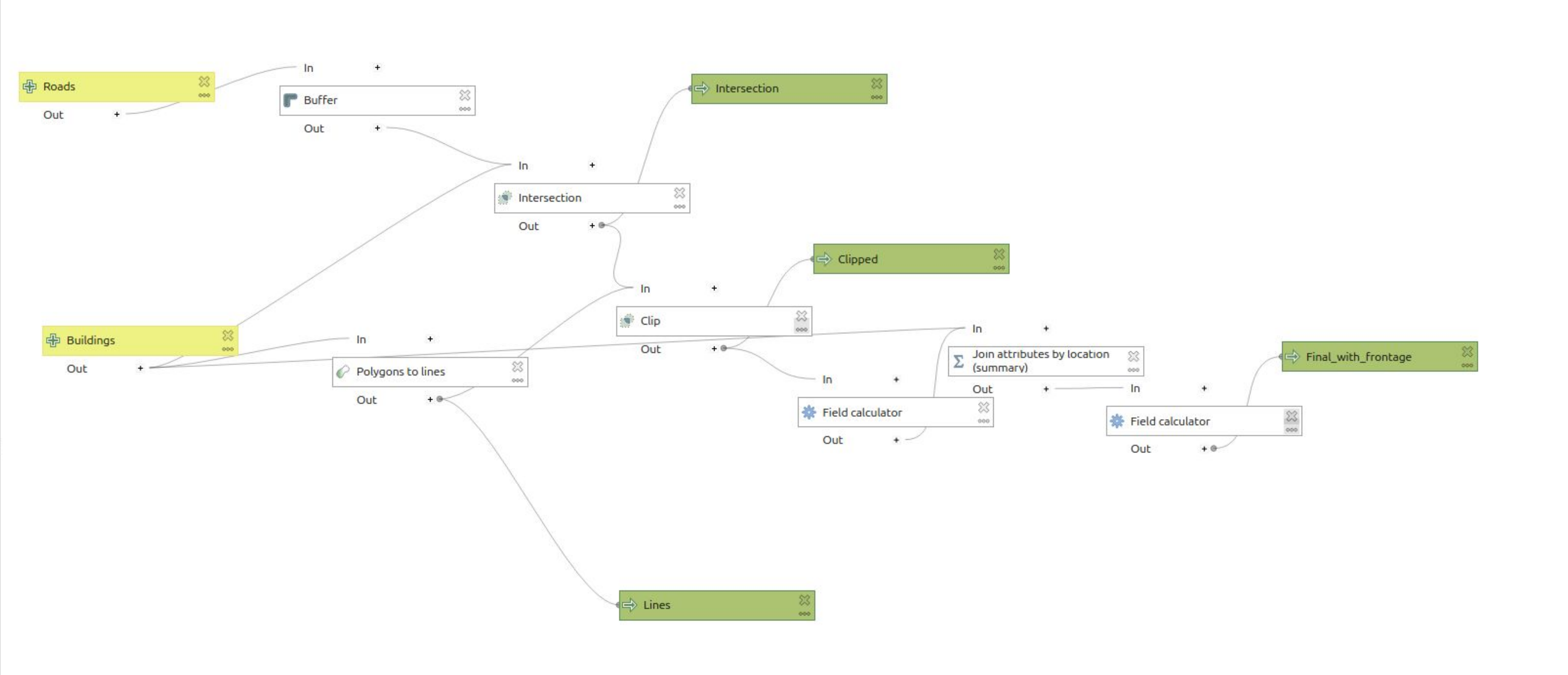


Non-Residential



Mixed

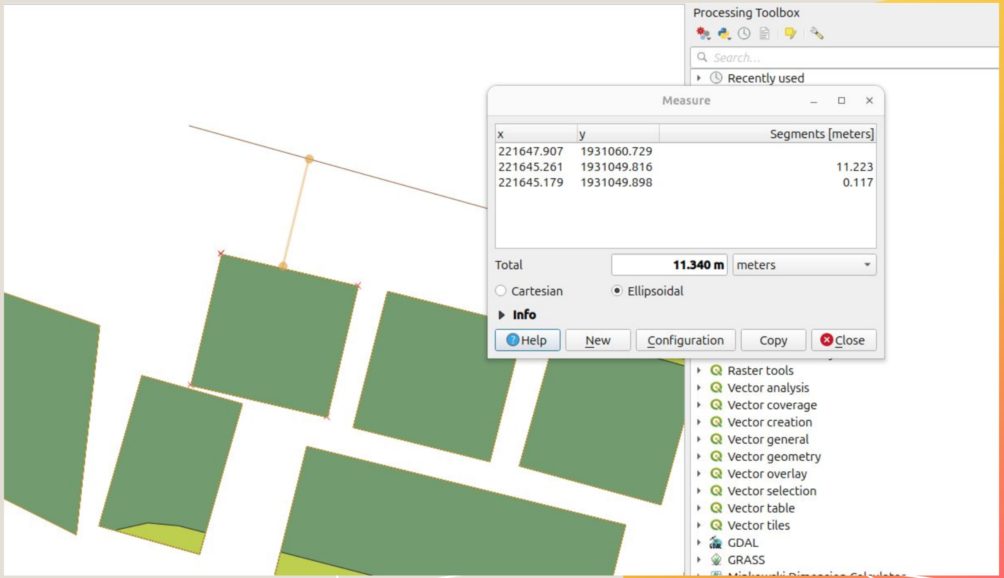
Frontage Ratio Calculation



Results

Our hypothesis is true as we can see from the histogram:

- Most non-residential buildings have frontage ratio in between 0.2 and 0.5
- Number of non-residential buildings with frontage_ratio > 0.5 is very less



Buffer not big enough

Possible rule in decision based classifier:

if frontage_ratio <0.2 -> Non-Residential
else if 0.2<=frontage_ratio <0.5 -> non-residential/mixed/residential
else frontage_ratio >=0.5 -> residential/mixed

89.2%

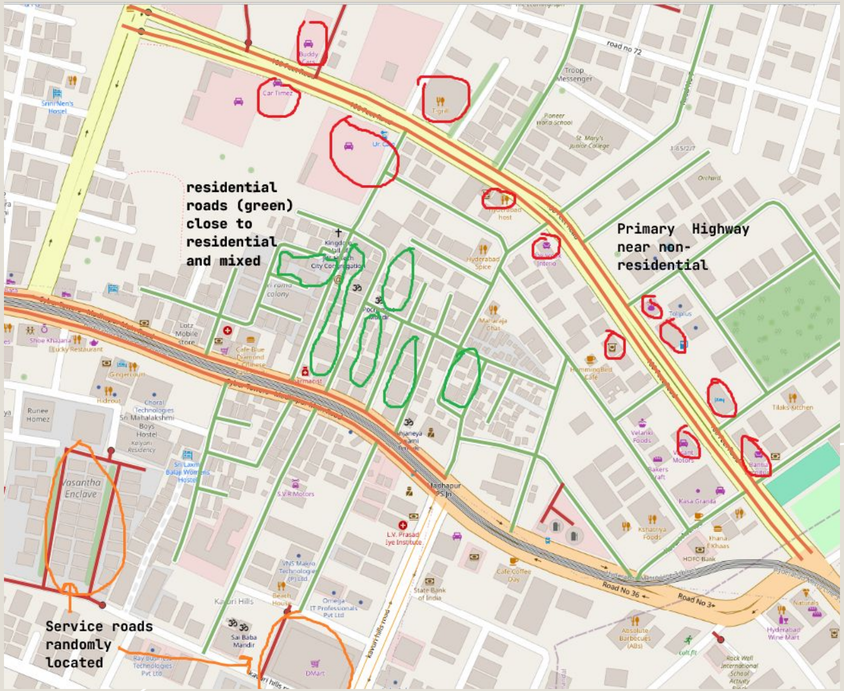
Buffer Distance to types of highways

Highways on OSM are classified into:

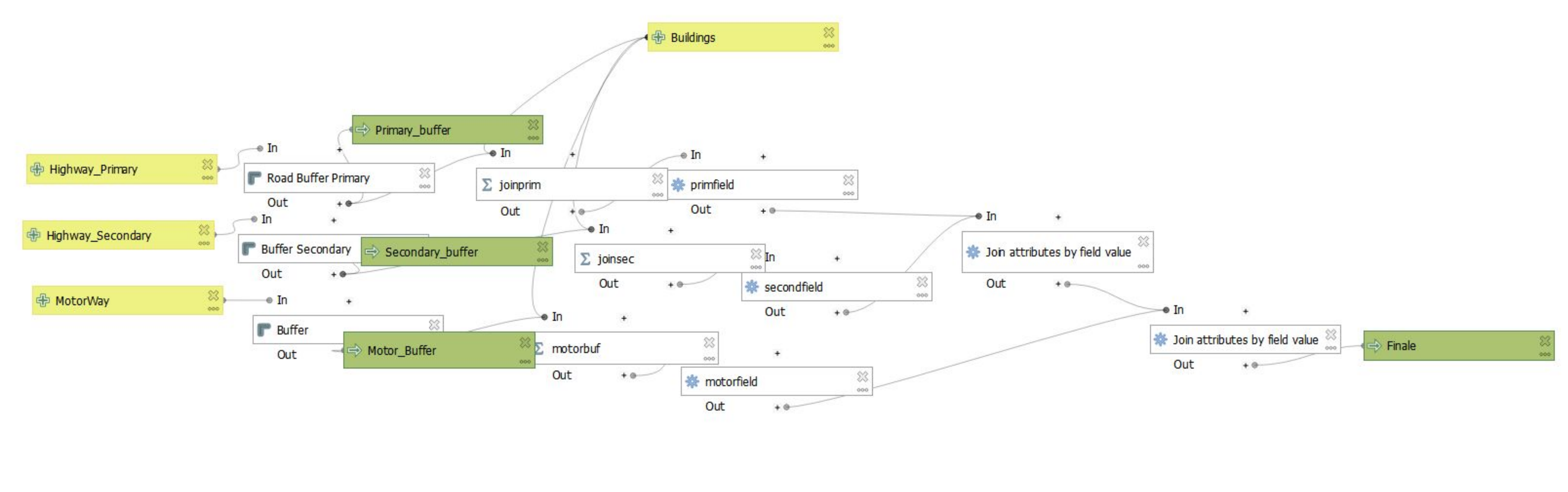
1. Primary, Secondary and Tertiary Highways
2. Motorways
3. Service Road
4. Residential

Initial Hypothesis:

- Residential Roads are the small tiny lanes and hence should be close to only for residential and mixed class of buildings
- Motorways controlled access expressways which are multilane and hence are close to only industrial zone and highway rest area rarely residential
- Primary and secondary highways are medium-width roads connecting towns or city sectors with commercial strips, petrol stations etc. Can have big Apartments rarely individual houses and hence can be a problem



Buffer Distance Calculation



Results

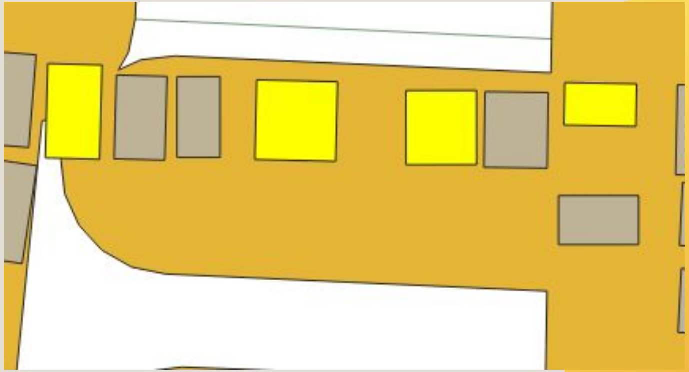
Highway 30m buffer -> only non-residential and mixed 0 residential buildings were present

Motorway -> none of our ground truth intersected with the motorway but logically still coherent that residential never intersects with motorway buffer

ServiceRoad->Slightly random but still statistically most probably non-residential (some small amount of residential and mixed were present)

residential -> All 3 classes of buildings are intersecting (small shops non-residential, houses and mixed)

<u>Possible rule in decision based classifier:</u>
If buffer Primary/Secondary Highway ->
Non-residential/Mixed
If Buffer Motorway:
non-residential



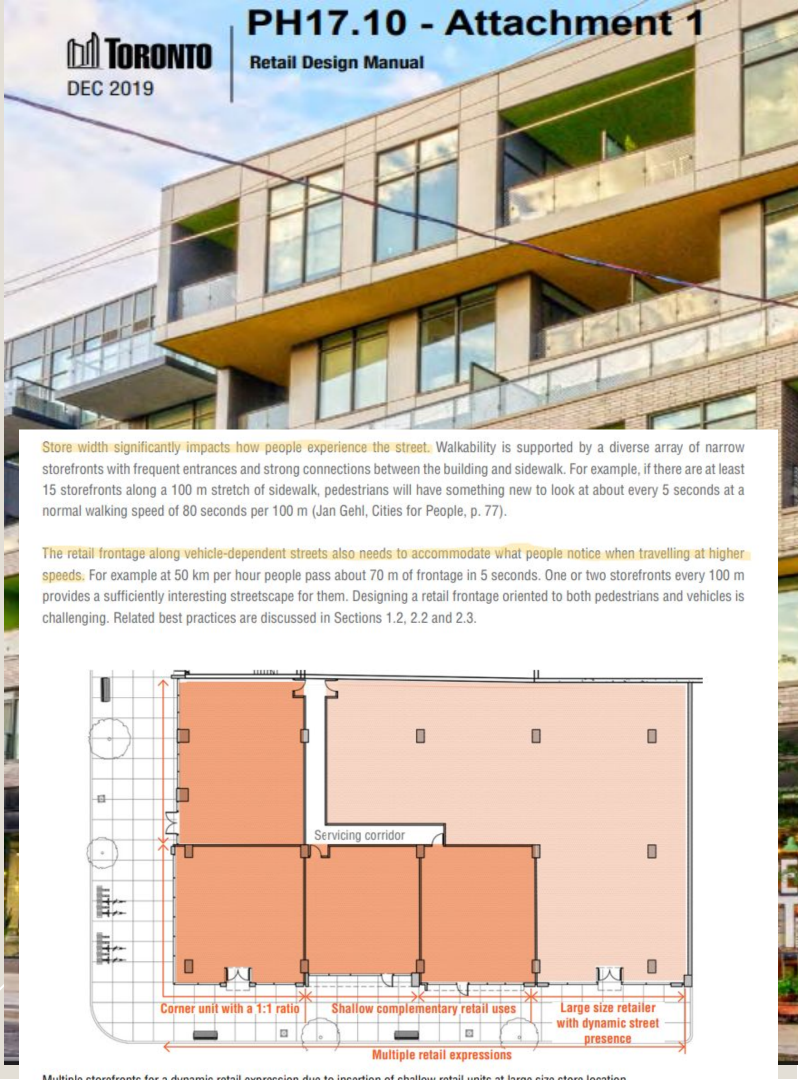
Small non-residential shops intersection with residential buffer

Service Roads intersecting both residential and non-residential

Street Alignment

Initial Hypothesis:

- Non-residential and mixed (Commercial buildings) need to be parallel with the road → Because that ensures maximum area to be visible to the people on road.
- Residential on the other hand do not have their orientation based on the road angle but rather other factors like solar access, privacy.
- Hence our hypothesis is if the angle is greater than some threshold we can rule out non-residential and mixed because that would not show enough area to the road thus leading to decrease in business.


PH17.10 - Attachment 1

TORONTO

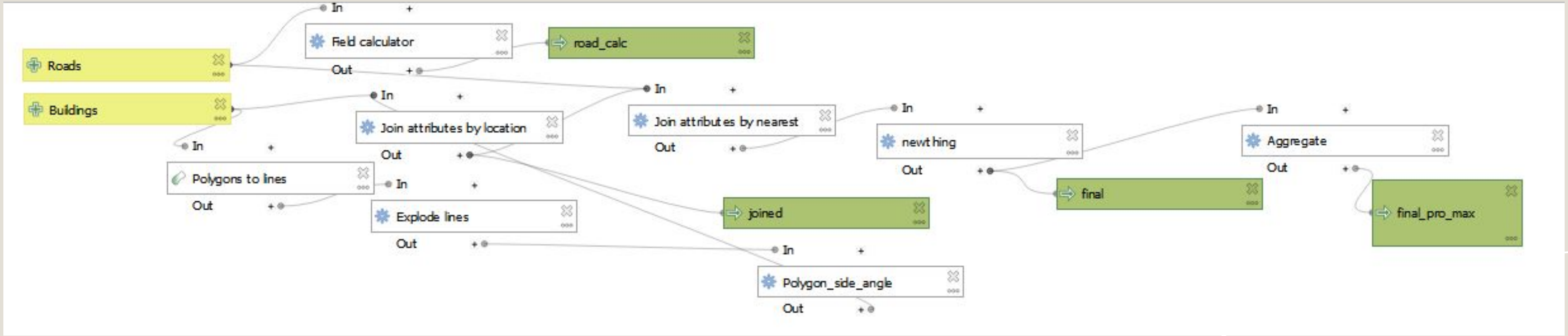
DEC 2019

Retail Design Manual

Store width significantly impacts how people experience the street. Walkability is supported by a diverse array of narrow storefronts with frequent entrances and strong connections between the building and sidewalk. For example, if there are at least 15 storefronts along a 100 m stretch of sidewalk, pedestrians will have something new to look at about every 5 seconds at a normal walking speed of 80 seconds per 100 m (Jan Gehl, Cities for People, p. 77).

The retail frontage along vehicle-dependent streets also needs to accommodate what people notice when travelling at higher speeds. For example at 50 km per hour people pass about 70 m of frontage in 5 seconds. One or two storefronts every 100 m provides a sufficiently interesting streetscape for them. Designing a retail frontage oriented to both pedestrians and vehicles is challenging. Related best practices are discussed in Sections 1.2, 2.2 and 2.3.

Street Alignment Calculation

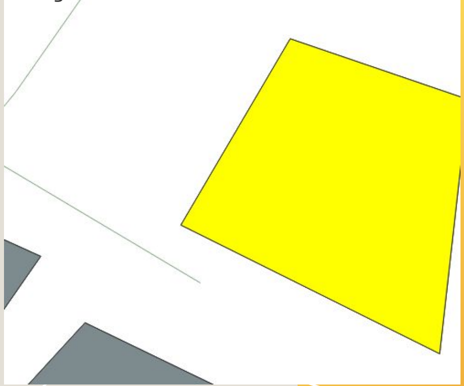


Results

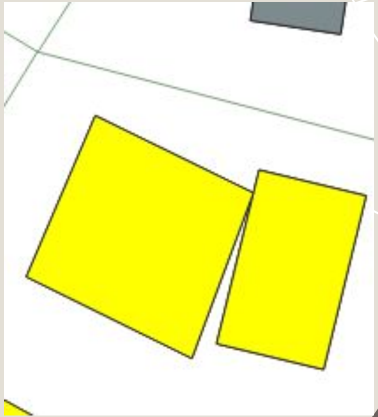
Hypothesis appears to be true.
Only 2 non-residential buildings out of 107 have alignment > 20 degrees.
Due to errors in geometry (attached image)
and some due to errors in calculation where multiple edges are close to the road (also attached)

However a ton of residential also seem to be aligned to the road with only ~10 residential having angle > 20 degrees.

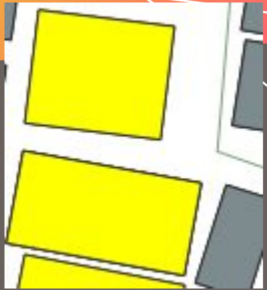
IF (STREET ALIGNMENT > 20 degrees):
    Residential
ELSE:
    Non-Residential/ Mixed/Residential



Non-residential but nearby road is incomplete leading to incorrect street align

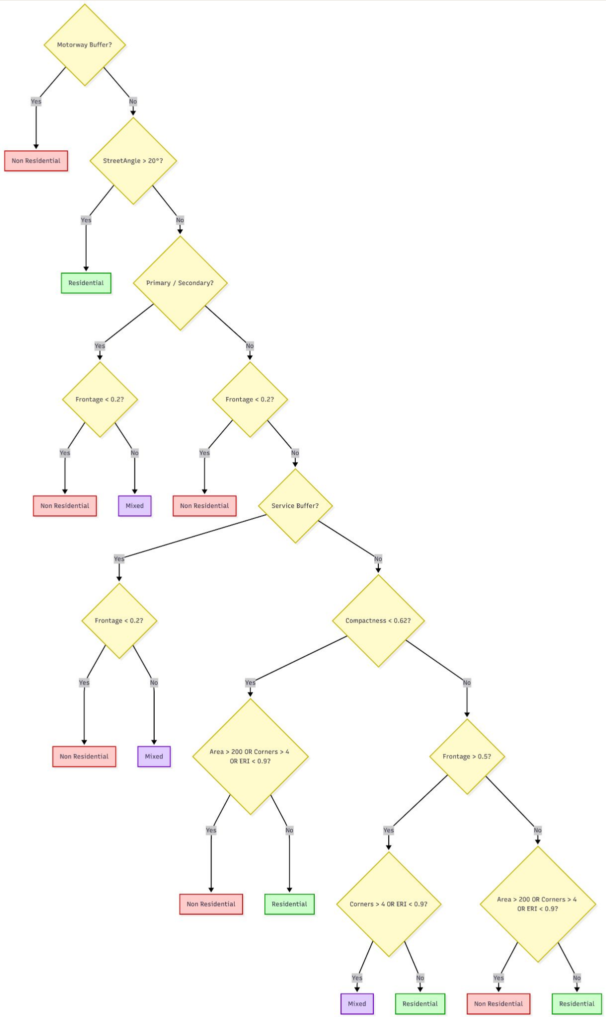


Non-residential but several edges close to road took wrong small edge to calculate angle



Residential with high angle

Final Tree



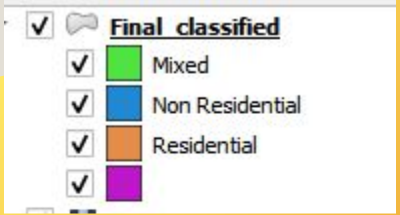
Motorway Buffer?
Yes
No
Non Residential
StreetAngle > 20°?
Yes
No
Residential
Primary / Secondary?
Yes
No
Frontage < 0.2?
Frontage < 0.2?
Yes
No
Yes
No
Non Residential
Mixed
Non Residential
Service Buffer?
Yes
No
Frontage < 0.2?
Compactness < 0.62?
Yes
No
Yes
No
Non Residential
Mixed
Area > 200 OR Corners > 4 OR ERI < 0.9?
Frontage > 0.5?
Yes
No
Yes
No
Non Residential
Residential
Corners > 4 OR ERI < 0.9?
Area > 200 OR Corners > 4 OR ERI < 0.9?
Yes
No
Yes
No
Mixed
Residential
Non Residential
Residential

Python Script for testing

```
(.venv) moelester@AryanPC:~/Sem3/SI/pygeo$ python3 main.py
Loading Final.gpkg...
Applying decision tree classification...

Classification Summary:
prediction
Residential        280
Non Residential    136
Mixed               45
Name: count, dtype: int64

Total polygons classified: 461

Saving results to Final_classified.gpkg...
```

```
Expected columns:
- MotorwayBuffer (boolean or 0/1)
- StreetAngle (float, in degrees)
- PrimarySecondary (boolean or 0/1)
- Frontage (float, 0-1 range)
- ServiceBuffer (boolean or 0/1)
- Compactness (float)
- Area (float)
- Corners (int)
- ERI (float, Elongation Ratio Index)
"""
```

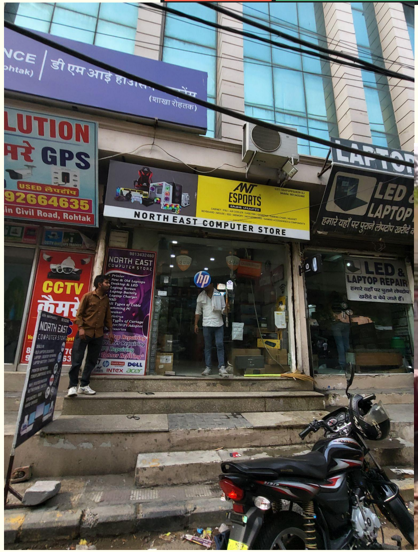
Inter City Running model (Blr - HSR LAYOUT)



PLEASE SCAN THE QR AND OPEN ON IIIT WIFI

http://10.2.130.115:8080/geoserver/Caffeine/wms?service=WMS&version=1.1.0&request=GetMap&layers=Caffeine%3AHSRLayoutClassified&bbox=135400.63609575597%2C1429457.81905472%2C136107.5046541763%2C1429883.7162932404&width=768&height=462&srs=EPSG%3A32644&styles=&format=application/openlayers#toggle

Picture based Prediction Model



Building Usage Classification in Indian Cities: Utilizing Street View Images and Object Detection Models

Yamini Sahu, Vasu Dhull, Satyajeet Shashwat, and Vaibhav Kumar

Indian Institute of Science Education and Research Bhopal (IISERB)
{yamini21,vasu21,satyajeet21,vaibhav}@iiserb.ac.in

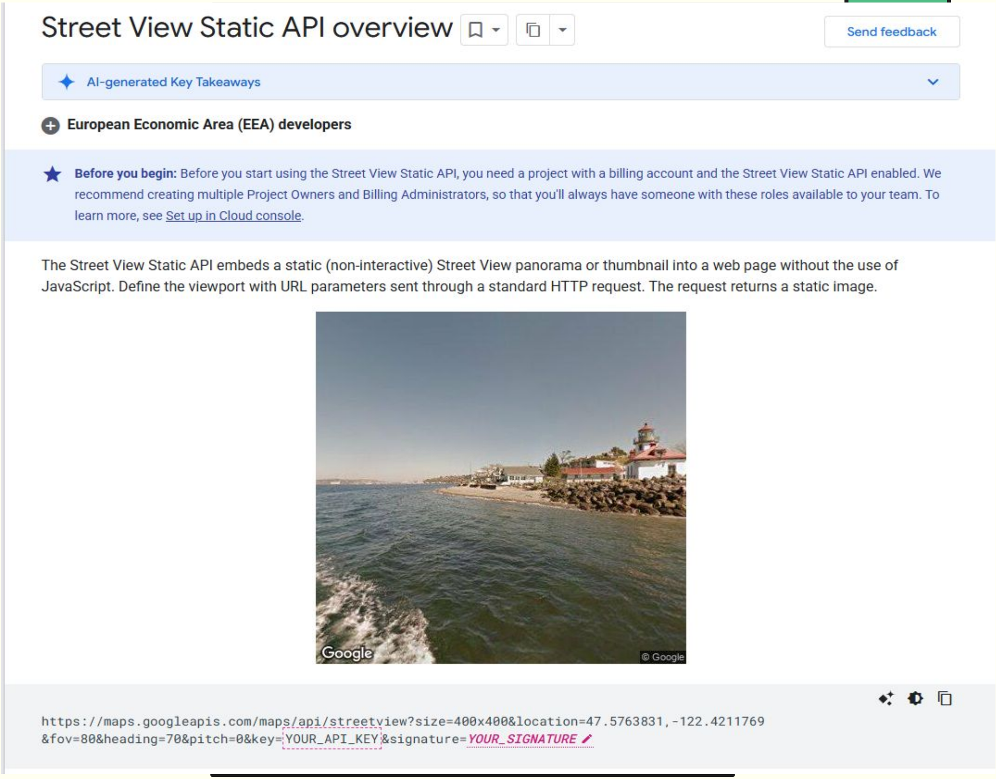
Abstract. Urban land use maps at the building instance level are crucial geo-information for many applications, yet they are challenging to obtain. Land-use classification based on spaceborne or aerial remote sensing images has been extensively studied over the last few decades. Such classification is usually a patch-wise or pixel-wise labeling over the whole image. However, for many applications, such as urban population density estimation or urban utility mapping, a classification map based on individual buildings (residential, commercial, mixed-type, and religious) is much more informative. Nonetheless, this type of semantic classification still poses fundamental challenges, such as retrieving fine boundaries of individual buildings. Street view images (SVI) are highly suited for predicting building functions because building facades provide clear hints. Although SVIs are used in many studies, their application in generating building usage maps is limited.
Furthermore, their application to Indian cities remains void. In this paper, we propose a comprehensive framework for classifying the functionality of individual buildings. Our method leverages the YOLOs model and utilizes SVIs, including those from Google Street View and OpenStreetMap. Geographic information is employed to mask individual buildings and associate them with the corresponding SVIs. We created our own dataset in Indian cities for training and evaluating our model.

Keywords: Building usage classification · Object detection · Street view images · Open street map · Urban planning

Ground Truth Collection

Street View API + Label Studio

1. Used the google street view api to try to capture some buildings
2. Use Label Studio to draw boxes around the buildings and label them
3. Export as yolo format
4. Split into train, val, test -> 70 15 15



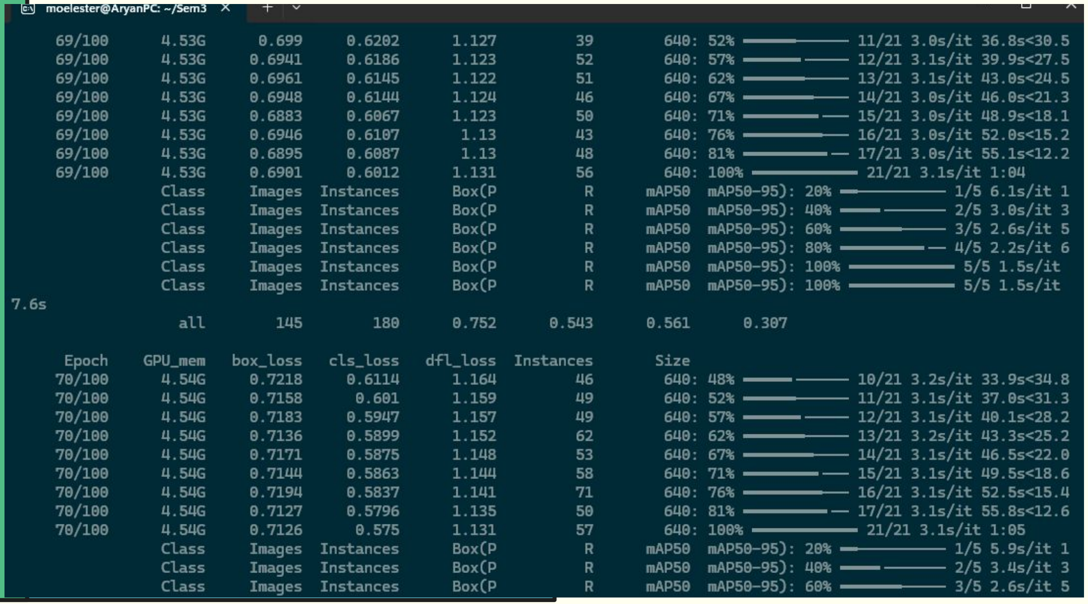
Model

Yolo 8

It scans the image once, at multiple scales, proposing rectangles and for each rectangle it predicts:

1. how good the box is (objectness),
2. the exact box coordinates, and
3. the probability of each class (residential/commercial/mix)

 Then it keeps only the top non-overlapping boxes.



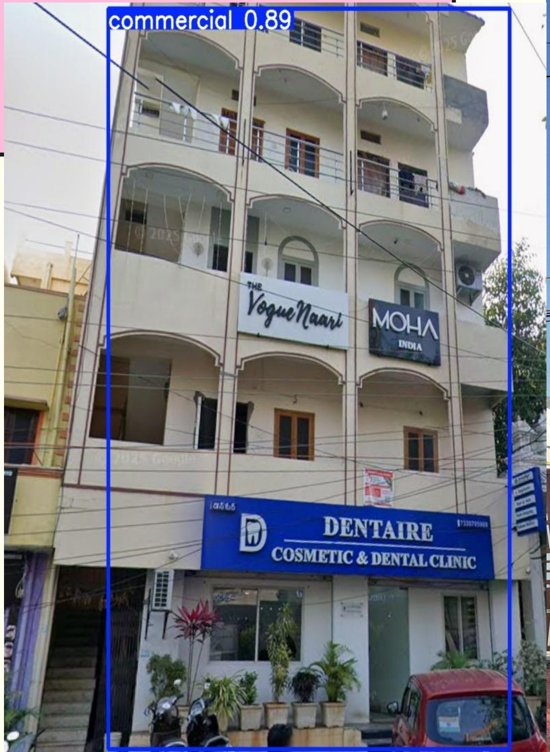
```
moelester@AryanPC: ~/Sem3
    69/100     4.53G     0.699    0.6202     1.127       39       640:  52% ━━━━━━        11/21 3.0s/it 36.8s<30.5
    69/100     4.53G    0.6941    0.6186     1.123       52       640:  57% ━━━━━━        12/21 3.1s/it 39.9s<27.5
    69/100     4.53G    0.6961    0.6145     1.122       51       640:  62% ━━━━━━        13/21 3.1s/it 43.0s<24.5
    69/100     4.53G    0.6948    0.6144     1.124       46       640:  67% ━━━━━━        14/21 3.0s/it 46.0s<21.3
    69/100     4.53G    0.6883    0.6067     1.123       50       640:  71% ━━━━━━        15/21 3.0s/it 48.9s<18.1
    69/100     4.53G    0.6946    0.6107      1.13       43       640:  76% ━━━━━━        16/21 3.0s/it 52.0s<15.2
    69/100     4.53G    0.6895    0.6087      1.13       48       640:  81% ━━━━━━        17/21 3.0s/it 55.1s<12.2
    69/100     4.53G    0.6901    0.6012     1.131       56       640: 100% ━━━━━━        21/21 3.1s/it 1:04
               Class    Images  Instances    Box(P        R     mAP50  mAP50-95): 20% ━━  1/5 6.1s/it 1
               Class    Images  Instances    Box(P        R     mAP50  mAP50-95): 40% ━━  2/5 3.0s/it 3
               Class    Images  Instances    Box(P        R     mAP50  mAP50-95): 60% ━━  3/5 2.6s/it 5
               Class    Images  Instances    Box(P        R     mAP50  mAP50-95): 80% ━━  4/5 2.2s/it 6
               Class    Images  Instances    Box(P        R     mAP50  mAP50-95): 100% ━━ 5/5 1.5s/it
               Class    Images  Instances    Box(P        R     mAP50  mAP50-95): 100% ━━ 5/5 1.5s/it
7.6s
                 all       145        180    0.752    0.543     0.561     0.307

      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
     70/100     4.54G     0.7218     0.6114      1.164         46        640:  48% ━━━━━━  10/21 3.2s/it 33.9s<34.8
     70/100     4.54G     0.7158      0.601      1.159         49        640:  52% ━━━━━━  11/21 3.1s/it 37.0s<31.3
     70/100     4.54G     0.7183     0.5947      1.157         49        640:  57% ━━━━━━  12/21 3.1s/it 40.1s<28.2
     70/100     4.54G     0.7136     0.5899      1.152         62        640:  62% ━━━━━━  13/21 3.2s/it 43.3s<25.2
     70/100     4.54G     0.7171     0.5875      1.148         53        640:  67% ━━━━━━  14/21 3.1s/it 46.5s<22.0
     70/100     4.54G     0.7144     0.5863      1.144         58        640:  71% ━━━━━━  15/21 3.1s/it 49.5s<18.6
     70/100     4.54G     0.7194     0.5837      1.141         71        640:  76% ━━━━━━  16/21 3.1s/it 52.5s<15.4
     70/100     4.54G     0.7127     0.5796      1.135         50        640:  81% ━━━━━━  17/21 3.1s/it 55.8s<12.6
     70/100     4.54G     0.7126      0.575      1.131         57        640: 100% ━━━━━━  21/21 3.1s/it 1:05
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 20% ━━  1/5 5.9s/it 1
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 40% ━━  2/5 3.4s/it 3
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 60% ━━  3/5 2.6s/it 5
```

Results

Table 2: Validation Performance Metrics of YOLOv8n.

Class	Images	Box(P)	Box(R)	mAP50	mAP50-95
all	145	0.657	0.467	0.466	0.213
commercial	85	0.718	0.641	0.729	0.309
mix	34	0.335	0.829	0.600	0.281
religious	11	1.000	0.000	0.094	0.042
residential	15	0.577	0.400	0.441	0.221

Theoretical results of paper



thank you!