Slide 1:

Good [morning/afternoon], everyone. Our project's primary objective is to develop an AI-driven, real-time occupancy detection system for smart homes. We've harnessed the power of advanced Convolutional Neural Networks, specifically models like ResNet50, MobileNet V3, and EfficientNet B0, to achieve this goal. Additionally, we leveraged diverse datasets, including hospital footage, to train our models effectively. The system's main features include real-time human presence detection, robust performance across varying conditions, and optimization for efficiency, making it suitable for real-world deployment.

Here the diagram shows that:

* Two simple diagrams demonstrating the input and output of the CNN model.
* The first diagram shows an input image of a hallway with a person walking, and the output is "Occupancy Detected."
* The second diagram shows an input image of an empty room, and the output is "Occupancy Not Detected.”

Slide 2:

Our system comprises two main components: hardware and software. On the hardware side, we use sensors, cameras, and microcontrollers, essential for deploying the system in real-life smart homes. The software component includes our CNN models, implemented in PyTorch for image classification. Each CNN model offers unique advantages: ResNet50 provides deep architecture for high accuracy, MobileNet V3 Large is efficient for mobile and embedded devices, EfficientNet B0 balances performance with computational efficiency, and MobileNet V2 is lightweight and ideal for resource-constrained environments.

Here the diagram shows that:

* A flowchart representing the overall workflow of the project.
* The workflow includes data collection, annotation, preprocessing, model training, evaluation, and final evaluation.
* Key steps involve hyperparameter tuning, model optimization, and performance assessment.

Slide 3:

We placed significant emphasis on data handling and preprocessing to ensure our models' accuracy. We extracted frames from various sources, including hospital videos, to create a comprehensive dataset covering diverse scenarios. To manage variability in lighting and environments, we applied advanced preprocessing and data augmentation techniques. Our models—ResNet50, MobileNet V3, EfficientNet B0, and MobileNet V2—underwent rigorous training and optimization. We enhanced parallel processing and utilized GPU acceleration to improve processing speed and overall system efficiency.

Here the 1st diagram describes this:

* A diagram illustrating the architecture of a Convolutional Neural Network (CNN) for occupancy detection.
* The CNN includes multiple convolutional and max pooling layers, followed by fully connected layers.
* The network takes input images and outputs a prediction of whether the scene is occupied or not.

The 2nd image shows the results of testing five different pre-trained models on a dataset. The models are ResNet50, MobileNetV3 Large, EfficientNet B0, MobileNetV2, and MobileNetV3 Small. The test loss and accuracy for each model are reported.

The best-performing model is MobileNetV2 with a test loss of 0.1205 and a test accuracy of 97.85%. The worst-performing model is MobileNetV3 Small with a test loss of 0.8295 and a test accuracy of 88.17%.

Slide 4:

Looking ahead, we're proposing several enhancements to our system. First, by integrating advanced sensors like thermal imaging and depth sensors, we can further improve occupancy detection accuracy. For scalability, we suggest developing a distributed version to handle larger datasets and more complex environments. Additionally, implementing an AI-driven continuous learning framework will allow the system to adapt to changing occupancy patterns over time. In conclusion, this project represents a significant advancement in smart home technologies, with a focus on adaptability and future-proofing through continuous improvements.