

May 2026

Problem Statement

PREDICTING HOUSING PRICES USING SATELLITE VIEW IMAGERY

Aimed Contribution;

“Help buyers identify underpriced or overpriced properties relative to comparable nearby alternatives, while explaining the latent trade offs responsible for the price difference.”

BY

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Literature Review-1

BENCY, ARCHITH J, RALLAPALLI S, GANTI RK, SRIVATSA M, S MB. BEYOND SPATIAL AUTO-REGRESSIVE MODELS: PREDICTING HOUSING PRICES WITH SATELLITE IMAGERY. ARXIV.ORG. PUBLISHED 2016. ACCESSED MAY 18, 2026. [HTTPS://ARXIV.ORG/ABS/1610.04805](https://arxiv.org/abs/1610.04805)

Methodology,

Map Static

Learn neighbourhood using spatial features in three groups using estimators-

Deep features(from Deep Convolutional networks),

House attributes are composed of number of bedrooms, bathrooms, reception rooms and floors.)

Point of Interest data(86 tags like cafe, beauty salon, clothing store and post office)

Accuracy,

Best when we combine Deep features and Point of Interest data suggesting that they are complementary(Shown in Table on next slide.)

Popular methods included **Decision Trees, MLP, Random Forests, Support Vector Machines (SVM), and Neural Networks**. They are preferred as they can handle the non-linear, high dimensional data and influence of features on each other more effectively than linear models.

GAP:WE ARE NOT ONLY CHECKING THE HOUSE ITSELF, BUT ITS SURROUNDINGS AS WELL.

Literature Review-2

1.

DE FIGUEIREDO OLIVEIRA AB, CASTELLI M, SUEL E. PREDICTING HOUSING PRICE, HOUSING DENSITY, AND GREEN AREA COVERAGE FROM COMBINED SATELLITE AND STREET VIEW IMAGERY USING DEEP LEARNING. DISCOVER CITIES. 2025;2(1). DOI:10.1007/S44327-025-00109-8

Methodology:

DL models for environmental analysis using remote sensing and SVI .

Images were 224×224 pixels in size with three channels (RGB) representing the red, green, and blue color components. Each input passed through a data augmentation layer with random transformations, followed by the **pre-trained EfficientNetB0** mode. EfficientNetB7, ResNet50V2, Xception , Accuracy:

1)34% for 4,054,695 parameters for EfficientNetB0

2)36% for 23,572,996 parameters for ResNetV2

3)39% for 20,869,676 parameters for Xception

SVI, IN PARTICULAR, IS FREQUENTLY USED TO ANALYZE HUMAN PERCEPTION OF URBAN ENVIRONMENTS

Table 2 Comparison of evaluation metrics between the models

Metric	Model		
	Price	Housing density	Green area
Time for training (hours) (30 epochs)	19.2	18.9	18.6
Accuracy Training (Best validation epoch)	73%	75%	69%
Accuracy Validation (Best validation epoch)	56%	62%	55%
Accuracy Test (Best validation epoch)	54%	60%	53%
Macro-Average Precision Test	0.49	0.57	0.55
Macro-Average recall Test	0.49	0.52	0.53
Macro-Average F1 score Test	0.49	0.54	0.53
Average AUC (one-vs-all) Test	0.66	0.69	0.68
Standard Deviation AUC Test	0.01	0.03	0.05
MAE Test	0.58	0.47	0.55

Literature Review-3

BELL AJ, SOLANO-KAMAIKO I, NOV O, STOYANOVICH J. IT'S JUST NOT THAT SIMPLE: AN EMPIRICAL STUDY OF THE ACCURACY-EXPLAINABILITY TRADE-OFF IN MACHINE LEARNING FOR PUBLIC POLICY. PUBLISHED ONLINE JUNE 20, 2022. DOI:10.1145/3531146.3533090

Methodology:

Used 2 policy use cases-Housing and Education

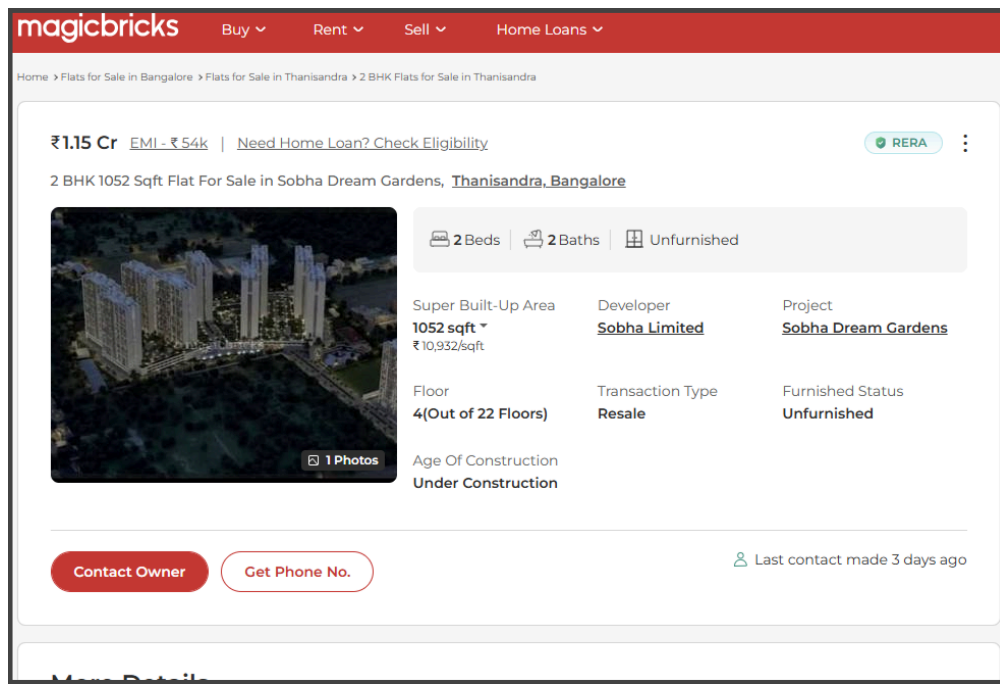
Collected Data via Exploratory Data Analysis(EDA)

Used 8 model types for different policy use-case

- 3 Black box models(XGBoost, extra trees, random forests)
- 4 interpretable models(decision tree, linear regression - Ridge, linear regression - Lasso, logistic regression)
- 1 dummy classifier for baseline

Use Post Hoc analysis such as LIME, QII, SHAP, and SAGE to explain black box models,

Providing More information to users on ML explanation confuses users due to information overload.



Data Collection

Accurately labeled training data is often difficult to obtain and usually depends on third party sources, such as governmental or private organizations

DE FIGUEIREDO OLIVEIRA AB, CASTELLI M, SUEL E. PREDICTING HOUSING PRICE, HOUSING DENSITY, AND GREEN AREA COVERAGE FROM COMBINED SATELLITE AND STREET VIEW IMAGERY USING DEEP LEARNING. DISCOVER CITIES. 2025;2(1). DOI:10.1007/S44327-025-00109-8

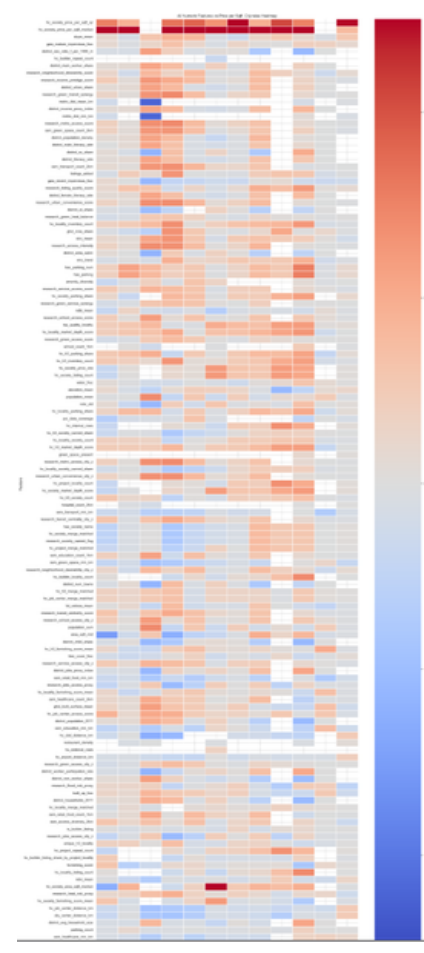
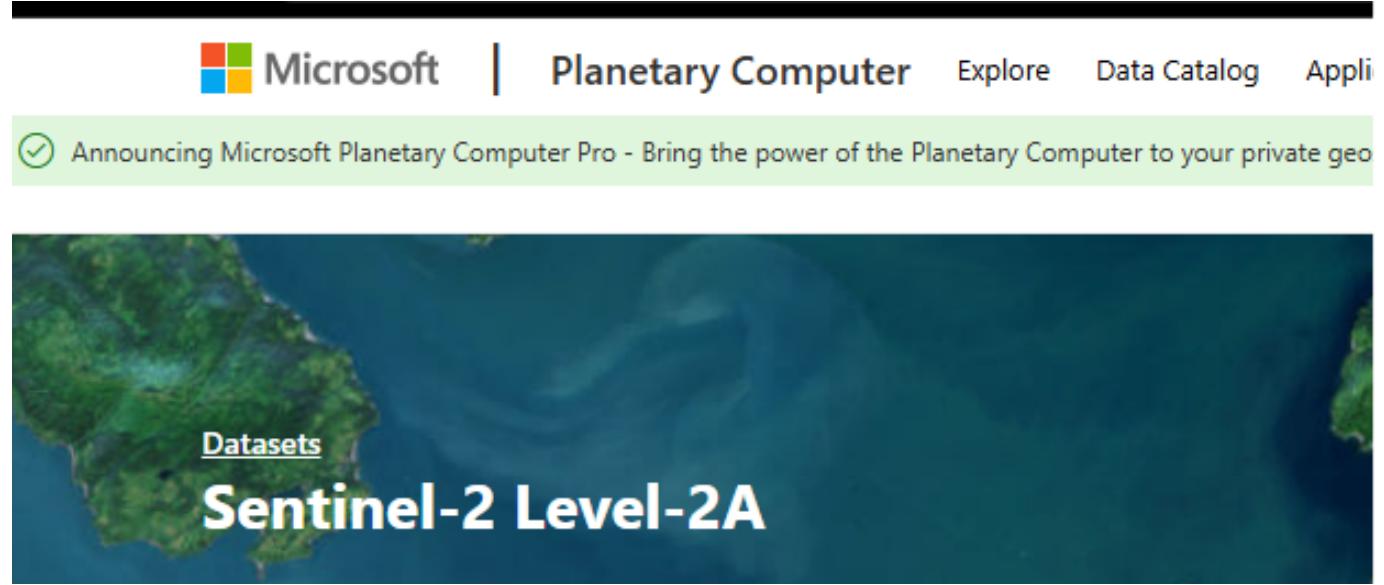
Scraped Realestate Listings on MagicBricks And satellite Data from GEE

Google Earth Engine

Tabular datasets like percentage conc., night time light



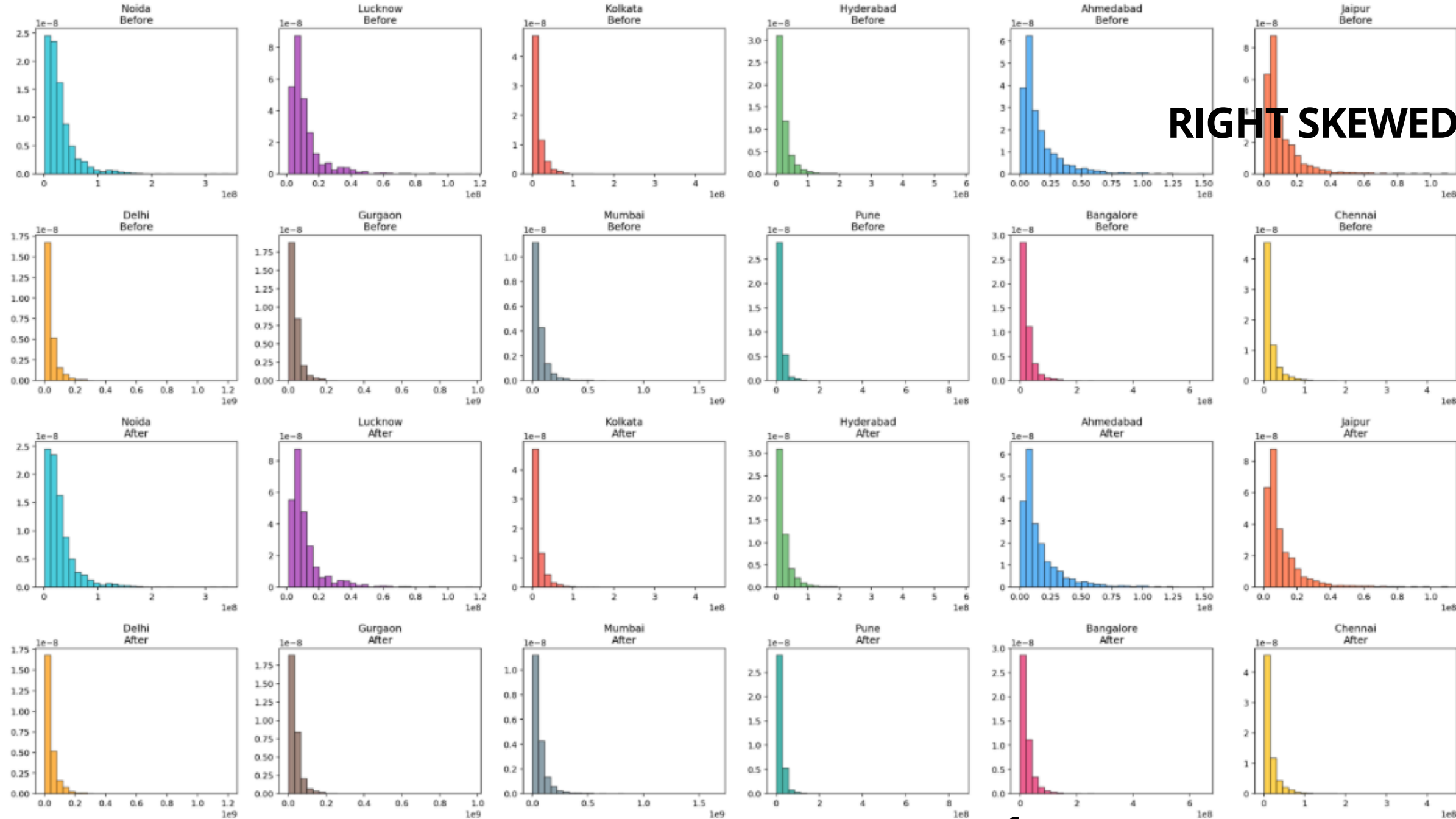
image embeddings



Preprocessing

Price-per-sqft distribution before vs after rental flagging

Price-per-sqft Distributions Before vs After Removing Suspected Rentals



RIGHT SKEWED DATA → Log transformation

Log(price)

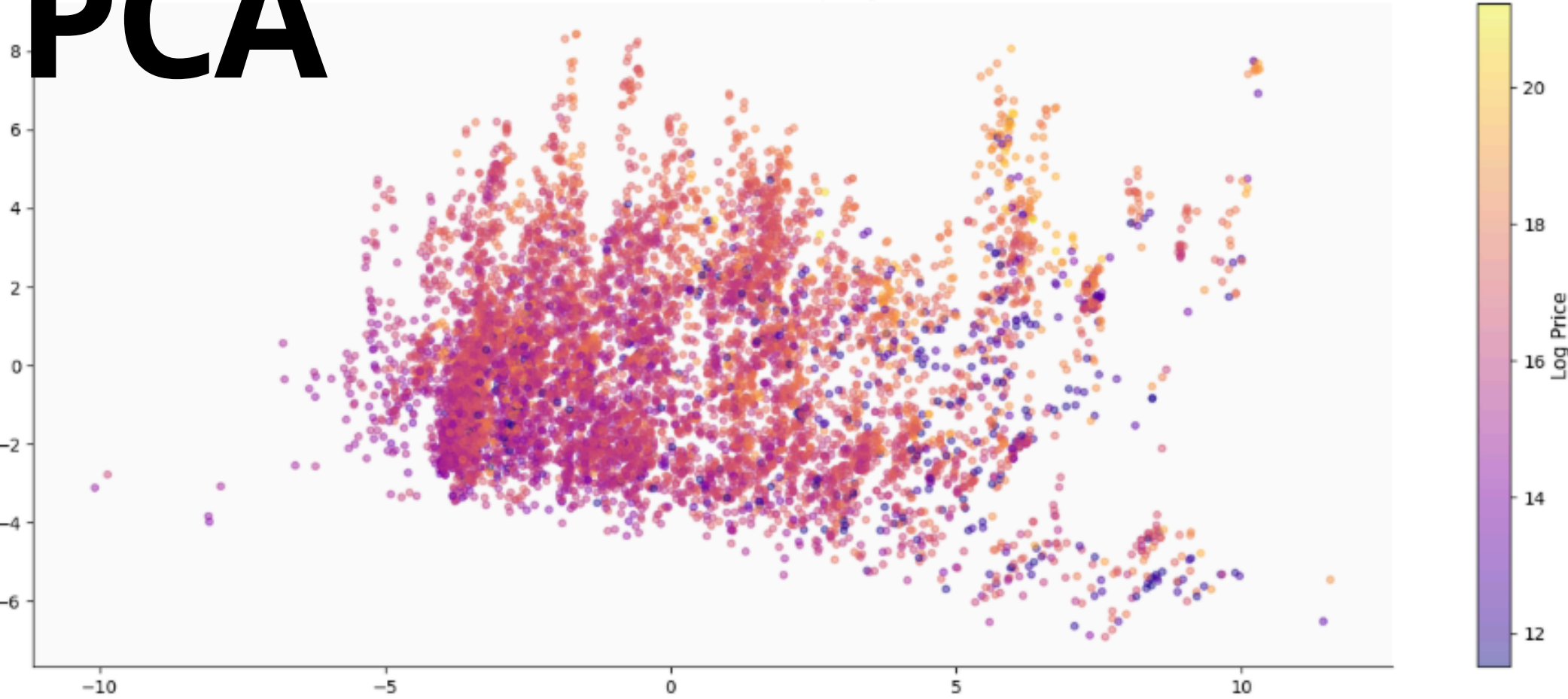
1.

Zhou S. Investigation of Influential Factors of Housing Price. Advances in Economics, Management and Political Sciences. 2024;105(1):64-71. doi:10.54254/2754-1169/105/20241950

Preprocessing

PCA

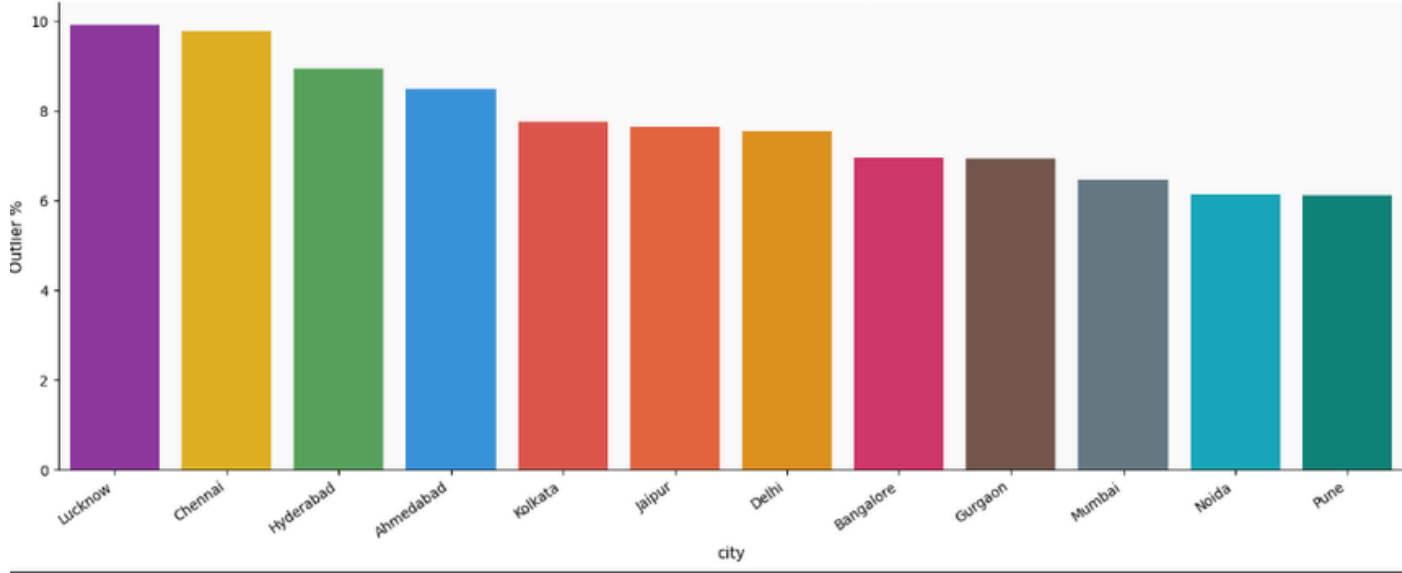
PCA — PC1 vs PC2 coloured by Log Price



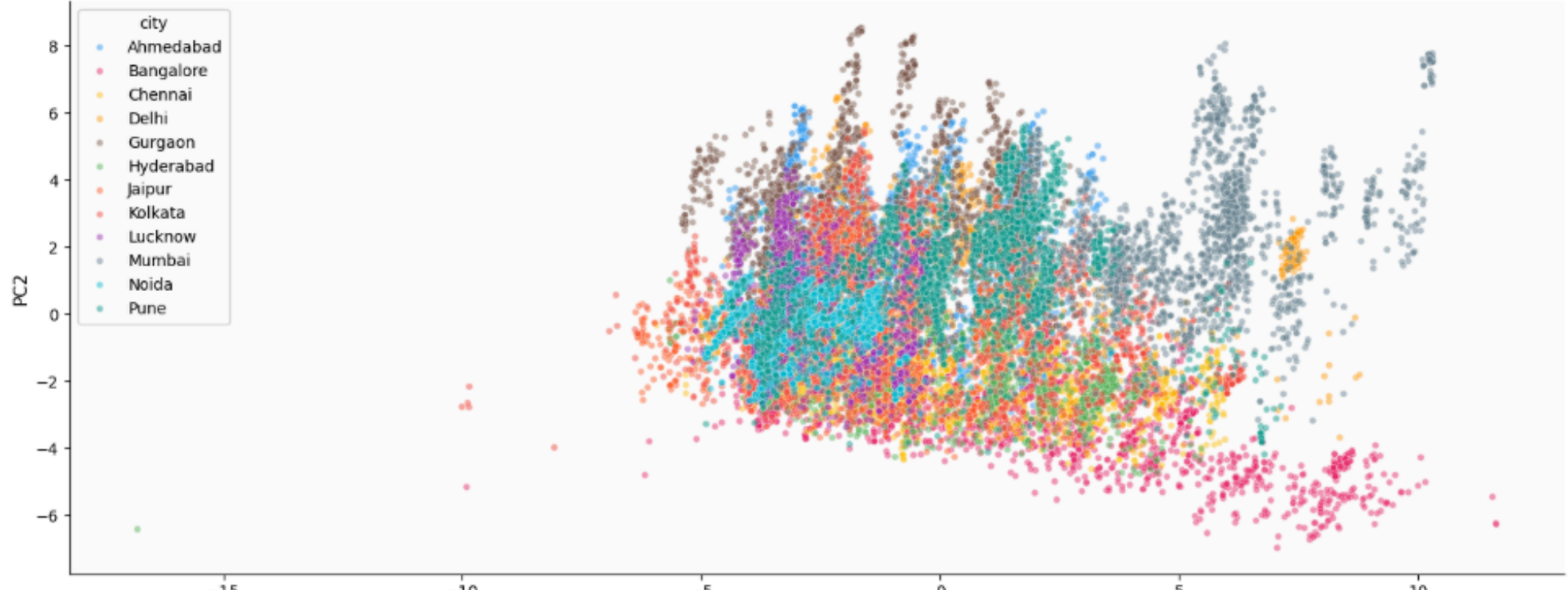
OUTLIER REMOVAL (IQR)

city	mean	median	std	iqr	skewness
Ahmedabad	16,843,375.25	10,000,000.00	18,529,002.26	14,415,000.00	2.72
Bangalore	24,542,453.14	16,450,000.00	30,640,804.26	21,500,000.00	5.42
Chennai	17,231,053.17	9,500,000.00	25,009,820.56	13,200,000.00	6.40
Delhi	41,403,872.26	28,500,000.00	59,815,049.14	37,500,000.00	8.22
Gurgaon	36,762,560.79	26,300,000.00	49,950,984.32	26,200,000.00	9.09
Hyderabad	25,844,753.01	16,400,000.00	34,854,839.64	19,000,000.00	7.13
Jaipur	11,677,566.18	6,900,000.00	14,040,889.56	10,000,000.00	3.32
Kolkata	14,826,368.42	8,500,000.00	20,735,194.93	14,150,000.00	5.94
Lucknow	11,685,684.79	8,200,000.00	11,422,684.53	7,700,000.00	3.09
Mumbai	63,863,659.42	41,950,000.00	91,246,989.97	66,000,000.00	5.94
Noida	29,750,070.19	21,000,000.00	29,753,533.51	26,500,000.00	3.05
Pune	19,058,689.06	12,100,000.00	28,333,925.27	17,125,000.00	14.43

IQR-Based Outlier Share by City



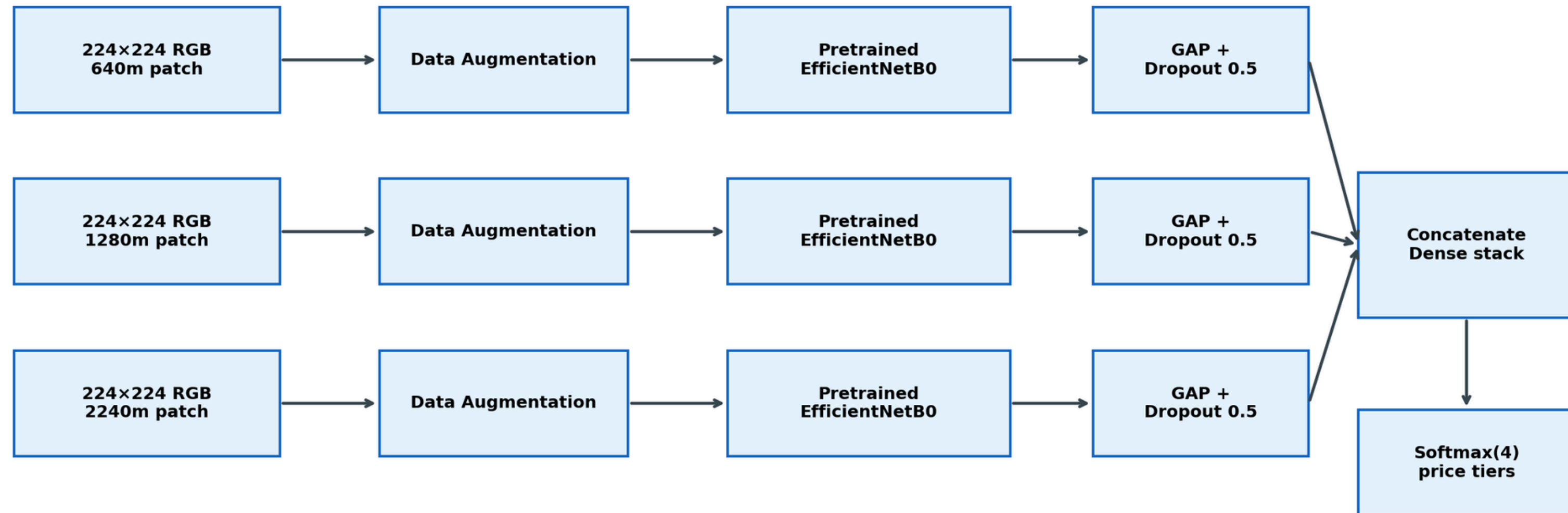
PCA — PC1 vs PC2 coloured by City



Sattelite Image embeddings

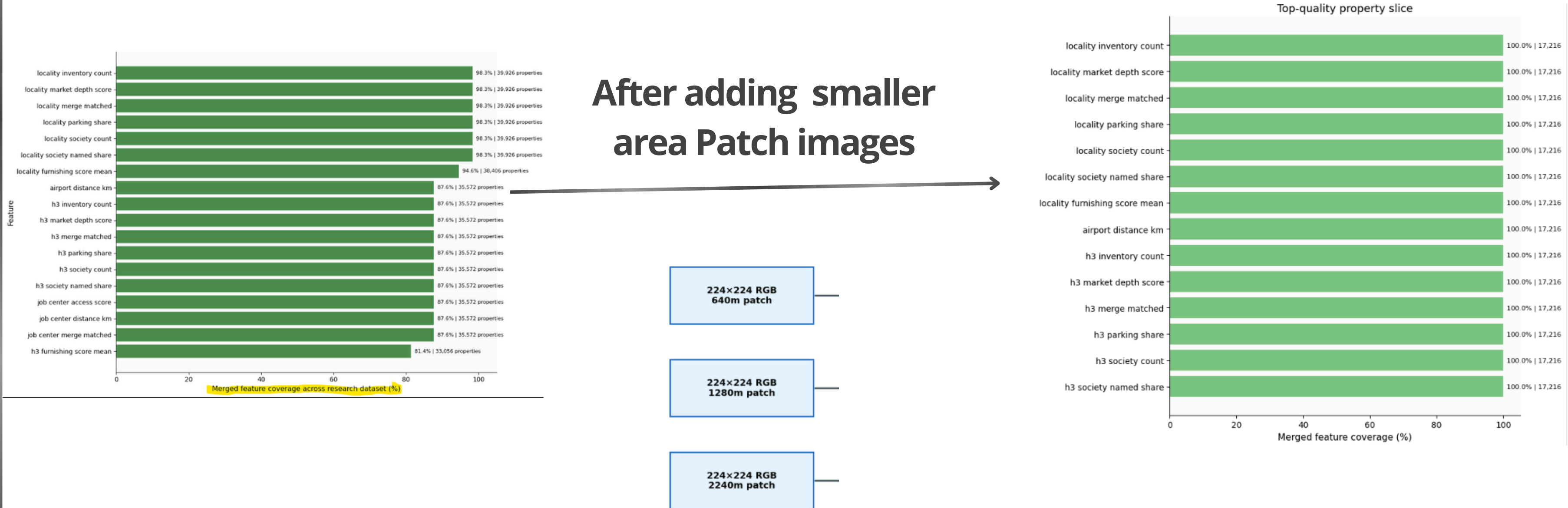


Future-Work Multiscale EfficientNetB0 Architecture



Preprocessing

Sattelite Merging



Transfer Learning

EfficientNetB0+MLP

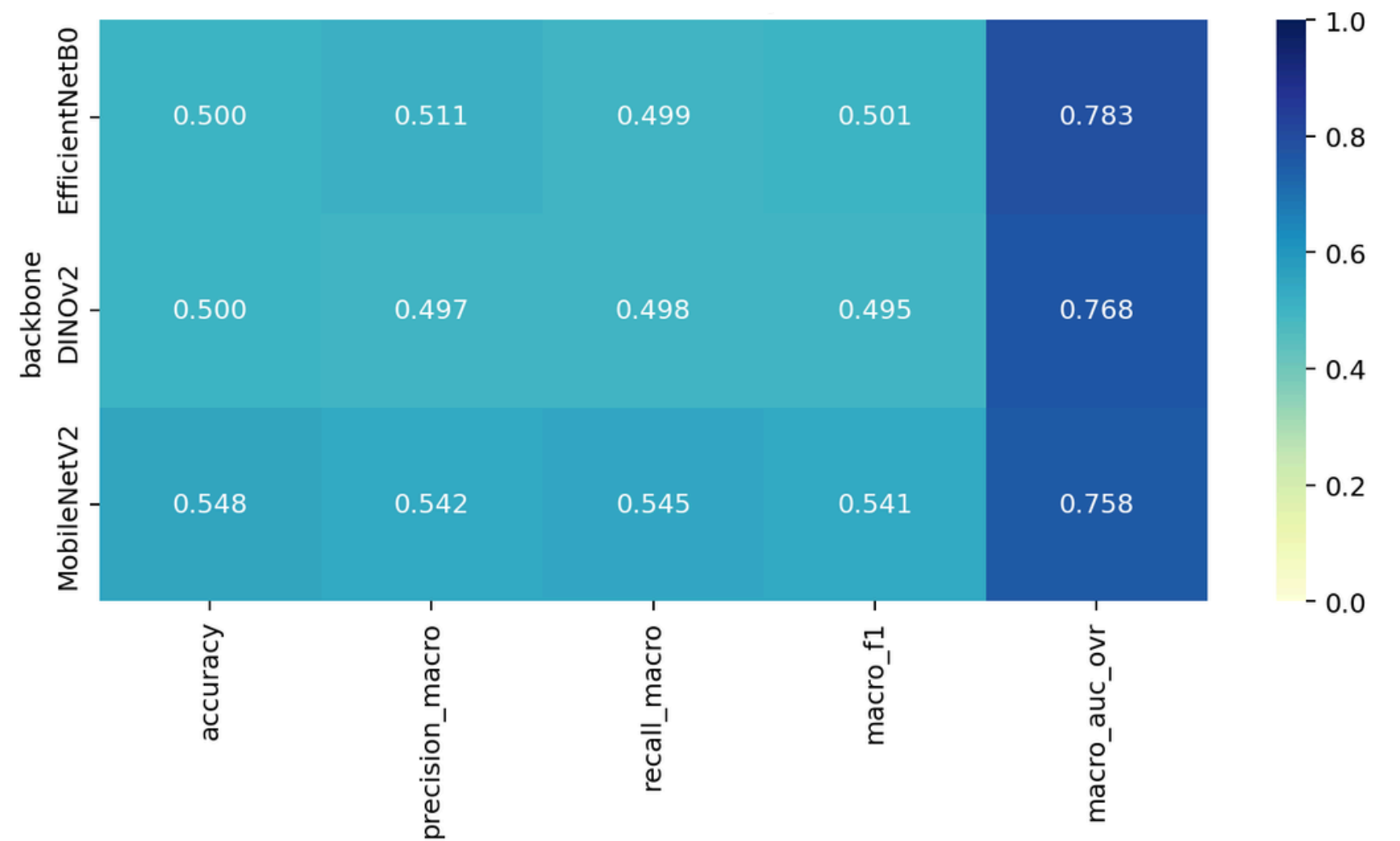
accuracy = 0.500

precision_macro = 0.511

recall_macro = 0.499

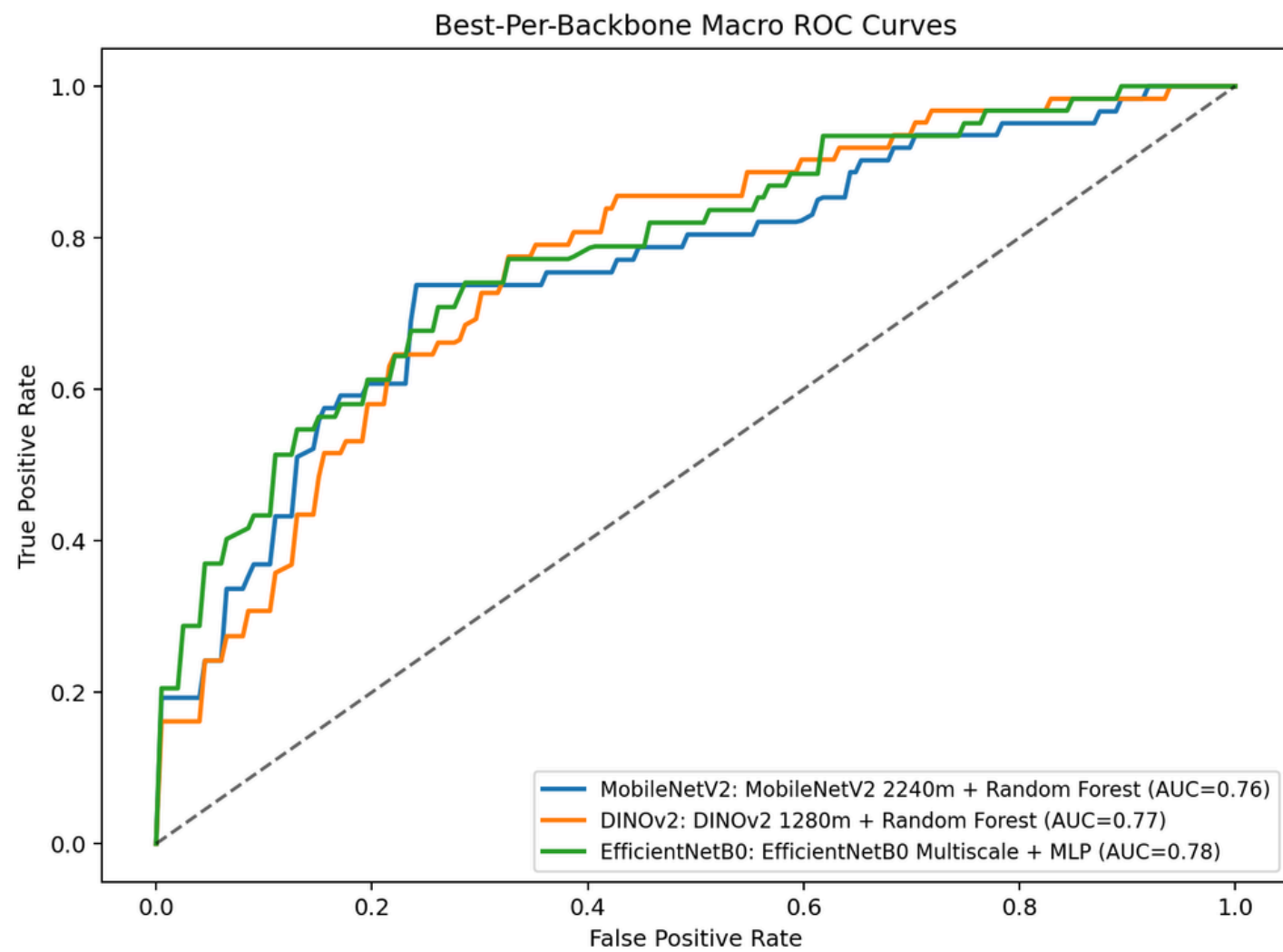
macro_f1 = 0.501

macro_auc_ovr = 0.783

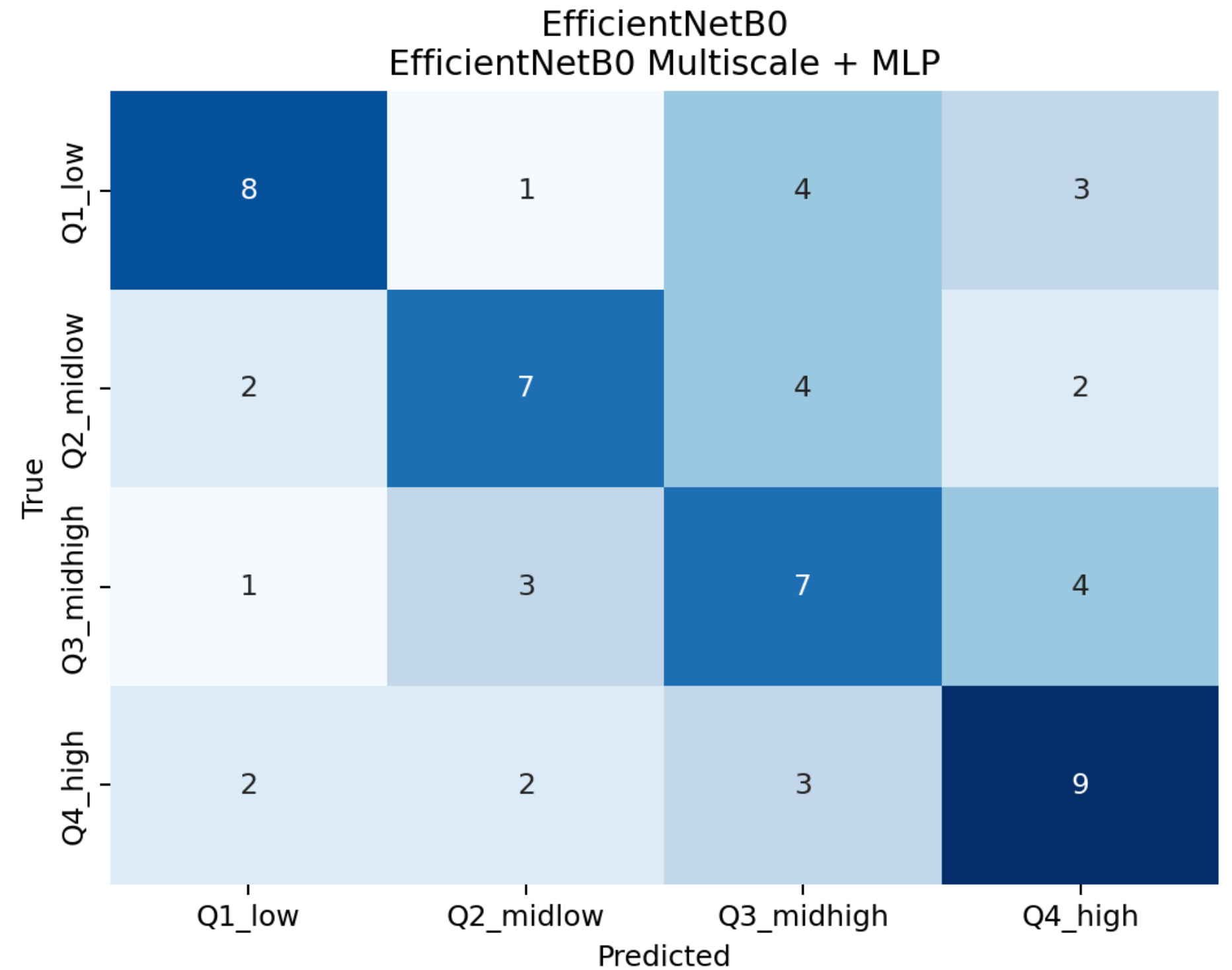


Transfer Learning

EfficientNetB0+MLP



AUC = 0.78



Transfer Learning

DINOv2+RandomForest

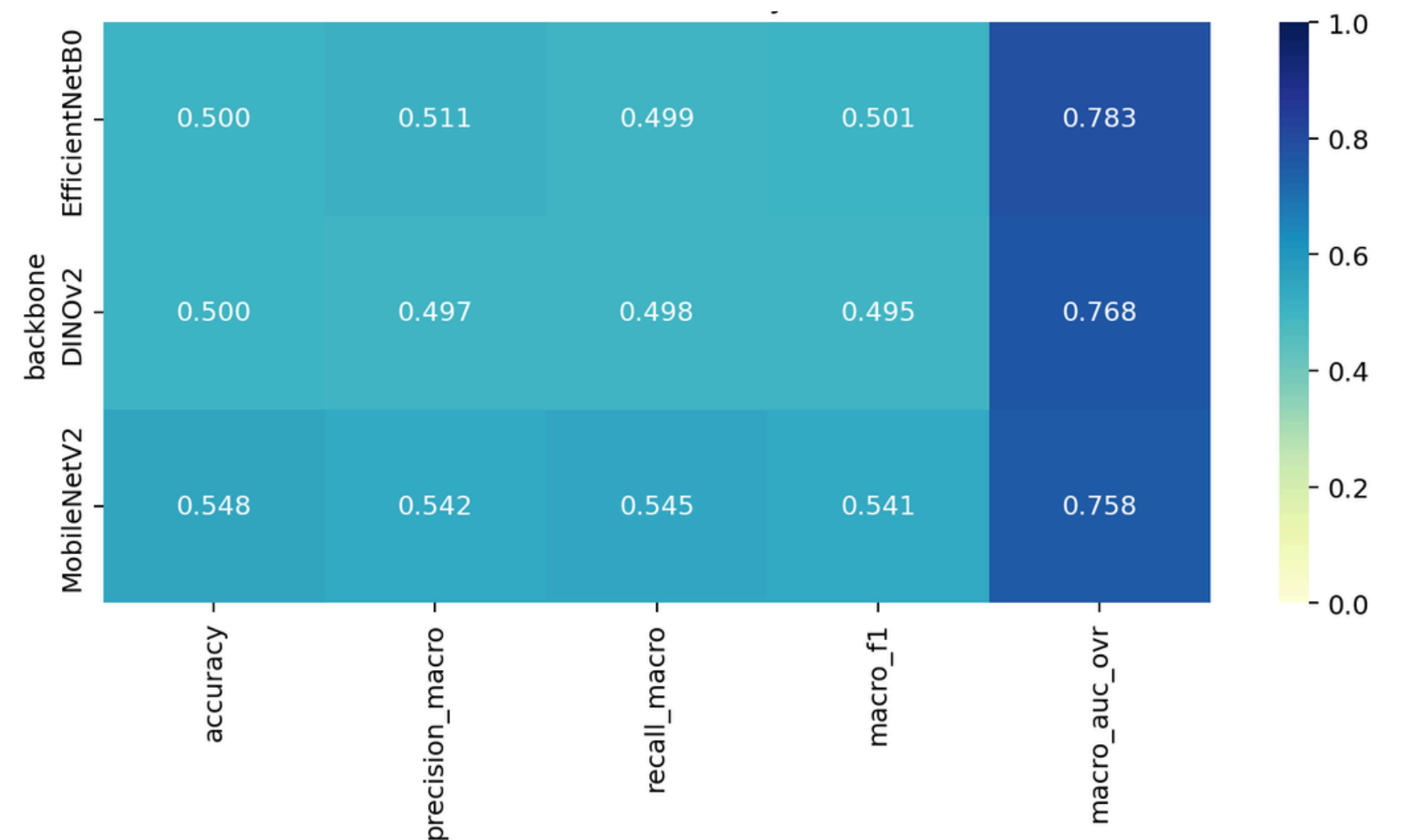
accuracy = 0.500

precision_macro = 0.497

recall_macro = 0.498

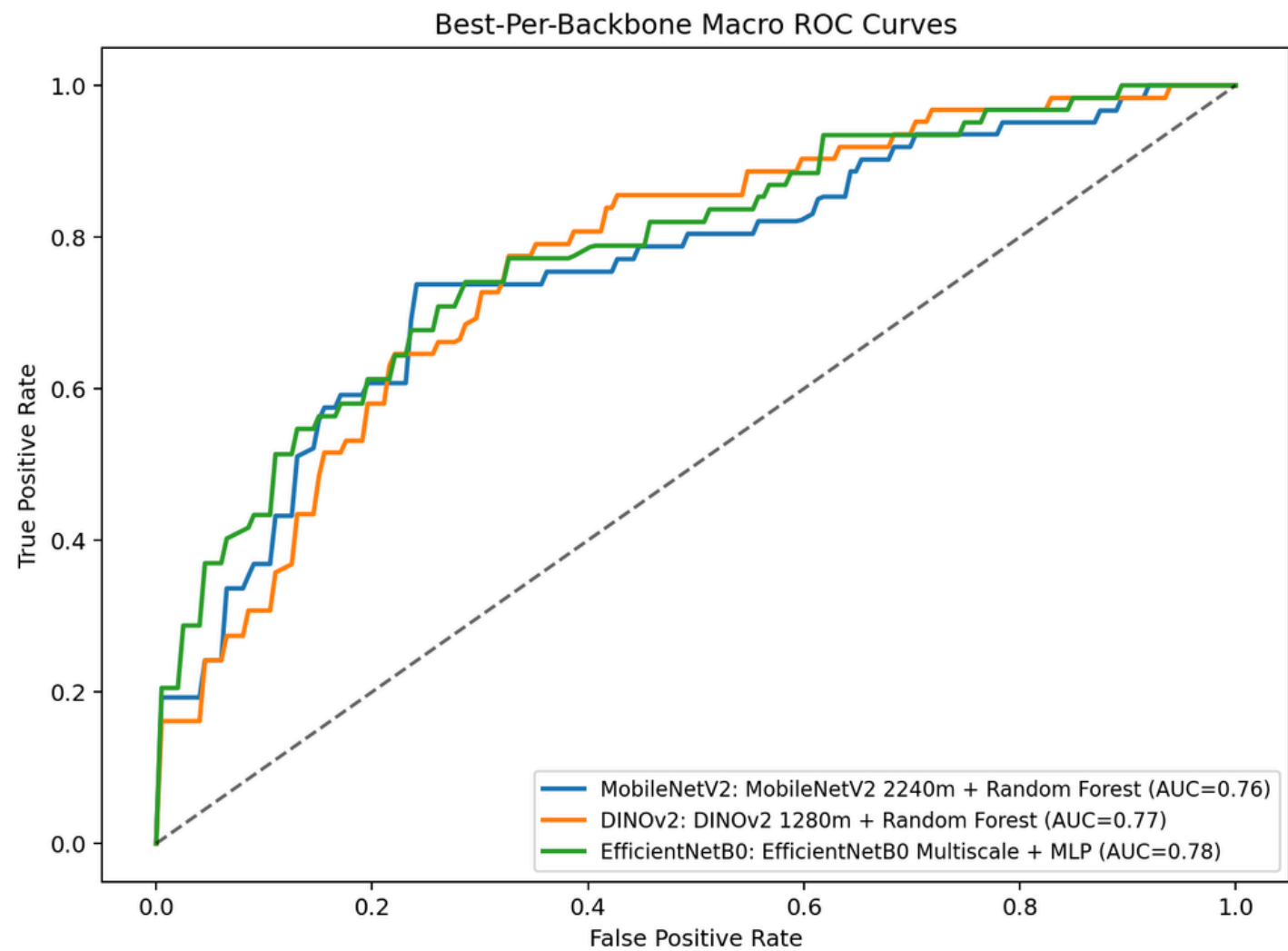
macro_f1 = 0.495

macro_auc_ovr = 0.768

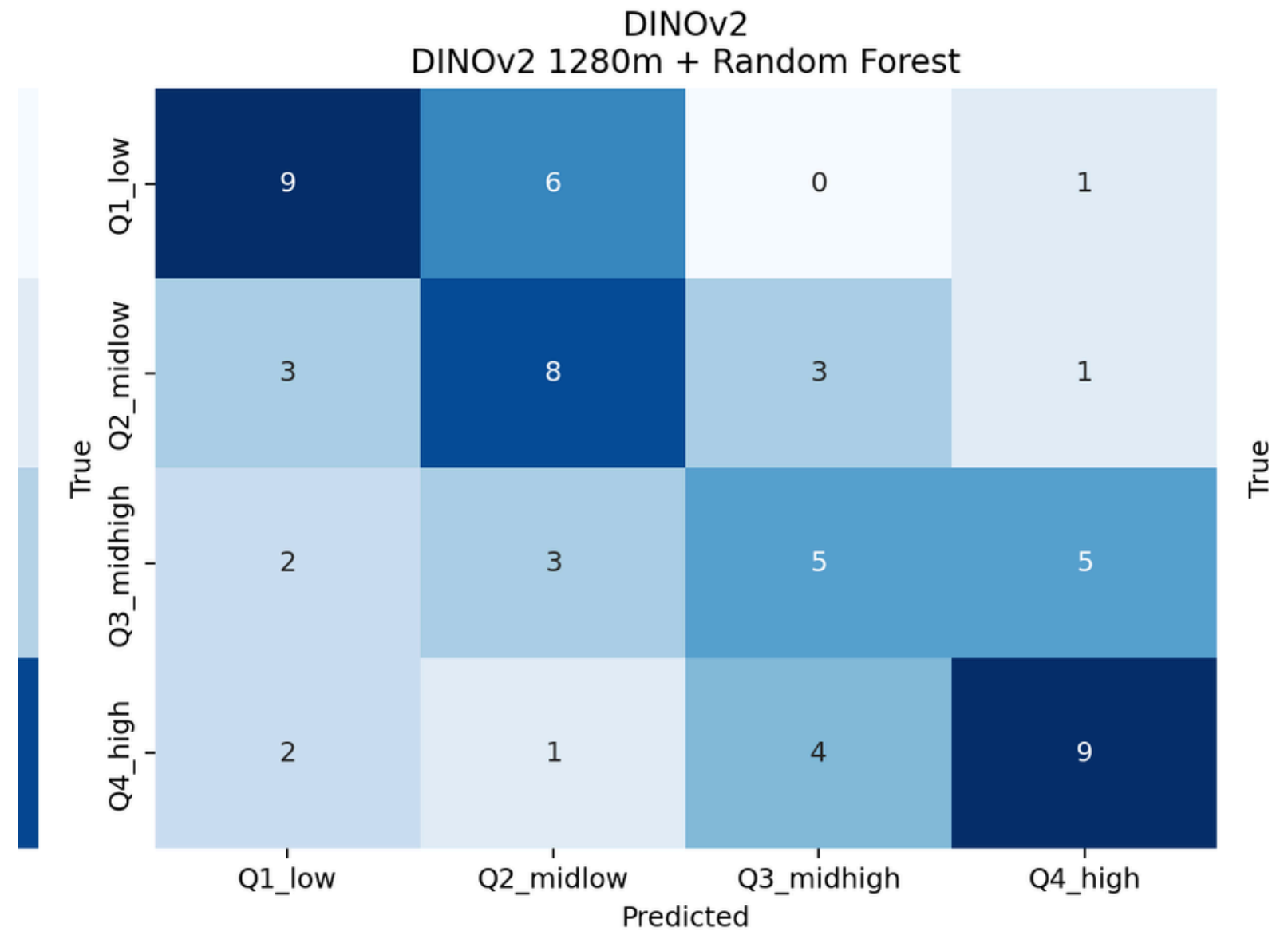


Transfer Learning

DINOv2+RandomForest



AUC = 0.77



Transfer Learning

MobileNetV2+Random Forest

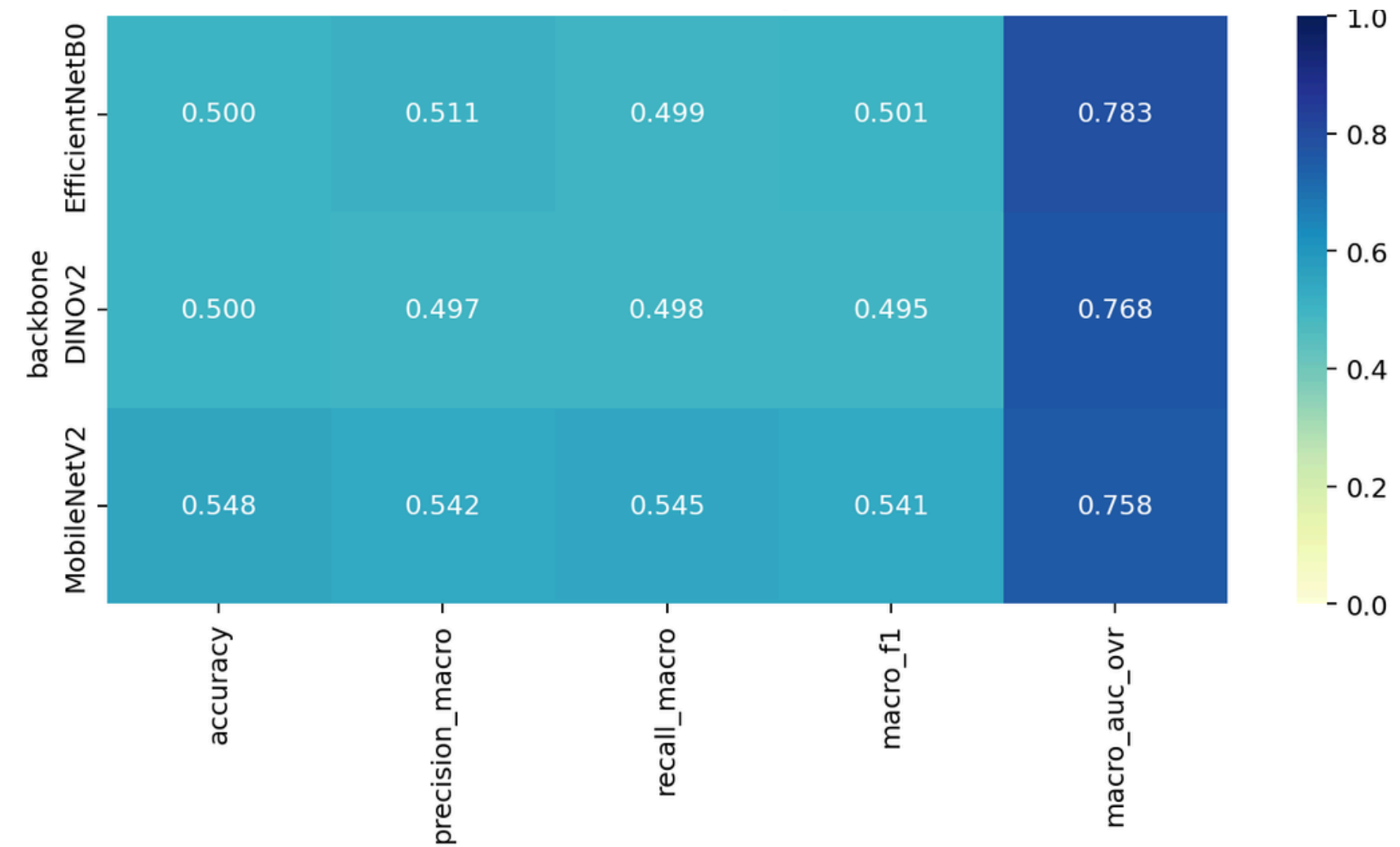
accuracy = 0.548

precision_macro = 0.542

recall_macro = 0.545

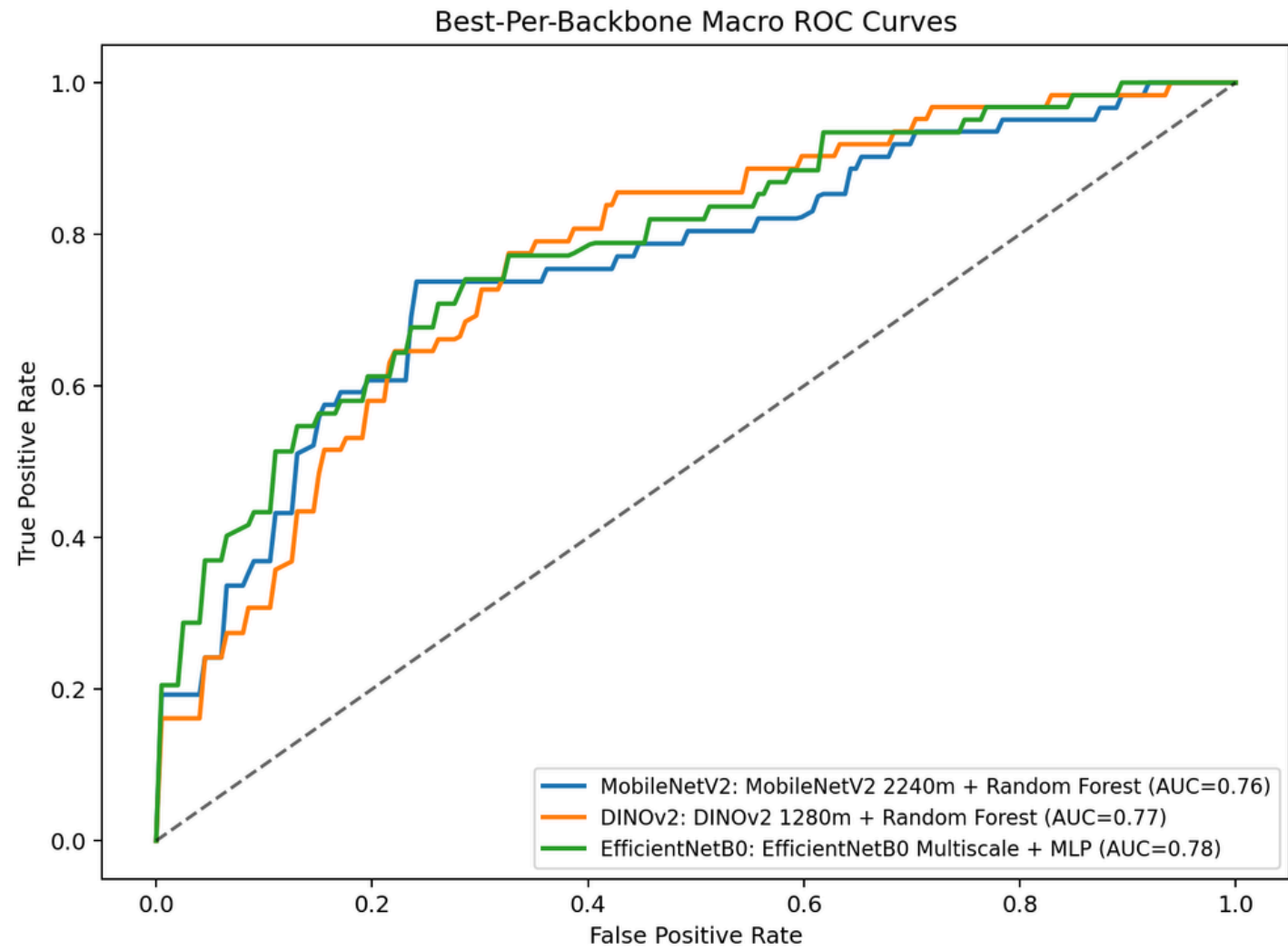
macro_f1 = 0.541

macro_auc_ovr = 0.758

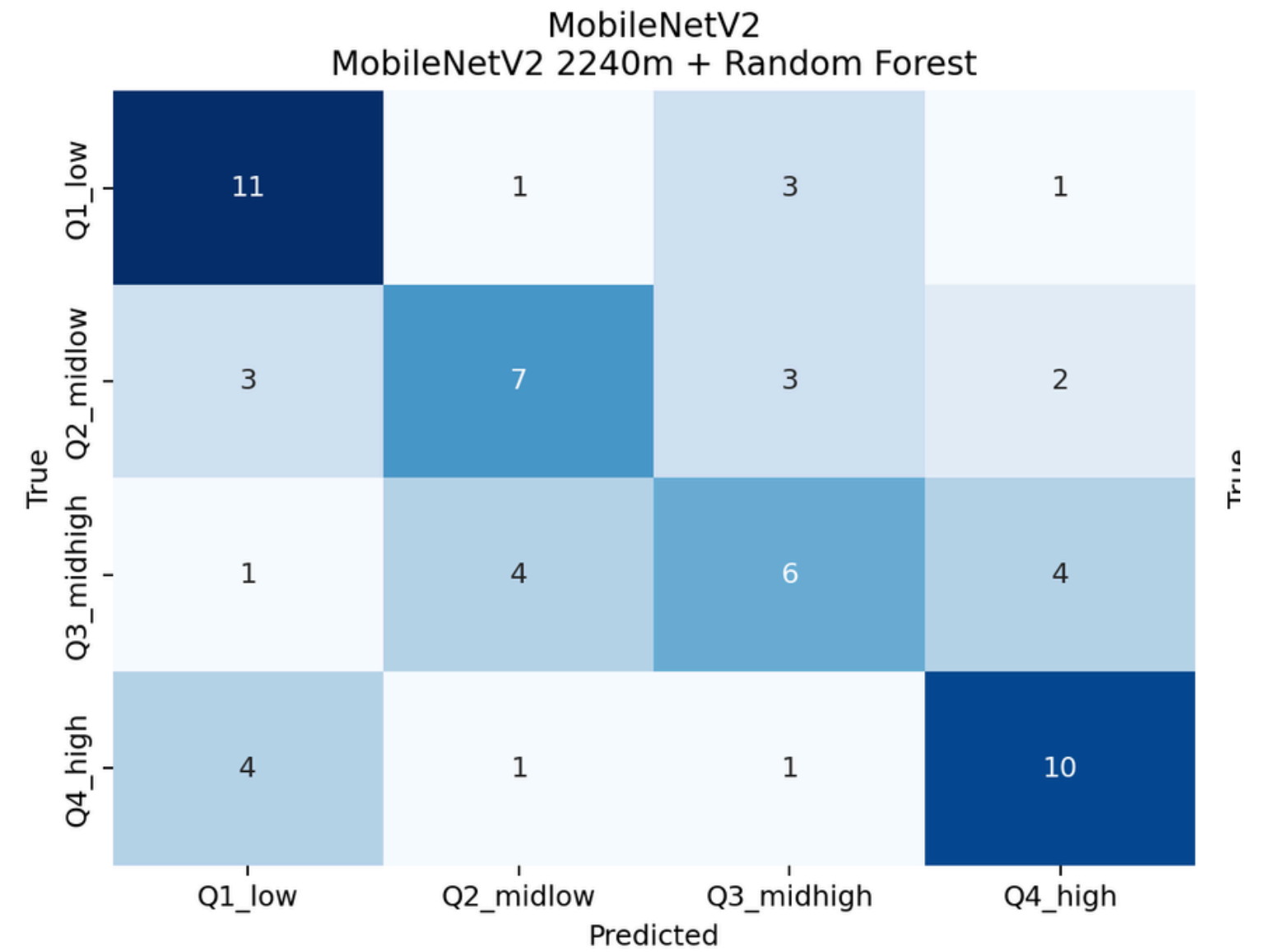


Transfer Learning

MobileNetV2+RandomForest



AUC = 0.76

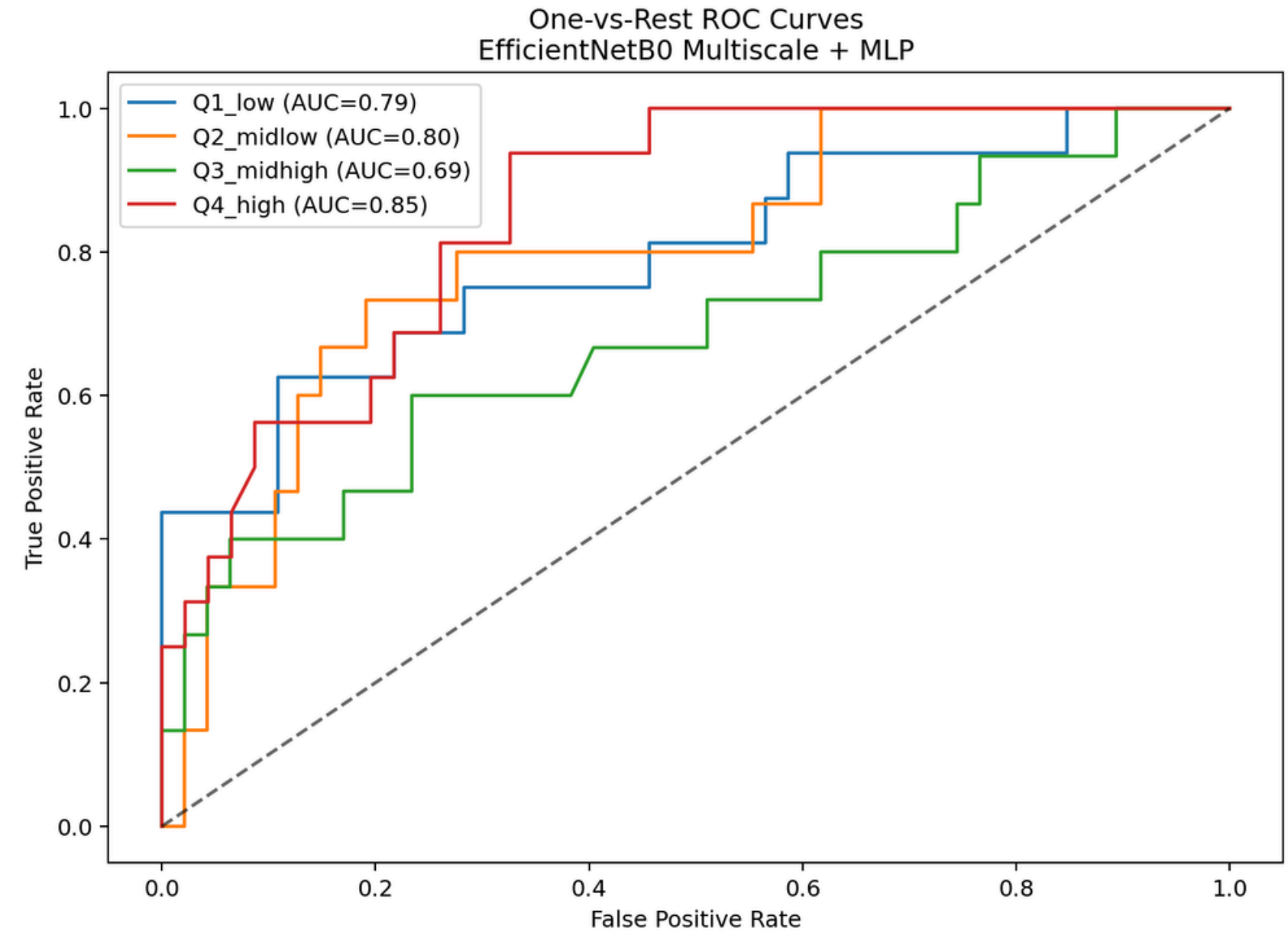


One-vs-Rest ROC — EfficientNetB0 Multiscale + MLP

Macro AUC = 0.78 — all four price tiers are discriminated above chance

- Q4_high (AUC = 0.85)
- Q2_midLow(AUC = 0.8)
- Q1_low (AUC = 0.79)
- Q3_midhigh (AUC = 0.69)

Imagery alone carries more signal at price extremes than in the middle — suggesting tabular features (BHK, locality, floor) are essential complements for the mid-range tier.



Contribution to Humanity

“Help buyers identify underpriced or overpriced properties relative to comparable nearby alternatives, while explaining the trade offs responsible for the price difference.”

+ Is what the optimal point where we get good explainability without hindering Accuracy? So the advise given is good

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