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Residential property price forecasting model for central Pangasinan, Philippines: Input to enhancing resilient planning and disaster mitigation strategies

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Key words: Residential property price forecasting model, Supervised learning, Random Forest, Resilient planning, Disaster mitigation

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Abstract

This quantitative-experimental study aims to develop a residential property price forecasting model for the fourteen municipalities and cities of central Pangasinan, Philippines. Employing supervised learning classification algorithms (linear regression and decision tree), the model predicts whether the value of real properties will increase or decrease in the future. Additionally, classic statistical forecasting techniques (straight line, moving average, simple linear regression, and multiple linear regression) are utilized to predict the rate of increase or decrease, with a margin of error of +/- 5%. The study sources data from the Residential Real Estate Price Index (RREPI) of the Banko Sentral ng Pilipinas (BSP) from 2016 to 2021, Zonal Valuations (ZV) from the Bureau of Internal Revenue (BIR) from 1990 to 2023, and the Housing Cost Construction Index (HCCI) from the Philippine Statistics Authority (PSA) from 2006 to 2021, following an 80:20 training-testing data split ratio. The resulting model, employing the RandomForest algorithm, exhibits a significant accuracy rate of 93% and a precision rate of 93%. Comparative analysis demonstrates that machine learning-based algorithms, particularly Random Forest, outperform classic statistical forecasting techniques such as multiple linear regression, attaining an average prediction distance point of 4.32% versus 12.46%. The study's findings carry profound implications for resilient planning and disaster mitigation in Central Pangasinan. By identifying areas with predicted property value increases, the model empowers local governments and community organizations to prioritize resilient planning efforts. This includes the strategic implementation of disaster mitigation strategies, such as flood control measures and coastal protection, in regions projected to experience property value growth. Moreover, the model's predictive capabilities enable the assessment of specific areas' vulnerability to climate-related risks, guiding informed decisions on sustainable development practices and environmental preservation.

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Introduction

Resilient planning and disaster mitigation have become critical components of sustainable development worldwide, as nations grapple with the growing impact of climate change and increasing urbanization. The United Nations' Sustainable Development Goals (SDGs) highlight the need to build resilient communities that can withstand and recover from various shocks and stresses. Central Pangasinan in the Philippines, like many other regions, faces these challenges and seeks to adopt innovative strategies to enhance community resilience and sustainable development. Resilient planning and disaster mitigation have emerged as critical components of sustainable development, aiming to enhance a community's capacity to withstand and recover from various shocks and stresses (IPCC, 2014; UNDRR, 2015). As the Philippines faces the challenges of rapid urbanization and climate change impacts, resilient planning becomes paramount to address potential risks and vulnerabilities (World Bank, 2019). In this context, understanding the dynamics of residential property prices becomes crucial for local authorities and policymakers to make informed decisions that promote community resilience and environmental sustainability.

Investing in residential real properties has been a surefire way of growing one's equity be it among personal, business or corporate capitalization. Over the years, we have seen the long-term and consistent rise of real property values among rich nations and developing countries, hence, more and more individuals and corporations have considered real property investment to be always on top of their investment diversification portfolio. However, investing in residential real properties is not easy and initially requires sufficient residential pricing information in order for one's capital to be invested securely and properly.

Residential property price information in the Philippines is currently fragmented and decentralized across various government agencies and departments, leading to a lack of a centralized and comprehensive database. This situation arises from the departmentalized nature of the Philippine government functions mandated by the 1987 Constitution. The constitution ensures co-equal independence of the three branches of government: executive, legislative, and judiciary, each with distinct departmental objectives. Additionally, the constitution recognizes the vital role of local government units, further contributing to the establishment of various departments at both national and local levels, managing unique geopolitical subdivisions. While the departmentalized approach aims to provide quality services, it has led to information silos rather than centralized data sharing. As a result, individuals seeking timely, reliable, and comprehensive public information, particularly regarding residential property prices, must navigate multiple bureaus and offices. To obtain complete residential property price information, one must visit various entities, such as the Banko Sentral ng Pilipinas (BSP) for the Residential Real Estate Price Index, the Bureau of Internal Revenue (BIR) for Zonal Values, and the Philippine Statistics Agency (PSA) for the average housing cost index. Furthermore, individuals need to approach the Securities and Exchange Commission (SEC) and Housing and Land Use Regulatory Board (HLURB) to verify the legitimacy of real estate companies offering properties. Additionally, local and provincial offices, including Land Registration Authority (LRA), Registry of Deeds (RD), City or Municipal Assessor's Office, Treasury Office, and Mayor's Office, must be consulted to verify land ownership and title possession. This decentralized system results in inefficiency and difficulty for stakeholders in accessing comprehensive property price information. A centralized and unified platform for residential property price data would enhance transparency, ease information accessibility, and facilitate informed decision-making for property buyers, sellers, investors, and policymakers alike. Such a centralized database could bridge the information gaps between different government agencies, leading to a more coherent and reliable residential property price information system for the entire Philippines.

Another root case of the lack of centralized information for residential real property pricing information is the absence of a one-stop hub for residential property pricing information and real property transfer of registration. Although Republic Act No. 11032 which is commonly known as the Ease of Doing Business and Efficient Government Service Delivery Act of 2018 was signed into law that aims to reorganize and simplify the provision of government services to improve the establishment, registration and conduct of doing business in the country and lessen or totally irradicate Red Tape along the process (BusinessWorld, 2022), no one-stop hub was created solely where the public can get reliable, updated and consolidated information regarding residential property pricing, centralized and faster checking, registration and transfer of real properties.

Internal and external factors affecting the price of a residential property are also a major contributary issue to the root causes of the lack of a centralized residential property pricing information in the Philippines. There are several factors that are involved in residential property pricing which includes zonal values, housing construction material costs, labor and professional services costs, demand and availability of stock housing, population and inflation to name a few (Bual, 2023; Hoppler Editorial Board, 2018). With so many parameters applicable for different locations, it is certainly difficult to determine the actual residential property price especially when you have incomplete parameter information (Uy, 2021).

Meanwhile, in the sector of information and communications technology (ICT), several apps and online websites have been tapping the power of the Internet to provide residential property information among the netizens. However, these websites and apps offer only residential real property price information based on what the seller, landlord or lessor has intentionally indicated and not based on standardized pricing model. On the other hand, several recent studies conducted have shown that relevant real estate data can be aggregated to come up with a real property pricing model (Alam & Isikal, 2021; Kannan & Zhang, 2021; Chen, *et al.*, 2022; and Lu & Zhang, 2022).

In October 2022, the group of Mora, Cespedes, and Perez conducted a research regarding housing price prediction using machine learning algorithms among 49,875 residential properties for sale, lease and rent in Alicante City, Spain. Mora, *et al.* (2022) utilized six ensemble learning algorithms namely gradient boosting, light gradient boosting, extreme gradient boosting, RandomForest and extra-trees regression in a Python program to predict housing price with 28 features. Mora and co-researchers found out that both gradient boosting and random forest algorithms performed better as compared to other algorithms when evaluated using error metrics mean absolute error (MAE), mean squared error (MSE), median absolute error (MedAE), and coefficient of determination (R2) (Mora, *et al.*, 2022).

Meanwhile, a similar study was conducted by Ihre and Engström (2019) using Ames, Iowa housing dataset which is composed of 3,000 entries of houses with 80 variables. The researchers utilized k-Nearest Neighbor (k-NN) and Random Forests algorithm to predict future housing prices. Results revealed that RandomForest better at predicting future house prices than k-NN. The researchers also utilized the error metrics in evaluating the prediction results.

Given the current situation, it is the ultimate goal of this research to establish a real property pricing model out of available data from several related government agencies such as the Residential Real Estate Pricing Index (RREPI) from the Banko Sentral ng Pilipinas (BSP), Zonal Valuations (ZV) per political (barangay) subdivisions from the Department of Finance and Bureau of Internal Revenue, and the Housing Construction Cost Index (HCCI) from the Philippine Statistics Authority (PSA) for residential areas within the cities and municipalities of Central Pangasinan which includes Dagupan City, San Carlos City, Aguilar, Basista, Bayambang, Binmaley, Bugallon, Calasiao, Lingayen, Malasiqui, Mangaldan, Mangatarem, Sta. Barbara, and Urbiztondo. Data mining techniques, classic statistical forecasting methods and machine learning classification methods will be employed to predict the future value of residential properties which can be deployed later via web or mobile apps for data consumption.

This research holds tremendous potential to benefit various stakeholders, including individuals, investors, and corporations looking to engage in real estate transactions within Central Pangasinan. By developing a highly accurate residential property pricing model, this study establishes itself as a valuable reference for current and future residential property pricing information in the region. For individuals and potential homebuyers, the model serves as a reliable tool to assess whether a residential property's price falls within its expected pricing range. Armed with this information, prospective buyers can make informed decisions, ensuring they pay a fair and competitive price for their desired properties. Moreover, the model's predictive capabilities offer insights into the future value of properties, enabling buyers to identify areas with potential price appreciation, thus making sound long-term investment decisions.

Real estate investors and corporations can leverage the forecasting model to identify lucrative opportunities for property investment within Central Pangasinan. By analyzing the model's predictions, investors can pinpoint regions expected to experience substantial property value growth, indicating potentially high returns on investment. This empowers them to allocate resources strategically and optimize their portfolios based on the region's dynamic property market trends. Furthermore, the model acts as a risk assessment tool for all stakeholders involved in real estate transactions. By accurately predicting property prices, it enables buyers, sellers, and investors to gauge the market's stability and minimize risks associated with overpaying or underselling properties. This enhances the overall transparency and efficiency of real estate transactions, fostering a healthy and thriving property market in Central Pangasinan.The implications of this research extend beyond individual interests and investments. The model's predictive capacity plays a crucial role in promoting sustainable development and disaster mitigation strategies. By identifying regions with projected property value increases, local authorities can prioritize resilient planning efforts and implement targeted disaster mitigation measures. This supports the creation of environmentally conscious and disaster-resistant communities, thus contributing to the region's overall long-term sustainability.

This research aims to benefit individuals or corporations eyeing to invest, sell, or acquire real properties within Central Pangasinan by establishing itself as a current or future residential property pricing information reference so that stakeholders will get a gist whether the price of residential property is within its pricing range, has a good future value on it, and will be a worthwhile investment.

Materials and methods

Research Design

The Quantitative-Experimental method of research was utilized by the researcher for this study as machine learning uses quantitative research methods with experimental research design being the de facto research approach (Abu-El-Haija & Al-Khateeb, 2022).

Data Collection and Pre-Processing

The data for this study came from official government data releases which are readily downloadable from their respective official website. The data are divided into three sources: the Residential Real Estate Price Index (RREPI) of the Banko Sentral ng Pilipinas (BSP) from 2016 to 2021; the Zonal Valuations (ZV) from the Bureau of Internal Revenue (BIR) from 1990 to 2023 composed of 12 valuations per city/municipality; and the Housing Cost Construction Index (HCCI) from the Philippine Statistics Authority (PSA) based on its average construction cost per square meter based on approved building permits aggregated from 2006 to 2021. The fourteen cities and municipalities of Central Pangasinan which this study covered include Dagupan City, San Carlos City, Aguilar, Basista, Bayambang, Binmaley, Bugallon, Calasiao, Lingayen, Malasiqui, Mangaldan, Mangatarem, Sta. Barbara, and Urbiztondo. Table 1 presents the distribution of collected data for each covered location.

Table 1. Distribution of Collected Data per Covered Location.

SL	Location	Barangays	RREPI	ZV	HCCI	Total Data Rows
1	San Carlos	86	602	1,032	1,376	3,010
2	Dagupan City	31	217	372	496	1,085
3	Aguilar	16	112	192	256	560
4	Basista	13	91	156	208	455
5	Bayambang	77	539	924	1,232	2,695
6	Binmaley	33	231	396	528	1,155
7	Bugallon	24	168	288	384	840
8	Calasiao	24	168	288	384	840
9	Lingayen	32	224	384	512	1,120
10	Malasiqui	73	511	876	1,168	2,555
11	Mangaldan	30	210	360	480	1,050
12	Mangatarem	86	602	1,032	1,376	3,010
13	Santa Barbara	29	203	348	464	1,015
14	Urbiztondo	21	147	252	336	735
Total		575	4,025	6,900	9,200	20,125

Legend: RREPI = Residential Real Estate Pricing Index; ZV = Zonal Valuation; HCCI = Housing Construction Cost Index

The researcher merged the three datasets into one final dataset by referencing each location and data year of RREPI, ZV, and HCCI per row. Data transformation was applied to location by instituting Location ID. Meanwhile, for rows where RREPI, ZV and HCCI do not have the same year, the most recent RREPI, ZV or HCCI value prior to that year was encoded to avoid zero values which will indicate a total decrease in value. A Delta Value(*Delta*) attribute was added by the researcher to the final dataset which is computed based on the difference of the current(c) and previous(p) RREPI(R), ZV(Z), HCCI(H) values of the same Barangay(b). RREPI(R), ZV(Z) and HCCI values are each given a 1/3 weight. The Delta Value (*Delta*) is computed using the following equation:

$$Delta_b = \left(\frac{R}{3}+\frac{Z}{3}+\frac{H}{3}\right)_c - \left(\frac{R}{3}+\frac{Z}{3}+\frac{H}{3}\right)_p \qquad (1)$$

Likewise, a Movement attribute was added by the researcher which indicates whether the Delta Value of the Barangay increased (value is 1), remained the same (value is 0.5) or decreased (value is 0). In the end, a final dataset composed of seven (7) attributes (Barangay, City, RREPI, ZV, HCCI, Delta, Movement) and 19,550 rows was created and was saved as a comma-separated values (CSV) format file.

Data Modelling

The researcher used the Python programming language to develop the model by utilizing PyCharm as the integrated development environment (IDE). The final dataset was imported and was split to two: 80% or 20,125 rows of data or observations as the training dataset and 20% or 4,025 as the test dataset.

Two algorithms were used to evaluate which output model can better predict Delta Value which include linear regression and Random Forest. Linear regression is considered as one of the commonly used technique in forecasting in different fields such as computer science, economics, and social sciences as it is among the simplest regression techniques to implement and its results are easier to interpret (Kumar & Srivastava, 2020; and Ismail & Al-Ghamdi, 2021). Meanwhile, RandomForest is an ensemble machine learning algorithm which is widely known in the computing industry for its high accuracy in forecasting by combining multiple decision trees in order to render predictions which significantly helps in reducing the variance of the predictions, hence, improve overall precision and accuracy (Alam & Siddiqui, 2021; and Zhang, *et al.*, 2022). The researcher utilized the default parameters for each algorithm to avoid bias.

Performance Evaluation

For the Linear Regression algorithm, the researcher utilized the Ordinary Least Squares (OLS) assumptions to measure accuracy. The formula for OLS is as follows:

$$Y = \beta o + \Sigma j{=}1..p\ \beta j X j + \varepsilon \qquad (2)$$

where Y equals the dependent variable, βo corresponds the intersection point or intercept of the model, Xj refers to the jth or maximum explanatory instance alterable value of the model from j= 1 to p, and e relates to the random error value with expectation value of between o and variance σ^2.

Conversely, for the RandomForest algorithm, the confusion matrix derivatives such as accuracy, precision, recall and F1-score metrics were used to evaluate the performance of the model. The number of accurate and inaccurate predictions made by the classification model in relation to the actual results (target value) in the data are displayed in a Confusion Matrix or Table. *N* is the number of target values (classes), and the matrix is *N*x*N*. The data in the matrix is frequently used to assess the performance of classification models (Duggal, 2023).

The confusion matrix usually provides the base values for Accuracy, Precision and Recall. Accuracy refers the proportion of the total number of predictions that were correct and is defined as:

$$Accuracy = \frac{TP+TN}{n} \quad (3)$$

where TP refers to True Positives, TN represents True Negatives and n is the total number predictions (Biecek & Burzykowski, 2020). Meanwhile, precision, which is also referred to as the positive predictive value, is the number of correct predictions among the predicted successes and is characterized to be of high value if false positives are low. Precision is mathematically defined (Berrar, 2019) as:

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

Recall, which is also referred to as sensitivity or the true-positive rate, is the fraction of portion of correct predictions among the true successes and is also characterized to have a high value if there are few false negatives. It can be written using the following formula (Harrel, 2018):

$$Recall = \frac{TP}{TP+FN} \quad (5)$$

Finally, F1-score is the harmonic average or mean of Precision and Recall and has a direct similar effect Precision and Recall, that is, it has a higher value if Precision or recall is high and F1-score tend to be low if either Precision or Recall is low. It can be mathematically written (Biecek & Burzykowski, 2020) as:

$$F1 - score = 2\frac{Precision * Recall}{Precision + Recall} \quad (6)$$

To check the overall prediction performance and allow visualization, the researcher employed a Prediction Distance for each algorithm based on its predicted Delta value. Prediction Distance is the absolute Euclidian distance of the algorithm's predicted Delta value less than that of the observed or truth value, hence, the smaller the prediction distance, the nearer the prediction value is to the observed value and the larger the prediction distance, the farther away the prediction value is to the observed value. The Prediction Distance formula is as follows:

$$Prediction\ Distance = |OV - PV| \ (7)$$

where *OV* equals to the observed value and *PV* corresponds to the algorithm's predicted value.

The researcher also implemented four classic statistical forecasting techniques over the final dataset to compare with the outcomes of the two machine learning-based algorithms. These techniques include straight line, moving average, simple linear regression, and multiple linear regression.

Results and discussion

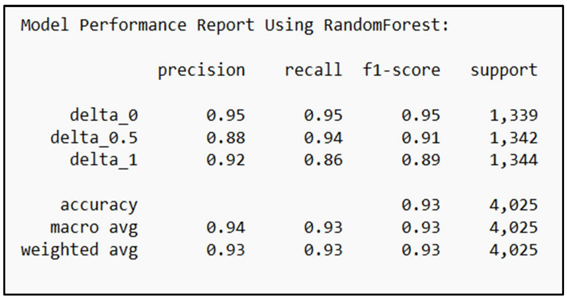
Fig. 1 exhibits the evaluation accuracy result of the residential property pricing model created with Python programming language implementing Linear Regression algorithm. The Ordinary Least Squares (OLS) measure was utilized to evaluate the accuracy of the resulting model over its Delta attribute as the dependent variable which obtained 94.3% R-squared accuracy and 92.8% adjusted R-squared value.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  Delta   R-squared:                       0.943
Model:                            OLS   Adj. R-squared:                  0.928
Method:                 Least Squares   F-statistic:                     65.64
Date:                Mon, 26 Jun 2022   Prob (F-statistic):               0.00
Time:                        14:03:29   Log-Likelihood:                 1111.4
No. Observations                20,125   AIC:                            -1753.
Df Residuals:                   16,100   BIC:                            -563.1
Df Model:                        4,025
Covariance Type:            nonrobust
```

Fig. 1. Evaluation Accuracy Result of Model using Linear Regression Algorithm.

As expected, the linear regression algorithm got a significantly high accuracy rating of 92.8% considering that the dataset's main attributes (RREPI, ZV, HCCI, and Delta) are mostly numeric in nature, hence, can be characterized as well-behaved data. The linear regression-based model has achieved a very high accuracy since the algorithm employed the least squares method which has been proven to minimize the error between the predicted and truth values.

Fig. 2 displays the evaluation accuracy result of the residential property pricing model developed with the Python programming language and implementing Random Forest algorithm.



```
Model Performance Report Using RandomForest:

              precision    recall  f1-score   support

     delta_0       0.95      0.95      0.95     1,339
   delta_0.5       0.88      0.94      0.91     1,342
     delta_1       0.92      0.86      0.89     1,344

    accuracy                           0.93     4,025
   macro avg       0.94      0.93      0.93     4,025
weighted avg       0.93      0.93      0.93     4,025
```

Fig. 2. Evaluation Accuracy Result of Model using Random Forest Algorithm.

The confusion matrix derivates, such as accuracy, precision, recall, and F1-score measures were employed to evaluate the performance of the output model among the 4,025 test dataset which represents data that the model has not yet encountered or seen. An average evaluation accuracy rate of 93% was obtained and a weighted average precision rate of also 93% was achieved which signifies a significantly higher level of prediction accuracy and precision.

In comparison with the linear regression-based model, the Random Forest-based model is significantly superior, although in just a very small difference. However, with the RandomForest-based model, we are assured of the same significant weighted average accuracy precision, recall and F1-score (all 93%) in terms of individual classes. Fig. 3 shows the comparative Prediction Distance line graphs of techniques used.

Since the goal of the Prediction Distance is to empirically identify how near or far the prediction values of the algorithm than that of the actual values, lower values of prediction distance are desired. Based on the line graphs shown on Fig. 3, Random Forest outperforms all the forecasting techniques used in this study on majority of the cities and municipalities and followed by the Linear Regression. Meanwhile, the Straight Line and Moving Average forecasting techniques rank the least among the techniques utilized in the study having the highest Prediction Distance among the majority of the subject cities and municipalities of the research.

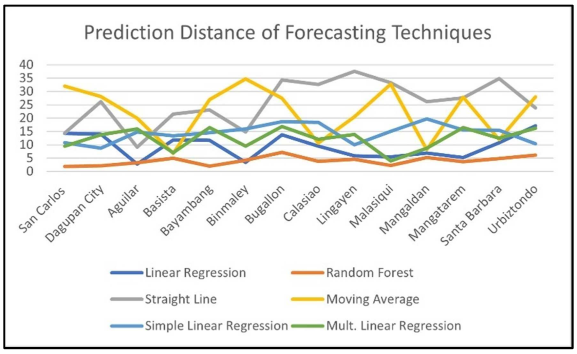


Fig. 3. Prediction Distance Results of Forecasting Techniques Implemented.

The data on Fig. 3 also proves that forecasting using machine learning-based prediction techniques performs better than the four classic statistical forecasting methods. Fig. 4 highlights the overall average comparative Prediction Distance obtained by each forecasting technique used.

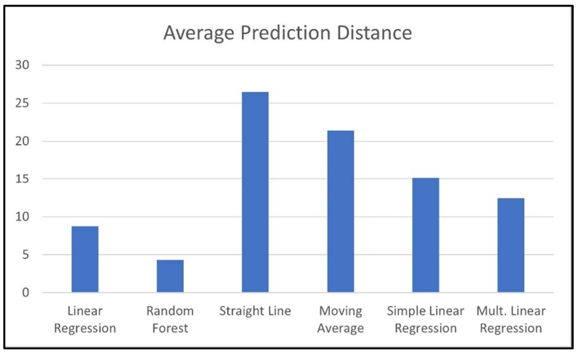


Fig. 4. Overall Average Prediction Distance Results of Forecasting Techniques Used.

The Random Forest algorithm ranks first among the forecasting techniques utilized in this research with an overall average predicted distance of 4.32 points closer among all actual values of the evaluation dataset and which was followed by the Linear Regression with an overall average predicted distance of 8.75 points, Multiple Linear Regression with 12.46 points, and Simple Linear Regression with 15.11 points. Meanwhile, the Straight Line and Moving Average techniques ranked the lowest among the forecasting methods with an overall average distance point of 26.47 and 21.40, respectively.

The data highlighted on Fig. 4 again proves that predicting using machine learning-based forecasting techniques accomplishes better results than the four classic statistical forecasting methods.

Conclusion

Based on the results of the data modelling and evaluation conducted, a residential property pricing model was developed with a significantly excellent accuracy rate of 93% and precision rate of 93% by utilizing Random Forest machine learning algorithm that can accurately predict future values of real properties within the cities and municipalities of Central Pangasinan, Philippines based on historical records of residential real estate pricing index, zonal valuations and housing construction cost index. Further, the Random Forest algorithm outperforms the rest of the forecasting techniques used in this study in terms of the lowest overall average Prediction Distance value with only 4.32 points signifying that majority of its prediction values are almost near the actual values.

Implications to Resilient Planning and Disaster Mitigation

The residential property pricing model developed for Central Pangasinan carries profound implications for resilient planning and disaster mitigation. With its high accuracy and precision rates, the model provides valuable insights to support informed decision-making by local authorities and policymakers. By leveraging this forecasting tool, Central Pangasinan can take significant strides towards building resilient and sustainable communities, equipped to withstand the challenges of urbanization and climate change while prioritizing the preservation of the region's environmental and cultural heritage. Resilient planning is crucial for Central Pangasinan, as the region faces the challenges of rapid urbanization and climate change impacts. By accurately predicting property values, local authorities and policymakers can proactively identify areas that are likely to experience significant value appreciation. This insight allows for informed decision-making in allocating resources for infrastructure development, public services, and green spaces. With a focus on sustainable urban planning, resilient communities can be established, integrating eco-friendly design, green infrastructure, and disaster-resistant structures.

Moreover, the model's predictive capacity plays a crucial role in disaster mitigation strategies. By identifying regions with projected property value increases, disaster-prone areas can be pinpointed, prompting the implementation of targeted disaster mitigation measures. Coastal zones and flood-prone areas, for example, can be prioritized for the construction of protective infrastructure, such as seawalls and flood barriers. In combination with resilient land-use planning, this approach contributes to enhancing community resilience and reducing vulnerability to natural disasters. The model's ability to generate near-actual prediction values further strengthens its significance for disaster mitigation. With accurate property value forecasts, local governments can determine insurance coverage requirements and estimate potential economic losses in the event of disasters. This information aids in disaster preparedness planning and ensures that communities are financially equipped to cope with the aftermath of calamities. Additionally, the model's application to disaster-prone regions can guide the promotion of sustainable development practices. Encouraging eco-friendly and energy-efficient building designs in areas with projected property value increases fosters community resilience while mitigating the environmental impact of urban expansion.

Recommendations

By implementing these practical recommendations, the Residential Property Price Forecasting Model for Central Pangasinan can become an invaluable input for enhancing resilient planning and disaster mitigation strategies in the region. The integration of accurate property price forecasts with disaster risk assessment and community engagement can pave the way for a more resilient and sustainable future for Central Pangasinan. To enhance resilient planning and disaster mitigation strategies in Central Pangasinan, the Residential Property Price Forecasting Model can serve as a valuable input by implementing the following recommendations. Firstly, collaborating with relevant government agencies, including the Banko Sentral ng Pilipinas (BSP), Bureau of Internal Revenue (BIR), and Philippine Statistics Agency (PSA), to establish a centralized residential property database that is regularly updated and easily accessible to all stakeholders will provide comprehensive and reliable information for decision-making. Secondly, integrating the model's predictions and property price trends into disaster risk assessment frameworks will enable local governments to prioritize resilient planning efforts and disaster mitigation measures in areas prone to climate-related risks and natural disasters. Thirdly, utilizing the model's insights to guide targeted infrastructure investments in regions projected to experience significant property value growth will contribute to sustainable and disaster-resilient development.

Fourthly, offering incentives or tax breaks for property developers who incorporate green and disaster-resilient features in their projects will promote eco-friendly construction and enhanced community preparedness. Fifthly, engaging with local communities and stakeholders to raise awareness about the model's findings and involving them in decision-making processes will ensure community needs are considered in development initiatives. Sixthly, leveraging the model's accurate property price predictions to estimate potential economic losses in the event of disasters will inform disaster response planning and resource allocation for post-disaster recovery. Seventhly, providing capacity-building programs for local authorities on utilizing the residential property pricing model will enhance their ability to implement effective resilient planning and disaster mitigation strategies. Lastly, facilitating interagency collaboration to streamline information sharing and data exchange will improve the overall efficiency and effectiveness of disaster mitigation efforts.

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