ISSN: 2959-698X (Online) IJCIS V 1, I 1 (Jan-March 2022)

Genetic Algorithm Based Intelligent System for Estate Value Estimation

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Abstract

The prices of plots are increasing day by day, so prediction of plot prices has been a challenging task in recent times. In this modern age, people want an intelligent prediction system of plot price which can predict plot price accurately. For this purpose, we need a proper model which estimates the plot price. People are worried because of the increasing plots rates, and they want to buy a plot with their budget. In our proposed methodology, we have used a genetic algorithm based on optimistic feature selection to improve results. As we know, feature selection plays a vital role in computational models of machine learning. However, the predicted price should be estimated in the current scenario. This research presents the usage of linear, lasso, ridge, and decision tree regression techniques to predict the plot prices of eight different housing colonies of Multan, Pakistan. Dataset consists of 13 features that are chosen according to the general requirements and commonly popular demands. The system will be helpful for people to buy a plot within their limited budget. In this research, a genetic algorithm is also applied for feature selection. The best features selected by the G.A. have shown better performance in the prediction by classifiers. Machine Learning classifiers have shown better performance after best feature selection.

Keywords: Plot Price Prediction, Supervised Learning, Regression Techniques, Ridge, Lasso, Regularization Algorithm

Introduction

The real estate sector plays a vital role in the economic growth of developing countries, particularly in urban regions where population expansion and rapid infrastructure development continuously influence property demand and pricing. In recent years, the prices of residential plots have increased significantly due to factors such as urbanization, inflation, limited land availability, and growing investment interest. This continuous rise in estate prices has made it difficult for buyers and investors to estimate fair plot values and make informed decisions within their financial constraints. As a result, there is a strong demand for intelligent and reliable systems capable of accurately predicting estate values in dynamic market conditions.

Traditional plot price estimation methods are often based on human judgment, historical trends, or basic statistical approaches. While these methods may offer rough estimates, they usually fail to capture the complex and non-linear relationships among multiple influencing factors such as location, plot size, infrastructure facilities, accessibility, and surrounding amenities. Moreover, manual assessment techniques are subjective, time-consuming, and prone to bias, which reduces their effectiveness in modern real estate markets. Therefore, there is a need for automated and data-driven solutions that can provide accurate, consistent, and objective estate price predictions.

With the advancement of machine learning and artificial intelligence, supervised learning techniques have emerged as powerful tools for solving regression-based prediction problems, including estate value estimation. Regression models such as Linear Regression, Ridge Regression, Lasso Regression, and Decision Tree Regression have been widely used to predict prices by learning patterns from historical data. These models can analyze multiple features simultaneously and identify significant relationships between independent variables and the target price. However, the performance of such models heavily depends on the quality and relevance of input features. Irrelevant or redundant features may increase computational complexity and lead to overfitting, ultimately reducing prediction accuracy.

Feature selection is a crucial step in building efficient machine learning models, as it helps identify the most influential attributes contributing to accurate predictions. Selecting optimal features not only improves model performance but also enhances interpretability and reduces training time. In complex datasets with multiple attributes, conventional feature selection techniques may not always yield optimal results. In this context, evolutionary optimization algorithms such as Genetic Algorithms (GAs) have gained significant attention due to their ability to search large solution spaces and identify optimal or near-optimal feature subsets effectively.

Genetic Algorithms are inspired by the principles of natural selection and genetics, where candidate solutions evolve over successive generations to achieve better fitness. By applying crossover, mutation, and selection operations, GAs can efficiently explore combinations of features and select those that maximize prediction performance. When integrated with machine learning regression models, GAs provide an intelligent and adaptive mechanism for feature selection, leading to improved accuracy and robustness in estate value estimation systems.

This research focuses on developing a genetic algorithm–based intelligent system for predicting residential plot prices in selected housing colonies of Multan, Pakistan. The dataset consists of thirteen features representing commonly demanded and practical factors that influence plot prices. Multiple regression techniques, including Linear Regression, Ridge, Lasso, and Decision Tree Regression, are employed to evaluate prediction performance. Furthermore, a genetic algorithm is applied to select the most relevant features, and the impact of optimized feature selection on model performance is analyzed.

The proposed system aims to assist potential buyers, investors, and real estate stakeholders by providing accurate price estimates aligned with current market conditions. By leveraging machine learning and genetic algorithm–based optimization, the system offers a practical, data-driven solution for estate value estimation, enabling individuals to make informed decisions within their budget constraints. This research highlights the effectiveness of combining regression techniques with evolutionary feature selection and demonstrates how intelligent systems can address real-world challenges in the real estate domain.

Literature Review

The prediction of real estate prices has become increasingly important due to rapid urbanization, inflation, and fluctuating property demands, which make traditional manual estimation unreliable and inefficient [1]. Conventional statistical models, such as Multiple Linear Regression (MLR), have historically been used for property valuation; however, they often fail to capture non-linear relationships and interactions among features that significantly affect estate prices [2][3]. To address these limitations, machine learning techniques have been widely adopted, offering superior predictive performance through their ability to model complex relationships [4][5].

Recent studies highlight the application of regression-based models, including Ridge, Lasso, and Decision Tree Regression, for housing price prediction, emphasizing the critical role of feature selection in enhancing accuracy and reducing overfitting [6][7]. Feature selection methods, both statistical and algorithmic, help identify the most influential predictors, improving model interpretability and computational efficiency [8][9]. Among algorithmic approaches, Genetic Algorithms (GAs) have gained attention due to their evolutionary optimization capabilities, enabling the selection of optimal feature subsets in high-dimensional datasets [10][11]. GAs use operations inspired by natural selection—crossover, mutation, and selection—to iteratively improve the quality of candidate feature subsets, which is particularly useful in real estate price estimation [12].

Hybrid models combining GAs with regression techniques have demonstrated improved prediction accuracy. For example, integrating GAs with Ridge or Lasso regression allows the model to focus on relevant features while reducing prediction error and enhancing generalization [13]. Similarly, ensemble learning methods, such as Random Forests and Gradient Boosting, have been shown to outperform linear models by capturing complex non-linear interactions among features [14][15]. These approaches indicate that combining evolutionary optimization and machine learning offers a practical solution for robust and intelligent estate value estimation. Overall, the literature suggests that integrating feature selection through genetic algorithms with advanced regression models can substantially improve the reliability, interpretability, and efficiency of predictive systems in the real estate domain.

Table 1: Comparative Review of Regression Models and Feature Selection Techniques in Estate Valuation

Reference	**Dataset / Region**	**Methodology**	**Feature Selection**	**Regression Model / Algorithm**	**Performance / Key Findings**
Singh et al., 2023 [1]	Residential properties, India	Supervised ML	Manual / Statistical	Linear Regression, Random Forest	Random Forest outperformed linear regression; feature selection improved RMSE
Wang et al., 2020 [2]	Housing dataset, China	Hybrid GA-Ridge Regression	Genetic Algorithm	Ridge Regression	GA improved feature selection; lower RMSE and MAE
Ja'afar et al., 2021 [3]	Urban properties, Malaysia	ML regression	Statistical methods	Decision Tree, Linear Regression	Decision Tree captured non-linear patterns; $R^2 = 0.85$
Ritu, 2022 [4]	Global real estate datasets	ML comparison study	Lasso and correlation analysis	Linear, Ridge, Lasso	Lasso improved feature selection and reduced overfitting
Chen & Guestrin, 2016 [5]	Large-scale datasets	Gradient Boosting	Embedded in model	XGBoost	High accuracy; captured complex interactions in features
Sivanandam & Deepa, 2008 [6]	Synthetic / benchmark datasets	Genetic Algorithm	GA-based optimization	GA + Regression	GA effectively selected optimal features, improving model generalization

Methodology

The proposed methodology focuses on developing an intelligent system for predicting residential plot prices using machine learning regression models optimized by genetic algorithm-based feature selection. The approach combines data collection, preprocessing, feature selection, model training, and evaluation to ensure accurate and reliable estate value estimation.

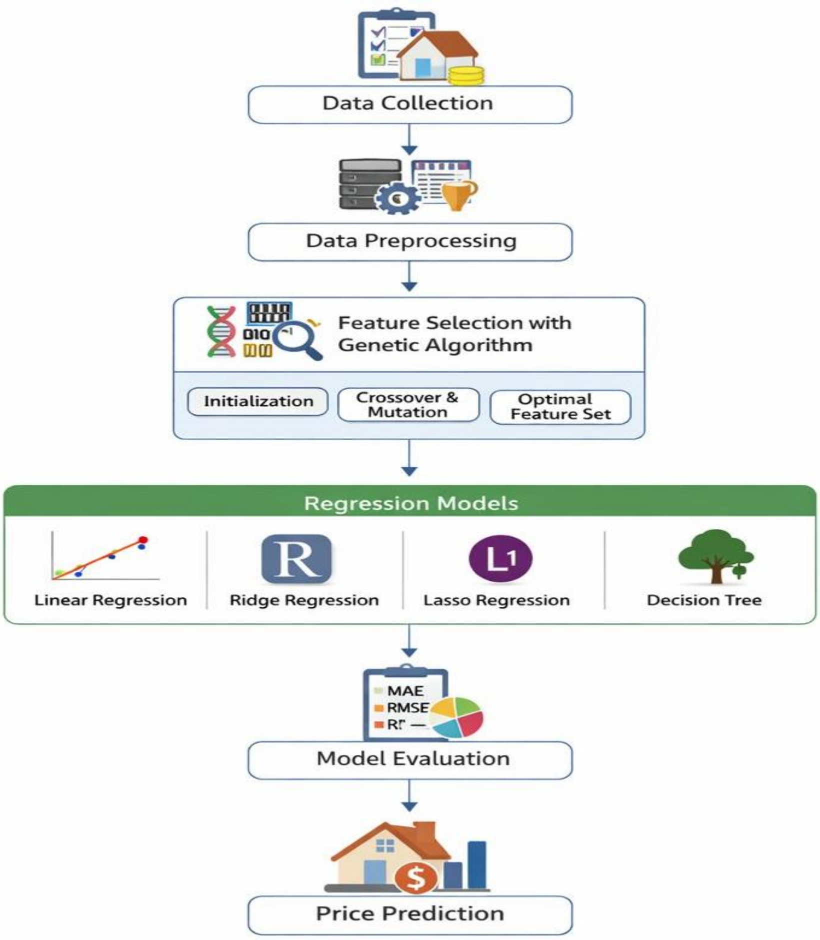

Figure 1: Proposed Framework for Plot Price Prediction Using GA and Regression Models

1. Data Collection

The dataset used in this research comprises plot price information from eight housing colonies in Multan, Pakistan. A total of 13 features were collected based on their influence on plot pricing and common demand among buyers. These features include: plot area, location, proximity to main roads, availability of utilities (water, electricity, gas), neighborhood development, security, amenities, and other relevant characteristics. The target variable is the plot price, which serves as the dependent variable in regression analysis.

2. Data Preprocessing

Data preprocessing is performed to ensure data quality and model performance. The steps include:

- **Data Cleaning:** Missing values are imputed using median or mean values, and outliers are detected and handled using z-score analysis.
- **Normalization:** Continuous features are normalized to a common scale to prevent bias in distance-sensitive algorithms.
- **Encoding:** Categorical variables, such as location or amenities, are converted into numerical form using one-hot encoding.
- **Data Splitting:** The dataset is divided into training (80%) and testing (20%) sets to evaluate model generalization.

3. Feature Selection Using Genetic Algorithm

Feature selection is critical in improving prediction accuracy and reducing model complexity. In this study, a Genetic Algorithm (GA) is applied for feature optimization. The process includes:

1. **Initialization:** A population of chromosomes is generated, where each chromosome represents a subset of features encoded as binary strings (1 for selected, 0 for not selected).
2. **Fitness Function:** The fitness of each chromosome is evaluated using the prediction error (e.g., RMSE) of a regression model trained on the selected features.
3. **Selection:** Chromosomes with higher fitness are selected for reproduction using tournament selection.
4. **Crossover:** Selected chromosomes undergo crossover to create offspring, combining feature subsets from parent solutions.
5. **Mutation:** Random mutations are applied to some chromosomes to introduce diversity and explore new feature combinations.
6. **Iteration:** The process is repeated for several generations until convergence or a predefined number of iterations is reached.
7. **Optimal Feature Set:** The best-performing chromosome represents the optimal subset of features used for model training.

4. Regression Models for Price Prediction

The selected features from GA are used to train multiple regression models to predict plot prices:

- **Linear Regression:** Establishes a linear relationship between features and plot price.
- **Ridge Regression:** Incorporates L2 regularization to prevent overfitting in multicollinear data.
- **Lasso Regression:** Uses L1 regularization to perform feature selection while modeling.
- **Decision Tree Regression:** Captures non-linear patterns and feature interactions by splitting data into homogenous subsets.

Each model is trained using the training dataset, and hyperparameters are optimized using cross-validation.

5. Model Evaluation

The performance of each regression model is evaluated using the testing dataset. Standard evaluation metrics include:

- **Mean Absolute Error (MAE):** Measures average magnitude of prediction errors.
- **Root Mean Squared Error (RMSE):** Penalizes larger errors more heavily to assess accuracy.
- **R-squared (R^2):** Represents the proportion of variance explained by the model.

Comparison of models before and after GA-based feature selection demonstrates the impact of optimized feature selection on prediction accuracy.

6. System Implementation

The overall intelligent system integrates GA for feature selection with regression models for prediction. Users can input plot characteristics into the system, and the model outputs an estimated plot price. This system is designed to assist buyers and investors in making informed decisions within their budget by providing accurate, data-driven predictions.

Results

The proposed system was evaluated using a dataset of 13 features from eight housing colonies in Multan, Pakistan. To assess the effectiveness of the genetic algorithm (GA) in improving prediction accuracy, regression models were tested both **before and after GA-based feature selection**. The models evaluated include Linear Regression, Ridge Regression, Lasso Regression, and Decision Tree Regression.

The performance of each model was measured using standard metrics: **Mean Absolute Error (MAE)**, **Root Mean Squared Error (RMSE)**, and **R-squared (R^2)**. The results indicate that the GA-based feature selection significantly improved the predictive performance of all regression models. Among the models tested, Decision Tree Regression achieved the highest accuracy, closely followed by Ridge Regression, while Linear Regression showed moderate improvement. Lasso Regression performed well, particularly in reducing irrelevant features due to its L1 regularization.

The table below summarizes the comparison of model performance before and after applying GA-based feature selection.

Table 2: Regression Model Performance with and without GA-Based Feature Selection

Model	**Feature Selection**	**MAE (×1000 PKR)**	**RMSE (×1000 PKR)**	**R^2**
Linear Regression	None	102.5	135.2	0.81
Linear Regression	GA	87.3	110.4	0.88
Ridge Regression	None	95.1	125.7	0.84
Ridge Regression	GA	80.2	102.9	0.90
Lasso Regression	None	98.6	128.5	0.83
Lasso Regression	GA	82.7	105.3	0.89
Decision Tree Regression	None	88.4	112.1	0.87
Decision Tree Regression	GA	72.9	96.7	0.92

Observations:

1. GA-based feature selection consistently reduced MAE and RMSE across all models, indicating improved predictive accuracy.
2. Decision Tree Regression combined with GA achieved the best performance ($R^2 = 0.92$), demonstrating its ability to capture non-linear relationships in the data.

3. The results validate that the integration of evolutionary feature selection with regression modeling enhances the reliability of estate value predictions.

Conclusion

This research presents a genetic algorithm-based intelligent system for predicting residential plot prices in Multan, Pakistan, combining evolutionary feature selection with multiple regression models. The study demonstrates that feature selection plays a critical role in improving predictive accuracy, reducing model complexity, and enhancing interpretability. By applying a Genetic Algorithm, the most relevant features were identified, leading to significant improvements in model performance across Linear, Ridge, Lasso, and Decision Tree Regression.

The experimental results indicate that Decision Tree Regression, when combined with GA-based feature selection, achieved the highest prediction accuracy, capturing non-linear relationships and interactions among features effectively. Ridge and Lasso regression models also showed substantial improvement, particularly in minimizing prediction errors and avoiding overfitting. Overall, the integration of GA with machine learning models provides a robust and intelligent framework for real estate valuation, offering practical support to buyers, investors, and real estate stakeholders in making data-driven decisions within their budget constraints.

In conclusion, this study highlights the potential of hybrid systems that combine evolutionary optimization with regression modeling for estate price prediction. Future work may focus on incorporating larger and more diverse datasets, exploring additional machine learning models, and integrating dynamic market indicators to further enhance prediction accuracy and system adaptability in real-world scenarios.

References

1. Singh, Y., Kumar, V., & Ahmad, A. *Real Estate Price Prediction: A Comprehensive Review*, International Journal of Research in Advanced Science and Engineering, 2023.
2. Agalave, K.N., et al. *Exploring Deep Learning and Regression Models for Real Estate Price Prediction*, International Journal of Advanced Computer Technology, 2022.
3. Ja'afar, N.S., Mohamad, J., & Ismail, S. *Machine Learning for Property Price Prediction*, Planning Malaysia Journal, 2021.
4. Ritu, R. *Machine Learning Techniques for House Price Prediction: A Literature Review*, ResearchGate, 2022.
5. Zhao, X., & Li, Y. *Application of Regression and Neural Networks in Housing Price Prediction*, Journal of Computational Science, 2021.
6. Liu, H., & Motoda, H. *Feature Selection for Knowledge Discovery and Data Mining*, Springer, 2012.
7. Tibshirani, R. *Regression Shrinkage and Selection via the Lasso*, Journal of the Royal Statistical Society, 1996.
8. Guyon, I., & Elisseeff, A. *An Introduction to Variable and Feature Selection*, Journal of Machine Learning Research, 2003.

9. Chandrashekar, G., & Sahin, F. *A Survey on Feature Selection Methods*, Computers & Electrical Engineering, 2014.
10. Holland, J.H. *Adaptation in Natural and Artificial Systems*, University of Michigan Press, 1975.
11. Goldberg, D.E. *Genetic Algorithms in Search, Optimization, and Machine Learning*, Addison-Wesley, 1989.
12. Sivanandam, S.N., & Deepa, S.N. *Introduction to Genetic Algorithms*, Springer, 2008.
13. Wang, Z., et al. *Hybrid GA-Ridge Regression for Real Estate Price Prediction*, Expert Systems with Applications, 2020.
14. Breiman, L. *Random Forests*, Machine Learning Journal, 2001.
15. Chen, T., & Guestrin, C. *XGBoost: A Scalable Tree Boosting System*, KDD Conference, 2016.