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# Satellite Image–Derived Road Quality Index (RQI) for Machine Learning – Based Real Estate Price Prediction

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**ABSTRACT:** Getting accurate predictions about real estate prices is important for investors, homebuyers, city planners, and government officials. It helps them make smart choices when dealing with changing housing markets. Traditional predictive models mostly rely on features like property size, number of bedrooms, how old the building is, and where it's located, along with economic data. But these models usually ignore important factors related to infrastructure, especially **road quality**. Road quality has a big impact on how easy it is to get to the property, how safe it is, and how attractive the area is overall. Collecting road condition data at scale is challenging, which has limited its inclusion in automated valuation systems.

This paper introduces a new method for forecasting real estate prices by combining a **Road Quality Index (RQI)**, which is created using detailed satellite images. Road areas near properties are studied using special computer tools called convolutional neural networks to find out things like how smooth the road is, if there are cracks, where the lines are, and how well the roads connect to each other. The resulting RQI quantifies the overall quality of the surrounding road infrastructure. By combining RQI with traditional property features in machine learning regression models, the approach captures both structural and infrastructural factors influencing property values.

Tests show that adding RQI helps predictions become more accurate than when only regular features are used. The results show that using remote sensing and computer vision can create reliable, unbiased, and affordable measures of infrastructure that improve how we value real estate. This study sets the stage for evaluating property values based on infrastructure and offers valuable information for building smarter cities, planning urban areas, and making informed investment choices.

**KEYWORDS:** Real estate prediction, Road Quality Index (RQI), satellite imagery, CNN, machine learning, remote sensing, infrastructure analytics.

## I. INTRODUCTION

Real estate valuation is important for economic growth, planning investments, and managing city development. Being able to predict property prices correctly helps people who buy or sell homes, real estate professionals, and government officials make better choices. Traditional price prediction models mainly use features like the number of bedrooms, total square footage, how old the building is, where it's located, and what extra features it has. They also look at economic factors such as interest rates and inflation. Although these models are capable of achieving a respectable degree of accuracy, they frequently fall short in capturing the impact of infrastructure-related issues, especially road



condition, which has a substantial impact on property accessibility, safety, and desirability. Properties connected by well-maintained roads tend to attract higher prices due to ease of mobility, lower vehicle maintenance costs, and overall convenience, whereas poor-quality roads can reduce property value even in prime locations.

Despite its importance, road infrastructure has been underutilized in automated real estate valuation because **collecting large-scale, objective road condition data is challenging**. Manual surveys are costly, time-consuming, and often inconsistent, making it difficult to integrate road quality into predictive models. A possible method for extracting road condition measurements at scale is provided by the current availability of **high-resolution satellite images** in conjunction with sophisticated **computer vision and deep learning techniques**. Infrastructure quality can be immediately incorporated into prediction models for property assessment by translating satellite photos into quantitative **Road Quality Index (RQI)** scores.

This paper introduces a new method for predicting real estate prices that uses RQI, which is gathered from satellite images, along with machine learning models. Using convolutional neural networks (CNNs), the approach analyzes road segments surrounding properties to detect cracks, surface smoothness, lane markings, and connectivity, resulting in an objective RQI metric. This index is then combined with traditional property features in regression-based models to predict property prices more accurately. The new method not only makes predictions more accurate but also provides a way to value real estate that is scalable, affordable, and takes into account the existing infrastructure, giving useful information for planning smart cities, developing urban areas, and making investment decisions.

## II. LITERATURE SURVEY

**Rosen [1]** introduced hedonic pricing models to estimate property values based on structural and locational features, demonstrating the foundational approach for real estate valuation. **Breiman [2]** introduced Random Forests, demonstrating that using groups of models together in machine learning can better understand complex connections between property features and prices, leading to more accurate predictions compared to older statistical approaches. **Chen and Guestrin [3]** created XGBoost, a boosting method that uses tree models and works well with large datasets. It is popular for predicting housing prices because it performs better than other methods when dealing with data that has many features.

**Zhang et al. [4]** employed high-resolution satellite imagery for urban land-use classification, highlighting the potential of remote sensing in extracting environmental and infrastructural features relevant to property assessment. **Li and Fang [5]** showed that convolutional neural networks (CNNs) work well for looking at satellite images to find out things like how roads are connected and the quality of neighborhoods. These studies inspired our approach to quantify road infrastructure quality from satellite imagery for inclusion in property valuation models.

**Hutto and Gilbert [6]** proposed VADER, a sentiment analysis approach extensively used to extract the subjective data from textual data, which highlights the benefit of embracing additional data sources beyond typical numerical features. **Bajaj et al. [7]** investigated machine learning methods for real estate price prediction, showing the advantages of integrating diverse feature sets to improve accuracy.

Building on these discoveries, our study fills the research vacuum in integrating objective road condition measures into real estate valuation prediction models by introducing a **Road Quality Index (RQI)** obtained from satellite photos as a unique infrastructure-related feature.

## III. PROBLEM STATEMENT

Predicting real estate prices accurately is difficult because of the intricate interactions between environmental characteristics, economic considerations, and property traits. Traditional predictive models rely primarily on structural property characteristics, basic location data, and historical transaction prices, often neglecting critical infrastructure-related factors such as **road quality**.

Due to the difficulties of gathering extensive, objective road data, the majority of current automated valuation models do not take into consideration the detrimental effects that poor road conditions can have on property accessibility, safety,

and general desirability. Manual surveys are time-consuming, costly, and often inconsistent, making it infeasible to integrate road infrastructure information into predictive models.

When enabling automated evaluation of road conditions, recent developments in **satellite photography and computer vision techniques** offer a chance to close this gap.

However, the **Road Quality Index (RQI)**, which is obtained from satellite data, has not yet been thoroughly investigated as a feature in machine learning models for real estate price prediction. There is a clear need for a **scalable, objective, and data-driven** approach that incorporates infrastructure quality into predictive frameworks to improve accuracy and provide actionable insights for buyers, investors, and urban planners.

This research aims to bridge this gap by developing a framework that quantifies road quality from satellite images, integrates it with traditional property features, and evaluates its impact on the accuracy of real estate price prediction models. The study seeks to demonstrate that incorporating RQI can greatly improve predictive performance, offering a more **infrastructure-aware, reliable, and practical solution** for modern property valuation.

#### **IV. PROPOSED METHOD**

This study integrates a **road-infrastructure-aware real estate price prediction framework** by integrating a **Road Quality Index (RQI)** obtained from satellite imagery with traditional property features. The goal is to design a scalable, cost-effective, and objective system capable of predicting property prices while incorporating infrastructure quality, which is often overlooked in conventional models.

##### **1. System Architecture**

The architecture consists of three main components: **property feature database, satellite image processing module, and machine learning prediction module.**

- **Property Feature Database:** Contains structured data such as area, number of bedrooms and bathrooms, age of construction, location coordinates, and nearby amenities.
- **Satellite Image Processing Module:** High-resolution satellite images of road networks surrounding each property are collected and preprocessed. Convolutional neural networks (CNNs) are used to extract road attributes such as surface smoothness, cracks, potholes, lane markings, and connectivity. For each property, characteristics are combined to provide a **quantitative Road Quality Index (RQI)**.
- **Machine Learning Prediction Module:** The RQI is combined with traditional property features to form a hybrid feature set.
- To forecast real estate prices, regression models such as Random Forest, XGBoost, Linear Regression, and Stacked Ensemble models are trained on this feature set.

##### **2. RQI Extraction Workflow**

The RQI extraction process involves the following steps:

- a. Satellite image acquisition and preprocessing (resizing, normalization, segmentation).
- b. CNN-based feature extraction to detect road surface quality, cracks, and lane markings.
- c. Aggregation of extracted road features into a single **RQI score**, representing infrastructure quality near each property.
- d. Normalization of RQI to align with other property features for machine learning input.

##### **3. Feature Integration and Model Training**

The hybrid feature set combines RQI with structural property features. Models are trained using:

- **Linear Regression** for baseline comparisons.
- **Random Forest and XGBoost** to capture non-linear interactions.
- To increase overall prediction accuracy, use a stacked ensemble.
- **Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R2 score** are used to assess performance.

**4. Dataset and Simulation Environment**

- **Structured Property Data:** Collected from public real estate listings, including area, bedrooms, age, location, and amenities.
- **Satellite Imagery:** Obtained from Google Earth or open-source repositories.
- Road segments are mapped to each property to simulate real-world urban environments and infrastructure conditions.

**5. Evaluation Metrics**

The predictive models are evaluated using:

- **RMSE and MAE:** Measure prediction error.
- **R2 Score:** Indicates the percentage of variance that the model can account for.
- **Impact of RQI:** Performance is compared between models with and without RQI to quantify its contribution.

**6. Deployment Considerations**

The framework is designed to be **scalable and computationally efficient**. CNN processing can be batched, and feature extraction is performed offline to reduce computation during model training. This model supports **infrastructure-aware urban planning and property valuation** and may be easily expanded to other cities or regions.

**V. METHODOLOGY**

The proposed framework for real estate price estimation incorporates a **Road Quality Index (RQI)** extracted from satellite imagery with traditional property features. The methodology is implemented through a structured multi-phase approach, focusing on data acquisition, road quality quantification, hybrid feature integration, and predictive model training and evaluation.

**A. Data Collection and Preprocessing**

- Structured properties data are gathered from public real estate listings, including area, number of bedrooms and bathrooms, age of construction, location coordinates, and nearby amenities.
- High-resolution satellite images of the road network surrounding each property are obtained from Google Earth or open-source satellite repositories.
- Property data and road images are cleaned, normalized, and formatted to create a consistent dataset suitable for machine learning models.

**B. Road Quality Index (RQI) Extraction**

- Satellite images undergo preprocessing steps including resizing, normalization, segmentation, and noise reduction.
- Convolutional Neural Network models (CNN) are applied to extract road characteristics such as surface smoothness, cracks, potholes, lane markings, and connectivity.
- Extracted road attributes are aggregated to generate a quantitative RQI score for each property, representing the overall infrastructure quality near the property.

**C. Feature Integration**

- The RQI is combined with traditional property features to form a hybrid feature vector.
- All features are normalized, and categorical features are one-hot encoded for compatibility with machine learning models.
- To preserve representative property and infrastructure distributions, the dataset is divided into training (70%) and testing (30%) subsets.

**D. Model Training**

- Multiple regression models are trained on the hybrid dataset:
  - Linear Regression as a baseline.
  - Random Forest and XGBoost to capture nonlinear relationships.
  - Stacked Ensemble Model to enhance predictive performance and robustness.
- Hyperparameters are tuned using grid search and cross-validation to optimize model performance.

**E. Evaluation Metrics**

- To measure prediction accuracy, models are assessed using the root mean squared error (RMSE), the mean absolute error (MAE), and  $R^2$  Score.
- The impact of RQI is assessed by comparing models trained with and without RQI as a feature.
- Sensitivity analysis is performed to examine how variations in road quality affect predicted property prices.

**F. Deployment Considerations**

- The framework is designed to be scalable and computationally efficient. CNN-based RQI extraction is performed offline to reduce training time.
- The model can be applied to different cities or regions with minimal adaptation, supporting infrastructure-aware urban planning and investment decision-making.

**VI. IMPLEMENTATION**

The deployment of the proposed framework focuses on **data acquisition, road quality extraction, feature integration, and predictive modeling**, leveraging modern machine learning and deep learning techniques.

**A. Data Acquisition**

- **Property Features:** Structured real estate data such as area, number of bedrooms and bathrooms, age, location, and nearby amenities are collected from publicly available listings.
- **Satellite Imagery:** High-resolution satellite images covering road networks around each property are obtained from Google Earth and other open satellite repositories.
- Road segments within a predefined radius (e.g., 500 meters) of each property are selected for analysis.

**B. Road Quality Index (RQI) Extraction**

- **Image Preprocessing:** Satellite images are resized to 224×224 pixels, normalized, and segmented to isolate road regions. Noise reduction and edge detection enhance feature extraction.
- **CNN Feature Extraction:** A convolutional neural network is trained to detect road surface quality attributes, including smoothness, cracks, potholes, lane markings, and connectivity.
- **RQI Calculation:** Extracted features are aggregated into a single **Road Quality Index (RQI)** score per property, scaled between 0 and 1, where higher values indicate better road quality.

**C. Feature Integration**

- The RQI is combined with traditional property features to form a **hybrid feature vector** for each property.
- Categorical features (e.g., location, amenities) are one-hot encoded, and all characteristics are normalized.
- The data set is divided into **training (70%)** and **testing (30%)** subsets, ensuring representative coverage of property types and infrastructure quality.

**D. Model Training and Evaluation**

- **Models Used:** Linear Regression (baseline), Random Forest, XGBoost, and a Stacked Ensemble model.
- **Hyperparameter Tuning:** Grid search and cross-validation are performed to optimize model performance.
- **Training Process:**
  - Input: Hybrid feature vector (property features + RQI).
  - Output: Predicted property price.
- **Evaluation Metrics:**
  - Root Mean Squared Error (RMSE)
  - Mean Absolute Error (MAE)
  - $R^2$  Score
- To assess how adding RQI affects prediction accuracy, comparative analysis is carried out.

**E. Tools and Libraries**

- **Python** is used as the primary programming language.
- **TensorFlow/Keras:** CNN for RQI extraction.

- **Scikit-learn & XGBoost:** Machine learning regression models.
- **OpenCV:** Image preprocessing and segmentation.
- **Pandas and NumPy:** Data handling and feature processing.

**F. Deployment Considerations**

- CNN-based RQI extraction is performed offline to reduce computational overhead.
- The trained regression models can be deployed in real estate platforms for **infrastructure-aware price predictions**.
- The framework is scalable and could be expanded to further cities or regions with minimal adaptation.

**VII. RESULT ANALYSIS**

The functionality of the suggested Road Quality Index (RQI)-based real estate price prediction framework is evaluated using multiple machine learning models. The effects of incorporating RQI is analyzed by comparing models trained regardless of this infrastructure-related feature.

**A. Experimental Setup**

- **Dataset Split:** The hybrid dataset (property features + RQI) is split into 70% training and 30% testing subsets.
- **Models Evaluated:** Linear Regression (baseline), Random Forest, XGBoost, and Stacked Ensemble.
- **Evaluation Metrics:**
  - **The Root Mean Squared Error (RMSE)** – measures prediction error magnitude.
  - **The Mean Absolute Error (MAE)** – quantifies average deviation between expected and actual rates.
  - **The R<sup>2</sup> Score** – this shows how much of the variation in real estate price can be accounted for by the model.

**B. Comparative Performance Analysis**

Model	RMSE (Without RQI)	RMSE (With RQI)	MAE (With RQI)	R <sup>2</sup> Score (With RQI)
Linear Regression	45,200	38,750	28,430	0.78
Random Forest	33,480	27,150	19,890	0.87
XGBoost	32,200	25,860	18,450	0.89
Stacked Ensemble	30,750	24,320	17,920	0.91

**Observations:**

1. Incorporating RQI consistently reduces prediction error (RMSE and MAE) across all models.
2. The **Stacked Ensemble model with RQI** achieves the highest accuracy with **R<sup>2</sup> = 0.91**, highlighting the significance of infrastructure-aware features.
3. Random Forest and XGBoost outperform Linear Regression, demonstrating the importance of capturing nonlinear interactions between property features and RQI.

**C. Impact of RQI**

- Including the Road Quality Index improves model accuracy by **15–20%** across different regression models.
- Properties located in areas with higher road quality tend to have higher predicted prices, aligning with real-world market behavior.
- Sensitivity analysis shows that variations in RQI strongly influence predicted prices, confirming that road infrastructure is a critical determinant of property valuation.



#### **D. Discussion**

The results indicate that **satellite-derived RQI** provides a scalable, objective, and quantifiable measure of road quality, which enhances the predictive capability of machine learning algorithms. By taking into account how road conditions effect property value, this infrastructure-aware strategy can assist investors and urban planners in making smarter decisions. The framework is a generalisable approach for real estate valuation since it shoes promise for deployment in other cities or locations with only minor adjustments .

#### **VIII. CONCLUSION**

This paper presents a novel framework for real estate price prediction by incorporating a Road Quality Index (RQI) derived from satellite imagery alongside traditional property features. The experimental results demonstrate that integrating RQI significantly improves prediction accuracy across multiple regression models, with the Stacked Ensemble model achieving the highest  $R^2$  of 0.91. The study highlights the importance of considering infrastructure quality, particularly road conditions, in property valuation, which is often overlooked in conventional approaches.

The proposed framework provides a scalable, objective, and data-driven solution for infrastructure-aware real estate valuation, offering valuable insights for investors, urban planners, and policymakers. Quantifying road quality, it enables more informed decision-making and identifies areas where infrastructure improvements could positively influence property prices.

#### **IX. FUTURE WORK**

While the proposed framework demonstrates promising results for infrastructure-aware real estate price prediction using **Road Quality Index (RQI)** derived from satellite imagery, several directions remain for future investigation. First, enhancing model generalisation techniques to better accommodate **regional heterogeneity in property markets** may further improve prediction accuracy and applicability across diverse urban settings. Second, integrating additional **infrastructure and environmental features**—such as public transport accessibility, walkability scores, green spaces, and pollution levels—could provide a more comprehensive assessment of factors influencing property values. Third, exploring **temporal analysis using time-series satellite imagery** may capture the impact of infrastructure development trends on property prices over time.

Additionally, improving the robustness of the predictive models against **noisy or incomplete satellite data** and irregular property datasets is crucial to ensure reliable real-world deployment. Developing **computationally efficient processing pipelines**, including CNN model optimization and feature extraction techniques, will be essential to handle large-scale satellite imagery and minimize training time. Future work may also explore **real-time predictive systems** capable of dynamically updating property valuations as new data becomes available, enabling proactive urban planning and investment decisions. Finally, extensive **cross-city and cross-region studies** are necessary to validate the generalizability and scalability of the framework across diverse geographic and infrastructural contexts.

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