Impact of Macroeconomic Factors on Newly Built Residential Property Prices in Dublin

MSc Research Project
Data Analytics

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Impact of Macroeconomic Factors on Newly Built Residential Property Prices in Dublin

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Abstract

Dublin’s residential property market has come under increasing strain from rising interest rates and limited housing supply. Yet, the combined influence of macroeconomic and geospatial factors on property prices remains insufficiently understood. To address this gap, comprehensive data from the Property Services Regulatory Authority (2019–2023), integrated interest rate trends, and new construction activity into predictive models. Comparison of Random Forest, Decision Tree, XGBoost, LightGBM, and Gradient Boosting Regressor models revealed that the Random Forest Regressor delivered an 88% prediction accuracy, outperforming all other approaches and effectively capturing the complex interactions among economic and spatial variables. These results reinforce existing research on the pronounced impact of interest rates on affordability while offering fresh insights into how evolving regional supply-demand dynamics shape Dublin’s housing landscape. These findings can guide policymakers and real estate professionals in crafting data-driven strategies to promote market stability and inform development decisions. Nevertheless, factors such as neighborhood-specific attributes and emerging economic disruptors lie beyond the current scope, highlighting opportunities for future research to refine forecasting and enhance policy interventions.

Keywords:- Dublin Housing Market, Residential Property Prices, Macroeconomic factors, Interest Rates, New Housing Construction, PRSA, Geospatial Data

1 Introduction

Dublin, The city of Dublin, the capital of Ireland, has been at the heart of the country’s economic growth, with its housing market playing a crucial role in financial stability and social cohesion. However, in recent years, middle-income buyers have faced significant challenges in affording new homes as prices have surged amid limited supply. In 2018, the Central Statistics Office reported that only the top 25% of earners could afford a home with a 90% mortgage. House prices in Ireland have been more than doubling since 2014, with a significant rise of 12.4% in the latter half of that time through 2022. A lack of new supply and increasing demand means the prices have risen even higher in Dublin. Added to that, buyers are being challenged by the widening disparity between stated and actual sale prices, often at the whim of websites like Rent.ie and Daft.ie. These patterns highlight the need to look at the larger economic factors driving Dublin's increasingly stressed real estate market, including interest rates, housing supply, and regional pricing differences.

This paper attempts to investigate the trend of Dublin residential property prices, considering some key macroeconomic factors like interest rates, new housing supply, and price differentials by location, between 2019 and 2023. The main data come from the Irish Property Services Regulatory Authority in charge of price regulation and monitoring and residential and commercial property information in Ireland. It supplements information on interest rates and new home developments in Dublin. The combined data set carries the sale date, address of the property, sale price, market price, information on VAT, description of the property, land area, interest rates, and the number of newly built houses as its key features. Advanced machine learning is used to bring these diverse data elements together to reveal the predictive information regarding the drivers of Dublin property price movement.

The suggested research study looks into the following research question to obtain an answer.

- **RQ:** How do macroeconomic factors influence the price of newly built residential properties in Dublin?

- **Sub-RQ:** What is the role of interest rates and new housing construction in determining property prices?

The Main Research Objectives of the Research project are:

- Investigate state-of-art-work predictive modelling for housing markets.

- Design a predictive framework incorporating macroeconomic factors, seasonal trends, and locational data, using feature engineering to optimize the regression models for accurate predictions.

- Analyze the role of seasonal trends and location in shaping property prices.

- Evaluate the accuracy and reliability of the predictive model using metrics such as RMSE.

While this study provides useful insights on how macroeconomic factors influence the prices of newly built residential property in Dublin, it has its own drawbacks. First, it doesn't include neighborhood qualities in the analysis, like available local amenities, infrastructure, or socio-economic characteristics of those living in the neighborhoods; these are very strong price determinants of property. Additionally, the study does not consider such external disruptors as sudden economic shocks or policy changes that may alter housing market dynamics. This has been due to a lack of granular data availability and the need for focusing on a specific scope of work. Future research may incorporate more diverse datasets in such a way that would offer a higher degree of predictability by considering additional variables.

The rest of the paper is divided into the following sections. Section 2 provides an overview of the literature survey, emphasizing the work's context. Section 3 covers the model-building technique, followed by Section 4 which defines the design tools. Section 5shows the steps used during implementation, Section 6 briefly, contrasts the chosen models and defines the optimal technique, and Section 7 summarizes the conclusion and future work.

2 Related Work

This section provides a general overview of the current state of knowledge on the interaction of interest rates and new house construction in determining house prices, focusing on Dublin. Indeed, over the last decade, studies have increasingly pointed to how interest rate changes affect the affordability of, and therefore demand for, housing, while construction rates impact the supply of housing. In Dublin, the interaction between these factors has been pivotal in determining housing market stability and price dynamics, reflecting broader macroeconomic trends and localized challenges. This survey is concerned with historical and current methodologies for evaluating the dual impacts of interest rates and new house construction on Dublin's housing prices. The analysis is divided into three broad sections: how macroeconomic factors, such as interest rates, are affecting the affordability and demand of housing in Dublin; how construction trends are influencing supply-side imperatives; and, finally, advanced statistical and machine learning approaches to predicting house prices based on these key variables.

2.1 Influence of Macroeconomic Factors (Interest Rates) on Housing Affordability and Demand in Dublin

Interest rates play a critical role in shaping housing demand and affordability. Lyons, 2018 (Lyons, 2018), examines empirically the influence of macroeconomic variables-interest rate and inflation-on housing affordability in Dublin. The research examined housing prices and trends in rents, together with relevant macroeconomic indicators, using a time-series dataset from 2000 to 2016. Results showed that economic growth, supported by record-low interest rates, boosted demand for housing, pushing up average annual prices by 9%. The regression analysis shows that with every 1% decrease in interest rates, the housing prices went up by 0.8%, thus indicating the responsiveness of affordability to macroeconomic changes. This, indeed, pointed out how increases in income amplified price growth in cities like Dublin. However, the study did not incorporate locational data into its analysis, hence its shortcoming in showing trends specific to a neighborhood. Despite this, the research can provide very important information concerning the greater macroeconomic factor affecting the housing market of Dublin and help lay a platform for further in-depth analysis of local factors.

The authors, Agnew and Lyons (2018) (Agnew, 2018), conducted research into the level of employment in relation to housing market trends in Ireland, paying specific attention to how economic growth influences housing supply and demand. With regression techniques using data on job postings and property transactions between 2009 and 2013, the study isolated a strong correlation between growth in employment and house prices. The results indicated that a 1% increase in employment levels added 1-2% to the prices of housing, more so in areas of high employment densities. Supply constraints in such urban centers as Dublin augmented these price increases and made house purchases unaffordable by middle-income buyers. Although this research shows a good correlation between the trend of employment and housing, it does not incorporate macroeconomic variables, which are central to the focus of this research:

interest rates. Nevertheless, this study also reiterates that incorporating employment data in analyses of housing prices is quite essential.

The researcher, Goodman et al. (2022) (Goodman, 2022) examined what increased mortgage rates would mean in terms of the afford ability of houses in the U.S., providing international context. Data from 2015-2021 was collected and modelled using affordability indices and panel regression analysis for mortgage rates against affordability of housing across various income levels. Results indicated that, from the prior affordability, middle-income buyers lost approximately 8% each time there was an increase of 1% in mortgage rate levels, especially for urban area dwellers. The study emphasized the double-edged effect of increased rates: it reined in demand due to reduced purchasing power while also having a stabilizing effect on prices through a reduction in speculative activities. However, the study did not look into the spatial variation of these effects, which may be different for different regions. This research provides a valuable context in which to set the understanding of how macroeconomic policies influence housing affordability, particularly through interest rate mechanisms.

Another researcher, Corrigan et al. (2019) (Corrigan, 2019), constructed a housing market affordability index to assess the trends in Ireland's housing affordability. The research, informed by micro-level data across the period 2006 to 2016, analyzed housing costs about household incomes along different demographic lines. The results indicated that housing costs consumed up to 40% of income in low-income households, while affordability improved slightly as higher-income groups benefited from increased wages. It indicates that the most significant decline in affordability was for urban areas like Dublin, where demand for housing exceeded supply. While this study provides an effective quantification of the affordability variable, it does not encapsulate exogenous variables such as interest rates and inflation, hence being narrow in scope. This work provides a good starting point for observing the trends in affordability over time.

Author, Savva 2018 (Savva, 2018), conducted research on the resilience of housing markets during economic declines in 24 European countries, which included Ireland. By applying panel data regression, the research investigated the effects of interest rates, inflation, and unemployment on housing prices between 2000 and 2015. The results indicated that those regions that had sound economic fundamentals, such as low unemployment and stable inflation, were more resilient and their housing prices remained stable even during financial crises. However, the study noted that a rise in interest rates affects the affordability of urban centers disproportionately. While it lacks a specific focus on Dublin, the analysis done on macroeconomic resilience offers a useful framework for understanding the interaction of economic policies and housing markets.

2.2 Locational and Geospatial Influences on Property Prices

The author, Stanley et al. (2016) (Stanley, 2016), empirically showed that the energy performance rating of Dublin houses has a significant impact on their market prices. The study employed a hedonic pricing model on a dataset of 2,792 properties listed on daft.ie, incorporating information on house location, type, size, and number of bedrooms. The results showed that with every 50-point rise in the EPI, there is an appreciation in list price by 1.5%. This can be explained by the size variable, commanding a better price for detached house types. From the regression results, it could also be deduced that older buildings appreciated in value, probably due to historical reasons and prime location. This study has however noticed one limitation: the fact that over 40% of listings were without BER, reducing the generalization of such results. Despite this, the study highlights energy efficiency as a significant determinant of property prices in Dublin.

Author Lima 2019 (Lima, 2019) investigated the impact of short-term rental platforms such as Airbnb on the housing market in Dublin. The information included Airbnb listings and the statistics of the long-term rental market between the year 2015 and 2018; the study used econometric modeling to assess the change in the availability of rentals and their prices. It indicated that a 10% increase in Airbnb listings leads to a 15% rise in property prices in the most demanded areas, seriously shrinking long-term rental affordability. According to the study, the demand for short-term rentals forced out long-term tenants, increasing affordability problems in the central part of Dublin. In their study, they successfully show location-specific pressure on housing prices but did not take macroeconomic factors into account, such as interest rates. Nevertheless, the study is important in understanding how emerging market dynamics reshape Dublin's housing affordability.

A study by Dupre 2020 (Dupre, 2020) did a spatiotemporal analysis of Dublin's housing market to assess how locational and temporal trends affect property prices. Using geospatial modeling and Extreme Gradient Boosting, the study analyzed PSRA transaction data with socioeconomic variables such as proximity to schools, commercial hubs, and public transportation. The study showed that homes located close to transport and commercial hubs were priced at a 10-12% premium on the average, and the city's faraway areas experienced slower growth. This emphasized the mobility of a city as a primary factor affecting property prices. However, the authors also admitted the fact that there might be traffic problems that stifle the mobility convenience factor in the area. Consequently, the minor modifications to the supply chain model and the dynamic pricing proved to be more accurate than the aggregate price trend. To this end, the study explains the GIS approach of previous research and its relation to the location variable in property price prediction.

The findings by Moro, Mayor, and Lyons S. (2013) (Moro, 2013), studied the intertwining of urban infrastructure and cultural heritage sites on housing demand and prices in Greater Dublin. Through hedonic regression of the property sales from 2001-2006, the inquiry was able to find that the closer proximity to cultural heritage sites was associated with the higher price of the property by the amount of 0.4%-0.6% while infrastructure that is in poor condition has the opposite effect on house prices. The results also demonstrated that housing demand was attracted to the urban areas with good public transport networks. Though the study has missed to consider other vital factors i.e., macroeconomic trends or construction rates. It is still a very good piece that talks about the urban planning and location of the house to determine the house prices.

The researcher Li et al. (2021) (Li, 2021) conducted a study on the spatiotemporal in Dublin's housing market post-2010 using geospatial techniques (Li, 2021). The study integrated transaction data from the PSRA in combination with temporal variables such as seasonality, and macroeconomic elements like interest rates. The outcomes showed a 12% increment in housing prices, especially due to the proximity of commercial centers and public transport. Also, seasonal trends that are springs and summers, having higher transaction volumes and prices, were significant impacts on trends. The paper consists of geospatial and temporal data, but it does not imply intelligent machine learning techniques that can give higher prediction accuracy. This is a good example of how location and macroeconomic variables are interrelated in the Dublin housing market.

2.3 Predictive Models for Housing Price Analysis

Another researchers, Roche and M.J, 2001 (M.J., 2001), have estimated speculative bubbles in regime-switching models for Dublin's housing market. The investigation by the authors focused on differentiating between the fundamental and speculative components of prices, based on housing transactions from 1985 to 2000. The results showed that speculation made significant contributions to volatility, where the fundamental values deviated up to 30% during peak speculative periods. The study concluded that housing prices in Dublin were highly sensitive to market sentiment and speculative behavior. However, the research did not employ predictive modeling techniques that could be of any practical use for future price forecasting. Despite this, it provides the basic understanding of market dynamics for modern machine learning approaches.

The authors, Wu and Wang (2018) (Wu, 2018), applied Random Forest models to predict housing prices using a dataset of 26,800 property transactions. The study aimed to assess the efficiency of Random Forest in contrast to traditional regression methods. The results showed that Random Forest outperformed linear regression with an RMSE of 0.15 and R^2 of 0.85. The model was especially good at capturing nonlinear relationships in the data. The paper was based on property-specific attributes without incorporating any macroeconomic variables. This study justifies the use of ensemble models for prediction, and hence the subject matter falls within the advanced regression techniques.

Studies conducted by Rana et al. 2020 (Rana, 2020) compared the performance of different machine learning models, namely Gradient Boosting and XGBoost, in housing price prediction. They used a Kaggle dataset with 10,000 records to investigate the ability of the metrics RMSE and MAE to predict the data using the models. These are among the research that pointed out that Gradient Boosting is the most complex model with the best generalizability as it attained a low RMSE of almost 0.10, while XGBoost and Random Forest remained behind in the few data scenarios. Thus, it brought the importance of model parameter tuning again into the spotlight. The study mainly focused on the work they did on synthetic data and it very much showed well the extreme nature of Gradient Boosting in dealing with difficult prediction) tasks.

Researchers Lu et al. (2019) (Lu, 2019) were the ones who developed a hybrid deep learning framework putting together Convolutional Neural Networks (CNN) and XGBoost to foretell housing prices. The research worked with a dataset of property images and numerical attributes and proved that the model accuracy increases by investigating the visual and numerical data together. The combination model achieved an MAE of 0.0332 which was much better than conventional regression methods. Nevertheless, the model depends on property images only that limits its application to datasets without visual elements. This study shows the potential of hybrid modeling, despite the fact that it concentrated on different techniques than the one presented here, namely the macroeconomic and geospatial variables.

The study by Zhongyun et al. (2019) (Zhongyun, 2019) used a feed-forward neural network to estimate house prices using geospatial and other property-specific attributes in

China. It had an accuracy of 95.59% and hence showed its efficiency in uncovering very complex patterns. Property location and size emerged as strong predictors of the price. Although neural networks achieve high accuracy, this work does not utilize economic indicators and thus is also less relevant for macroeconomic-focused analyses. This study gives an idea of the capability of deep learning, but simpler ensemble models, such as Gradient Boosting, may be more interpretable for this study.

In another study Tang et al. (2019) (Tang, 2019) have compared bagging and boosting algorithms, including Random Forest and Gradient Boosting, on housing price prediction. With a dataset size of 50,000 records, the study concluded that Gradient Boosting outperformed Random Forest with an RMSE of 0.08. It also highlighted that ensemble methods are necessary for the nonlinear interaction between the variables present in the housing datasets. However, it did not focus on any geospatial or macroeconomic variables. This research justifies the robustness of Gradient Boosting and thus reinforces its choice in this study.

The researcher Tran et al. (2017) (Tran, 2017) developed hybrid regression models that combined Lasso and Gradient Boosting for the prediction of housing prices. The study used a Kaggle dataset and obtained an R^2 of 0.86, which outperformed the single-method models. The hybrid approach thus improved feature selection and reduced model complexity without compromising accuracy. However, this study did not consider macroeconomic data. The results again underline the potential of hybrid modeling, something this study tries to realize by integrating several data sources for better predictions.

The author, Savva (2021) (C, 2021), analyzed post-pandemic shifts in European housing markets, focusing on interest rates and inflation. Using panel data from 2019 to 2021, the study found that interest rates had the most significant impact on affordability, with housing prices rising by 8%-12% annually post-COVID. The research demonstrated that macroeconomic factors outweighed locational influences during this period. However, the lack of Dublin-specific analysis limits its direct applicability. Thus, the study justifies the incorporation of macroeconomic variables into forecasts of housing prices.

The study by, Gupta and Mehra 2020 (Gupta, 2020), applied several ensemble learning methods, namely, Random Forest, Gradient Boosting, and XGBoost, to housing price prediction. The models were evaluated for RMSE and MAE, where Gradient Boosting performed the best with a minimum RMSE of 0.12. It was concluded that hyperparameter tuning plays an important role in enhancing a model's performance. Although this study was based on property-specific attributes, the validation of Gradient Boosting reinforces its relevance to this research.

Findings from Zhang et al. (2021) (Zhang, 2021) considered the temporal dynamics of housing markets, treated with dynamic network analysis. They analyzed the price data over the period of 2000-2020, showing that regional housing markets mostly travel in convoys while Dublin demonstrates unique temporal trends. Their findings on price changes showed that it was mainly economically justified in Dublin by the rate of growth and interest rates. Nevertheless, this work did no predictive modeling but rather a descriptive analysis. This research focuses on the integration of temporal data, which was in agreement with the time-series analysis of this study.

In conclusion, the related wok highlights the critical roles of macroeconomic factors, locational attributes, and predictive modeling in understanding housing prices. However, most studies fail to integrate these variables comprehensively or address Dublin-specific dynamics. This research bridges these gaps by combining macroeconomic (interest rates, construction trends) and geospatial data with advanced machine learning techniques to develop a predictive framework for Dublin's housing market. By addressing these methodological shortcomings, this study contributes to both academic understanding and practical policymaking aimed at stabilizing Dublin's housing market.

2.4 Comparison of state of art work

Table 1: State of the Art Table

Authors	Year	Methodology	Strengths	Weakness	Key Findings
Lyons	2018	Time-series regression on housing prices and macroeconomic indicators	Demonstrates the impact of interest rates and inflation on affordability in Dublin housing markets.	Lacks locational data, limiting insights into neighbourhood-specific trends	Economic growth and low-interest rates drove a 9% annual price increase in housing prices.
Stanley et al.	2016	Hedonic pricing model on energy performance data from 2,792 Dublin properties	Quantifies the effect of energy efficiency on housing prices and demonstrates regional price disparities.	40% of listings lacked BER ratings, reducing the generalizability of the results.	A 50-point increase in EPI resulted in a 1.5% increase in list price, with detached homes commanding a premium.
Rana et al.	2020	Gradient Boosting regression compared with other machine learning models	Demonstrates superior generalizability of Gradient Boosting, especially for small datasets.	Used synthetic data, reducing real-world applicability.	Gradient Boosting outperformed Random Forest and XGBoost, achieving the lowest RMSE of 0.10.
Dupre	2020	Geospatial analysis using XGBoost on Dublin housing transaction data	Highlights the role of locational variables like transport and commercial	Limited ability to capture rapid changes due to reliance on static datasets.	Properties near transport hubs had a 10%-12% price premium;

			proximity on prices.		suburban areas exhibited slower growth.
Tang et al.	2019	Comparative analysis of Random Forest and Gradient Boosting on 50,000 records	Validates ensemble learning techniques for housing price prediction with high accuracy.	Limited focus on macroeconomic or locational data, reducing holistic applicability.	Gradient Boosting achieved superior performance with an RMSE of 0.08, capturing nonlinear interactions effectively.
Savva	2021	Panel data analysis on post-COVID-19 housing trends across Europe	Demonstrates macroeconomic impacts, particularly interest rates and inflation, on housing affordability	Lack of Dublin-specific focus, limiting regional relevance.	Interest rates and inflation drove an 8%-12% annual increase in housing prices post-COVID-19.

3 Research Methodology

This section elaborates on the steps followed to accomplish the goals stated in Section 1. The methodology deviates from conventional frameworks of data analysis and instead follows a carefully crafted sequence that best suits the determination of an optimal approach to predict residential housing outcomes. Figure 1 illustrates this step-by-step research process. The literature review, therefore, shaped the research plan in terms of state-of-the-art methodologies, their strengths, and limitations summarized in Table 1. Given the peculiar nature of the dataset adopted for this study, a customized strategy was developed. This approach, which was not only tailored to the needs of the data, also made this methodology stand out in its application.

3.1 Data Collection

This analysis has been based on three datasets, all of which are meticulously cleaned and prepared to ensure their validity and consistency. First is the dataset from the Property Services Regulatory Authority (PRSA), containing information on the sales of homes, sale prices, transaction dates, and locations of properties. While enhancing these records, the geospatial data were added using the Mapbox API; filling in missing or erroneous data, such as postcodes, latitude, and longitude. Some unusual transaction prices were found and then removed using a method called interquartile range analysis. Missing values in important fields were either filled in or removed. The second dataset, relating to interest rate data, was carefully checked for errors. A third dataset contained annual records of houses built in the city of Dublin. To clarify this, they standardized the region names, reformatted the dates to be consistent, and created seasonal categories—winter, summer, autumn, and spring based on calculated ratios of total housing. Each of the three datasets was run through validation checks to confirm their validity and had common columns standardized, such as year, month, and Eircode, so they were easily joinable. Its careful processing ensured that data was correct, complete, and could be used for detailed analysis and modeling.

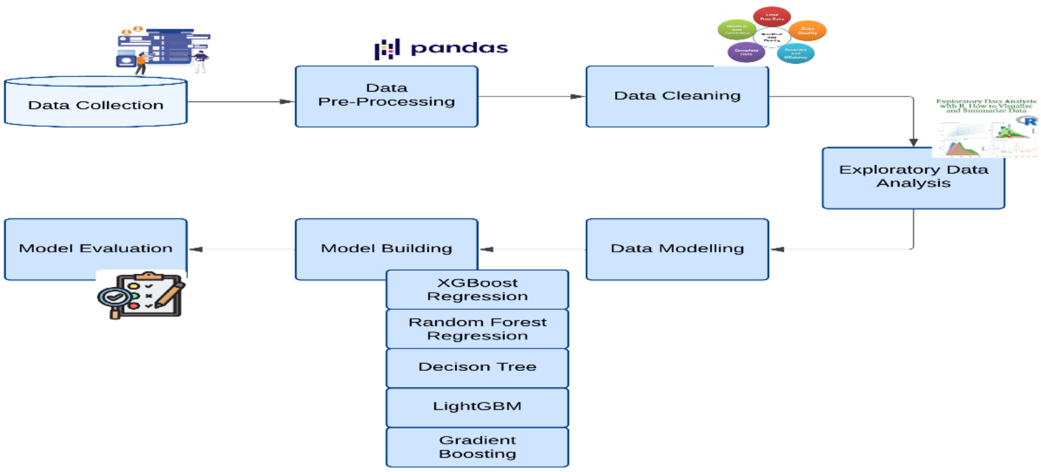

Figure 1: Proposed Research Methodology for Prediction of Dublin Housing Prices

3.2 Pre-processing the Data

Data preprocessing is an important step in this research so that the data sets are accurate and relevant for analysis; missing values, noise and outliers affect the accuracy of the predictions. The raw data from PRSA, mortgage interest rates as well as new house construction were further subjected to a systematic review in to order deal with missing and inconsistent values. It was necessary to check the attributes for null values; completion or deletion was done in accordance with the need. Some data preparation operations were employed in this paper including data type conversion, normalization of numerical variables and encoding of categorical variables in order to bring the data into a analyzable state. Some specific transformations including the standardization of interest rates as well as categorization of property types were performed in order to achieve the compatibility and comparability of the data. Also, the seasonal proportion was calculated for housing construction data to observe the trend of the seasonal distribution. All these ensured that the data sets were properly arranged and could be integrated and modeled for analysis and this formed a very solid foundation for the application of predictive analytics.

3.3 Cleaning Data

Data cleaning played a key role to ensure the analysis had reliability. This step matters because outliers and noise can throw off predictions if we don't deal with them. We ran thorough checks on the datasets to find missing values, noise, and outliers. This helped us keep the data quality and integrity high. When we found missing values, we used the right methods to fill them in. This kept our datasets complete. We also took out any entries that didn't fit with what we were trying to study. We used stats tools like IQR analysis and set limits on standard deviation to spot outliers that could mess up our results. We then fixed or removed these outliers based on how important they were to the dataset. This helped keep our data valid. We also cut down on noise, which often comes from wrong or mixed-up values. To do this, we checked against the original sources when we could and smoothed things out when needed. All this cleaning made sure our datasets were neat, made sense, and were in good shape to analyze later. You can find more details on how we handled missing values and outliers in Section 5.

3.4 Exploratory Data Analysis

With After cleaning the dataset, we dug into exploratory data analysis (EDA) to uncover patterns, connections, and trends between independent and dependent variables. This gave us a better understanding of the data. We made different charts, like scatter plots, histograms, bar plots, and box plots, to check how the data was spread out how things were related, and if there were any outliers. We used some cool Python tools for making pictures, both still and moving ones. These included Matplotlib, Seaborn, Geopandas, and Folium. They helped us see the data better, when it came to space and time. These visual tools showed us important stuff, like how mortgage interest rates affect house prices and how new building changes the housing supply. What we saw from EDA helped us come up with ideas and decide how to make our models. You can find more about how we did this and what we learned in Section 5.

3.5 Data Modelling

Data modelling involved feature selection and transformation to prepare the dataset for developing a robust predictive model. Key attributes, such as house sales, mortgage interest rates, and new house construction, were refined through feature engineering techniques to enhance the dataset's predictive power. Categorical variables were transformed into machine-readable formats using one-hot encoding, ensuring compatibility with machine learning algorithms. Numerical features were normalized through scaling, standardizing their ranges for better comparability and improved model performance. These transformations structured the dataset into a well-organized and standardized format, balancing simplicity with predictive accuracy. Detailed methodologies and processes related to data modelling are further elaborated in the Implementation section.

3.6 Model Building

With a deep understanding of both the target and independent variable, some suitable algorithms for house price prediction were identified. Given the continuous nature of the target variable, two important criteria for model-building techniques were insights from state-of-the-art methodologies in related research, besides the continuous nature of the dependent target variable. Literature from similar problem domains highlighted that ensemble learning techniques prove very effective, given that most of them boast predictive accuracy and robustness. Five algorithms have been considered in this study: XGBoost, Gradient Boosting, Random Forest, Decision Tree, and LightGBM. These models can deal with regression problems and highlight an excellent strength in catching the complex pattern inside the data. The key objective at this stage was to test the performance of these models against each other in order to establish which algorithm yielded the best predictive accuracy.

3.7 Model Evaluation

Model evaluation is the last step of the approach and contains testing the performance of the predictive models using established regression metrics. Key evaluation parameters considered are R-Square, RMSE, and MAE for their effectiveness in measuring prediction accuracy and the magnitude of error in any regression task. They are compared in terms of the closeness of the model predictions to actual values; in other words, which one offers the best balance of accuracy and reliability. Detailed results, including charts for each model prediction, are discussed in Section 6 and provided in the code artifact.

4 Design Specification

This study intends to come up with an all-inclusive blueprint of predicting house prices by osmosis of tasks from varied sources of data and the use of machine learning methodology. The method is divided into different phases, the starting phase is data preprocessing, which is followed by exploratory data analysis (EDA), then comes the feature engineering, and lastly, model training. It builds its backbone on three main sets of data: the PRSA's housing sales records, the monthly interest rates on mortgages, and an annual survey of new housing in Dublin. These datasets together play a complementary role in providing the awareness of the key elements and the recognition of the housing market trends. The framework, initially, was designed to manage big data, and at the same time, it could be scaled up and adapted for different applications.

The setup of the pipeline ensures that each step is well executed and hence contributing to the process as a whole. Preprocessing of data includes the handling of missing values, filtering the data with outliers, and the categorical data are transformed into machine-readable format by the use of label encoding. Feature engineering cleanses the datasets further; for example, numerical data can be normalized to help in model performance. EDA is beneficial in the identification of major patterns and relationships between variables with the aid of visualizations produced by Python tools such as Matplotlib, Seaborn, and Geopandas. These observations are of primary importance in the quest of finding the features that influence house prices the most.

Five very popular machine learning algorithms are being employed for model training in this research: XGBoost, Gradient Boosting, Random Forest, Decision Tree, and LightGBM. There algorithms are the most suitable in regression problems since they have the potential to handle non-linear patterns and hence avoid overfitting. The models were evaluated through the performance of error metrics such as MSE and R^2 to obtain the most reliable predictions. The main Python modules needed for the machine learning procedure include Pandas, Scikit-learn, and other libraries such as XGBoost and LightGBM. This framework is meant to systematically determine which model is doing the best in forecasting housing prices, simultaneously keeping the balance between accuracy and interpretability.

5 Implementation

At this stage of the study we have carefully examined three key datasets: Property sales in Dublin, interest rate and new housing construction statistics to prepare for the forecast. We have combined each data set, identify key variables then dig into more information. This part of the project explains how we collect and organize data, find trends, and build models to predict trends, such as house prices.

5.1 Data Preprocessing

We used three main datasets for this study: house sales data from the Property Registration Authority of Ireland (PRSA), interest rate information from the Central Bank of Ireland, and county-by-county housing construction stats. These datasets cover the period from 2019 to 2023, giving us a clear picture of the housing market before, during, and after the COVID-19 pademic. The house sales dataset had more than 15,000 transaction-level records, while interest rate and construction data were in time-series and regional formats. Integrating these datasets into one was pretty challenging due to their differences in structure and granularity; hence, careful preprocessing was required.

The raw data were imported into Python as Pandas dataframes and went through several steps of transformation to make it consistent and usable. Among the key preprocessing steps performed were:

- **Reviewing the Columns:** Inconsistent column naming across datasets was standardized, while numeric fields like "Price" were cleaned to remove special characters such as euro signs, and non-numeric values.
- **Adjustment of Data Types:** Data type errors, like in columns of statistical labels from the interest rate and construction datasets, were corrected through removing invalid characters such as question marks.
- **Derivation of New Attributes:** The "Year," "Month," "Quarter," and "Season" temporal features were extracted from date columns in all the datasets, while latitude, longitude, and eircodes were derived as geospatial features from the "Address" column in the house sales dataset using the Mapbox API, thus allowing the implementation of time-based and spatial analysis, respectively.
- **Seasonality in Construction Data:** Historical seasonal patterns were then used to create quarterly estimates, with construction data allocated in the following way: winter, 15 percent of houses; spring, 25 percent of houses; summer, 40 percent of houses; autumn, 20 percent of houses. For all these various distributions, there was assigned a new attribute called "Season," facilitating detailed construction trends analysis together with any eventuate alignment in the housing market because of COVID-19.

After merging, cleaning, and transforming the datasets, this final preprocessed dataset lays a unified and structured basis for analyses. The resulting data frame is shown in Figure 2, which shows the harmony in integrating sales, interest rates, and construction data.

5.2 Data Cleaning

The most important processes in making these datasets valid and accurate for analysis and modeling involved data cleaning. Imputation for missing values in the house sales dataset included those in the column "Postal Code," which used regional patterns derived from similar entries in the same area. In the case of categorical fields, such as "Property Type," mode imputation was used for filling in missing values with the most common category. For the construction dataset, categorical data was filled in with regional averages, while time-series data was interpolated to ensure continuity and temporal trends were preserved. Similarly, the same procedure was followed for the interest rate time series.

Outliers in important numerical columns, such as the "Price" column in the house sales dataset and construction counts, were identified using the IQR method. These outliers, if they represented invalid data, were removed, or, in case of valid data, adjusted to fall in line with historical trends so as not to skew the analysis. Duplicate records have been systematically removed across all datasets to eliminate redundancy and ensure unique entries. This was done by taking into consideration major columns like transaction IDs, addresses, and timestamps so that the integrity of the data is maintained.

These cleaning processes ensured that the datasets were free from inconsistencies, outliers, and missing values, providing a robust foundation for further analysis and modeling.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6712 entries, 0 to 6711
Data columns (total 17 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   Date of Sale (dd/mm/yyyy)  6712 non-null   object
 1   Address                    6712 non-null   object
 2   County                     6712 non-null   object
 3   Price                      6712 non-null   float64
 4   Not Full Market Price      6712 non-null   object
 5   VAT Exclusive              6712 non-null   object
 6   Description of Property    6712 non-null   object
 7   Sale_Year                  6712 non-null   int64
 8   Sale_Month                 6712 non-null   int64
 9   Season                     6712 non-null   object
 10  Price_Level                6712 non-null   object
 11  Quarter                    6712 non-null   object
 12  latitude                   6712 non-null   float64
 13  longitude                  6712 non-null   float64
 14  eircode                    6712 non-null   object
 15  interest_rate              6712 non-null   float64
 16  Seasonal_Value             6712 non-null   float64
dtypes: float64(5), int64(2), object(10)
memory usage: 891.6+ KB
None
```

Figure 2: Pre-Processed Dataset

5.3 Exploratory Data Analysis

EDA was, therefore, conducted to identify patterns, trends, and relationships in these sets for deeper insights into house prices' drivers within this period of COVID-19. This analysis was based on insights derived from several visualizations and summary statistics to explore how house price interacts with mortgage interest rates and house construction in Dublin and its county. Such insights informed the modeling process and highlighted major market dynamics.

- **Seasonal Sales Distribution:** The bar chart shows the distribution of property sales by season over the period under consideration, with winter standing out as the most profitable, while other seasons were left far behind, with summer and autumn trailing it below, and spring making only the smallest sales. This is opposite to the usual property market with seasonal trends, where the most selling time is spring and summer because of better weather conditions and a more pleasant lifestyle. Sales of properties during the analyzed period might be different due to the unsatisfactory weather conditions, which are influenced by the COVID-19 pandemic and therefore are drawing customer focus away from property sales. As such, the market was modified during the period by these external drivers, which are both local and global.
- **Mortgage Rate Trends:** A line chart illustrates the trend of mortgage rates from 2019 to 2023. During the early period of COVID-19, rates were flat at approximately 3.0%. Since late 2021, a steep upward trend could be observed, and in 2023, rates crossed over 4.4%. This hike coincided with the post-pandemic economic adjustments, including those of inflation and central bank policies, which considerably affected housing affordability and demand. It also underlines the critical role of morgage rates in shaping housing market developments and their likely impact on price dynamics and buyer behavior over this period.

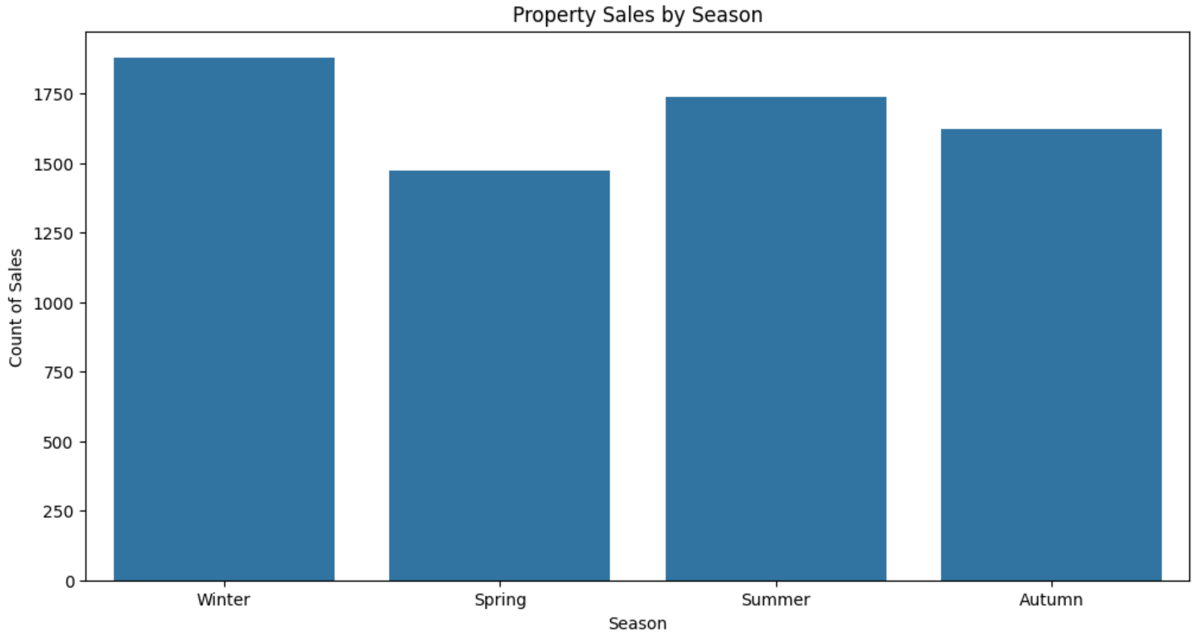

Figure 4: Seasonal sales Pattern

5.4 Future Engineering

Feature engineering was really essential to transform raw data into the format that could work in machine learning models. There were many categorical features in the dataset, which needed to be converted into numerical formats for the models to understand. Therefore, label encoding was applied to categorical variables to change them into a machine-readable format, thereby enabling the models to work on them. Key features engineered included Not Full Market Price, indicating whether the sale represented a full market transaction; Price Level, which categorized property prices into predefined ranges; VAT Exclusive, indicating whether VAT was included in the sale price; and temporal features such as Season and Quarter, which captured seasonal and quarterly variations in housing trends.

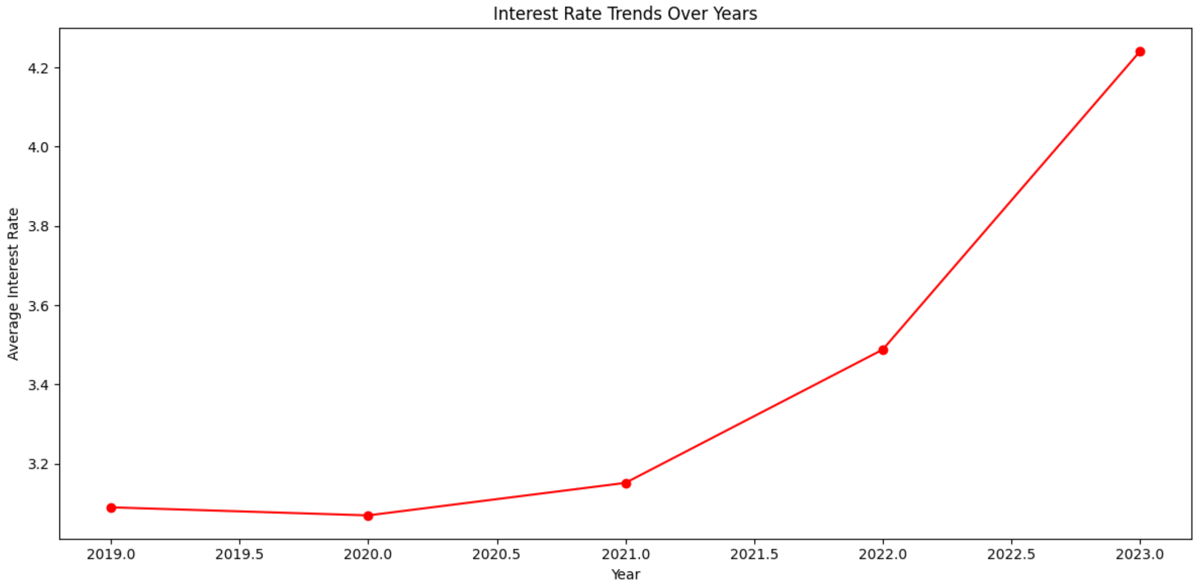

Figure 4: Trend of Mortgage Rates Over Time

Temporal features were then engineered to deeply understand the trend and fluctuation in house prices over time. The feature Year, extracted from the column Date of Sale, helped analyze the long-term market trends, while the feature Quarter allowed for a more granular breakdown of the variation in prices within a year. Seasonal adjustments have been performed on the new housing construction dataset to reflect historical patterns. Concretely, the annual construction was distributed into seasonal proportions: winter got 15%, spring received 25%, summer took up 40%, and autumn garnered 20%. This adjustment enabled us to create the Season feature in a way that captures the time-series dynamics of housing supply and real-world construction behavior.

These transformations greatly enriched the predictive power of the dataset in the light of categorical and temporal dynamics. With these features engineered, the models became even more capable of analyzing complex relationships within the data, especially those which pertained to understanding trends and fluctuations caused by COVID-19 and thereafter in the Dublin housing market.

5.5 Model Selection

In Section 2.3, five regression algorithms were chosen for evaluation, informed by a comprehensive review of the literature on machine learning approaches to price prediction. The review has indicated the strengths of classic, hybrid, and ensemble learning methods for capturing complex relationships within housing market data. An overview of related works that have informed the choice of models is given in Table 1. The chosen algorithms to conduct this study are Random Forest Regressor, XGBoost Regressor, Decision Tree Regressor, LightGBM Regressor, and Gradient Boosting. These models can deal with nonlinear relationships and are robust against overfitting; thus, they are scalable for large datasets. Before model development, the dataset was split into an 80% to 20% ratio between training and testing subsets to avoid any biased evaluation.

- **Hyperparameter Tuning:** Hyperparameter tuning was done to improve the model performance using RandomizedSearchCV. This algorithm efficiently searches a pre-defined grid of hyperparameters by randomly sampling combinations and evaluating them through cross-validation. For the Random Forest Regressor, important hyperparameters tuned were the number of estimators, maximum features, depth of trees, minimum samples to split, and minimum samples per leaf. This search was run for 50 iterations with 5-fold cross-validation to ensure that the selection of parameters is robust. It selects the model with the lowest error and R^2 score for the final evaluation. This step was important in fine-tuning the models to reach optimum accuracy and generalization on unseen data.

This paper tries to identify the best performance model for predicting house prices, systematically selecting and tuning various algorithms to balance accuracy and interpretability.

5.6 Model Implementation

This study implements five machine learning regression algorithms each selected for its ability to handle complex data patterns and deliver reliable predictions. Hyperparameter tuning for all models was performed using the RandomizedSearchCV, ensuring optimal configurations to each algorithm.

- **Random Forest Regression:** Random forest is a cluster learning method that creates multiple decision trees during training and averages predictions to improve accuracy and reduce overfitting. This model is robust to noise and can capture complex relationships between features and target variables. Advanced special parameters include the number of trees. Tree depth selection criteria and properties all of which are used RandomizedSearchCV. The Random Forest Regenerator also comes with key measures that provide insights into key determinants of habitat value. This research is therefore extremely valuable.
- **XGBoost Regressor:** XGBoost is a scalable and efficient gradient boosting algorithm for high predictive accuracy. Building trees in sequence, each tries to correct the errors of the others. For the best possible performance of the models, three important hyperparameters are tuned: the learning rate, the tree depth, and the subsample ratio. XGBoost has the particular advantages of dealing with big datasets and minute patterns, such as interaction among interest rates, seasonal construction trends, and location-

based features. Its ability to handle complex and high-dimensional data makes it very important in this study.

- **Gradient Boosting Regressor:** The concept is similar to XGBoost, wherein Gradient Boosting builds trees sequentially, with each new tree trying to minimize the residual errors of the previous trees. The hyperparameters tuned for this model are the number of estimators, learning rate, and tree depth. Gradient Boosting does exceptionally well in modeling nonlinear relationships and complicated interactions among features, such as how geospatial attributes and interest rates influence house prices. The predictive power of this model is crucial for the analysis of complex housing market dynamics.
- **Decision Tree Regressor:** Decision Trees are non-linear models that split data into branches concerning feature thresholds, hence effectively capturing complex patterns. Performance optimization was done with the use of RandomizedSearchCV on the hyperparameters: Tree depth, minimum samples for splitting, and minimum samples per leaf. This model will be valuable in understanding the hierarchical relationships among the variables and knowing exactly how different factors influence house price fluctuations.
- **LightGBM:** LightGBM is a gradient boosting framework that is optimized for efficiency and scaling. It uses a histogram-based algorithm that can handle big datasets with ease and natively supports categorical features, adding much to its efficiency while handling complex data. The tuned hyperparameters are the number of leaves (num_leaves), the learning rate, and the tree depth (max_depth). Therefore, LightGBM it finds its perfect application in this study since the house price predictions have both temporal and spatial aspects that incorporate minute details in setting the trend of the housing market.

6 Evaluation

This section provides an overall analysis of the predictive performance of the selected models, interpreting the key findings and their implications. The three statistical metrics used in evaluating the models are R^2 Score, Mean Squared Error, and Mean Absolute Error. The results bring forth the capability of the models in capturing complex patterns within the Dublin housing market and their relevance to both academic research and practical applications.

- **Random Forest Regressor:** The Random Forest Regressor gave a very impressive R^2 Score of 0.88, considering that 88% of the variance in house prices was explained well. MSE of $2*10^{10}$ and MAE of 28,752. Though this model has turned in robust results. Its strength lies in accommodating diverse datasets and offering feature importance metrics, thus being suitable for practical purposes of housing price estimation.
- **XGBoost Regressor:** XGBoost appeared as the best among all, for which the R^2 Score is 0.87, the MSE is $2.1*10^{10}$, and the MAE is 29,402. It generalized very well by keeping the error to a minimum, hence outperforming another strong competitor, Random Forest. The combination of the hyperparameters of subsample=0.8 and max_depth=7 really balanced the model's complexity and accuracy. These results underline the robustness of XGBoost in forecasting housing prices and extend their applicability to both academics and practical applications.

- **Decision Tree Regressor:** It follows then that the Decision Tree Regressor had an R^2 Score of 0.83, MSE of $2.8*10^{10}$, and MAE of 33,351, relatively slightly less compared to the ensemble-based methods. The larger error metrics obtained here suggest that standalone decision trees can be limited in handling more complex datasets. However, because of its simplicity and interpretability, it may still be useful in some exploratory data analysis or in understanding hierarchical relationships among variables.
- **Gradient Boosting Regressor:** The best performance was recorded by the Gradient Boosting Regressor, among all models explored, with an R^2 Score of 0.87, MSE of $2.1*10^{10}$, and MAE of 30,644. In the process, the model learns in detail the relationships inherent in the data by iteratively correcting residual errors. Performing hyperparameter tuning at n_estimators=300 and learning_rate =0.05 optimized the bias-variance tradeoff and, hence, made Gradient Boosting the most reliable technique for housing price prediction in this study.
- **LightGBM:** The LightGBM Regressor performed comparably, with an R^2 Score of 0.87, MSE of $2.2*10^{10}$, and MAE of 31,176. While slightly less accurate than Gradient Boosting and XGBoost, LightGBM's computational efficiency and scalability make it a strong candidate for large-scale problems. Optimized with num_leaves=50 and learning_rate=0.05, it effectively handled the high-dimensional data of this study, making it practical for real-time applications.

The evaluation showed that Random Forest Regressor had the best predictions and was always closest to the actual housing prices. XGBoost follows next, which is very good at minimizing error and is highly scalable. Gradient Boosting and LightGBM had good competitive predictions but sometimes deviated a little more from actual values. The Decision Tree model, though interpretable, was not able to generalize too well for this dataset. These results highlight how ensemble techniques, including Random Forest Regressor and Gradient Boosting Regressor, are useful for estimating intricate relationships and patterns in the housing market. Academically speaking, this result supports the ability of such models to solve high-dimensional and nonlinear problems. The insights offer helpful guidance for selecting algorithms that yield accurate house price estimates; the best algorithm for estimating the prices of homes in Dublin's housing market is Random Forest Regressor.

Table 2: Actual Vs Predicted

Model	Actual Value	Predicted Value
Random Forest Regressor	426872	429093
XGBoost Regressor	514449	567844
Decision Tree Regressor	436123	434864
Gradient Boosting Regressor	440528	438380
LightGBM	572687	522603

7 Conclusion and Future Work

This research work was done to determine the best machine learning strategy that could predict residential property prices in Dublin for the period 2019–2023. Using advanced techniques such as Gradient Boosting Regressor, Random Forest, XGBoost, Decision Tree, and LightGBM, the research proved that Random Forest Regressor was always giving the best prediction. The value of this research, besides predictive modeling, lies significantly in feature engineering through encoding categorical variables, adding geographic attributes, and capturing seasonal variations using Recursive Feature Elimination. Exploratory Data Analysis revealed important features of latitude, longitude, and seasonality that would comprehensively help explain the dynamics of housing market determination. These results clearly indicate that such ensemble methods coupled with heavy feature engineering have a better view of giving precise property price estimates. However, there were also some limitations related to using a certain kind of dataset to develop a model which fails to capture external economic influences such as inflation and regional economic trends.

This research met all its aims but there was some room for enhancement and enlargement. Future work could extend this dataset to include further characteristics from the properties themselves, such as year of construction, energy efficiency ratings, and renovation levels. Attributes about the neighborhood, like proximity to schools, healthcare facilities, and public transport, or crime statistics, would also significantly contribute to the granularity and precision of the models. This would make the research even more influential, integrating engaging visualizations and developing a dynamic property price portal that empowers stakeholders-including policymakers, home buyers, and researchers-to make data-driven decisions. Expanding to include external factors such as economic trends would provide a holistic understanding of property value dynamics. Such enhancements would not only raise the academic contribution of the work but also its applicability in real situations.

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