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REPORT

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Design Discovery: A Guide to Image-Based Interior Recommendations

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ARTICLE

Design Discovery: A Guide to Image-Based Interior Recommendations

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Abstract

In the realm of interior design, the evolution of technology has ushered in a new era of creativity and convenience. "Design Discovery: A Guide to Image-Based Interior Recommendations" explores the intersection of design and technology, offering readers an insightful journey into the world of image-driven recommendations. This article delves into the innovative approach of leveraging interior design images to suggest similar and complementary elements, facilitating a seamless and personalized decor discovery process.

Keywords: CNN ; Interior Design; Image-based recommender system

Abbreviations: CNN: Convolutional Neural Network , KNN: K-Nearest Neighbors

1. Introduction

Welcome to the era where online furniture shopping meets personalized, visually stunning recommendations. In this article, we unveil "Design Discovery," a game-changing image-based interior recommendation system that taps into the magic of Convolutional Neural Networks (CNNs) to redefine how we discover and choose home furnishings to the era where online furniture shopping meets personalized, visually stunning recommendations. In this article, we unveil "Design Discovery," a game-changing image-based interior recommendation system that taps into the magic of Convolutional Neural Networks (CNNs) to redefine how we discover and choose home furnishings.

At the heart of Design Discovery lies the ResNet50 model, a powerhouse in image recognition. We'll guide you through the ins and outs of how this system transforms high-resolution furniture images into a language it understands, capturing the subtleties of design and style. No need to fear the tech jargon; we're here to demystify the process and showcase how CNNs play a pivotal role in deciphering the visual cues that make each piece of furniture unique.

Our journey takes us through the creation of a robust dataset and the fine-tuning of the model to become a master of recognizing various furniture attributes. We'll break down the nitty-gritty of feature extraction, explaining how images are prepped for analysis and how informative feature representations are derived. And yes, we promise it's more intriguing than it sounds.

In a nutshell, this article introduces an advanced image-based interior recommendation system and acts as your go-to manual for diving into this exciting field. Design Discovery isn't just about cutting-edge tech; it's about making online furniture shopping an experience that's uniquely yours. Join us as we explore the future of personalized interior design recommendations

2. Related works

Table 1. Comparison of Articles

	Article 1 - [1]What Looks Good with my Sofa: Multimodal Search Engine for Interior Design	**Article 2 - [2]Image-Based Fashion Product Recommendation with Deep Learning**	**Article 3 - [3]DeepRec: Efficient Product Recommendation Model for E-Commerce using CNN**
Method	YOLO 9000 object detection Deep , neural networks (ResNet, VGG) , Word2Vec-based textual representations and Feature similarity blending approach for improved search accuracy	Training CNNs for category and texture classification, then using the models as feature extractors for a k-NN algorithm to provide similarity-based fashion product recommendations	The method uses a 1D Convolutional Neural Network (CNN) with dropout regularization for training an e-commerce recommender model based on user behavior features
Advantage	- Combining between all those methods give better results	- The two-stage deep learning framework enhances recommendation robustness and performance by combining visually-aware feature extraction with a ranking algorithm, accommodating diverse customer styles.	- The use of 1D Convolutional Neural Network allows the model to capture sequential patterns in user behavior, enhancing its ability to provide personalized product recommendations.
Disadvantage	- YOLO 9000's use in the Style Search Engine may struggle with complex scenes causing inaccuracies and reduced precision in detecting overlapping objects	The article notes the challenge of inherent subjectivity in evaluating recommendation quality, making it difficult to establish a precise and objective criterion for comparing the proposed system with others in a standardized manner	- Training deep learning models, such as CNNs, may require substantial computational resources and time, making it computationally intensive and potentially challenging for resource-constrained environments
Evaluation Metrics	- Hit@6	Loss and Accuracy	Loss and Accuracy

3. Methods

3.1 IkEA Dataset

In this study, we utilized the IKEA dataset, as introduced in the initial research article [1]. This dataset was meticulously curated from the IKEA.com website, specifically tailored for the development of our Interior Design Recommender System. The dataset comprises a total of 2193 photographs featuring individual objects or products. Additionally, it encompasses 298 contextual photographs capturing room scenes in which these objects naturally coexist, providing a comprehensive and diverse collection for our recommender system's training and evaluation purposes.

3.2 Proposed Framework

3.2.1 Transfer learning via ResNet50:

We selected ResNet50 for transfer learning due to its exceptional performance in image recognition tasks. ResNet50 is a deep convolutional neural network (CNN) architecture known for its ability to capture intricate features and patterns in images. Trained on the extensive ImageNet dataset, ResNet50 brings a wealth of knowledge about general visual features. This pre-trained model is well-suited for our Interior Design Recommender System as it can efficiently extract high-level features from our specific IKEA dataset, enabling us to decipher the nuances of interior design elements. The robustness and versatility of ResNet50 make it an ideal choice for transfer learning, allowing us to leverage its learned features for our targeted recommendation system.

3.2.2 Similarity calculation:

The k-NN algorithm was chosen for similarity calculation to navigate the intricacies of feature space effectively. After the transfer learning phase with ResNet50, we obtain a feature vector, F(X), representing the unique characteristics of each interior design element in our IKEA dataset. The k-NN algorithm excels in comparing these feature vectors, identifying items with similar characteristics. Its ability to measure similarity based on distance metrics allows us to explore the feature space comprehensively. By choosing the k-NN algorithm, we enhance the precision of our recommendations, ensuring that the suggested items align closely with the rich visual representations learned during transfer learning with ResNet50. This synergistic combination of transfer learning and k-NN facilitates a powerful and nuanced approach to image-based interior design recommendations.

4. Results and Discussions

4.0.1 Results

The experimental evaluation involved testing the recommender system with diverse similarity distance metrics, namely Manhattan, Cosine, and Euclidean distances. These metrics were employed to quantify the dissimilarity or similarity between feature vectors within the k-NN algorithm. The obtained results shed light on the impact of each distance metric on the system's performance in recommending interior design items.

For Manhattan distance, the system evaluated the linear spatial gap between feature vectors, emphasizing the sum of absolute differences. Cosine similarity, on the other hand, focused on the cosine of the angle between vectors, capturing directional similarities irrespective of magnitude. Lastly, Euclidean distance measured the direct spatial separation between vectors, considering both magnitude and orientation. This is the results after using each distance.

Figure 1. Results for Manhattan Distance.

Figure 2. Results for Cosine Distance.

Figure 3. Results for Euclidean Distance.

Table 2. Comparison between distances

Type	Average distance
Cosin	0.16215608755906108
Manhattan	16.38105038864832
Euclidean	0.569161891996847

4.0.2 Discussions

4.0.3 Interpretation of Results

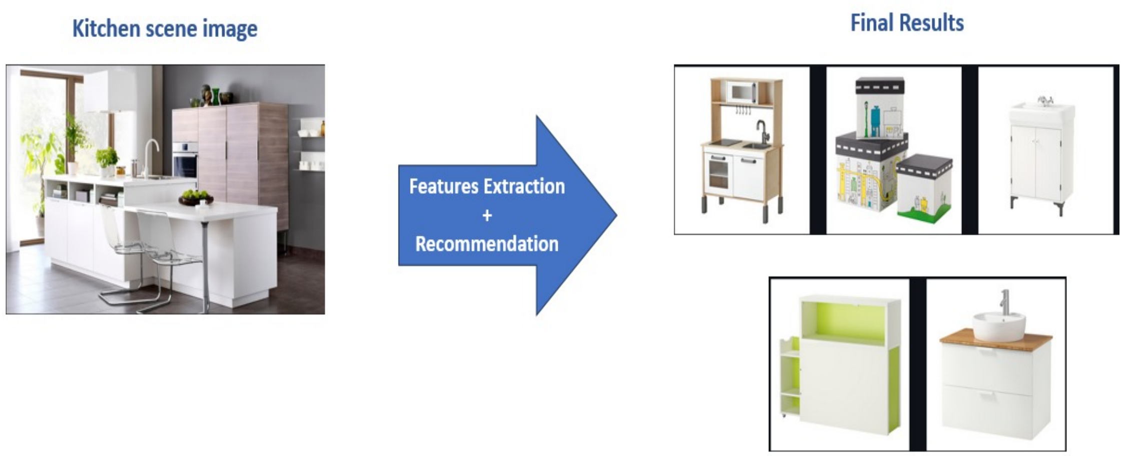
The Cosine similarity metric yielded an average distance of 0.162, indicating a relatively close alignment between feature vectors. This suggests that the system excelled in capturing directional similarities among interior design elements, regardless of their magnitude. In contrast, the Manhattan distance metric produced a significantly higher average distance of 16.38. This suggests a broader spatial gap between feature vectors, emphasizing the sum of absolute differences. The system's evaluation using Manhattan distance indicates a preference for dissimilarity based on linear spatial arrangement. The Euclidean distance metric resulted in an average distance of 0.569, positioning it between Cosine and Manhattan. Euclidean distance considered both magnitude and orientation, providing a nuanced measure of spatial separation between feature vectors.

4.0.4 Relevance of Cosine Similarity

The choice to work with the Cosine similarity metric aligns with its focus on directional similarities. In the context of interior design recommendations, where visual aesthetics and style are crucial, Cosine similarity proves to be a valuable metric. Cosine similarity's emphasis on capturing the angle between vectors enables the system to recognize similarities in design direction, even if the magnitude of features varies. This aligns well with the subjective nature of interior design preferences.

4.0.5 Limitations and Future Work:

Acknowledge that the focus on Cosine similarity doesn't imply its superiority in all scenarios. The choice of distance metric should align with user preferences and the nature of interior design elements. Future work could explore the integration of user feedback to further refine the recommendation system and continually enhance its performance.



5. Conclusion

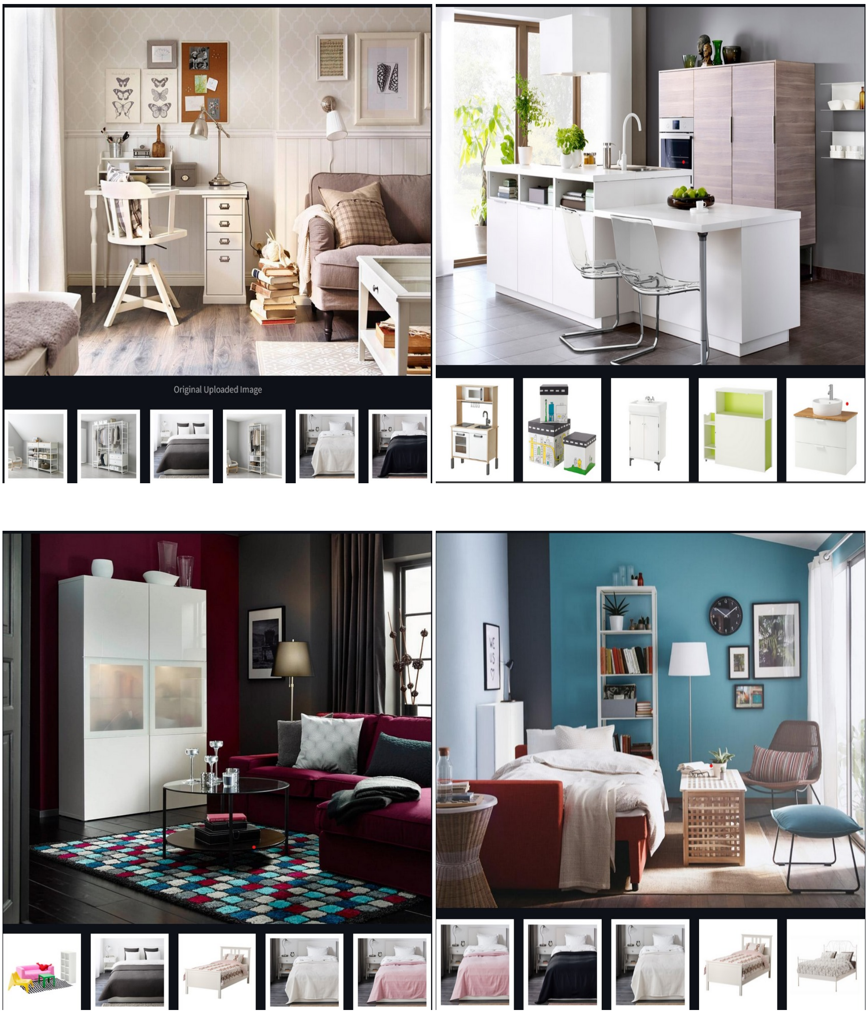
In the dynamic field of interior design, the "Design Discovery" Interior Design Recommender System emerges as a transformative force, seamlessly blending technology and creativity. Explored in detail in our article, this system redefines the way we interact with interior decor through a novel approach to image-driven recommendations. As we embark on a journey into the era of personalized and visually captivating recommendations, the unveiling of "Design Discovery" signifies a paradigm shift. Fueled by the strategic fusion of transfer learning via ResNet50 and the k-NN algorithm for similarity calculation, this system becomes a game-changer. The synergy between these elements elevates recommendation precision, providing a robust and nuanced approach to image-based interior design recommendations. In essence, "Design Discovery" transcends the boundaries of technology, evolving into a guide that tailors the online furniture shopping experience to the individual. As we peer into the future of personalized interior design recommendations, this system stands as a beacon, showcasing the boundless possibilities at the intersection of technology and interior design.

References

[1] Ivona Tautkute[1,3], Aleksandra Mozejko[3], Wojciech Stokowiec[1,3], Tomasz Trzcinski[2,3], Łukasz Brocki[1], and Krzysztof Marasek[1] . What Looks Good with my Sofa: Multimodal Search Engine for Interior Design

[2] Hessel Tuinhof[1], Clemens Pirker[2], , and Markus Haltmeier[3], Image-Based Fashion Product Recommendation with Deep Learning

[3] Mohammad Diqi, Hamzah Hamzah, , Erizal Erizal, DeepRec: Efficient Product Recommendation Model for E-Commerce using CNN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