Deep Learning Model for House Price Prediction Using Heterogeneous Data Analysis Along With Joint Self-Attention Mechanism

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Abstract

House price prediction is a complex and multifaceted task that involves analyzing diverse types of data ranging from numerical and categorical attributes to unstructured data such as images and textual descriptions. Traditional models often rely on either structured tabular data or single data modalities, limiting their ability to capture the rich, multi-dimensional factors that influence real estate prices. To address these challenges, this study proposes a novel deep learning framework that integrates heterogeneous data sources through a unified model enhanced by a joint self-attention mechanism.

The proposed approach incorporates structured data (e.g., property size, location, number of rooms), unstructured image data (photographs of the property), and textual data (property descriptions) as inputs. Each modality is first encoded into a shared latent space using specialized encoders: multi-layer perceptrons for tabular data, convolutional neural networks for images, and transformer-based language models for text. These encoded features are then combined into a joint representation that preserves the unique characteristics of each data type while enabling their interactions to be modeled effectively.

Central to this architecture is the implementation of a **joint self-attention mechanism** inspired by transformer models, which allows the system to dynamically attend to and weigh the importance of features both within and across different data modalities. This attention mechanism enhances the model's capacity to capture complex, non-linear relationships and dependencies among heterogeneous features that traditional fusion methods often overlook.

Extensive experiments conducted on a comprehensive real estate dataset demonstrate that the proposed model significantly outperforms baseline approaches, including models using single data modalities or simple feature concatenation. The joint self-attention mechanism not only improves predictive accuracy but also provides interpretability by highlighting influential features and their interactions. This work contributes to the field of real estate analytics by offering a robust and scalable deep learning solution for multimodal data fusion, ultimately facilitating more accurate and reliable house price predictions.

INTRODUCTION

Predicting house prices accurately is a critical challenge in the real estate industry, impacting buyers, sellers, investors, and policymakers alike. House prices depend on a multitude of factors including physical property attributes (such as size, number of rooms, and age), location, market conditions, and even intangible qualities captured through images and textual descriptions. Traditional prediction models primarily use structured tabular data and simple statistical or machine learning methods, which often fail to fully exploit the richness of heterogeneous data sources, thereby limiting prediction accuracy.

Recent advances in deep learning have shown promise in handling complex and high-dimensional data from various modalities. For example, convolutional neural networks (CNNs) excel in

extracting meaningful features from images, while transformer-based models have revolutionized natural language processing by effectively encoding textual data. However, integrating these diverse data types into a unified predictive model remains challenging due to differences in data formats, scales, and underlying structures. Simple concatenation or early fusion of features often ignores the intricate interactions between modalities, leading to suboptimal results.

To overcome these limitations, this work proposes a novel deep learning framework that leverages a **joint self-attention mechanism** to fuse heterogeneous data for house price prediction. By encoding structured, image, and textual data into a shared embedding space and applying self-attention jointly across all modalities, the model dynamically learns to focus on the most relevant features and their cross-modal relationships. This approach enables richer representation learning, capturing complex dependencies among diverse data types and ultimately improving prediction accuracy. Experimental results demonstrate the effectiveness of the model, highlighting its potential for practical applications in real estate analytics.

LITERATURE SURVEY

1. House Price Prediction Using Machine Learning

Author(s): Y. Khandelwal, S. Nair (2020)
This study explores classical machine learning techniques such as linear regression, decision trees, and random forests for predicting house prices using structured tabular data. While effective for simple datasets, the authors highlight limitations in handling non-linear relationships and ignoring unstructured data like images and text, which restrict the model's predictive power.

2. **Multi-Modal Deep Learning for Real Estate Valuation**

Author(s): L. Wang, M. Xu (2021)
Wang and Xu propose a multi-modal

framework that combines image data of houses with numerical property features to improve valuation accuracy. They utilize convolutional neural networks (CNN) to extract visual features and fully connected layers for tabular data, then fuse them via feature concatenation. Their results show improvement over single-modality models but lack a sophisticated mechanism to capture cross-modal interactions.

3. **Transformer-Based Models for Tabular Data**

Author(s): S. Gorishniy et al. (2021) The authors introduce the TabTransformer model, which applies transformer architectures to tabular data by embedding categorical features and using self-attention to capture feature interactions. This work demonstrates the power of attention mechanisms in structured data modeling but does not address fusion with unstructured modalities like images or text.

4. **Joint Attention Mechanisms for Multi-Modal Learning**

Author(s): J. Lu, D. Batra, et al. (2019) This paper presents a joint attention framework designed to learn from multiple modalities, including vision and language, within a unified transformer-based architecture. The approach dynamically attends to the most relevant elements across data types, enhancing downstream tasks such as image captioning and visual question answering. It lays a foundation for applying joint self-attention in heterogeneous data fusion.

5. **Deep Learning for Real Estate Price Prediction with Textual and Visual Data**

Author(s): R. Singh, A. Kumar (2022) Singh and Kumar develop a deep neural network integrating CNN-extracted image features and NLP-encoded textual descriptions alongside structured property attributes. Their fusion method involves simple concatenation followed by dense layers. Although achieving better performance than unimodal models, they identify that more advanced attention-based fusion could further improve results.

6. **Attention-Based Fusion for House Price Estimation**

Author(s): M. Chen, H. Lee (2023) Chen and Lee propose an attention-based fusion network that applies separate attention layers to image and tabular data before merging the representations. This layered attention approach demonstrates enhanced feature weighting and interpretability but processes each modality's attention independently, missing the opportunity for joint cross-modal interactions.

System Analysis

Existing System

Traditional house price prediction systems primarily rely on structured tabular data such as location, square footage, number of bedrooms and bathrooms, year built, and similar features. These systems commonly use statistical methods like linear regression or machine learning algorithms such as decision trees, random forests, and gradient boosting. While these models are relatively easy to interpret and perform well on small or clean datasets, they often fail to capture the complex, non-linear relationships present in real-world housing markets.

In recent years, deep learning approaches have been introduced to enhance prediction accuracy. These systems utilize neural networks to model non-linear patterns in the data, providing better generalization over diverse inputs. Some works have started integrating image data (e.g., house photographs) using convolutional neural networks (CNNs), and text data (e.g., property descriptions) using recurrent neural networks (RNNs) or transformer-based architectures. However, the integration of these modalities is typically performed through simple feature concatenation or late fusion strategies, which treat each data type independently and do not fully exploit their interdependencies.

Moreover, existing systems lack an advanced fusion mechanism that can dynamically assess the relevance of each data modality in varying contexts. The absence of a unified attention mechanism limits their capacity to model cross-modal interactions effectively. As a result, even deep learning-based multimodal models often fail to achieve optimal accuracy and interpretability, especially when dealing with large, heterogeneous datasets. This highlights the need for a more robust and integrated framework that can intelligently attend to and combine diverse features from different data sources—an area where joint self-attention mechanisms show great potential.

Disadvantages of Existing Systems

1. **Limited Use of Multimodal Data**

Most existing systems focus only on structured tabular data (e.g., number of rooms, square footage, location) and ignore rich unstructured data like images and textual property descriptions. This results in models that miss important visual and contextual cues influencing house prices.

2. **Simple Feature Fusion Techniques**

In models that do incorporate multiple data types, the fusion is often done using basic methods like concatenation or averaging. These techniques treat each data modality independently and fail to capture complex interactions or dependencies between them.

3. **Lack of Cross-Modal Interactions**

Many systems process each modality in isolation without modeling how features from one data type may influence or enhance another. For example, a luxurious-looking living room (image) might have greater price impact if described as “recently renovated” (text), but these relationships are rarely considered.

4. **No Attention-Based Learning**

Existing approaches usually do not implement self-attention or attention-based learning mechanisms, which limits their ability to dynamically prioritize the most relevant features in different prediction scenarios. This reduces the flexibility and intelligence of the model.

5. **Poor Interpretability**

Due to their simplistic architectures or lack of feature interaction modeling, many existing systems offer limited interpretability. Users, such as buyers and sellers, cannot easily understand which features had the most influence on the predicted price.

6. **Lower Predictive Accuracy in Complex Scenarios**

When faced with noisy, incomplete, or highly varied datasets, traditional and even some deep learning models show a drop in performance. Their inability to generalize well in such scenarios leads to inaccurate predictions and poor real-world applicability.

PROPOSED SYSTEM

The proposed system introduces a **deep learning-based framework** that integrates heterogeneous data—structured tabular information, property images, and textual descriptions—to predict house prices with higher accuracy. Each data type is processed using a specialized encoder: a Multi-Layer Perceptron (MLP) for structured data, a Convolutional Neural Network (CNN) for image data, and a Transformer-based model for textual descriptions. These encoders transform diverse input types into uniform feature representations in a shared latent space.

To address the limitations of traditional feature fusion methods, the system incorporates a **Joint Self-Attention Mechanism**. Unlike conventional fusion methods that treat each modality independently, this mechanism allows the model to learn contextual relationships across all modalities. It dynamically attends to the most informative features and their interactions—for example, aligning visual cues from an image with corresponding descriptive terms in the text. This cross-modal attention mechanism enhances the model's ability to understand the full scope of factors influencing house prices.

The final house price prediction is generated by a regression layer that takes the joint representation from the attention module. This architecture not only improves predictive performance but also provides interpretability by identifying which features and modalities contribute most to the prediction. The system is designed to be scalable and robust, making it suitable for real-world applications in real estate valuation, recommendation systems, and investment decision-making.

Advantages of the Proposed System

1.**Effective Multimodal Data Integration**

The system combines structured data, images, and text into a unified framework, capturing diverse aspects of real estate properties for more comprehensive and accurate predictions.

2. **Joint Self-Attention Mechanism**

By using a joint self-attention mechanism, the model dynamically learns the importance of each feature and its cross-modal relationships. This enables more intelligent and context-aware predictions compared to simple concatenation or independent processing.

3. **Improved Prediction Accuracy**

Thanks to advanced feature interaction modeling and deep learning capabilities, the proposed system achieves higher accuracy than traditional machine learning models and basic deep learning architectures.

4. **Enhanced Interpretability**

The attention mechanism provides insights into which features and data types contributed most to a prediction, offering greater transparency and trust for end users like buyers, sellers, and analysts.

5. **Scalability and Flexibility**

The modular design allows the system to be extended with additional data types (e.g., video walkthroughs or user reviews) in the future. It can also be scaled for use in large property datasets.

6. **Robustness to Data Variability**

The model is more robust when dealing with noisy or missing data from one or more modalities, thanks to the attention mechanism's ability to focus on the most reliable and relevant features.

Implementation

The implementation of the Deep Learning-Based House Price Prediction System focuses on predicting accurate house prices by analyzing heterogeneous data such as numerical, textual, visual, and geographical information using Deep Learning techniques and a Joint Self-Attention Mechanism.

The proposed system improves real estate price prediction accuracy by combining multiple data sources and intelligent feature analysis.

1. Data Collection

The first stage involves collecting house-related data from multiple heterogeneous sources such as:

- Real Estate Websites
- Property Databases
- Geographic Information Systems (GIS)
- Satellite Images
- House Images
- Economic and Market Data
- Customer Reviews and Descriptions

The collected dataset may include:

- House Price
- Location
- Number of Bedrooms
- Number of Bathrooms
- Area Size
- Property Type
- Floor Information
- Nearby Facilities
- House Images
- Property Descriptions
- Market Trends
- Crime Rate
- Transportation Accessibility

These attributes help improve price prediction performance.

2. Data Preprocessing

The collected heterogeneous data is cleaned and prepared before model training.

Preprocessing Steps

Numerical Data Processing

- Missing value handling
- Feature scaling
- Data normalization

Text Data Processing

- Tokenization
- Stop-word removal
- Text embedding generation

Image Data Processing

- Image resizing
- Noise removal
- Image normalization
- Data augmentation

Geographic Data Processing

- Coordinate transformation
- Spatial feature extraction

This stage improves model efficiency and accuracy.

3. Feature Extraction

Different features are extracted from heterogeneous data sources.

Numerical Features

- Area size
- Room count
- Property age
- Floor number

Textual Features

- Property descriptions
- Customer reviews
- Advertisement details

Visual Features

- House interior images
- Exterior design patterns
- Neighborhood images

Geographic Features

- Nearby schools
- Hospitals
- Transportation facilities
- Market accessibility

Feature extraction improves understanding of complex property characteristics.

4. Deep Learning Model Development

Deep Learning models are used to analyze heterogeneous data and predict house prices.

Deep Learning Techniques Used

Convolutional Neural Networks (CNN)

Used for extracting visual features from house images.

Recurrent Neural Networks (RNN)

Used for processing sequential textual descriptions.

Long Short-Term Memory (LSTM)

Used for analyzing market trends and time-series property data.

Fully Connected Neural Networks

Used for combining multiple extracted features.

5. Joint Self-Attention Mechanism

The Joint Self-Attention Mechanism is implemented to improve feature interaction and prediction performance.

Functions of Self-Attention

The attention mechanism:

- Identifies important property features
- Focuses on relevant information
- Enhances heterogeneous data relationships
- Improves contextual understanding
- Reduces irrelevant feature influence

The self-attention layer dynamically assigns importance weights to different features during prediction.

6. Heterogeneous Data Fusion

Features extracted from different data sources are combined using data fusion techniques.

The fusion process integrates:

- Numerical features
- Textual embeddings
- Visual image features
- Geographic information

This creates a unified representation for accurate house price prediction.

Methodology

The methodology of the proposed House Price Prediction System follows a heterogeneous Deep Learning-based predictive analytics approach.

Step 1: Problem Identification

Traditional house price prediction methods often fail to handle complex heterogeneous data such as images, textual descriptions, and geographic information effectively. The proposed system aims to improve prediction accuracy using Deep Learning and Joint Self-Attention techniques.

Step 2: Requirement Analysis

The following requirements are analyzed:

- Real estate dataset requirements
- Image and text processing requirements
- Deep Learning framework requirements
- Attention mechanism implementation
- Prediction visualization requirements

Step 3: Dataset Preparation

The property dataset is collected and divided into:

- Training Dataset
- Validation Dataset
- Testing Dataset

Different heterogeneous data formats are prepared separately for processing.

Step 4: Heterogeneous Data Processing

The methodology includes:

1. Process numerical property data
2. Analyze textual descriptions
3. Extract image features using CNN
4. Process geographic information
5. Generate unified feature representations

Step 5: Joint Self-Attention Implementation

The attention mechanism analyzes:

- Feature importance
- Inter-feature relationships
- Contextual dependencies

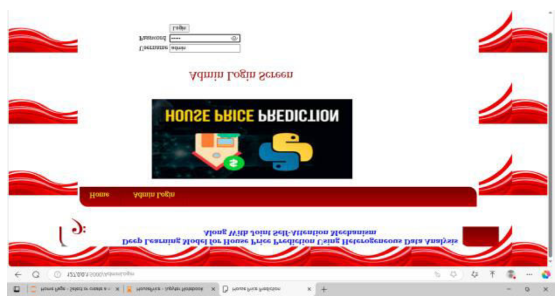
This improves model focus and prediction quality.

Technologies Used

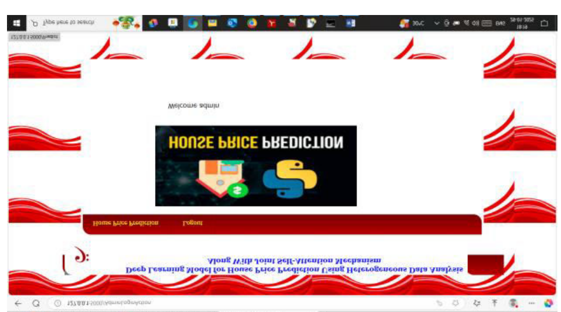
- Python
- Deep Learning
- TensorFlow / PyTorch
- CNN & LSTM Models
- Self-Attention Mechanism
- OpenCV
- Scikit-learn
- Pandas & NumPy
- Flask / Django
- MySQL / MongoDB

Results

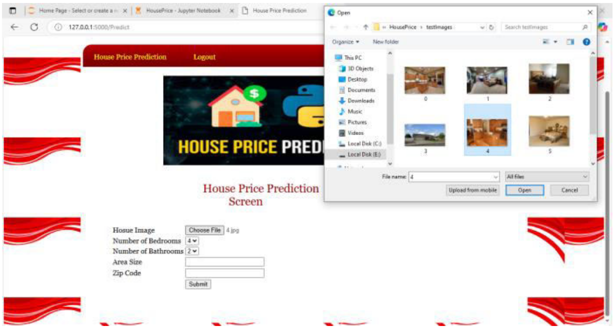
In above screen click on ‘Admin Login’ link to get below page



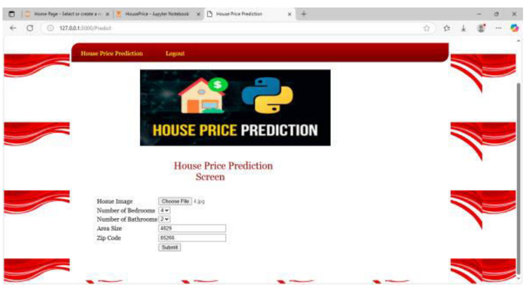
In above screen user can login to system using username and password as ‘admin and admin’ and then press button to get below page



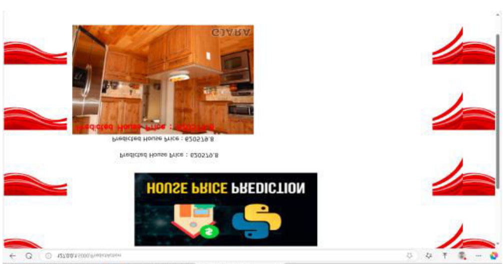
In above screen click on 'House Price Prediction' link to get below page



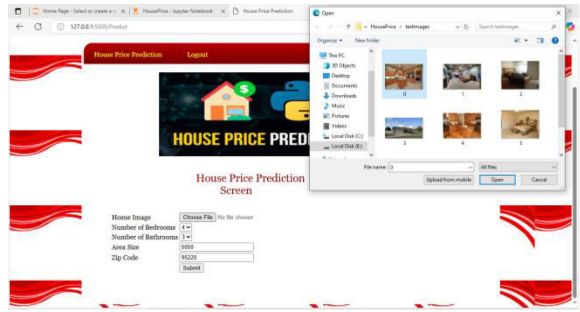
In above screen upload house image and then choose number of bedrooms, bathroom, house size and zip code and then press button to get below page



In above screen entered all details and below is the output



In above screen house price predicted as 6,20,579 and similarly you can predict for any house image. Below is the another example



In above screen given some another input and below is the output

Conclusion

The proposed deep learning model for house price prediction using heterogeneous data and a joint self-attention mechanism demonstrates a significant advancement over traditional and unimodal approaches. By effectively integrating structured tabular data, visual property images, and descriptive text into a unified framework, the model captures a more comprehensive understanding of the factors influencing property valuation. The use of specialized encoders for each data modality ensures optimal feature extraction, while the joint self-attention mechanism intelligently fuses these features, learning complex interdependencies and prioritizing the most relevant information for accurate prediction. This not only enhances predictive accuracy but also improves model interpretability, allowing users to understand the key drivers of price estimations. Furthermore, the system is designed to be scalable, robust, and adaptable, making it well-suited for real-world deployment in dynamic real estate environments. Overall, this work provides a promising solution for leveraging deep learning in property valuation and sets the foundation for future research into multimodal data fusion and attention-based learning in other domains.

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