# ZASTOSOWANIE MODELU TILE2VEC DLA DANYCH EUROSAT W WARIANCIE MULTISPEKTRALNYM

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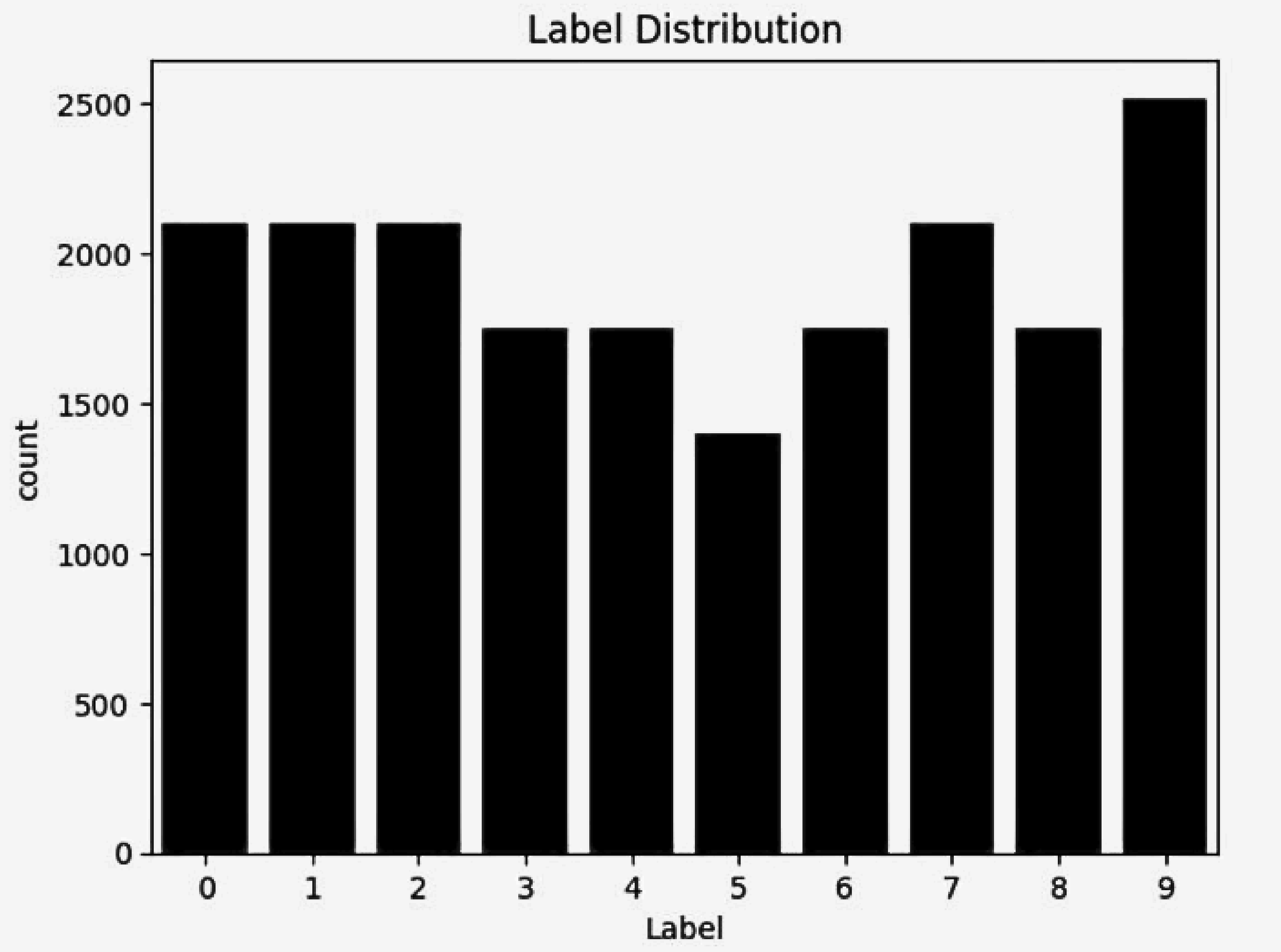
# ZBIÓR DANYCH

## EuroSAT multispectral

https://www.kaggle.com/datasets/apollo2506/eurosat-dataset

Dane satelitarne pochodzące z satelity Sentinel-2 w wariancie wielospektralnym. Dane zawierają etykiety opisujące jakiego rodzaju jest obiekt na zdjęciu.




| | |
|---|---|
| Annual Crop | 0 |
| Forest | 1 |
| Herbaceous Vegetation | 2 |
| Highway | 3 |
| Industrial | 4 |
| Pasture | 5 |
| Permanent Crop | 6 |
| Residential | 7 |
| River | 8 |
| Sea Lake | 9 |

# MODEL TILE2VEC

- Analogia do metod NLP, gdzie słowa o podobnym brzmieniu mają  podobne  znaczenie, tutaj obrazy geograficznie sąsiednie są do siebie podobne
- Unsupervised
- Trenujemy sieć na trójkach płytek: podstawowa (anchor),  sąsiadująca (neighbor) i odległa (distant)
- Działa nie tylko dla danych obrazowych

# HIPOTEZY

# HIPOTEZA 1

## CONTRASTIVE LEARNING

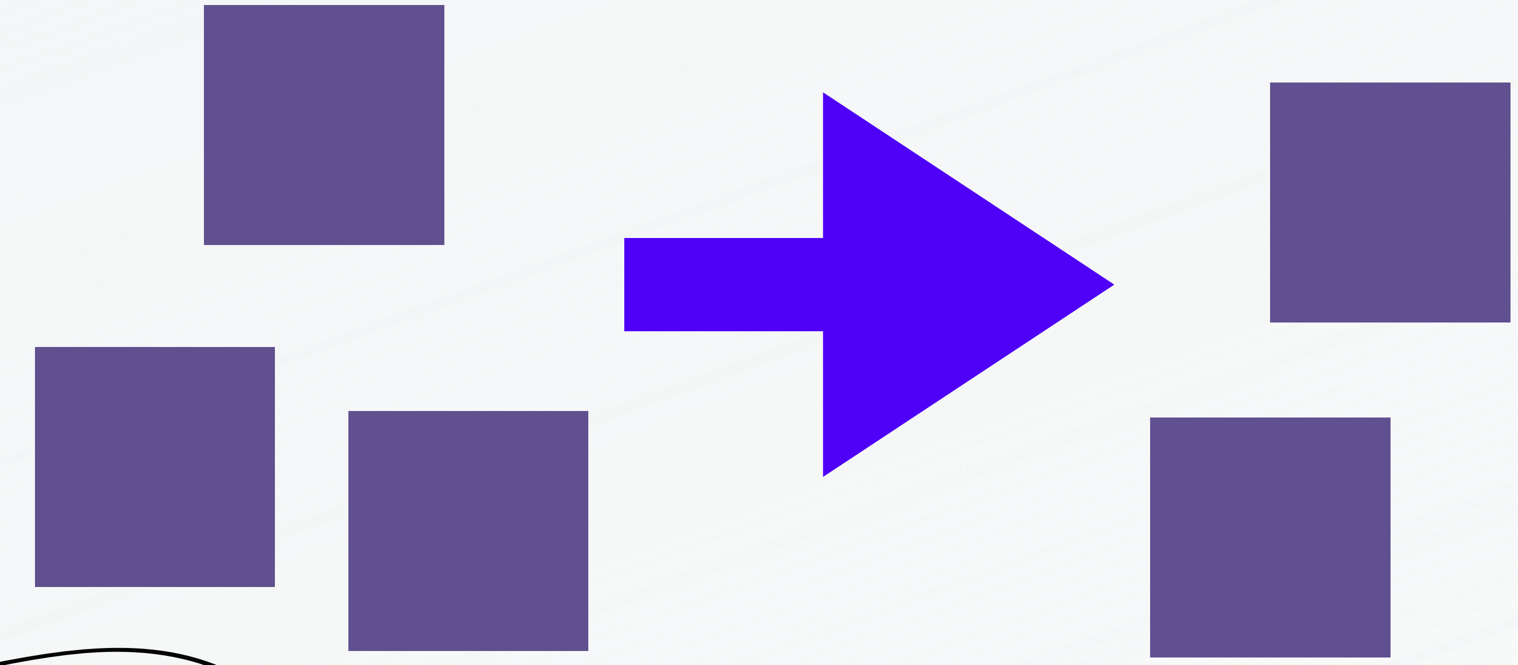
~~TRIPLET LOSS~~

CONTRASTIVE LOSS

# MODYFIKACJE TILE2VEC

## L2 DISTANCE

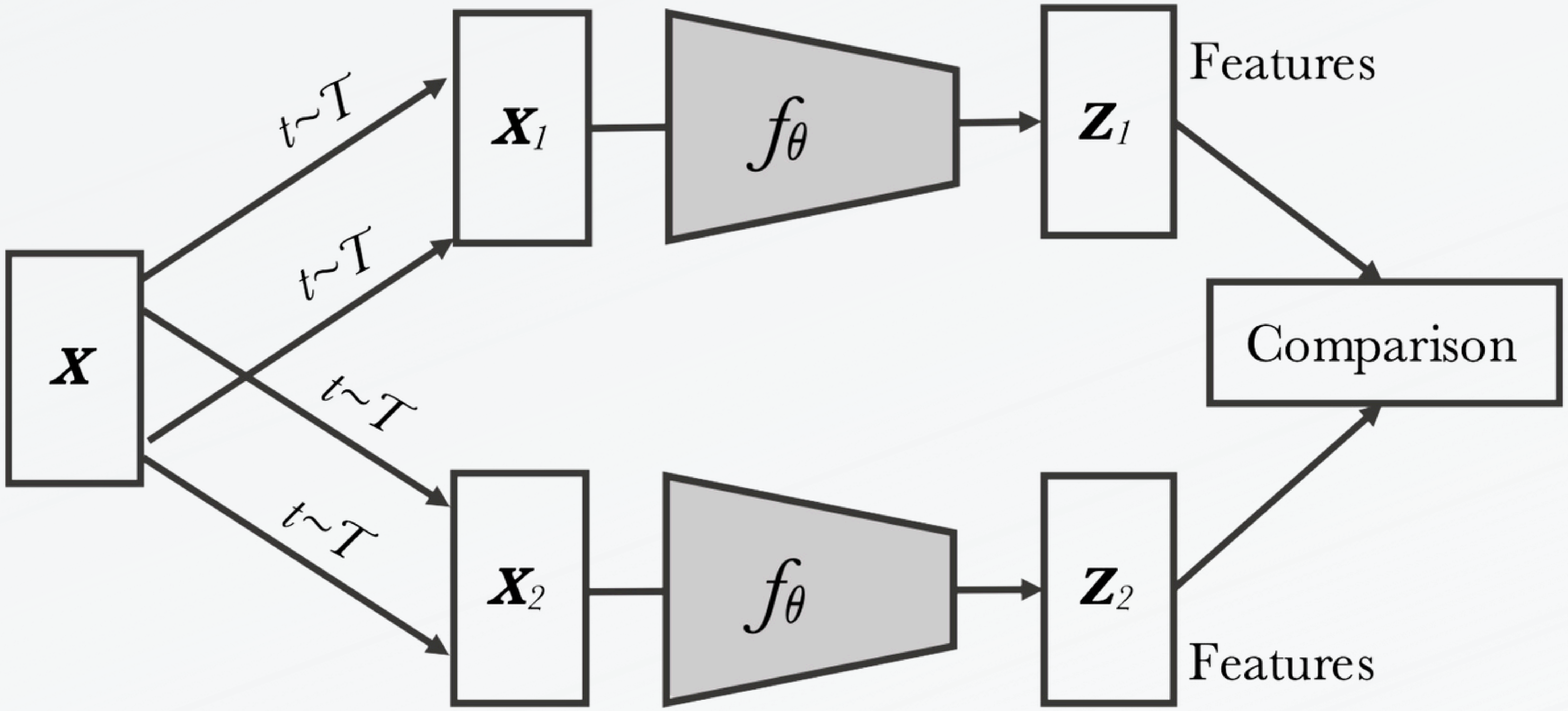
$$\|x-y\|_2=\sqrt{\sum_{i=1}^{n}(x_i-y_i)^2}=\sqrt{(x_1-y_1)^2+(x_2-y_2)^2+\ldots+(x_n-y_n)^2}$$



## COSINE SIMILARITY

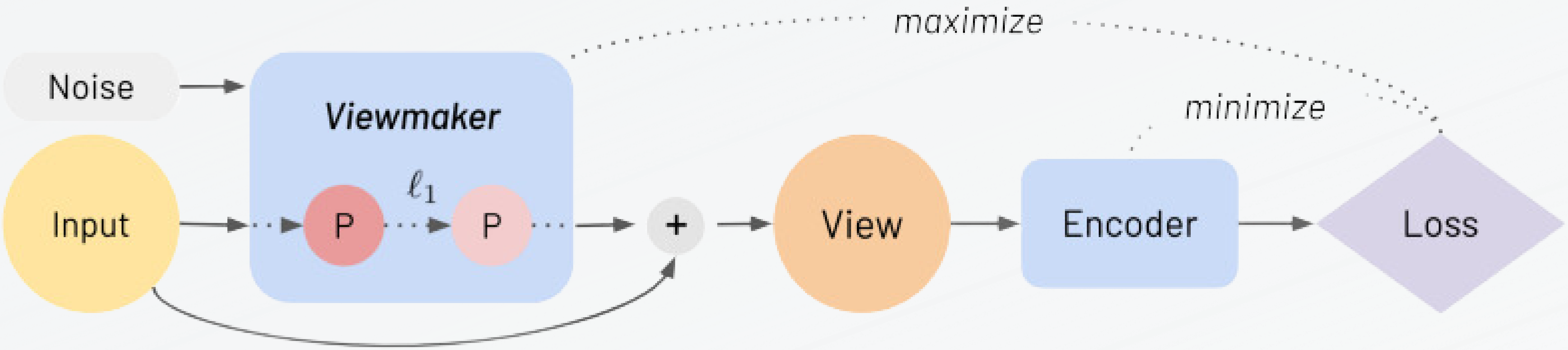
$$cos(\theta)=\frac{x\cdot y}{||x||\cdot||y||}$$

# SIMPLIFIED SIMCLR



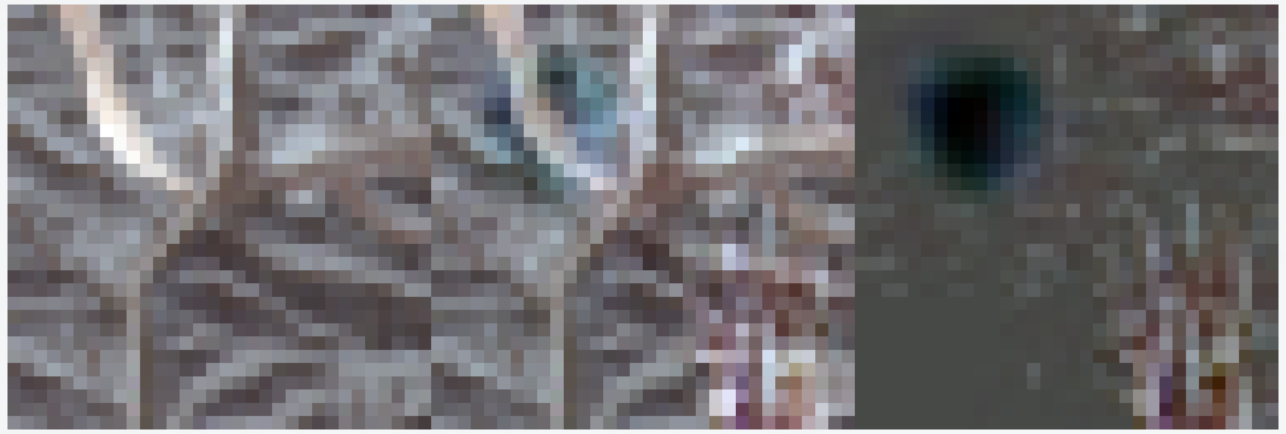

**THE MOST BASIC CONTRASTIVE LEARNING FRAMEWORK WITH ROBUST IMPLEMENTATION**

# VIEWMAKER

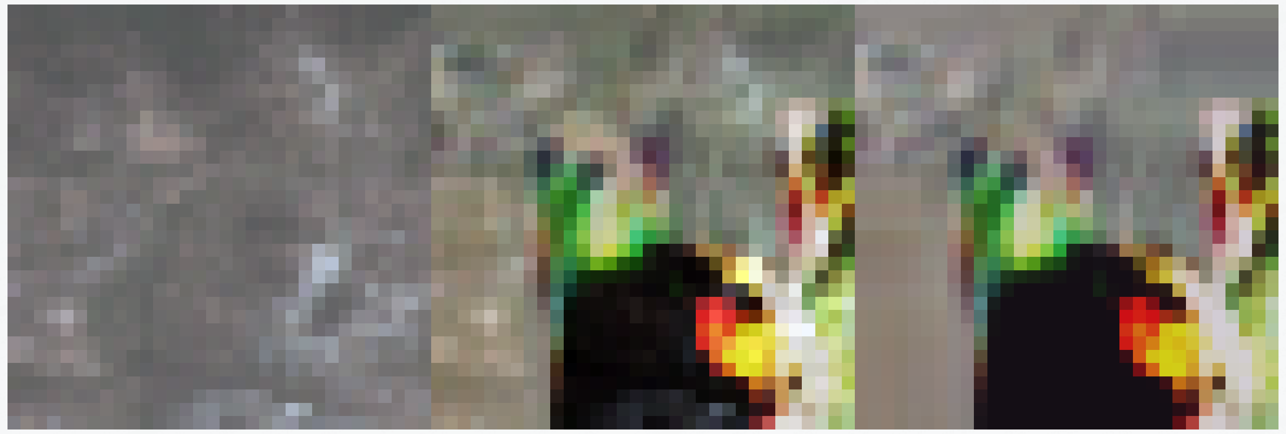



STOCHASTIC ADVERSARIAL VIEWS RESTRICTED TO L1 SPHERE AROUND THE INPUT

# DIVMAKER VS VIEWMAKER



VIEWMAKER
ADVERSARIAL VIEW GENERATION

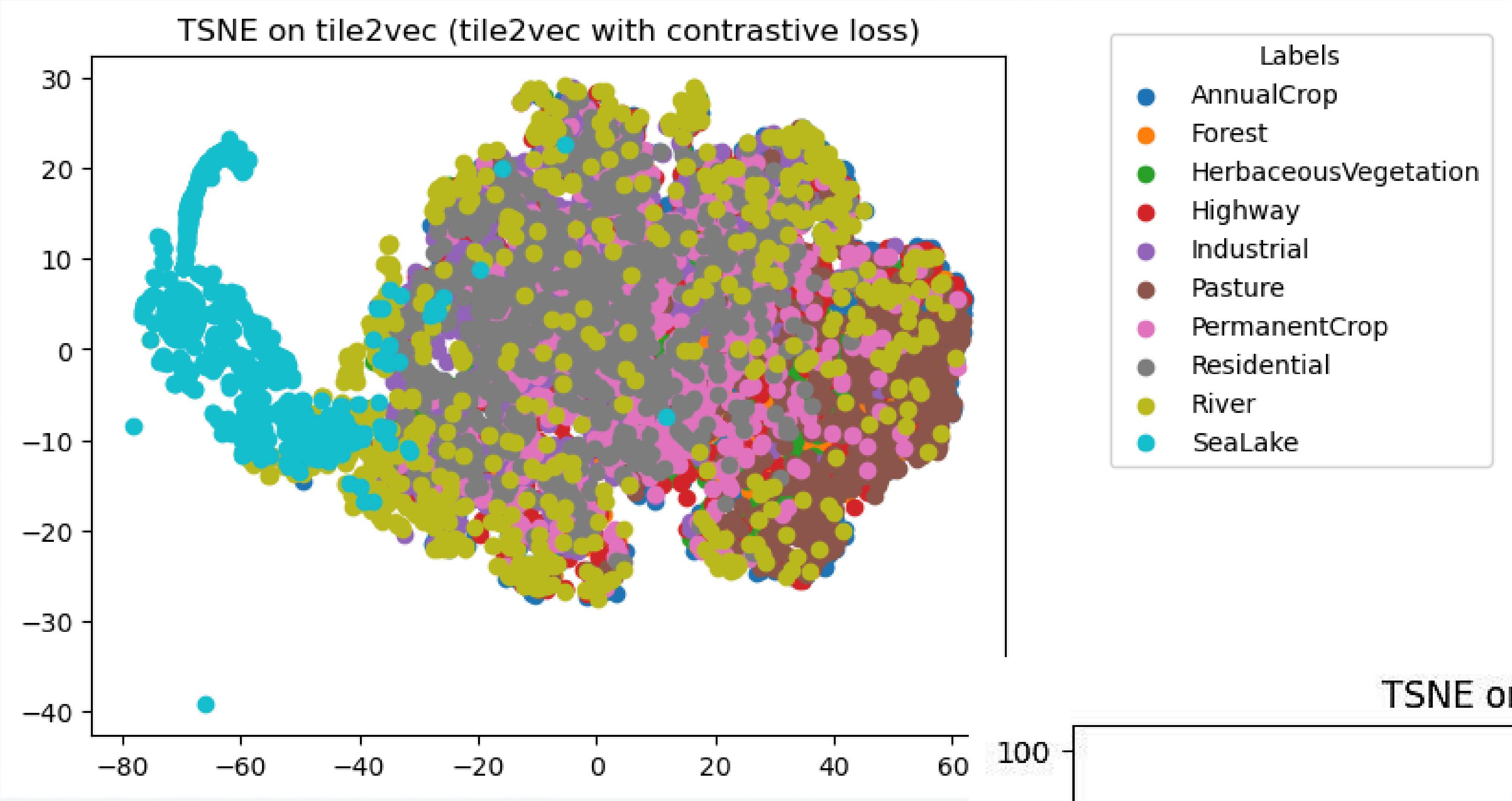


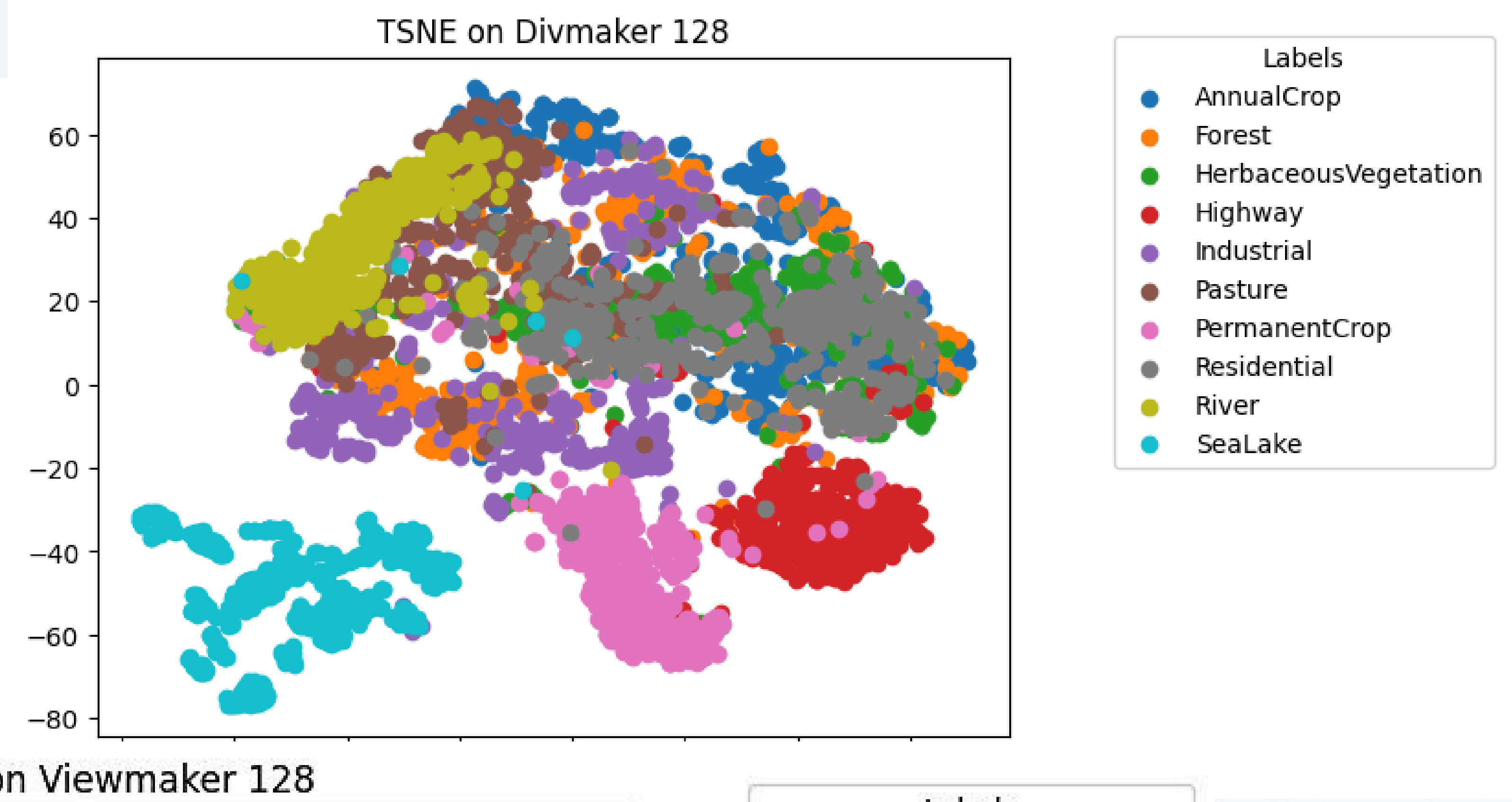
DIVMAKER
VIEW GENERATION FOR DIVERSITY OF AUGUMENTED VIEWS

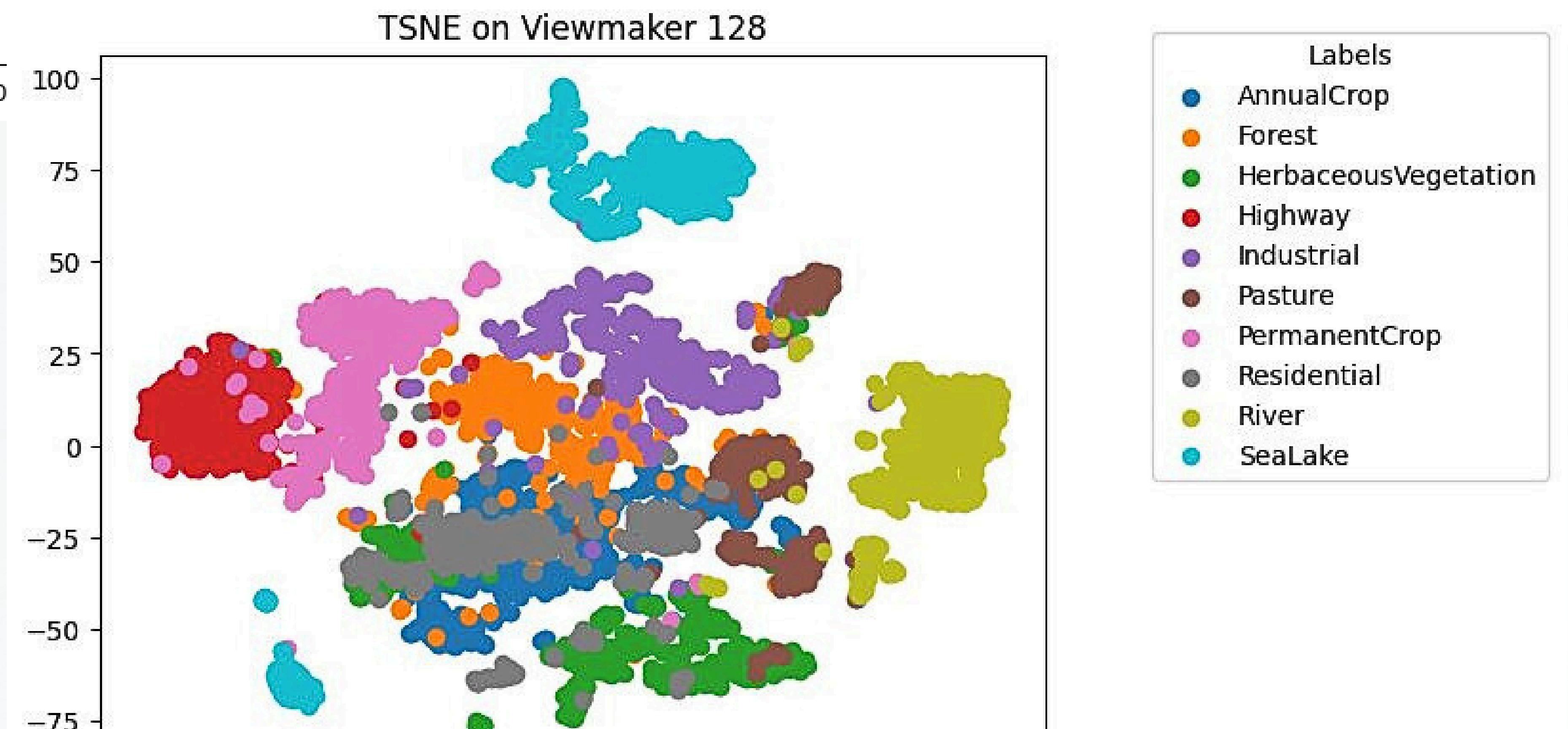
# SIMCLR, DIVMAKER, VIEWMAKER

| Typ modelu | accuracy | v-measure | silhouette |
|---|---|---|---|
| contrastive tile2vec | 44.79±0.98% | 0.26±0.01 | 0.30±0.01 |
| contrastive tile2vec (cos) | 44.41±0.77% | 0.26±0.01 | 0.33±0.01 |
| SimCLR | 86.09±0.50% | 0.15±0.01 | 0.03±0.01 |
| Viewmaker 512 | 92.83±0.60% | 0.54±0.02 | 0.10±0.01 |
| Viewmaker 128 | 94.08±0.35% | 0.51±0.01 | 0.10±0.01 |
| Divmaker 512 | 62.16±1.74% | 0.32±0.01 | 0.29±0.01 |
| Divmaker 128 | 84.57±1.79% | 0.50±0.01 | 0.19±0.01 |

# WYNIKI UCZENIA KONTRASTOWEGO



# HIPOTEZA 2
## HARD NEGATIVE MINING

# WYBÓR PŁYTEK

~~RANDOM~~

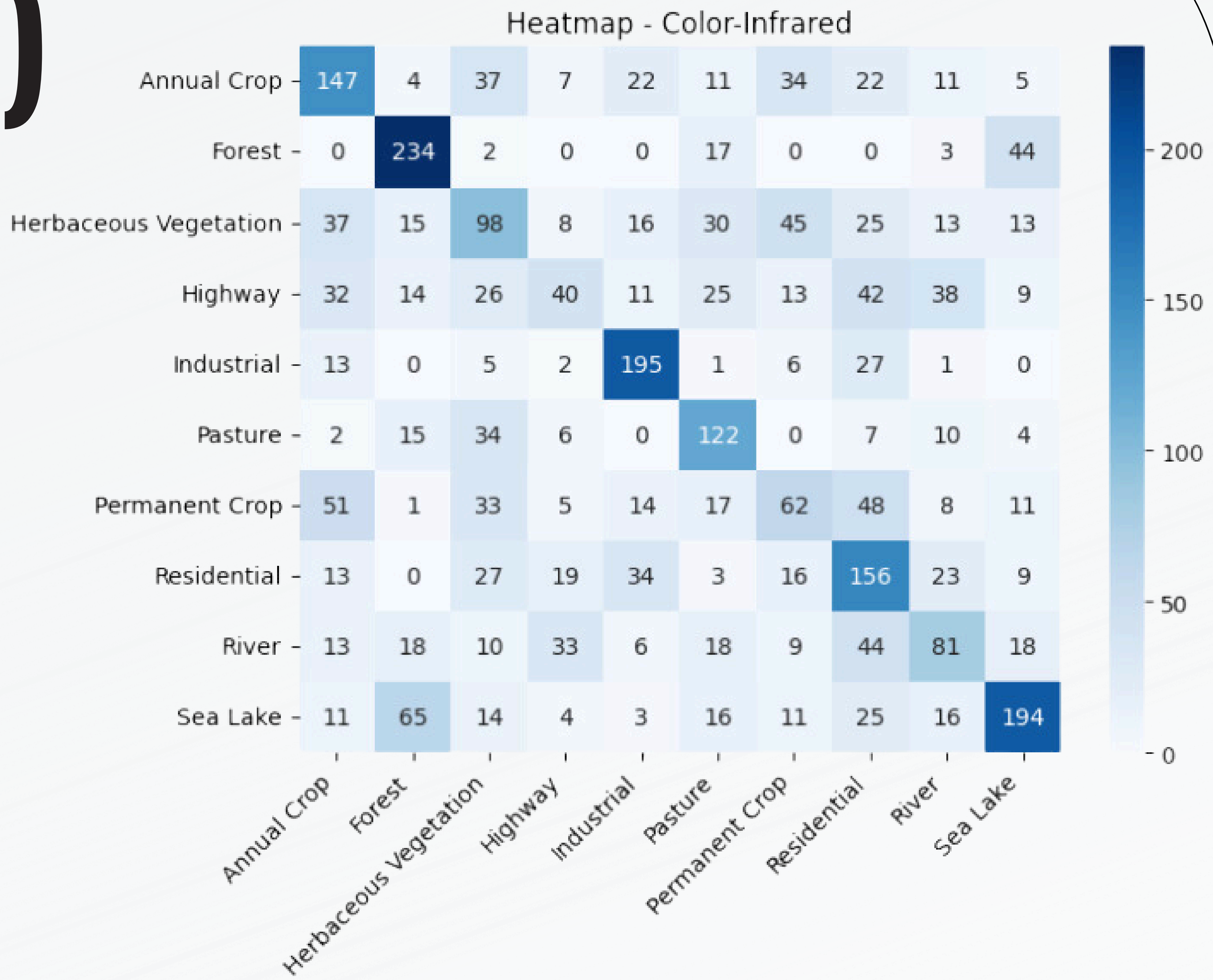
LABELS

# WYNIKI HARD MINING

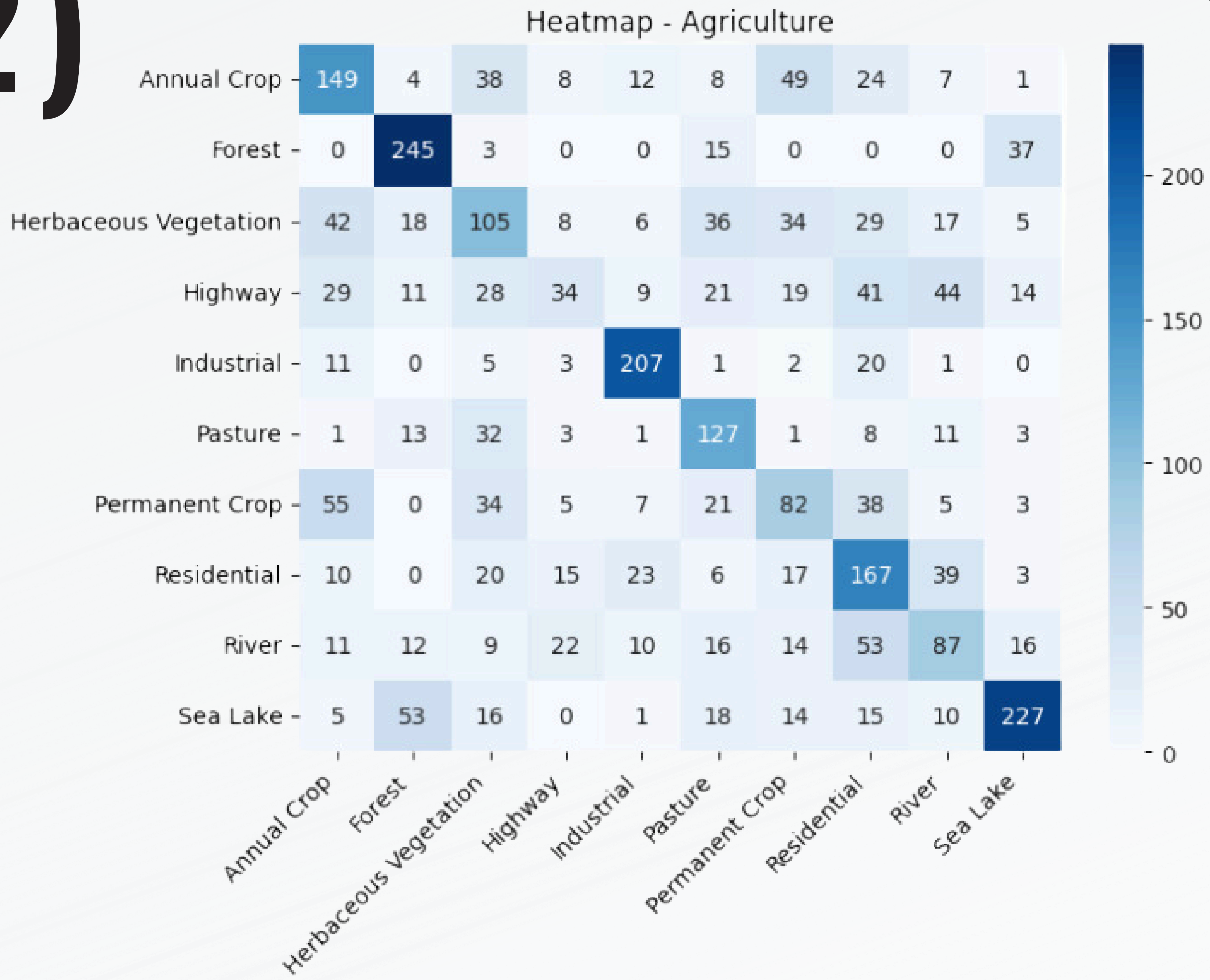
| Model Name | Accuracy |
| --- | --- |
| Our tile2vec | 55.88 ± 0.73 |
| Hard Negative Mining | 65.92 ± 0.71 |

# HIPOTEZA 3
# PRACTICAL APPLICATION

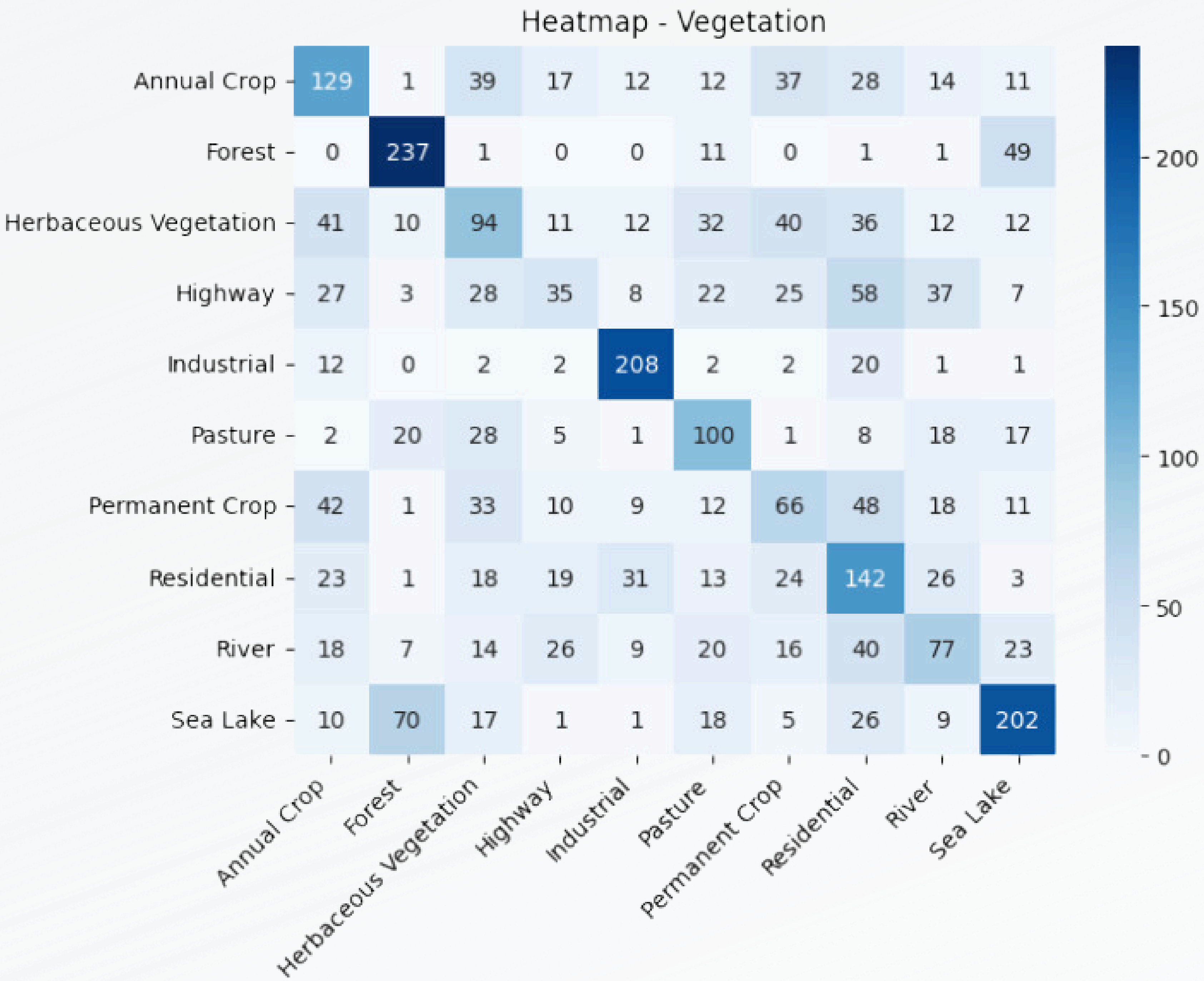
# COLOR INFRARED (B8, B4, B3)



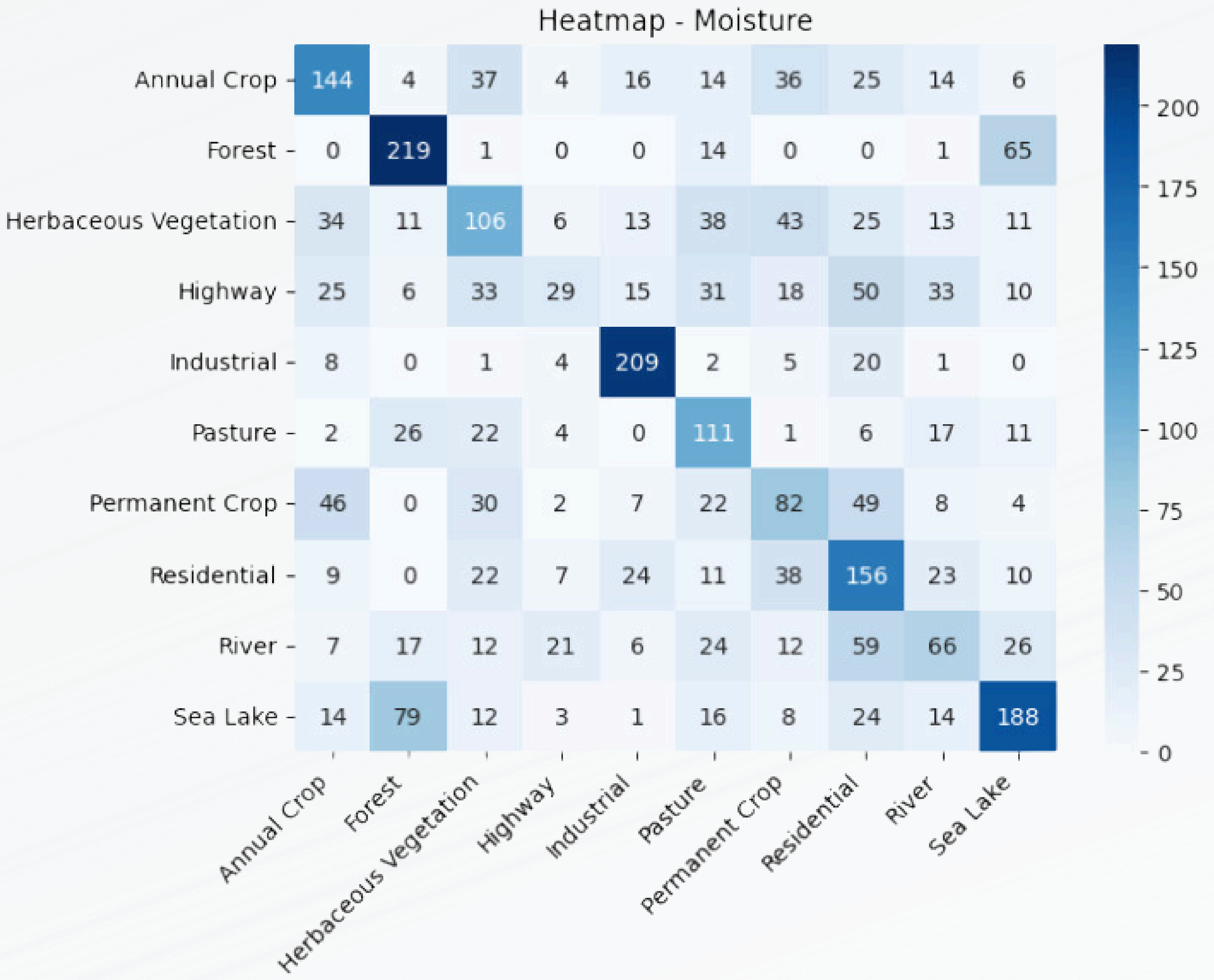
# AGGRICULTURE (B11, B8, B2)



# VEGETATION INDEX (B8 - B4)/(B8 + B4)



# MOISTURE INDEX (B8A-B11)/(B8A + B11)



# PORÓWNANIE WYNIKÓW

| | | wszystkie bandy | color-infrated | agriculture | vegetation | moisture |
|---|---|---|---|---|---|---|
| 0 | Annual Crop | 57.39% | 47.61% | 48.31% | 44.04% | 44.77% |
| 1 | Forest | 89.38% | 77.94% | 80.88% | 79.21% | 77.83% |
| 2 | Herb. Vegetation | 41.42% | 35.19% | 36.15% | 32.77% | 33.79% |
| 3 | Highway | 17.39% | 11.66% | 14.35% | 16.30% | 10.45% |
| 4 | Industrial | 37.77% | 78.99% | 86.29% | 84.26% | 83.83% |
| 5 | Pasture | 57.52% | 62.68% | 63.97% | 53.66% | 58.30% |
| 6 | Permanent Crop | 39.72% | 26.36% | 29.65% | 28.46% | 29.55% |
| 7 | Residential | 49.49% | 53.02% | 53.57% | 45.92% | 52.29% |
| 8 | River | 75.63% | 32.16% | 31.94% | 28.40% | 26.93% |
| 9 | Sea Lake | 99.26% | 57.46% | 64.10% | 58.91% | 55.67% |

# WNIOSKI

VIEWMAKER:

HARD NEGATIVE MINING:

# DOSTOSOWANE MODELE

- zauważalne są drobne zależności między dostosowanymi modelami, a wynikami
- zależności te jednak nie są mocno zauważalne
- wpływ różnych modeli na wyniki nie jest jednoznaczny
- model agriculture ma najlepsze wyniki na większości labeli
- na 3 labelach dostosowane modele działają lepiej niż podstawowy model

# DZIĘKUJEMY ZA UWAGĘ

# LITERATURA

[1] https://github.com/ermongroup/tile2vec.

[2] https://www.kaggle.com/datasets/apollo2506/eurosat-dataset.

[3] Jasmine Bayrooti, Noah Goodman, and Alex Tamkin. Multispectral contrastive learning with viewmaker networks, 2023.

[4] Alex Tamkin, Mike Wu, and Noah Goodman. Viewmaker networks: Learning views for unsupervised representation learning, 2021.