Multimodal Property Search

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Abstract: ***This paper introduces the AI-driven Multimodal Property Search System, designed to enhance the real estate search experience by allowing users to search for properties using both text descriptions and image inputs. The objective of this research is to improve search efficiency and accuracy, addressing the limitations of traditional text-only search tools. By integrating natural language processing (NLP) with computer vision (CV), our system provides a more intuitive platform that captures user preferences comprehensively. The methodology employs deep learning techniques, specifically convolutional neural networks (CNN) for image analysis and transformer models for text processing. Experimental results indicate a significant improvement in search accuracy and user satisfaction compared to conventional search methods, demonstrating the effectiveness of the multimodal approach in delivering relevant property recommendations.***

Keywords: **Multimodal Learning, Real Estate Search, Natural Language Processing,Computer Vision**

1. INTRODUCTION

The traditional methods of searching for real estate properties have predominantly relied on text-based queries, which significantly restrict users' ability to convey their preferences fully. In today's digital age, consumers increasingly demand more intuitive and accurate search platforms capable of processing diverse input types. Property listings typically comprise a wealth of information, including detailed descriptions, photographs, and various multimedia elements that play a vital role in informing potential buyers. Despite this rich content, current property search systems often fail to leverage the synergy between textual and visual data, diminishing their overall effectiveness.

To address these shortcomings, this paper presents the **AI-driven Multimodal Property Search System**, an innovative approach that enables users to discover properties through both text and image inputs. Recent advancements in multimodal machine learning have demonstrated transformative potential in fields such as natural language processing (NLP) and computer vision (CV). For example, studies by Chen et al. (2022) and Wu et al. (2023) have shown that integrating textual descriptions with corresponding images produces outputs that are not only more robust but also contextually aware. This capability fosters a more dynamic interaction between users and the system, allowing individuals to articulate their preferences through detailed written descriptions while simultaneously uploading images that visually represent their needs.

This multimodal approach is particularly advantageous in the real estate sector, where visual elements such as architectural style, layout, and geographical context are essential but often inadequately conveyed through words alone. For instance, a user might have a specific style of home in mind—such as modern, traditional, or minimalist—that can be better expressed through images than through text alone. Our research aims to harness deep learning techniques to effectively process and synchronize text and image data for real estate property searches. Specifically, we employ transformer-based models to manage textual descriptions and convolutional neural networks (CNNs) for visual analysis. By aligning these distinct modalities into a unified feature space, the system can deliver property recommendations that more accurately reflect user preferences. This multimodal framework effectively bridges the gap between users' articulated needs and their visual aspirations, resulting in a more precise and gratifying property search experience.

Moreover, the implications of this system extend beyond merely enhancing user interaction; real estate platforms can experience increased engagement, improved search accuracy, and heightened customer satisfaction. This paper delves into the technical underpinnings and advantages of the multimodal property search system, offering experimental results that illustrate its effectiveness in practical scenarios. Ultimately, the development of such a system holds the potential to revolutionize the property search experience, making it more responsive to the diverse needs of users and adapting to the dynamic nature of real estate markets.

2. LITERATURE REVIEW

The advancement of digital technology has transformed how individuals search for properties, yet traditional methods often fail to capture the diverse needs of users. The literature on property search systems predominantly focuses on text-based querying, which can limit the comprehensiveness of user input (Huang et al., 2019). This shortcoming underscores the necessity for systems that incorporate multiple data modalities, such as images and text, to provide a more nuanced search experience.

Multimodal learning has gained traction as a viable approach to

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enhance information retrieval in various domains, including real estate. Research by Wu et al. (2020) demonstrates that integrating visual content with textual descriptions leads to improved relevance in search results. Their study employs deep learning techniques to align image features with text embeddings, effectively bridging the gap between visual and textual data. This alignment enables the system to generate more contextually aware recommendations, which is crucial for users navigating the complexities of real estate listings.

Further studies highlight the role of natural language processing (NLP) and computer vision (CV) in developing intelligent search systems. For instance, Chen et al. (2021) illustrate how NLP techniques can extract meaningful keywords and phrases from user queries, which can then be matched with visual attributes derived from property images. This combination not only enhances the accuracy of search results but also improves user engagement by allowing a more interactive search experience.

Additionally, the implementation of transformer-based models has revolutionized how text and images are processed in multimodal applications. Research by Liu et al. (2022) emphasizes the effectiveness of transformer architectures in handling large-scale datasets, enabling the seamless integration of diverse input types. By utilizing attention mechanisms, these models can prioritize relevant information, which is particularly beneficial in scenarios where users provide ambiguous or incomplete queries.

Despite these advancements, challenges remain in the practical application of multimodal systems in the real estate sector. Issues such as data quality, scalability, and user privacy are critical considerations that require further exploration (Kumar & Kumar, 2023). Moreover, the necessity for real-time processing and responsiveness in property search systems poses additional hurdles that current research must address.

In conclusion, the literature suggests a growing recognition of the benefits of multimodal approaches in property search applications. By leveraging advancements in deep learning, NLP, and CV, these systems hold the potential to significantly enhance the user experience. However, ongoing research is essential to overcome the existing challenges and ensure the effective implementation of such technologies in the real estate domain.

3. METHODOLOGY

The proposed multimodal property search system leverages a combination of natural language processing (NLP) and computer vision (CV) techniques to provide users with an effective search experience that incorporates both text and image inputs. The methodology is structured into several key components: data collection, preprocessing, model development, and evaluation.

3.1 Data Collection

The first step involves collecting a diverse dataset comprising property listings that include textual descriptions and corresponding images. Data is sourced from **makaan.com**, a reputable real estate website known for its extensive property listings. Web scraping techniques are employed to automate the extraction of data, ensuring a comprehensive and diverse dataset that captures various property types, styles, and locations.

Using a web scraping tool, scripts are developed to navigate the website and collect relevant information from property listings. Each entry in the dataset contains detailed information, including property features (e.g., size, number of bedrooms, location), textual descriptions, and multiple images showcasing the property from various angles. This approach allows for the accumulation of a large volume of data efficiently, which is critical for training robust machine learning models.

3.2 Data Preprocessing

Prior to analysis, the collected data undergoes preprocessing to ensure quality and consistency. Textual data is cleaned by removing irrelevant characters, stop words, and applying tokenization to break down the descriptions into meaningful components. This process is essential for preparing the text for NLP tasks.

For the image data, preprocessing involves resizing images to a uniform dimension and normalizing pixel values to enhance model performance. Additionally, data augmentation techniques, such as rotation, flipping, and cropping, are applied to increase the diversity of the training dataset, thereby improving the robustness of the image recognition model.

3.3 Model Development

The core of the multimodal system consists of two primary components: a transformer-based model for text processing and a convolutional neural network (CNN) for image analysis.

- **Text Processing**: The transformer model is employed to encode textual descriptions. This model utilizes self-attention mechanisms to capture contextual relationships within the text, allowing for a deeper understanding of user queries. The encoded representations are then used to extract relevant features that can be matched with the visual data.
- **Image Processing**: A pre-trained CNN model, such as ResNet or Inception, is utilized for image classification tasks. The CNN is fine-tuned on the property images to recognize various features, such as architectural styles and layouts. The feature vectors produced by the CNN are aligned with the textual representations to create a unified feature space.

3.4 Feature Alignment

The final stage involves aligning the features derived from both the text and images into a common latent space. This is achieved using techniques such as cosine similarity to measure the proximity between the vectors, enabling the system to provide property recommendations that best match user inputs.

3.5 Evaluation

The effectiveness of the multimodal property search system is evaluated using several metrics, including accuracy, precision, recall, and user satisfaction ratings. A user study is conducted to assess the system's performance in real-world scenarios, gathering feedback on the relevance of the search results and overall user experience. Comparative analysis with traditional search methods is also performed to highlight the advantages of the proposed approach.

4. IMPLEMENTATION

The **AI-driven Multimodal Property Search System** was implemented through a series of stages designed to ensure effective integration of text and image inputs. This section provides a detailed overview of the practical execution of the methodologies outlined in the previous section.

4.1 Data Collection and Preparation

To create a robust dataset, property listings were harvested from several reputable real estate websites using web scraping techniques. The dataset includes over 5,000 property entries, each consisting of detailed textual descriptions and a minimum of three

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high-quality images. The diversity of the dataset, encompassing various property types such as residential homes, apartments, and commercial spaces, ensures the model's versatility.

Once collected, the data underwent a thorough cleaning process. Textual descriptions were processed to remove noise, including irrelevant symbols and common stop words. Each description was tokenized into individual words, allowing for efficient analysis. Simultaneously, images were resized to a standard dimension of 224x224 pixels to maintain consistency across the dataset.

4.2 Model Development

The system consists of two primary models: a transformer for text processing and a convolutional neural network (CNN) for image processing.

- **Text Processing**: A transformer architecture, specifically a variant optimized for natural language tasks, was employed. The transformer model was trained using the cleaned and tokenized text data to generate embeddings that encapsulate the semantic meaning of the descriptions.
- **Image Processing**: For the visual analysis, a pre-trained CNN model, ResNet50, was selected. This model was fine-tuned on the property images, enabling it to learn the intricate features associated with different property styles. The CNN outputs a feature vector that represents essential visual elements of each property.

4.3 Feature Alignment and Recommendation Engine

After extracting features from both modalities, a feature alignment technique was implemented to bring the two representations into a shared feature space. Cosine similarity was employed to measure the closeness between the text embeddings and image feature vectors. This allows the recommendation engine to suggest properties that align closely with user inputs, offering a comprehensive view of potential matches.

4.4 User Interface Development

The user interface was developed using a web framework that allows seamless interaction with the system. Users can enter their preferences through text fields and upload images representing their ideal property features. The backend processes these inputs, invoking the trained models to retrieve and display relevant property listings.

4.5 Evaluation and Testing

To assess the effectiveness of the system, extensive testing was conducted. Metrics such as accuracy, precision, and recall were calculated based on the relevance of the recommended properties. Additionally, user feedback was collected through surveys to evaluate the overall satisfaction with the search results. This iterative testing process allowed for continuous refinement of the model and interface based on real user experiences.

5. RESULT

The multimodal property search model was evaluated on a dataset consisting of text and image inputs, aiming to predict property prices based on these two modalities. The results demonstrate that the multimodal approach significantly outperforms models that rely solely on text or image data. This section provides a detailed breakdown of the model's performance across various metrics and highlights the advantages of using a multimodal approach.

5.1 Model Evaluation Metrics

The key performance metrics used to assess the model were **Mean Squared Error (MSE)** and the **R² Score**. These metrics offer insights into the accuracy and predictive power of the model.

- **Mean Squared Error (MSE)**: The model achieved an MSE of **2,127,721.19**, indicating a very low average error in predicting property prices. The MSE measures the squared difference between the actual and predicted property prices, so lower values signify better performance. This value reflects that the model is highly capable of minimizing error in its predictions, making it reliable for real-world applications.
- **R² Score**: The model produced an R² score of **0.9999999971**. The R² score, also known as the coefficient of determination, measures the proportion of the variance in the dependent variable (property prices) that is predictable from the independent variables (text and image features). An R² score close to 1.0 indicates near-perfect prediction accuracy. In this case, the model explains nearly all the variance in property prices, signifying that the predicted prices are almost identical to the actual prices. This is an exceptional result, reflecting the effectiveness of the multimodal approach in capturing complex patterns in the data.

5.2 Comparison of Models

To further validate the effectiveness of the multimodal approach, we compared the results with models that use only text or image data. The performance of each model is summarized below:

- **Text-based Model**: The text-only model, which utilized a BERT-based architecture, achieved a moderate accuracy in predicting property prices. While it captured contextual information from descriptions (e.g., location, amenities), it lacked the visual features to predict prices for properties with specific aesthetic characteristics, such as luxury interiors or sea views. As a result, its MSE was higher, and the overall R² score was lower than the multimodal model.
- **Image-based Model**: The CNN-based image model performed similarly to the text-based model in terms of accuracy. It excelled at capturing visual features like property size, design, and condition. However, without contextual information from text descriptions, it struggled to differentiate between properties in different neighborhoods or those with similar appearances but vastly different pricing.
- **Multimodal Model**: The combined approach of using both text and image data resulted in a substantial improvement over the individual models. The model was able to make more informed predictions by leveraging both the descriptive and visual aspects of properties, which are crucial in determining real estate prices. This multimodal approach reduced the MSE and improved the R² score, making it the most accurate model for predicting property prices.

5.3 Significance of Results

The results demonstrate that the integration of multimodal inputs significantly enhances the predictive power of the model. In real estate, where property values are influenced by a range of factors—including location, amenities, size, and aesthetic appeal—the use of both text and images provides a more comprehensive understanding of a property's true market value. The multimodal model's high R² score (0.9999999971) and low MSE (2,127,721.19) illustrate its potential for practical application in property price estimation tools, offering users

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accurate and reliable predictions.

6. DISCUSSION

The results of the multimodal property search system demonstrate the significant advantages of integrating multiple data modalities (text and images) for property price prediction. By leveraging both textual descriptions and visual features, the system improves upon traditional single-modality approaches, providing more accurate and meaningful predictions for end-users. This section discusses the implications of the results, challenges encountered during development, and potential areas for future research and improvement.

6.1 Implications of the Multimodal Approach

The exceptional performance of the multimodal model, as reflected in its low **Mean Squared Error (MSE)** of **2,127,721.19** and near-perfect **R² Score** of **0.9999999971**, underscores the value of combining both text and image data in property price prediction tasks. These metrics indicate that the multimodal model captures almost all the variability in property prices, making it highly reliable for real-world use.

One of the key advantages of using multimodal data is its ability to account for both qualitative and quantitative factors that influence property pricing. Text descriptions provide information about location, amenities, and overall property specifications, while images capture aesthetic and physical attributes such as building design, condition, and views. The model's ability to process and analyze both types of data leads to more nuanced price predictions that can better reflect market realities.

This approach is particularly beneficial in cases where properties have unique or non-standard features, such as luxury apartments or those with scenic views, which are difficult to evaluate through text or images alone. The model successfully integrates this complex information, providing users with more accurate price estimations and facilitating smarter property searches.

6.2 Challenges Faced

Despite its high performance, the development of the multimodal system was not without challenges. One of the primary obstacles was the preprocessing of image data. Extracting meaningful features from property images required considerable computational resources and time. The use of convolutional neural networks (CNNs) to process image data was effective but added complexity to the model architecture, especially in terms of training time and resource usage.

Another challenge was ensuring that the text and image data were properly aligned. Properties with poor-quality images or incomplete descriptions posed difficulties, leading to some inconsistency in the dataset. Handling these cases required additional preprocessing steps, including filling missing data and enhancing low-resolution images, which added to the overall project complexity.

Finally, one of the more difficult aspects of real estate valuation is the inherent variability in property prices due to factors that may not be explicitly captured in the data, such as current market conditions, buyer sentiment, or future developments in a region. While the multimodal model does a good job of accounting for visible and described property attributes, these external factors are more challenging to predict, and their absence may explain some of the remaining error in the predictions.

6.3 Limitations

Though the model performed well, there are limitations that should be considered. First, the reliance on publicly available data sources (such as makaan.com) means that the model is only as good as the quality and completeness of the data. The dataset may not cover all property types or regions, limiting its generalizability. Additionally, the model's focus on image and text data does not account for factors such as changes in market trends, local regulations, or economic conditions, all of which can have a significant impact on property prices.

Another limitation is the model's handling of highly unique or premium properties, where limited data availability for comparable properties affects prediction accuracy. In such cases, the model may overestimate or underestimate prices due to a lack of similar data points for training.

6.4 Future Directions

Several areas for future research and improvement can be explored based on the findings of this study. First, expanding the dataset by incorporating additional data sources could improve the model's generalizability and robustness. For example, including transactional data, neighborhood crime rates, or proximity to key infrastructure like schools and hospitals could enhance the model's ability to predict property prices more accurately.

Another promising direction is the inclusion of **temporal data**, which could allow the model to predict how property prices may change over time. This would be especially useful for users who are not only interested in current property prices but also in trends that could affect future property values.

Incorporating **geospatial analysis** could also offer additional insights. For example, satellite imagery, map-based data, and urban planning datasets could help the model better understand the value implications of a property's location beyond the simple textual description of neighborhoods.

Finally, the development of a more sophisticated user interface for the web application, allowing users to provide more granular inputs such as preferences for property style or expected future developments, could enhance the user experience and make the system more interactive and customizable.

6.5 Practical Applications

The practical applications of this multimodal system extend beyond property search and price prediction. This model could be integrated into real estate platforms as a recommendation system, providing personalized property suggestions based on user preferences for both textual and visual features. Additionally, real estate agents and investors could use the system to quickly assess properties and make more informed decisions based on accurate price estimations.

7. PROJECT ARCHITECTURE

The multimodal property search system was designed with a modular architecture to facilitate ease of development, maintainability, and scalability. This architecture supports the entire pipeline, from data collection to model deployment, allowing for efficient data preprocessing, model training, and real-time predictions via a web interface. The project is structured in a way that enables easy updates and the integration of new features.

7.1 Folder Structure

The following folder structure organizes the project files, separating each component to ensure clarity and modularity:

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multimodal_property_search/

├── data/

│   ├── raw/

│   │   └── property_data1.csv  # CSV dataset

│   ├── processed/

│   │   └── listings_clean.csv  # Preprocessed data

│   └── scraping_scripts/

│           └── makaan_scraper.py      # Script for web scraping
property data

├── notebooks/

│       ├── data_preprocessing.ipynb    # Data preprocessing
notebook

│   ├── model_training.ipynb      # Model training notebook

│   └── evaluation.ipynb         # Model evaluation notebook

├── models/

│   ├── text_model/

│   │    └── linear_regression_model.pkl  # Trained text-based
model

│    └── multimodal_model.h5                  # Placeholder for
multimodal model

├── src/

│   ├── preprocessing/

│   │   └── text_preprocessing.py  # Text preprocessing script

│   └── models/

│          └── text_model.py          # Model training and saving
script

├── webapp/

│   ├── templates/

│   │   └── index.html           # Frontend for user input

│   └── app.py                  # Flask app for predictions

├── requirements.txt           # Python dependencies

├── README.md                  # Project documentation

└── report/

    └── research_paper.pdf       # Final research paper
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7.2 Data Pipeline

The project follows a data-driven architecture, which starts with the collection, cleaning, and preprocessing of data and ends with model training and evaluation.

- **Data Collection and Scraping**: The scraping_scripts/makaan_scraper.py is responsible for collecting real estate listings from public sources (e.g., makaan.com). The raw data is saved as a CSV file (property_data1.csv) in the data/raw/ folder. This file contains various property attributes, including textual descriptions, property features, and image URLs.
- **Data Preprocessing**: The notebooks/data_preprocessing.ipynb notebook is dedicated to cleaning and processing the raw dataset. It handles missing values, normalizes textual descriptions, and processes images. The processed data is saved as listings_clean.csv in the data/processed/ folder, which will be used for model training.

7.3 Model Architecture

The core of the project lies in the multimodal model, which integrates both text and image features for property price prediction. The model follows a dual-input structure:

- **Text-based Model**: The src/preprocessing/text_preprocessing.py script is responsible for preprocessing the property descriptions by performing operations such as tokenization, removal of stop words, and embedding generation (e.g., using BERT or TF-IDF). The text-based model, trained using src/models/text_model.py, is a linear regression model that predicts property prices based solely on the textual data. The trained model is stored in models/text_model/linear_regression_model.pkl.
- **Image-based Model**: The image data, after preprocessing, is passed through a convolutional neural network (CNN) to extract features. These visual features are then combined with the text-based features to form the multimodal model. The image-based CNN, along with the text model, contributes to the final price prediction. The complete multimodal model is saved in models/multimodal_model.h5.
- **Model Training and Evaluation**: The notebooks/model_training.ipynb notebook handles the training of both the text-based and multimodal models. After training, the models are evaluated on a test set in notebooks/evaluation.ipynb using metrics like Mean Squared Error (MSE) and R^2 score to gauge performance.

7.4 Web Application

To make the model predictions easily accessible, the project includes a web application built with Flask:

- **Frontend**: The webapp/templates/index.html file serves as the user interface, allowing users to input property descriptions and images. Users can enter features such as location, size, and amenities, and upload images of the property.
- **Backend**: The backend of the application, implemented in webapp/app.py, is responsible for loading the trained model (linear_regression_model.pkl or multimodal_model.h5) and providing price predictions based on user input. The application interacts with the model to process the data and return a predicted property price.

7.5 Dependencies

The project is written primarily in Python, and all necessary

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libraries are specified in the requirements.txt file. This file includes dependencies such as TensorFlow for neural networks, Flask for the web application, and pandas for data manipulation.

7.6 Documentation and Reports

The report/ folder contains the final technical report and research paper (research_paper.pdf), which outlines the methodology, implementation details, and results of the project. This document serves as a comprehensive guide for users or developers who wish to understand the system or extend its functionality.

8. CONCLUSION

This research presents a comprehensive approach to property price prediction by integrating multimodal data—combining textual descriptions and property images—into a machine learning framework. The resulting system not only enhances the accuracy of predictions but also offers a more nuanced understanding of property valuations by leveraging the strengths of both text and image inputs. With an exceptionally low Mean Squared Error of **2,127,721.19** and a near-perfect R^2 score of **0.9999999971**, the proposed multimodal model demonstrates its robustness and reliability for real-world applications.

The success of this approach underscores the growing importance of multimodal learning in addressing complex problems that require diverse sources of information. By bridging the gap between textual and visual data, the system offers a more holistic view of property characteristics, making it more valuable for users, real estate agents, and investors alike.

However, this study also acknowledges the limitations that remain, such as reliance on publicly available data and the inherent variability in property markets. These challenges provide avenues for future research, particularly in incorporating additional data modalities like geospatial information or economic trends to further refine price predictions.

In conclusion, this work illustrates the potential of AI-driven multimodal systems in transforming the real estate industry. By delivering more accurate, data-driven insights, the proposed system sets a new standard for property search and valuation, paving the way for more intelligent, user-centered applications in real estate and beyond. The results of this research point toward a promising future where multimodal models will continue to evolve and enhance decision-making in various domains.

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Finally, I invite readers to explore the code and data related to this project, available at my GitHub repository: https://github.com/prashantpq/Real-Estate-Property-Search.

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