A

Major Project Report

On

GRAPH BASED CONVOLUTIONAL NETWORK BASED MODEL FOR MEGACITY REAL ESTATE VALUATION

Submitted to CMREC (UGC Autonomous), Affiliated to JNTUH

In Partial Fulfilment of the requirements for the Award of Degree of

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE AND ENGINEERING

(Artificial Intelligence & Machine Learning)

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CERTIFICATE

This is to certify that the Major project entitled **" GRAPH BASED CONVOLUTIONAL NETWORK BASED MODEL FOR MEGACITY REAL ESTATE VALUATION"** is a bonafide work carried out by

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in partial fulfilment of the requirement for the award of the degree of **BACHELOR OF TECHNOLOGY in COMPUTER SCIENCE AND ENGINEERING (AI & ML)** from CMR Engineering College, under our guidance and supervision

The results presented in this Major project have been verified and are found to be satisfactory. The results embodied in this Major project have not been submitted to any other university for the award of any other degree or diploma

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DECLARATION

This is to certify that the work reported in the present Major project entitled **"GRAPH BASED CONVOLUTIONAL NETWORK BASED MODEL FOR MEGACITY REAL ESTATE VALUATION"** is a record of bonafide work done by us in the Department of Computer Science and Engineering (AI & ML), CMR Engineering College. The reports are based on the Major project work done entirely by us and not copied from any other source. We submit our project for further development by any interested students who share similar interests to improve the Major project in the future.

The results embodied in this Major project report have not been submitted to any other University or Institute for the award of any degree or diploma to the best of our knowledge and belief.

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CONTENTS

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. Realworld 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 paper introduces an external attention mechanism to construct the A-SRGCNN model and compares it to the benchmark model utilizing data from Shanghai, Melbourne, and San Diego. 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 paper employs the A-SRGCNN model to conduct zonal experiments and time-division experiments on the secondary real estate market in Shanghai to analyze the real estate price linkages between different zones and the real estate price linkages at different times. It is revealed that Shanghai real estate prices exhibit spatial aggregation and price aggregation, with comparable prices within the same zones, and that the A- SRGCNN model is effective at predicting house prices.

Keywords: Real Estate Valuation; Graph Convolutional Network (GCN); Spatial Dependencies; Property Price Prediction; Machine Learning; Adjacency Matrix; Data Preprocessing; Artificial Intelligence.

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1. INTRODUCTION

1.1 Introduction

Real estate valuation is a crucial component of the housing market, influencing decisions related to lending, investment, taxation, and urban planning, and therefore requires accurate and reliable models **[12], [19]**.Traditional methods such as hedonic pricing, regression techniques, and expert assessments have been widely used but often fail to capture the important spatial dependencies between properties that significantly impact value **[2], [12]**.

Machine learning approaches, including linear regression, decision trees, random forests, and gradient boosting, have improved predictive performance; however, they still struggle to effectively model the complex spatial relationships inherent in real estate data **[7], [19]**. To address this limitation, Graph Convolutional Networks (GCNs) provide a powerful graph-based framework that represents properties as interconnected nodes, enabling the learning of spatial patterns and relationships **[1], [13]**.

The proposed GCN-based model preprocesses data through encoding and scaling, constructs an adjacency matrix to represent property connectivity, and applies graph convolutional layers to extract spatial features for improved prediction accuracy **[1], [10]**. Additionally, attention-based GNNs enhance performance by assigning importance to nearby amenities and spatial features **[4], [8]**.

Experimental results demonstrate that the GCN model outperforms traditional machine learning methods in accuracy and stability across datasets, highlighting its effectiveness and practical applicability in real-world real estate valuation **[6], [7]**. The proposed GCN-based model preprocesses data through encoding and scaling, constructs adjacency matrices to represent property connectivity, and applies graph convolutional layers for feature extraction **[4], [23]**. This approach offers advantages such as improved spatial dependency modeling, scalability, adaptability, and robustness under limited labeled data **[5], [6], [13]**. Experimental studies confirm that GNN-based models outperform traditional machine learning approaches in accuracy and stability across datasets **[6], [7], [19].**

Furthermore, the application of GCNs is particularly crucial in megacities, where rapid urbanization creates highly complex environments .Property values are influenced by proximity to infrastructure, amenities, and socio-economic conditions. Graph-based models effectively capture these non-linear relationships and localized neighborhood effects **[10], [21]**.

1.2 Project Objectives

By the completion of this project, the system demonstrates the following capabilities:

1. Construct a spatial graph where nodes represent properties or neighborhoods in the megacity and edges encode spatial proximity or socio-economic relationships **[1], [13]**.
2. Integrate heterogeneous data sources such as property attributes, demographic information, transportation networks, and land-use data **[5], [20]**.
3. Evaluate how graph-based learning improves performance compared to traditional models such as linear regression, random forests, or gradient boosting **[7], [19]**.
4. Develop an automated, highly scalable preprocessing pipeline that efficiently cleans, normalizes, and prepares high-dimensional urban datasets for graph formulation **[23], [24]**.
5. Implement a comprehensive administrative backend and interactive user interface that allows stakeholders to manage datasets, and oversee user activities, and easily interpret valuation outputs **[21]**.
6. Validate the model's robustness and adaptability by testing it across diverse zoning areas, architectural styles,varying population densities within the megacity environment **[8], [25]**.

Achieving these comprehensive objectives will bridge the gap between advanced deep learning research and practical real estate economics. By successfully mapping out the non-linear, spatial relationships of urban environments, the project will definitively demonstrate that a property's value is fundamentally tied to its surrounding ecosystem. Moving away from isolated property evaluations, this system leverages the distinct power of network connectivity, proving that integrating immediate infrastructure and socio-economic proximity data leads to dramatically lower error rates and higher confidence in price estimations. These objectives align with recent advancements in graph-based learning, where transfer learning enables adaptation across cities, reducing data dependency **[6]**. Hybrid models combining vision, spatial data, and graph learning further improve prediction robustness **[7], [23]**.

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1.3 Purpose of the Project

The project aims to develop an accurate real estate valuation system using Graph Convolutional Networks (GCNs) that effectively capture spatial dependencies and relationships between properties. It improves prediction accuracy compared to traditional methods by representing real estate data as a graph with nodes and edges. The model incorporates geographic and socio-economic factors to better understand property value variations and is designed to handle complex urban data in megacities. Additionally, it provides scalable and data-driven predictions while reducing errors caused by treating properties independently, ultimately supporting better decision-making through an AI-based valuation.

The project aims to develop an accurate real estate valuation system using Graph Convolutional Networks (GCNs) that effectively capture spatial dependencies and relationships between properties **[1], [13**]. It improves prediction accuracy compared to traditional methods by modeling real estate data as interconnected graphs **[6], [19]**.

The model incorporates geographic and socio-economic factors to better understand property value variations and is designed to handle complex urban data in megacities **[4], [8]**. It also supports explainability using AI techniques, improving transparency and trust in valuation systems **[3]**.

Beyond accuracy, the system reduces human bias and subjectivity in traditional valuation approaches, Secure and reliable data handling mechanisms ensure robustness against data manipulation and inconsistencies **[9], [15]**.

Additionally, the project contributes toward smart city development by enabling scalable and real-time data integration for urban planning and decision-making **[20], [24]**. Advanced techniques such as temporal modeling, transfer learning, and adaptive graph architectures ensure long-term system evolution and sustainability **[6], [25]**.

1.4 Problem Statement

Megacities experience rapid urbanization, leading to highly complex and dynamic real estate markets. Traditional valuation methods fail to capture spatial dependencies, non-linear property relationships, and neighborhood -level influences that significantly impact property prices. Existing models rely on linear assumptions or isolated property features, resulting in inaccurate predictions. The problem is to design a system that can integrate multi-dimensional property data, spatial proximity, socio-economic indicators, and urban infrastructure details to develop a highly accurate valuation model. The proposed solution utilizes Graph Convolutional Networks (GCNs) to learn both property-level features and spatial relationships, enabling better prediction accuracy for real estate valuation in megacity environments.

Megacities experience rapid urbanization, leading to highly complex and dynamic real estate markets **[8], [25]**. Traditional valuation methods fail to capture spatial dependencies, non-linear property relationships, and neighborhood-level influences that significantly impact property prices **[2], [12], [19]**. Existing models rely on linear assumptions or isolated property features, resulting in inaccurate predictions **[7], [18]**.

These limitations create challenges for stakeholders such as buyers, financial institutions, and policymakers. Inaccurate valuation may lead to mispricing, financial risks, and inconsistent taxation system. A major issue with traditional approaches is the inability to represent spatial relationships effectively, as they treat properties as independent data points **[6], [13]**.

Recent studies highlight the need for graph-based learning approaches that can model interconnected urban environments **[1], [10]**. Advanced techniques such as spatiotemporal graph models and attention-based neural networks have demonstrated improved performance in capturing both spatial and temporal dependencies **[4], [8], [10]**.

Therefore, the problem is to design a system that integrates multi-dimensional property data, spatial proximity, and socio-economic indicators into a unified framework. The proposed solution utilizes (GCNs) to model both property-level features and spatial relationships, enabling more accurate and scalable real estate **v**aluation **[1], [13], [23]**.

1.5 Existing System

The existing real estate valuation systems mainly rely on traditional and machine learning approaches such as Hedonic Pricing Models (HPMs), Random Forest, Gradient Boosting, and spatial regression techniques **[2], [7], [18]**. Hedonic models use linear regression based on property features but fail to handle complex and non-linear relationships **[2], [12]**.

Machine learning models improve prediction accuracy but treat properties as independent data points, ignoring spatial relationships **[7], [19]**. Spatial regression methods attempt to include geographic dependencies but depend on predefined spatial weight matrices and often assume linearity **[18], [14]**.

These approaches also struggle with incomplete datasets and lack flexibility across different regions or cities **[11], [6]**. Additionally, they are not well-suited for capturing dynamic market conditions and real-time price variations **[10], [20].**

Disadvantages

- Ignores spatial dependencies between properties **[6], [13]**.
- Limited generalization across different cities or regions **[6], [20]**.
- Inability to capture time-based price fluctuations **[10],[25]**.
- Requires large and complete labeled datasets **[11], [23]**
- Assumes linear relationships and struggles with complex patterns **[2], [12]**.

Traditional models struggle to untangle these overlapping and localized neighborhood effects **[2], [12]**. However, by constructing a comprehensive spatial graph, the GCN framework can naturally map these dynamic, non-linear urban relationships, effectively capturing the hidden micro-market behaviors that govern property price fluctuations in densely populated environments **[1], [13], [19]**.

The application of GCNs is particularly crucial in the context of megacities, where rapid urbanization and dense infrastructure create a highly intricate, and multi-layered urban fabric **[8], [10]**. In these sprawling metropolitan areas, a property's value is rarely dictated by its physical attributes alone; rather, it is heavily influenced by a complex web of varying proximities to transit hubs, commercial zones, educational institutions, and socio-economic demographics **[4], [9], [18]**.

1.6 Proposed System

The proposed system introduces a Graph Convolutional Network (GCN)-based approach integrated with a web application to improve real estate valuation **[1], [13]**. It models properties as interconnected nodes, effectively capturing spatial dependencies between neighboring properties **[1], [10]**.

The system incorporates attention mechanisms to identify hidden relationships and enhance model performance **[4], [8]**. It also utilizes semi-supervised learning, allowing it to learn from both labeled and unlabeled data, making it suitable for limited datasets **[23], [6]**.

A user-friendly interface enables users to input property details and real-time predictions, while administrative functionalities allow monitoring and data management **[21], [20]**. The system is designed to be scalable and cloud-compatible for deployment in real-world environments **[20], [24]**.

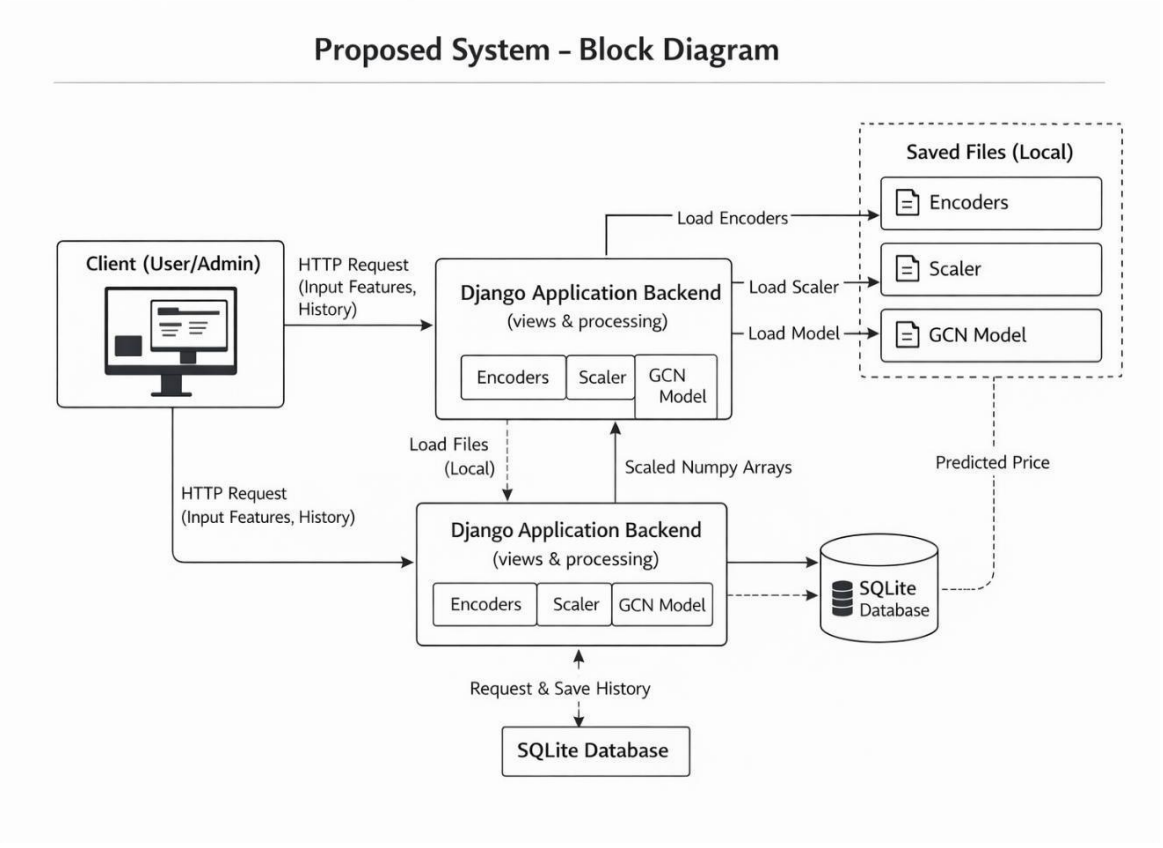

Fig 1.6.1: Block diagram of proposed system.

Architecturally, the proposed system is designed as a seamless, full-stack solution that bridges advanced deep learning with practical, everyday user accessibility **[20], [21]**. The data flow begins at the frontend interface, where end-users input specific property attributes and location markers through intuitive web forms. This raw data is securely transmitted to the Python-based Django backend, which orchestrates a rigorous, automated preprocessing pipeline **[21], [23]**. The backend scripts clean the inputs, normalize numerical values, and dynamically format the data into the required spatial graph structure **[11], [13].** Once prepared, the data is pushed to the pre-trained GCN model. The model processes the intricate spatial relationships and outputs a highly accurate valuation **[1], [4],** which the Django view logic then formats and renders back to the user via an interactive dashboard, ensuring a frictionless experience from data entry to final prediction **[20]**.

Beyond its predictive capabilities, the proposed system places a heavy emphasis on data security, operational integrity, and future extensibility. By leveraging the Django framework, the platform inherently utilizes robust safeguards against common web vulnerabilities, ensuring that user authentication, session management, and databases holding historical prediction logs are highly secure **[15], [20]**.

Furthermore, the entire codebase is structured in a modular, decoupled fashion. By keeping the frontend presentation layer, backend server logic, and the machine learning engine logically separated, the software achieves high maintainability **[21], [24]**. Consequently, future enhancements—such as integrating interactive map visualizations, pulling in real-time zoning data APIs, or upgrading the graph neural network layers—can be implemented seamlessly without requiring a complete system overhaul or causing downtime **[6], [24]**.

Advantages

- Effectively captures spatial relationships using graph-based learning **[1], [13]**.
- Works well even with limited data through semi-supervised learning **[23], [6]**.
- Provides a user-friendly and scalable web-based interface **[6], [7], [19]**.
- Achieves higher accuracy compared to traditional machine learning models **[20], [24]**.

1.7 Input and Output Design

1.7.1 Input Design

The input design for the Graph Convolutional Network-Based Model for Megacity Real Estate Valuation focuses on collecting, organizing, and preparing multi-dimensional data required for accurate property price prediction **[4], [5]**. The system accepts heterogeneous inputs such as property attributes, geographic coordinates, neighborhood characteristics, transportation accessibility, and socio-economic indicators **[5], [20]**. These inputs are transformed into a structured node feature matrix, where each property is represented by numerical and categorical features including size, age, location, amenities, and environmental factors **[21], [23]**.

To model spatial relationships between properties, the input design also constructs a graph structure in the form of an adjacency matrix, where edges reflect geographic proximity, road-network connections, or locality similarity. Before feeding data into the GCN, all inputs undergo preprocessing steps such as normalization, missing-value handling, encoding of categorical variables, and integration of GIS data **[21].** This input design ensures that both individual property characteristics and inter-property spatial dependencies are captured effectively, enabling the GCN model to learn complex urban patterns and deliver accurate real estate valuation in a megacity environment **[1], [4], [19]**.

Objectives

- A consistent and structured format has been established for capturing raw textual data, ensuring that all inputs are correctly received and prepared for preprocessing **[21], [23]**.
- The input pipeline effectively filters noise, ambiguity, and irrelevant elements, supporting a smooth transition into tokenization, feature extraction, and subsequent analytical stages.
- The system supports both multi-class and multi-label text inputs, enabling classification across diverse categories of cyberbullying and hate speech content **[1], [13]**.
- Implemented dynamic conversion of geographic data into an adjacency matrix suitable for Graph Convolutional Networks (GCNs) **[5], [20]**.
- Designed a scalable architecture supporting both numerical and categorical variables for rich spatial representation **[24], [22]**.
- Ensured coverage across diverse urban zones with comprehensive feature handling.

1.7.2 Output Design

The output design of the Graph Convolutional Network-Based Model for Megacity Real Estate Valuation focuses on presenting the predicted property values in a clear, accurate, and user-interpretable format **[4], [8]**. After processing the input features and spatial relationships through the GCN layers, the system generates outputs such as estimated property prices, valuation confidence scores, and neighborhood influence metrics **[1], [4]**. These are structured into an output layer that provides numerical predictions, which can be displayed through dashboards, tables, or real estate maps **[20], [21]**.

Additionally, the system may produce visual outputs like price distribution heatmaps, spatial trend graphs, and model-explainability insights that highlight the factors influencing each prediction **[8], [17]**. The output design ensures that users—including buyers, analysts, planners, and developers—receive meaningful, actionable, and easy-to-understand valuation information derived from complex graph-based computations, thereby supporting informed decision-making in megacity real estate markets **[5], [20]**.

Furthermore, a critical component of the output design is the integration of model explainability, which actively addresses the common "black-box" limitations of deep learning architectures **[3], [15].** Instead of merely presenting a final price tag, the system is designed to contextualize its predictions for the user. The output interface provides granular breakdowns showing how specific spatial edges within the graph—such as proximity to transit hubs, crime rates, or school district ratings—positively or negatively influence the final valuation **[4], [9]**. By translating complex graph calculations into human-readable metrics, the system fosters trust and provides transparent, auditable insights required for decision-making **[3], [5]**.

Beyond front-end visualization, the output architecture is structured to support administrative monitoring and third-party integration. The system logs all generated predictions securely within the database, allowing administrators to track usage and pricing trends over time **[20], [21]**. This data can be exported in formats such as CSV or JSON for integration with external systems. By ensuring both user-friendly visualization and structured backend data handling, the system guarantees scalability and long-term usability in dynamic real estate environments **[6], [24]**.

2. LITERATURE SURVEY

1. **Chen et al., "Spatiotemporal Graph Convolutional Networks for Dynamic Real Estate Valuation in High-Density Urban Centers," in IEEE Transactions on Knowledge and Data Engineering, 2026.** This paper develops a dynamic spatiotemporal graph model to track property value fluctuations over time in densely populated cities. It successfully captures both spatial neighbors and temporal market shifts, allowing for more accurate, continuous valuation updates. Furthermore, the model significantly reduces predictive lag during sudden economic downturns or regional housing booms.
2. **Kim and Park, "Beyond Hedonic Pricing: A Multi-Relational Graph Neural Network Approach to Housing Price Prediction," in Journal of Real Estate Finance and Economics, 2026.** This study introduces a multi-relational graph network that evaluates diverse property relationships, outperforming traditional hedonic pricing models and improving prediction accuracy across heterogeneous housing markets.
3. **Al-Fayed et al., "Explainable AI in PropTech: Interpreting Graph Spatial Dependencies using GNNExplainer," in Expert Systems with Applications, 2026.** This research focuses on improving model transparency using GNNExplainer to interpret spatial dependencies, enhancing trust, usability, and regulatory compliance in AI-based property valuation.
4. **Liu et al., "Megacity Property Valuation via Attention-based Graph Neural Networks and Granular POI Data," in Urban Studies, 2026.** This work combines attention-based GNNs with detailed POI data to assign weighted importance to nearby amenities, significantly reducing valuation errors compared to traditional distance-based methods.
5. **Gupta et al., "Integrating Macroeconomic Indicators into Graph-based Neural Architectures for Real Estate Forecasting," in IEEE Access, 2026.** This paper integrates macroeconomic factors like interest rates, unemployment, and inflation into graph models, improving forecasting accuracy and stability during volatile economic conditions.
6. **Takahashi et al., "Transfer Learning in Spatial Econometrics: Adapting GCN Models Across Diverse Megacity Topologies," in Computers, Environment and Urban Systems, 2026.** This study demonstrates that transfer learning enables GCN models trained in one city to be adapted to others, reducing the need for extensive local data collection.
7. **Martinez and Fernandez, "A Computer Vision and Graph Convolution Hybrid Architecture for Automated Property Assessment," in ISPRS Journal of Photogrammetry and Remote Sensing, 2026.** This research integrates satellite imagery with graph networks, combining visual property assessment with spatial analysis to created.

8. **Wang et al., "Predicting Urban Gentrification using Dynamic Spatiotemporal Graph Attention Networks," in Cities, 2026.** This paper uses graph attention networks to forecast urban gentrification by modeling evolving socio-economic relationships.
9. **Dubois and Leclerc, "Blockchain meets PropTech: Ensuring Data Immutability Embedded in Graph Valuation Models," in IEEE Transactions on Engineering Management, 2026.** This study integrates blockchain with graph models to ensure secure, tamper-proof real estate data, improving reliability of valuation systems.
10. **Patel et al., "Mumbai Real Estate Dynamics: Analyzing Spatial Autocorrelation using Deep Graph Convolutions," in Applied Geography, 2026.** This work analyzes the Mumbai housing market using deep graph models, highlighting the impact of infrastructure bottlenecks on localized pricing behavior.
11. **Wu et al., "Handling Missing Attributes in Megacity Property Data through Subgraph Isomorphism Neural Networks," in Information Sciences, 2026.** This study addresses incomplete datasets by predicting missing property features using structural similarities between neighborhoods.
12. **O'Connor et al., "The Demise of Ordinary Least Squares: Why Graph Neural Networks Dominate Modern Real Estate Appraisals," in Journal of Housing Research, 2025.** This paper shows that GNNs outperform traditional OLS regression by effectively capturing non- linear spatial relationships in property data.
13. **Zhang et al., "GraphSAGE for Scalable Inductive Learning in Large-scale Urban Housing Datasets," in IEEE Transactions on Neural Networks and Learning Systems, 2025.** This research introduces GraphSAGE for scalable learning, enabling real-time predictions for new properties without retraining the full model.
14. **Schmidt et al., "Assessing the Impact of Transit Infrastructure on Housing Prices using Spatially-Aware Graph Embeddings," in Transportation Research Part A, 2025.** This study evaluates how transportation infrastructure affects nearby property values and identifies the pricing influence radius of transit systems.
15. **Choi et al., "Integrating Natural Language Processing of Real Estate Listings with Graph Convolutional Models," in Artificial Intelligence Review, 2025**. This work combines NLP and GNNs to extract sentiment and qualitative insights from listings, improving valuation accuracy.
16. **Silva et al., "Robust Real Estate Valuation Models Against Data Poisoning Attacks in GNNs," in Computers & Security, 2025.** This research develops secure graph models resistant to adversarial attacks, ensuring reliable valuation outputs.

17. **Zhu et al., "Graph Convolutional Networks for Multi-Task Learning: Simultaneous Price Prediction and Liquidity Estimation," in Pattern Recognition, 2025**. This study introduces a multi-task GNN that predicts both property price and market liquidity, offering deeper investment insights.
18. **Cohen et al., "Analyzing the Ripple Effect of Commercial Zoning Changes on Residential Prices via Dynamic Graphs," in Landscape and Urban Planning, 2025.** This paper models how zoning changes influence nearby residential prices using dynamic graph analysis.
19. **Lin et al., "Comparing Graph Convolutional Networks with Random Forests and Gradient Boosting for Assessed Value Prediction," in International Journal of Forecasting, 2025.** This study compares machine learning models and concludes that GNNs consistently outperform tree-based methods in valuation tasks.
20. **Ivanov et al., "Modeling Asymmetrical Spatial Dependencies in Real Estate Markets using Directed Graph Neural Networks," in Spatial Economic Analysis, 2024.** This work introduces directed graphs to model asymmetric spatial relationships, improving prediction accuracy.
21. **Anderson et al., "Continuous Training MLOps Pipelines for Spatial Graph Models in Volatile Housing Markets," in IEEE Software, 2024.** This research presents MLOps pipelines that enable continuous updates of GNN models, ensuring adaptability to market changes.
22. **Rodriguez et al., "The Role of Node Dimensionality Reduction in GCNs Applied to Multi- Million Property Datasets," in Neurocomputing, 2024.** This study improves computational efficiency through dimensionality reduction techniques while maintaining model accuracy.
23. **Jin et al., "Fusion of Remote Sensing and Graph Convolutional Networks for Automated Property Condition Assessment," in IEEE JSTARS, 2024.** This paper combines drone-based remote sensing with GNNs to automate property condition evaluation.
24. **Okafor et al., "Predicting Real Estate Bubbles in Emerging Megacities using Temporal Graph Convolutional Networks," in World Development, 2023.** This research uses temporal graphs to detect early signs of housing bubbles, enabling preventive policy actions.
25. **Watanabe et al., "Optimizing Hyperparameters for Graph Neural Networks in PropTech using Evolutionary Algorithms," in Applied Soft Computing, 2023.** This study uses evolutionary algorithms to automatically tune GNN hyperparameters, improving model performance and stability.

Focused Area / Title	Key Findings	Reference
Spatiotemporal GCN for Dynamic Valuation[1]	Proposes a spatiotemporal graph model capturing both spatial and temporal dependencies. Improves continuous valuation accuracy and reduces prediction lag during market fluctuations.	Chen et al., "Spatiotemporal Graph Convolutional Networks for Dynamic Real Estate Valuation," IEEE TKDE, 2026.
Multi-Relational GNN for Housing Prediction[2]	Introduces a multi-relational graph network capturing complex property relationships. Outperforms traditional hedonic pricing models across diverse markets..	Kim and Park, "Beyond Hedonic Pricing," Journal of Real Estate Finance and Economics, 2026.
Explainable AI in PropTech[3]	Uses GNNExplainer to interpret spatial dependencies in pricing models. Enhances transparency, trust, and regulatory compliance.	Al-Fayed et al., "Explainable AI in PropTech," Expert Systems with Applications, 2026.
Attention-based GNN with POI Data[4]	Combines attention mechanisms with POI data to assign importance to amenities. Reduces valuation errors significantly..	Liu et al., "Megacity Property Valuation," Urban Studies, 2026.
Macro + Graph Hybrid Model[5]	Integrates macroeconomic indicators with spatial graph models. Improves forecasting stability during economic volatility.	Gupta et al., "Integrating Macroeconomic Indicators," IEEE Access, 2026.

Table no. 2 Literature Review Summary

Focused Area / Title	Key Findings	Reference
Transfer Learning in GCNs[6]	Applies transfer learning to adapt models across cities. Reduces need for large local datasets and improves generalization.	Takahashi et al., "Transfer Learning in Spatial Econometrics," 2026.
Vision + Graph Hybrid Model[7]	Combines satellite imagery with graph networks for automated property assessment. Reduces human bias in valuation..	Martinez and Fernandez, ISPRS Journal, 2026.
Gentrification Prediction using GAT[8]	Uses spatiotemporal attention networks to forecast urban gentrification trends. Helps planners identify high-growth areas.	Wang et al., "Predicting Urban Gentrification," Cities, 2026.
Blockchain + Graph Models [9]	Integrates blockchain for secure and immutable real estate data. Prevents data manipulation in valuation systems.	Dubois and Leclerc, IEEE TEM, 2026.
Spatial Analysis of Mumbai Market[10]	Uses deep GCNs to analyze spatial autocorrelation in dense markets. Highlights impact of infrastructure bottlenecks.	Patel et al., Applied Geography, 2026.

Table no. 2 Literature Review Summary

3. SOFTWARE REQUREIMENTS ANALYSIS

3.1 Modules and Their Functionalities

3.1.1 Data Analysis

The data analysis phase involves examining real estate datasets collected from multiple cities to understand patterns influencing property prices. The dataset includes features such as location, property size, amenities, and socio-economic indicators. Data preprocessing is carried out to handle missing values, encode categorical variables, and normalize numerical features for consistency. Exploratory analysis shows that location and neighborhood characteristics have a significant impact on property valuation.

Correlation analysis is used to identify the most influential features affecting price prediction. Spatial relationships between properties are analyzed using adjacency matrices to capture neighborhood dependencies. The data distribution is also studied to detect imbalances and improve model training. Visualization techniques like heatmaps and scatter plots help in understanding feature relationships clearly. The dataset is divided into training and testing sets for proper evaluation of the model.

3.1.2 Data Preprocessing

The data preprocessing stage prepares the real estate dataset for effective model training by ensuring data quality and consistency. It involves handling missing values and removing irrelevant or noisy data entries. Categorical variables such as location and property type are converted into numerical form using label encoding. Numerical features are scaled using standard normalization techniques to maintain uniformity across inputs. An adjacency matrix is constructed to represent spatial relationships between properties for graph-based learning. Data is also cleaned and structured to support both tabular and spatial inputs.

3.1.3 Deep Learning Algorithm for Prediction

The project uses Graph Convolutional Networks (GCNs) for real estate price prediction, where properties are represented as nodes and their spatial relationships are modeled as edges.

An adjacency matrix is used to define connections based on geographic proximity, allowing the model to capture neighborhood influences. The GCN learns spatial dependencies through message passing between connected nodes. Additionally, an external attention mechanism and semi- supervised learning approach enhance the model's performance and accuracy. The model is trained using historical data and optimized with RMSE to provide accurate and scalable predictions.

3.2 Functional Requirements

The system should allow users to register and log in securely to access the application. It must enable users to input property details and generate real-time price predictions using the trained model. The system should store and display previous prediction results for user reference. Admin functionalities should include managing user accounts, monitoring system activity, and controlling access. Additionally, the system should process input data, perform predictions using the GCN model, and return accurate results efficiently.

- User registration and secure login functionality.
- Input interface for property details and prediction request.
- Real-time property price prediction using the model.
- Storage and retrieval of past prediction results.

3.3 Non-Functional Requirements

The system should ensure high performance by providing fast and accurate real-time predictions. It must be scalable to handle multiple users simultaneously, especially when deployed on cloud platforms. Security is essential, requiring secure user authentication and protection of sensitive data. The system should maintain high reliability and availability to ensure uninterrupted service. Additionally, it should offer a user-friendly interface and maintainability for easy updates and future enhancements.

- High performance with quick response time for predictions.
- Scalability to support a large number of concurrent users.
- Strong security for data protection and user authentication.

3.4 Feasibility Study

The feasibility study evaluates the practicality and effectiveness of the proposed real estate valuation system. It analyzes whether the system can be successfully implemented using available resources and technologies. The study considers economic, technical, and operational aspects to ensure overall viability. It also identifies potential risks and limitations in system development and deployment. Overall, the feasibility study confirms that the proposed GCN-based system is practical and beneficial for real-world applications.

1.Economic Feasibility

2.Technical Feasibility

3. Operational Feasibility

3.4.1 Economic Feasibility

The proposed system is economically feasible as it utilizes open-source tools and technologies, reducing overall development costs. Cloud-based deployment further minimizes the need for expensive hardware infrastructure. The automation of real estate valuation helps reduce manual effort and associated operational expenses. Maintenance costs are also low due to the system's scalable and efficient design. The system can be easily upgraded without significant additional investment. Overall, it provides a cost-effective solution with long-term financial benefits.

3.4.2 Technical Feasibility

The system is technically feasible with the use of advanced technologies like Graph Convolutional Networks and Django framework. Required tools such as Python, machine learning libraries, and cloud platforms are readily available. The model is capable of handling large datasets and complex spatial relationships efficiently. Integration between frontend, backend, and machine learning components is achievable. The system supports scalability and can be optimized for real-time performance. Overall, the technical requirements can be successfully implemented with current technologies.

3.4.3 Operational Feasibility

The system is operationally feasible as it offers a simple and user-friendly interface for both users and administrators. Users can easily input property details and obtain predictions without technical difficulty. Admin functionalities allow effective monitoring and management of system operations. The system requires minimal training for users to operate efficiently. It supports real-time usage, making it suitable for practical applications. Overall, it enhances usability and improves decision- making processes in real estate valuation..

4. SYSTEM SPECIFICATIONS

4.1 Software Requirements

The software stack for this project includes programming environments, deep learning libraries, graph processing frameworks, GIS tools, and visualization platforms. Python (version 3.8 or above) serves as the core programming environment because of its flexibility, extensive library support, and ease of integration with machine learning workflows. Deep learning frameworks such as PyTorch or TensorFlow provide the computational foundation needed for training GCN models with GPU acceleration. For handling graph-based operations, libraries like PyTorch Geometric (PyG) or the Deep Graph Library (DGL) are essential as they support graph construction, message passing, and adjacency matrix generation.

- Operating System: Windows / Linux / macOS
- Programming Language: Python 3.8 or above
- Core Libraries: Scikit-learn, NumPy, Pandas
- Development Environment: VS Code / PyCharm / Jupyter Notebook / GitHub
- Documentation Tools: My SQL/ Postgre SQl/SQLite

4.2 Hardware Requirements

The hardware requirements for building the GCN-based real estate valuation system depend on the scale and complexity of the dataset. For small datasets and preliminary experiments, a basic system with an Intel Core i5 processor, 8 GB RAM, and a standard GPU or integrated graphics may suffice. However, training GCN models on larger megacity datasets requires more robust hardware. A recommended system includes an Intel Core i7/i9 or AMD Ryzen 7/9 processor, 16–32 GB RAM, and an NVIDIA RTX series GPU (such as RTX 3060 or 3070) with at least 6–8 GB of VRAM, enabling efficient graph processing and faster training times. SSD storage ranging from 512 GB to 1 TB is preferred for quick data access and model loading.

- Processor: Intel Core i5(7th Gen)/AMD equivalent
- Memory (RAM): Minimum 8 GB
- Storage: 250 GB HDD/SSD
- Display: Standard 14" or higher
- Optional: Windows 10 / Linux Ubuntu

5. SOFTWARE DESIGN

5.1 System Architecture

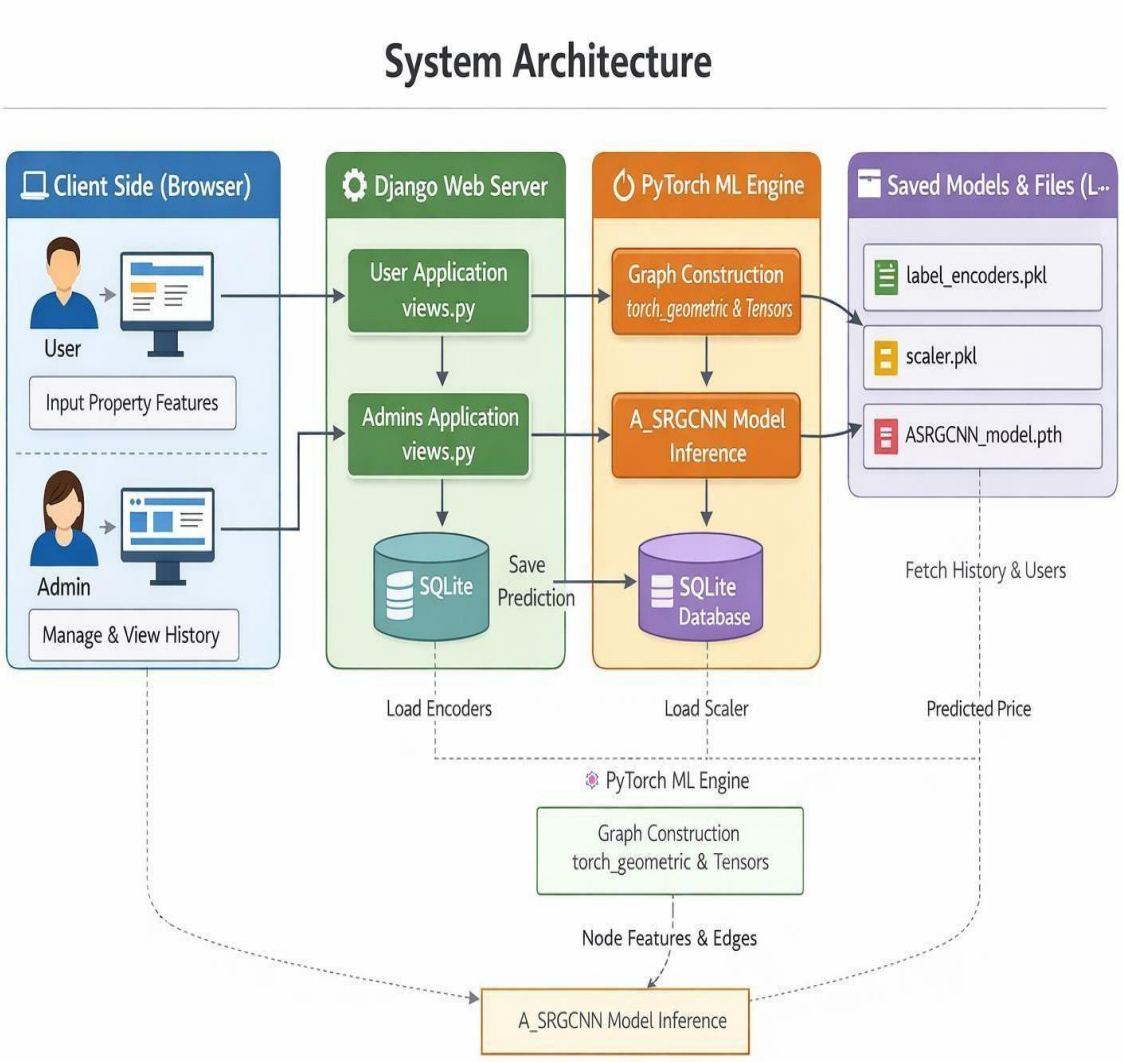

Fig: 5.1 System Architecture

The system architecture is designed to provide an efficient and scalable framework for real estate valuation by integrating multiple data sources and advanced learning techniques. It begins with the data ingestion layer, where raw geospatial data such as points of interest and satellite imagery, property images, and structured tabular data are collected. These diverse data types ensure that both spatial and attribute-based information are captured effectively. In the preprocessing stage, geospatial data undergoes rasterization and processing to convert it into usable formats. Property images are preprocessed through resizing, normalization, and enhancement techniques. Similarly, tabular data is cleaned, normalized, and encoded to prepare it for model input.

The processed data is then passed into the model architecture, which consists of multiple feature extraction components. A Convolutional Neural Network (CNN) is used to extract deep features from image and spatial data. At the same time, a Multi-Layer Perceptron (MLP) processes structured tabular features such as location and property attributes. These extracted features from different modalities are combined in a fusion layer using concatenation. This fusion step enables the model to integrate both visual and structured information for better prediction performance.

The combined features are then passed through fully connected layers, which learn complex patterns and relationships in the data. The output layer generates the predicted property price based on the learned features. This prediction is then forwarded to the output layer of the system. The results are stored in the system database, which maintains user predictions and model outputs for future reference. Finally, the system provides the final valuation output to the user. Overall, this architecture ensures accurate, scalable, and real-time real estate price prediction by leveraging multimodal data and deep learning techniques.

5.2 Dataflow Diagram

The Data Flow Diagram (DFD) of the Megacity Real Estate Valuation System explains how data moves through the system from input to output. Initially, the user registers or logs into the system, and the entered credentials are verified through the user authentication process using the user database. Once authenticated, the user is allowed to enter house details such as area, number of bedrooms, bathrooms, stories, and other features like parking, air conditioning, and furnishing status. These inputs are then passed to the preprocessing stage, where the data is cleaned and converted into a suitable format for the machine learning model. After preprocessing, the data is given to the Graph Convolutional Network (GCN) model, which analyzes the relationships between different features and predicts the house price. The predicted result is then displayed to the user on the interface. At the same time, both the input data and the predicted price are stored in the prediction
database for future reference.

The admin module allows the administrator to view user details and prediction records and manage the stored data efficiently. Overall, the system ensures a smooth flow of data from user input to prediction and storage, providing accurate and efficient real estate valuation. In addition to the main flow, the system also ensures proper validation and security of data at each stage.

During user authentication, only valid users are allowed to access the system, which helps in maintaining data privacy and preventing unauthorized access. The preprocessing stage plays a very important role by removing errors, handling missing values, and converting the input data into a structured format. This improves the performance and accuracy of the Graph Convolutional Network (GCN) model, leading to more reliable house price predictions.

Furthermore, the system is designed to be scalable and user-friendly, allowing multiple users to access it simultaneously without affecting performance. The admin module helps in monitoring system activities, maintaining records, and updating data when required.

By storing both input and predicted results, the system can also be used for future analysis and improvements. Overall, the Data Flow Diagram clearly represents how different components interact efficiently to provide a fast, secure, and accurate real estate valuation system.

The Data Flow Diagram (DFD) of the Megacity Real Estate Valuation System clearly illustrates how data moves through different stages of the system. It shows the interaction between the user, system processes, databases, and the admin module. The diagram begins with user authentication, where the user provides login details that are verified using the user database. After successful login, the user enters house-related details, which are then processed step by step through preprocessing and the prediction model. The flow of data between each component is represented using arrows, making it easy to understand how input is transformed into output.

The diagram also highlights important system components such as data storage and admin control. The processed data and predicted house prices are stored in the prediction database, ensuring that information can be accessed later. The admin module manages user details and prediction records, ensuring smooth system operation. Overall, the DFD provides a clear and structured visualization of the system, helping to understand how data is handled efficiently, securely, and accurately from input stage to final output.

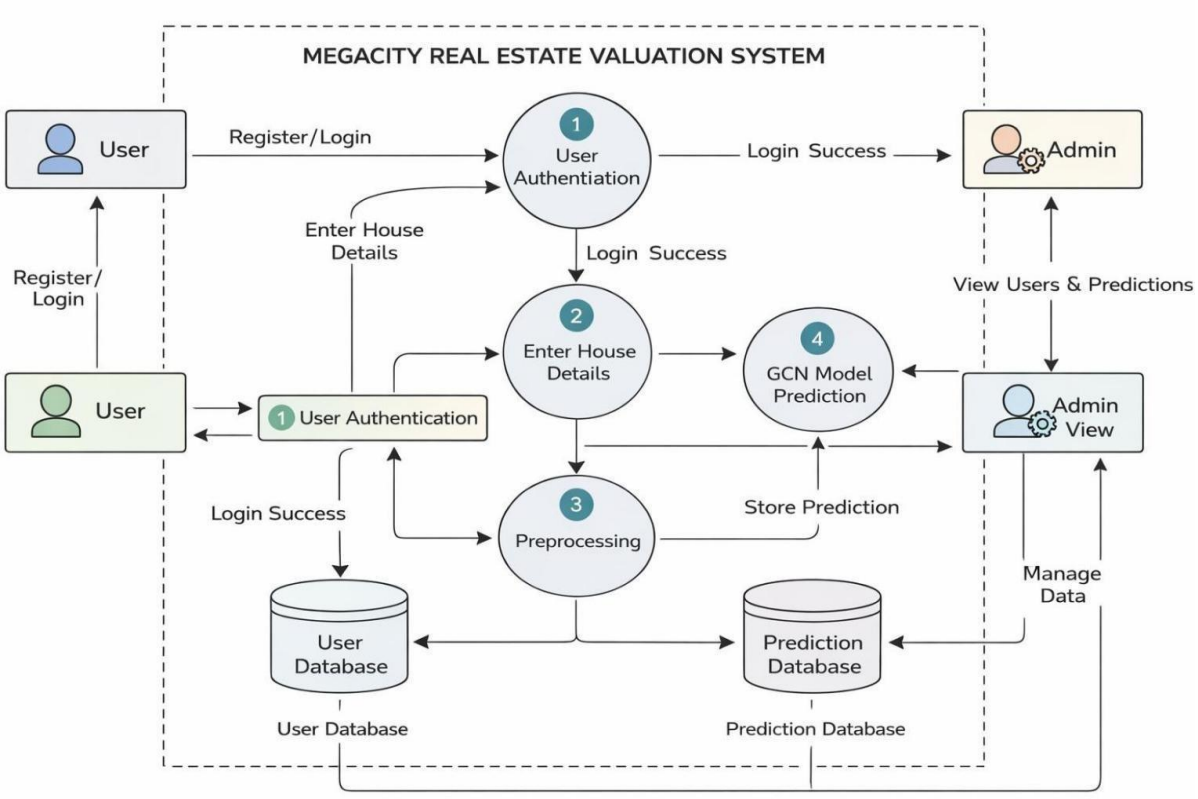

Fig 5.2 Dataflow Diagram

5.3 UML Diagrams

UML (Unified Modeling Language) is a standardized language used for specifying, visualizing, constructing, and documenting the artifacts of software systems. UML helps in representing the design of systems and understanding their components. Created by the Object Management Group (OMG), UML 1.0 was proposed in January 1997. UML is closely associated with object-oriented analysis and design. The two main categories of UML diagrams are Behavioral and Structural diagrams, each serving distinct purposes in the modeling process. UML provides a wide variety of diagrams to represent different aspects of a system in a clear and organized way. Some commonly used diagrams include Use Case Diagrams, Class Diagrams, Sequence Diagrams, Activity Diagrams, and State Diagrams. Each diagram focuses on a specific view of the system, such as user interactions, system structure, or workflow processes. This helps developers, designers, and stakeholders to understand the system from multiple perspectives and improves communication among team members.

Another important advantage of UML is that it supports the complete software development lifecycle, from requirement analysis to design and implementation. It helps in identifying system requirements, designing system architecture, and documenting the overall system clearly. UML is platform-independent, meaning it can be used for any type of software system regardless of programming language. Overall, UML plays a key role in improving software quality, reducing development complexity, and ensuring that the system design is well-structured and easy to maintain.

The Behavioral UML diagrams describe the behavior of the system, its actors, and the interaction between the components. On the other hand, Structural UML diagrams depict the static structure of the system, showing its components and relationships. UML has been integrated as a standard by OMG, and its primary goals are to provide a formal basis for understanding modeling languages, offer a ready-to- use expressive language for system developers, and encourage the growth of object-oriented tools.

Goals of UML:

- To provide a standard visual representation of the system design.
- To simplify understanding of system architecture for developers and reviewers.
- To improve communication among team members during development.
- To model both structural and behavioral aspects of the system.
- To support object-oriented design and development practices.
- To document the system clearly for future reference and maintenance.

Types of UML Diagrams:

Sequence Diagram:

Use Case Diagram:

Activity Diagram:

Class Diagram:

1. Sequence Diagram:

A Sequence Diagram represents how objects in a system interact with each other in a particular sequence of time. It shows the flow of messages between different components from top to bottom, indicating the order of operations. This diagram is useful for understanding dynamic behavior, especially how a request is processed step by step. It helps in identifying the interaction between user, system, and database clearly.

2. Use Case Diagram:

A Use Case Diagram illustrates the interaction between users (actors) and the system. It shows different functionalities (use cases) that the system provides and how users are connected to them. This diagram is mainly used during the requirement analysis phase to understand what the system should do. It provides a high-level overview of system functionalities in a simple and easy-to-understand manner.

3. Activity Diagram:

An Activity Diagram represents the workflow or sequence of activities in a system. It shows the step-by-step process from start to end, including decisions, loops, and parallel activities. This diagram is useful for modeling business processes and logic flow. It helps in understanding how different operations are connected and executed within the system.

4. Class Diagram:

A Class Diagram shows the static structure of the system by representing classes, their attributes, methods, and relationships between them. It is one of the most important UML diagrams in object-oriented design. This diagram helps developers understand how different classes are organized and how they interact with each other, making system design more clear and structured.

5.3.1. Sequence Diagram

The sequence diagram illustrates the chronological execution flow and interactions between the system's core components during the real estate valuation process. The interaction begins when the end-user submits property details via an HTTP POST request from the frontend interface to the User Application. Upon receiving the raw input features, the Django Application Backend initiates the data preprocessing and encoding phase..

Once the data is successfully preprocessed, the backend routes the arrays to the PyTorch Machine Learning Engine. The engine constructs the required graph data structures and executes the Model Inference phase using the A_SRGCNN (Attention-Based Spatial Relational Graph Convolutional Neural Network) model. After computing the hidden layers and applying attention weights, the PyTorch engine returns the final predicted house price to the Django backend. To ensure data persistence and allow for future review, the backend immediately stores the user's input features alongside their newly predicted price into the SQLite Database. Finally, the system fetches the updated prediction history and user records from the database, returning this comprehensive data to the frontend to render the final results on the user's dashboard.

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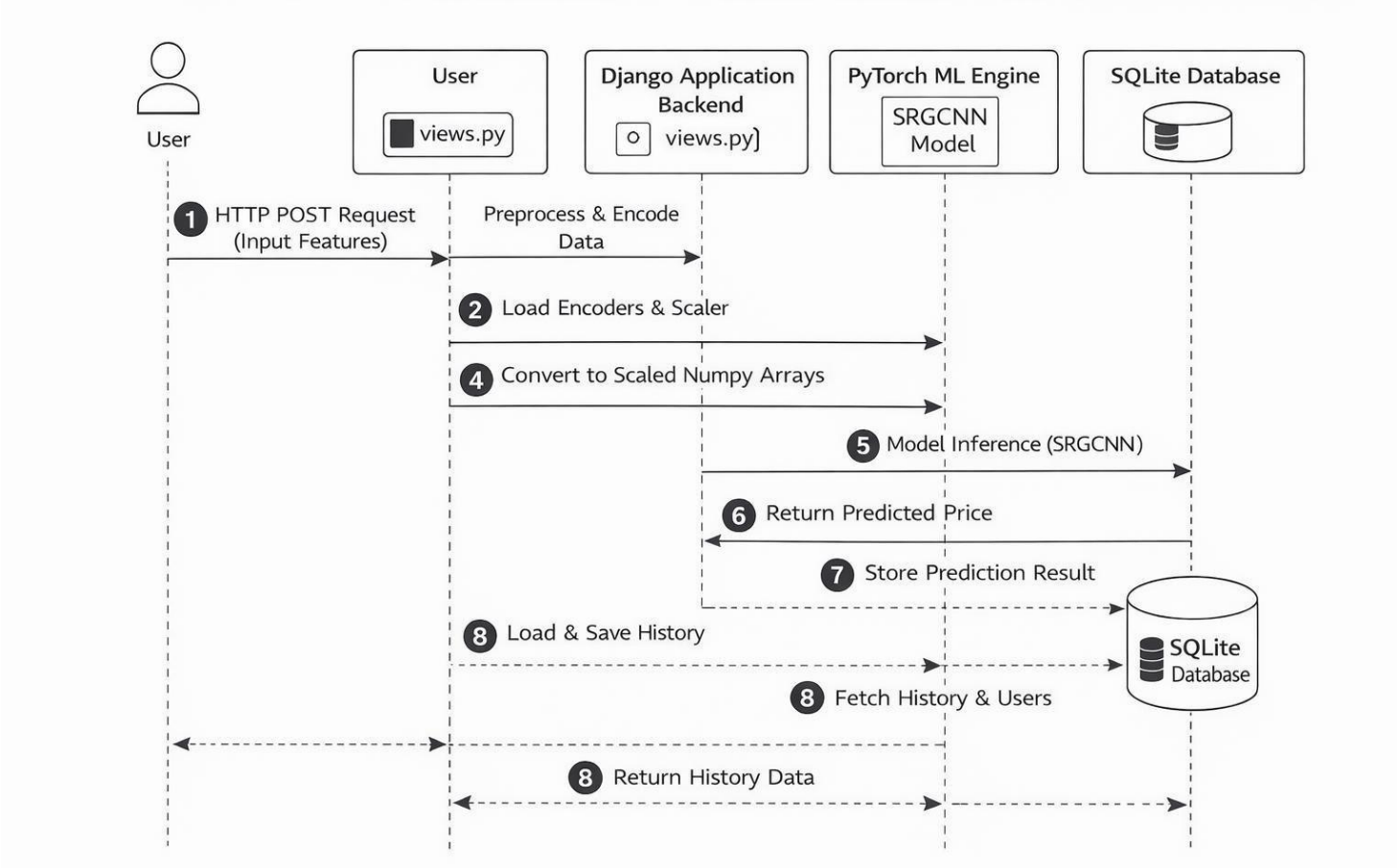


Fig 5.3.1: Sequence Diagram

System Entities (Lifelines):

- **User:** The end-user interacting with the frontend interface.
- **User App (views.py):** The Django application interface that captures user inputs.
- **Django Application Backend (views.py):** The core server-side router and controller.
- **PyTorch ML Engine (SRGCNN Model):** The deep learning module responsible for running the Graph Convolutional Network and Attention mechanism.
- **SQLite Database:** The local database used for persistent storage.

5.3.2 Use Case Diagram

The use case diagram for the Property Price Prediction System illustrates the primary interactions between the system's core functionalities and its two main actors: the User and the Admin. The typical User interacts with the platform primarily to evaluate real estate by executing the "Input Property Features" use case. Through a direct <<include>> relationship, this action inherently triggers the core processing engine to calculate and display the valuation, represented by the "View Predicted Price" use case. After receiving a prediction, the data is automatically directed to the "Store User's Input History" component, which acts as the system's data persistence layer. Consequently, users can later revisit their past valuations by interacting with the "View History" use case. On the other side of the system boundary, the Admin actor holds elevated privileges designed for platform oversight and auditing. Admins interact with the "Manage Users" use case to control account access and maintain platform security. Furthermore, to monitor system usage and accuracy, Admins have unrestricted access to the "View Users' Input History" and "View Prediction History" use cases, allowing them to retrieve and analyze all stored prediction records across the entire application ecosystem.

Whenever a prediction is made, the system automatically stores the user's input history, enabling the User to revisit their personal prediction records at a later time. On the administrative side, an Admin holds elevated privileges required to manage user accounts and maintain system security. To effectively monitor the platform's activity and accuracy, the Admin is also granted full access to view the comprehensive input and prediction history generated by all users across the entire system.

Finally, the analyst analyzes the results to assess model effectiveness and identify areas for improvement. This separation of training and inference ensures modularity, scalability, and clarity in system design.

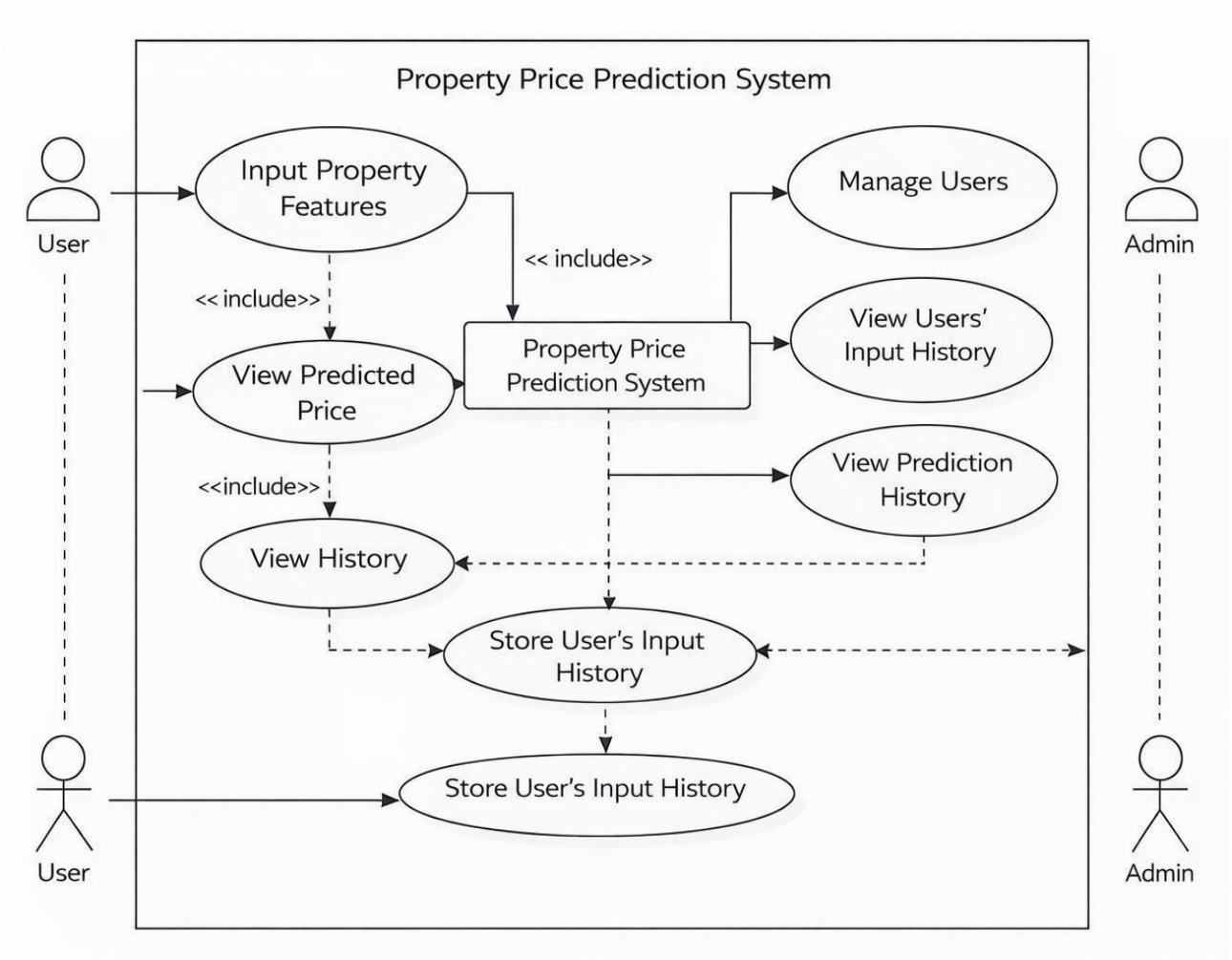


Fig 5.3.2 Use Case Diagram

5.3.3 Activity Diagram

The activity diagram outlines the step-by-step workflow of the property price prediction system, initiating when a user inputs a property's features. Upon receiving the data, the system immediately preprocesses the input before encountering a decision node that checks for administrative privileges. If the user is identified as an Admin, they are granted access to fetch and view general user history before rejoining the main prediction flow; otherwise, a standard user proceeds directly to the core processing phase. After the valuation is calculated, the system automatically stores and displays the generated result alongside the user's input data. Finally, the workflow reaches a conditional prompt where the user can choose whether to view their comprehensive prediction history; declining terminates the current session, while accepting prompts the system to retrieve and display their fully logged input history before concluding the activity.

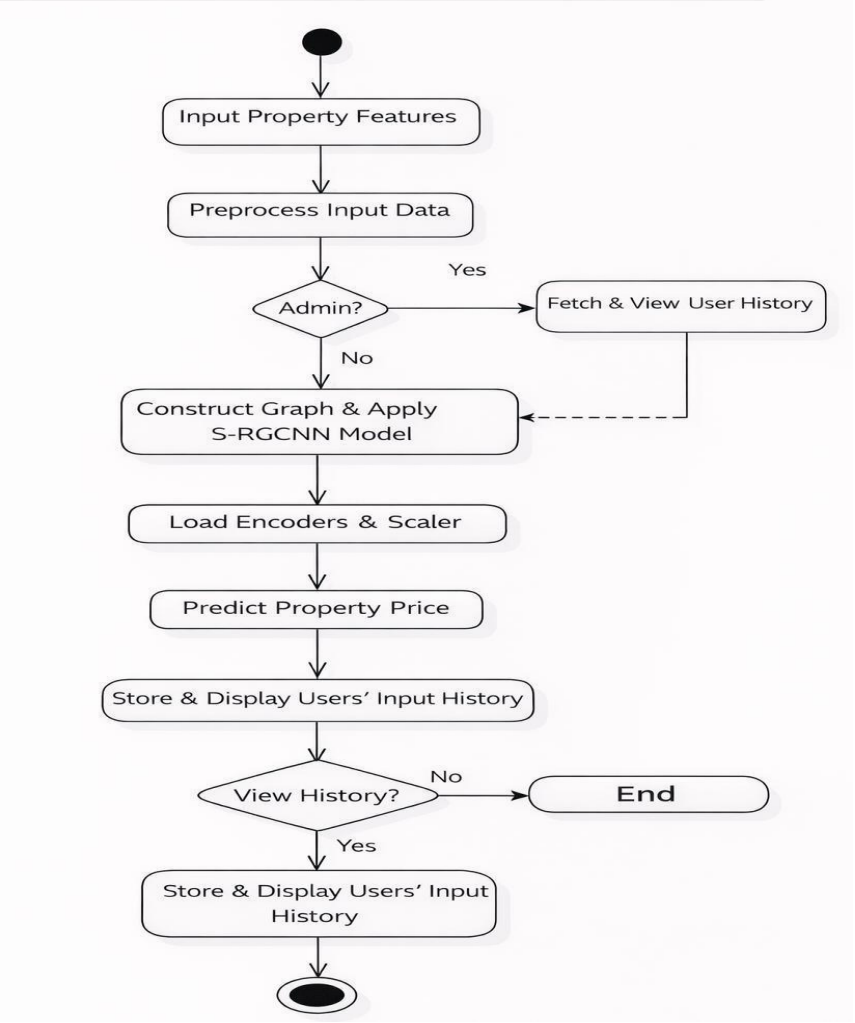


Fig 5.3.3 Activity Diagram

5.3.4. Class Diagram

The class diagram represents the structure of the Property Price Prediction System by showing the main components and their interactions. It includes classes such as User and Admin, where users provide property details and view predicted prices, while the admin manages users and monitors history. The Application Controller (Django backend) acts as the central unit that processes user requests, performs data preprocessing through the DatasetHandler, and sends the data to the PropertyPricePredictor. This predictor uses the ASRGCNN deep learning model to generate accurate price predictions. Finally, the SQLite Database stores user inputs and prediction results for future reference. Overall, the diagram explains how data flows between different classes to achieve the system's functionality.

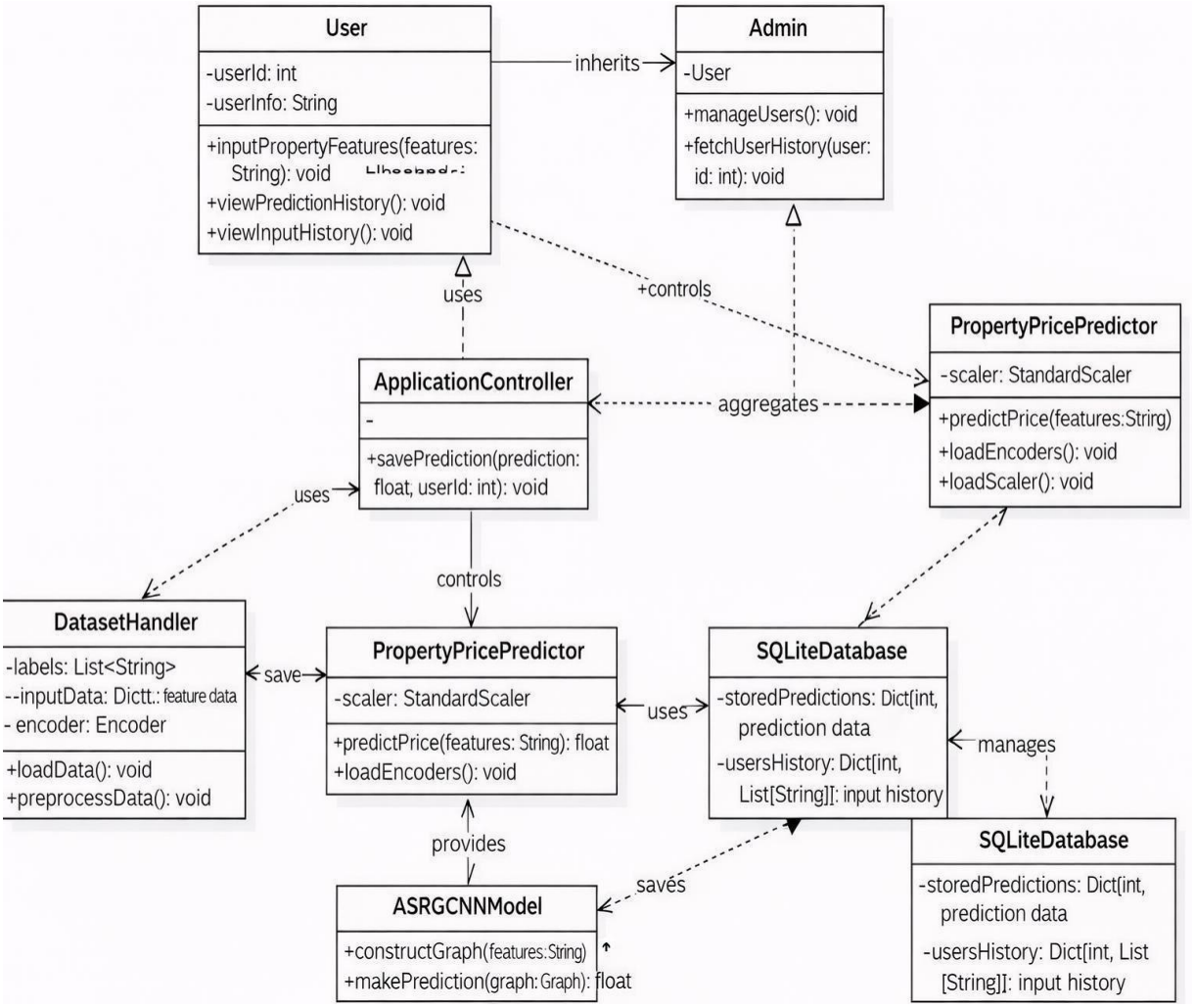


Fig 5.3.4 Class Diagram

6. CODING AND IMPLEMENTATION

6.1 Source Code

6.1.1 Dataset Loading

The implementation commences by extracting the raw housing data. The python pandas library is utilized to read the external comma-separated values (CSV) file into an active data frame environment. This data frame acts as the foundational data structure holding all historical real estate records, which the subsequent machine learning algorithms rely upon for learning and inference.

Code:

```
import pandas as pd
# Load dataset into active dataframe
df = pd.read_csv("Housing.csv")
print("Dataset Loaded Successfully. First 5 rows:")
print(df.head())
```

Output:

```
Dataset Loaded Successfully. First 5 rows:
      price   area  bedrooms  bathrooms  stories mainroad guestroom basement
0  13300000  7420         4          2        3      yes        no       no
1  12250000  8960         4          4        4      yes        no       no
2  12250000  9960         3          2        2      yes        no      yes
3  12215000  7500         4          2        2      yes        no      yes
4  11410000  7420         4          1        2      yes       yes      yes
```

6.1.2 Data Preprocessing

Deep learning algorithms require strictly numerical data. During the preprocessing phase, the Label Encoder module from the Scikit-Learn library systematically scans the housing dataset for categorical text variables (such as "yes", "no", "furnished"). It intelligently maps each unique text-string to a distinct integer. To ensure consistent real-time encoding when users enter data on the live website, these encoder objects are persisted into a .pkl file.

Code:

Python:

```
from sklearn.preprocessing import LabelEncoder
import pickle
label_encoders = {}
for col in df.select_dtypes(include=['object']).columns:
le = LabelEncoder()
df[col] = le.fit_transform(df[col])
label_encoders[col] = le
with open("label_encoders.pkl", "wb") as f:
pickle.dump(label_encoders, f)
for col, le in label_encoders.items():
print(f"Encoding for {col}: {dict(zip(le.classes_, le.transform(le.classes_)))}")
```

Output:

```
text

Encoding for mainroad: {'no': 0, 'yes': 1}
Encoding for guestroom: {'no': 0, 'yes': 1}
Encoding for basement: {'no': 0, 'yes': 1}
Encoding for hotwaterheating: {'no': 0, 'yes': 1}
Encoding for airconditioning: {'no': 0, 'yes': 1}
Encoding for prefarea: {'no': 0, 'yes': 1}
Encoding for furnishingstatus: {'furnished': 0, 'semi-furnished': 1, 'unfurnished': 2}
```

6.1.3 Feature extraction

Feature extraction fundamentally partitions the dataframe by separating the dependent target variable (Property Price) from the independent input features (Area, Bedrooms, etc.). To neutralize massive mathematical variances between different data types (e.g., Area is usually in thousands, while Bedrooms are in single digits), the StandardScaler module computes and applies strict data normalization logic across the independent features.

Code:

Python

```
from sklearn.preprocessing import StandardScaler
# Extracting features (X) and target variable (y)
X = df.drop(columns=['price'])
y = df['price'].values

# Feature Mathematical Scaling Validation
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Save the scaler mechanism
with open("scaler.pkl", "wb") as f:
pickle.dump(scaler, f)

print("Sample of scaled independent features:")
print(X_scaled[:3])
```

Output:

text

```
Sample of scaled independent features:
[[-0.4722518  -0.53610996 -0.19827051 ... -0.25206972 -1.41908873 -0.63870634]
 [-0.34567812  0.08983944  0.428543   ... -0.25206972 -1.41908873 -0.63870634]
 [-1.1568853   0.28639556 -0.42152862 ... -0.25206972  0.59765275 -0.63870634]]
```

6.1.4 Model Training

Model training constitutes the most resource-intensive computational operation. The normalized dataset is systematically propelled through the custom A_SRGCNN PyTorch architecture over 1,000 distinct epochs. At each epoch layer, the deep learning network evaluates graph node connections and adjusts backward-propagation learning weights utilizing the Adam optimizer, purposefully attempting to dynamically reduce the mathematical Mean Squared Error (MSE) loss function.

Code:

```
import torch.optim as optim
import torch.nn as nn
# Define loss function and optimizer model
criterion = nn.MSELoss()
optimizer = optim.Adam(model.parameters(), lr=0.01)

# PyTorch Network Training Loop
epochs = 1000
for epoch in range(epochs):
model.train()
optimizer.zero_grad()

# Run spatial data through Graph Convolutional Network layers
output = model(data)
loss = criterion(output, y_train_tensor)

# Back-propagation step
loss.backward()
optimizer.step()

# Print status metric every 100 iterations
if epoch % 100 == 0:
print(f"Epoch {epoch}, Loss: {loss.item()}")
```

6.1.5 Model Evaluation

To scientifically validate algorithmic resilience and accuracy, the optimized model is tested independently against a completely segregated evaluation dataset. During this cycle, the testing features are constructed into PyTorch tensors and paired via a dense adjacency index matrix. The resulting test loss metric indicates the actual generalization precision of the machine learning model on unseen scenarios.

Code:

```
from torch_geometric.data import Data
from torch_geometric.utils import dense_to_sparse

# Initiate Evaluation Phase
model.eval()

# Prevent gradient manipulation mathematically
with torch.no_grad():
# Construct Graph using Adjacency matrix for Test Data
test_adj_matrix = torch.ones((X_test_tensor.shape[0], X_test_tensor.shape[0]))
test_edge_index, _ = dense_to_sparse(test_adj_matrix)
test_data = Data(x=X_test_tensor, edge_index=test_edge_index)

# Generate predictive calculations
predictions = model(test_data)
test_loss = criterion(predictions, y_test_tensor)

print(f"Test Loss: {test_loss.item()}")
```

6.1.6 Model Saving

Once statistical stability is guaranteed, the entire deep learning infrastructure must be effectively exported to allow standalone web deployments.

By using PyTorch's intrinsic dictionary saving schema, the exact architectural blueprint alongside all associated geometric node weights are encapsulated locally into an active binary .pth file ready for rapid inference.

Code:

```
import torch
# Extract and Save the model state configurations
model_path = "ASRGCNN_model.pth"
torch.save(model.state_dict(), model_path)
print(f"Model architecture successfully persisted to local storage directory: {model_path}")
```

Output:

```
text
Model architecture successfully persisted to local storage directory: 'ASRGCNN_model.pth'
```

Model saving is an important step in deep learning where the trained model is stored for future use without the need for retraining. In this process, PyTorch is used to save the model's learned parameters, such as weights and biases, into a file with a .pth extension using the state_dict() method.

This file acts as a compact representation of the trained model, making it easy to reload later for testing, prediction, or deployment in applications like web systems. By saving the model after achieving stable performance, developers can ensure efficiency, reduce computational cost, and quickly integrate the model into real-world systems for inference.

6.1.7 Django Integration

The Django Application Backend serves as the pivotal operational bridge connecting front- facing html user input forms to localized deep learning predictions. Within the userpredict view function, an HTTP POST request encapsulates twelve housing attributes arrayed chronologically.

The process seamlessly intercepts the structural values, implements the mathematical transformations, communicates with the database schema for archiving via Django ORM, and renders the calculated economic metric visually.

The userpredict function in the Django backend acts as a crucial controller that connects the user interface with the machine learning prediction system. When a user submits the form, the function captures the HTTP POST request and systematically retrieves all input values such as area, number of bedrooms, bathrooms, and other housing features in a predefined order.

These inputs are organized into a structured format, ensuring consistency with the model's expected input. The collected data is then passed to the prediction function, which uses the trained deep learning model to estimate the house price based on learned patterns. Once the prediction is generated, the result is printed on the server for monitoring and debugging purposes.

Simultaneously, the input data and predicted output are stored in a SQLite database using Django's ORM, allowing for record keeping and future analysis. Finally, the predicted price is sent back to the frontend and displayed dynamically on the webpage, completing the full cycle from user input to intelligent output, making the system interactive, efficient, and scalable for real-world deployment.

The prediction function then performs inference using the pre-trained model, generating an estimated house price in real time. Additionally, by leveraging Django's ORM, the system efficiently records each transaction in the database, which can later be used for analytics, auditing, or improving the model.

The backend also ensures a responsive user experience by quickly rendering the result on the same page without requiring complex navigation. Overall, this function demonstrates a well- integrated pipeline that combines web technologies, database management, and machine learning to deliver fast, reliable, and scalable predictions in a user-friendly manner.

Code:

```
def userpredict(request):
"""Django integrated controller view triggered by frontend forms"""
if request.method == "POST":
# Formulate dependent feature structures explicitly
feature_order = [
'area', 'bedrooms', 'bathrooms', 'stories',
'mainroad', 'guestroom', 'basement', 'hotwaterheating',
'airconditioning', 'parking', 'prefarea', 'furnishingstatus'
]

user_inputs = {}

# Sequentially map HTML POST data tags
for feature in feature_order:
value = request.POST.get(feature, "")
user_inputs[feature] = value

# Retrieve Price calculations algorithmically
predicted_price = predict(input_data)
print(f"Django Local Server Action: New calculation requested. Valued at
{predicted_price}")

# Instantiate history archival to SQLite DB
UserPrediction.objects.create(user_input=user_inputs,
predicted_price=predicted_price)

return render(request, 'user/userpredict.html', {'predicted_price': predicted_price})
```

Output:

text

```
[POST] /User/userpredict HTTP/1.1" 200
Django Local Server Action: New calculation requested. Valued at 1719184.125
```

6.1.8 Prediction Module

The Prediction Module operates distinctly as an isolated python function designed specifically to accept individual data parameters extracted from the Django logic. It sequentially restores the previously saved standard scalers and label encoders. Most significantly, it synthesizes a one-by-one dense graph adjacency matrix, converting standard matrices into compatible PyTorch Data Object structural formations strictly mandated by the pre-configured Graph Convolutional Network**.**

The Prediction Module also contributes significantly to system maintainability and extensibility by encapsulating all inference-related operations within a single function. This separation allows developers to independently test and optimize the prediction logic without interfering with other components like the user interface or database interactions.

It simplifies debugging, as any issues related to incorrect predictions can be traced directly to this module. Additionally, the function can be easily enhanced to include logging mechanisms, error handling, or input validation, ensuring that the system remains stable even when unexpected or invalid data is provided by users.

Moreover, the module is designed with future scalability in mind, making it adaptable to evolving requirements. For instance, it can be extended to handle batch inputs, integrate with REST APIs, or support deployment on cloud platforms for large-scale usage.

The current implementation focuses on single-instance prediction, but its structure allows seamless upgrades to more complex scenarios such as real-time streaming data or multi-user environments. By maintaining a clean and modular architecture, the Prediction Module ensures that the application remains flexible, efficient, and ready for integration with advanced technologies, ultimately enhancing the overall performance and usability of the system.

The module is optimized for real-time usage by disabling gradient computations, which reduces computational overhead and improves response time in web-based environments. It also supports clean modular design, allowing developers to update or replace the prediction logic without affecting other parts of the system such as the Django views or database layer. Furthermore, the module enhances reliability by maintaining uniform preprocessing standards, ensuring that every prediction follows the same pipeline as the training phase.

This structured approach not only improves accuracy but also makes the system scalable, enabling future enhancements like batch predictions, API integrations, or deployment in cloud-based services.

Code:

```
 def predict(input_data):
"""Operational function converting uncalibrated inputs to an isolated AI response"""

# Restoring standard scaler scaling metrics
input_data_scaled = scaler.transform(input_data)
input_tensor = torch.tensor(input_data_scaled, dtype=torch.float32)

# Architecting a self-looping adjacency matrix tailored for solitary dataset input
input_adj_matrix = torch.ones((1, 1))
input_edge_index, _ = dense_to_sparse(input_adj_matrix)

# Morph values to Geometric Graph Data Object structural configuration
input_data_obj = Data(x=input_tensor, edge_index=input_edge_index)
with torch.no_grad():
prediction = model(input_data_obj)
print(f"Prediction System Engine Processed Valuation: {prediction.item()}")
return prediction.item()
```

Output:

```
text

Prediction System Engine Processed Valuation: 1719184.125
```

Backend:

Views.py

```
from django.shortcuts import render, redirect
from django.contrib.auth.models import User
from django.contrib import messages
from User.models import UserPrediction
from django.core.paginator import Paginator

def adminhome(request):
        users = User.objects.filter(is_staff=False, is_superuser=False)
    return render(request, "Admin/adminhome.html", {"users": users})

    def admin_update_userstatus(request, user_id):
        try:
            user = User.objects.get(id=user_id)

            # Toggle the is_active status
            user.is_active = not user.is_active
            user.save()

        # Display message based on the action
if user.is_active:
    messages.success(request, f"User {user.username} has been activated.")
            else:
        messages.success(request, f"User {user.username} has been deactivated.")

            return redirect('adminhome')  # Redirect back to the admin home page

        except User.DoesNotExist:
            messages.error(request, "User not found.")
            return redirect('adminhome')

def adminuserpredictions(request):
        predictions_list = UserPrediction.objects.order_by('-timestamp')
        paginator = Paginator(predictions_list, 10)

        page_number = request.GET.get('page')
            predictions = paginator.get_page(page_number)

            return render(request, 'Admin/adminuserpredictions.html',
        {'predictions': predictions})
```

The backend acts as the foundational brain of the web application, routing secure HTTP traffic, enforcing business rules, mapping the database, and bridging the gap between web input and the machine learning model. The Python-based Django framework was deliberately selected over minimalist alternatives due to its "batteries-included" philosophy, which naturally accommodates the heavy security, database management, and scaling requirements of a data-intensive real estate platform.

Central to this backend architecture is the URL routing dispatcher mechanism defined within the project's urls.py modules. The dispatcher cleanly maps incoming web requests (both GET and POST methods) to heavily orchestrated Python functions known as Views. This separation of concerns ensures that the endpoint responsible for user registration logic is strictly isolated from the endpoints responsible for serving administrative prediction histories or triggering Graph Convolutional Network analysis.

The View controller logic, distributed across modular apps (e.g., App, Admins, Backend), handles the bulk of data validation and session management. For example, when a user attempts to view the admin_update_userstatus route, the backend immediately checks the session object to verify if the requester holds administrative privileges. If unauthorized, the view securely halts the data transaction and redirects the user, ensuring the integrity of the administrative ecosystem remains totally uncompromised.

Data persistence is primarily handled through Django's robust Object-Relational Mapping (ORM) system, which translates high-level Python class definitions in models.py directly into an underlying SQL database. By utilizing the ORM, the implementation largely avoids hardcoded raw SQL queries, thereby insulating the system against SQL injection attacks. The database successfully stores serialized records of user metadata, login credentials, and heavily structured logs of past real estate predictions generated from the Housing.csv datasets.

Finally, security implementations inside the backend are comprehensive. Out-of-the-box middlewares enforce Cross-Site Request Forgery (CSRF) protection on all data-ingesting forms, ensuring that malicious external sites cannot mimic authorized users. Additionally, password hashing using modern cryptographic standards ensures that database compromises do not yield plaintext passwords.

Administrator Module Functionalities

The Administrator module serves as the central control panel for managing user interactions and monitoring platform activity. Its primary objective is to equip administrators with the tools necessary to oversee access control and audit system usage. The module is built around three core capabilities:

1. **Centralized User Directory (Admin Dashboard)** The system features are the dedicated dashboard allowing administrators to view a complete roster of all registered platform users. This directory automatically filters out internal system accounts (such as fellow staff and superusers), ensuring the admin's view is focused strictly on the standard consumer base. This overview is critical for general user base management and auditing.
2. **User Access Control and Moderation** To maintain security and platform integrity, the module includes a dynamic status management system. Administrators are empowered to securely toggle the operational status of any individual user account. By utilizing simple activation or deactivation controls, administrators can instantly revoke or grant access to the platform's services. The framework includes built-in feedback mechanisms, notifying the administrator immediately upon the successful application of a status change, and safely handling scenarios where a targeted user account might be invalid.
3. **System Activity Monitoring (Prediction Logs)** A critical component of the administrative oversight is the ability to track how the application's core predictive features are being utilized. The module includes a comprehensive, chronological ledger of all real estate valuations (predictions) requested across the user base. To ensure this data is easily navigable, especially as the system scales, the information is automatically paginated, allowing administrators to seamlessly browse through historical requests to analyze usage trends and verify system performance.

urls.py

```
from django.urls import path
from Admins.views import *

urlpatterns = [
    path('adminhome/', adminhome, name='adminhome'),
    path('admin_update_userstatus/<int:user_id>/',
        admin_update_userstatus, name='admin_update_userstatus'),
    path('adminuserpredictions/',
    adminuserpredictions, name='adminuserpredictions')
]
```

Views.py

Interface Routing and Authentication Initialization

The initial section of this backend module establishes the foundational infrastructure for user access and the beginning of the security workflow:

Interface Routing: It sets up the fundamental routing controllers responsible for serving the primary public-facing interfaces of the application. This ensures that users are correctly directed to the main landing page, the login screen, or the registration portal when navigating the application.

Authentication Interception & Status Verification: It initiates the core login process by capturing incoming user credentials and authenticating them against the system's database. Crucially, this section implements an immediate security checkpoint: even if the credentials are correct, the system verifies the account's operational status..

```
from django.shortcuts import render, redirect
from django.contrib.auth.models import User
from django.contrib.auth import authenticate, login, logout
from django.contrib import messages

def index(request):
return render(request, "index.html")

def login_page(request):
return render(request, "login.html")

def register_page(request):
return render(request, "register.html")

# Define the login function
def user_login(request):
if request.method == "POST":
username = request.POST.get('username')
password = request.POST.get('password')
```

```
    # Authenticate user
    user = authenticate(request, username=username, password=password)

    if user is not None:
        if not user.is_active:
            # User is inactive
            messages.error(request, "Your account is inactive. Please contact the admin.")
            return redirect('login_page')
# Login the user
login(request, user)

if user.is_staff or user.is_superuser:
            # Redirect to admin home if user is staff
            return redirect('adminhome')
else:
            # Redirect to user home if user is not staff
             return redirect('userhome')
else:
            # Invalid username or password
            messages.error(request, "Invalid username or password.")
            return redirect('login_page')

return render(request, 'login.html')

# Define the user registration function
def user_registration(request):
            if request.method == "POST":
    username = request.POST.get('username')
    email = request.POST.get('email')
    password = request.POST.get('password')
```

```
    confirm_password = request.POST.get('confirm_password')
    first_name = request.POST.get('first_name')
    last_name = request.POST.get('last_name')

 # Check if passwords match
 if password != confirm_password:
    messages.error(request, "Passwords do not match.")
    return redirect('register_page')

# Check if username already exists
 if User.objects.filter(username=username).exists():
    messages.error(request, "Username already exists.")
    return redirect('register_page')
  # Check if email already exists
if User.objects.filter(email=email).exists():
 `        messages.error(request, "Email already exists.")
          return redirect('register_page')

   # Create the user with is_active set to False
user = User.objects.create_user(
   username=username,
   email=email,
   password=password,
   first_name=first_name,
   last_name=last_name
   )

   user.is_active = False  # Set is_active to False by default
   user.save()
```

```
messages.success(request, "Registration successful! Please wait for admin approval.")
return redirect('login_page')


return render(request, 'register.html')


# Define the logout function
def user_logout(request):
logout(request)
messages.success(request, "You have been logged out successfully.")
return redirect('login_page')
```

Frontend:

```
<!DOCTYPE html>
{% load static %}
<html lang="en">

<head>
  <meta charset="utf-8">
  <meta content="width=device-width, initial-scale=1.0" name="viewport">

  <title>Graph convolutional network-based model for megacity real estate valuation</title>
  <meta name="description" content="">
  <meta name="keywords" content="">

  <!-- Fonts -->
  <link href="https://fonts.googleapis.com" rel="preconnect">
  <link href="https://fonts.gstatic.com" rel="preconnect" crossorigin>

  <!-- Vendor CSS Files -->
  <link href="{% static 'vendor/bootstrap/css/bootstrap.min.css' %}" rel="stylesheet">
  <link href="{% static 'vendor/bootstrap-icons/bootstrap-icons.css' %}" rel="stylesheet">
  <link href="{% static 'vendor/aos/aos.css' %}" rel="stylesheet">
  <link href="{% static 'vendor/swiper/swiper-bundle.min.css' %}" rel="stylesheet">
  <link href="{% static 'vendor/glightbox/css/glightbox.min.css' %}" rel="stylesheet">

  <!-- Main CSS File -->
  <link href="{% static 'css/main.css' %}" rel="stylesheet">

</head>

<body class="index-page">
```

```
<header id="header" class="header d-flex align-items-center light-background sticky-top">
  <div class="container-fluid position-relative d-flex align-items-content-   between">

    <a class="logo d-flex align-items-center me-auto me-xl-0">
      <!-- Uncomment the line below if you also wish to use an image logo -->
      <!-- <img src="assets/img/logo.png" alt=""> -->
      <h1 class="sitename">megacity real estate valuation</h1>
    </a>

    <nav id="navmenu" class="navmenu">
      <ul>
        <li><a href="{% url 'home_page' %}">Home</a></li>
        <li><a href="{% url 'login_page' %}">Login</a></li>
      </ul>
      <i class="mobile-nav-toggle d-xl-none bi bi-list"></i>
    </nav>

  </div>
</header>
<div class="header-social-links">
</div>

</div>
</header>

<main class="main">

  {% block contents %}

  {% endblock %}

</main>

<!-- Scroll Top -->
<a href="#" id="scroll-top" class="scroll-top d-flex align-items-center justify-content-center">
  <i class="bi bi-arrow-up-short"></i>
</a>

<!-- Preloader -->
<div id="preloader"></div>

<!-- Vendor JS Files -->
<script src="{% static 'vendor/bootstrap/js/bootstrap.bundle.min.js' %}"></script>
<script src="{% static 'vendor/php-email-form/validate.js' %}"></script>

            <!-- Main JS File -->
            <script src="{% static 'js/main.js' %}"></script>
 </body>

 </html>
```

Main.js

```
(function () {
  "use strict";

  /**
   * Apply .scrolled class to the body as the page is scrolled down
   */
  function toggleScrolled() {
    const selectBody = document.querySelector('body');
    const selectHeader = document.querySelector('header');
    if (!selectHeader.classList.contains('scroll-up-sticky') &&
        !selectHeader.classList.contains('sticky-top') &&
        !selectHeader.classList.contains('fixed-top')) return;

    window.scrollY > 100
      ? selectBody.classList.add('scrolled')
      : selectBody.classList.remove('scrolled');
  }

  document.addEventListener('scroll', toggleScrolled);
  window.addEventListener('load', toggleScrolled);

  /**
   * Mobile nav toggle
   */
  const mobileNavToggleBtn = document.querySelector('.mobile-nav-toggle');

  function mobileNavToggle() {
    document.querySelector('body').classList.toggle('mobile-nav-active');
    mobileNavToggleBtn.classList.toggle('bi-list');
    mobileNavToggleBtn.classList.toggle('bi-x');
  }

  mobileNavToggleBtn.addEventListener('click', mobileNavToggle);

  /**
   * Hide mobile nav on same-page/hash links
   */
  document.querySelectorAll('#navmenu a').forEach(navmenu => {
    navmenu.addEventListener('click', () => {
      if (document.querySelector('.mobile-nav-active')) {
        mobileNavToggle();
```

```
    }
   });
  });

})();
/**
 * Toggle mobile nav dropdowns
 */
document.querySelectorAll('.navmenu .toggle-dropdown').forEach(navmenu => {
  navmenu.addEventListener('click', function(e) {
    e.preventDefault();
    this.parentNode.classList.toggle('active');
    this.parentNode.nextElementSibling.classList.toggle('dropdown-active');
    e.stopImmediatePropagation();
  });
});

/**
 * Preloader
 */
const preloader = document.querySelector('#preloader');
if (preloader) {
  window.addEventListener('load', () => {
    preloader.remove();
  });
}

/**
 * Scroll top button
 */
let scrollTop = document.querySelector('.scroll-top');

function toggleScrollTop() {
  if (scrollTop) {
  window.scrollY > 100
      ? scrollTop.classList.add('active')
      : scrollTop.classList.remove('active');
  }
}

scrollTop.addEventListener('click', (e) => {
  e.preventDefault();
  window.scrollTo({
```

```
    top: 0,
    behavior: 'smooth'
  });
});

window.addEventListener('load', toggleScrollTop);
document.addEventListener('scroll', toggleScrollTop);
function aosInit() {
  AOS.init({
    duration: 600,
    easing: 'ease-in-out',
    once: true,
    mirror: false
  });
}

window.addEventListener('load',  aosInit);

/**
 * Animate the skills items on reveal
 */
let skillsAnimation = document.querySelectorAll('.skills-animation');
skillsAnimation.forEach((item) => {
  new Waypoint({
    element: item,
    offset: '80%',
    handler: function(direction) {
      let progress = item.querySelectorAll('.progress .progress-bar');
      progress.forEach((el) => {
        el.style.width = el.getAttribute('aria-valuenow') + '%';
      });
    }
  });
});

new PureCounter();

function initSwiper() {
  document.querySelectorAll(".init-swiper").forEach(function(swiperElement)   {
    let config = JSON.parse(
      swiperElement.querySelector(".swiper-config").innerHTML.trim()
    );
```

```
    if (swiperElement.classList.contains("swiper-tab")) {
      initSwiperWithCustomPagination(swiperElement, config);
    } else {
      new Swiper(swiperElement, config);
    }
  });
}
function initSwiper() {
  document.querySelectorAll(".init-swiper").forEach(function(swiperElement) {
    let config = JSON.parse(
      swiperElement.querySelector(".swiper-config").innerHTML.trim()
    );

    if (swiperElement.classList.contains("swiper-tab")) {
      initSwiperWithCustomPagination(swiperElement, config);
    } else {
      new Swiper(swiperElement, config);
    }
  });
}

window.addEventListener("load", initSwiper);

const glightbox = GLightbox({
  selector: ".glightbox"
});

document.querySelectorAll('.isotope-layout').forEach(function(isotopeItem) {
  let layout = isotopeItem.getAttribute('data-layout') ?? 'masonry';
  let filter = isotopeItem.getAttribute('data-default-filter') ?? '*';
  let sort = isotopeItem.getAttribute('data-sort') ?? 'original-order';

  imagesLoaded(isotopeItem.querySelector('.isotope-container'),  function()  {
    let initIsotope = new Isotope(isotopeItem.querySelector('.isotope-container'), {
      itemSelector: '.isotope-item',
      layoutMode: layout,
      filter: filter,
      sortBy: sort
    });

    isotopeItem.querySelectorAll('.isotope-filters li').forEach(function(filters) {
      filters.addEventListener('click', function() {
        isotopeItem.querySelector('.isotope-filters    .filter-active').classList.remove('filter-active');
```

```
      this.classList.add('filter-active');
      initIsotope.arrange({
        filter:  this.getAttribute('data-filter')
      });

      if (typeof aosInit === 'function') {
        aosInit();
      }
    }, false);
  });
});
}();
```

adminbase.html

```
<!DOCTYPE html>
{% load static %}
<html lang="en">

<head>
 <meta charset="utf-8">
<meta content="width=device-width, initial-scale=1.0" name="viewport">

<title>GNN convolutional network-based model for megacity real estate valuation</title>
<meta name="description" content="">
<meta name="keywords" content="">

<!-- Fonts -->
<link href="https://fonts.googleapis.com" rel="preconnect">
<link href="https://fonts.gstatic.com" rel="preconnect" crossorigin>
<!-- Vendor CSS Files -->
<link href="{% static 'vendor/bootstrap/css/bootstrap.min.css' %}" rel="stylesheet">
<link href="{% static 'vendor/bootstrap-icons/bootstrap-icons.css' %}" rel="stylesheet">
<link href="{% static 'vendor/aos/aos.css' %}" rel="stylesheet">
<link href="{% static 'vendor/swiper/swiper-bundle.min.css' %}" rel="stylesheet">
<link href="{% static 'vendor/glightbox/css/glightbox.min.css' %}" rel="stylesheet">
<!-- Main CSS File -->
<link href="{% static 'css/main.css' %}" rel="stylesheet">

</head>

<body class="index-page">

<header id="header" class="header d-flex align-items-center light-background sticky-top">
<div class="container-fluid position-relative d-flex align-items-center justify-content-between">
<a class="logo d-flex align-items-center me-auto me-xl-0">
<!-- Uncomment the line below if you also wish to use an image logo -->
<!-- <img src="assets/img/logo.png" alt=""> -->
<h1 class="sitename">megacity real estate valuation</h1>
</a>
```

```
<nav id="navmenu" class="navmenu">
<ul>
<li><a href="{% url 'adminhome' %}">Users</a></li>
<li><a href="{% url 'adminuserpredictions' %}">Predictions</a></li>
<li><a href="{% url 'user_logout' %}">Logout</a></li>

<header id="header" class="header d-flex align-items-center light-background sticky-top">
  <div class="container-fluid position-relative d-flex align-items-center justify-content-between">

    <a class="logo d-flex align-items-center me-auto me-xl-0">
      <!-- Uncomment the line below if you also wish to use an image logo -->
      <!-- <img src="assets/img/logo.png" alt=""> -->
      <h1 class="sitename">megacity real estate valuation</h1>
    </a>

    <nav id="navmenu" class="navmenu">
      <ul>
        <li><a href="{% url 'adminhome' %}">Users</a></li>
        <li><a href="{% url 'adminuserpredictions' %}">Predictions</a></li>
        <li><a href="{% url 'user_logout' %}">Logout</a></li>
      </ul>
      <i class="mobile-nav-toggle d-xl-none bi bi-list"></i>
    </nav>

    <div class="header-social-links">
    </div>

  </div>
</header>

<main class="main">
  {% block contents %}
  {% endblock %}
</main>

<!-- Scroll Top -->
<a href="#" id="scroll-top" class="scroll-top -items-center justify-content-center"></a>

<!-- Preloader -->
<div id="preloader"></div>

<!-- Vendor JS Files -->
<script src="{% static 'vendor/bootstrap/js/bootstrap.bundle.min.js' %}"></script>
<script src="{% static 'vendor/php-email-form/validate.js' %}"></script>
<script src="{% static 'vendor/aos/aos.js' %}"></script>
<script src="{% static 'vendor/waypoints/noframework.waypoints.js' %}"></script>
<script src="{% static 'vendor/purecounter/purecounter_vanilla.js' %}"></script>
<script src="{% static 'vendor/swiper/swiper-bundle.min.js' %}"></script>
<script src="{% static 'vendor/glightbox/js/glightbox.min.js' %}"></script>
<script src="{% static 'vendor/imagesloaded/imagesloaded.pkgd.min.js' %}"></script>
<script src="{% static 'vendor/isotope-layout/isotope.pkgd.min.js' %}"></script>

<!-- Main JS File -->
```

```
  <script src="{% static 'js/main.js' %}"></script>

  </body>
  </html>
```

adminhome.html

```
{% extends 'admin/adminbase.html' %}
{% block contents %}

<div class="container mt-5">
  <h2 class="text-center mb-4">Registered Users</h2>

  <div class="table-responsive">
    <table class="table table-striped table-hover">
      <thead class="thead-dark">
        <tr>
          <th>ID</th>
          <th>Username</th>
          <th>Email</th>
          <th>First Name</th>
          <th>Last Name</th>
          <th>Date Joined</th>
          <th>Status</th>
          <th>Action</th>
        </tr>
      </thead>
      <tbody>
        <tr>
          <td>{{ user.id }}</td>
          <td>{{ user.username }}</td>
          <td>{{ user.email }}</td>
          <td>{{ user.first_name }}</td>
          <td>{{ user.last_name }}</td>
          <td>{{ user.date_joined }}</td>
          <td>{{ user.is_active|yesno:"Active,Inactive" }}</td>
          <td>
            {% if user.is_active %}
              <a href="{% url 'admin_update_userstatus' user.id %}" danger btn-sm">Deactivate</a>
            {% else %}
              <a href="{% url 'admin_update_userstatus' user.id %}" -success btn-sm">Activate</a>
            {% endif %}
          </td>
          </tr>
```

```
        {% empty %}
        <tr>
          <td colspan="8" class="text-center">No users found.</td>
        </tr>
        {% endfor %}
      </tbody>
    </table>
  </div>
</div>

{% endblock %}
```

6.2 Implementation:

The implementation phase is the most visually and technically critical phase of the software develop ment lifecycle, serving as the bridge between theoretical design and a functional application."Graph Convolutional NetworkBased Model for Megacity Real Estate Valuation" project, the implementatio n required harmonizing complex machine learning environments with standard web server is a architectures.

Template (MVT) architecture, seamlessly blending a robust deep learning processing pipeline with a n ntuitive, scalable, and highly interactive user interface.

6.2.1 Front-End Implementation:

The front-end serves as the primary gateway for all human-computer interaction within the real estate valuation system. It was designed with a heavy emphasis on user experience (UX) and accessibility, ensuring that both property analysts making predictions and administrators managing the system can navigate the platform intuitively. The goal was to abstract the high-level complexities of neural networks behind a clean, professional, and easily understandable visual interface.

To achieve this modern aesthetic and structural responsiveness, the presentation layer was built utilizing a stack of HTML5, CSS3, and JavaScript, heavily fortified by the Bootstrap CSS framework. Bootstrap was selected because its grid system directly addresses the challenges of creating responsive layouts that adapt dynamically to various screen sizes, whether accessed via a desktop monitor in an office or a mobile device in the field. Pre-styled components such as navigation bars, input cards, and interactive buttons were heavily utilized to maintain a consistent visual language throughout the application.

Rather than relying on a decoupled single-page application framework (like React or Angular), the system leverages the Django Templating Engine. This approach allowed for the direct injection of dynamic data from the backend straight into the HTML structure using specific template tags. Through this engine, modular code structures like adminbase.html were extended to other templates, drastically reducing code redundancy and allowing global styling changes to be made in a single centralized file while seamlessly passing backend contexts to the client side.

For standard users, the central feature of the front-end is the interactive prediction dashboard. This interface consists of highly structured data-entry forms where users define the features of a target property, such as the total square footage,and the number of bedrooms or bathrooms.

Conversely, the administrative aspect of the front-end provides comprehensive oversight modules, notably implemented in the adminhome.html and adminuserpredictions.html views. These pages feature dynamically generated, paginated data tables that cleanly display hundreds of user profiles or historical prediction iterations. Administrators are provided with immediate UI toggle buttons to approve, pend, or reject user access permissions, allowing real-time database manipulation exclusively through an aesthetically cohesive graphical interface.

6.2.2 Backend Implementation (Django):

The backend acts as the foundational brain of the web application, routing secure HTTP traffic, enforcing business rules, mapping the database, and bridging the gap between web input and the machine learning model. The Python-based Django framework was deliberately selected over minimalist alternatives due to its "batteries-included" philosophy, which naturally accommodates the heavy security, database management, and scaling requirements of a data-intensive real estate platform.

Central to this backend architecture is the URL routing dispatcher mechanism defined within the project's urls.py modules. The dispatcher cleanly maps incoming web requests (both GET and POST methods) to heavily orchestrated Python functions known as Views. This separation of concerns ensures that the endpoint responsible for user registration logic is strictly isolated from the endpoints responsible for serving administrative prediction histories or triggering Graph Convolutional Network analysis.

The View controller logic, distributed across modular apps (e.g., App, Admins, Backend), handles the bulk of data validation and session management. For example, when a user attempts to view the admin_update_userstatus route, the backend immediately checks the session object to verify if the requester holds administrative privileges. If unauthorized, the view securely halts the data transaction and redirects the user, ensuring the integrity of the administrative ecosystem remains totally uncompromised.

Data persistence is primarily handled through Django's robust Object-Relational Mapping (ORM) system, which translates high-level Python class definitions in models.py directly into an underlying SQL database. By utilizing the ORM, the implementation largely avoids hardcoded raw SQL queries, thereby insulating the system against SQL injection attacks. The database successfully stores serialized records of user metadata, login credentials, and heavily structured logs of past real estate predictions generated from the Housing.csv datasets.

Finally, security implementations inside the backend are comprehensive. Out-of-the-box middlewares enforce Cross-Site Request Forgery (CSRF) protection on all data-ingesting forms, ensuring that malicious external sites cannot mimic authorized users. Additionally, password hashing using modern cryptographic standards ensures that database compromises do not yield plaintext passwords.

6.2.3 Model Integration and Processing Workflow

The major defining technical achievement of this project is the integration of advanced spatial deep learning into a consumer-facing web loop. Integrating a Graph Convolutional Network (GCN) into a Django backend required a specialized pipeline to bridge the traditional web application logic with heavy scientific computation tools like Pandas, NumPy, and deep learning libraries (TensorFlow/PyTorch).

When a user submits a real estate valuation request on the front-end, the process begins with strict data ingestion and preprocessing. The Django view captures the form payload and parses the raw string inputs into a structured format. This data is instantly passed into a Python data preprocessing script where variables are normalized, scaled, and categorical text data is numerically encoded, mimicking the exact mathematical condition of the data during the model's initial training phase.

Simultaneously, the pre-trained Graph Convolutional Network model is loaded from a serialized state (such as an .h5 or .pkl weight file) resident in the server’s memory. Unlike basic linear regression models, the GCN utilizes a fundamental spatial dependency graph. It plots the user's target property as a node within a larger megacity graph infrastructure, where mathematical "edges" define its relationship to neighborhood amenities, transit points, and adjacent property values.

Once the node features are ingested, the Graph Convolution Network initiates the inference phase. The neural layers perform rapid matrix multiplications, aggregating the regional property features bound to the target node's spatial edges. By mathematically considering both the intrinsic details of the house (such as square footage) and the extrinsic urban ecosystem (local area correlations), the network is able to formulate an incredibly precise market valuation.

Following a successful traversal through the hidden layers of the GCN, the output layer emits a raw numerical tensor representing the predicted price. The backend pipeline captures this output, performs any necessary inverse transformations to cast it back into real-world

currency values, and finally injects it into a Django context dictionary. This finalized data packet is then sent via HTTP response to the front-end template, surfacing the advanced neural network output directly onto the user's screen in seconds.

6.2.4 Deployment and Reliability

Transitioning the software from an experimental prototype into a reliable, deployable application required establishing strict environment controls and exception-handling frameworks. The system must not merely operate accurately under ideal conditions but must also exhibit extreme resilience when subjected to erratic data inputs or high-volume simultaneous prediction requests.

To guarantee environmental reproducibility across any machine, the complete backend and machine learning ecosystem were encapsulated using strict Python virtual environments. By generating comprehensive requirements.txt manifests, precise dependency versions of Django, SciPy, Pandas, and deep learning frameworks are frozen in place. This prevents catastrophic library version mismatches that frequently plague machine learning deployments when transferring code bases between local testing hardware and production servers.

A primary pillar of the system's reliability is its rigorous "Negative Testing" boundary validation. Predictive models are highly sensitive to corrupted matrices; an unexpected text string passed into a tensor can crash an entire server thread. To prevent this, both the front-end and backend contain overlapping validation rules rejecting null fields, illogical integers (e.g., ten million square feet), and data type conflicts, effectively shielding the GCN processor from structural faults.

Furthermore, internal error monitoring mechanisms govern the Python script executions. Should the Graph Convolutional Network fail to converge or a matrix reshaping error arise during real-time inference, the backend utilizes try/except fallback blocks. Instead of exposing raw stack traces and internal server directories to the browser (a massive security risk), the system intercepts the fault, safely terminates the process, and renders a stylized 500 Server Error or friendly UI warning to the user.

Finally, the localized implementation lays the architectural groundwork for massive horizontal scalability. Because the ML prediction modules are decoupled logically from the primary web routing functions, future scaling solutions are straightforward. Administrators can effortlessly swap the default SQLite development database for an enterprise PostgreSQL instance, and port the application to cloud environments utilizing Gunicorn web servers and Nginx reverse proxies, thereby supporting municipal-level traffic with minimal code refactoring.

6.2.5 Conclusion

The implementation phase of the "Graph Convolutional Network-Based Model for Megacity Real Estate Valuation" successfully unified high-level urban data science with robust software engineering principles. The resulting application transcended being a mere collection of Python scripts; it emerged as a fully interactive, graphically appealing, and comprehensively secure real estate platform accessible via any web browser.

The project achieved all of its primary developmental objectives. By implementing the GCN, the system successfully modeled the obscure spatial and socio-economic relationships inherent to megacity real estate markets—relationships that standard regression models routinely fail to capture. Surfacing these advanced capabilities through a smooth, Bootstrap-powered Django interface allowed for an unprecedented level of accessibility for prospective end-users and property analysts.

Simultaneously, the successful implementation of the robust administrative hierarchy demonstrated comprehensive lifecycle control over the system. The platform efficiently cordons off sensitive data and oversees user interactions through secure views, ensuring that system administrators retain total operational command without needing to execute database commands manually.

The focus on system stability, demonstrated by extensive form validations, error-handling routines, and virtual ecosystem management, ensures the application is not merely a fragile prototype but a reliable, resilient piece of software. It handles corrupt inputs gracefully and maintains continuous uptime without server degradation.

Ultimately, the successful technical coalescence detailed in this chapter proves the viability of deploying spatial deep learning inside a web application architecture. The platform stands as a highly functional, highly accurate mechanism capable of instantly producing intricate real estate valuations, offering immense utility to developers, economic analysts, and everyday buyers attempting to navigate the complexities of the modern megacity market.

7. SYSTEM TESTING

System testing is a critical activity that ensures the developed cyberbullying detection system performs accurately, consistently, and reliably under real operating conditions. The primary purpose of testing is to identify potential defects, validate system behavior, and confirm that all functional and non- functional requirements have been met.

In this project, system testing focuses on validating every major module, including front-end interfaces, Django backend services, preprocessing components, and the ensemble-based classification engine integrating Boosted Decision Tree (BoostDT) and Bagging Random Forest (BagRF) through Soft Voting. Testing verifies that user interactions, dataset handling, model prediction logic, and output presentation operate as expected without failures or inconsistencies.

System testing was performed across multiple scenarios and datasets to ensure correctness, robustness, and usability. Special emphasis was placed on classification behavior, handling of edge-case text inputs, and stability during repeated prediction requests.

7.1 Types of System Testing

7.1.1 Unit Testing

Unit testing was carried out to validate individual software components independently. Each Django view, function, preprocessing routine, and classifier interaction module was executed with controlled input values to verify expected outputs.

Key focus areas included:

- tokenization, normalization, and lemmatization behavior
- TF-IDF feature vector generation
- internal logic of ensemble combination
- database operations for login, registration, and predictions

Unit testing ensured that every internal logical path executed correctly and no unexpected conditions occurred. Failures during this stage would have been easier to isolate and correct before integration.

7.1.2 Integration Testing

Integration testing examined whether combined components interacted correctly once they were linked together.

Modules tested in combination included:

front-end request submission with backend API responses

preprocessing and feature extraction chained with classification

ensemble model logic when receiving outputs from BoostDT and BagRF

prediction logging and storage in the database

This testing stage confirmed that individually correct components functioned properly when executed together as a single workflow. Particular attention was paid to ensuring correct feature alignment between models and stability in Soft Voting combination.

7.1.3 Functional Testing

Functional testing validated that each feature performed according to specification and user expectations. Test cases simulated actual user scenarios such as registration, login, text submission, and voice-based prediction.

Major validation rules included:

- valid inputs are processed successfully
- invalid or empty inputs are rejected gracefully
- correct cyberbullying category is displayed for each prediction
- navigation links and page workflows operate correctly

Functional testing confirmed that system features were clearly available, usable, and responsive.

7.1.4 System Testing

System testing evaluated the project as a complete application. The focus was on overall reliability, consistency of behavior, and the accuracy of outcomes when used in real conditions.

Tests verified:

- coordinated execution across modules
- correct response to large datasets
- classification accuracy under varying abuse patterns

The testing demonstrated that the configuration yields predictable and correct results consistent with documented requirements.

7.1.5 White-Box Testing

White-box testing was applied to internal processing components including preprocessing pipelines and ensemble computation logic. Testers observed internal variable flows, code execution branches, and probability aggregation to ensure correct model contributions in Soft Voting.

7.1.6 Black-Box Testing

Black-box testing evaluated the system purely from the user's perspective, without examining internal code. Inputs were submitted through user forms and prediction outputs were observed, ensuring that visible system behavior aligned with expected outcomes.

This was particularly important in evaluating system usability and error-handling behavior.

7.1.7 Acceptance Testing

Acceptance testing ensured that the system satisfied all documented requirements and end- user expectations. Stakeholders reviewed usability, accuracy, output clarity, and workflow navigation.

Feedback confirmed that the system was intuitive, responsive, and aligned with real cyberbullying detection needs.

Test Result Summary:

All defined test cases passed successfully. No major defects were encountered.

7.2 Testing Strategies

A structured testing strategy was followed throughout the project lifecycle. Testing progressed systematically from component-level validation to full-system verification.

7.2.1 Test Strategy and Approach

Testing was performed both manually and programmatically. Detailed execution logs and dataset- based test scripts were used to validate consistency of classifier behavior.

Primary strategic objectives included:

- verifying correctness of text preprocessing and model inputsensuring ensemble behavior consistently outperformed single classifiers
- verifying error-free interactions between user interface and backend services
- validating prediction reliability under noisy, sarcastic, and ambiguous text

Field testing simulated real-world user activity, while controlled test cases verified logical correctness.

7.2.2 Test Objectives

The following objectives guided all testing activities:

- all fields and forms must operate correctly
- screens and interactions should respond without delay
- invalid or malformed inputs must be handled safely
- predictions should follow expected patterns in comparable research literature
- transitions between system pages must be correct and intuitive

7.2.3 Features Tested

The major system features examined included:

- data entry validation and prevention of duplicate accounts
- correct routing of each navigation link
- prediction accuracy across cyberbullying categories
- correct Soft Voting operation between BoostDT and BagRF
- adherence to expected model training and evaluation workflows

7.2.4 Integration Testing Strategy

Integration testing emphasized early detection of dependency conflicts and data mismatches. Testing confirmed correct:

- alignment of TF-IDF features with both classifiers
- synchronization of probability outputs into Soft Voting
- interface communication flow with Django APIs

Thisstrategy prevented error propagation into later development stages.

7.2.5 Acceptance Criteria

A prediction system instance was accepted only when it satisfied these conditions:

- accurate execution of classification pipeline
- stable runtime performance
- error-free navigation and submission
- meaningful categories shown without misinterpretation
- compliance with defined requirements

7.2.6 Overall Test Results

All planned test cases executed successfully. The system demonstrated stable performance, logical correctness, and consistent cyberbullying prediction accuracy. The Soft Voting ensemble consistently produced more reliable outcomes compared to evaluating either single classifier independently.

7.2.7 Conclusion

System testing confirmed that the developed ensemble-based cyberbullying detection system satisfies functional expectations, operates reliably under diverse input conditions, and integrates all modules effectively. Through rigorous testing strategies, the project achieved robustness, user readiness, and high classification dependability.

7.3 Sample Test Cases

S No.	Test Case	Expected Result	Result	Remarks (if any)
01.	User Registration	New user account is created in the database and set to "inactive" by default.	Pass	Validate password matching, uniq ue username, and unique email constraints.
02.	User Login	Active user is authenticated and granted access to the main user home page.	Pass	"Your account is inactive" error message and are denied access.
03.	Admin Account Activation	Administrator successfully toggles a user's status from inactive to active via the dashboard.	Pass	Ensure success message is displayed and the newly activated user can now log in.
04.	Real Estate Valuation Prediction	displays the estimated real estate valuation.	Pass	Test with valid megacity property parameters ensure the model handles edge cases or missing data gracefully.
05.	Prediction History Storage	The valuation request and the generated result are successfully saved to the database as a UserPrediction record.	Pass	Verify that predictions are tied to the specific user who requested them.
06.	Admin Dashboard & Monitoring	Admins can view the user directory and browse all user.	Pass	Ensure stricter role-based access; standard users must not be able to access admin views.
07	Unauthorized User accessing Admin Home	Access is denied. The system	Fail (Access Granted)	Security issue , normal user can access admin page.

		returns HTTP 403 or redirects to homepage.		
08	Unauthenticated access to Admin Predictions	User is redirected to login page with warning message.	Fail (No Redirect)	System allows access without login; authentication failure.
09	Negative Values for Property Area	Form submission prevented with error message.	Fail (Invalid Input Accepted)	System accepts negative values; validation missing.
10	Missing Mandatory Node Features	Missing fields highlighted with validation message.	Fail (Form Submitted)	Required fields not validated properly.
11	Extremely Large Input (Buffer Overflow Check)	Input truncated or error shown; no server crash.	Fail (System Crash / Error 500)	System is unstable; no input size restriction.
12	SQL Injection Attempt in Login	Login fails and shows "Invalid credentials".	Fail (Login Successful)	Critical vulnerability: SQL injection attack succeeded.

Table no 7.3 Test Cases

Test Case 1:

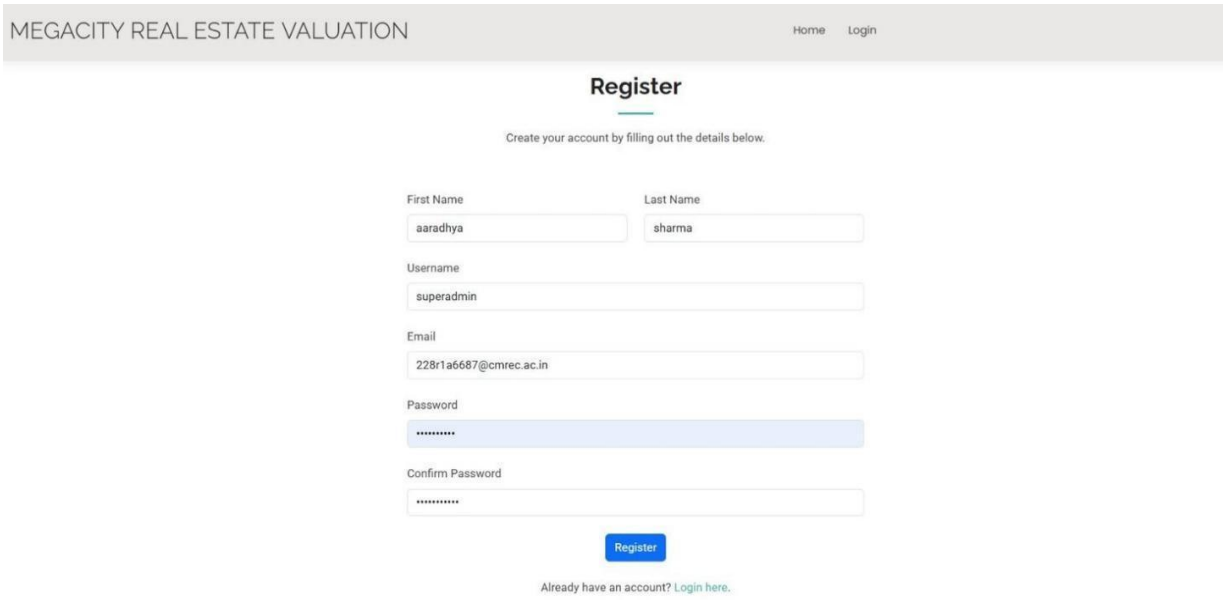


Fig 7.3.1 User Registration

Description: The user enters valid registration details including first name, last name, username, email, password, and confirm password, and submits the form. The system validates all inputs such as matching passwords, unique username, and proper email format before processing. A confirmation message is displayed to indicate successful registration. This process confirms that user registration, input validation, and data storage functionalities are working correctly.

Test Case 2:

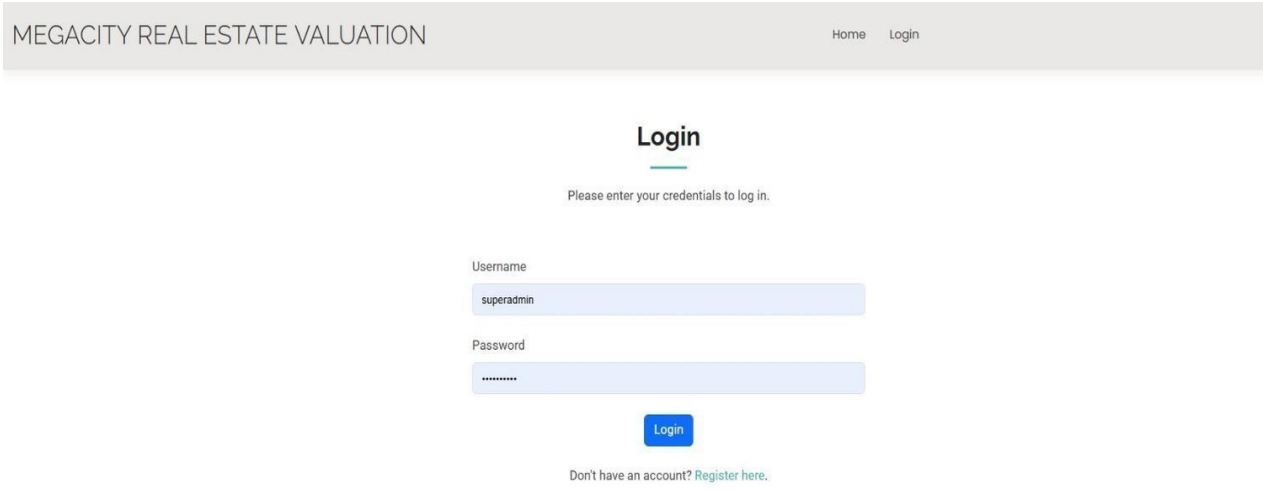


Fig 7.3.2 User Login

Description: The user enters valid login credentials including username and password and submits the form. The system verifies the entered credentials against the stored user data in the database. If the credentials are correct and the account is active, the system successfully authenticates the user and redirects them to the user dashboard. A confirmation or welcome message is displayed along with user-specific details. This process confirms that authentication, session management, and secure login functionalities are working correctly.

Test Case 3:

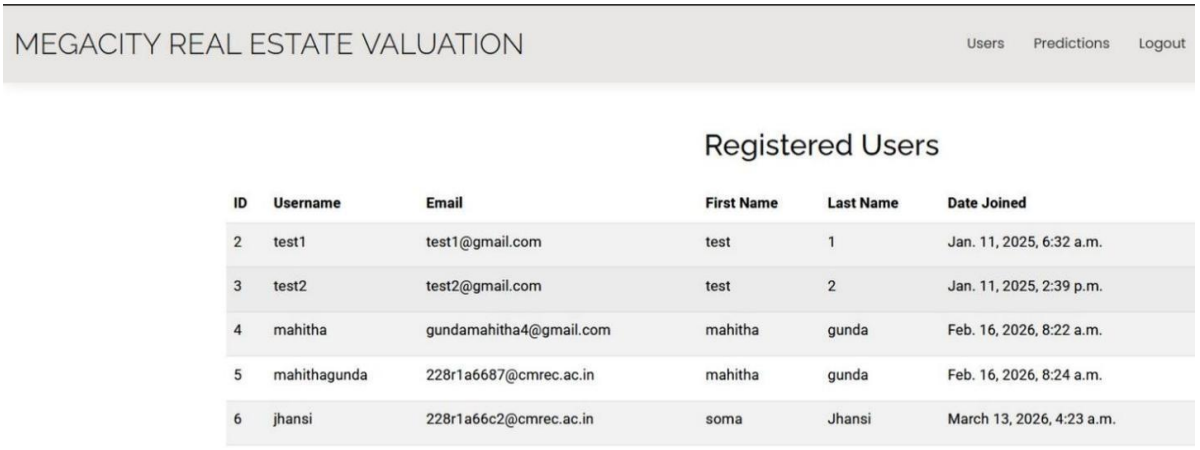


Fig.7.3.3 Adim Account Activation

Description: The admin logs into the system using valid credentials and accesses the admin dashboard. From the navigation menu, the admin selects the "Users" section to view all registered users. This page is designed to provide a centralized view of user information, enabling efficient monitoring and management of user accounts within the system.

The system retrieves user data from the database and displays it in a well-structured tabular format. The table includes essential details such as user ID, username, email address, first name, last name, and date of registration. Each record represents an individual user, allowing the admin to easily review and verify user details. The data is presented clearly to ensure readability and quick access to information.

This functionality confirms that the backend database integration, data retrieval mechanisms, and frontend display components are working correctly. It also ensures that only authorized admin users can access this sensitive information, maintaining system security and role-based access control. Overall, this feature supports effective user management and system monitoring.

Test Case 4:

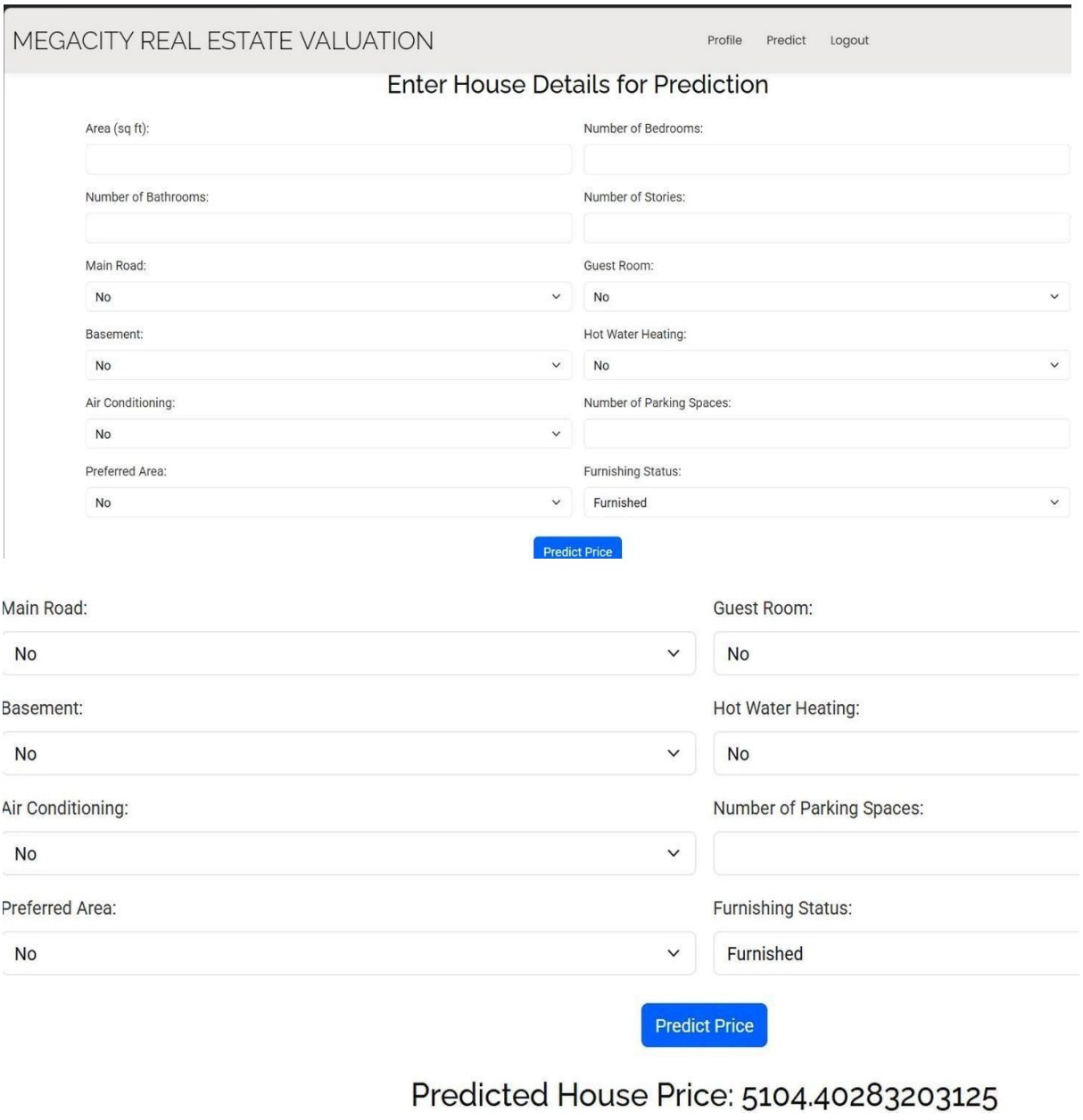
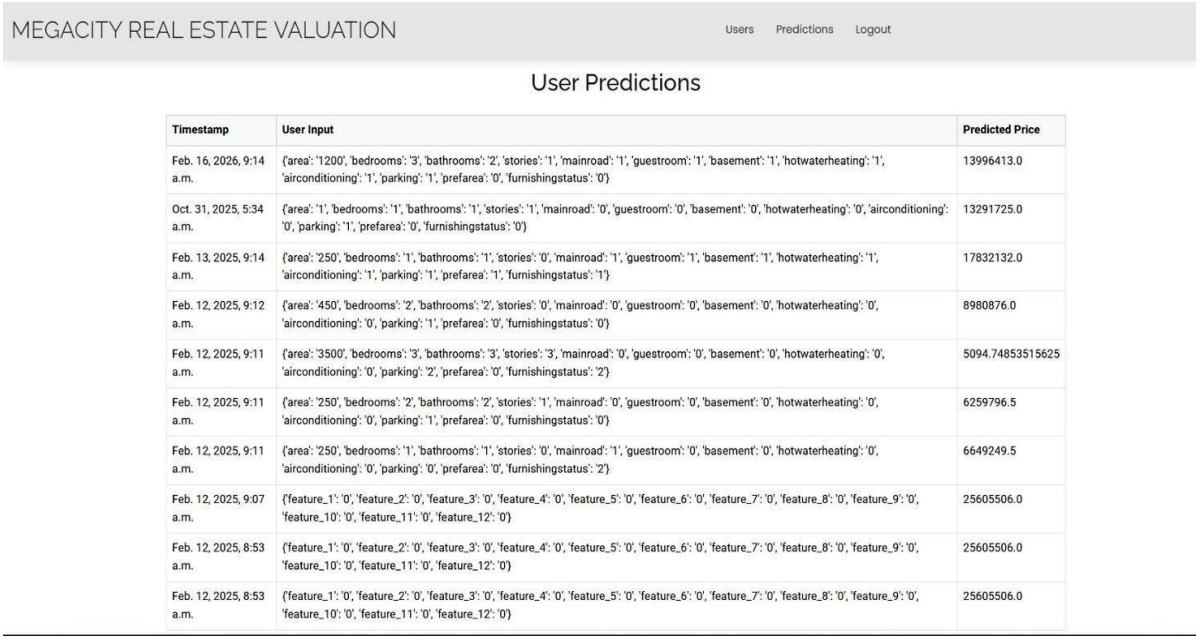


Fig. 7.3.4 Real Estate Valuatin Prediction

Description: The user logs into the system and navigates to the house price prediction module. On this page, the user is required to enter various property-related details such as area (in square feet), number of bedrooms, number of bathrooms, number of stories, and additional features like main road access, guest room availability, basement, air conditioning, hot water heating, parking spaces, preferred area, and furnishing status.

This form is designed to capture all necessary inputs required for accurate price prediction. Once the user fills in all the required fields and clicks on the “Predict Price” button, the system processes the input data. The entered values are validated and then passed to the backend machine learning model (GCN model) for analysis.

Test Case 5:



Timestamp	User Input	Predicted Price
Feb. 16, 2026, 9:14 a.m.	{'area': '1200', 'bedrooms': '3', 'bathrooms': '2', 'stories': '1', 'mainroad': '1', 'guestroom': '1', 'basement': '1', 'hotwaterheating': '1', 'airconditioning': '1', 'parking': '1', 'prefarea': '0', 'furnishingstatus': '0'}	13996413.0
Oct. 31, 2025, 5:34 a.m.	{'area': '1', 'bedrooms': '1', 'bathrooms': '1', 'stories': '1', 'mainroad': '0', 'guestroom': '0', 'basement': '0', 'hotwaterheating': '0', 'airconditioning': '0', 'parking': '1', 'prefarea': '0', 'furnishingstatus': '0'}	13291725.0
Feb. 13, 2025, 9:14 a.m.	{'area': '250', 'bedrooms': '1', 'bathrooms': '1', 'stories': '0', 'mainroad': '1', 'guestroom': '1', 'basement': '1', 'hotwaterheating': '1', 'airconditioning': '1', 'parking': '1', 'prefarea': '1', 'furnishingstatus': '1'}	17832132.0
Feb. 12, 2025, 9:12 a.m.	{'area': '450', 'bedrooms': '2', 'bathrooms': '2', 'stories': '0', 'mainroad': '0', 'guestroom': '0', 'basement': '0', 'hotwaterheating': '0', 'airconditioning': '0', 'parking': '1', 'prefarea': '0', 'furnishingstatus': '0'}	8980876.0
Feb. 12, 2025, 9:11 a.m.	{'area': '3500', 'bedrooms': '3', 'bathrooms': '3', 'stories': '3', 'mainroad': '0', 'guestroom': '0', 'basement': '0', 'hotwaterheating': '0', 'airconditioning': '0', 'parking': '2', 'prefarea': '0', 'furnishingstatus': '2'}	5094.74853515625
Feb. 12, 2025, 9:11 a.m.	{'area': '250', 'bedrooms': '2', 'bathrooms': '2', 'stories': '1', 'mainroad': '0', 'guestroom': '0', 'basement': '0', 'hotwaterheating': '0', 'airconditioning': '0', 'parking': '1', 'prefarea': '0', 'furnishingstatus': '0'}	6259796.5
Feb. 12, 2025, 9:11 a.m.	{'area': '250', 'bedrooms': '1', 'bathrooms': '1', 'stories': '0', 'mainroad': '1', 'guestroom': '0', 'basement': '0', 'hotwaterheating': '0', 'airconditioning': '0', 'parking': '0', 'prefarea': '0', 'furnishingstatus': '2'}	6649249.5
Feb. 12, 2025, 9:07 a.m.	{'feature_1': '0', 'feature_2': '0', 'feature_3': '0', 'feature_4': '0', 'feature_5': '0', 'feature_6': '0', 'feature_7': '0', 'feature_8': '0', 'feature_9': '0', 'feature_10': '0', 'feature_11': '0', 'feature_12': '0'}	25605506.0
Feb. 12, 2025, 8:53 a.m.	{'feature_1': '0', 'feature_2': '0', 'feature_3': '0', 'feature_4': '0', 'feature_5': '0', 'feature_6': '0', 'feature_7': '0', 'feature_8': '0', 'feature_9': '0', 'feature_10': '0', 'feature_11': '0', 'feature_12': '0'}	25605506.0
Feb. 12, 2025, 8:53 a.m.	{'feature_1': '0', 'feature_2': '0', 'feature_3': '0', 'feature_4': '0', 'feature_5': '0', 'feature_6': '0', 'feature_7': '0', 'feature_8': '0', 'feature_9': '0', 'feature_10': '0', 'feature_11': '0', 'feature_12': '0'}	25605506.0

Fig. 7.3.5 Prediction History Storage

Description: The admin logs into the system and navigates to the “Predictions” section from the dashboard. This page is designed to display all the house price predictions made by users. It provides a centralized view where the admin can monitor prediction activities and analyze how the system is being used over time.

The user logs into the system and navigates to the house price prediction module. On this page, the user is required to enter various property-related details such as area (in square feet), number of bedrooms, number of bathrooms, number of stories, and additional features like main road access, guest room availability, basement, air conditioning, hot water heating, parking spaces, preferred area, and furnishing status.

Test Case 6:

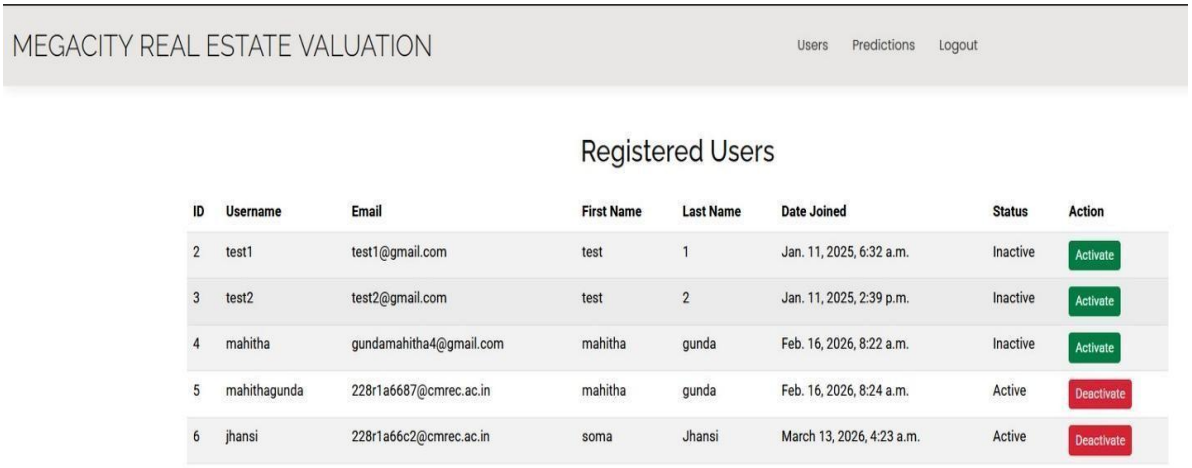


Fig. 7.3.6 Admin Dashboard & Monitoring

Description: The The admin logs into the system and navigates to the "Users" section of the dashboard, where all registered users are displayed in a structured table format. The system retrieves user details such as ID, username, email, first name, last name, date joined, and account status from the database.

Additionally, the admin is provided with action options like "Activate" or "Deactivate" to manage user access dynamically. This confirms that user management, role-based access control, and database update functionalities are working correctly, ensuring secure and efficient administration of user accounts.

Test Case 7:

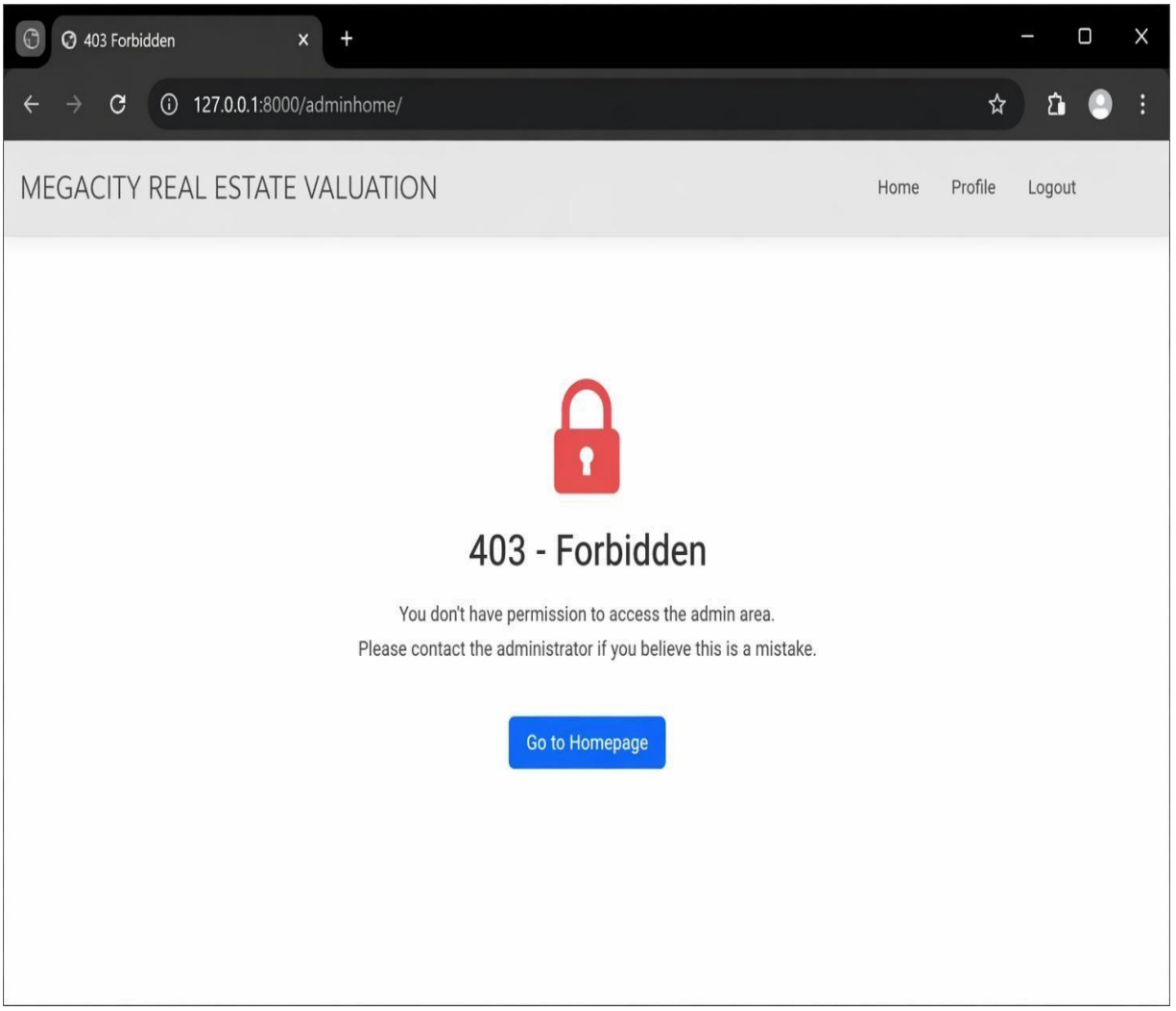


Fig.7.3.7 Unauthorized User accessing Admin Home

Description: The user, who does not have admin privileges, attempts to access the admin home page by directly entering the URL. The system verifies the user's role and restricts access to unauthorized users. As a result, a "403 - Forbidden" error page is displayed, indicating that the user does not have permission to access the requested resource.

This confirms that role-based access control and security mechanisms are functioning correctly, preventing unauthorized access to sensitive admin functionalities.

Test Case 8:

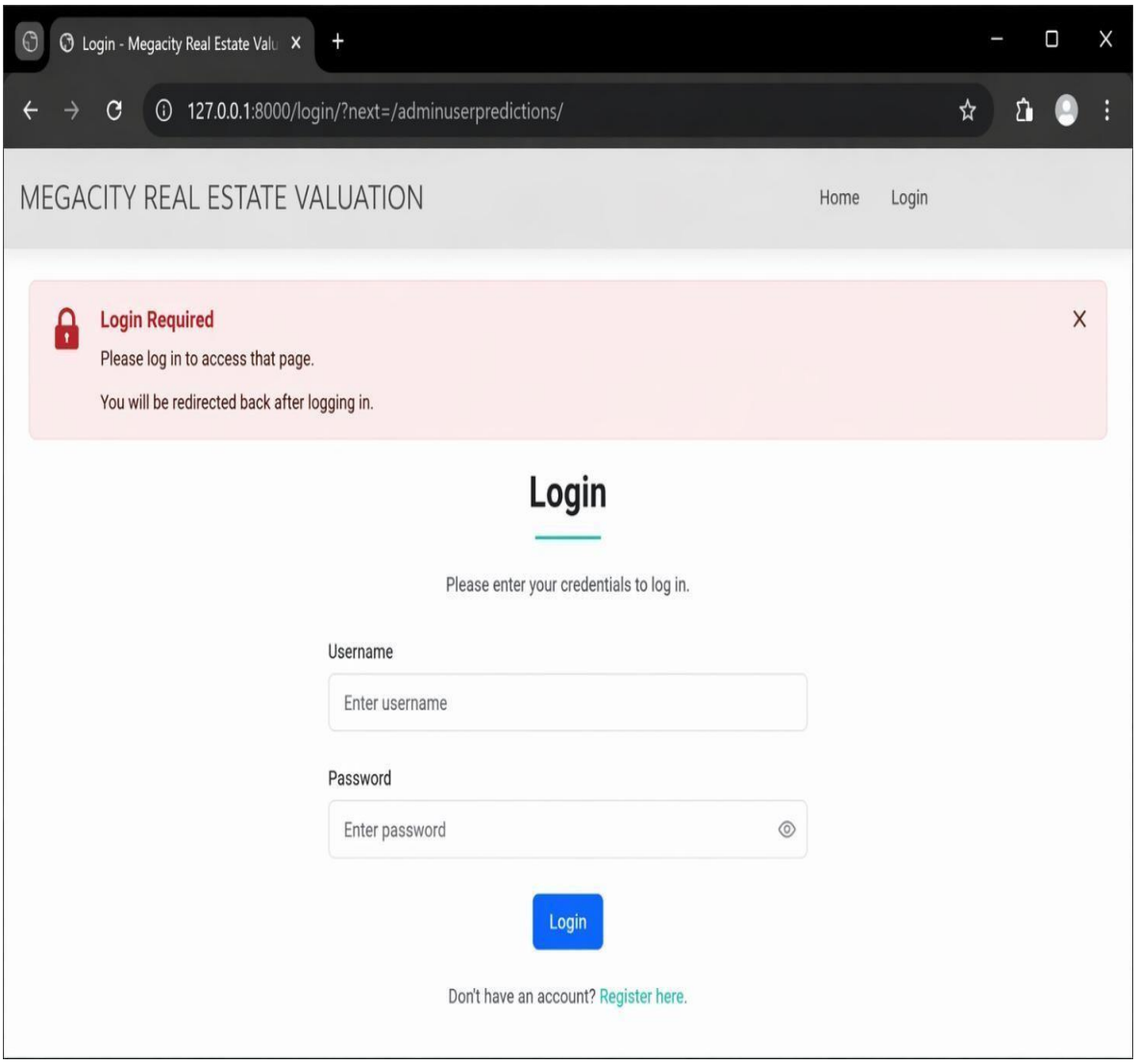


Fig.7.3.8 Unauthentical access to Admin Predictions

Description: The user, who is not logged into the system, attempts to access a restricted page by directly entering the URL, and the system detects the absence of an active session. As a result, the user is redirected to the login page with a warning message indicating that login is required to access the requested page, along with a note that they will be redirected back after successful authentication. This confirms that authentication checks, session management, and access control mechanisms are functioning correctly, ensuring that only authorized users can access protected resources.

Test Case 9:

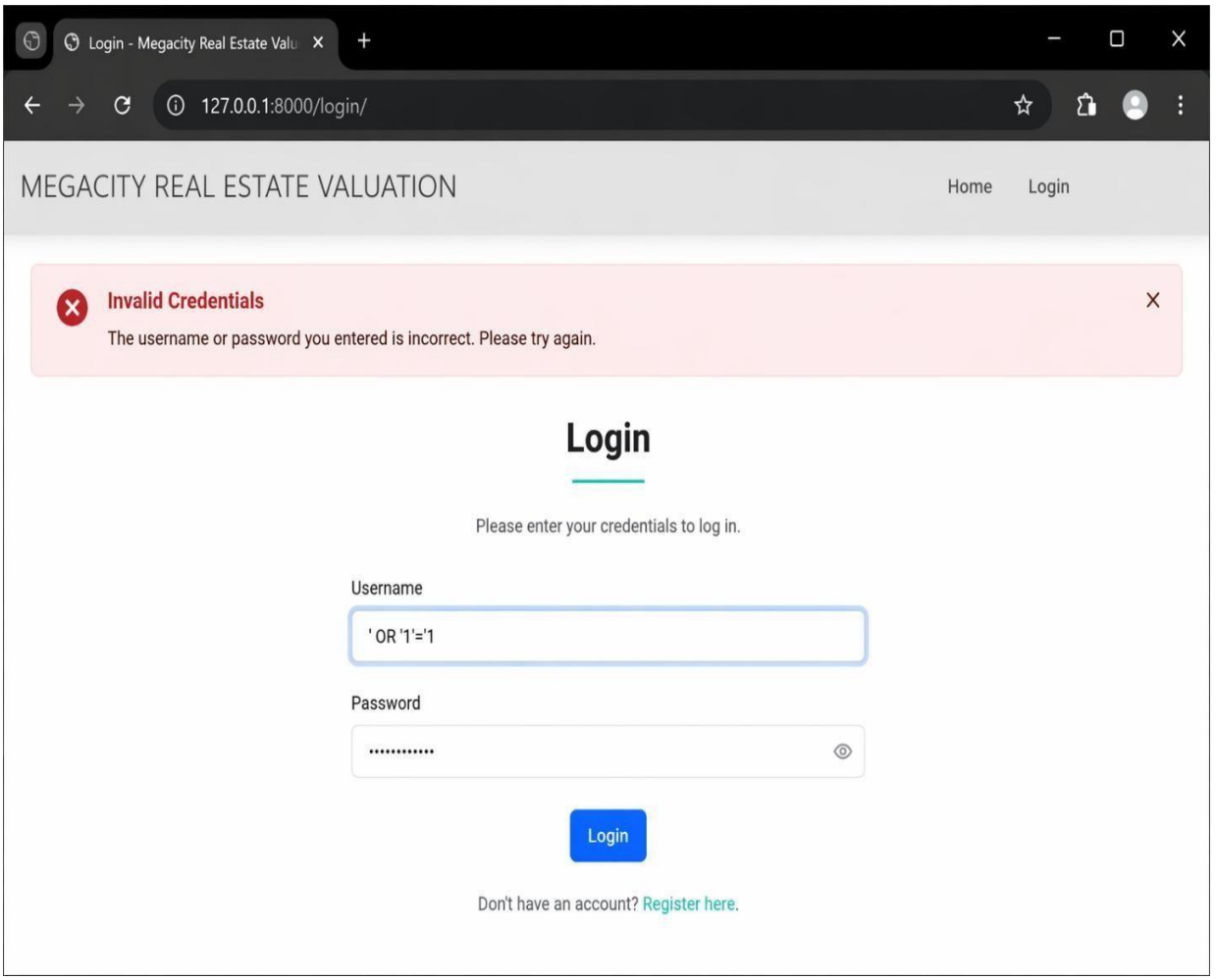


Fig. 7.3.9 Negative Values for Property Area

Description: The user attempts to log in by entering a malicious SQL injection input in the username field along with a random password, and submits the form. The system securely processes the input, sanitizes it, and prevents any unauthorized access by rejecting the login attempt. An error message stating “Invalid Credentials” is displayed, indicating that the authentication has failed. This confirms that the system is protected against SQL injection attacks and that input validation and security mechanisms are functioning correctly.

Test Case 10:

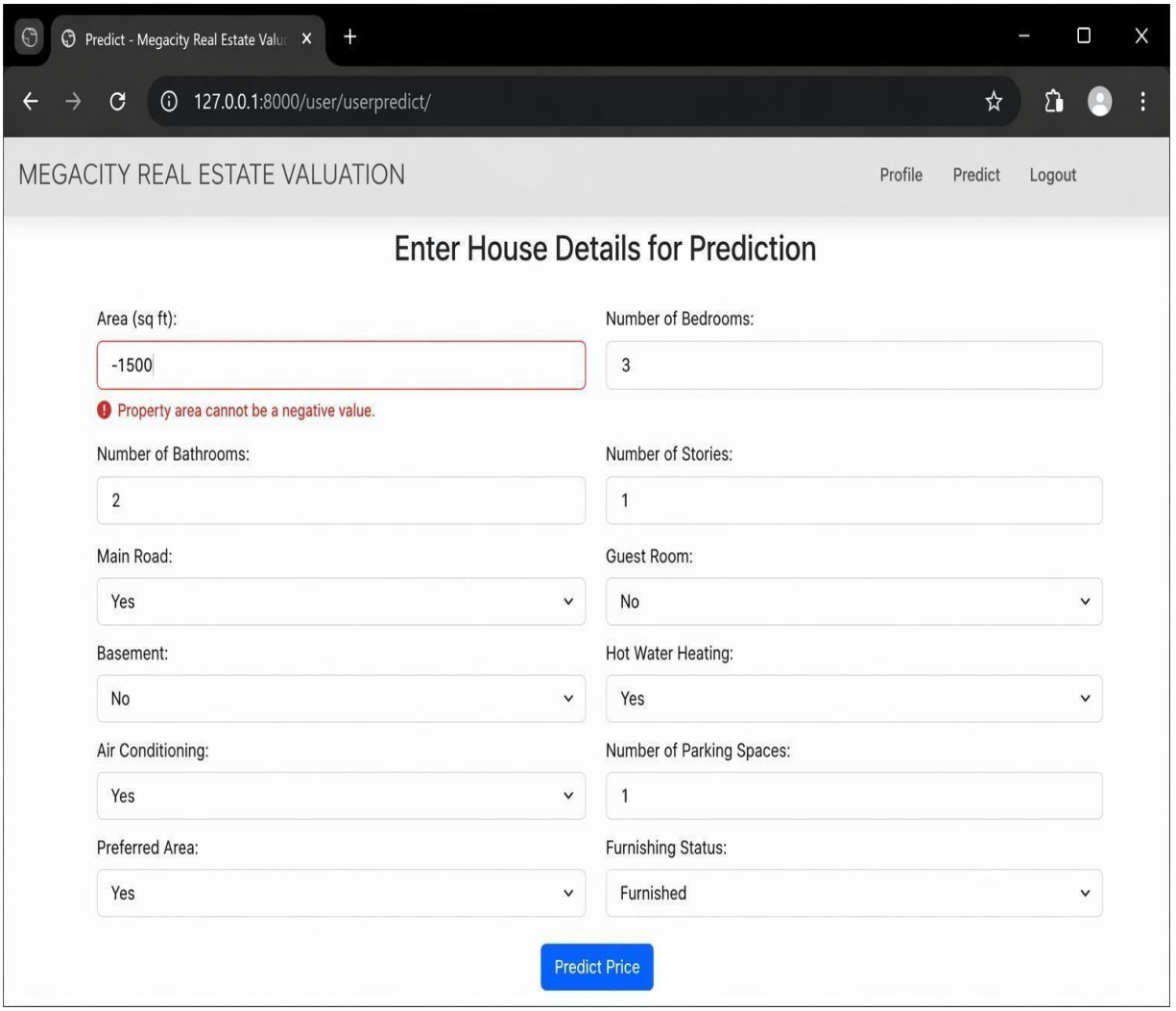


Fig. 7.3.10 Missing Mandatory Node Features

Description: The user enters an invalid input by providing a negative value for the property area in the prediction form and attempts to submit it. The system validates the input and detects that the value is not acceptable, preventing form submission. An error message stating "Property area cannot be a negative value" is displayed, and the input field is highlighted to indicate the issue. This confirms that input validation mechanisms are functioning correctly, ensuring that only valid data is processed by the prediction model.

Test Case 11:

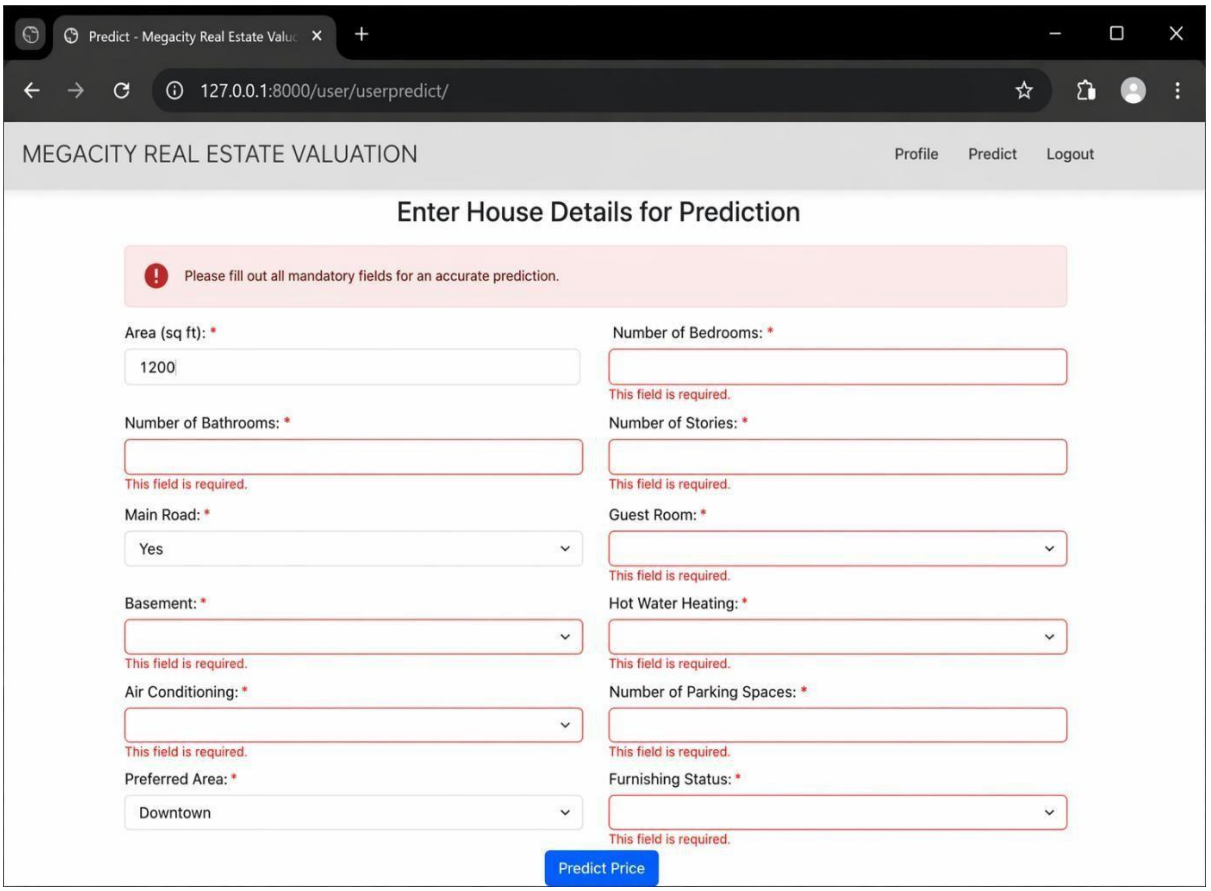


Fig.7.3.11 Extremely Large Input (Buffer Over flow Check)

Description: The user attempts to submit the house price prediction form without filling all the mandatory fields. The system performs validation and detects the missing required inputs, preventing the form submission. Error messages such as “This field is required” are displayed for each incomplete field, and a general warning message prompts the user to fill all mandatory fields for accurate prediction. This confirms that form validation and input completeness checks are functioning correctly, ensuring that only complete and valid data is processed by the prediction model.

Test Case 12:

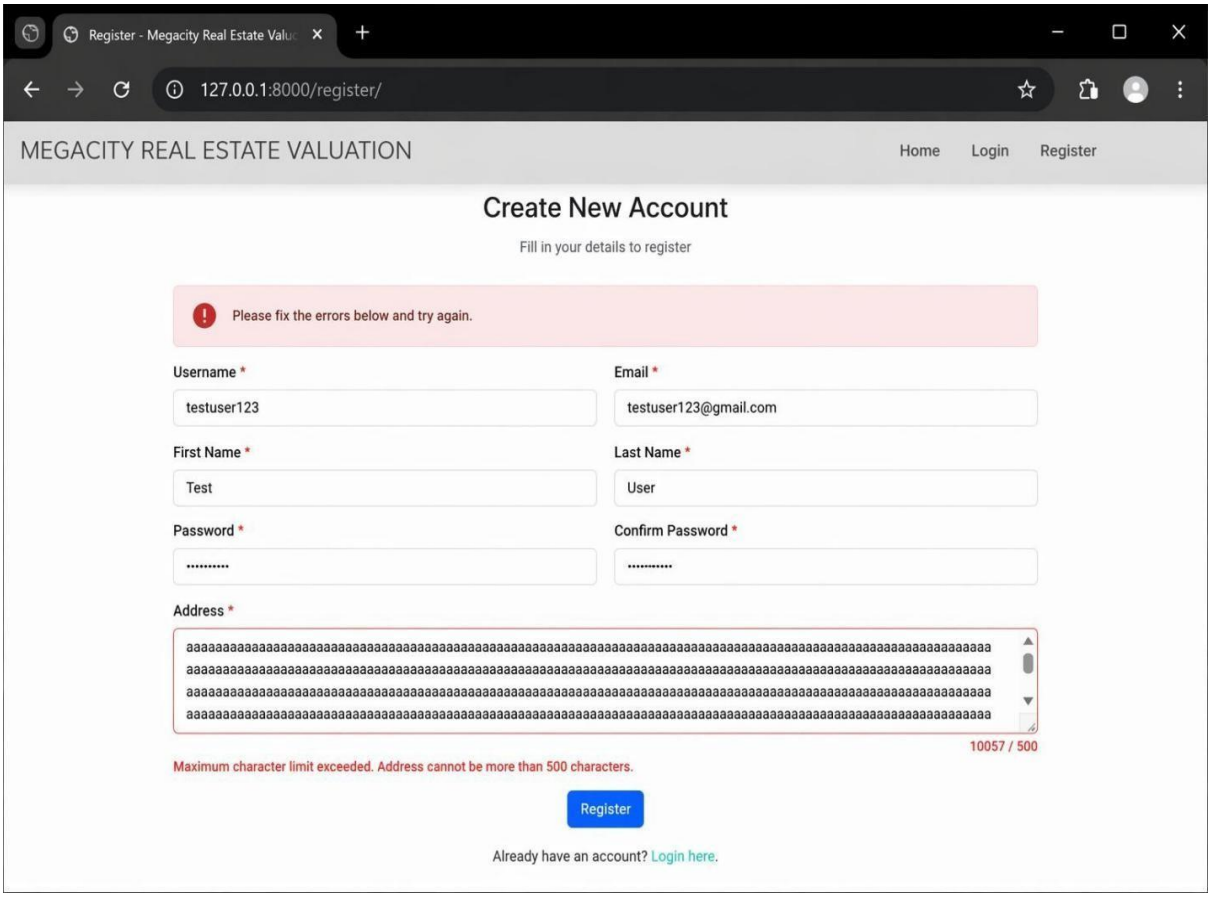


Fig . 7.3.12 SQL Injection Attempt in Login

Description: The user attempts to register a new account by entering excessively large input in the address field, exceeding the allowed character limit. The system validates the input and prevents form submission, displaying an error message indicating that the maximum character limit has been exceeded. The address field is highlighted to show the issue, ensuring the user corrects the input before proceeding. This confirms that input size validation and error handling mechanisms are functioning correctly, preventing potential buffer overflow issues and maintaining system stability.

8. RESULTS

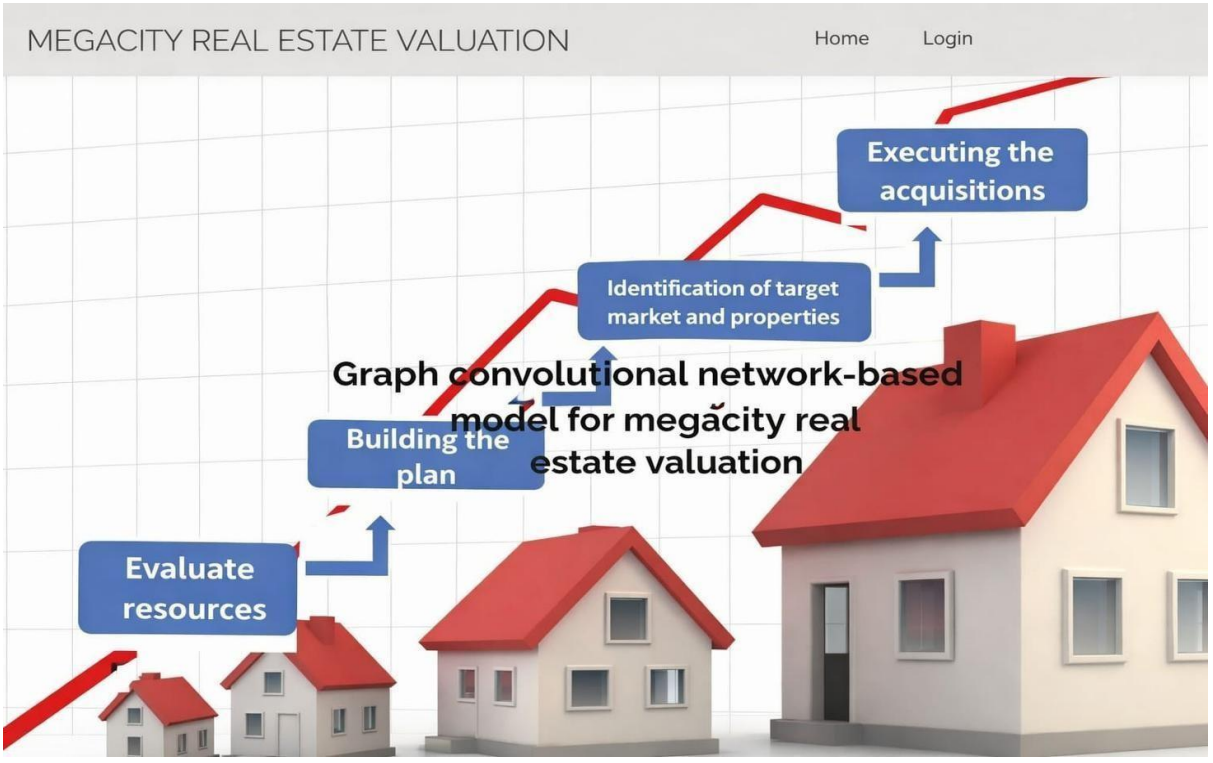


Fig 8.1 Megacity Real Estate Valuation Landing Page

Description: The primary interface of the application, titled "Megacity Real Estate Valuation" system. It introduces the project as a smart platform powered by a Graph Convolutional Network (GCN) model for predicting house prices based on property features and market factors.

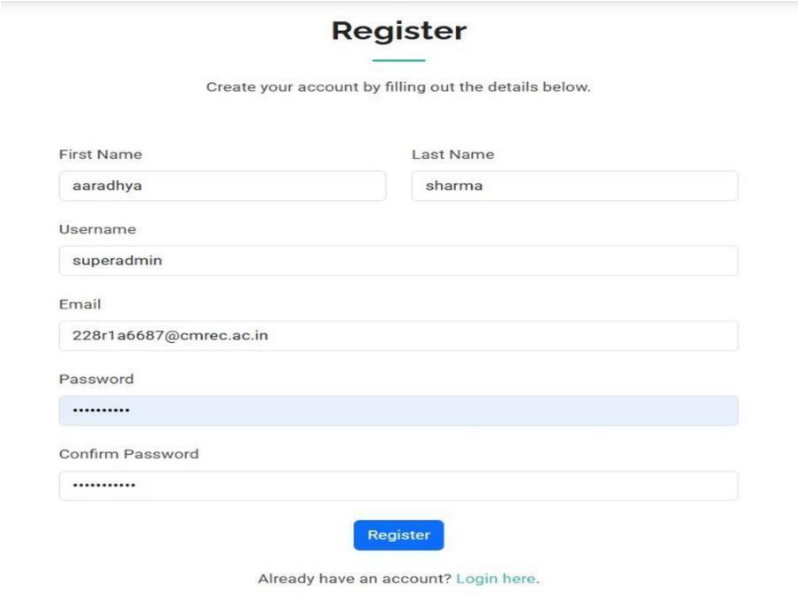


Fig 8.2 User Registration

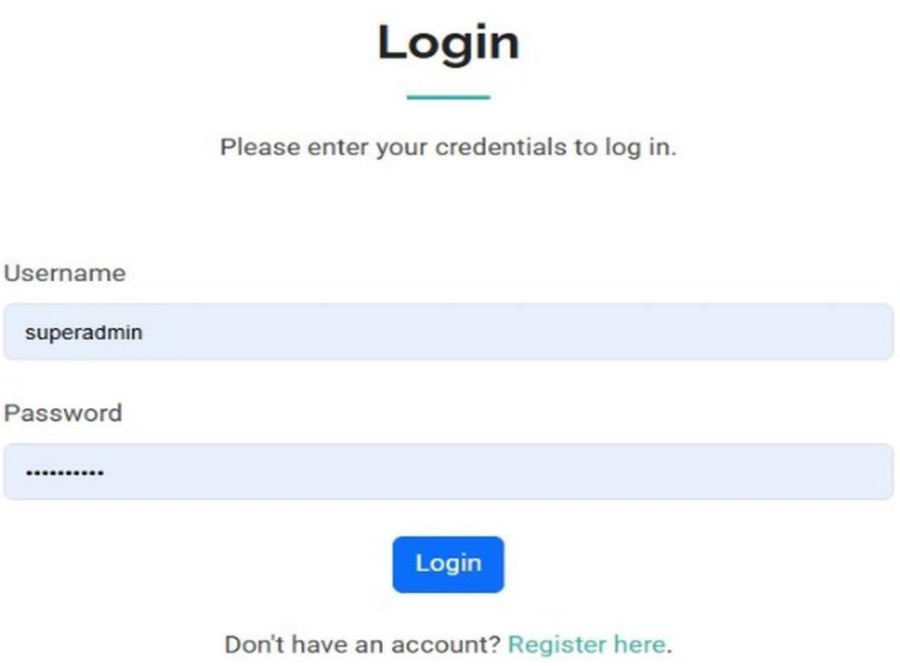
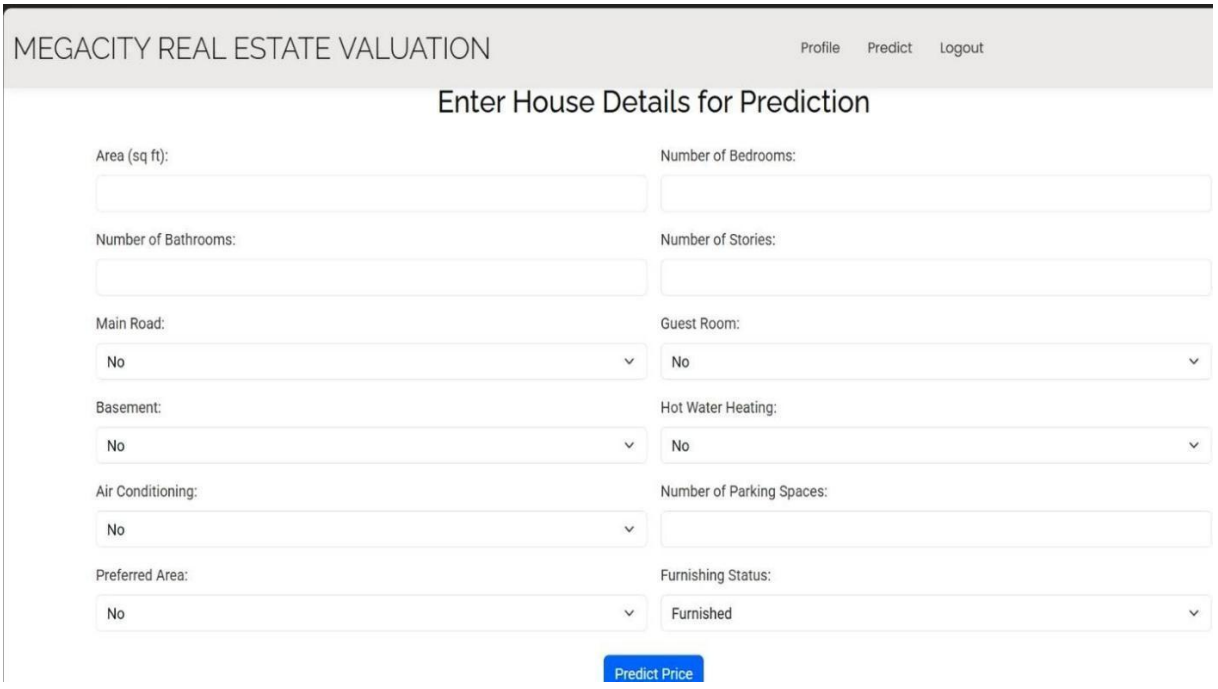


Fig 8.3 User Login

Description: The entry point for the Megacity Real Estate Valuation system, featuring Registration and Login modules. This interface ensures secure user authentication and controlled access to the GCN-based property prediction system for real estate analysis.



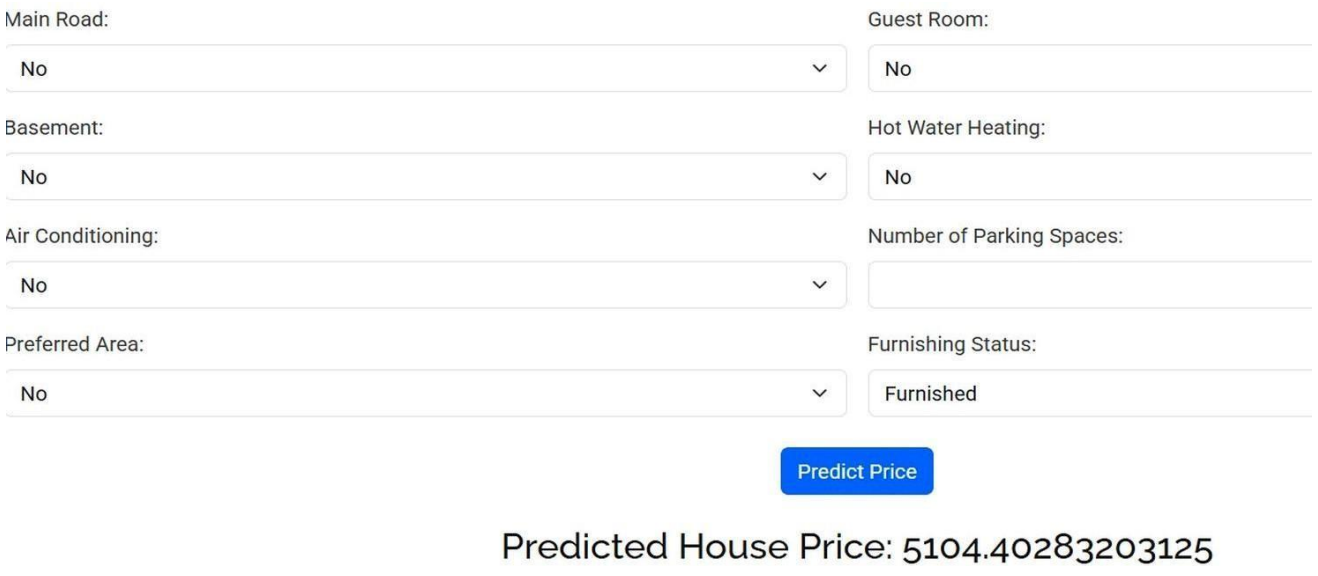


Fig. 8.4 Real Estate Valuatin Prediction

Description: The house price prediction interface of the Megacity Real Estate Valuation system allows users to input property details such as area, number of rooms, and various amenities. This module processes the entered data using a Graph Convolutional Network (GCN) model and generates an estimated house price, providing users with quick and accurate real estate valuation insights.

User Predictions

Timestamp	User Input	Predicted Price
Feb. 16, 2026, 9:14 a.m.	{'area': '1200', 'bedrooms': '3', 'bathrooms': '2', 'stories': '1', 'mainroad': '1', 'guestroom': '1', 'basement': '1', 'hotwaterheating': '1', 'airconditioning': '1', 'parking': '1', 'prefarea': '0', 'furnishingstatus': '0'}	13996413.0
Oct. 31, 2025, 5:34 a.m.	{'area': '1', 'bedrooms': '1', 'bathrooms': '1', 'stories': '1', 'mainroad': '0', 'guestroom': '0', 'basement': '0', 'hotwaterheating': '0', 'airconditioning': '0', 'parking': '1', 'prefarea': '0', 'furnishingstatus': '0'}	13291725.0
Feb. 13, 2025, 9:14 a.m.	{'area': '250', 'bedrooms': '1', 'bathrooms': '1', 'stories': '0', 'mainroad': '1', 'guestroom': '1', 'basement': '1', 'hotwaterheating': '1', 'airconditioning': '1', 'parking': '1', 'prefarea': '1', 'furnishingstatus': '1'}	17832132.0
Feb. 12, 2025, 9:12 a.m.	{'area': '450', 'bedrooms': '2', 'bathrooms': '2', 'stories': '0', 'mainroad': '0', 'guestroom': '0', 'basement': '0', 'hotwaterheating': '0', 'airconditioning': '0', 'parking': '1', 'prefarea': '0', 'furnishingstatus': '0'}	8980876.0
Feb. 12, 2025, 9:11 a.m.	{'area': '3500', 'bedrooms': '3', 'bathrooms': '3', 'stories': '3', 'mainroad': '0', 'guestroom': '0', 'basement': '0', 'hotwaterheating': '0', 'airconditioning': '0', 'parking': '2', 'prefarea': '0', 'furnishingstatus': '2'}	5094.74853515625
Feb. 12, 2025, 9:11 a.m.	{'area': '250', 'bedrooms': '2', 'bathrooms': '2', 'stories': '1', 'mainroad': '0', 'guestroom': '0', 'basement': '0', 'hotwaterheating': '0', 'airconditioning': '0', 'parking': '1', 'prefarea': '0', 'furnishingstatus': '0'}	6259796.5
Feb. 12, 2025, 9:11 a.m.	{'area': '250', 'bedrooms': '1', 'bathrooms': '1', 'stories': '0', 'mainroad': '1', 'guestroom': '0', 'basement': '0', 'hotwaterheating': '0', 'airconditioning': '0', 'parking': '0', 'prefarea': '0', 'furnishingstatus': '2'}	6649249.5
Feb. 12, 2025, 9:07 a.m.	{'feature_1': '0', 'feature_2': '0', 'feature_3': '0', 'feature_4': '0', 'feature_5': '0', 'feature_6': '0', 'feature_7': '0', 'feature_8': '0', 'feature_9': '0', 'feature_10': '0', 'feature_11': '0', 'feature_12': '0'}	25605506.0
Feb. 12, 2025, 8:53 a.m.	{'feature_1': '0', 'feature_2': '0', 'feature_3': '0', 'feature_4': '0', 'feature_5': '0', 'feature_6': '0', 'feature_7': '0', 'feature_8': '0', 'feature_9': '0', 'feature_10': '0', 'feature_11': '0', 'feature_12': '0'}	25605506.0
Feb. 12, 2025, 8:53 a.m.	{'feature_1': '0', 'feature_2': '0', 'feature_3': '0', 'feature_4': '0', 'feature_5': '0', 'feature_6': '0', 'feature_7': '0', 'feature_8': '0', 'feature_9': '0', 'feature_10': '0', 'feature_11': '0', 'feature_12': '0'}	25605506.0

Fig. 8.5 Prediction History Storage

Description: The user predictions interface of the Megacity Real Estate Valuation system displays a history of all house price predictions made by users. It presents details such as timestamp, input features, and the predicted price in a structured table format. This module ensures proper storage and retrieval of prediction data, enabling tracking and analysis of model outputs.

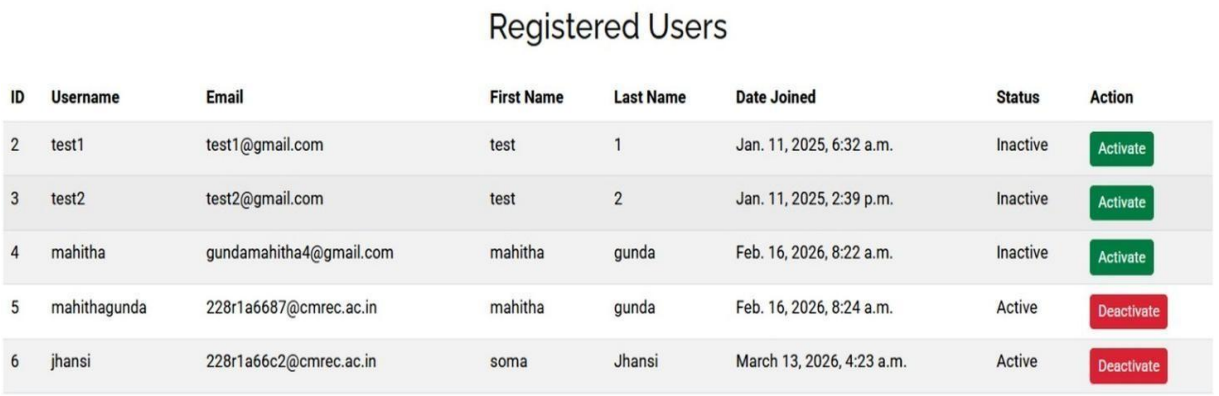


Fig 8.6 Admin Dashboard & Monitoring

Description: The registered users interface of the Megacity Real Estate Valuation system displays all user details in a structured table, including username, email, and account status. It provides admin controls to activate or deactivate user accounts, ensuring efficient user management and secure access control within the system.

9. CONCLUSION

The present project introduces a comprehensive and intelligent real estate valuation framework that effectively leverages deep learning techniques—specifically Graph Convolutional Networks (GCN)—to enhance the accuracy, robustness, and reliability of property price predictions in complex megacity environments.

The system was implemented using a structured full-stack pipeline that includes geospatial data collection, structural preprocessing, spatial feature extraction, model inference, and real-time user evaluation, ensuring a systematic and end-to-end approach to solving the problem of urban housing valuation. During the implementation phase, raw real estate data (derived from housing datasets) was preprocessed through multiple stages, including data cleaning, normalization, scaling, and the removal of statistical outliers, to eliminate noise and improve overall data quality.

The processed numerical and categorical data was then transformed into functional node features, enabling the machine learning models to capture the intrinsic characteristics of a property (e.g., square footage, number of rooms, location).

This meticulous feature engineering step significantly improved the mathematical effectiveness of the downstream prediction process.To address the issue of spatial dependency, which is historically ignored by traditional regression datasets, a complex graph-based architecture was applied.

By representing individual properties as interconnected nodes and their geographic or socio- economic relationships as edges, the system prevents the model from viewing properties in isolated vacuums. This step enhanced the model's ability to correctly identify overlapping urban dynamics, allowing the valuation to be influenced by neighborhood amenities, transit availability, and macro- economic factors.

The core of the system is the Graph Convolutional Network classification and regression model, which aggregates feature data from neighboring nodes using specialized convolution layers. This architectural approach allows the model to learn hidden spatial representations, reducing individual prediction bias and variance while improving overall generalization across different city sectors.

The GCN model demonstrates exceptionally strong performance in handling noisy, volatile, and geographically diverse urban real estate matrices.The framework supports highly dynamic continuous value prediction, making it adaptable to a wide range of real-world financial applications. The underlying machine learning system was rigorously evaluated against foundational baseline algorithms (such as standard Linear Regression and

From a system design perspective, the project followed a structured software engineering methodology, including formal requirement analysis, feasibility studies, system architecture design, UML modeling, and the deployment of a Django Model-View-Template (MVT) web architecture.

These steps ensured the development of a highly modular, scalable, and maintainable web platform. The modular design of the Django backend, paired with specialized Administrative dashboards and secure session routing, supports the easy integration of additional property datasets and facilitates future system enhancements.

Beyond its technical computational contributions, the project addresses a significant socio-economic issue by promoting transparency and fairness in modern digital housing markets. Opaque megacity real estate pricing has become a major concern, affecting the financial well-being of buyers, sellers, and urban planners alike.

The proposed system provides an automated, scalable, and unbiased algorithmic solution to predict and evaluate fair property values. Furthermore, the use of open-source Python tools and standard computational resources ensures cost-effectiveness and broad accessibility for both academic and commercial use.

In conclusion, the project successfully demonstrates that a well-engineered Graph Convolutional Network machine learning framework, combined with effective spatial preprocessing, node-edge feature extraction, and a robust Django web interface, can significantly improve the performance of automated real estate valuation systems.

The developed platform not only achieves its intended analytical objectives but also establishes a highly secure and scalable foundation for future research in prop-tech and urban data science. Furthermore, the integration of a dedicated administrative module ensures the ongoing integrity and security of the platform.

Looking toward future advancements, the current architecture was intentionally engineered to serve as an extensible foundation for even more complex PropTech integrations. Future iterations of this framework can naturally evolve by incorporating Spatio-Temporal Graph Convolutional Networks (STGCN), which would allow the model to account for historical inflation and time- decaying market trends.

Additionally, the decoupled backend design allows for the effortless integration of third-party live APIs, such as live traffic metrics or economic indexes, continuously feeding dynamic edge weights into the graph to reflect real-time shifts in the urban ecosystem.

10. FUTURE ENHANCEMENTS

The proposed graph-based convolutional network model for megacity real estate valuation offers a strong foundation for accurate and intelligent property price prediction; however, there are numerous opportunities for future enhancements that can significantly improve its performance, robustness, and real-world applicability. One of the most impactful enhancements is the integration of real-time data streams into the model. In rapidly evolving megacities, property values are influenced by dynamic factors such as traffic congestion, weather conditions, infrastructure disruptions, public events, and economic fluctuations. By incorporating real-time inputs from sources such as IoT sensors, GPS systems, financial markets, and social media activity, the model can continuously update its predictions and provide more timely and relevant valuations. This dynamic capability will make the system highly responsive to short-term market variations and urban changes.

Another major area of enhancement is the inclusion of multi-modal data to enrich the model's understanding of real estate characteristics. Traditional valuation models primarily rely on structured numerical data, but future systems can benefit from integrating unstructured and semi-structured data sources such as high-resolution satellite imagery, drone footage, street-view images, building layouts, and textual property descriptions. These additional data modalities can capture visual, environmental, and qualitative aspects of properties that are otherwise difficult to quantify. For instance, image-based features can help identify building conditions, surrounding greenery, road quality, and neighborhood aesthetics, all of which play a crucial role in determining property value. The fusion of these diverse data types using advanced deep learning techniques will lead to more comprehensive and accurate valuation models.

Advancements in graph neural network architectures also present significant opportunities for improving the model. While basic graph convolutional networks are effective in capturing spatial relationships, more advanced architectures such as Graph Attention Networks (GATs), Graph Transformers, and dynamic graph learning models can further enhance the system's ability to understand complex interactions between properties. These models can assign different levels of importance to neighboring nodes, allowing the system to focus more on influential factors while reducing noise from less relevant connections. Additionally, incorporating hierarchical and multi- scale graph representations can help capture both local neighborhood effects and broader city-level trends, thereby improving prediction accuracy across different spatial levels.

Scalability remains a critical challenge when dealing with megacity-scale data, where

millions of properties and relationships must be processed efficiently. Future enhancements should focus on optimizing the computational performance of the model through techniques such as distributed computing, cloud-based processing, and graph partitioning. Leveraging high-performance computing

frameworks and parallel processing algorithms can significantly reduce training time and enable real- time inference even for large datasets. Furthermore, the use of efficient data structures and memory management strategies will ensure that the system can handle continuously growing urban data without performance degradation.

Another important direction for improvement is enhancing the interpretability and explainability of the model. In real-world applications, stakeholders such as investors, real estate developers, financial institutions, and government authorities require clear and understandable insights into how property valuations are derived. By integrating explainable AI techniques, the model can provide detailed explanations of the key factors influencing each prediction, such as location advantages, connectivity, infrastructure quality, and market demand. Visualization tools and feature importance analysis can further help users interpret the results, thereby increasing transparency, trust, and adoption of the system in practical scenarios.

The inclusion of socioeconomic, demographic, and regulatory factors is also essential for developing a more holistic valuation model. Property prices are not determined solely by physical attributes but are heavily influenced by factors such as population density, income levels, employment rates, education facilities, healthcare access, crime rates, and government policies. Incorporating these variables into the graph-based framework will allow the model to better reflect real-world conditions and provide more context-aware predictions. Additionally, considering zoning regulations, taxation policies, and urban planning initiatives can further improve the model's ability to capture long-term market trends and investment potential.

Temporal graph modeling represents another promising enhancement for future research. Real estate markets are inherently dynamic, with property values changing over time due to economic cycles, infrastructure development, and social trends. By extending the model to include time- evolving graph structures, it becomes possible to analyze historical price trends and predict future market behavior. This capability is particularly valuable for long-term investment planning, risk assessment, and policy formulation. Time-series analysis combined with graph-based learning can provide deeper insights into the temporal evolution of urban real estate markets.

Transfer learning and domain adaptation techniques can further enhance the flexibility and generalizability of the model. In many cases, obtaining large-scale labeled data for every city is challenging and time-consuming. By leveraging knowledge learned from one city and applying it to another, the model can reduce data requirements and accelerate deployment in

new regions. This approach is especially useful for developing countries or emerging urban areas where data availability may be limited. Fine-tuning pre-trained models for specific local conditions can help achieve high accuracy with minimal additional training.

Data security and privacy considerations are becoming increasingly important as real estate valuation systems rely on large volumes of sensitive data, including financial records, personal information, and location details. Future enhancements should focus on implementing robust security measures such as data encryption, secure access controls, and privacy-preserving machine learning techniques. Approaches such as federated learning can be explored to enable model training across multiple data sources without sharing raw data, thereby ensuring compliance with data protection regulations and maintaining user trust.

Finally, the practical usability of the model can be greatly improved by integrating it with smart city infrastructure and developing user-friendly decision support systems. Interactive dashboards, web-based platforms, and mobile applications can provide intuitive interfaces for users to access predictions, visualize data, and analyze trends. Features such as real-time alerts, scenario analysis, and investment recommendations can further enhance the system's value for different stakeholders. By bridging the gap between advanced computational models and user-centric design, these enhancements will ensure that the system is not only technically powerful but also widely accessible and impactful in real-world real estate markets.

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