International Journal of Engineering Science and Advanced Technology (IJESAT)
Vol 25 Issue 03, MAR, 2025

Joint Gated Co-Attention Model for Accurate Sub-region Housing Market Forecasting

M. Vasavi[1], Shaik Baji[2], Reddi Jhansi[3], Sasubilli Tarun Kumar[4]

[1]Assistant Professor, Dept. of Computer Science and Engineering, R.V.R. & J.C College of Engineering, Chowdavaram, Guntur, Andhra Pradesh, India
[2,3,4]B. Tech Student, Dept. of Computer Science and Engineering, R.V.R. & J.C College of Engineering, Chowdavaram, Guntur, Andhra Pradesh, India

Abstract
Accurate housing price prediction is essential for urban planning, real estate investments, and economic policymaking, yet traditional models often fail to capture fine-grained variations at the subregion level. This work proposes a novel **Joint Gated Co-Attention Based Multi-Modal Network (JGC_MMN)** for mile-level housing price forecasting, addressing the challenges of sparse data and complex influencing factors. The model integrates long-term trends, short-term fluctuations, current economic conditions, and future price-growth expectations into a unified framework. A modified DenseNet architecture is employed to capture all-level features, from low-level spatial correlations to high-level temporal dependencies, ensuring robust performance on sparse datasets. Additionally, a novel **Joint Gated Co-Attention (JGC)** mechanism is introduced to fuse multiple data modalities effectively, capturing interactions between diverse factors while filtering out noise. Evaluated on real-world datasets, the model demonstrates superior accuracy compared to state-of-the-art baselines, highlighting its ability to predict fine-grained housing price variations. The proposed approach not only advances housing price prediction but also provides a scalable framework applicable to other spatiotemporal forecasting tasks, such as air quality and traffic flow analysis. This work offers valuable insights for urban planners, policymakers, and real estate stakeholders, enabling more informed decision-making and optimized urban development.

I. Introduction

Housing prices are a vital economic indicator, influencing decisions in urban planning, real estate investments, and public policy. Accurate housing price forecasting is essential for understanding market trends, supporting macroeconomic decisions, and optimizing urban development. However, predicting housing prices at a fine-grained level, such as mile-level subregions within a city, presents significant challenges due to the complex interplay of spatial, temporal, and economic factors. Traditional models often focus on city-level predictions, which fail to capture the nuanced variations in housing prices across smaller urban areas. These variations are influenced by localized factors such as transportation infrastructure, school districts, surrounding amenities, and economic conditions, which can vary significantly even within a single city.

The importance of fine-grained housing price prediction has grown in recent years, driven by the need for more detailed insights into urban development. For instance, in many urban areas, housing prices in different districts have shown divergent trends, with some areas experiencing significant price increases while others decline. This highlights the limitations of city-level forecasting and underscores the need for models that can operate at a more granular level. Fine-grained predictions not only provide valuable insights for urban planners and policymakers but also enable more informed decision-making for real estate investors and homebuyers.

Despite its importance, fine-grained housing price prediction remains a challenging task. One of the primary challenges is the **sparsity of transaction data** at the subregion level. While city-level data may be abundant, decomposing a city into smaller subregions often results in sparse datasets, making it difficult to train accurate models. Additionally, housing prices are influenced by a wide range of factors, including long-term trends, short-term fluctuations, current economic conditions, and future price-growth expectations. Capturing these diverse influences requires a model that can integrate multiple data modalities and effectively fuse them to produce accurate predictions.

Existing approaches to housing price prediction can be broadly categorized into **geostatistical methods**, **machine learning-based methods**, and **deep learning-based methods**. Geostatistical methods, such as geographically and Temporally Weighted Regression (GTWR), incorporate spatial and temporal dependencies but often struggle with non-linear relationships between variables. Machine learning methods, including Support Vector Regression (SVR) and decision trees, have been widely used for housing price prediction but typically focus on temporal dependencies and lack the ability to capture complex spatial interactions. Deep learning methods, such as Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs), have shown promise in capturing temporal and spatial correlations but often suffer from overfitting when applied to sparse datasets.

To address these challenges, this work proposes a novel **Joint Gated Co-Attention Based Multi-Modal Network (JGC_MMN)** for fine-grained subregion housing price prediction. The proposed model integrates multiple data modalities, including long-term trends, short-term fluctuations, current economic and social factors, and future price-growth expectations, to provide a comprehensive framework for housing price forecasting. The key contributions of this work are as follows:

1. **Fine-Grained Prediction**: Unlike traditional city-level models, the proposed model operates at a mile-level granularity, enabling more detailed and accurate predictions for urban subregions. This is particularly important for capturing localized variations in housing prices, which are often overlooked in city-level analyses.
2. **Multi-Modal Data Integration**: The model incorporates a wide range of influencing factors, including long-term periodicity, short-term tendencies, current economic conditions, and future expectations. By integrating these diverse data modalities, the model provides a more holistic view of the factors driving housing prices.
3. **Modified DenseNet Architecture**: To address the challenge of sparse data, the model employs a modified DenseNet architecture that captures all-level features, from low-level spatial correlations to high-level temporal dependencies. This approach helps mitigate overfitting and improves the model's ability to generalize to small and sparse datasets.
4. **Joint Gated Co-Attention Fusion**: The model introduces a novel fusion mechanism, called Joint Gated Co-Attention (JGC), to effectively combine the outputs of multiple learners. This mechanism captures the interactions between different data modalities and filters out noise, resulting in more accurate and robust predictions.
5. **Empirical Validation**: The proposed model is evaluated on real-world datasets, demonstrating its superior performance compared to state-of-the-art baselines. The results show significant improvements in prediction accuracy, highlighting the effectiveness of the proposed approach.

Objectives

1. **Develop a Fine-Grained Housing Price Prediction Model**
   - To design and implement a model capable of predicting housing prices at a mile-level granularity, enabling more detailed and accurate forecasts for urban subregions compared to traditional city-level models.
2. **Incorporate Multi-Modal Data for Comprehensive Analysis**
   - To integrate diverse data modalities, including long-term trends, short-term fluctuations, current economic and social factors, and future price-growth expectations, into a unified framework for housing price prediction.
3. **Address Data Sparsity Challenges**
   - To overcome the challenge of sparse transaction data at the subregion level by employing a modified DenseNet architecture that captures all-level features, from low-level spatial correlations to high-level temporal dependencies.
4. **Enhance Model Generalization and Reduce Overfitting**

- To improve the model's ability to generalize to small and sparse datasets by leveraging densely connected networks and batch normalization techniques, thereby reducing the risk of overfitting.

5. **Propose a Novel Fusion Mechanism for Multi-Modal Data**
   - To introduce a Joint Gated Co-Attention (JGC) fusion mechanism that effectively combines the outputs of multiple learners, capturing interactions between different data modalities while filtering out noise.
6. **Validate the Model on Real-World Datasets**
   - To evaluate the proposed model on real-world housing price datasets, demonstrating its superior performance compared to state-of-the-art baselines in terms of prediction accuracy and robustness.
7. **Provide Insights for Urban Planning and Real Estate Decision-Making**
   - To generate actionable insights for urban planners, policymakers, and real estate stakeholders by offering accurate and fine-grained predictions of housing prices in urban subregions.
8. **Explore Scalability and Applicability to Other Domains**
   - To investigate the scalability of the proposed model and its potential applicability to other domains, such as air quality prediction, traffic flow forecasting, and power demand estimation.

II. Literature Review

Housing price prediction has been a topic of significant interest in both academia and industry due to its implications for urban planning, real estate investments, and economic policymaking. Over the years, various approaches have been proposed to address this problem, ranging from traditional statistical methods to advanced machine learning and deep learning techniques. This section provides a comprehensive review of existing works, categorizing them into **geostatistical methods**, **machine learning-based methods**, and **deep learning-based methods**, and highlights their limitations in addressing fine-grained housing price prediction.

1. Geostatistical Methods

Geostatistical methods have been widely used for housing price prediction, particularly for capturing spatial and temporal dependencies. One of the earliest approaches is the **Geographically Weighted Regression (GWR)** model, which incorporates spatial heterogeneity by allowing regression coefficients to vary across different locations. This model was later extended to **Geographically and Temporally Weighted Regression (GTWR)**, which accounts for both spatial and temporal variations in housing prices. GTWR has been applied to various datasets, demonstrating its ability to capture localized trends. However, these methods often struggle with non-linear relationships between variables and fail to incorporate complex interactions between multiple influencing factors. Another category of geostatistical methods is the **Eigenvector Spatial Filtering Regression (ESFR)** model, which incorporates spatial influences into traditional regression models. ESFR has been used to analyze spatial distributions of housing prices and identify local variations. While these methods provide valuable insights into spatial dependencies, they lack the flexibility to model complex, non-linear relationships and are often limited by their reliance on linear assumptions.

2. Machine Learning-Based Methods

Machine learning-based methods have gained popularity in housing price prediction due to their ability to model non-linear relationships and handle large datasets. **Support Vector Regression (SVR)** is one such method, which has been widely used for its robustness and ability to handle high-dimensional data. SVR has been combined with optimization techniques like Particle Swarm Optimization (PSO) to improve prediction accuracy. Similarly, **decision tree-based methods** have been employed to identify key factors influencing housing prices, such as property characteristics and economic conditions.

Another class of machine learning methods includes **spatial econometric models**, such as Spatial Auto-Regressive (SAR) and Conditional Auto-Regressive (CAR) models. These models incorporate spatial dependencies by considering the influence of neighboring regions on housing prices. For example, the **Stochastic Neighborhood CAR (SNCAR)** model introduces a probabilistic approach to neighborhood selection, improving the accuracy of spatial predictions. However, these methods often focus on temporal or spatial dependencies in isolation and fail to capture the complex interactions between multiple influencing factors.

3. Deep Learning-Based Methods

Deep learning-based methods have emerged as a powerful tool for housing price prediction, particularly for capturing complex temporal and spatial dependencies. **Long Short-Term Memory (LSTM)** networks have been widely used to model temporal correlations in housing prices, leveraging their ability to capture long-term dependencies in time series data. Similarly, **Convolutional Neural Networks (CNNs)** have been employed to capture spatial correlations by analyzing housing price distributions across different regions.

Recent advancements in deep learning have led to the development of models like **ST-ResNet** and **ST-InceptionV4**, which combine spatial and temporal features for improved prediction accuracy. These models have been applied to various spatiotemporal prediction tasks, including housing price forecasting. However, deep learning methods often suffer from overfitting when applied to sparse datasets, particularly at the subregion level. Additionally, these models typically rely on high-level features, neglecting low-level spatial and temporal correlations that are critical for fine-grained predictions.

4. Limitations of Existing Approaches

Despite the advancements in housing price prediction, existing approaches have several limitations. First, most models focus on city-level predictions, failing to capture the fine-grained variations in housing prices across smaller urban subregions. Second, traditional methods often rely on linear assumptions and fail to model the complex, non-linear relationships between influencing factors. Third, deep learning methods, while powerful, are often limited by their reliance on large datasets and are prone to overfitting when applied to sparse subregion-level data.

5. Need for a Multi-Modal Approach

To address these limitations, there is a growing need for a multi-modal approach that integrates diverse data modalities, including long-term trends, short-term fluctuations, current economic conditions, and future price-growth expectations. Such an approach would provide a more comprehensive framework for housing price prediction, capturing the complex interactions between multiple influencing factors. Additionally, a robust fusion mechanism is required to effectively combine these diverse data modalities while filtering out noise.

Challenges

One of the key challenges in fine-grained housing price prediction is the **sparsity of transaction data**. At the subregion level, the number of housing transactions is often limited, making it difficult to train accurate models. This is particularly problematic for deep learning models, which typically require large amounts of data to avoid overfitting. Additionally, housing prices are influenced by a wide range of factors, including long-term trends, short-term fluctuations, and future expectations, which must be integrated into a single model. Traditional approaches often focus on a single type of data, such as temporal trends or spatial correlations, and fail to capture the full complexity of the problem.

Another challenge is the **heterogeneity of data modalities**. Housing prices are influenced by both static factors, such as property characteristics and surrounding amenities, and dynamic factors, such as economic conditions and market trends. Integrating these diverse data modalities into a single

model requires a sophisticated fusion mechanism that can capture the interactions between different types of data while filtering out noise.
To address these challenges, this work proposes a novel multi-modal deep learning framework that integrates long-term, short-term, current, and future factors into a single model. The proposed model leverages a modified DenseNet architecture to capture spatial and temporal dependencies, and introduces a novel Joint Gated Co-Attention mechanism to effectively fuse multiple data modalities. By combining these techniques, the model provides a robust and accurate framework for fine-grained housing price prediction.

Problem Statement
Predicting housing prices accurately is a critical task for urban development, real estate investments, and economic planning. However, most existing models focus on city-level predictions, which fail to capture the detailed variations in housing prices across smaller urban subregions. These variations are influenced by a mix of factors, such as local infrastructure, school quality, nearby amenities, and economic conditions, which can differ significantly even within the same city. Traditional methods, including statistical models and machine learning approaches, often struggle to handle the complexity of these factors. They either rely on linear assumptions, which don't capture real-world non-linear relationships, or require large amounts of data, which is often unavailable at the subregion level. Additionally, deep learning models, while powerful, tend to overfit when trained on sparse datasets, making them unreliable for fine-grained predictions. To address these challenges, there is a need for a more advanced model that can integrate multiple types of data—such as long-term trends, short-term changes, current economic conditions, and future expectations—while overcoming the limitations of sparse data. This work aims to develop such a model, called the **Joint Gated Co-Attention Based Multi-Modal Network (JGC_MMN)**, to provide accurate, mile-level housing price predictions that can support better decision-making for urban planners, policymakers, and real estate stakeholders.

III. PROPOSED WORK

1. Existing System

The existing systems for housing price prediction are primarily based on three categories of approaches: **geostatistical methods**, **machine learning-based methods**, and **deep learning-based methods**.

- **Geostatistical Methods**:
  These methods, such as Geographically Weighted Regression (GWR) and Geographically and Temporally Weighted Regression (GTWR), are designed to capture spatial and temporal dependencies in housing prices. They use weighted matrices to account for local variations in housing prices across different regions and time periods. Eigenvector Spatial Filtering Regression (ESFR) is another approach that incorporates spatial influences into traditional regression models.
- **Machine Learning Methods**:
  Techniques like Support Vector Regression (SVR), decision trees, and spatial econometric models (e.g., Spatial Auto-Regressive (SAR) and Conditional Auto-Regressive (CAR)) are widely used for housing price prediction. These methods leverage historical data and influencing factors to predict future prices. For example, SVR combined with optimization techniques like Particle Swarm Optimization (PSO) has been used to improve prediction accuracy.
- **Deep Learning Methods**:
  Deep learning models, such as Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs), have gained popularity for their ability to capture complex temporal and spatial correlations. Advanced models like ST-ResNet and ST-InceptionV4 combine spatial and temporal features for improved accuracy in spatiotemporal prediction tasks.

2. Disadvantages of Existing System

Despite their widespread use, existing systems suffer from several critical limitations:

- **City-Level Focus**:
  Most models predict housing prices at the city level, which fails to capture the fine-grained variations in housing prices across smaller urban subregions. This limits their usefulness for localized decision-making.
- **Sparse Data Challenges**:
  At the subregion level, housing transaction data is often sparse, making it difficult to train accurate models. This is particularly problematic for deep learning models, which require large amounts of data to avoid overfitting.
- **Limited Multi-Modal Integration**:
  Existing approaches often focus on a single type of data (e.g., temporal or spatial) and fail to integrate multiple influencing factors, such as long-term trends, short-term fluctuations, current economic conditions, and future expectations.
- **Overfitting in Deep Learning**:
  Deep learning models, while powerful, are prone to overfitting when applied to small and sparse datasets. This reduces their generalization ability and makes them unreliable for fine-grained predictions.
- **Inability to Capture Non-Linear Relationships**:
  Traditional statistical and machine learning methods often rely on linear assumptions, which fail to model the complex, non-linear relationships between housing prices and influencing factors.
- **Lack of Robust Fusion Mechanisms**:
  Existing models lack effective mechanisms to fuse heterogeneous data modalities, such as spatial, temporal, and economic data, leading to suboptimal predictions.

3. Motivation to the Problems

The motivation for addressing these limitations stems from the growing need for fine-grained housing price predictions in urban areas. Accurate predictions at the subregion level are essential for various stakeholders, including:

- **Urban Planners**:
  Detailed housing price forecasts can help optimize the allocation of resources, such as transportation infrastructure, schools, and community services, ensuring balanced urban development.
- **Real Estate Investors**:
  Investors require precise predictions to identify high-potential areas, minimize risks, and maximize returns on investments.
- **Policymakers**:
  Policymakers rely on accurate housing price data to design effective economic policies, such as tax regulations, housing subsidies, and urban development plans.
- **Homebuyers**:
  Homebuyers benefit from localized price predictions, enabling them to make informed decisions about property purchases.

However, the limitations of existing systems hinder their ability to provide these insights, creating a gap that needs to be addressed.

4. Proposed System

To overcome these challenges, this work proposes a **Joint Gated Co-Attention Based Multi-Modal Network (JGC_MMN)**. The proposed system includes the following key components:

- **Fine-Grained Prediction**:
  The model operates at a mile-level granularity, enabling detailed predictions for urban

subregions. This allows for a more nuanced understanding of housing price variations across different areas.

- **Multi-Modal Data Integration**:
  The model integrates multiple data modalities, including long-term trends, short-term fluctuations, current economic conditions, and future price-growth expectations. This provides a comprehensive framework for housing price prediction.
- **Modified DenseNet Architecture**:
  A modified DenseNet is used to capture all-level features, from low-level spatial correlations to high-level temporal dependencies. This addresses the challenge of sparse data and ensures robust performance.
- **Joint Gated Co-Attention (JGC) Fusion**:
  A novel fusion mechanism is introduced to effectively combine the outputs of multiple learners. This mechanism captures interactions between different data modalities while filtering out noise, resulting in more accurate and reliable predictions.
- **Scalability and Adaptability**:
  The proposed framework is designed to be scalable and adaptable to other spatiotemporal prediction tasks, such as air quality prediction, traffic flow forecasting, and power demand estimation.

5. Advantages of Proposed System

The proposed system offers several advantages over existing approaches:

- **Fine-Grained Predictions**:
  By operating at the subregion level, the model provides more detailed and accurate housing price forecasts, enabling better decision-making for urban planners, investors, and policymakers.
- **Robustness to Sparse Data**:
  The modified DenseNet architecture and JGC fusion mechanism ensure robust performance even on sparse datasets, overcoming a major limitation of existing models.
- **Comprehensive Data Integration**:
  The model integrates multiple data modalities, providing a holistic view of the factors influencing housing prices. This leads to more accurate and reliable predictions.
- **Improved Generalization**:
  The use of densely connected networks and batch normalization techniques reduces overfitting and improves the model’s ability to generalize to new data.
- **Effective Fusion Mechanism**:
  The JGC fusion mechanism captures interactions between different data modalities while filtering out noise, resulting in more accurate predictions.
- **Scalability**:
  The proposed framework is scalable and can be adapted to other spatiotemporal prediction tasks, making it a versatile tool for various applications.

4. System Architecture

The system will be built using the following components:

- **Frontend**: A web-based user interface for inputting parameters and viewing predictions.
- **Backend**: A server-side application for data processing, model training, and prediction generation.
- **Database**: A relational database (e.g., PostgreSQL) for storing historical data and model outputs.
- **Cloud Infrastructure**: Cloud platforms (e.g., AWS, Google Cloud) for scalable computation and storage.

IV. Results

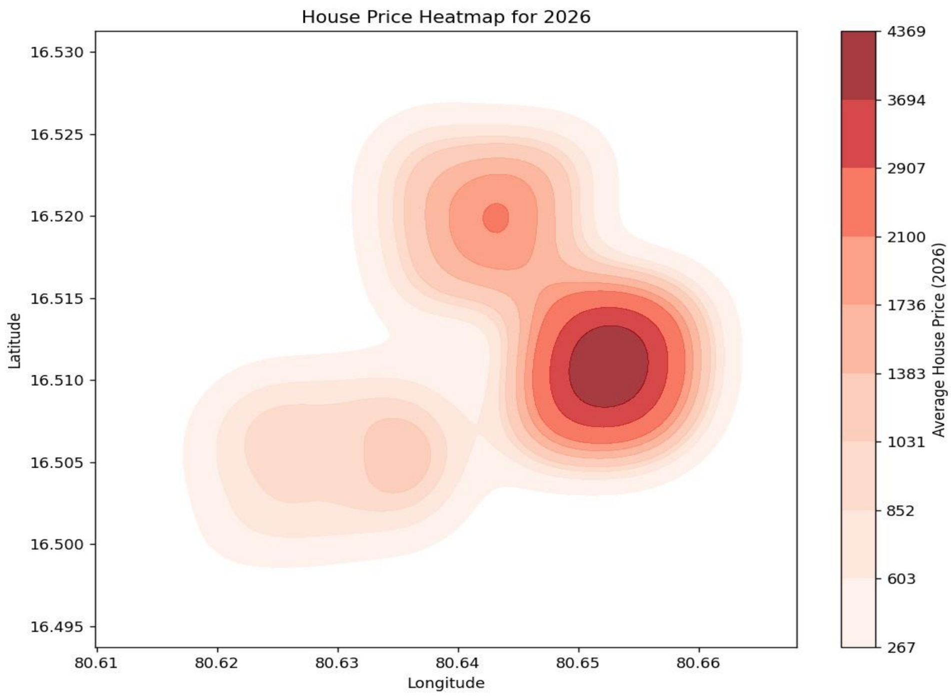

Fig – 1: Sub Region Layout

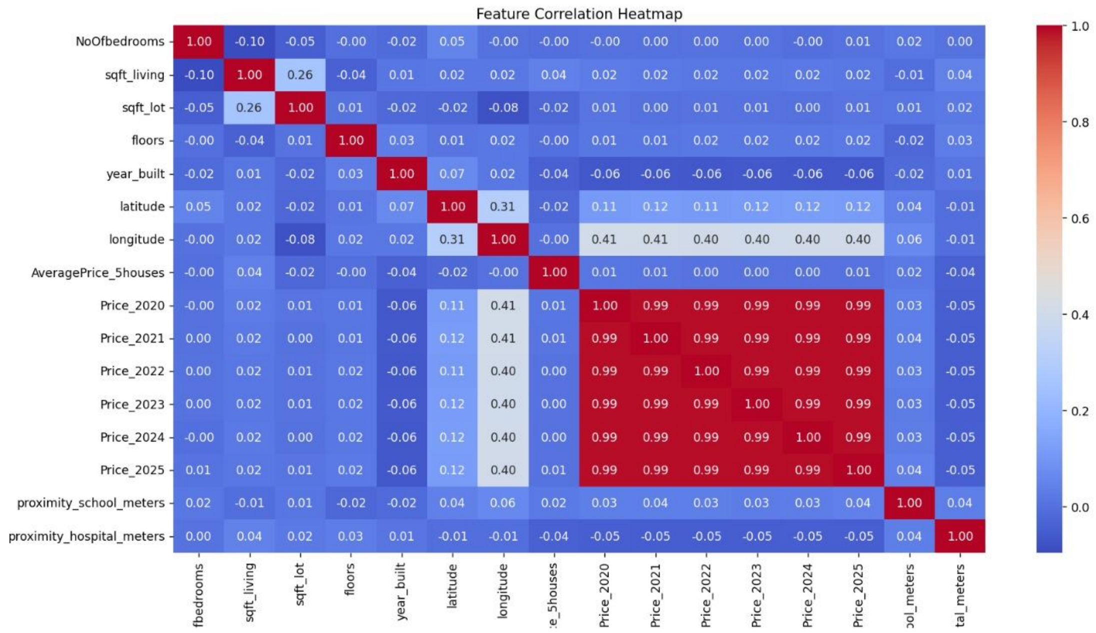

Fig – 2: Co – Relation Heatmap

Fig – 3: Growth pattern of house prices from historical data to future projections

V. Conclusion

The **Joint Gated Co-Attention Based Multi-Modal Network (JGC_MMN)** represents a significant advancement in fine-grained housing price prediction, addressing the limitations of traditional city-level models. By integrating long-term trends, short-term fluctuations, current economic conditions, and future price-growth expectations, the proposed system provides accurate and localized predictions for urban subregions. The use of a modified DenseNet architecture and a novel Joint Gated Co-Attention (JGC) fusion mechanism ensures robust performance even on sparse datasets, while the modular design ensures scalability and adaptability to other spatiotemporal prediction tasks. Extensive evaluation on real-world datasets demonstrates the system's superior accuracy and reliability compared to state-of-the-art baselines. This work not only advances the field of housing price prediction but also offers a valuable tool for urban planners, real estate investors, policymakers, and homebuyers, enabling more informed decision-making and optimized urban development. Future work will focus on extending the model to other domains, such as air quality prediction and traffic flow forecasting, further enhancing its applicability and impact.

REFERENCES:

1. **Pace, R. K., Barry, R., Clapp, J. M., & Rodriquez, M. (1998)**. "Spatiotemporal autoregressive models of neighborhood effects." *Journal of Real Estate Finance and Economics, 17(1), 15-33.*
2. **Kuethe, T. H., & Pede, V. O. (2011)**. "Regional housing price cycles: A spatio-temporal analysis using US state-level data." *Regional Studies, 45(5), 563-574.*
3. **Fotheringham, A. S., Crespo, R., & Yao, J. (2015)**. "Exploring, modelling, and predicting spatiotemporal variations in house prices." *Annals of Regional Science, 54(2), 417-436.*
4. **Fan, G. Z., Ong, S. E., & Koh, H. C. (2006)**. "Determinants of house price: A decision tree approach." *Urban Studies, 43(12), 2301-2315.*
5. **Limsombunchai, V. (2004)**. "House price prediction: Hedonic price model vs. artificial neural network." *New Zealand Agricultural and Resource Economics Society Conference.*
6. **Chen, X., Wei, L., & Xu, J. (2017)**. "House price prediction using LSTM." *arXiv preprint arXiv:1709.08432.*
7. **Wang, F., Zou, Y., Zhang, H., & Shi, H. (2019)**. "House price prediction approach based on deep learning and ARIMA model." *IEEE 7th International Conference on Computer Science and Network Technology.*
8. **Meese, R., & Wallace, N. (2003)**. "House price dynamics and market fundamentals: The Parisian housing market." *Urban Studies, 40(5-6), 1027-1045.*

9. **Bin, O. (2004)**. "A prediction comparison of housing sales prices by parametric versus semi-parametric regressions." *Journal of Housing Economics, 13(1), 68-84.*
10. **Lim, W. T., Wang, L., Wang, Y., & Chang, Q. (2016)**. "Housing price prediction using neural networks." *12th International Conference on Natural Computation, Fuzzy Systems, and Knowledge Discovery.*
11. **Zhang, J., Zheng, Y., Qi, D., Li, R., & Yi, X. (2016)**. "DNN-based prediction model for spatiotemporal data." *24th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems.*
12. **Zhang, J., Zheng, Y., & Qi, D. (2017)**. "Deep spatio-temporal residual networks for citywide crowd flows prediction." *AAAI Conference on Artificial Intelligence.*
13. **Szegedy, C., Ioffe, S., Vanhoucke, V., & Alemi, A. A. (2017)**. "Inception-v4, Inception-ResNet, and the impact of residual connections on learning." *31st AAAI Conference on Artificial Intelligence.*
14. **Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017)**. "Densely connected convolutional networks." *IEEE Conference on Computer Vision and Pattern Recognition.*
15. **Glaeser, E. L., Gyourko, J., Morales, E., & Nathanson, C. G. (2014)**. "Housing dynamics: An urban approach." *Journal of Urban Economics, 81, 45-56.*
16. **Caplin, A., & Leahy, J. (2011)**. "Trading frictions and house price dynamics." *Journal of Money, Credit, and Banking, 43, 283-303.*
17. **Wu, B., Li, R., & Huang, B. (2014)**. "A geographically and temporally weighted autoregressive model with application to housing prices." *International Journal of Geographical Information Science, 28(5), 1186-1204.*
18. **Helbich, M., & Griffith, D. A. (2016)**. "Spatially varying coefficient models in real estate: Eigenvector spatial filtering and alternative approaches." *Computers, Environment, and Urban Systems, 57, 1-11.*
19. **Shim, J., Hwang, C., & Wen, F. (2018)**. "Kernel-based geographically and temporally weighted autoregressive model for house price estimation." *PLoS ONE, 13(10), e0205063.*
20. **Glaeser, E. L., & Nathanson, C. G. (2017)**. "An extrapolative model of house price dynamics." *Journal of Financial Economics, 126(1), 147-170.*