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Research Article

Property Price Prediction Using Machine Learning

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ABSTRACT

To make smart investment choices in the rapidly evolving property sector market of today, it's critical to have reliable tools for estimating property prices This study aims to come up with a comprehensive machine learning-based system for forecasting property prices. The proposed solution incorporates historical property data and takes into consideration the future development plans to enhance prediction accuracy.

Using crucial factors that effects the property prices such as location, square footage, count of bedrooms, and bathrooms, this study presents a machine learning model that assists in estimating residential sector pricing. The model also accounts for actual developments that may impact property value, such as new highways, train stations, airports, retail centres, and other public infrastructure. The system also integrates financial tools, including an EMI calculator and a rent estimator based on user-defined profit margins. In the advanced phase, a decade's worth of historical data, combined with categorized property classes and reasons for annual price shifts, was used to further enhance accuracy. A "Future Factors Database" was incorporated to account for upcoming infrastructure projects, enabling future growth predictions. The system is developed using Python and Flask, with plans to transition from CSV to a MySQL database for dynamic data handling.

Keywords: Machine Learning, Property, Price, Prediction, Algorithms, Datasets, Random Forest, Forecasting, Model.

INTRODUCTION

Any nation's economic progress is significantly influenced by the real estate industry. In urban environments, Property prices are shaped through a complex combination of factors, with location being a major element as well as configuration, surrounding infrastructure, and projected urban development. Forecasting property prices accurately has become increasingly essential not only for buyers and investors but also for policymakers, urban planners, and financial institutions. Traditional methods of property valuation often fall short in dynamically adapting to evolving factors such as changing cityscapes, road developments, or market demand surges. With the growing availability of advancements in computational power and data, machine learning is now recognized as a robust alternative to conventional valuation techniques. By leveraging patterns hidden within large datasets, models of machine learning can predict residential sector prices with remarkable accuracy and consistency.

This study aims to establish a comprehensive machine learning-based system for fore property prices. The proposed solution incorporates both historical property data and forward-looking features such as future development plans to enhance prediction accuracy. The model takes in key attributes like location, count of bedrooms (BHK), the count of bathrooms, and square feet, and it is trained using advanced algorithms like XGBoost and Random Forest. In addition to predicting the prices, the system integrates financial calculators to assist users with loan estimations and rental income planning, thereby adding practical usability to the tool.

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Furthermore, the project introduces a classification framework for properties based on cost brackets and enriches the dataset with temporal insights from the past decade. By integrating a dual-dataset architecture—comprising historical property values and future development indicators—this study addresses both spatial and temporal dimensions of real estate valuation, resulting in a more holistic and reliable pricing model.

This article is made into five sections: Section 1 contains the introduction and background of the study; Section 2 examines the existing literature and related work; Section 3 details the methodology along with the proposed system; Section 4 covers the implementation and experimental results; and Section 5 concludes the study and outlines future scope for development.

The next section explores the Literature Review, analyzing prior study and methodologies relevant to property price estimation and machine learning applications in the real estate domain.

LITERATURE REVIEW

This section examines the previous study and methodologies regarding real estate price forecasting, the use of machine learning in property analytics, and related technological advancements that form the foundation for the proposed system.

As demonstrated by (Sharma *,2022),* machine learning can effectively predict house prices using regression models. Additional customer benefit features can also be added to the system without compromising its critical performance. As highlighted in (Zulkifley,2020), data mining and models of machine learning such as SVR, ANN, and XG Boost have demonstrated significant potential in predicting house prices based on critical factors including location and structure. These models provide a practical advantage for both developers and buyers by ensuring data-driven pricing and strategic planning. According to (Dabreo,2021), various algorithms of machine learning significantly impact the accuracy of real estate price forecasting, especially when applied to different datasets with proper preprocessing and feature selection. (Singh, Rastogi,2021) explored several machine learning models and emphasized the role of feature engineering in enhancing model accuracy of housing price forecasting. Their study also highlighted how different algorithms perform under varying dataset conditions, reinforcing the need for tailored approaches based on data characteristics. (Hernes,2024) demonstrated that the use of Gradient Boosting and Random Forest algorithms significantly improves price forecasting accuracy, achieving up to 98.9% precision on the Wroclaw primary market dataset. As demonstrated by (Ho, Tang, Wong,2020), algorithms of machine learning such as Random Forest as well as SVM-based regression can accurately predict property prices, leveraging structured datasets that account for various property features and market conditions. (Adetunji,2022) explored the use of the Random Forest algorithm for residential property value estimation using the housing dataset of Boston. Their model achieved a satisfactory error rate of ±5%, showcasing its capability for reliable real – world application. et (Varma,2018) emphasize the lack of transparency in the real estate industry and focus on using various regression induced techniques to predict housing prices based on real-world factors. Their approach, which combines multiple techniques for weighted mean results, achieved minimal error and maximum accuracy compared to individual models. They also propose using real-time neighbourhood details via Google Maps for more accurate valuations. (Qureshi,2022) put forwarded a framework of machine learning for home price forecasting, where an ensemble model combining Random Forest and XGBoost yielded the highest accurate results on data from Northern Virginia. In their study, (Hjort, Scheel,2022) analysed how different loss functions brings down the performance of XGBoost models in forecasting house prices. They found that models using the SPE loss function delivered better results for properties in lower price ranges, whereas the standard SE loss function performed more accurately for higher-value properties. To leverage the strengths of both, the authors proposed a hybrid model that combines the two approaches, which achieved an improved accuracy of 90.4% under the 20% error threshold. (Konwar, Kakati,2021) examine various models for residential estate rate prediction, with a focus on the Boston housing market. They collected data from Kaggle, followed by data cleaning and preprocessing, and evaluated several machine learning (ML) models, including Random Forest, SVM, Linear Regression, and XGBoost. Their findings revealed that the Random Forest model achieved higher prediction accuracy than the remaining models. (Zhang, 2024) explore house price forecasting using both non-textual and non-textual data from five Canadian cities. Their experiments show that incorporating house descriptions via techniques like Word2Vec improves model accuracy, especially when combined with non-textual features. The best results were achieved using a DNN model. (Bhagat,2023) examines various machine learning

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algorithms were applied to estimate residential estate prices, with linear regression achieving the best accuracy of about 84 to 85%, as compared to decision tree and Lasso regression.

METHODS

This section overviews the methodology of the machine learning-based system that predicts property prices depending on the various development factors influencing the price. [Figure 1]

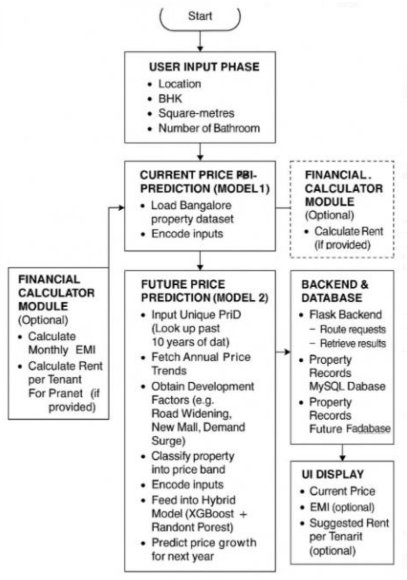

Figure 1. Flow Chart of Proposed Algorithm property features and future developments

Two main datasets are used. The first dataset included 10 years of historical property data such as location, count of bedrooms (BHK), the count of bathrooms, square footage, and the actual selling rate [Figure 2]. Details about what caused the price to rise or fall each year — for example, new roads, increased demand, or the construction of shopping malls nearby are added. The second dataset, which is called the "Future Factors Database," contains data about upcoming development plans around each property. This includes things like proposed infrastructure projects, upcoming metro stations, or new schools and business areas. These developments can hold a big influence on how much a property's value might grow in the coming years.

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	Location	Location C	BHK	Bath	Price (in la	Price Year	Price Year	Price Year	Price Year	Price Year	Price Year	Price Year	Price Year
2	1st Block J	A	4	4	428	428	NONE	433	ROAD WID	439	DEMAND S	438	NONE
3	1st Block J	A	3	3	194	194	NONE	200	NEW MALL	202	NEW PARK	208	NEW MALL
4	1st Block J	A	3	2	235	235	NONE	239	INFLATION	242	ROAD WID	245	NEW PARK
5	1st Block J	A	3	2	130	130	NONE	141	NEW METR	147	NEW MALL	153	NEW METR
6	1st Block J	A	2	2	148	148	NONE	149	NONE	156	NEW SCH	164	NEW METR
7	1st Block J	A	4	4	413	413	NONE	419	NEW MALL	423	NEW MALL	425	NEW PARK
8	1st Block J	A	4	4	368	368	NONE	377	NEW MALL	382	DEMAND S	395	NEW METR
9	1st Phase .	A	3	3	167	167	NONE	171	NEW SCH	183	NEW METR	187	NEW SCH
10	1st Phase .	C	5	5	85	85	NONE	96	NEW METR	99	ROAD WID	98	NONE
11	1st Phase .	A	3	4	210	210	NONE	219	NEW MALL	222	ROAD WID	226	ROAD WID
12	1st Phase .	A	3	3	225	225	NONE	223	NONE	224	NEW PARK	228	ROAD WID
13	1st Phase .	B	2	2	100	100	NONE	101	NEW PARK	108	DEMAND S	112	INFLATION
14	1st Phase .	B	2	2	93	93	NONE	106	NEW METR	113	NEW SCH	121	NEW METR
15	1st Phase .	A	2	2	180	180	NONE	181	NONE	188	NEW SCH	183	NONE
16	1st Phase .	D	1	2	50	50	NONE	54	DEMAND S	49	NONE	51	NEW SCH
17	1st Phase .	A	3	3	131	131	NONE	138	DEMAND S	146	NEW MALL	147	NONE
18	1st Phase .	A	3	3	210	210	NONE	212	NEW SCH	222	NEW METR	221	NONE
19	1st Phase .	C	2	2	88.5	88.5	NONE	93.5	ROAD WID	98.5	NEW METR	99.5	NONE
20	1st Phase .	C	2	2	86	86	NONE	91	ROAD WID	87	NONE	82	NONE
21	1st Phase .	C	2	2	85	85	NONE	89	NEW SCH	93	INFLATION	94	NEW PARK
22	1st Phase .	A	3	3	175	175	NONE	181	NEW METR	181	NONE	185	NEW MALL
23	1st Phase .	C	2	2	85	85	NONE	86	NONE	88	NEW SCH	83	NONE
24	1st Phase .	C	2	2	75	75	NONE	82	NEW SCH	79	NONE	82	NEW SCH
25	2nd Phase	D	3	2	50.75	50.75	NONE	45.75	NONE	40.75	NONE	44.75	INFLATION
26	2nd Phase	D	2	2	40.25	40.25	NONE	44.25	ROAD WID	45.25	INFLATION	48.25	INFLATION
27	2nd Phase	D	3	2	47.25	47.25	NONE	52.25	NEW MALL	52.25	NONE	48.25	NONE
28	2nd Phase	D	3	2	47.25	47.25	NONE	60.25	NEW METR	67.25	NEW SCH	68.25	NONE
29	2nd Phase	D	2	2	41	41	NONE	49	NEW METR	56	DEMAND S	68	NEW METR
30	2nd Phase	C	3	3	69	69	NONE	72	ROAD WID	74	NEW SCH	83	NEW MALL
31	2nd Phase	D	3	2	47.25	47.25	NONE	52.25	NEW SCH	56.25	DEMAND S	55.25	NONE

	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
1	Price Year	Price Year	Price Year	Price Year	Price Year	Price Year	Price Year	Price Year	Price Year	Price Year	Price Year	Price Year	10 Rea
2	443	DEMAND S	447	NEW SCH	453	NEW SCH	457	INFLATION	454	NONE	455	NEW PARK	
3	212	DEMAND S	214	INFLATION	215	NEW PARK	216	INFLATION	230	NEW METR	228	NONE	
4	248	NEW PARK	251	INFLATION	255	INFLATION	262	NEW METR	268	DEMAND S	270	ROAD WIDENING	
5	156	NEW MALL	163	NEW MALL	169	NEW MALL	172	INFLATION	175	INFLATION	176	INFLATION	
6	170	NEW MALL	178	NEW MALL	180	NEW PARK	186	NEW MALL	187	NEW PARK	190	ROAD WIDENING	
7	430	ROAD WID	435	ROAD WID	438	NEW PARK	439	INFLATION	440	NEW PARK	439	NONE	
8	403	DEMAND S	416	NEW METR	418	ROAD WID	413	NONE	417	INFLATION	418	NONE	
9	196	NEW METR	205	NEW MALL	208	NEW MALL	211	INFLATION	223	NEW METR	225	INFLATION	
10	103	NEW SCH	103	NONE	107	NEW SCH	114	NEW METR	120	DEMAND S	129	NEW METRO	
11	240	NEW METR	246	NEW MALL	252	DEMAND S	257	ROAD WID	259	ROAD WID	260	INFLATION	
12	234	DEMAND S	241	DEMAND S	247	DEMAND S	254	NEW SCH	256	INFLATION	263	NEW MALL	
13	116	INFLATION	118	NEW PARK	121	NEW SCH	126	ROAD WID	137	NEW METR	138	NEW PARK	
14	125	DEMAND S	132	NEW SCH	129	NONE	138	NEW METR	145	NEW METR	151	NEW MALL	
15	184	INFLATION	185	NEW PARK	191	NEW MALL	193	INFLATION	196	ROAD WID	198	NEW SCHOOL	
16	55	NEW MALL	57	INFLATION	59	ROAD WID	54	NONE	61	NEW METR	63	NEW PARK	
17	150	INFLATION	154	NEW SCH	164	NEW METR	163	NONE	165	INFLATION	167	NEW PARK	
18	226	NEW SCH	229	INFLATION	232	INFLATION	237	NEW MALL	241	ROAD WID	245	INFLATION	
19	102.5	NEW MALL	107.5	NEW SCH	120.5	NEW METR	129.5	NEW MALL	132.5	ROAD WID	137.5	NEW MALL	
20	86	INFLATION	92	NEW METR	101	NEW METR	107	DEMAND S	109	ROAD WID	116	NEW METRO	
21	92	NONE	94	NEW SCH	92	NONE	94	NEW PARK	101	NEW SCH	108	NEW METRO	
22	188	NEW PARK	187	NONE	195	NEW METR	203	NEW METR	212	NEW METR	210	NONE	
23	81	NONE	85	NEW SCH	88	NEW PARK	90	NEW PARK	92	NEW PARK	93	NEW PARK	
24	86	DEMAND S	89	INFLATION	84	NONE	91	DEMAND S	97	DEMAND S	100	INFLATION	
25	45.75	NEW PARK	46.75	NEW PARK	49.75	NEW PARK	50.75	INFLATION	58.75	DEMAND S	67.75	NEW METRO	
26	56.25	DEMAND S	57.25	NONE	64.25	NEW METR	60.25	NONE	74.25	NEW METR	77.25	ROAD WIDENING	
27	49.25	NONE	52.25	NEW PARK	61.25	NEW MALL	64.25	NEW SCH	68.25	NEW MALL	80.25	NEW METRO	
28	73.25	DEMAND S	76.25	ROAD WID	79.25	NEW SCH	91.25	NEW METR	98.25	DEMAND S	107.25	NEW MALL	
29	68	NONE	68	NONE	71	INFLATION	75	ROAD WID	77	INFLATION	86	NEW MALL	
30	84	NEW PARK	86	NEW PARK	94	NEW MALL	102	NEW METR	110	NEW MALL	113	ROAD WIDENING	
31	59.25	INFLATION	60.25	INFLATION	65.25	ROAD WID	66.25	NEW PARK	64.25	NONE	67.25	NEW PARK	

Fig 2: Dataset of ten years of historical property prices along with detailed records of surrounding infrastructural developments

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Before training the model, the data was cleaned by handling missing values, removing outliers, and converting location names into a format the model could understand. Then the two datasets were combined using the property ID so that the model could learn from both past trends and future expectations. The most important features, such as square footage, location, the count of rooms, and development plans nearby were carefully selected.

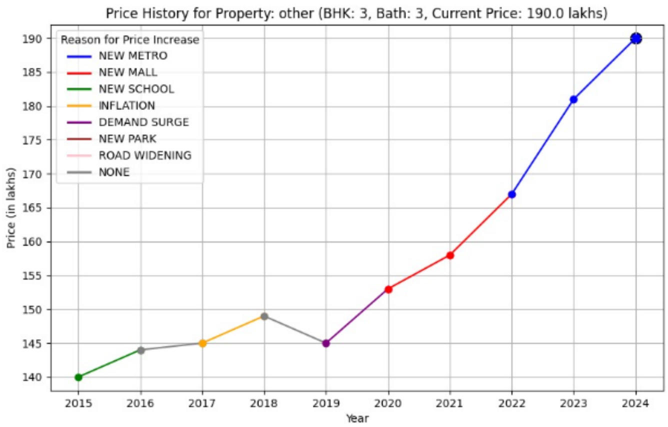

Figure 3: **Price History for Property from last 10 years varying on Various Developmental Factors**

A price history visualization [Figure 3] has been generated to analyse how the property price evolved over the past 10 years. This plot highlights the impact of various developmental factors. Each color-coded segment represents a specific reason for price growth during that period. Each property was given a unique alphanumeric ID to help track and connect it easily across the two datasets. The properties have been divided into classes based on prices, for example, Class D for properties under ₹60 lakhs, up to Class A for those above ₹2 crores — to better organize and analyze the data.

Several algorithms of machine learning were tested, including Linear Regression, Random Forest, XGBoost, and ANN. After many experiments, it was clear that Random Forest and XGBoost performed the best. Both use decision trees to make predictions and can handle complex patterns in data. Finally, it was decided to use a combination of both models to get the best of their strengths. The parameters were fine-tuned using techniques like grid search to make the model as accurate as possible. Apart from just predicting prices, the model was designed to be helpful for users in making financial decisions. Features were added where users can enter their loan interest rate and see what their monthly payments would be. If someone wants to rent out the property and earn a profit, they can enter how many tenants they have and what percentage profit they want, and the system will suggest the ideal rent amount per tenant to meet that goal.

To effectively carry out these stages, a set of Python-based tools and libraries were employed. These facilitated tasks ranging from data handling and visualization to model building and evaluation. The user interface was created using Flask, so users can enter property and financial details through a simple web form and get results instantly. While CSV files were initially used to store data, it will be soon moved to a MySQL database. This will make it easier to update the Future Factors Database over time and keep the model relevant.

Overall, the approach brings together real-world data, future planning information, and smart algorithms to help people make better decisions when buying or renting out property. The next section explains how the implementation of everything was done and the results got from the model.

IMPLEMENTATION AND EXPERIMENTAL RESULTS

The implementation of the property price forecasting model relied on several Python libraries, each serving a specific role in the workflow:

Pandas library was used for data loading, cleaning, and manipulation. It enabled efficient tabular data processing throughout the project. **NumPy** assisted with numerical computations, including operations on arrays and matrices. **matplotlib.pyplot** were utilized to create visualizations such as histograms, scatter plots, and model performance

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charts. **random and string libraries** were used during preprocessing to generate synthetic examples and perform string operations. **scikit-learn (sklearn): LinearRegression** was implemented as a baseline regression model. **RandomForestRegressor** served as the main prediction model due to its high accuracy as well as its robustness. **train_test_split** was employed to divide the dataset as training and testing phases. **mean_absolute_error, r2_score** used for accurately evaluating model performance with appropriate metrics. **pickle** was utilized for model serialization, allowing the trained model to be saved in a pkl file and reused without retraining.

The dataset consisted of property data from 0 to 10 years. The data from the first 0–7 years was used to train the model, while the 8–10-year price data was used for testing and accuracy evaluation. Initial models included linear regressors and decision trees. To improve prediction performance, ensemble models were introduced. A combination of Random Forest based Regression model and XGBoost yielded the best results. The final ensemble model gave an accuracy of **97.65%**, with an **R^2 score of 0.99**, indicating a very high level of predictive power. A combination of Random Forest Regressor and XGBoost yielded the best results. To assess the performance of the residential real estate prediction model, implementation and comparison of three well-established algorithms of machine learning: XGBoost, Random Forest, and ANN, were done.

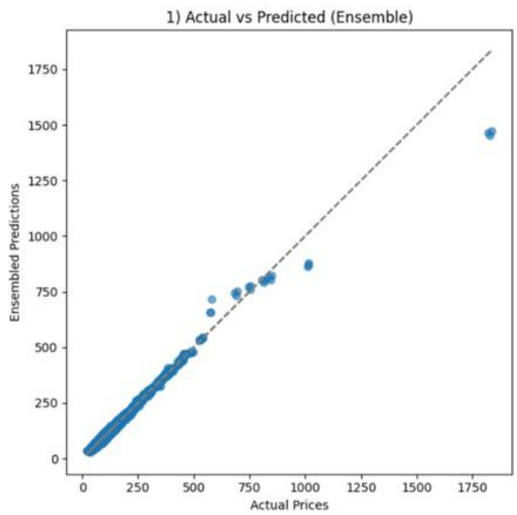

Figure 6. **Scatter plot displaying the relationship between actual and forecasted house price property prices from an Ensemble model.**

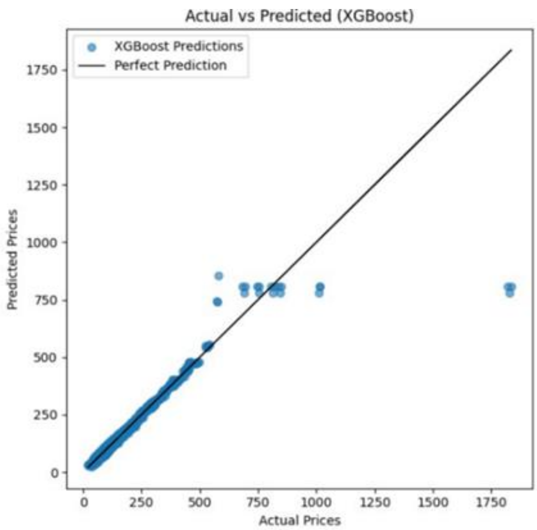

Figure 4. **Scatter plot displaying the relationship between actual and forecasted real estate prices from a XG Boost model.**

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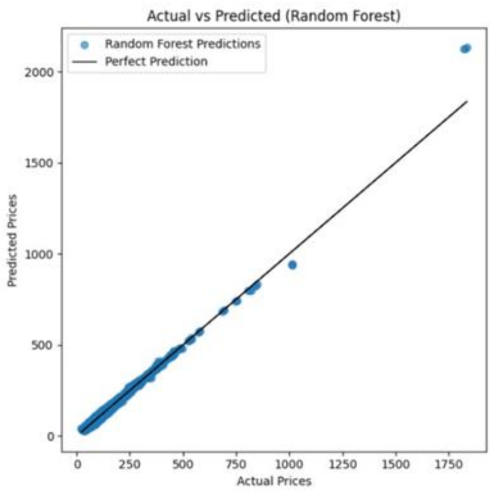

Figure 5. Scatter plot displaying the relationship between actual and forecasted property prices from a Random Forest Regressor model.

Forecasted prices were plotted against actual property prices. Among the models tested, the **ensemble model** [Figure 6] demonstrates the best performance, showing the closest alignment to the perfect prediction line. This suggests that combining multiple models leads to the most accurate and reliable predictions. While the **XGBoost model** [Figure 4] and **Random Forest model** [Figure 5] also perform well, the ensemble model provides more consistent and robust results, particularly in handling higher-value properties. The integrated version of XG Boost and Random Forest got the highest prediction accuracy of 97.65%, with XGBoost and ANN closely following at 95.15% and 95.09% respectively, as detailed in Table 1.

Model Name:	XGBoost	Random Forest	ANN	Ensemble
Accuracy:	95.15	96.78	95.09	97.65

Table.1

The results obtained shows that decision tree-based ensemble models are very much effective in handling the multifaceted nature of real estate data. The final output of the property predictor is given in [Figure.7]

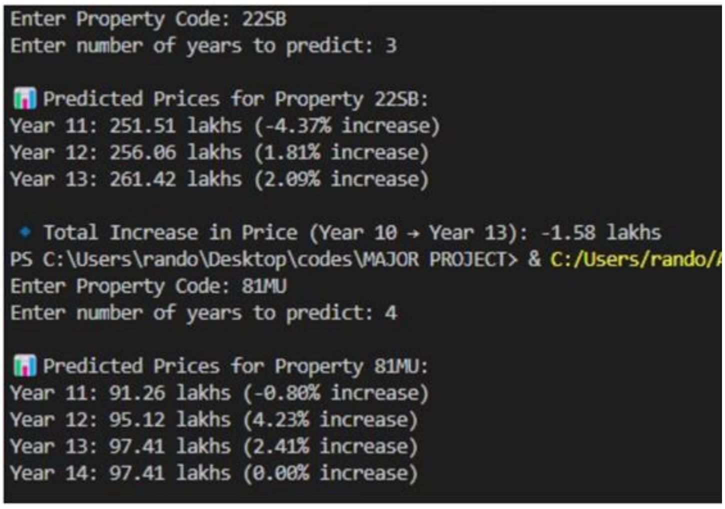

Fig. 7: Property Price Prediction output

In addition to the prediction model, two user-oriented features were also integrated: a rent calculation tool and a property finance estimator. The rent calculator enables users to determine fair tenant charges based on desired profit margins [Figure 8], while the finance tool estimates monthly loan payments depending on interest rates and

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repayment duration [Figure 9]. These functionalities aim to support more informed and practical decision-making for users navigating the real estate market.

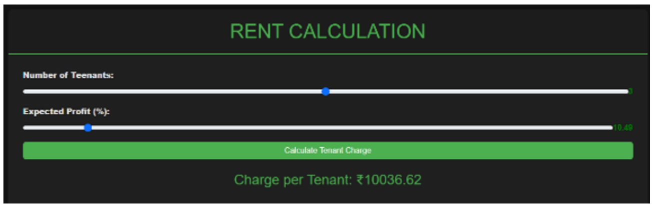

Figure 8. Rent Calculation Module

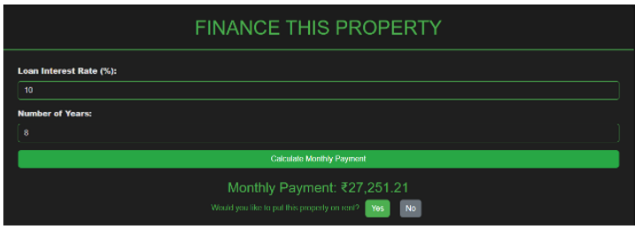

Figure 9. Financing Module

CONCLUSION AND FURTHER DISCUSSION

This is the final section of this study which overviews the conclusion and further discussion. This study presents a thorough and inclusive approach to property price forecasting using techniques of machine learning, aimed at improving the accuracy and practicality of real estate valuation in urban contexts. By leveraging a dual-dataset strategy, one capturing historical property trends and another outlining future infrastructural development the hybrid model effectively simulates real-world market dynamics.

The integration of **Random Forest** and **XGBoost** models, trained on key attributes like location, BHK, count of bathrooms, and square footage, enabled robust predictive performance. The inclusion of future development indicators via the **Future Factors Database** provided an additional layer of contextual intelligence to the model, improving its adaptability in a volatile market.

Moreover, the application extends beyond static predictions by incorporating **financial planning tools** for users. These features allow users to compute loan repayments, determine rent pricing for desired profit margins, and make informed investment decisions. The user-facing interface built with Flask ensures accessibility and ease of interaction, while backend enhancements like transitioning to a **MySQL database** further strengthen the application's scalability. While the current system delivers strong performance and practical features, several opportunities for advancement remain:

Inclusion of Satellite and Geospatial Data: Using imagery or map-based features can enhance the spatial accuracy of property evaluations.

User Personalization: Adding features like user profiling could allow the system to give investment suggestions tailored to different investor goals and risk appetites.

Deployment and Public Access: The tool can be deployed as a public web application with login features, enabling broader adoption by prospective homebuyers and real estate professionals.

In conclusion, this study lays a strong foundation for intelligent property price forecasting systems that go beyond static valuations, offering actionable insights by combining machine learning with real-world economic factors.

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