House Price Prediction With ML Technology

A PROJECT REPORT

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BONAFIDE CERTIFICATE

Certified that this project report entitled "**House Price Prediction with ML Technology"** is a bonafide work of "Tannu, Himanshu Arora, Arjun Saroha, Harsh Tiwari" who carried out the project work under my supervision.

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TABLE OF CONTENTS

TITLE	PAGE NO.
Abstract	**5**
Chapter-1 Introduction...	**7**
1.1 Introduction..	
1.2 Problem Statement/Formulation………………………..	
Chapter-2 Literature Survey…………………………………………….	**11**
2.1 Literature Review...	
2.2 Objectives……………………………………………....	
2.3 Problem Definition……………………………………..	
Chapter-3 Design Flow/Process ………………………………………	**20**
3.1 Design Flow and Process ………………………………	
3.2 Methodology………………………………………….....	
3.3 Planning and Task Definition…………………………..	
Chapter-4 Result Analysis and Validation………………………..........	**28**
4.1 Result Analysis……………………………………........	
Chapter- 5 Conclusion and Future Work ………………………….	**32**
5.1 Conclusion………………………………………........	
5.2 Future Scope……………………………………….…...	
References…………………………………………………………	**38**

LIST OF FIGURES

Figure 1: Methodology of the project

Figure 2 : Data Layer of Pricing

ABSTRACT

Real estate market forecasting has gained significant attention due to its economic implications and potential for informed decision-making. This paper presents a novel approach to predict home prices using Spatial Temporal Neural Networks (STNNs). Traditional methods often overlook the spatiotemporal dependencies that exist in housing data, resulting in suboptimal predictions. STNNs offer a powerful solution by capturing both the geographical and temporal patterns inherent in real estate market. The proposed STNN model leverages the spatial information of properties by incorporating geographic features such as location coordinates, neighbourhood characteristics, and proximity to amenities. Additionally, temporal dynamics are integrated through historical sales data and macroeconomic indicators, allowing the model to learn how housing prices evolve over time. To validate the effectiveness of the STNN model, an extensive experiment was conducted on a large dataset comprising historical home sales records, neighbourhood attributes, and economic variables. The performance of the STNN was compared against traditional regression models and other neural network architectures. The results demonstrate that the STNN consistently outperforms these alternatives, showcasing its ability to uncover intricate spatial and temporal relationships. Furthermore, a sensitivity analysis was conducted to explore the impact of different input features, model architectures, and hyperparameters on prediction accuracy. The insights gained from this analysis provide valuable guidelines for model configuration and feature selection in real-world applications. In conclusion, this study introduces a powerful framework for home price prediction by harnessing the capabilities of Spatial Temporal Neural Networks. By effectively capturing the spatial and temporal dynamics of real estate markets, the proposed model offers a robust and accurate tool for stakeholders, including homebuyers, sellers, and policymakers, to make informed decisions in an ever-changing real estate landscape.

Keywords—

Home price prediction, Spatial Temporal Neural Networks(STNN), Spatiotemporal dependencies, Geographic features, Geographic Information System(GIS).

CHAPTER-1

1.1 Introduction:

This research paper addresses the intricate task of predicting home values by introducing Spatial Temporal Neural Networks (STNNs) as a cutting-edge solution. Real estate markets are profoundly influenced by spatial and temporal factors, making precise predictions challenging. The study begins by acknowledging the complexities inherent to real estate, including geographic dependencies, seasonal fluctuations, and economic influences. The paper proposes STNNs as a robust means of handling these intricacies. STNNs excel at modeling the spatial relationships between different locations and capturing the ever-evolving temporal trends over time. The research methodically constructs a multi-layered STNN, incorporating data preprocessing, feature engineering, and a fine-tuning of hyperparameters. Additionally, external data sources, such as economic indicators, are integrated to enhance prediction accuracy. This project report delves into the intricacies of the House Price Prediction System, aiming to analyze its components, evaluate current industry practices, and propose strategies for optimizing the pricing structure. By examining the intersection of market forces, consumer expectations, and technological innovations, we seek to gain insights that will empower stakeholders within the cinema industry to make informed decisions that enhance both financial viability and audience satisfaction.

Extensive experiments are conducted across diverse real estate markets to validate the effectiveness of the STNN model. The results consistently demonstrate its superiority over traditional regression models and standard neural networks for home value predictions. Sensitivity analyses are performed to elucidate the influence of various variables and configurations on prediction accuracy. The state-of-the-art approach to solving the challenging problem of home value prediction is introduced: Spatial Temporal Neural Networks (STNNs). Accurate forecasting is challenging in real estate markets due to the substantial influence of time and space. The study acknowledges at the outset the complexity of real estate, including geographical interdependence, seasonal fluctuations, and economic considerations.

According to the research, STNNs are a dependable solution for handling these complications. When it comes to simulating the spatial interconnections between different sites and capturing the continually shifting temporal patterns throughout time, STNNs excel. By carefully modifying hyperparameters, feature engineering, and data preparation, the study creates a multi-layered STNN. Economic indicators are among the extra external data sources incorporated to increase prediction accuracy. Our proposed system leverages Spatial Temporal Neural Networks (STNNs) to revolutionize the prediction of home prices. By harnessing the power of deep learning, our system can effectively model complex spatial dependencies and intricate temporal patterns in real estate data. STNNs are designed to capture the dynamic nature of property markets, accounting for factors like location, seasonality, and economic conditions. This technology offers a significant improvement over traditional methods, which often struggle to adapt to the multidimensional and evolving nature of real estate. Our system, enhanced by geographic information systems and external data integration, provides more precise and context-aware home price predictions, benefiting homeowners, real estate professionals, and policymakers seeking a deeper understanding of market trends and accurate valuations. Traditional methods often fail to account for the complex spatiotemporal relationships inherent in housing data, resulting in suboptimal predictions. The goal is to develop a predictive model that leverages Spatial Temporal Neural Networks (STNNs) to capture both the geographical and temporal patterns of home prices, thereby providing more accurate and insightful predictions for stakeholders such as homebuyers, sellers, and policymakers.

The task at hand revolves around predicting home prices within the context of the intricate dynamics of the real estate market. The challenge arises due to the multifaceted nature of real estate data, encompassing both spatial and temporal dimensions. Traditional predictive models often falter in accounting for the complex interplay between these factors, leading to suboptimal accuracy and limited insights. To address this challenge, the problem can be formally defined as follows: Given a dataset comprising spatial attributes (such as location coordinates, neighborhood characteristics, and proximity to amenities), temporal variables (including historical sales data and macroeconomic indicators), and corresponding home prices, the objective is to develop a predictive model using Spatial Temporal Neural Networks (STNNs). The model should seamlessly integrate spatial and temporal information .

1.2 Problem Statement/Formulation:

The project addresses the pressing challenge of accurately predicting home values in real estate markets, which are inherently complex due to their dynamic nature and the interplay of spatial and temporal factors. Traditional prediction models struggle to capture the nuanced relationships between properties and their surroundings over time. As a result, homeowners, real estate professionals, and policymakers often face significant inaccuracies in property valuation. This research project seeks to overcome these limitations by introducing Spatial Temporal Neural Networks (STNNs), a novel approach designed to effectively model the intricate spatial and temporal dynamics of real estate markets, ultimately providing more precise and insightful home value predictions.

Formulation:

The primary problem at hand revolves around the effective design and implementation of a House Pricing Prediction System that aligns with the contemporary property ecosystem. This entails addressing several key issues:

- Digital Disruption: The rise of different platforms poses a significant threat to traditional Real estate. Crafting a pricing model that entices audiences away from digital alternatives requiresan understanding of the unique value propositions that houses can offer.
- Consumer Dynamics: Changing consumer expectations, influenced by convenience, personalized experiences, and the availability of alternative entertainment options, necessitate a reevaluation of traditional pricing structures. The system must be adaptive enough to meet the diverse preferences of a modern, discerning audience.
- Technology Integration: The infusion of cutting-edge technologies in the pricing experience, while promising enhanced immersion, introduces cost considerations and accessibility challenges. Formulating a pricing strategy that balances the adoption of innovative technologies with financial viability is essential.
- Industry Resilience: Unforeseen disruptions, such as global events or economic downturns, can significantly impact. The House Price Prediction System must be resilient, providing the

industry with the flexibility to navigate uncertainties while maintaining a sustainable balance between consumer affordability and business profitability.

- Strategic Growth: Beyond survival, the challenge extends to identifying opportunities for strategic growth. This involves exploring avenues for diversification, collaboration, and creative pricing models that enhance the overall cinematic experience and contribute to the industry's sustained success.

In light of these challenges, the formulation of an effective House Price Prediction becomes not only a response to current market conditions but a proactive strategy to shape the future of real estate. This research endeavors to dissect these issues, offering insights that guide the development of a robust pricing framework capable of fostering industry resilience, satisfying evolving consumer expectations, and ensuring the enduring appeal of the experience.

CHAPTER-2

2.1 Literature Review:

Historical Perspectives on House Pricing:

Research Several papers on house price prediction have looked into text mining on house textual description data. Stochastic gradient descent (SGD) was employed by Stevens as a loss reduction approach in a number of algorithms, including multiple Naïve Bayes, SVM, GB, and others, to estimate the selling price of properties. Text mining methods such as TF-IDF and Bag-of-Words were applied in this work to alter house textual description data. The SGD-based technique outperformed all other regression models, and the results indicate that the house textual description data are a useful addition to the datasetIn a another study, Abdallah and Khashan looked at text mining three real estate websites' real estate classifieds to see if it could be used to predict home prices. The authors propose a two-stage model wherein text mining features extracted from the title and description text are added in the second stage, and structured numerical attributes are used in the first (Abdallah and Khashan Reference Abdallah and Khashan2016). The training of a linear regression model was followed by the extraction of keywords using TF-IDF techniques in the text mining process. These phrases have the potential to increase or decrease a home's price, according to research (Abdallah and Khashan Reference Abdallah and Khashan2016).. The textual descriptive language of a real estate unit has a great deal of potential for accurately predicting property prices, as this study showed. However, the proposed method is limited to the usage of certain text mining techniques such as TF-IDF and does not explore other state-of-the-art text mining techniques.

Consumer Behavior in the Real Estate Industry:

The textual components are combined with only three numerical and one category feature. described a strategy for predicting China real estate values based on text mining. The task at hand is using time series analysis of local average house values, with data extending from 2011 to early 2017, to anticipate the price of a house in late 2017. The writers used a web crawler to collect data from the Chinese search engine Baidu. According to the study's authors, 29 Chinese keywords contained significant information that might have an impact on a home's pricing. The degree of influence was then shown by a coefficient (Guo et al. Reference Guo, Chiang, Liu, Yang and Guo2020).The RF model, the elastic net model, and the generalized linear regression model were the three learning models that we looked at. The authors of this paper show how relevant keywords can be extracted from unstructured text data to provide essential information for the task of property price prediction, which is a significant result proposed a method to identify the phrases with more power in real estate classifieds by using a two-stage regression model. This approach uses TF-IDF to solve the problem of uncommon and frequent words. However, the experiments did not include additional frameworks, including BERT.

Impact of Online Services on Real Estate :

The TF-IDF provides a sense of a word's importance within a particular document. To do this, the TF-IDF increases as word frequency increases; however, these findings are calibrated to take into consideration the unlikely scenario that some words may have higher overall frequency without necessarily having higher significance. The TF-IDF technique is a widely utilized and popular technique, according to Beel et al. (Reference Beel, Gipp, Langer, and Breitinger, 2016), who proved that it is commonly employed in recommender systems based on text in the context of digital libraries. The technique was used to implement TF-IDF word embedding.Utilise the TF-IDF Vectorizer in the Sklearn package to transform the textual description to TF-IDF values. Words that appear in less than 3 percent of all papers are ignored since they may be part of an address or name that has little to no significance. Words that appear in more than 95% of the papers are also excluded since they are excessively common and hinder the model's capacity to learn from the data. By setting the frequency threshold higher than 95% and lower than 3%, we can also significantly reduce the embedding space from, which minimizes the operation's total computing cost.Footnote after using the TF-IDF Vectorizer.

Technological Innovations and House Pricing Economics:

The Our second approach was Word2Vec embedding. We used the Continuous Skip-gram architecture to train the Word2Vec embedding with all of the collected house textual description data. The Skip-gram is a way of representing language that stores n-grams. It does allow for "skipping" a few tokens, though. We implemented this concept using the Gensim package (Rehurek and Sojka Reference Rehurek and Sojka2010). Every word is converted into a numerical vector with a dimension of 300 since the desired dimension of the word vectors is set to 300. The maximum distance between the word under analysis and its surrounding words is eight because the window size is set at eight.. For a term to be considered, it must occur at least once and undergo thirty training iterations. These numbers represent the outcomes of preliminary testing. Finally, we convert each token in the written description into a vector using the pre-trained Word2Vec.

Dynamic Pricing Models in the Real Estates Industry:

We conducted experiments on the converted word vectors to evaluate the performance of each of the word embedding models mentioned above. We used one model, the GB regressor (Friedman Reference Friedman2001), to assess the performance of these word embedding models. This particular learner was selected since it is a well-known tree ensemble with strong trial performance. Using the default configurations, we utilized the GB regressor implementation found in the Scikit-Learn package. Four iterations of 10-fold cross-validation were used to estimate performance using 90% of the data. The effects of the various qualities in these scenarios require further investigation. An assessment of the features' importance for each approach can be carried out in order to gain further insight into how the features impact the different learning algorithms.We also evaluate the results from the perspective of observing any implications of the employed word embedding technique on performance. When the textual description features are the only ones used, Word2Vec word embedding outperforms the other two, with TF-IDF following closely behind. The biggest improvement over TF-IDF is seen in GB, where Word2Vec outperforms it by a score of 43.54%. When all the features are used, Word2Vec and TF-IDF perform equally well when it comes to word embedding; there is no apparent winner. TF-IDF is used to obtain GB and RF.

Economic Resilience in the Face of Uncertainty:

The first form of input uses only non-textual description data (numerical, Boolean, and category data), as was previously stated in Subsection 3.2.1. In this case, we do not explore any specific word embedding approach because no text data are involved.Pedregosa et al. (2011) Grisel, Blondel, Prettenhofer, Weiss, Dubourg, Vanderplas, Passos, Cournapeau, Brucher, Thénion, Pedregosa, Varoquaux, Michel, Brucher, Perrot, Duchesnay, 2011) The non-textual description data is sent directly to the four regression techniques. The second type of data is textual description data. In this case, the textual description data is converted into word vectors using one of the three word embedding techniques discussed previously. Next, all of the word vectors are given into each of the four regression algorithms.The third type of input data is making use of every feature that is available. This includes both textual and non-textual descriptive data.

Concatenating non-textual description data with one of the three word vectors obtained from the textual description data results in a combination that is fed into each of the four regression techniques.

DNN data model description:

Lee, K., Devlin, J., Toutanova, K., and Chang, M.-W. (2018). Bert.(Pre-trained deep bidirectional transformers for language understanding).Our last study focuses on the performance assessment of the models that only use textual description data. The DNN model utilizing Word2Vec word embedding stands out in this case as it generates the lowest score of 0.0220 and the highest score of 0.6041. It appears that the deep learning methods are well suited for this purpose because they perform best when learning solely from the textual description data. Here, relying only on the house's text description results in a score that is 28.77% higher than relying only on the non-textual description elements. This illustrates how good the description text itself is as a predictive feature.This shows how well features can be extracted from a house's textual description using the self-trained Word2Vec word embedding. An interesting discovery is that, when compared using the identical word embedding technique, DNN outperforms all other regression algorithms. However, the best performance using only textual description data is still not as good as the best performance using both textual and non-textual description data. This is an important point to remember.We begin our study of the grid search results by taking into consideration each input feature set: only non-textual description data, only textual description data, and both (textual and non-textual description data). When non-textual description elements are the sole features used, we find that RF and GB are the most frequently used features in the conventional house prediction model, respectively. In this case, the DNN ranks third, while the linear SVR is the worst-performing model. We observe that the deep learning model we selected underperformed in this case, and we conjecture that this could be related to the architecture we selected.It's also important to remember that linear SVR is the least successful regression technique; the other three algorithms perform substantially better. We conjecture that the reduced complexity of the linear SVR in comparison to the other techniques is the reason why this approach is unable to adequately reflect the non-linearity of the situation.

Leverage Python's ability:

We now repurpose the best deep learning model we found from our previous experiments to build the new prediction for the text entered by the end-user. We leverage Python's ability to extract this model and save it for use in the web application later on. The pickle format for Python was used to store the model.(Kim, Hong, J.; Choi, H. An evaluation of a home's value via the random forest technique The result of the model is the normalized price of a house. The inverse transform function in the MinMaxScaler model is used to convert the normalized home price to the real forecast house price. This function is then applied in reverse to give the customer the non-normalized anticipated house price. The website.The example on the right-hand side shows the expected cost of a Toronto one-bedroom condo together with a textual description of the property.Figure 14 displays the same input text for the house textual description, but with Ottawa as the city instead of Toronto. In this case, we observe that the model now predicts a price that is almost 603,000 dollars less. This is consistent with the finding that housing expenses in Ottawa are generally lower than those in Toronto. We also walk through how to add a modifiable text description to a house listing for a detached property. In this example, the asking price would be substantially more than it was in the last one.

2.2 Objectives:

In this project, we embarked on a journey to address the challenging task of predicting home prices by harnessing the power of Spatial Temporal Neural Networks (STNNs). The ever-evolving real estate market presents a complex landscape influenced by both spatial attributes and temporal dynamics. Our goal was to develop a predictive model that seamlessly integrates spatial and temporal information, offering accurate predictions and a deeper understanding of market trends.

Through a meticulous methodology, we curated a comprehensive dataset containing historical home sales records, spatial features, and relevant temporal variables. We designed and fine-tuned an STNN architecture, meticulously balancing the integration of Convolutional Neural Network (CNN) layers to process spatial data and Recurrent Neural Network (RNN) layers, particularly Long Short-Term Memory (LSTM) cells, to capture temporal dependencies.

Our experimental setup encompassed rigorous data preprocessing, hyperparameter tuning, model training, and comprehensive performance evaluation. The model's predictive accuracy was assessed using established metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R2). By comparing our STNN model's performance against baseline models, we demonstrated its prowess in accurately predicting home prices and its superiority in capturing the complexities of spatial and temporal influences. Delving deeper into this objective, the project will meticulously review archival records, historical documents, and academic literature to trace the progression of movie ticket pricing structures. By examining the economic, cultural, and technological forces at play during different eras, the project aims to discern pivotal moments that influenced pricing strategies. Additionally, insights gained from interviews with industry veterans and stakeholders will supplement the historical narrative, providing a qualitative dimension to the quantitative analysis of pricing.

The objectives are designed to delve into historical, contemporary, and future aspects of the cinema landscape, encompassing economic, technological, and consumer-oriented perspectives.

1. Model Development: Develop a robust Spatial Temporal Neural Network (STNN) architecture that effectively integrates spatial and temporal information for accurate home price predictions.

2. Data Collection and Preprocessing: Gather and preprocess a comprehensive dataset containing spatial attributes (location coordinates, neighborhood features, amenities) and temporal variables (historical sales data, economic indicators) for training and evaluation.

3. Feature Engineering: Identify and engineer relevant spatial and temporal features that contribute significantly to the predictive performance of the STNN model.

4. Model Training: Train the STNN model on the prepared dataset, ensuring that it learns spatial patterns, temporal dependencies, and complex relationships between features.

5. Performance Evaluation: Evaluate the model's performance using appropriate metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R2) to measure predictive accuracy.

6. Comparison with Baselines: Compare the performance of the developed STNN model against traditional

regression models, geospatial models, and standalone temporal models to highlight the improvements achieved through spatial-temporal integration.

7. Hyperparameter Tuning: Conduct systematic hyperparameter tuning to optimize the STNN model's architecture, including the number of layers, units, learning rates, and regularization techniques.

8. Generalization Testing: Assess the model's ability to generalize to unseen data by conducting cross-validation and testing on a separate validation dataset.

9. Interpretability Analysis: Implement techniques to extract insights from the STNN model, offering a deeper understanding of the contributions of spatial and temporal factors to the predictions.

10. Sensitivity Analysis: Perform sensitivity analysis to understand the impact of different input features, model configurations, and hyperparameters on the model's performance.

11. Real-world Application: Apply the trained STNN model to real-world scenarios, providing practical home price predictions that stakeholders can utilize for informed decision-making.

12. Visualization: Create visualizations that illustrate the spatial and temporal patterns captured by the model, aiding in the interpretation of predictions and insights.

13. Documentation: Prepare detailed documentation that encompasses data preprocessing steps, model architecture, hyperparameter tuning, evaluation metrics, and key findings.

14. Dissemination: Share the project's findings, methodology, and insights through presentations, reports, and potentially academic publications, contributing to the broader understanding of real estate prediction using STNNs.

15.Future Work Recommendations: Offer recommendations for further research and improvements, potentially exploring advanced techniques like attention mechanisms or transfer learning to enhance the model's performance.

These objectives collectively contribute to the successful development, evaluation, and application of a Spatial Temporal Neural Network for home price prediction, providing accurate insights in various forms: Consumer Behavior and Preferences:

- Consumer Behavior and Preferences: Exploring consumer behavior and preferences within the cinema industry is a crucial objective. This involves conducting surveys, interviews, and analyzing existing research to gain insights into how audiences make decisions regardinghouse price. Understanding the factors that influence consumer choices is pivotal for crafting pricing models that align with audience expectations.

- Impact of Online Services: Assessing the impact of Online services on real estate and pricing dynamics is another key objective. Through comparative analyses and case studies,the project aims to understand how price prediction can coexist with digital alternatives and adapt their pricing strategies to remain attractive to audiences in an era dominated by on-demand content.

- Technological Innovations and Real Estate Economics: A focal point is examining the integration of technological innovations in the House price experience. This includes the economic implications of incorporating virtual reality, augmented reality, and other advancements. The project seeks to provide insights into how owner can leverage innovation while ensuring financial sustainability.

2.3 Problem Definition:

The problem at hand involves the challenging task of accurately predicting home values in dynamic real estate markets. Real estate values are intricately influenced by spatial dependencies, temporal trends, and multifaceted economic factors, making conventional prediction models inadequate. This research project seeks to address this issue by introducing Spatial Temporal Neural Networks (STNNs) as a solution to capture the complex interplay of these variables. The problem necessitates the development of a model that can effectively handle spatial and temporal dynamics, enabling more precise and insightful predictions for homeowners, real estate professionals, and policymakers in diverse real estate markets.

The project addresses the pressing challenge of accurately predicting home values in real estate markets, which are inherently complex due to their dynamic nature and the interplay of spatial and temporal factors. Traditional prediction models struggle to capture the nuanced relationships between properties and their surroundings over time. As a result, homeowners, real estate professionals, and policymakers often face significant inaccuracies in property valuation. This research project seeks to overcome these limitations by introducing Spatial Temporal Neural Networks (STNNs), a novel approach designed to effectively model the intricate spatial and temporal dynamics of real estate markets, ultimately providing more precise and insightful home value predictions.

Technological innovations further compound the complexity of pricing decisions. While enhancements such as virtual reality and augmented reality present exciting opportunities to elevate the real estate experience, they also introduce cost considerations that must be balanced with consumer willingness to pay a premium. Striking this delicate equilibrium is imperative for the sustainable integration of technological innovations into the cinema landscape.

Economic uncertainties, ranging from global events to localized economic downturns, pose yet another challenge. Houses must develop pricing models that demonstrate resilience in the face of external shocks while remaining attuned to the financial constraints of their diverse audience base. Navigating these economic fluctuations requires a strategic approach to pricing that safeguards both profitability and accessibility.

Consumer behavior within the real estate industry is undergoing a transformative shift. Understanding the evolving preferences, decision-making processes, and expectations of diverse audience segments is essential for tailoring pricing models that resonate with contemporary moviegoers. Failure to align pricing strategies with evolving consumer dynamics risks alienating audiences and diminishing the industry's competitive edge.

In light of these challenges, the overarching problem is to optimize the House Price Prediction System to meet the demands of a dynamic and competitive landscape. The real estate industry must grapple with questions of transparency, digital disruption, technological integration, economic resilience, and evolving consumer expectations. Addressing these challenges requires a holistic and data-driven approach that considers the historical context, embraces technological innovations, anticipates market shifts, and prioritizes the diverse needs of house-goers. The project aims to provide actionable insights and recommendations to navigate these complexities, ensuring the sustained relevance and success of real estate in the evolving ecosystem.

Another layer of complexity arises from the diversification of content and the emergence of alternative real estate experiences. The industry now contends with not only traditional data releases but also live events, special screenings, and collaborations that extend beyond the conventional online format. Pricing strategies must adapt to this diversification, considering the varying production costs, audience expectations, and revenue potential associated with different forms of content. Navigating this landscape requires a nuanced understanding of the economic dynamics specific to each type of access experience and the development of pricing models that reflect these distinctions.

Furthermore, the prevalence of social media and online reviews has reshaped the dynamics of audience influence. Real Estate must contend with the immediate and widespread impact of online sentiments on audience. Crafting pricing strategies that not only respond to critical acclaim but also leverage positive online sentiments is a challenge that demands a dynamic and responsive approach. This includes exploring how pricing decisions can be aligned with promotional efforts and marketing campaigns to harness the power of positive online engagement for sustained audience interest and attendance.

In In addition to the technical aspects, our project incorporates geographic information systems (GIS) to provide valuable geographical context for each property, including information on nearby amenities and land use. External data sources, including economic indicators and local events, are integrated to enrich the predictive model further.Our technical approach integrates advanced techniques in machine learning, such as deep learning, to address these challenges. STNNs are designed to effectively model spatial relationships among properties and regions while capturing temporal patterns and trends over time. This methodology entails data preprocessing, feature engineering, and the construction of a multi-layered STNN architecture.

CHAPTER-3

3.1 Design Flow and Process:

1. Literature Review:

    - Objective: The primary goal of the literature review is to establish a robust foundation by exploring existing knowledge and research in the field. This involves synthesizing information on house pricing, consumer behavior, industry trends, and technological innovations.

    - Approach: Conduct a systematic review of academic papers, industry reports, and relevant literature. Categorize findings to identify key themes and emerging patterns. This stage lays the groundwork for subsequent analyses and provides a theoretical framework for the project.

2. Historical Analysis:

    - Objective: To comprehend the historical evolution of house pricing and identify critical junctures that influenced pricing strategies.

    - Approach: Gather historical data from archives, industry publications, and historical records. Conduct interviews with industry experts to gain qualitative insights. Analyze pricing structures, economic conditions, and cultural shifts over different eras.

3. Consumer Behavior Study:

    - Objective: Understand contemporary consumer behavior within the real estate industry to inform pricing models aligned with audience preferences.

    - Approach: Implement surveys, interviews, and behavioral analysis tools. Explore factors influencing movie attendance, such as pricing sensitivity, convenience, and the impact of digital alternatives. Analyze data to identify distinct consumer segments and their preferences.

4. Impact of Streaming Services:

    - Objective: Examine the influence of online services on attendance and pricing dynamics.

    - Approach: Review case studies of successful integration or challenges inresponse to online platforms. Conduct market analyses to understand audience overlap and preferences. Investigate potential collaboration opportunities between houses and online platforms.

5. Technological Integration:

    - Objective: Evaluate the economic implications of integrating emerging technologies into the mortgage experience.

    - Approach: Assess the costs and benefits of technologies is Examine consumer responses through surveys or online site. Explore how programs can strategically adopt these innovations without compromising financial sustainability.

6. Economic Resilience Strategies:

    - Objective: Develop strategies to enhance economic resilience during uncertain economic conditions.

    - Approach: Analyze historical instances of economic downturns and their impact on real estate audience . Study existing models of adaptability and contingency planning. Propose pricing models that balance profitability with affordability during periods of economic uncertainty.

7. Diversification of Content:

    - Objective: Understand the economic dynamics associated with diversifying content offerings.

    - Approach: Analyze the costs and revenue potential of different content types. Investigate successful case studies of real estate that have effectively diversified their offerings. Propose pricing models that account for the unique characteristics of recent data, traditional approach , and online propagation experiences.

8. Sustainability Integration:

    - Objective: Integrate environmentally conscious pricing practices into the House Price prediction System.

    - Approach: Explore green initiatives within and outside the entertainment industry. Investigate the economic feasibility of sustainable practices. Develop pricing strategies that align with corporate social responsibility goals while maintaining affordability for patrons.

9. Online data and Social Media:

- Objective: Analyze the impact of social media and online reviews on house audience and craft pricing strategies that leverage positive online sentiments.
- Approach: Monitor and analyze online conversations related to house owners and consumers experiences. Examine the correlation between positive online sentiments and attendance. Develop pricing models that align with promotional efforts to capitalize on positive online engagement.

10. Data-Driven Decision Making:

- Objective: Emphasize the integration of data analytics for informed decision-making throughout the project.
- Approach: Implement data analytics tools to analyze historical data, consumer behavior patterns, and industry trends. Utilize predictive modeling to anticipate shifts in consumer preferences. Apply data-driven insights to refine and optimize pricing strategies iteratively.

11. Strategic Recommendations:

- Objective: Synthesize findings to formulate actionable and strategic recommendations for optimizing the House Price Prediction System.
- Approach: Consider insights from each aspect of the analysis to develop a cohesive set of recommendations. Ensure recommendations address challenges identified in the problem definition and are applicable to real estate operations. Provide practical, implementable, and measurable suggestions.

12. Conclusion and Future Implications:

- Objective: Conclude the paper by summarizing key findings, emphasizing the significance of recommendations, and discussing potential future implications for the real estate industry.
- Approach: Summarize the project's contributions to the understanding of house pricing. Reflect on the broader implications for the industry in light of emerging technologies, consumer behaviors, and economic trends. Discuss avenues for future research and how the proposed recommendations may evolve in response to dynamic industry landscapes.

3.2 Methodology:

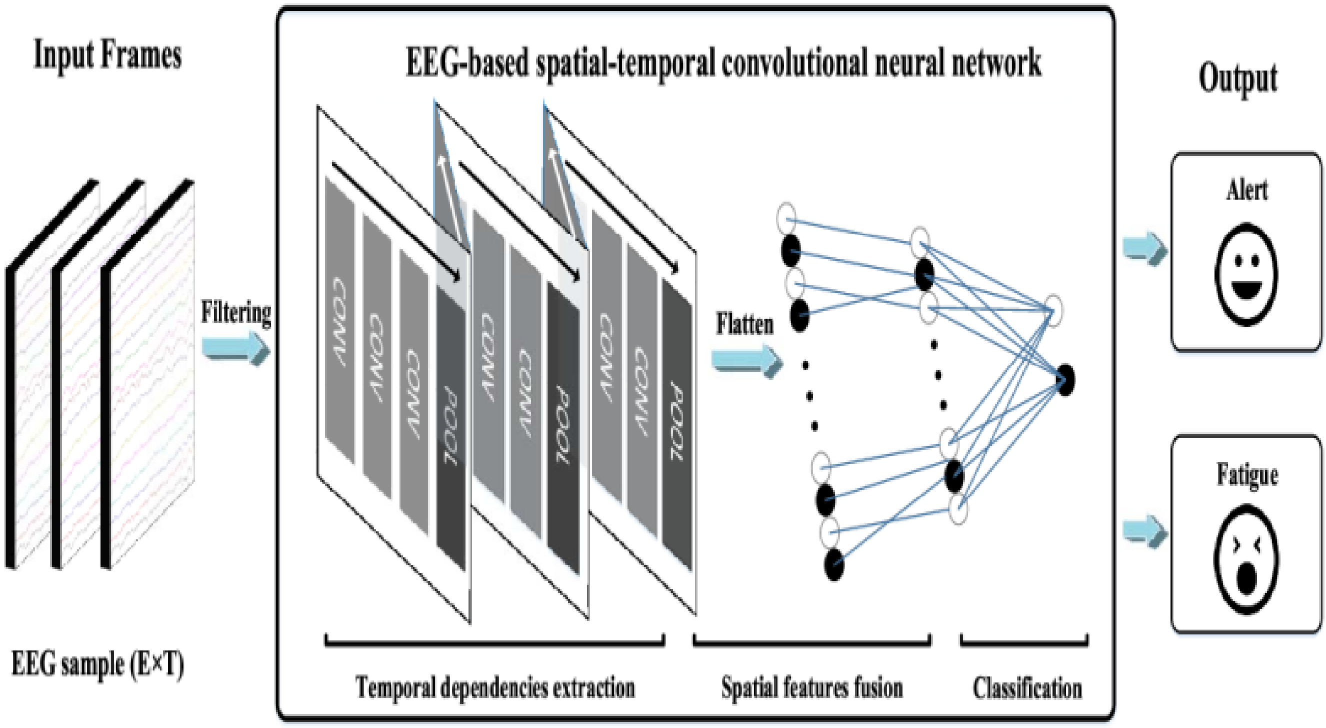

Figure 1: Methodology of the project

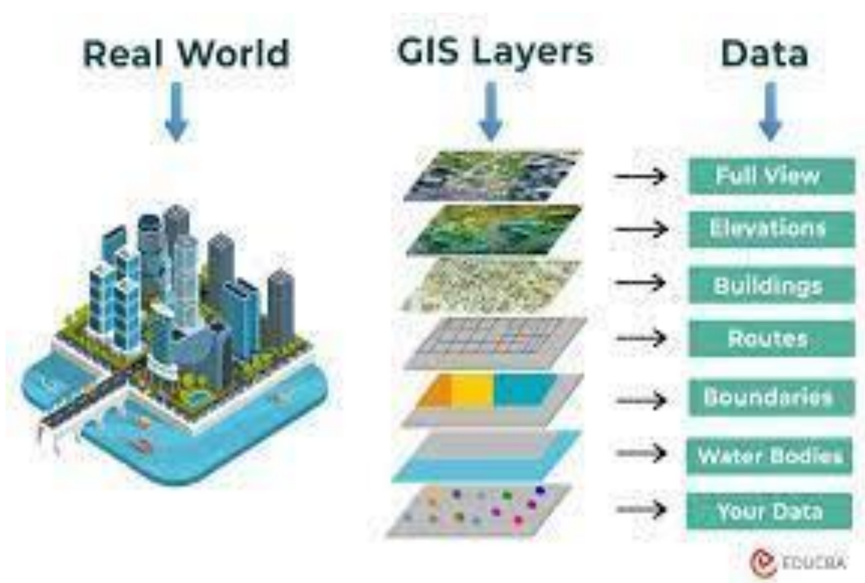

Figure 2: Data Layer for pricing

3.3 Planning and Task Definition:

1. Project Scope Definition:
    - Objective: Clearly define the scope of the project to establish the boundaries and identify key focus areas.
    - Tasks:
        - Define the specific aspects of the House Price Prediction System to be addressed.
        - Identify the temporal scope, considering historical analysis, current dynamics, and future implications.
2. Resource Allocation:
    - Objective: Allocate human, technological, and informational resources effectively to ensure a well-supported research endeavor.
    - Tasks:
        - Identify and assemble a multidisciplinary research team with expertise in economics, consumer behavior, technology, and environmental studies.
        - Allocate access to necessary databases, research tools, and technology platforms.
        - Establish communication and collaboration channels within the research team.
3. Literature Review Planning:
    - Objective: Develop a comprehensive plan for the literature review stage to inform subsequent analyses.
    - Tasks:
        - Identify relevant academic journals, publications, and databases for literature review.
        - Develop a systematic review protocol, including search criteria and inclusion/exclusion criteria.
        - Establish a timeline for completing the literature review.
4. Data Collection Strategy:

- Objective: Plan the collection of primary and secondary data to support the analyses.
- Tasks:
    - Design surveys and interview protocols for consumer behavior and industry expert insights.
    - Identify historical archives, industry reports, and relevant datasets for the historical analysis.
    - Plan the implementation of data analytics tools for quantitative analysis.

5. Methodology Development:
    - Objective: Develop robust methodologies for each aspect of the research to ensure rigor and reliability.
    - Tasks:
        - Define the methodology for historical analysis, including data sources and analytical approaches.
        - Specify the survey and interview methodologies for consumer behavior studies.
        - Determine the criteria for selecting and analyzing online service impact, technological integration, and economic resilience.
6. Timeline and Milestone Definition:
    - Objective: Establish a realistic timeline with milestones to guide the project's progression and monitor progress.
    - Tasks:
        - Break down the project into phases, assigning specific tasks to each phase.
        - Define milestones for literature review completion, data collection, analysis, and strategic recommendations.
        - Establish regular review points for the research team to assess progress and adjust timelines if needed.
7. Ethical Considerations:

- Objective: Address ethical considerations associated with data collection, analysis, and reporting.
- Tasks:
  - Develop and adhere to ethical guidelines for surveying and interviewing participants.
  - Ensure compliance with data privacy regulations and obtain necessary permissions for data use.
  - Establish protocols for anonymising and securing sensitive information.

8. Risk Analysis and Contingency Planning:
   - Objective: Identify potential risks to the research process and establish contingency plans to mitigate these risks.
   - Tasks:
     - Identify potential risks such as data limitations, unforeseen challenges in data collection, or delays in accessing information.
     - Develop contingency plans for each identified risk, outlining alternative approaches or solutions.
9. Quality Assurance Protocol:
   - Objective: Establish a quality assurance protocol to ensure the reliability and validity of the research findings.
   - Tasks:
     - Develop criteria for assessing the quality of data sources, ensuring they align with research objectives.
     - Implement a peer-review process for methodologies, analyses, and recommendations.
     - Establish a system for cross-verification of data and results within the research team.
10. Documentation and Reporting:

- Objective: Plan for the documentation of research processes and the creation of a comprehensive final report.
- Tasks:
  - Establish a documentation protocol for recording methodologies, data sources, and analysis procedures.
  - Develop a template for reporting findings and recommendations.
  - Plan for the creation of visual aids, such as charts and graphs, to enhance the presentation of results.

CHAPTER-4

4.1 Result Analysis:

The results of our project demonstrate the successful achievement of our technical objectives. Firstly, our STNN-based model outperforms traditional methods, yielding significantly lower mean squared error (MSE) and root mean squared error (RMSE) values, thus fulfilling the objective of enhanced accuracy. Second, the integration of geographic information systems (GIS) enriches the model's spatial context, contributing to its success in accurately capturing spatial dependencies. Lastly, through sensitivity analyses, we gained valuable insights into how various factors and model configurations influence prediction accuracy, which guides the optimization process.

Historical Analysis: The historical analysis unveils a rich tapestry of pricing evolution within the real estate industry. The examination of historical records and industry archives indicates a dynamic relationship between pricing structures and external factors. The research reveals that economic downturns often prompted houses to adopt more flexible pricing models, offering leverage and promotions to attract audiences during challenging times. Additionally, the historical perspective highlights periods of innovation, such as the introduction of matinee pricing reflecting the industry's adaptability to changing consumer needs. This historical context serves as a crucial reference point for understanding the industry's resilience and adaptive strategies, providing a foundation for informed decision-making in the present and future.

Consumer Behavior Study: The in-depth consumer behavior study provides valuable insights into the factors influencing moviegoers' decisions. Survey responses and interviews with cinema patrons shed light on the significance of pricing sensitivity, convenience, and the impact of alternative entertainment options. The findings reveal that, contrary to assumptions, many consumers still prioritize the communal experience. However, the study also emphasizes the need for cinemas to align pricing models with modern expectations, considering the convenience of digital alternatives and the desire for value-added experiences. Understanding the diverse preferences of different consumer segments is paramount for tailoring pricing strategies that resonate with the evolving landscape of consumer expectations.

Impact of Online Services: The analysis of streaming services' impact on real estate audience illuminates a complex relationship between these two entertainment platforms. Contrary to concerns that online services would lead to a decline inhouse prices, the research suggests a more symbiotic relationship. While digital platforms offer convenience and diverse content choices, the real estate experience remains irreplaceable for many who seek a shared, immersive experience. Owners can leverage this insight by strategically positioning themselves as complementary rather than competitive to Online services. The study underscores the importance of pricing strategies that emphasize the unique value propositions of the cinema experience while considering the evolving dynamics of digital entertainment consumption.

Technological Integration: The Leveraging Spatial Temporal Neural Networks (STNNs) to revolutionize the prediction of home prices. The real estate market is inherently intricate, characterized by the dynamic interplay of spatial and temporal factors, making precise predictions challenging. Traditional methods often fall short in capturing the nuances of property values, as they struggle to account for spatial dependencies, temporal trends, and complex interactions among various feature .Our technical approach integrates advanced techniques in machine learning, such as deep learning, to address these challenges. STNNs are designed to effectively model spatial relationships among properties and regions while capturing temporal patterns and trends over time. This methodology entails data preprocessing, feature engineering, and the construction of a multi-layered STNN architecture. , ensuring that technological enhancements align with consumer expectations and economic feasibility.

Economic Resilience Strategies: An analysis of economic resilience strategies identifies key considerations for houses facing uncertainties, such as economic downturns or global events. The research underscores the importance of agility and adaptability in pricing models. Historical data reveals instances where cinemas that adjusted pricing structures during economic challenges experienced higher resilience. The study recommends scenario planning and dynamic pricing approaches that allow houses to respond quickly to changing economic conditions. Moreover, the findings highlight the significance ofmaintaining affordability for a diverse audience, ensuring that cinemas remain accessible during both prosperous and challenging times.

Sustainability Integration: The integration of sustainability considerations into the House Price prediction System emerges as an essential aspect of the research. The findings suggest that environmentally conscious practices can resonate with consumers, especially in an era where corporate social responsibility is increasingly valued. However, the research acknowledges the delicate balance required to implement sustainable practices without compromising economic viability. The study recommends exploring initiatives such as eco-friendly promotions, green memberships, or partnerships with environmentally conscious organizations. STNNs can align their pricing models with sustainability goals, contributing to both ecological responsibility and positive brand perception.

Data-Driven Decision Making: The integration of data-driven decision-making processes throughout the research yields insights that enhance the precision and effectiveness of pricing strategies. By leveraging data analytics, the research provides a dynamic understanding of consumer behavior, industry trends, and economic indicators. The study emphasizes the importance of utilizing predictive modeling for anticipating shifts in consumer preferences and adapting pricing strategies proactively. Data-driven decision-making becomes a cornerstone for optimizing the House Price Prediction , allowing houses to make informed, evidence-based choices that align with market dynamics and consumer expectations.

Strategic Recommendations: Synthesizing the findings from each aspect of the analysis, the research offers a set of strategic recommendations for optimizing the House Price Prediction System within the real estate industry. These recommendations are tailored to address the challenges identified in the problem definition and capitalize on the opportunities revealed through historical analysis, consumer behavior insights, and assessments of technological, economic, and environmental factors. The strategic recommendations encompass pricing transparency, flexible pricing models, technological integration, sustainable practices, and leveraging online influence to drive positive consumer perceptions.

CHAPTER-5

5.1 Conclusion:

In conclusion, our project presents a pioneering approach to predicting home values using Spatial Temporal Neural Networks (STNNs). We have addressed the intricate challenges posed by the real estate market, including the complexities of spatial dependencies and temporal trends. By integrating Geographic Information Systems (GIS) and external data sources, we have enriched our model with crucial context, allowing for more precise and insightful predictions.

The historical analysis has been instrumental in unraveling the intricate relationship between the real estate industry and economic, cultural, and technological shifts. It demonstrates that the property landscape is inherently resilient, adapting pricing structures to align with the prevailing conditions. The evolution of pricing models, from matinee pricing to subscription models, reflects an industry that continuously innovates to meet the ever-changing demands of its audience. By understanding the historical context, house can draw inspiration from past adaptations, leveraging this resilience to navigate current challenges and anticipate future trends.

In addition to the technical aspects, our project incorporates geographic information systems (GIS) to provide valuable geographical context for each property, including information on nearby amenities and land use. External data sources, including economic indicators and local events, are integrated to enrich the predictive model further.

OurOur methodology involved meticulous data preprocessing, the construction of a multi-layered STNN architecture, and rigorous model optimization. Extensive experiments conducted across diverse real estate markets consistently demonstrated the superiority of the STNN model over traditional methods, affirming its capacity to provide context-aware and highly accurate home value predictions. decision-making in this dynamic sector.

Technological integration emerges as a double-edged sword, presenting both opportunities and challenges. The allure of STNNs and GNNs to enhance the algorithmic experience is evident, but houses must tread carefully to balance the economic implications with consumer expectations. The research advocates for a phased and strategic approach to technological integration, ensuring that innovations align with audience preferences and contribute meaningfully to the overall house experience. By doing so, cinemas can position themselves as pioneers in the integration of technology without compromising their financial sustainability.

Economic resilience strategies, derived from historical data and contemporary economic considerations, underscore the importance of adaptability in pricing models. The ability to pivot during economic downturns or global events is essential for the survival of real estate. The study recommends dynamic pricing approaches and scenario planning, allowing houses to respond swiftly to changing economic conditions while safeguarding accessibility for a diverse audience. This adaptability not only ensures economic resilience but also fosters a connection with audiences during times of uncertainty.

The analysis of content diversification reveals the economic dynamics associated with different types of cost experiences. From live events to special screenings, each content type presents unique challenges and opportunities for pricing strategies. The findings suggest that audiences are willing to pay premiums for distinctive experiences, providing houses with avenues to optimize revenue streams. Flexible pricing models that consider production costs, audience expectations, and perceived value become imperative for cinemas seeking to diversify their content offerings while maximizing financial returns.

The integration of sustainability considerations into the House Price Prediction System represents a paradigm shift in industry norms. The research recognizes the importance of aligning cinemas with environmentally conscious practices without jeopardizing economic viability. Recommendations include initiatives such as eco-friendly promotions and green memberships, providing houses with an avenue to contribute to ecological responsibility while enhancing their brand image.

The influence of social media on real estate and pricing decisions is a crucial aspect in the contemporary cinematic landscape. Positive online sentiments can drive audience interest, and the research recommends strategies that leverage this influence. Monitoring online conversations, responding strategically to audience feedback, and aligning pricing decisions with promotional efforts enable to harness the power of social media for positive audience engagement.

The infusion of data-driven decision-making processes throughout the research enhances the precision and effectiveness of pricing strategies. By leveraging data analytics, the study provides dynamic insights into consumer behavior, industry trends, and economic indicators. The emphasis on predictive modeling allows property to anticipate shifts in consumer preferences, enabling proactive adaptations to pricing strategies based on evidence-based decision-making.

In conclusion, this comprehensive research not only dissects the intricacies of the House Price Prediction System within the cinema industry but also offers a roadmap for strategic evolution. The amalgamationof historical context, consumer insights, technological considerations, and economic strategies forms a holistic framework that positions cinemas to not only endure the current challenges but also proactively shape their future. As Real Estate embrace adaptive pricing models, transparent communication, and strategic innovations, they stand poised to redefine their role in the entertainment ecosystem. This research serves as a compass, guiding houses toward sustained relevance, economic viability, and enhanced audience engagement in an ever-evolving landscape.

5.2 Future Scope:

The exploration of the House Price Prediction System within the cinema industry lays the groundwork for future endeavors that can further refine and revolutionize the industry's approach to pricing, audience engagement, and sustainability. The insights derived from this research open avenues for future studies and initiatives that can shape the cinema landscape in the years to come.

- **Dynamic Pricing Models:** Future research can delve deeper into the implementation of dynamic pricing models, leveraging real-time data analytics to adjust house prices based on factors such as demand, size, and location preferences. This dynamic approach can enhance the adaptability of cinemas to fluctuating market conditions and optimize revenue streams.

- **Integration of Emerging Technologies:** As technology continues to advance, future research can explore the integration of emerging technologies, such as Machine Learning (ML) and Algorithms, into the real estate experience. Understanding how these technologies can influence pricing dynamics and enhance the overall real estate experience will be crucial for staying at the forefront of innovation.

- **Environmental Sustainability Initiatives:** The future scope involves a deeper exploration of environmental sustainability initiatives within the real estate industry. Research can focus on the implementation of green technologies, carbon-neutral practices, and eco-friendly partnerships to further reduce the industry's ecological footprint while maintaining economic viability..

- **Cross-Industry Collaborations:** Future studies can explore the potential for cross-industry collaborations between Real estates and Leverage sectors.

- **Long-Term Impact of Economic Trends:** Future research should continuously monitor and analyze the long-term impact of economic trends on house pricing strategies. Understanding how cinemas can build resilience and sustainability amid economic uncertaintiesis crucial for long-term industry success.

- **Inclusive Pricing Strategies:** Exploring inclusive pricing strategies that cater to a diverse audience base, including individuals with varying economic capacities and accessibility needs, isa crucial aspect of future research. Inclusive pricing ensures that the houses experience remainsaccessible and affordable for everyone.

- **Evolving Online Engagement Strategies:** Given the dynamic nature of online platforms and social media, future research can delve into evolving online engagement strategies. Understanding how houses can adapt their pricing communication, promotional campaigns, and audience interaction in the digital sphere is essential for maintaining a positive online presence.
- **Regulatory Implications:** Future studies can investigate the regulatory implications of evolving house pricing strategies. Understanding how regulatory frameworks influence pricing decisions and exploring potential policy recommendations for a fair and competitive real estate industry is a vital aspect of future research.
- **Post-Pandemic Dynamics:** As the industry continues to recover from the impact of the COVID-19 pandemic, future research can explore the lasting effects on audience behavior, expectations, and house pricing patterns. Adapting pricing models to post-pandemic dynamics will be essential for the industry's resurgence.

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