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AI Based Virtual Interior Design

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ABSTRACT:

In response to the inefficiencies of traditional interior space design classification, this study proposes a deep learning-based approach using a Convolutional Neural Network (CNN) architecture to automate interior design type recognition. Specifically, the NASNetMobile model is employed to classify interior design images into five major categories: Bathroom, Bedroom, Dining, Kitchen, and Living Room. A web-based application was developed using the Flask framework, allowing users to input an interior type and retrieve relevant images. The model was trained on a curated dataset of interior design images and achieved high classification accuracy. Image preprocessing techniques such as resizing, normalization, and augmentation were applied to improve model generalization. The proposed system enhances the speed and accuracy of identifying interior design types, supporting both designers and end users in retrieving contextually appropriate design inspirations. This work demonstrates the potential of combining deep learning with web applications to build practical tools in the domain of computer vision and interior design automation.

1.INTRODUCTION:

In recent years, Artificial Intelligence (AI) has transformed various industries, including interior design. The project "AI-Based Virtual Interior Design" aims to revolutionize how people plan and visualize their living or working spaces by integrating AI with modern web technologies. Traditional interior design involves manual planning, physical mockups, and time-consuming consultations. However, this project provides a smarter, faster, and more interactive solution.

By using Convolutional Neural Networks (CNN) and the NASNet Mobile model, our system can process images of empty rooms and suggest furniture placements, color schemes, and design styles in real time. AI models are trained on large datasets of interior designs, allowing them to recognize patterns, styles, and spatial arrangements effectively. The system enhances decision-making by giving users a realistic preview of how a space will look before any physical setup is done.

The project is built with a Flask-based web application, where the frontend allows users to upload room images, and the backend uses AI to process and display virtual design suggestions. Libraries like TensorFlow, Keras, and OpenCV are used for image processing, feature extraction, and neural network operations.

This AI-driven approach makes interior design more accessible, cost-effective, and user-friendly. It is especially helpful for homeowners, architects, and interior decorators who want to experiment with different layouts and styles without spending extra time or money.

2.LITERATURE SURVEY

Title: Mycelium-Based Composites in Art, Architecture, and Interior Design: A Review
Authors: Sydor M., Bonenberg A., Doczekalska B., Cofta G.
Year: 2021
Description:
This comprehensive review investigates the emerging application of mycelium-based composites within the fields of art, architecture, and interior design. As sustainable development becomes an increasingly important theme, mycelium—a biodegradable material cultivated from fungal structures—presents a promising alternative to synthetic or environmentally harmful materials. The study explores the biological formation, mechanical behavior, and aesthetic potential of mycelium composites, highlighting their advantages such as low cost, low environmental impact, and adaptability. It also examines their use in furniture, panels, and architectural prototypes, addressing the technical limitations in durability and scalability. The authors conclude by discussing the need for further research into the structural reliability and long-term behavior of these materials in practical interior applications

Title: Pushing the Limits of Functionality-Multiplexing Capability in Metasurface Design Based on Statistical Machine Learning
Authors: Ma W., Xu Y., Xiong B., Deng L., Peng R., Wang M., Liu Y.
Year: 2022
Description:
This research explores the integration of statistical machine learning models with the design of multifunctional metasurfaces—engineered structures capable of manipulating electromagnetic waves. Traditional metasurface designs face

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challenges when expanding to high-dimensional, multifunctional configurations. To address this, the authors propose a data-driven approach that leverages statistical learning techniques to optimize multiple metasurface functionalities simultaneously. The study details the development of a large-scale database of structural and optical features and the training of predictive models to guide the inverse design process. By applying this method, the researchers demonstrate the creation of metasurfaces capable of performing several optical functions with high precision. The study highlights the potential of machine learning to transform material and optics design, reducing trial-and-error cycles and accelerating innovation.

Title: Deep Learning Framework for Material Design Space Exploration Using Active Transfer Learning and Data Augmentation
Authors: Kim Y., Kim Y., Yang C., Park K., Gu G. X., Ryu S.
Year: 2021
Description:
This paper presents a novel deep learning framework for exploring the material design space, which traditionally requires extensive experimentation and simulation. The authors incorporate active learning, transfer learning, and data augmentation to significantly reduce the dependency on large-scale labeled datasets, which are often scarce in materials science. The framework begins with a pretrained model that is incrementally fine-tuned using actively selected data samples that maximize learning efficiency. Augmented datasets help the model learn invariant features and improve its predictive performance. The system is applied to tasks such as predicting mechanical properties from microstructure images, demonstrating how deep learning can uncover meaningful correlations in material datasets. The framework not only expedites the material discovery process but also shows strong potential for generalization across diverse material types and domains.

Title: Influence of Occupant Behavior for Building Energy Conservation: A Systematic Review Study of Diverse Modeling and Simulation Approach
Authors: Uddin M. N., Wei H.-H., Chi H. L., Ni M.
Year: 2021
Description:
This systematic review focuses on the role of occupant behavior in achieving building energy efficiency, a factor often underrepresented in traditional energy modeling. The authors review a broad range of studies that apply diverse modeling and simulation approaches to quantify and predict how occupant actions—such as lighting use, HVAC control, and occupancy patterns—influence building performance. Techniques such as agent-based modeling, stochastic simulations, and machine learning are discussed, along with their respective strengths and limitations. The study identifies key gaps in existing models, including a lack of real-time behavioral data and insufficient integration with Building Information Modeling (BIM). It emphasizes the need for adaptive and dynamic modeling approaches that incorporate real occupant data to enable smarter, more efficient building design and management systems.

Title: Artificial Intelligence to Facilitate the Conceptual Stage of Interior Space Design: Conditional Generative Adversarial Network-Supported Long-Term Care Space Floor Plan Design of Retirement Home Buildings
Authors: Li Y., Chen H., Mao J., Chen Y., Zheng L., Yu J., Yan L., He L.
Year: 2024
Description:
This study proposes a deep learning-based solution to assist architects and interior designers in the early, conceptual stages of spatial planning, particularly within the healthcare sector. Focusing on long-term care facilities like retirement homes, the authors introduce a Conditional Generative Adversarial Network (cGAN) model that automatically generates functional and aesthetically coherent floor plans based on specified design constraints. The model learns from a dataset of existing care facility layouts and uses that knowledge to generate new, diverse floor plans that maintain usability and regulatory compliance. The generated designs aim to improve living conditions for elderly residents while streamlining the design process. This AI-assisted approach demonstrates how machine learning can contribute to user-centered, rapid design generation, ultimately reducing costs and saving time in the architectural workflow. The study also explores the interpretability and customization potential of generated designs, making the model a practical tool in the hands of professionals.

3.METHODOLOGIES:

The proposed system employs a deep learning approach centered around Convolutional Neural Networks (CNNs) for interior design type classification. The NASNetMobile architecture was selected for its efficiency and accuracy in image classification tasks. A curated dataset of labeled interior design images across five categories—Bathroom, Bedroom, Dining, Kitchen, and Living Room—was compiled and used for model training. Prior to training, comprehensive image preprocessing techniques were applied, including resizing to a uniform input size, normalization to standardize pixel values, and data augmentation to increase dataset variability and enhance generalization. The model was trained using

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supervised learning with categorical labels and evaluated using classification accuracy metrics

1. Data Collection

This module focuses on gathering relevant interior design images from publicly available sources such as Google and Kaggle. The images are selected based on their relevance to the five interior categories: Bathroom, Bedroom, Dining, Kitchen, and Living Room. The collected data forms the foundation for building and training the classification model.

2. Data Analysis

Once the data is collected, it is analyzed to understand the distribution and balance across different categories. This involves counting the number of images in each category and verifying that each class has sufficient representation. This analysis helps in ensuring the dataset is balanced and suitable for training.

3. Preprocessing

Preprocessing is a critical step to prepare the raw images for model training. Using TensorFlow tools, this module performs operations such as resizing images to a consistent dimension, normalizing pixel values, and applying transformations like rotation or flipping for data augmentation. These steps enhance the model's ability to generalize and improve overall performance.

4. Data Splitting

This module uses Scikit-learn to divide the preprocessed dataset into training, testing, and validation sets. Proper data splitting ensures that the model is trained on one portion of the data while being evaluated on unseen data, helping to prevent overfitting and assess the model's true performance.

5. Model Training

With the processed data in place, the CNN model (NASNetMobile) is applied to the training dataset. The model is trained over a defined number of epochs, with adjustments made to weights through backpropagation. This module is responsible for learning patterns and features from the interior images that enable accurate classification.

6. Model Accuracy Evaluation

After training, the model's performance is evaluated using metrics such as accuracy, precision, recall, and visualized using tools like Seaborn and Matplotlib. This module helps understand how well the model is performing and whether it is suitable for real-world deployment.

7. Classification and Prediction

The trained model is saved in an H5 format for reuse. This module is responsible for using the model to classify new, unseen images into one of the five interior categories. Users can input images or categories and retrieve predictions accordingly through a user-friendly interface.

CLASS DIAGRAM:

4.REQUIREMENTS ENGINEERING:

These are the requirements for doing the project. Without using these tools and software's we can't do the project. So we have two requirements to do the project. They are

1. Hardware Requirements.
2. Software Requirements.

Hardware Requirements

The hardware requirements may serve as the basis for for a contract for the implementation of the system and should therefore be a complete and consistent specification of the whole system. They are used by software engineers as the starting point for the system design. It shouls what the system do and not how it should be implemented.

- PROCESSOR : DUAL CORE 2 DUOS.
- RAM : 4GB DD RAM
- HARD DISK : 450 GB

Software Requirements

The software requirements document is the specification of the system. It should include both a definition and a specification of requirements. It is a set of what the system should do rather than how it should do it. The software requirements provide a basis for creating the software requirements specification. It is useful in estimating cost, planning team activities, performing tasks and tracking the teams and tracking the team's progress throughout the development activity.

- OPERATING SYSTEM: WINDOWS 10
- PLATFORM : SPYDER3
- PROGRAMMING LANGUAGE : PYTHON, HTML
- FRONT END : SPYDER3

5.DESIGN ENGINEERING :

Design Engineering deals with the various UML [Unified Modelling language] diagrams for the implementation of project. Design is a meaningful engineering representation of a thing that is to be built. Software design is a process through which the requirements are translated into representation of the software. Design is the place where quality is rendered in software engineering.

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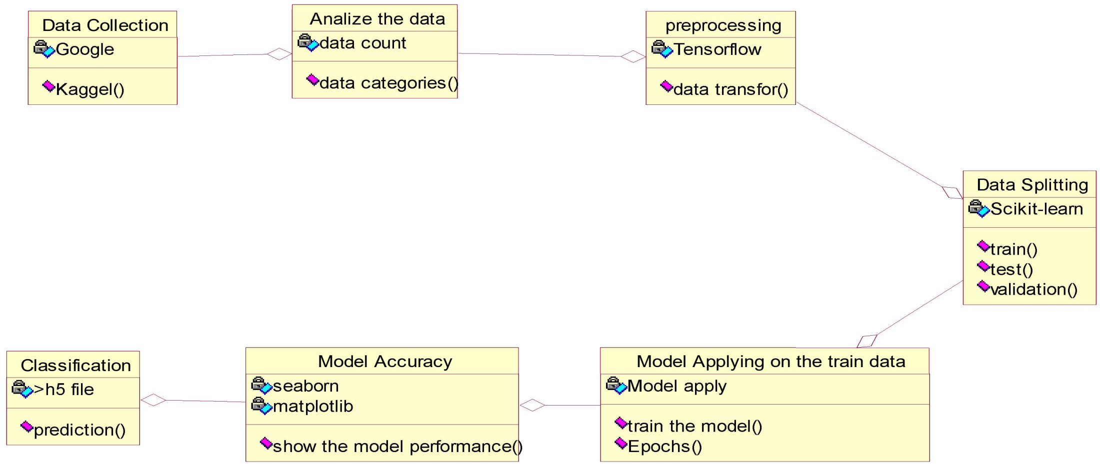
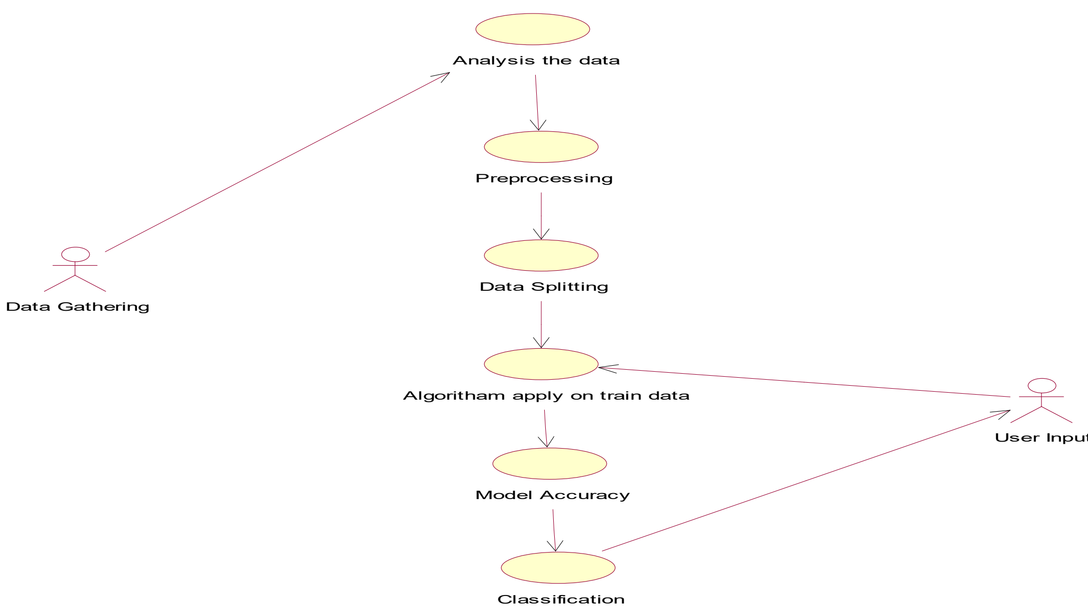


EXPLANATION:

In this class diagram represents how the classes with attributes and methods are linked together to perform the verification with security. From the above diagram shown the various classes involved in our project.

USECASE DIAGRAM :



EXPLANATION:

The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted. The above diagram consists of user as actor. Each will play a certain role to achieve the concept.

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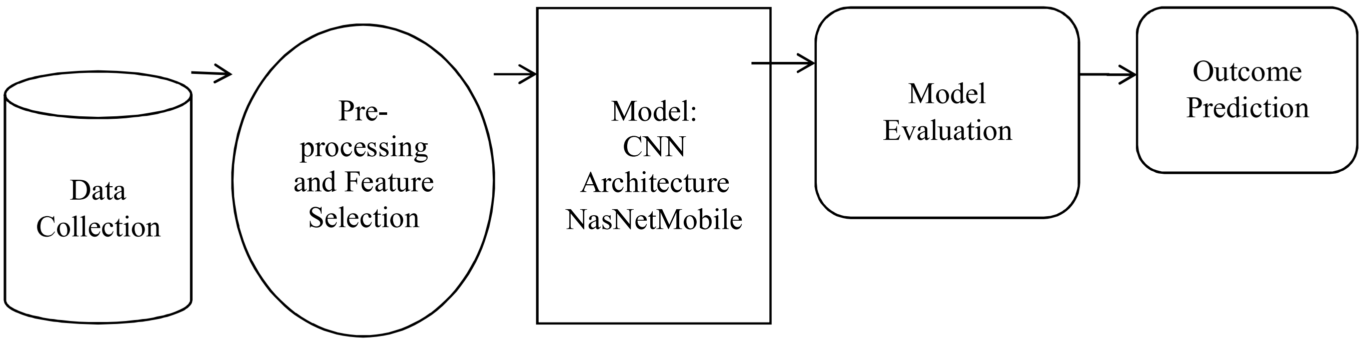
SYSTEM ARCHITECTURE:



6.IMPLEMENTATION :

Introduction:

The implementation of the AI-based virtual interior design system involves multiple stages, including data collection, preprocessing, model training, frontend-backend integration, and deployment. Below is a structured breakdown

1. Data Collection & Preprocessing

Collected a large dataset of room images with different furniture, styles, and layouts.

Images were resized to 224x224 pixels to match the input size requirement of NASNetMobile.

Preprocessing included normalization, augmentation, and label encoding to improve training efficiency and accuracy.

2. Model Selection and Training

Utilized NASNetMobile, a lightweight deep convolutional neural network suitable for mobile and web applications.

Frameworks used: TensorFlow and Keras.

Model trained to recognize room types and recommend suitable design elements like color schemes, furniture arrangement, etc.

Trained model was saved as .h5 file for integration with the backend.

3. Feature Extraction & Design Suggestions

Used CNN layers to extract spatial features from room images.

AI suggests interior designs based on:

Room type (bedroom, kitchen, etc.)

Current layout and available space

Detected color palette and lighting

Optional: User can upload an image and choose a theme (e.g., modern, classic), and the system recommends furniture and décor items.

4. Backend Development

Built using Flask (Python web framework).

Manages:

Image input handling

Sending image to AI model

Receiving predictions and suggestions

Interacting with frontend for display

Integrated OpenCV (cv2) for image processing and conversions

5. Frontend Design

Developed using HTML, CSS, and JavaScript.

Features:

Image upload interface

Real-time visualization of design recommendations

Display of before/after room design

6. System Integration & Testing

Flask app deployed locally for testing AI recommendations.

Verified:

Accuracy of interior design suggestions

Speed and responsiveness of the system

Compatibility across different image types

7. Deployment

Can be deployed on a local server, cloud (Heroku, AWS), or as a mobile/web app.

7. FUTURE ENHANCEMENTS:

In the future, the system can be expanded to support a wider variety of interior design categories,

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including specific styles such as contemporary, rustic, and minimalist designs. Personalization features can be integrated by considering user preferences and historical choices to provide tailored design recommendations. The application could also incorporate augmented reality (AR) functionality, allowing users to visualize the suggested interiors in real-time through their mobile devices. Voice search and natural language processing (NLP) capabilities can be added to enhance user interaction and ease of access. Moreover, a recommendation engine could be developed to suggest compatible furniture and decor items based on the identified room type and style. Continuous model training with more diverse datasets can further improve accuracy and adaptability. Enhancing the backend to support 3D models and spatial planning could make the system even more comprehensive. Integration with online marketplaces could allow users to purchase suggested items directly. Finally, implementing multilingual support would help reach a global audience and increase usability.
Lightweight model ensures faster loading and smooth performance on most devices.

7.CONCLUSION :

The proposed system leverages deep learning, specifically the NASNetMobile CNN architecture, to effectively classify interior design images into distinct categories. By automating the recognition of interior spaces such as bedrooms, kitchens, and living rooms, the system enhances the efficiency and accuracy of interior design workflows. The integration with a Flask-based web application makes it user-friendly and accessible for both designers and end users. Image preprocessing techniques like normalization and augmentation contribute significantly to the model's performance. The project demonstrates the practical application of computer vision in design automation. It offers a scalable and intelligent solution to support rapid and accurate interior classification. This research lays a strong foundation for future advancements in smart interior design systems.

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