IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

GRAPH CONVOLUTIONAL NETWORK-BASED MODEL FOR MEGACITY REAL ESTATE VALUATION

Mrs.R.Jhansi Rani[1] , Pokala Mahesh Kumar Reddy[2], Adimulam Kiran Kumari[3] , Talari Rajesh[4]
[1]Assistant Professor, Department of Computer Applications , Chadalawada Ramanamma Engineering College Tirupati , Andhra Pradhesh, India.
[2,3,4] Student, Department of Computer Applications, Chadalawada Ramanamma Engineering College Renigunta Rd, Tirupati, Andhra Pradesh, India

ABSTRACT

It is challenging to make precise assessments of real estate prices due to its elevated individual prices, complicated influencing factors, and ambiguous attribute selection. As a result of the high demand for owner-occupied and investment properties, real estate is also a substantial concern for society. A hot topic for research by major institutions has been how to accurately estimate its price. Real world applications of real estate valuation impose stringent requirements on the acquisition of datasets and the generalizability of models. On the basis of SRGCNN, a spatial regression model with excellent generalizability, this project introduces an external attention mechanism to construct the A-SRGCNN model .For spatial regression, A-SRGCNN employs graph convolutional neural networks, and the external attention mechanism implicitly considers the relationship between property data. Experiments indicate that the A-SRGCNN model outperforms the benchmark model and has improved real estate price estimation accuracy. In the meantime, this project employs the A-SRGCNN model to conduct zonal experiments and time-division experiments and it is revealed that real estate prices exhibit spatial aggregation and price aggregation, with comparable prices within the zones, and that the A-SRGCNN model is effective at predicting house prices.

I. INTRODUCTION

Appraising real estate prices is of paramount importance for banks to review loan mortgages and national real estate policy formulation. The timely and efficient valuation and forecasting of real estate prices not only brings significant economic benefits directly, but also has tremendous political implications, and major banks, insurance companies, and think tanks are searching for a precise, speedy, and cost-effective mechanism for real estate valuation. Qualitative analysis and quantitative analysis are the two most common categories used to objectively assess real estate prices. The qualitative study concentrates on the economics of macro policies, market trends, and other factors, whereas the quantitative analysis models the characteristics of house prices, such as real estate floor area, number of floors, historical sales prices, etc. Since qualitative analysis is influenced by subjective factors and is difficult to measure precisely and thoroughly, quantitative analysis is highly accurate and credible.The two predominant research directions in the quantitative analysis are the hedonic model and the machine learning model.

The need for realistic real estate valuation is taken into account. presume that the A-SRGCNN model is appropriate for real estate valuation since real estate price appraisal is indeed a very typical spatial regression scenario, and the SRGCNN appraisal model performs well in this scenario in comparison to older models . What's more, the external attention mechanism can delve deeper into the linkage between sample data, which corresponds to the close connection among real estate data, so the model would further work on improving the valuation consistent manner on the SRGCNN valuation model's impressive performance. Real estate appraisal models have high requirements in terms of their ability to generalize over validation sets and different data sets. The acquisition of certain attributes for real estate data samples regularly presents some challenges. Consequently, the A-SRGCNN real estate appraisal model is constructed in this project. The model is based on the spatial regression model SRGCNN, and the spatial regression algorithm shows good generalization ability and stable performance when it comes to different datasets. The most important parameter of the SRGCNN model is the spatial location of real estate, and the spatial information of real estate is often easier to obtain in reality. The A-SRGCNN approach incorporates an attention mechanism by adding an external attention layer before the final output, which is based on the use of the SRGCNN model. There are tight connections between real estate samples, and the external attention layer enhances the algorithm's truthfulness by capturing the global connections between property samples via shared memory units.

II. LITERATURE SURVEY

The Literature review plays a very important role in the research process. It is a source from here research ideas are drawn and developed into concepts and finally theories. It also provides the researchers a bird's eye view about the research done in that area so far. Depending on what is observed in the literature review, a researcher will understand where his/her research stands. Here in this literature survey, all primary, secondary and tertiary sources of information were searched. A literature survey or literature review means that researcher read and report on what the literature in the field has to say about the topic or subject. It is a study and review of relevant literature materials in relation to a topic that have been given

1) Title: Spatial autoregression techniques for real estate data

This paper describes how spatial techniques can be used to improve the accuracy of market value estimates obtained using multiple regression analysis. Rather than eliminating the problem of spatial residual dependencies through the inclusion of many independent variables, spatial statistical methods typically keep fewer independent variables and augment these with a simple model of the spatial error dependence.

2) Title: Geographically and temporally weighted regression for modeling spatio-temporal variation in house prices

By incorporating temporal effects into the geographically weighted regression (GWR) model, an extended GWR model, geographically and temporally weighted regression (GTWR), has been developed to deal with both spatial and temporal nonstationarity simultaneously in real estate market data. Unlike the standard GWR model, GTWR integrates both temporal and spatial information in the weighting matrices to capture spatial and temporal heterogeneity. The GTWR design embodies a local weighting scheme wherein GWR and temporally weighted regression (TWR) become special cases of GTWR. In order to test its improved performance, GTWR was compared with global ordinary least squares, TWR, and GWR in terms of goodness-of-fit and other statistical measures

3) Title: Neural network hedonic pricing models in mass real estate appraisal

Using a large sample of 46,467 residential properties, demonstrate using matched pairs that, relative to linear hedonic pricing models, artificial neural networks (ANN) generate significantly lower dollar pricing errors, have greater pricing precision out-of-sample, and extrapolate better from more volatile pricing environments. While a single layer ANN is functionally equivalent to OLS, multiple layered ANNs are capable of modeling complex nonlinearities. Moreover, because parameter estimation in ANN does not depend on the rank of the regressor matrix, ANN is better suited to hedonic models that typically utilize large numbers of dummy variables.

III. SYSTEM ANALYSIS

This project introduces an external attention mechanism to construct the A-SRGCNN model. For spatial regression, A-SRGCNN employs graph convolutional neural networks, and the external attention mechanism implicitly considers the relationship between property data. In Existing system, The hedonic framework was originally employed to examine the relationship between real estate prices and the living environment and utilized hedonic regression models to valuate the dynamic impact of market fundamentals on real estate prices. After many years of development, the hedonic model has become an established method of real estate price valuation, utilized in a large number of appraisal models and serving as a crucial foundation for bank loan approvals and government monetary policies. However, the hedonic method also has some drawbacks, such as the fact that the results of the hedonic model can vary depending on the estimation formula or process selected, which enhances the subjectivity of the appraisal, and necessitates a high demand for analysts with specialized knowledge, and necessitates a large quantity of property price data. In another research, Time series can also be incorporated into spatial regression models. In order to account for spatial and temporal heterogeneity and incorporate time effects into GWR models to assess house prices .Although these methods' performance in making forecasts is acceptable, their use in determining actual house prices is very limited. Although these methods' valuation performance is acceptable, there is very little use for them to determine real estate prices. The variables influencing real estate prices are intricate, making it challenging to monitor price changes. It is incredibly difficult for standard mathematical models to accurately model estate prices. Hedonic models have gained in popularity over the past few decades due to their affordability, accuracy, and complexity.

Disadvantages of Existing system

- Less Effective.
- Not Accurate
- Imbalanced

PROPOSED SYSTEM

The proposed system presumes that the A-SRGCNN model is appropriate for real estate valuation since real estate price appraisal is indeed a very typical spatial regression scenario, and the SRGCNN appraisal model performs well in this scenario in comparison to older models. What's more, the external attention mechanism can delve deeper into the linkage between sample data, which corresponds to the close connection among real estate data, so the model would further work on improving the valuation consistent manner on the SRGCNN valuation model's impressive performance. Real estate appraisal models have high requirements in terms of their ability to generalize over validation sets and different data sets. The acquisition of certain attributes for real estate data samples regularly presents some challenges. Consequently, the A-SRGCNN real estate appraisal model is constructed in this project. The model is based on the spatial regression model SRGCNN, and the spatial regression algorithm shows good generalization ability and stable performance when it comes to different datasets. The most important parameter of the SRGCNN model is the spatial location of real estate, and the spatial information of real estate is often easier to obtain in reality. The A-SRGCNN approach incorporates an attention mechanism by adding an external attention layer before the final output, which is based on the use of the SRGCNN model. There are tight connections between real estate samples, and the external attention layer enhances the algorithm's truthfulness by capturing the global connections between property samples via shared memory units. Accordingly, compared with popular regression valuation models, the A-SRGCNN proposed in this project is more generalizable, performs stably on different samples.

Advantages of Proposed system

- Accurate
- Balanced
- Effective
- The System proposes Qualitative analysis and quantitative analysis are the two most common categories used to objectively assess real estate prices.

IV. IMPLEMENTATION

There are two modules in the proposed system. They are :

1. Service Provider

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as Login, Browse Datasets and Train & Test Data Sets, View Trained and Tested Accuracy in Bar Chart, View Trained and Tested Accuracy Results, View Prediction Of Real Estate Valuation, View Real Estate Valuation Ratio, Down load Predicted Data Sets, View Real Estate Valuation Ratio Results, View All Remote Users.

2. Remote User

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like Register And Login, Predict Real Estate Valuation, View Your Profile

V. SCREENSHOTS

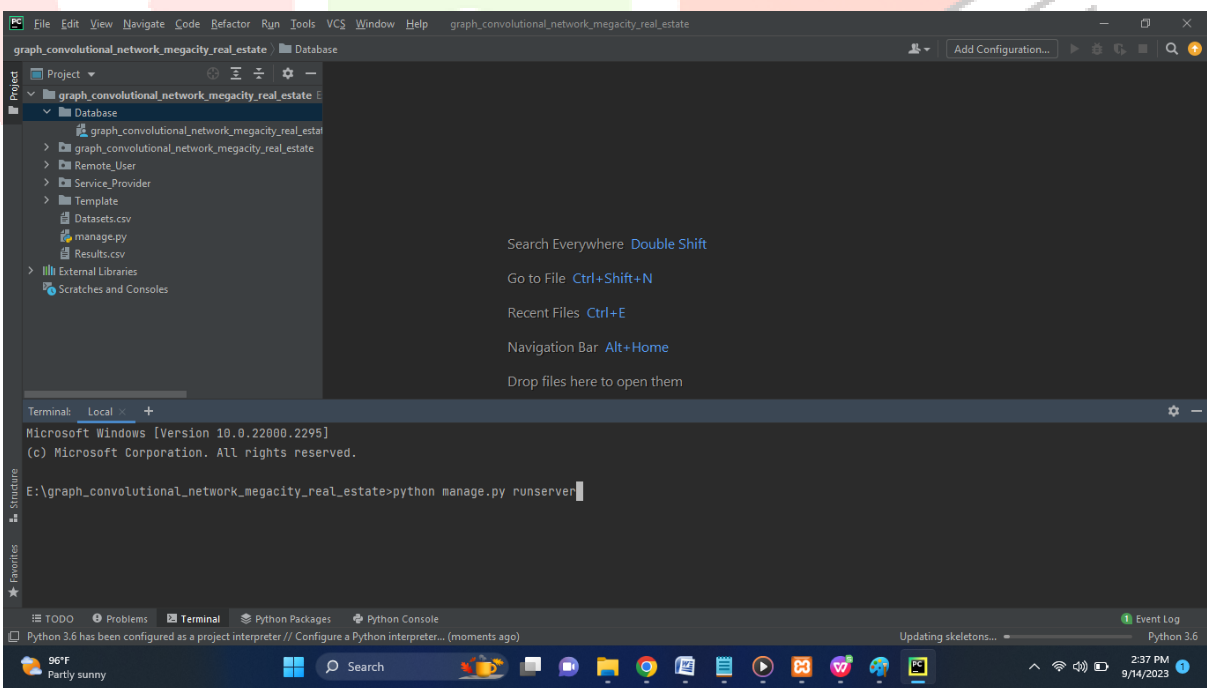


Fig 1. Running Command on Console

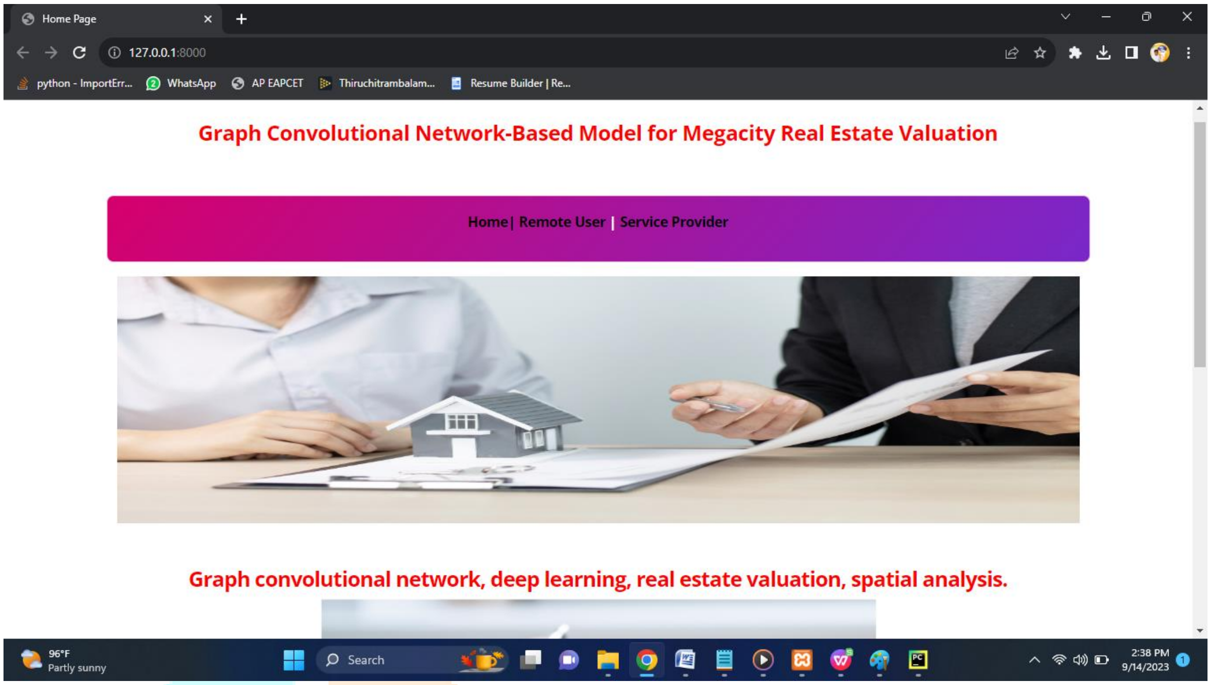
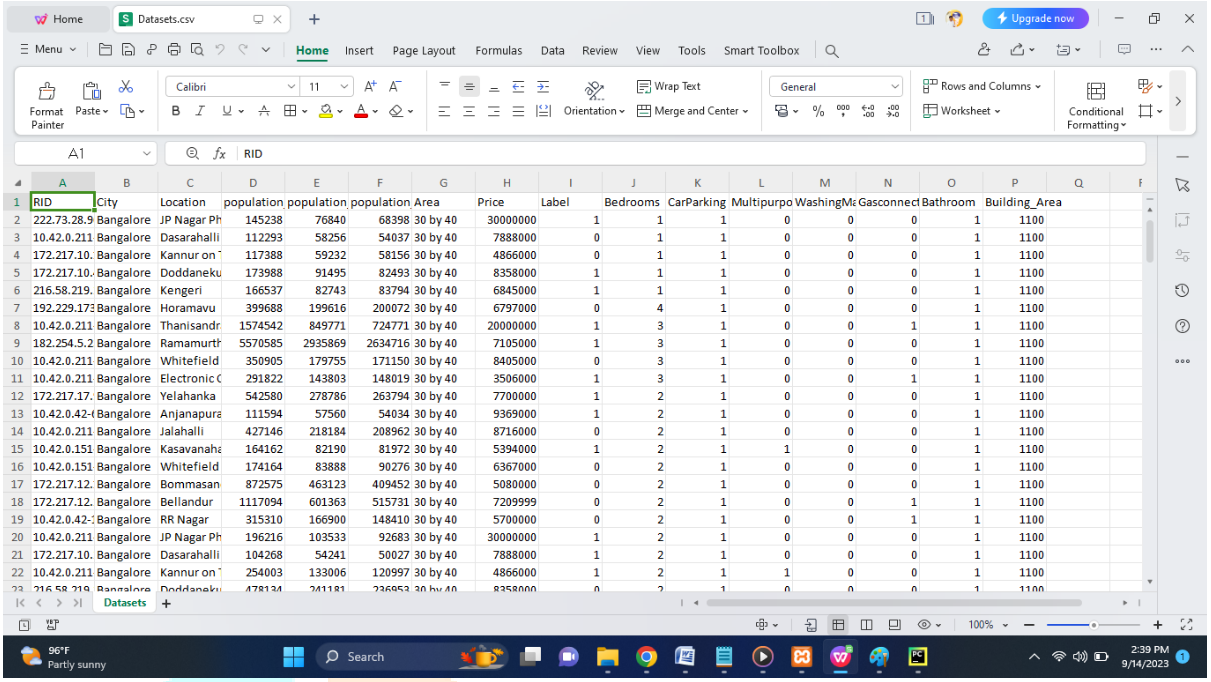


Fig 2. Home Page

Fig 3. Service Provider Login



RID	City	Location	population	population	population	Area	Price	Label	Bedrooms	CarParking	Multipurpo	WashingMa	Gasconnect	Bathroom	Building_Area
222.73.28.9	Bangalore	JP Nagar Ph	145238	76840	68398	30 by 40	30000000	1	1	1	0	0	0	1	1100
10.42.0.211	Bangalore	Dasarahalli	112293	58256	54037	30 by 40	7888000	0	1	1	0	0	0	1	1100
172.217.10.	Bangalore	Kannur on	117388	59232	58156	30 by 40	4866000	0	1	1	0	0	0	1	1100
172.217.10.	Bangalore	Doddaneku	173988	91495	82493	30 by 40	8358000	1	1	1	0	0	0	1	1100
216.58.219.	Bangalore	Kengeri	166537	82743	83794	30 by 40	6845000	1	1	1	0	0	0	1	1100
192.229.173	Bangalore	Horamavu	399688	199616	200072	30 by 40	6797000	0	4	1	0	0	0	1	1100
10.42.0.211	Bangalore	Thanisandr	1574542	849771	724771	30 by 40	20000000	1	3	1	0	0	1	1	1100
182.254.5.2	Bangalore	Ramamurth	5570585	2935869	2634716	30 by 40	7105000	1	3	1	0	0	0	1	1100
10.42.0.211	Bangalore	Whitefield	350905	179755	171150	30 by 40	8405000	0	3	1	0	0	0	1	1100
10.42.0.211	Bangalore	Electronic C	291822	143803	148019	30 by 40	3506000	1	3	1	0	0	1	1	1100
172.217.17.	Bangalore	Yelahanka	542580	278786	263794	30 by 40	7700000	1	2	1	0	0	0	1	1100
10.42.0.42-	Bangalore	Anjanapura	111594	57560	54034	30 by 40	9369000	1	2	1	0	0	0	1	1100
10.42.0.211	Bangalore	Jalahalli	427146	218184	208962	30 by 40	8716000	0	2	1	0	0	0	1	1100
10.42.0.151	Bangalore	Kasavanaha	164162	82190	81972	30 by 40	5394000	1	2	1	1	0	0	1	1100
10.42.0.151	Bangalore	Whitefield	174164	83888	90276	30 by 40	6367000	0	2	1	0	0	0	1	1100
172.217.12.	Bangalore	Bommasan	872575	463123	409452	30 by 40	5080000	0	2	1	0	0	0	1	1100
172.217.12.	Bangalore	Bellandur	1117094	601363	515731	30 by 40	7209999	0	2	1	0	0	1	1	1100
10.42.0.42-	Bangalore	RR Nagar	315310	166900	148410	30 by 40	5700000	0	2	1	0	0	1	1	1100
10.42.0.211	Bangalore	JP Nagar Ph	196216	103533	92683	30 by 40	30000000	1	2	1	0	0	0	1	1100
172.217.10.	Bangalore	Dasarahalli	104268	54241	50027	30 by 40	7888000	1	2	1	0	0	0	1	1100
10.42.0.211	Bangalore	Kannur on	254003	133006	120997	30 by 40	4866000	1	2	1	1	0	0	1	1100

Fig 4. Dataset Information

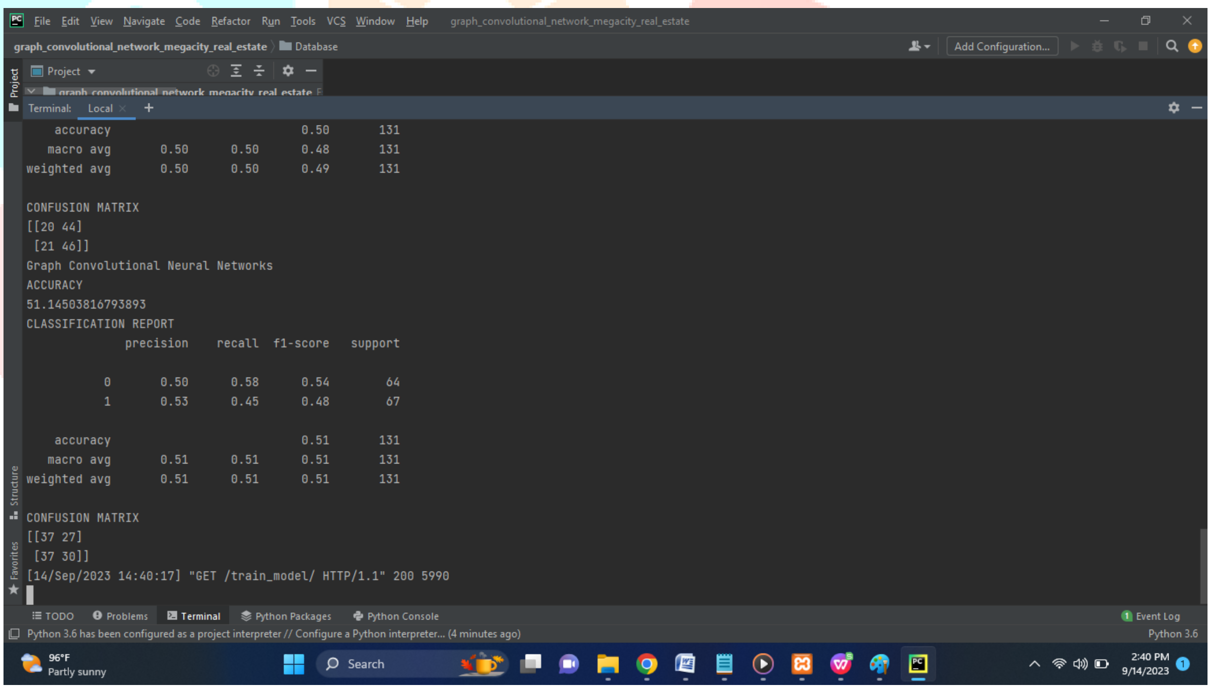


Fig 5. Training with ML Algorithms

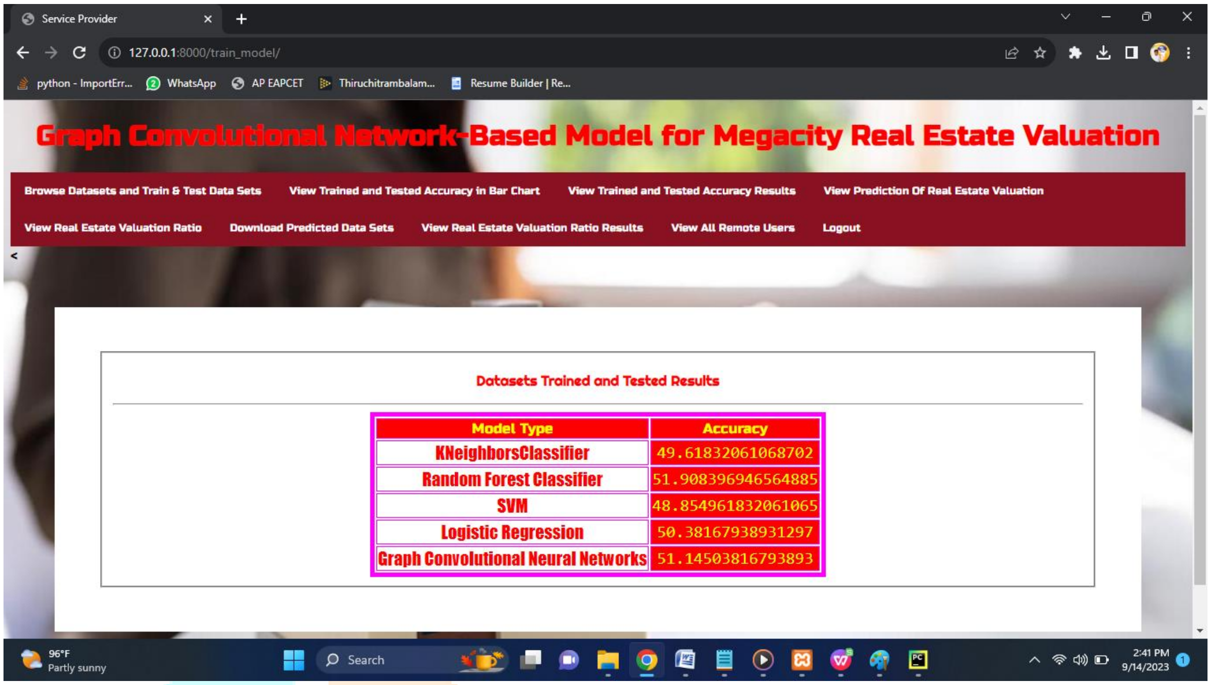


Fig 6. Dataset Trained and Tested Results

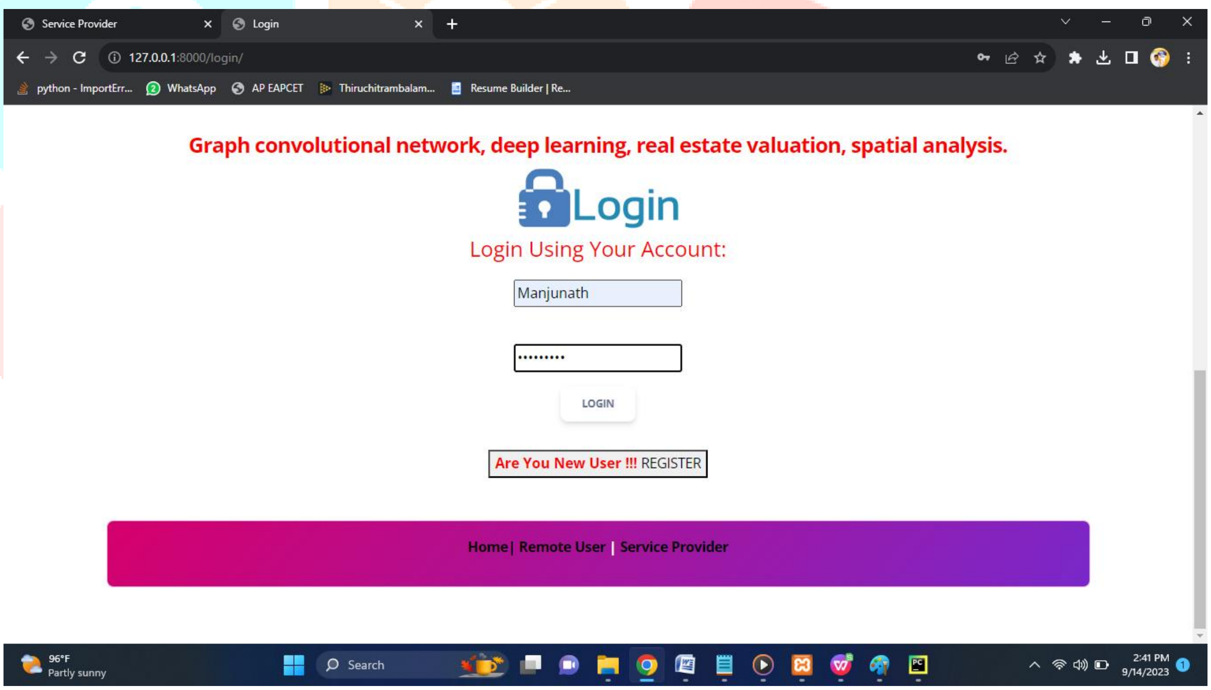


Fig 7. Remote User Login

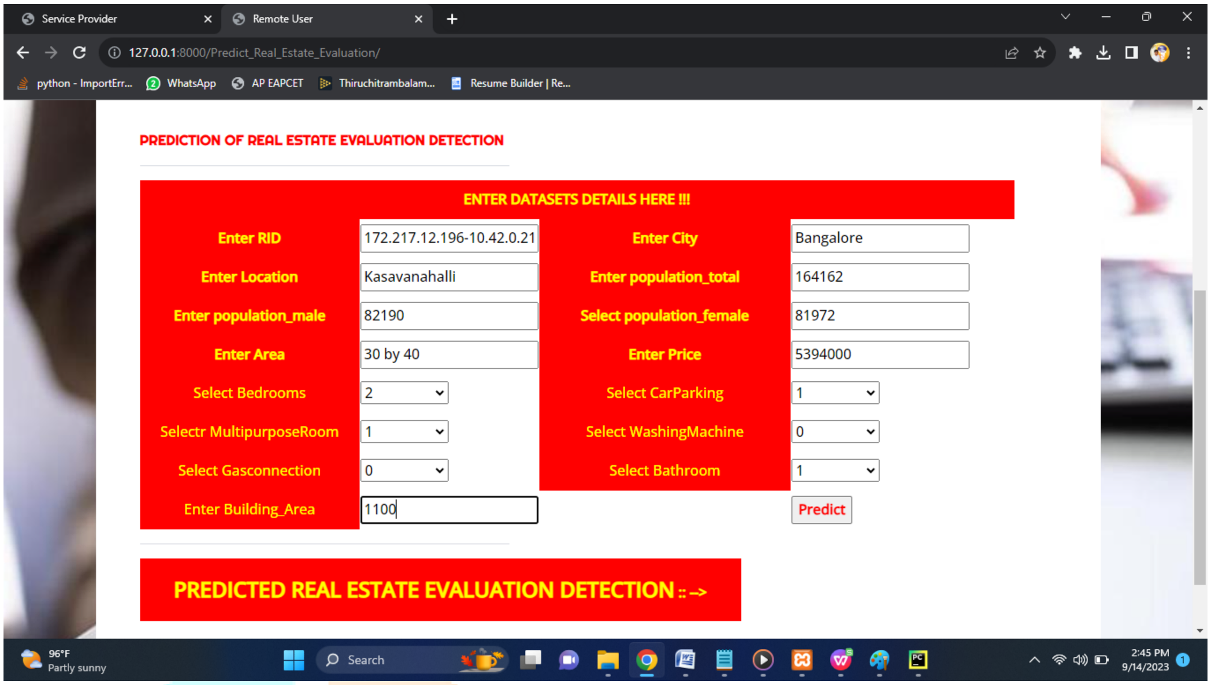


Fig 8. Enter Dataset Details

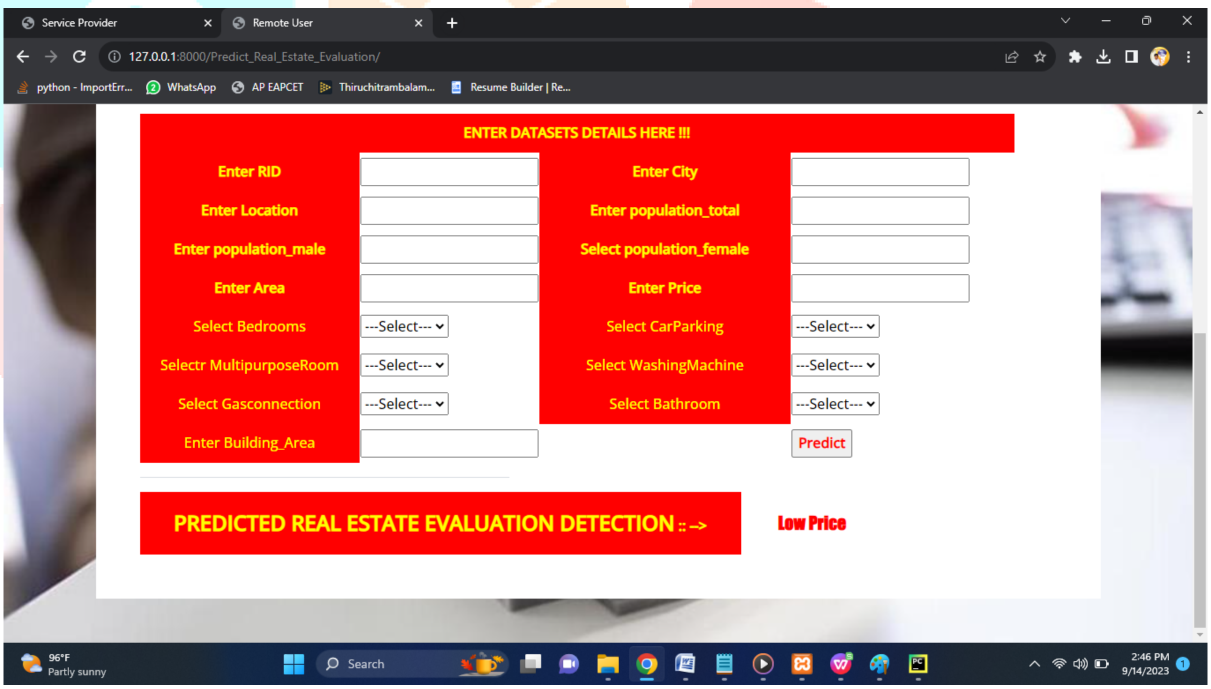


Fig 9. Prediction Result

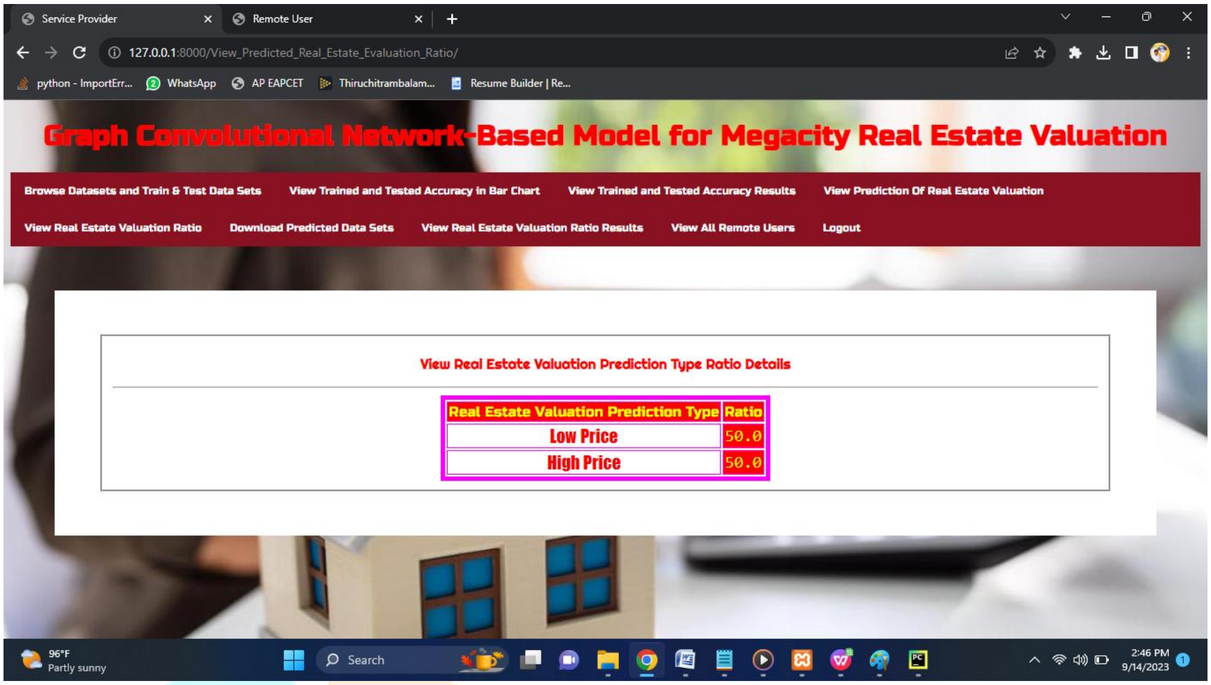


Fig 10. Real Estate Valuation Prediction Type Ratio Details

VI. CONCLUSION

In the meantime, this project employs the model to conduct zonal experiments and time-division experiments and it is revealed that real estate prices exhibit spatial aggregation and price aggregation, with comparable prices within the zones, and that the A-SRGCNN model is effective at predicting house prices.

REFERENCES

[1] S. Rosen, ‘‘Hedonic prices and implicit markets: Product differentiation in pure competition,’’ J. Political Economy, vol. 82, no. 1, pp. 34–55, 1974.

[2] R. Meese and N. Wallace, ‘‘House price dynamics and market fundamentals: The Parisian housing market,’’ Urban Stud., vol. 40, nos. 5–6, pp. 1027–1045, May 2003.

[3] R. Dubin, R. K. Pace, and T. G. Thibodeau, ‘‘Spatial autoregression techniques for real estate data,’’ J. Real Estate Literature, vol. 7, no. 1, pp. 79–96, 1999.

[4] R. Gupta, ‘‘Forecasting house prices for the four census regions and the aggregate U.S. economy in a data-rich environment,’’ Appl. Econ., vol. 45, no. 33, pp. 4677–4697, Nov. 2013.

[5] B. Huang, B. Wu, and M. Barry, ‘‘Geographically and temporally weighted regression for modeling spatio-temporal variation in house prices,’’ Int. J. Geograph. Inf. Sci., vol. 24, no. 3, pp. 383–401, Mar. 2010.

[6] H. Selim, ‘‘Determinants of house prices in turkey: Hedonic regression versus artificial neural network,’’ Exp. Syst. Appl., vol. 36, no. 2, pp. 2843–2852, Mar. 2009.

[7] S. Peterson and A. Flanagan, ‘‘Neural network hedonic pricing models in mass real estate appraisal,’’ J. Real Estate Res., vol. 31, no. 2, pp. 147–164, Jan. 2009.