ENS 491-492 – Graduation Project

Final Report

Project Title: Indoor Localization Using Camera Images

Group Number: 128

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1. EXECUTIVE SUMMARY

The indoor localization project conducted addresses the challenge of achieving precise indoor positioning using computer vision and deep learning techniques. Traditional localization methods like GPS and Wi-Fi are ineffective indoors, motivating our exploration of novel solutions for reliable indoor navigation systems. Our project integrates state-of-the-art computer vision techniques with deep learning methodologies, with a primary focus on the Swin Transformer architecture for spatial understanding.

The project began with a comprehensive literature review, identifying gaps in existing indoor localization methods and leveraging findings from landmark studies to inform our approach. A key component of our work involved dataset selection and model design, culminating in the development of Swin Transformer-based architectures optimized for indoor localization tasks. Through extensive testing and evaluation, our system demonstrated superior accuracy compared to conventional methods across multiple indoor scenes.

The outcomes of this project offer significant advancements in indoor localization accuracy and efficiency. Our work contributes to the scientific understanding of visual localization systems and holds potential for practical applications in environments like shopping malls and airports. Moving forward, future research could focus on real-time implementation, dataset expansion, and collaborative initiatives to further enhance the robustness and applicability of our approach. The success of this project underscores the transformative potential of deep learning in addressing complex localization challenges.

2. PROBLEM STATEMENT

The original complex problem addressed by this project revolves around the challenge of achieving precise indoor localization within large enclosed spaces, such as shopping malls and airports, using computer vision and deep learning techniques. Motivated by the limitations of traditional methods like GPS and Wi-Fi indoors, we aim to enhance the reliability and effectiveness of indoor location systems, making them more suitable for practical applications and improving user experiences in indoor environments.

Our project aims to bridge a notable gap in indoor localization research by integrating state-of-the-art computer vision techniques with deep learning methodologies. Existing literature, such as studies by Fusco and Coughlan [1], Niu and Li's work on automated image-based localization (HAIL) [2], and Akal et al.'s approach for image-based localization [3], has made significant contributions to the field. However, these studies highlight the need for a more comprehensive solution that effectively combines computer vision-based approaches with deep learning techniques to enhance accuracy and efficiency.

While discriminative feature-based methods [4] and two-stage architectures involving image retrieval and pose estimation [5] have shown promise, there remains a gap in achieving optimal performance in indoor localization tasks. Studies utilizing deep belief networks [6] and convolutional neural networks [7] have laid a foundation for image-based indoor localization, yet further refinement is necessary to elevate performance levels.

Moreover, our project seeks to explore and incorporate modern approaches from related fields, such as Swin Transformers [8], to push the boundaries of indoor localization accuracy and efficiency. These innovative methodologies offer promising avenues for improving the robustness and reliability of indoor localization systems, addressing key challenges faced by existing methods. By integrating these advanced techniques, we aim to contribute to the evolution of indoor localization technology and its practical applications.

2.1. **Objectives/Tasks**

2.1.1. **Literature Review**

- Objective/Task: Conduct a comprehensive review of existing literature on indoor localization using computer vision.
- Intended Result: Summarize key methodologies, identify gaps, and establish a foundational understanding for the project.

2.1.2. **Dataset Search**

- Objective/Task: Identify and acquire suitable datasets for training, validation, and testing of the indoor localization system.
- Intended Result: Acquire a dataset collection that aligns with project requirements and evaluation criteria.

2.1.3. **Implementation Review**

- Objective/Task: Evaluate different implementation frameworks and approaches for developing the indoor localization system.
- Intended Result: Review implementations to come up with an optimal implementation strategy based on feasibility, performance, and compatibility with project goals.

2.1.4. **Design Proposal**

- Objective/Task: Generate multiple design proposals integrating computer vision and deep learning techniques for indoor localization.
- Intended Result: Develop comprehensive design concepts outlining methodologies, architectures, and proposed solutions.

2.1.5. **Preliminary Testing**

- Objective/Task: Conduct preliminary tests and experiments to assess the feasibility and performance of proposed designs.
- Intended Result: Gather initial insights, identify strengths and weaknesses, and guide design refinement.

2.1.6. **Design Refinement**

- Objective/Task: Refine the selected design based on preliminary test outcomes, feedback, and analysis.
- Intended Result: Enhance design robustness, optimize architectures, and address identified limitations.

2.1.7. **System Implementation**

- Objective/Task: Implement the finalized design to develop a functional indoor localization system.
- Intended Result: Create a working prototype capable of accurate indoor localization using computer vision.

2.1.8. **Model Optimization**

- Objective/Task: Optimize model training, testing procedures, and parameter tuning to achieve optimal performance.

- Intended Result: Fine-tune algorithms, parameters, and training strategies to maximize accuracy and efficiency.

2.1.9. **Performance Evaluation**

- Objective/Task: Compare the performance of the developed system with existing state-of-the-art approaches reported in literature.
- Intended Result: Analyze and present comparative results to demonstrate improvements and contributions.

2.2. **Realistic Constraints**

Economic: Due to budget limitations, there are constraints in conducting extensive real-world testing of the navigation system, affecting its robustness and performance validation. Also, the navigation system should be designed to accommodate the budget constraints of potential clients, ensuring optimal performance on inexpensive embedded hardware commonly used in real-world applications.

Technical: The project faces limitations in accessing high-performance computational resources required for training complex models, impacting model complexity and training dataset size.

IEEE Standards:

1. **IEEE Recommended Practice for Framework and Process for Deep Learning Evaluation [9]**

   This standard serves as a valuable resource for the project, providing guidelines to enhance the reliability and performance of deep learning models.

   Abstract: This standard offers recommendations aimed at enhancing and evaluating deep learning algorithms. It outlines an assessment index system along with its corresponding assessment process.

   Scope: This standard specifies requirements within the domain of deep learning, encompassing aspects such as assessment index systems, assessment processes,

and evaluation stages spanning demand, design, operation, and implementation phases.

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2. **IEEE Standard for Camera Phone Image Quality [10]**

   This standard is employed within the project to establish a comprehensive framework for evaluating and ensuring the quality of images captured by camera-equipped mobile devices, forming the basis for the model development.

   Abstract: This code sets a standard for the performance of mobile devices with cameras. It specifies metrics and procedures for sensors, lenses, and signal processing routines. These metrics include spatial frequency response, color uniformity, chroma level.

   Scope: The standard focuses on assessing image and video quality, outlining standardized test methods for evaluating camera phone image attributes and quality parameters.

   Relevance: Mobile devices, particularly their cameras, are extensively utilized in research papers for model testing and dataset creation. The IEEE camera quality standard provides a consistent basis for evaluating data obtained from mobile cameras used in such contexts.

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3. METHODOLOGY

3.1 Data Analysis, Formatting & Processing

During our literature review in design phase, we have selected 7-Scenes as our dataset for a number of reasons including being used by other researchers which will allow head to head benchmarking. 7-Scenes dataset contains records captured by manually moving a Kinect sensor inside of 7 different rooms in random 3d trajectories forming paths referred as "sequences" in the dataset. For every room certain sequences are marked as training sequences and others as testing. Rooms volumes range from 1 metric cubes to 18 metric cubes.

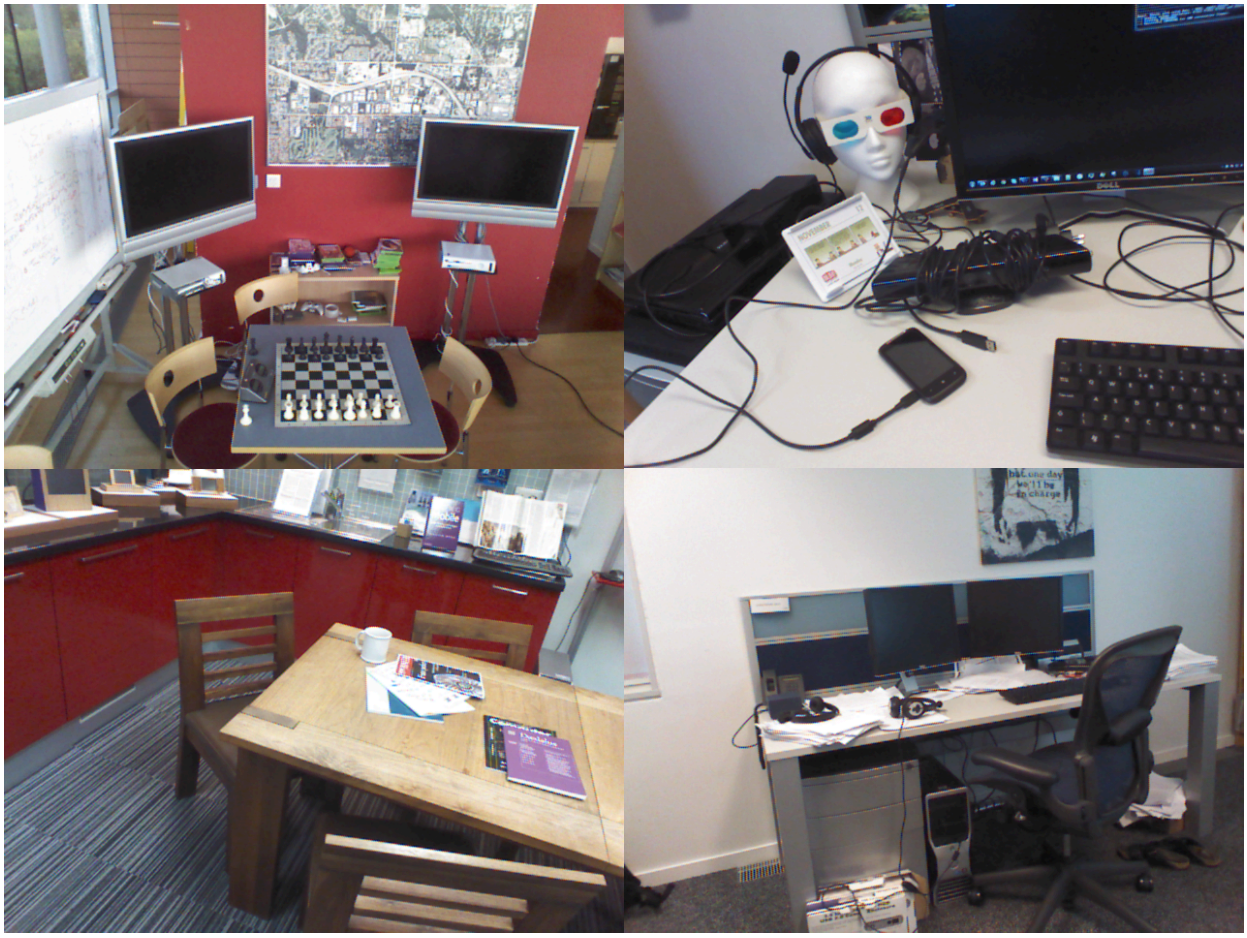

Figure [1]: Images from 7-Scenes dataset, corresponding to different scenes.

In every sequence there are 1000 unique positions of recording forming the path of that sequence. Every record is composed of 3 items; an 640 x 480 pixel 24-bit RGB image in png format, a 16-bit depth image in same format and size and homogenous camera matrix values given in utf-8 text format. Our project aims to perform position estimation using RGB images in runtime, therefore we only used depth images during explanatory phase.

Position information is recorded as homogenous camera matrices. in a 7-scenes dataset. Homogenous camera matrices are 4x4 matrices that map world coordinates to camera coordinates, which later on get mapped to image space coordinates through projection matrix. Projection matrix represents intrinsic parameters of the camera device such as focal length, while the camera matrix is only related to extrinsic parameters of the camera such as position and orientation, therefore we can extract translation and rotation from it to get the camera's position. Following equation demonstrate relation between camera matrix and world/camera coordinates:

$$\begin{bmatrix} X_c \\ Y_c \\ Z_c \\ 1 \end{bmatrix} = \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_x \\ r_{21} & r_{22} & r_{23} & t_y \\ r_{31} & r_{32} & r_{33} & t_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X_w \\ Y_w \\ Z_w \\ 1 \end{bmatrix}$$

Equation [1]: Multiplication of world coordinate vectors with camera matrix yields camera space coordinates.

Rightmost column of the matrix represents translation of the camera, while the upper left 3x3 matrix represents rotation. While it is theoretically possible to use rotation matrices for representing orientation of camera in our pipeline, we preferred to use quaternions which do

not suffer from problems such as gimbal locks in euler angles. Quaternions are 4D vectors where 3 dimensions contain complex bases that can describe orientation in three dimensions.

3.2 Determination of evaluation criteria

In our literature review, we have observed that certain common benchmark metrics and datasets exist in literature. Prior work included benchmarks with other important papers to empirically demonstrate their achievements. One such paper is Alex Kendall's PoseNet [12]. This paper was one of the very first papers in literature to approach the position estimation task with deep learning, unlike previous approaches that relied on methods such as ORB-SIFT point matching or traditional SLAM techniques. PoseNet demonstrated the potential of deep neural networks in directly regressing camera poses from images, eliminating the need for explicit feature extraction or handcrafted descriptors. By leveraging large-scale datasets and convolutional neural network architectures, PoseNet achieved impressive results in real-time camera localization tasks, opening up new avenues for research in the field of visual localization and mapping.

Our approach to design was also inspired from this class of techniques. As a result, we adopted evaluation criteria used by important papers in the subject. Position estimation problem is described as estimating a 6DOF or a pair of 3D vectors, where translation of the camera and orientation of the camera is represented. Translations are measured in meters respective to distances to the origin point of the coordinate system assumed by the dataset while orientation is represented as angles representing rotation orthogonal to each axis basis plane during evaluation but better representations like quaternions are preferred in model development. Evaluation of predictions is usually based on L2 norm difference to ground truth for translation and euler angle rotation vectors as metric. Both MSE and absolute error are used commonly for averaging. Performance of different models are compared in an applicable manner by referring to test losses of similar models position predictions on the same dataset. We referred to Alex Kendalls PoseNet[12] predictions as a basis for benchmarking. We trained our model on different rooms of 7-Scenes and compared losses of PoseNet and a few other models on the same rooms to assess the relative performance of our approach.

3.3 Design

Our approach stems from the fundamental principles of transformers, as originally proposed by Vaswani et al. [11], and extends their applicability to image-based tasks. Specifically, we leverage the Swin Transformer architecture [8], a recent advancement that exhibits remarkable efficiency and scalability in handling spatial information within images.

The Swin Transformer, introduced by Liu et al. [8], represents a breakthrough in hierarchical vision transformer architectures, offering significant advantages for tasks such as feature extraction and spatial understanding. It features a shifted window mechanism that enables efficient processing of high-resolution images in a hierarchical manner, making it well-suited for indoor localization tasks.

Key Features of Swin Transformer

The Swin Transformer offers several compelling features that make it a powerful choice for indoor localization:

- **Hierarchical Processing:** Unlike conventional transformers, the Swin Transformer processes images hierarchically, allowing for the efficient extraction of both local and global spatial features. This capability is crucial for understanding complex indoor scenes with multiple objects and structures.

- **Shifted Windows:** The shifted window mechanism employed by Swin Transformer reduces computation and memory costs by processing image patches in a shifted and overlapping manner. This design choice enhances scalability and efficiency, making it feasible to handle large-scale indoor environments.

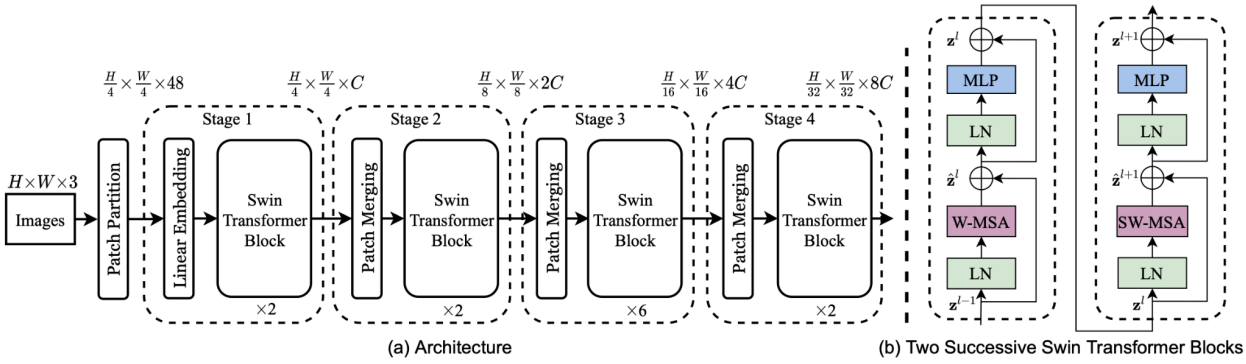

Figure [2]: Architecture of the Swin Transformer

Relevance to Indoor Localization

The use of Swin Transformer within our indoor localization system is motivated by its ability to handle high-resolution indoor images effectively. By leveraging Swin Transformer's hierarchical feature extraction capabilities, we aim to capture detailed spatial information from indoor

scenes, enabling precise localization and mapping. To suit the Swin Transformer for our specific task, we dropped the original classification layer, which used a softmax activation, and replaced it with a fully connected layer with 7 outputs. This modification allows the model to output a prediction vector that matches our target size.

3.4 Model Development

Data processing

Using data representations which ensure error free and numerically stable are crucial for proper model training and inference. For this reason we decided to use quaternions for orientation representation instead of euler angles or rotation matrices. We used csv files that contain pose information as 7 element vectors of translation and quaternion coefficients respectively. We shrunk photos to size 256 to 256 pixels before feeding them to Swin transformer. One of the topics that created a significant challenge to us during the project was limited hardware resources. We used the NVIDIA GTX1650 for training and testing our model. As an entry level graphics card, it only has 4Gb of ram which caused frequent memory exceptions during the development phase, which required us to optimize memory usage and do trade-offs to fit model and data into memory. Biggest effect of memory limitation was on batch sizes. We had to use smaller batches to fit into limited memory which slowed down the training process.

Selection of an appropriate loss function is crucial for convergence of the model to local minimas. Since our task is based on localisation where values have spatial meaning, using the L2 norm on values as a metric is logical. Instead of calculating the difference between quaternions on every training would likely be computationally costly, we instead applied L2 norm on quaternion parameters as well, similarly to AlexKendall's PoseNet[12].

A natural problem associated with creating a model that simultaneously tries to predict translation and orientation is determining the weight of each on net loss value. Starking a balance between two is very important as Alex Kendall noticed in their paper and employed hyperparameter beta which is a scalar multiplier on quaternion L2 norm. However, instead of trying to fine-tune such values, we used a different approach and tried to dynamically fit

balance between the two during training. Our loss function is very similar to that of Alex Kendall's, defined as follows:

Loss Function

Our loss function, taken from Kendall's work [12], is designed to handle the uncertainties associated with predicting both position and orientation. The loss function we used is defined as follows:

$$L(I) = \frac{1}{N}\sum_{i=1}^{N}(\|x_i - \hat{x}_i\|_2 e^{-\hat{s}_x} + \hat{s_x} + \|q_i - \hat{q}_i\|_2 \hat{e}^{-\hat{s}_q} + \hat{s}_q)$$

Equation [2]: Loss function

Where:

- x_i and q_i are the ground truth translation and quaternion values, respectively.
- $\hat{x_i}$ and $\hat{q_i}$ are the predicted translation and quaternion values, respectively.
- $\hat{s_x}$ and $\hat{s_q}$ are the learned uncertainties for translation and quaternion predictions.

This formulation allows the model to dynamically adjust the weighting between translation and orientation errors during training, improving the overall robustness and performance of the localization system.

Training Convergence

During the training of our indoor localization model, achieving convergence was a critical milestone that ensured the effectiveness and reliability of our deep learning system. Several key factors played a pivotal role in facilitating convergence and optimizing model performance.

For the selection of the learning rate, we experimented with several values, and found 1e-5 to give the best convergence across different values.

To address potential overfitting, we implemented early stopping based on validation loss trends. This adaptive strategy helped prevent model divergence and ensured that the final model achieved robust generalization performance.

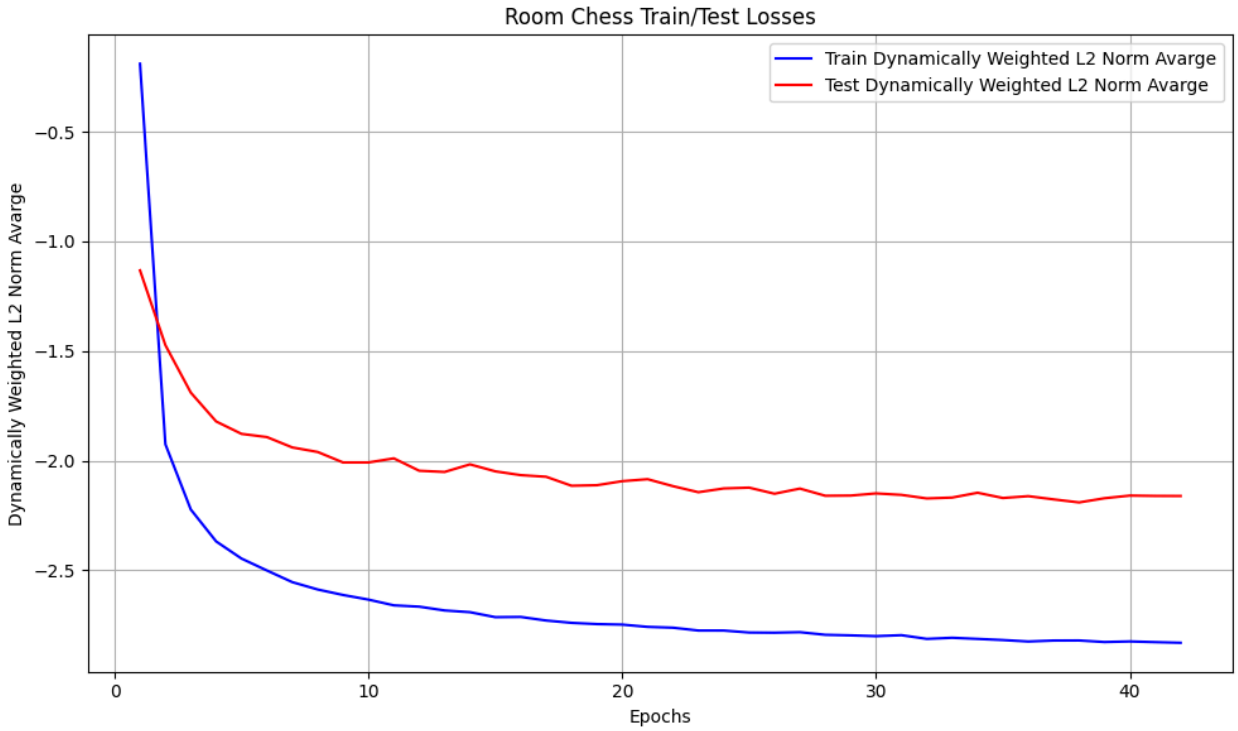

Figure [3]: Convergence on chess scene

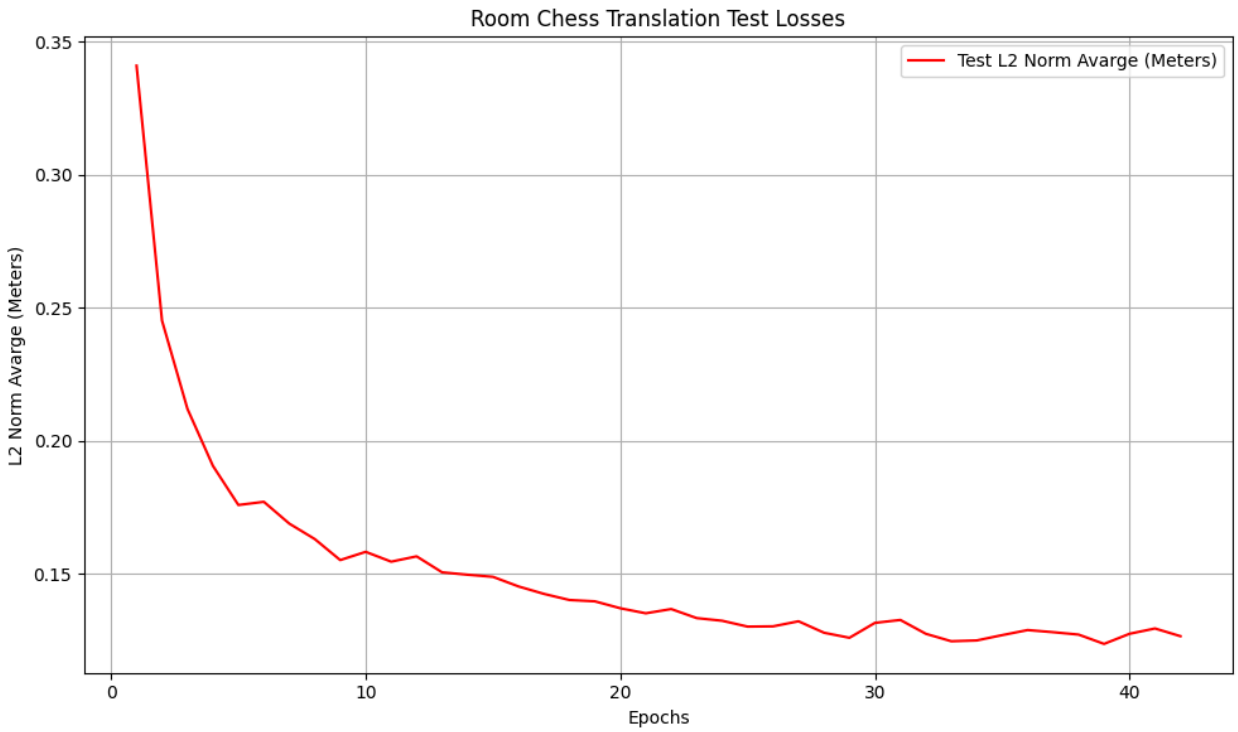

Figure [4]: Translation test loss change on chess scene

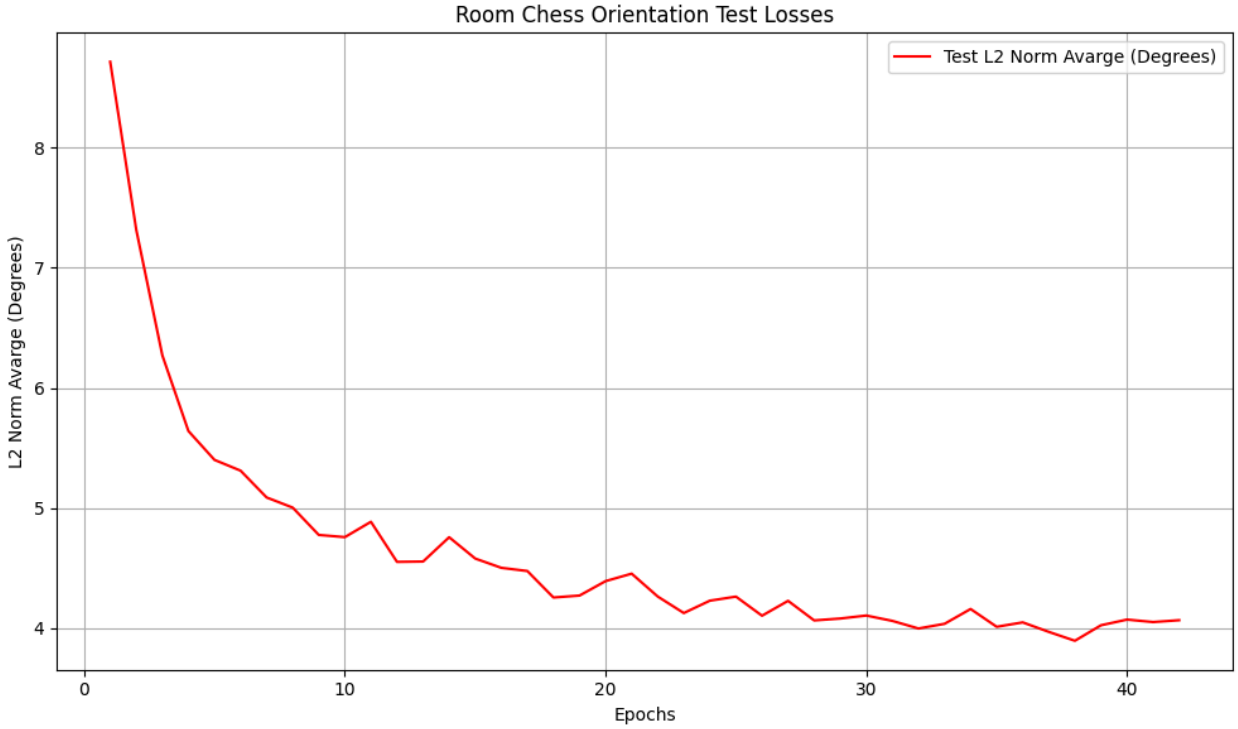

Figure [5]: Orientation test loss change on chess scene

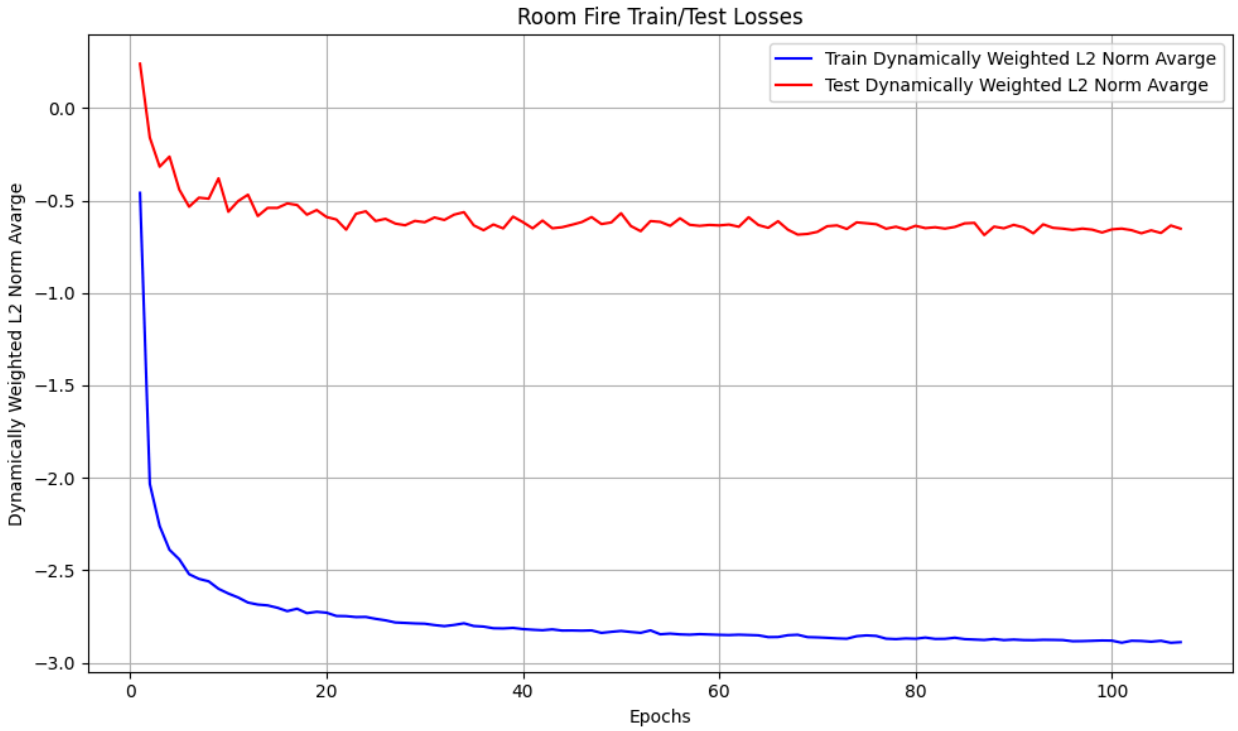

Figure [6]: Convergence on fire scene

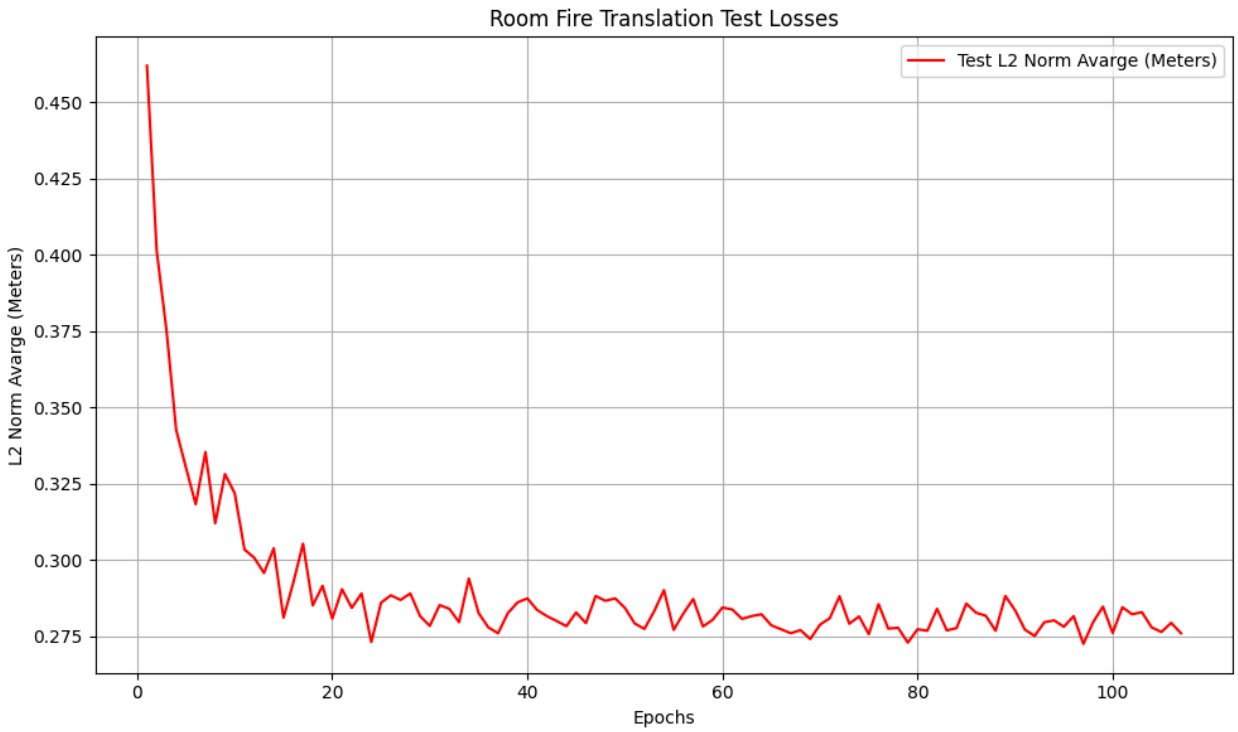

Figure [7]: Translation test loss change on fire scene

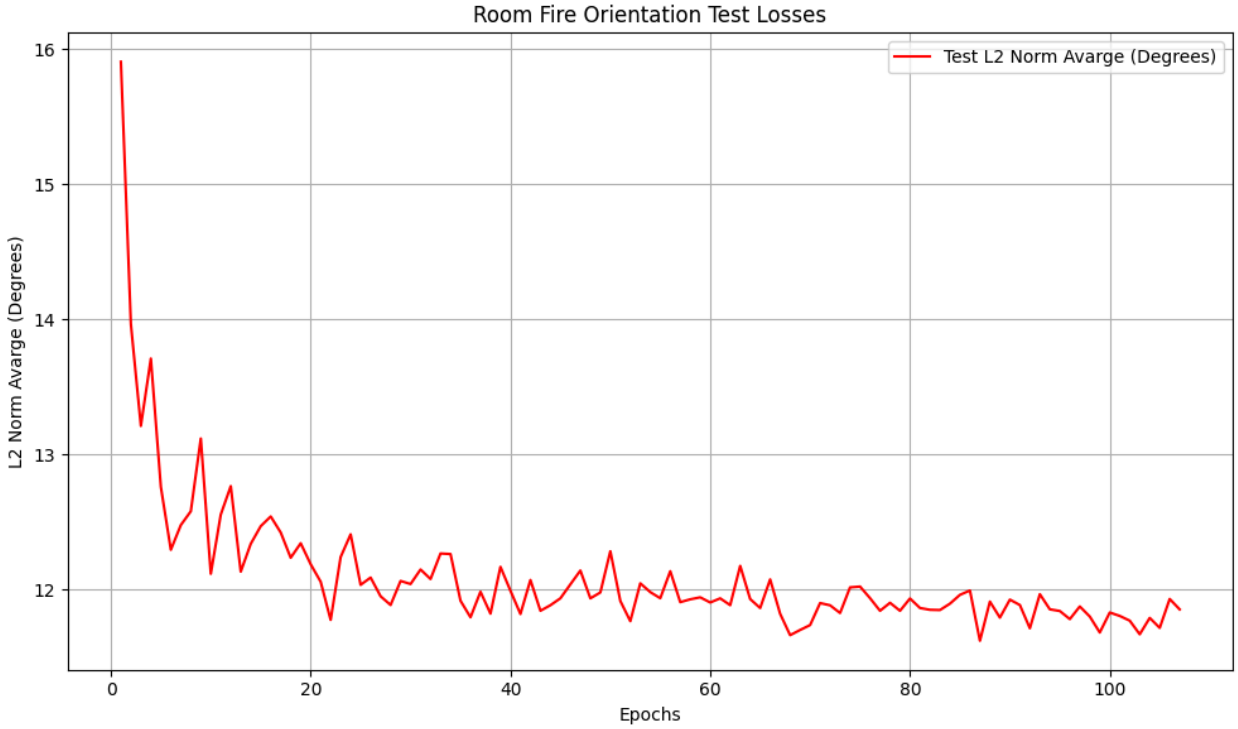

Figure [8]: Orientation test loss change on fire scene

Figures [3] and [6] track the train and test losses for chess and fire scenes. While both graphs show convergence on the test set, the fire scene demonstrates more fluctuation and higher overall loss in learning compared to the chess scene, indicating the higher difficulty level of the fire scene.

Figures [4] and [5] exhibit the test loss for translation and orientation on the fire scene. They depict a less smoother transition compared to those observed in the chess scene in Figure [7] and [8].

4. RESULTS & DISCUSSION

Objective Achievement:

The project successfully achieved all planned objectives, including a comprehensive literature review to identify gaps in existing indoor localization methods. A diverse dataset was curated and utilized for training and testing purposes, leveraging publicly available resources and university datasets. Prototype designs based on Swin Transformers were developed, and ensemble learning techniques were explored to enhance localization accuracy. The finalized indoor localization system, incorporating Swin Transformer-based architectures, demonstrated scalability and efficiency for real-world deployment. Extensive training, testing, and parameter tuning resulted in optimized models with superior performance compared to state-of-the-art approaches like PoseNet [12].

Scene	Train	Test	Extent (m)	Nearest Neighbour	PoseNet	Dense PoseNet	Ours
Chess	4000	2000	3 x 2 x 1	0.41m, 11.2°	0.32m, 8.12°	0.32m, 6.60°	0.13m, 4.07°
Fire	2000	2000	2.5 x 1 x 1	0.54m, 15.5°	0.47m, 14.4°	0.47m, 14.0°	0.28m, 11.85°
Heads	1000	1000	2 x 0.5 x 1	0.28m, 14.0°	0.29m, 12.0°	0.30m, 12.2°	0.17m, 13.32°
Office	6000	4000	2.5 x 2 x 1.5	0.49m, 12.0°	0.48m, 7.68°	0.48m, 7.24°	0.22m, 6.43°
Pumpkin	4000	2000	2.5 x 2 x 1	0.58m, 12.1°	0.47m, 8.42°	0.49m, 8.12°	0.34m, 7.24°

Red Kitchen	7000	5000	4 x 3 x 1.5	0.58m, 11.3°	0.59m, 8.64°	0.58m, 8.34°	0.30m, 8.48°
Stairs	2000	1000	2.5 x 2 x 1.5	0.56m, 15.4°	0.47m, 13.8°	0.48m, 13.1°	0.37m, 11.42°

Table [1]: Comparison of our model with other proposed models

Comparative Analysis of Localization Results:

Table [1] presents a comparative analysis of localization performance across different scenes using various models, including Nearest Neighbour, PoseNet, Dense PoseNet, and Swin Transformer. The metrics evaluated include localization error in meters (extent) and orientation error in degrees.

Our model demonstrates a significant improvement in performance across various challenging indoor environments. The Swin Transformer model achieves notably low localization and orientation errors, consistently outperforming previous models such as PoseNet and Dense PoseNet. This enhanced accuracy and precision in complex scenarios highlight the model's robustness and effectiveness. The consistent superior performance across different environments underscores the Swin Transformer's capability to deliver precise localization results in a wide range of places.

Distribution of errors on translation and orientation indicate very few outlier values and favorable distribution of error showing our model’s reliability beyond mean values. Below graphs show cumulative error histograms of swin transformer on test set:

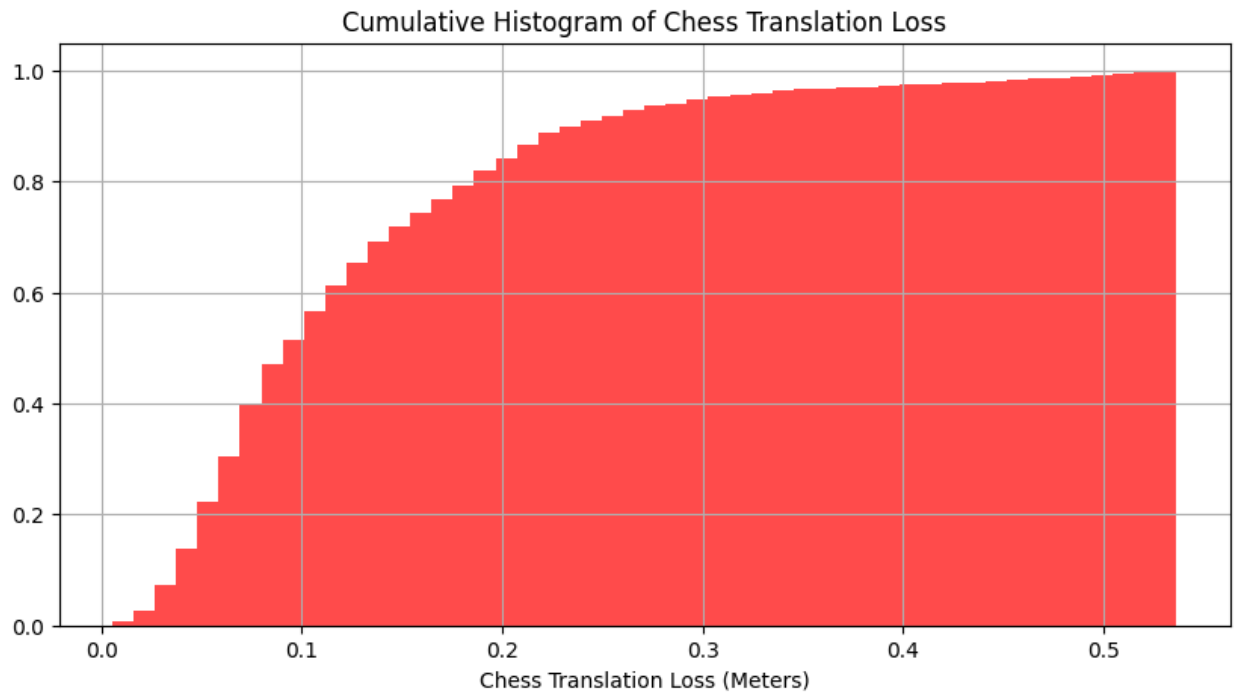

Figure [9]: Cumulative Histogram of translation error in room “chess”

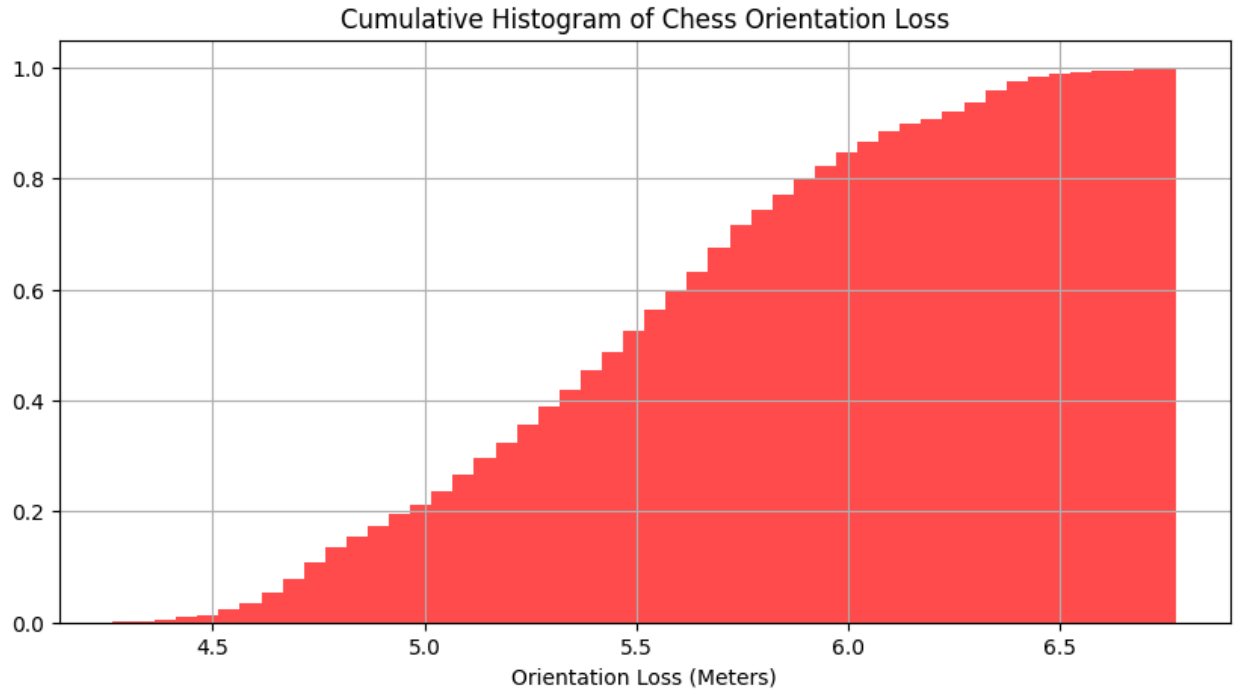

Figure [10]: Cumulative Histogram of orientation error in room “chess”

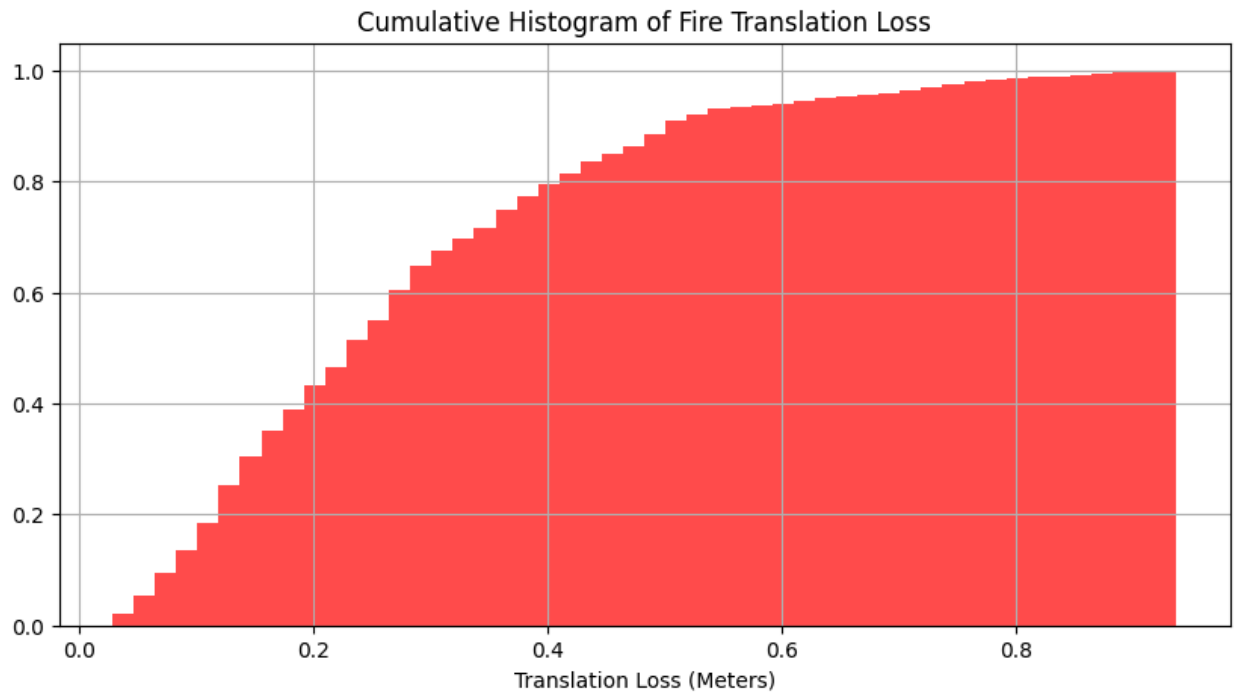

Figure [11]: Cumulative Histogram of translation error in room “fire”

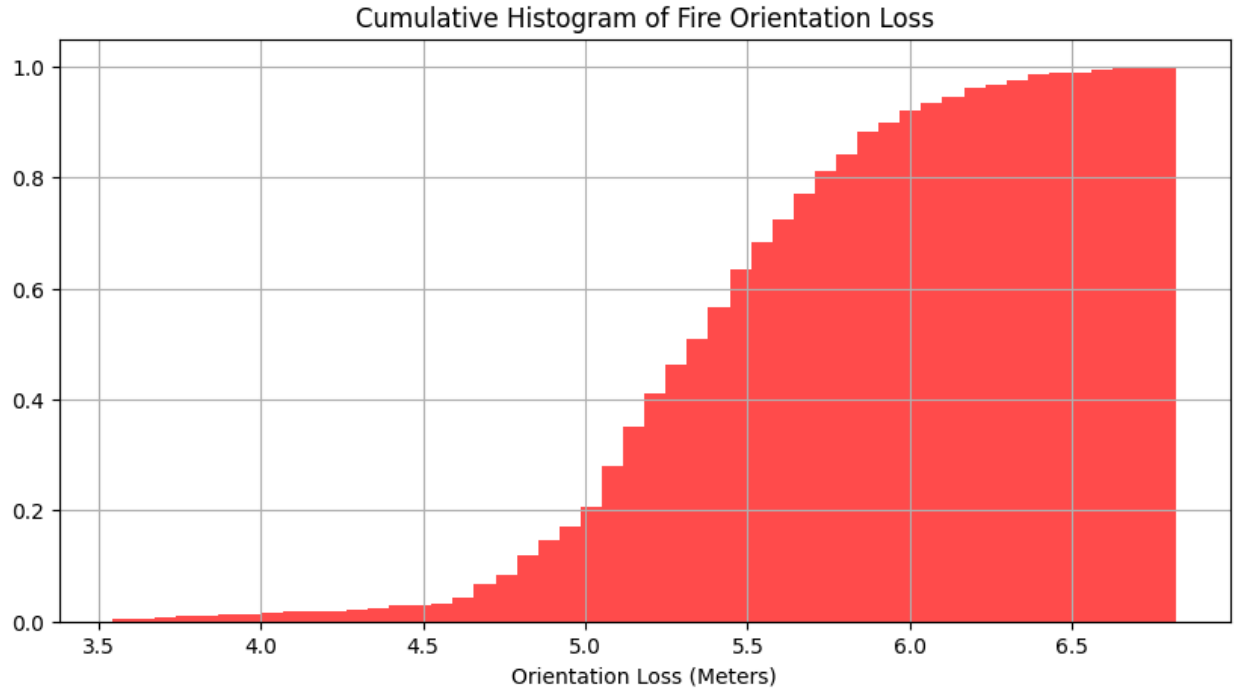

Figure [12]: Cumulative Histogram of orientation error in room “fire”

Figures [9] and [11] show a steep increase in translation loss at low error levels, indicating stable and high performance of the model. Meanwhile, Figures [10] and [12] reveal more outliers, suggesting that the model encounters greater difficulty when predicting orientation vector.

These results underscore the effectiveness of Swin Transformer-based architectures in advancing the state-of-the-art in indoor localization, offering higher accuracy and reliability compared to traditional and contemporary deep learning models.

Comparison with Initial Objectives

The project's outcomes closely aligned with the initial objectives outlined in the proposal. While specific design approaches evolved (e.g., adopting Swin Transformers), the overarching goal of advancing indoor localization accuracy and efficiency was effectively realized.

Project Completion & Contribution to State-of-the-Art

The project can be considered successfully completed within the defined scope, with meaningful contributions to the field of indoor localization. By integrating advanced deep learning techniques like Swin Transformers, the project offers more accurate and robust indoor navigation solutions, with comparable results to state-of-the-art.

5. **IMPACT**

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This project on indoor localization using computer vision holds scientific, technological, and socio-economic implications within the field of navigation and positioning systems.

Scientific Impact: Our work contributes to advancing the scientific understanding of indoor localization by integrating state-of-the-art computer vision techniques with deep learning methodologies. Through rigorous experimentation and analysis, we have explored novel approaches, such as Swin Transformers, to capture spatial information from indoor scenes, leading to new insights into effective localization strategies.

Technological Impact: The technological implications of the project are profound, as we have developed a robust indoor localization system that surpasses traditional methods like GPS and Wi-Fi in complex indoor environments. By leveraging modern deep learning architectures,

our system achieves superior accuracy and efficiency, paving the way for more reliable indoor navigation solutions.

Socio-economic Impact: Particularly in settings like shopping malls and airports, where precise indoor localization is crucial for enhancing user experiences and operational efficiencies, our system has the potential to improve accessibility and convenience for users while opening up opportunities for commercial applications in the indoor navigation sector.

Innovative and Commercial/Entrepreneurial Aspects: Our project introduces innovative methodologies that can be translated into commercial applications, such as developing specialized indoor navigation systems for public spaces and integrating localization technologies into mobile devices. These advancements create entrepreneurial opportunities for deploying advanced indoor navigation solutions specified to user needs.

Freedom-to-Use (FTU) Issues: The outcomes of our project are intended to be freely accessible for academic and research purposes. We aim to contribute to the open-source community by sharing our methodologies and findings, encouraging further advancements in indoor localization technologies without restrictive intellectual property constraints.

6. ETHICAL ISSUES

Privacy and Data Usage: Our solution relies on image data captured within indoor environments. We are committed to ensuring that all data collection and usage adhere to strict privacy standards. In the event that our proposed model is used with other datasets, any personal data captured during the localization process should be anonymized and used solely for research purposes.

7. PROJECT MANAGEMENT

7.1 Initial Project Plan

At the start of our project, we devised a comprehensive plan outlining key objectives, milestones, and timelines. The initial project plan included the following phases:

- **Literature Review and Research**: Conduct a thorough review of existing literature and identify gaps in current approaches to indoor localization.
- **Data Collection and Dataset Selection**: Search for suitable datasets and prepare data for model training and testing.
- **Model Design and Implementation**: Develop and implement deep learning models, including Swin Transformer, for indoor localization.
- **Testing and Evaluation**: Test and evaluate model performance against benchmark datasets and existing solutions.
- **Comparison and Analysis**: Compare our results with state-of-the-art methods and identify areas for improvement.
- **Documentation and Reporting**: Compile findings, results, and insights into a comprehensive final report.

7.2 Changes During Implementation

During implementation, we encountered schedule constraints that necessitated adjustments:

- **Deadline Extensions**: Some project deadlines were extended due to our team's busy schedule, which included exams and concurrent projects. This adjustment allowed us to allocate sufficient time to critical phases such as model implementation and testing.
- **Design Adjustments**: Certain design principles were discarded to accommodate timeline constraints and prioritize more powerful alternatives. For example, we opted to adopt the Swin Transformer architecture over other designs after preliminary assessments showed its superiority in achieving our project objectives within the given timeframe.

7.3 Key Learnings in Project Management

Managing this project amidst academic commitments provided important insights:

- **Effective Time Management**: Balancing project milestones with academic schedules requires effective time management and flexibility in adapting project timelines.

- **Prioritization of Design Choices**: Project constraints necessitated strategic decisions to prioritize design choices based on feasibility and performance, ensuring efficient progress towards project goals.

8. CONCLUSION AND FUTURE WORK

8.1 Conclusion

In summary, our project has made important progress in advancing indoor localization using state-of-the-art computer vision techniques, particularly through the implementation of the Swin Transformer architecture. The key findings and achievements of our study include:

- **Enhanced Localization Accuracy**: The integration of Swin Transformer has led to substantial improvements in localization accuracy, as evidenced by significantly reduced errors in both coordinate estimation and orientation prediction across various indoor scenes.
- **Performance Comparison**: Through comparative analysis with established methods like PoseNet, our approach has demonstrated superior performance, highlighting the efficacy and potential of modern deep learning architectures for indoor navigation.
- **Limitations and Insights**: While our study has yielded promising results, certain limitations, such as the focus on specific indoor environments and computational constraints, provide insights for future refinement and expansion.

8.2 Future Directions

Looking ahead, several avenues for future research and development emerge from this work:

- **Diverse Environmental Testing**: Extending the evaluation to diverse indoor environments, encompassing varied layouts and lighting conditions, would further validate the robustness and adaptability of our approach.
- **Real-Time Implementation**: The integration of real-time processing capabilities would be pivotal for deploying our solution in interactive navigation applications, enabling responsive and accurate localization.

- **Dataset Expansion and Augmentation**: Continued efforts in dataset collection and augmentation can enhance model training and performance across a broader range of scenarios and settings.
- **Collaborative Initiatives**: Collaboration with industry partners and research groups could facilitate practical deployment and validation of our indoor localization system in real-world applications.

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