

Analyzing the Impact of Visual and Listing Features in Real Estate Listings

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Abstract. This study investigates the relationship between the visual and listing features of real estate listings and their corresponding Click-Through Rates (CTR). Several machine learning methods were used to identify the key attributes influencing CTR, including Decision Tree, Linear Regression, Random Forrest and XG-Boost. The models were trained and evaluated using a dataset comprising 3000 real estate listings. Visual features were extracted from listings' cover images, while listing-related features – such as price, number of rooms, and district, were derived. Our findings indicate that visual image features and listing features have impact on CTR. In the study we also isolate the visual image and listing features and observed their individual contribution to CTR.

Keywords: Image feature extraction · CTR · image quality · feature selection · machine learning · real estate

1 Introduction

In recent years, real estate platforms have become the primary channels through which individuals search for properties. These platforms offer rich and detailed listings that combine textual information with visual content, such as cover images. Given their widespread use, understanding what drives user engagement on these platforms is of significant interest—both from a user experience perspective and for optimizing platform performance.

A widely used metric to quantify user engagement is the Click-Through Rate (CTR), which measures how frequently users click on a property listing after viewing it. Identifying the factors that influence CTR can help improve both listing effectiveness and user satisfaction.

This study aims to identify the relationship between various listing and image attributes and their impact on CTR. To achieve this, we analyzed a dataset of 3,000 listings. The dataset was obtained from a real estate website operated by iLab Holding, one of Turkey's leading digital advertising groups. iLab is well known for its strong

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presence in Turkey's digital ecosystem. Its group companies collectively reach 65% of the country's internet audience and employ over 2,000 people.

iLab's advertising strategies involve a comprehensive approach, including social media analysis, marketing mix modeling, and brand tracking tools.

Property listings, examining two types of features:

i. Listing features, such as price, price, transaction type (sale/rent), property type (apartment/ mansion/ villa/ summer house/ residence), district, neighborhood, floor number, gross square meters, number of rooms, number of days on the platform, search count (number of listing is up), web/mobile usage ratio, and weighted position in listing results.
ii. Visual image quality features, including low-level quality features (e.g. warm hue, saturation, brightness, contrast of brightness, image clarity, rule of thirds, diagonal dominance, texture and area differences, visual balance of intensity and color).
iii. High-level image content features, (e.g. predicted scene type (interior/exterior), second prediction/room type (kitchen/bedroom/ building façade/floor plan), presence of scenery, windows, sunlight, furniture; perceived clutter, modernity, and luxury.

To determine the most influential features, several feature selection techniques were applied. The selected features were then used as inputs to a set of machine learning models, including Decision Tree, Linear Regression, Random Forrest, and XG-Boost. The performance of these models was compared to evaluate the predictive power of different feature sets in relation to CTR.

This research contributes the following findings:

– Listing features and visual image features contributes CTR.
– Observing listing and visual image features contribution on CTR shows that visual image features have slightly greater impact.

The remainder of this paper is organized as follows: Sect. 2 reviews related works on image aesthetic assessment and the use of CTR as a measure of user engagement. Section 3 describes the datasets used in this study and details the extracted image quality features. Section 4 presents experimental results, including model performance evaluations. Finally, Section 5 concludes the paper by summarizing key findings, offering recommendations, and identifying open issues for future research.

2 Related Work

2.1 Image Aesthetic Assessment

The topics of image quality assessment and image aesthetic assessment have attracted significant research interest in recent years. These studies use a variety of image quality features and machine learning algorithms to evaluate and predict image quality.

A widely used dataset in this domain is AVA (Aesthetic Visual Analysis), a public dataset introduced by Murray, Machicote and Perronnin in 2012 [4]. It contains over 250,000 user-scored photos, with aesthetic scores ranging from 1 to 10.

Zhang, Lee, Singh and Srinivasan [1] thoroughly investigated how image quality affects the property demand on Airbnb platform. The dataset comprised 13,000 listings

and 510,000 images. In order to label the images, the authors sed Amazon Mechanical Turk (a popular crowdsourcing platform for human tasks), classifying images as either'high quality' or 'low quality'. The study revealed that 12 interpretable image attributes scored significantly higher in images taken by professional Airbnb photographers, referred to as verified images. Moreover, the study demonstrated that property demand is influenced by multiple factors, including price, location, room type (private room vs. entire home), super-host status, number of reviews, star rating, and description content. To isolate the effect of image quality, comparisons were made between listings with similar attributes but differing in image verification status. The findings indicated that listing with verified images had higher occupancy rates. Additionally, the 12 interpretable image quality attributes were found to significantly contribute to increased demand.

In a separate work, Deng, Loy and Tang [2] introduced an experimental survey on image aesthetic quality assessment, focusing particularly on deep learning methods. Their analysis emphasizes the shift from traditional handcrafted features (e.g. rule of thirds, contrast) to advanced deep learning-based aesthetic classifiers. The authors demonstrated that deep learning approaches consistently outperform classical feature-engineered models. The models were evaluated using various metrics, including overall accuracy, balanced accuracy, ROC curve, and mean average precision.

Uçan [3] applied deep learning approaches to the domain of real estate images. The study highlighted AVA dataset do not cover real estate specific characteristics. Therefore, the study introduced a new dataset: the Real-Estate Aesthetics Assessment Dataset (RAAD). RAAD includes 2,071 real estate images, each rated by users on a 1–10 scale. Scores of 6 or above were labeled as aesthetic, while those below 6 were considered non-aesthetic. Initially, handcrafted features such as hue, saturation, brightness and energy were extracted, but no significant correlation was found between these features and the user scores. Subsequently, classical classification algorithms were tested, with multi-class regression performing best in the 10-class setting and SVM performing best in the binary classification setting. For deep learning-based feature extraction and classification, models such as VGG16, DenseNet121, and Vision Transformer were evaluated, with Vision Transformer achieving the highest performance.

2.2 Click Through Rate (CTR)

CTR is a critical metric used to evaluate user engagement with search results, content, or listings. While CTR is commonly employed in web search and e-commerce platforms, it also plays a significant role in real estate listing platforms.

Chapelle and Zhang [5] introduced a Dynamic Bayesian Network Click Model to enhance the estimation of CTR and relevance in web search rankings. This technique incorporates both perceived relevance and actual relevance to provide a more nuanced understanding of user behavior. Unlike earlier CTR models, which relied primarily on position bias and limited user actions such as one click, The Dynamic Bayesian Network approach overcomes these limitations and offers a more robust and reliable method for CTR estimation.

3 Methodology

The proposed methodology of this research is explained in the Fig. 1. The process begins with data collection, where we collect different types of data which we believe has an impact on CTR. Following this step, feature extraction process begins and feature selection methods were applied. After selecting the top 15 features, machine learning models were employed. Finally, their performance evaluation was discussed.

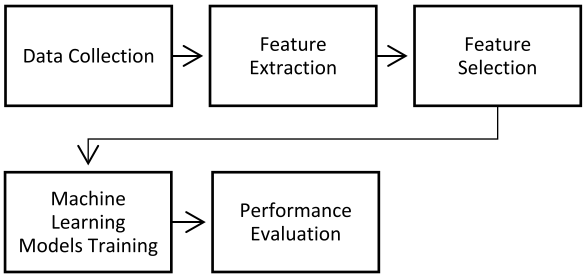

Fig. 1. The flowchart of the proposed methodology

3.1 Dataset Description

The dataset used in this study consists of 3000 real estate listings obtained from a real estate website operated by iLab Holding based in Turkey. Each listing has a cover image and listing features such as listing price, gross square meter, location, floor and other features. From dataset cover images various visual features have been extracted. In order to analyze user interaction CTR is used.

Listing Features. Listing features included in our data frame are listed below:

Transaction type: Indicates whether the property is for rent or sale.

Property type: Specifies the type of the property such as apartment, mansion, villa, summer house or residence.

District: Indicates the district where the property is located.

Neighborhood: Denotes the neighborhood where the property is located.

Floor: Indicates which floor the property is located in the building.

M2 gross: Represents the gross square meter area of the property.

Number of rooms: Indicates the total number of rooms of the property.

Price: Specifies the listed price of the property.

Listing Age: Represents the number of days the listing has been active.

Search count: Indicates how many listings appeared in user's search result.

Web mobile ratio: Refers to the distribution of user's usage web platform over mobile platform.

Weighted position: Indicates the position of the listing in the search results.

Visual Image Quality Features. In order to explore the relationship between image quality and user engagement in real estate, we employed a feature extraction methodology inspired by Zhang, Lee, Singh and Srinivasan [1] Their study shows that mentioned 12 features have an impact on demand which encouraged us to extract these features from the dataset and observe the impact on CTR.

The visual features were extracted from listing cover images which includes warm hue, saturation, brightness, contrast of brightness, image clarity, rule of thirds, diagonal dominance, texture difference, area difference, and color difference, visual balance of intensity and visual balance of color.

Warm hue refers to dominance of warm colors (yellow, orange and red) over cold colors (blue and purple). Warm colors known to have a connection between high excitement levels [6, 7].

Saturation indicates the intensity of colors in an image. Images with high saturation appears to look full of colors, whereas low saturation images look faded [1].

Brightness refers to the whole illumination level of an image and it significantly affects the appeal to viewers. Brighter images seem to be more appealing to the viewers. Adequate illumination enhances the clarity of an image [6–8].

Contrast of brightness denotes to the variation in illumination and indicate if the illumination is uniformly distributed across the image.

Image clarity is affected by the brightness levels in the Hue Saturation Value color space and saturation. Images with low image clarity often have desaturated colors or has near-zero hue intensities. These images can look unclear and hazy [1].

Rule of thirds indicates an image can be divided into nine equal sections using horizontal and vertical lines. This rule suggests that key objects in the image should be on these lines or close to the intersections.

Diagonal dominance can be expressed as visual elements being near to the diagonal lines from corner to corner which is the longest lines in the images [9].

Texture difference refers to the difference between the figure and the ground in terms of texture.

Area difference refers to the area difference between the figure and the ground.

Color difference refers to the color difference between figure and the ground.

Visual balance of intensity and visual balance of color can be explained as the symmetry of visual elements in an image. Symmetry and visual balance are positively correlated [10].

High-Level Image Content Features. Predicted scene type: Indicates whether the image represents an indoor or outdoor setting.

Second prediction/ room type: Indicates the type of room or structure shown in the image such as kitchen, bedroom, building or floor plan.

Presence of scenery: Indicates whether scenic elements are visible in the image such as natural landscapes, views.

Eye catching objects is present: Identifies whether the image features any visually striking or attention capturing object.

Windows: Indicates whether windows are present in the image.

Sunlight: Specifies whether sunlight is present in the image.

Furniture: Indicates whether furniture is present in the image.

Perceived clutter: Assesses whether the furniture is neat or cluttered.
Modernity: Indicates whether the furniture in the image is modernly decorated.
Luxury: Specifies whether the furniture in the image is luxurious.

3.2 Machine Learning Algorithms

We deployed several machine learning algorithms in order to model the relationship between the selected features and CTR. These machine learning algorithms are Decision Tree Regressor, Linear Regression, Random Forest Regressor and XG-Boost Regressor. First, we have detected the top 15 features using different methods then we built our models using these selected features.

Decision Tree Regressor is a tree-based model which employs a recursive partitioning approach to reduce prediction errors. At each step data is partitioned based on a selected feature and every leaf node represents a final prediction class. It is an efficient algorithm for modeling non-linear relationships. This algorithm can comprehend complex interactions and conditional dependencies.

Linear Regression is a supervised learning algorithm which assumes there is a linear relationship between features and the label. This algorithm is straightforward and simple but it may not capture the complex non-linear relationships.

Random Forest Regressor is based on multiple decision trees that aggregates their predictions for improved robustness and generalization. Compared to single decision trees, overfitting risk is reduced. This algorithm is suitable for analyzing complex interactions.

XG-Boost Regressor is based on gradient-boosted decision trees. Every tree is taught to correct the previous mistakes which causes progressively improved accuracy. This algorithm is known for its high performance and ability to handle complex feature interactions.

4 Experimental Results

CTR is commonly known as Click Through Rate which can be used to understand how attractive a content is to its viewers. It's a crucial metric to measure user engagement. In our dataset there are various features which can affect CTR. In this section we have employed different feature selection methods and applied several machine learning algorithms to observe the impact of these features on CTR.

4.1 Feature Selection Results

Feature selection is a key point in order to improve the model performance. In this study we have listing features, image quality features and extracted image features. Various feature selection methods have been used and their performances were compared. ANOVA F-test, Mutual Information Regression, Lasso and Pearson correlation.

Table 1 shows the selected 15 features for every feature selection method can be observed. Several features can be seen in the multiple selection methods. Luxury, brightness, sunlight and price occur in every feature selection method.

Presence of scenery, web mobile ratio, texture difference, image clarity, saturation, diagonal dominance and visual balance of color occur in three models.

Table 1. Top 15 Selected Features by Feature Selection Methods

Anova (F-Test)	Mutual Information	Lasso	Pearson Correlation
luxury	m2 gross	price	luxury
image clarity	price	m2 gross	image clarity
rule of thirds	furniture	listing age	rule of thirds
brightness	eye catching objects is present	search count	brightness
presence of scenery	texture difference	web mobile ratio	presence of scenery
texture difference	search count	weighted position	texture difference
visual balance of color	diagonal dominance	presence of scenery	visual balance of color
visual balance of intensity	brightness	eye catching object is present	visual balance of intensity
color difference	sunlight	windows	color difference
area difference	visual balance of color	sunlight	area difference
web mobile ratio	windows	furniture	web mobile ratio
saturation	luxury	luxury	saturation
price	warm hue	warm hue	price
sunlight	contrast of brightness	saturation	sunlight
diagonal dominance	image clarity	brightness	diagonal dominance

4.2 Prediction Results for CTR with Selected Features

In this section, machine learning algorithms performances with selected features are discussed. From the conducted feature selection methods, top 15 features have been selected and machine learning models have built with these features.

Decision Tree Regressor. Decision tree showed modest performance predicting CTR compared to other machine learning models. For fine tuning process, the grid search approach is used to select the depth and minimum sample split hyper parameters. For all feature selection methods, max depth 5 and minimum sample split is 10.

The following Table 2 includes the results of Decision Tree Regressor Model. Lasso feature selection method demonstrated slightly better performance with Decision Tree Regressor Model.

Linear Regression. Linear regression has the weakest performance among the algorithms that are used. The reason that linear regression is not adequate can be the relationships between CTR and the features may not be linear.

Table 3 consists of the results of Linear Regression Model. Anova (F-test) and Pearson correlation feature selection methods demonstrated slightly better performance with Decision Tree Regressor Model.

Table 2. Decision Tree Regressor Performance Evaluations

Feature selection	R2 Score	RMSE	MAE	Pearson's Correlation Coefficient
ANOVA (F-test)	0.28627	0.04427	0.03137	0.53917
Mutual Info	0.28627	0.04427	0.03137	0.53917
Lasso	0.28839	0.04421	0.03164	0.54223
Pearson Corr	0.28627	0.04427	0.03137	0.53917
ANOVA (F-test)	0.28627	0.04427	0.03137	0.53917

Table 3. Liner Regressor Performance Evaluations

Feature selection	R2 Score	RMSE	MAE	Pearson's Correlation Coefficient
ANOVA (F-test)	0.02389	0.05178	0.0386	0.17749
Mutual Info	0.00755	0.05221	0.03903	0.13025
Lasso	0.00411	0.0523	0.03911	0.12226
Pearson Corr	0.02389	0.05178	0.0386	0.17749
ANOVA (F-test)	0.02389	0.05178	0.0386	0.17749

Random Forest Regressor. Table 4 includes the performance evaluation of Random Forest Regressor. Random Forest Regressor have reached the highest overall performance. Random forest regressor can deal with complex feature interactions. CTR is also a very complex measure that depends on countless features.

For fine tuning process, the grid search approach is used to select the depth and minimum sample split hyper parameters. For all feature selection methods, max depth = 5, minimum sample split = 2, n_estimators is 200 for Lasso and 100 for the other feature selection methods. The best feature selection method is mutual information-based feature selection.

Table 4. Random Forest Regressor Performance Evaluations

Feature selection	R2 Score	RMSE	MAE	Pearson's Correlation Coefficient
ANOVA (F-test)	0.31186	0.04347	0.03109	0.562
Mutual Info	0.32993	0.0429	0.03071	0.57802
Lasso	0.32603	0.04302	0.03058	0.57363
Pearson Corr	0.31186	0.04347	0.03109	0.562
ANOVA (F-test)	0.31186	0.04347	0.03109	0.562

XG-Boost Regressor. Table 5 includes the performance evaluation of XG-Boost Regressor which has shown better performance compared to Linear Regression and Decision Tree. Best performed feature selection method is Lasso. XG-Boost regressor is also known for dealing with complex nonlinear relationships that may be the reason that XG-Boost performed better.

The best performance results are taken by setting hyperparameters learning_rate = 0.1, max_depth = 3 and n_estimators = 50. It can be observed that isolating the image quality features causes improvement in the model performance.

Table 5. XG-Boost Regressor Performance Evaluations

Feature selection	R2 Score	RMSE	MAE	Pearson's Correlation Coefficient
ANOVA (F-test)	0.30609	0.04366	0.03111	0.5632
Mutual Info	0.31153	0.04348	0.03043	0.56114
Lasso	0.31922	0.04324	0.03065	0.56702
Pearson Corr	0.30609	0.04366	0.03111	0.5632
ANOVA (F-test)	0.30609	0.04366	0.03111	0.5632

4.3 Prediction Results for Only Image Quality Features

In order to observe the isolated effect of the image quality features on CTR we have set the listing features as control variables such as price, district, number of rooms and other listing features. This enabled us to observe the distinctive contribution of image quality features. The two of the best performed algorithms used in this experiment.

XG-Boost Regressor. XG-Boost Regressor were used to analyze the image quality effect on CTR by setting the other features as control variables.

Table 6 shows the performance evaluation of XG-Boost Regressor for only image features. The best performance results are taken by setting hyperparameters learning_rate = 0.1, max_depth = 5 and n_estimators = 100. It can be observed that isolating the image quality features causes improvement in the model performance.

Table 6. XG-Boost Regressor Performance Evaluations Considering Image Quality Features

Feature selection	R2 Score	RMSE	MAE	Pearson's Correlation Coefficient
ANOVA (F-test)	0.3593	0.0419	0.0296	0.602

Random Forest Regressor. Random Forest Regressor were used to analyze the image quality effect on CTR by setting the other features as control variables.

Table 7 shows the performance evaluation of Random Forest Regressor for only image features. The best performance results are taken by setting hyperparameters max_depth = 15, min_sample_splits = 2 and n_estimators = 200. It can be observed that isolating the image quality features causes even better improvement in the model performance with random forest regressor.

Table 7. Random Forest Regressor Performance Evaluations Considering Image Quality Features

Feature selection	R2 Score	RMSE	MAE	Pearson's Correlation Coefficient
ANOVA (F-test)	0.3819	0.0412	0.0296	0.602

4.4 Prediction Results for Only Listing Features

In this section, we aim to analyze the isolated effect that listing features has on the CTR. We have set the image quality and extracted image features as control variables. This enabled us to observe the distinctive contribution of listing features. The two of the best performed algorithms used in this experiment.

XG-Boost Regressor. XG-Boost Regressor were used to analyze the listing features effect on CTR by setting the other features as control variables.

Table 8 shows the performance evaluation of XG-Boost Regressor for only listing features. The best performance results are taken by setting hyperparameters learning_rate = 0.1, max_depth = 5 and n_estimators = 100. It can be observed that isolating the image quality features causes improvement in the model performance compared to having all the features in the model.

Table 8. XG-Boost Regressor Performance Evaluations Considering Listing Features

Feature selection	R2 Score	RMSE	MAE	Pearson's Correlation Coefficient
ANOVA (F-test)	0.3644	0.0418	0.0295	0.6048

Random Forest Regressor. Rrandom Forest Regressor were used to analyze the listing features effect on CTR by setting the other features as control variables.

Table 9 shows the performance evaluation of Random Forest Regressor for only listing features. The best performance results are taken by setting hyperparameters max_depth = 10, min_sample_splits = 5 and n_estimators = 200. Random forest regressor have very similar results compared to XG Boost regressor.

Considering the experimental results it can be observed that, image quality and listing features has impact on CTR. When evaluated independently the predictive performances of models increased. Isolating the image quality features have even better performance compared to other set of features. According to these results we can say that image quality has impact on user engagement.

Table 9. Random Forest Regressor Performance Evaluations Considering Listing Features

Feature selection	R2 Score	RMSE	MAE	Pearson's Correlation Coefficient
ANOVA (F-test)	0.3643	0.0418	0.0297	0.6047

4.5 Limitations

It should be acknowledged that CTR is a measurement which depends on countless aspects and would be truly challenging to predict. CTR can vary according to user profiles or the listings shown nearby. In the study 3000 listing were used. Models' performances can be improved by using a larger set of listings. The number of features is numerous which increases the complexity of the models.

5 Conclusion

In this research, we analyzed the impact of various listing and image attributes on CTR. To achieve this, we analyzed a dataset of 3,000 listings. A set of visual and listing features were extracted. Several feature selection techniques were employed and top 15 features were selected. Machine learning models were trained with these features and performances are evaluated. Random Forest Regressor had the highest overall performance among all models with mutual information-based feature selection. XG-Boost performance results were similar to Random Forest Regressor with Lasso feature selection method.

This study also investigates the isolated effect of listing and image quality features separately. Both experiments showed that these features have significant contributions to CTR separately. The experiments performed with only image features have slightly better performance. Enhancing image quality might increases CTR. Scope of the study includes certain features that effects CTR which can explain only a part of CTR's variance.

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