Training and Deploying Computer Vision Models for Indoor Localisation

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Abstract

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1 Introduction

Knowing where you are is crucial for human life. For as long as humans have lived, they have tried to determine their position on the earth. First, by observing the position of the sun, and later by using the stars. With advances in technology in the second half of the 20th century, specifically the invention and commercialisation of GPS (Global Positioning System), a satellite-based localisation system, localisation has become more efficient and accurate than ever before. Gradual commercialisation led to the technology rapidly transforming entire industries and personal navigation systems. Today, outdoor localisation is widely considered a *solved problem*.

The same cannot be said for indoor localisation. Because the transmitted radio signals sent out by the satellites in the GPS systems are not strong enough to penetrate through walls and struggle with reflections from large buildings, the technology yields inaccurate results at best, and often becomes dysfunctional in indoor spaces.

Finding alternative solutions to provide an accurate, cheap and robust indoor localisation systems has been a main focus of research in the past decades, and is becoming increasingly important in the light of the ongoing urbanisation of our living spaces and the emergence of autonomous robots and vehicles in our everyday life. Nonetheless, commercial applications are still rare and not unified in their approach.

Decades of research have led to the development of a variety of different indoor localisation technologies. Hardware-based systems use radio signals, transmitted by beacons, like Bluetooth, and Ultra-Wideband (UWB) or Wi-Fi, to localise an agent in a known environment. Software-based systems, like Simultaneous Localisation and Mapping (SLAM) algorithms, use sensors, like cameras or distance-measuring laser sensors, to localise an agent, while simultaneously creating a map of the environment.

However, hardware-based system require an expensive initial setup, continuous maintenance of the beacons, and are often not feasible in large environments, like shopping malls, or in environments that are frequently changing, like offices. SLAM algorithms, on the other hand, require a meticulously handcrafted pipeline of feature detection, feature matching, and pose estimation that has to be fine-tuned for each indoor space, to achieve outstanding results. Furthermore, some SLAM algorithms require specific types of sensors to be used, which are not available to use in all environments.

In an attempt to overcome the limitations of the aforementioned indoor localisation technologies, and to provide a simple, unified indoor localisation system this thesis proposes a novel approach to indoor localisation, by framing the problem of indoor localisation as a simple classification task. In our setup, location labels are continuously predicted from a stream of images, using different types of modern deep neural networks, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs). With the advances in the computational power of modern mobile devices, the pipeline is proven to provide real-time estimates of the agent's position in the environment. Furthermore, the proposed method requires minimal initial setup in the environment and the devices, and is therefore suitable for commercial applications.

In this thesis we describe the data collection, model architecture, training procedure, and then rigorously evaluate the proposed method in three dimensions.

- **Accuracy:** Are the location estimates correct?
- **Robustness** Are the location estimates correct when encountering noise?
- **Efficiency:** How much data needs to be collected to train high-performance models? How quick is the inference times?

2 Background

Producing accurate, robust and cheap localisation systems is not a novel task, but has been a focus of research at the intersection of robotics, computer vision and machine learning for decades.

Amongst the most promising approaches are SLAM (Simultaneous Localisation and Mapping) algorithms. SLAM algorithms aim to localise an agent inside an unknown environment, while simultaneously building a consistent map of the environment. There exist a variety of different approaches to SLAM, depending on the type of sensors that are used for estimating position and mapping the environment. For example, Visual SLAM (V-SLAM) algorithms use camera input, and LidarSLAM algorithms use distance-measuring laser sensors. Initial proposal of such algorithms use a pipeline of feature detection, feature matching, and pose estimation to estimate the position of the agent and the environment.

The methodology most related to our approach are monocular V-SLAM algorithms, which use a single camera to estimate the position of the agent. The very first monocular feature-based V-SLAM algorithms is called MonoSLAM [2] and was proposed in 2007. The researchers proved that their approach is capable of simultaneously localising an agent and mapping an environment, using a single camera. Thus, overcoming the main challenge of inaccurate depth estimation using a single camera.

Since then, many adjustments and optimisation have been proposed to the algorithm to make it more robust and accurate. For example, the ORB-SLAM [6] algorithm uses a bag-of-words approach to feature matching, and the PTAM [4] algorithm uses a parallel tracking and mapping approach to improve the accuracy of the algorithm.

With machine and deep learning becoming more and more popular in the past decade, many researchers have started to apply these techniques to SLAM algorithms. For example, the DeepVO [8] algorithm uses a convolutional neural network to estimate the camera pose from a sequence of images. All the above mentioned approaches are similar to our approach in that they use deep learning at some part of the pipeline, but differ in that simply replace the original components in a SLAM pipeline, such as feature extraction, feature matching, or pose estimation, with a deep neural network, whereas we use deep learning to learn a mapping from images to location

3 Methodology

The project is an end-to-end machine learning pipeline, meaning that it starts with the collection of data, and ends with the deployment of a production-ready model.

3.1 Data Collection

Framing the problem of indoor localisation as a classification task requires a labelled data set, which consists of sequentially-arranged pairs of video frames and location labels. A single video clip C consists of a sequence of n frames $x_0, ..., x_n$ and a sequence of n location labels $y_0, ..., y_n$, where the i-th pair of the sequence is the tuple (x_i, y_i) and denotes the location at a specific frame. A single frame x_i is a RGB image, represented as a three-dimensional tensor of shape $3 \times H \times W$, where H and W are the height and width of the image, respectively. A single location label y_i is a scalar value, which identifies the location of the agent at the time of the frame.

The data set was collected from a single camera of a mobile device [1] that was hand-held by a human agent while walking around an indoor building. The chosen location for the data collection was the main building of the Southern Campus of the Copenhagen University (Danish: Københavns Universitet, KU) in Copenhagen S, Denmark. The building is a large multi-storey building with a total of six floors, and is used for teaching and research purposes. The location was deemed ideal for this initial research, as it both has distinctive indoor features (e.g. coloured walls, unique structures, etc.), but also poses a challenge for the model, for example, due to the similarity of the floor plan across floors. For the scope of this project, the data collection was limited to the first two floors. The publicly accessible areas were separated into 21 different location labels (Figure 1), in close correspondence to the official building's floor plan. The location labels were denoted with descriptive identifiers (e.g. `Ground Floor Atrium`, `First Floor Red Area`, etc.)

(a) Ground Floor (b) First Floor

Figure 1: Map of KU Southern Campus Main Building with Location Labels

To match the location labels to the video footage, each clip C was manually annotated by denoting the starting and ending time stamps of a location label. The information was stored in a standardised format and later used in the pre-processing of clips into frame-location pairs.

A total of 53 video clips were recorded, with an average duration of 57s, amounting to a total number of ~ 50 minutes of footage. Out of the total 53 video clips that were recorded, 37 were used for training and 16 were used for validation. Table 1 shows more statistics of the raw data in the two different splits.

An ideal model learns robust indoor features that are invariant to natural variations in the indoor space from training data collected in a minimal time span, as this minimises the initial cost and effort for data collection. To evaluate the model's robustness towards these variations, a different philosophy was adopted for the collection of training and testing data.

While the 37 training clips were recorded on just two days, the 16 testing clips were recorded on four different days, two to four weeks after the initial training data collection. This was

[1] iPhone 11 Pro recording at 30 FPS with 2426x1125 HD resolution

Split	Total Clips	Total Seconds	Total Minutes
Training	37	2240	37
Testing	16	783	13

Table 1: Statistics of the Raw Data in Training and Testing Splits

done to make the testing data closer resemble real-world scenarios, and thereby make the testing metrics more robust.

3.2 Data Preprocessing

The raw video clips and manual annotation of location labels, had to be pre-processed before they could be used for training deep learning models.

The video footage was resized to a resolution of 224x224 pixels, which is the input resolution of most modern foundation models for image and video classification, which were used in this project. Furthermore, it decreases the total data amount significantly, which allowed for less disk usage and faster loads into memory during training.

Next, instead of extracting all 30 frames per second, the video footage was downsampled to a much lower frame rate of 1 FPS. This was done to reduce the total data amount, and to reduce over-fitting of the model to the training data. It was hypothesised, that because of the strong local dependency of consecutive frames, consecutive frames are highly correlated, thus including such frames does not introduce any additional variance, but redundancies that are harmful for the model's generalisation ability. Empirical experiments confirmed that downsampling indeed reduces over-fitting, and was therefore adopted across all experiments.

Finally, the pre-processed video footage was aligned with the manual location labels by extracting a frame per second from the video and matching it against the location label that was active at that time. After pre-preprocessing, there exist pairs (x_i, y_i), where x_i is pre-processed, extracted frame of size 224x224 pixels, and y_i is the corresponding location identifier. The frames were stored in a way that allowed for easily sampling both a random frame-location pair (x_i, y_i) for image classification models, or a sequence of consecutive n frames from a clip $([x_0, \dots, x_n], [y_i, \dots y_n])$ for video classification models. Here the sequence of frames was represented as a 4D-tensor of size $n \times 3 \times 224 \times 224$.

Figure 2 shows $n = 4$ consecutive frame-location label pairs after preprocessing. As can be seen, even at a frame rate of 1 FPS, neighbouring frames are still similar to each other. Further, the annotation at the transition from one location to another was often difficult to determine, as one could annotate strictly according to the device position or the view of the camera. This likely resulted in some frames being annotated with the wrong location label.

3.3 Models

A deep learning model is supposed to learn a function $f : X \to Y$, where X represents the input space and Y the output space. By having framed the task of indoor localisation as a classification problem, the output space is the discrete set of location labels, $Y = \{l_1, \dots, l_n\}$. Two approaches are viable for the input space X:

1. **Image Classification**: The input space X is a single frame, $(3, H, W)$ and the output space is a single location label $y \in Y$. The model treats consecutive frames independently, and therefore disregards the temporal dimension of the video.

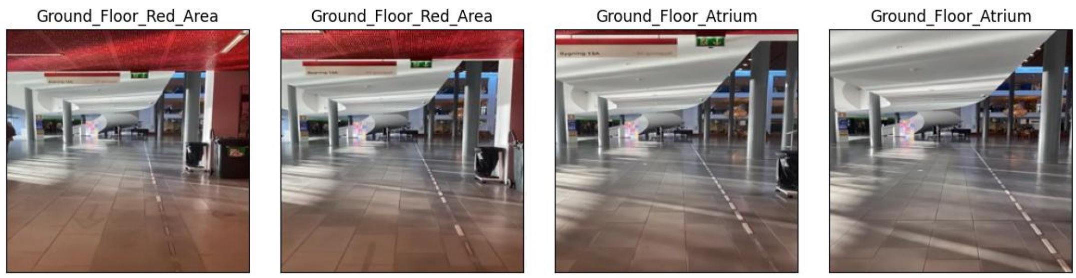
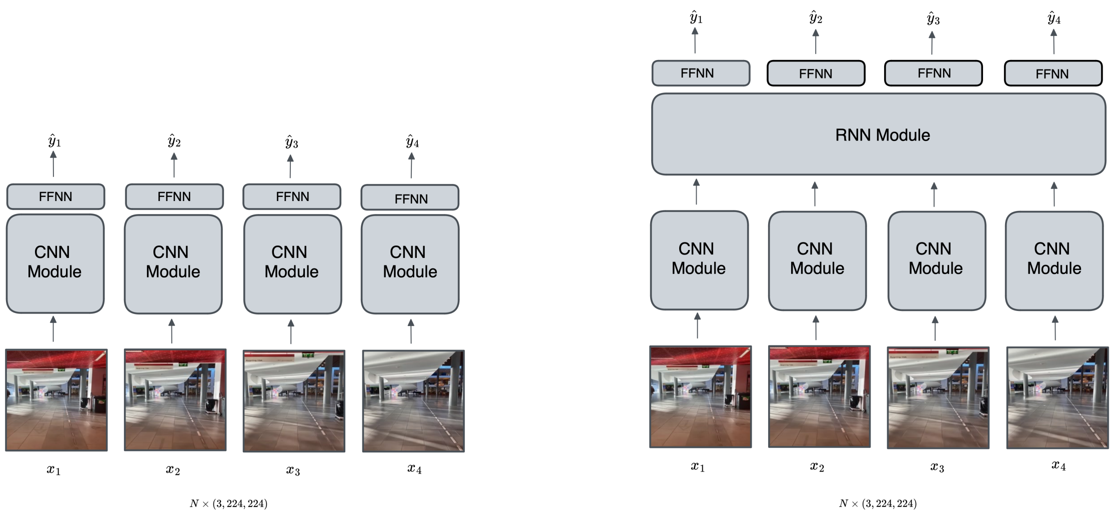


Figure 2: Examples of preprocessed frame-location pairs

2. **Video Classification**: The input space X is a sequence of N frames, $(x_1, \ldots, x_n)$, and the output space Y is a sequence of N location labels, $(y_0, \ldots, y_n)$, where each $y_i \in Y$. The model considers the temporal dimension of the video, and learns to classify the location label of a sequence of frames. In reality, the input sequence has a maximum context length K, meaning that the model continuously predicts on the previous K frames.



(a) Image Classification Architecture

(b) Video Classification Architecture

Figure 3: Model Architectures

Figure 3 shows the high-level architecture of the two approaches. For an image classification model, a sequence of N (here $N = 4$) frames are independently fed into a convolutional neural network (CNN), which outputs a feature vector for each frame. CNNs are a class of deep neural networks that are applied to analyse visual imagery. They are composed of several layers of alternating convolutional and pooling filters, which are applied to the input image to extract high-level feature representations. These high-level feature representations are then fed into a fully connected neural network (FCNN), which outputs a probability distribution over the location labels.

For a video classification model, all N consecutive frames are independently passed through a CNN module. The sequence of high-level feature representations is then fed into a recurrent neural network (RNN), which outputs a probability distribution over the location labels for each frame by placing a fully connected layer (classification head) to the output vector associated to each frame in the RNN module. A recurrent neural network (RNN) is a class of deep neural networks that is applied to analyse sequential data. Although they are mostly applied to natural language processing tasks, the generality of their architecture allows to also apply them to computer vision tasks with sequential data, such as a sequence of frames in video classification. For each input x_i in a sequence of inputs, the RNN computes an output as a function of the current input x_i and a hidden state h_{i-1} that is computed as a function of all previous inputs. In that way, the RNN can learn to model the temporal dependencies between frames, e.g. consider that all previous frames were predicted to be at one specific location, and therefore the current frame is also likely to be at that location.

To evaluate the performance of both approaches, a selection of well-performing CNN and RNN modules were chosen, and combined to form different image and video classifiers. The modules, alongside meta information about their number of parameters, size in Megabyte (MB) and GFLOPS (Giga Floating Point Operations per Second) are provided in Table 2. Generally speaking, smaller model sizes are preferred, as they are faster to train and during inference and require less memory, making them more suitable to be deployed on low-resource devices like mobile phones and embedded devices. It is expected that more complex, larger models will perform better, so the goal is to choose the smallest model that works well enough to perform the task with sufficient accuracy.

Type	Name	#Params	GFLOPS	Size (MB)
CNN Module	Resnet18 [3]	11.6M	1.81	44.7
	Resnet50 [3]	25.6M	4.09	99.8
	MobileNet-V3	2.5M	0.06	9.8
	Alexnet	61.1M	0.71	233.1
RNN Module	RNN	0.26	N/A	1.04
	LSTM	1.05	N/A	4.2

Table 2: CNN and RNN Modules

By replacing the final fully connected layer of the CNN with a linear layer with N outputs, where N is the number of location labels, each CNN module can be used as an image classifier. Because the different RNN modules expect a one-dimensional input for each element in the input sequence of frames, the RNN modules are combined with a CNN module to form a CNN-RNN architecture. Given the 4 different CNN modules and the 2 different RNN modules, 8 different CNN-RNN architectures were formed for the video classification approach. The list of all image and video classifiers that were evaluated is provided in Table 3.

3.4 Training

All models were implemented using the PyTorch framework [1] and the training was performed locally on a MacBook Pro M1 with 16GB of memory and MPS-acceleration enabled (where possible[2]) to allow for fast experiment iteration. The loss function $\mathcal{L}$ used for all models was cross-entropy loss (Equation 1), which is a standard loss function for multi-class classification problems.

[2]MobileNet-V3-based models do not support GPU acceleration

Name	**CNN Module**	**RNN Module**
resnet18	ResNet18	-
resnet50	ResNet50	-
mobilenet_v3_small	MobileNet-V3	-
alexnet	AlexNet	-
resnet18-rnn	Resnet18	RNN
resnet50-rnn	ResNet50	RNN
mobilenet_v3_small-rnn	MobileNet-V3	RNN
alexnet-rnn	AlexNet	RNN
resnet18-lstm	Resnet18	LSTM
resnet50-lstm	ResNet50	LSTM
mobilenet_v3_small-lstm	MobileNet-V3	LSTM
alexnet-lstm	AlexNet	LSTM

Table 3: List of all Models

$$\mathcal{L}(\hat{y}, y) = -\sum_{i=1}^{K} y_i \log(\hat{y}_i) \tag{1}$$

Here, $\hat{y}$ is the predicted probability distribution over the K classes and y is the one-hot encoded ground truth label. The models were trained using the AdamW [5] optimiser with default parameters, except for the learning rate, which was set to a constant of $1e^{-4}$. Step-wise learning rate scheduling was used for all models, which reduced the learning rate by a factor of 10 every 5 epochs. The batch size was set to 32 for all image classifiers and 8 for all video classifiers for memory-optimal training. Unless otherwise specified, all image and video classifiers were trained with the same set of training hyper-parameters, which are specified in Table 4.

Classifier	Batch Size	Epochs	Optimiser	Learning Rate Scheduler
Image Classifier	32	10	AdamW ($\gamma = 1e^{-4}$)	Step-LR ($\gamma = 1e^{-1}, s = 5$)
Video Classifier	8	10	AdamW ($\gamma = 1e^{-4}$)	Step-LR ($\gamma = 1e^{-1}, s = 5$)

Table 4: Default Hyperparameters for Image and Video Classifiers

3.5 Evaluation

The goal of the evaluation is to have a rigorous comparison of the different models and to determine the best model for the task of location classification. In this context, a "well-performing" model is not just the model that is most accurate in most cases, but also the model that is most robust to a wide-range of different natural variations that can occur and that is efficient. To achieve this, a series of *quantitative* and *qualitative* experiments are performed on the models, which are then used in Section 5 and Section 6.

Quantitative Experiments. To quantitatively assess the performance of the model on the task of location classification, the models were evaluated on the test set using a wide-range of different performance metrics. To assess the overall accuracy of the model, two metrics are computed: **Multi-class Accuracy** (Equation 2) is the most wide-spread performance metric in classification task and is defined as the number of correct predictions divided by the total number of predictions. It gives a good first indication for the overall performance of the model, but can be misleading in cases where the dataset is imbalanced.

$$\text{Multi-class Accuracy} = \frac{1}{N} \sum_{i=1}^{N} \mathbb{I}(y_i = \hat{y}_i) \tag{2}$$

Here, $\mathbb{I}$ is an indicator that is 1 if the condition is true and 0 otherwise. On top of the standard, multi-class accuracy, a variant of the formula, the **Top-3 Multi-class Accuracy** is also computed, which counts a prediction as correct if the correct label is one of the top-3 predicted labels.

As some location labels are underrepresented in the dataset due to the natural variation in size of the different locations, the **Macro F1-Score** is used to compute a more fine-grained metric. The Macro F1-Score is the average of the class-specific F1-scores, which are defined as the harmonic mean of precision P_i and recall R_i (Equation 3).

$$\text{Macro F1-Score} = \frac{1}{N} \sum_{i=1}^{N} \frac{2 \cdot P_i \cdot R_i}{P_i + R_i} \tag{3}$$

Here, P_i and R_i are the precision and recall for class i, which are defined as follows (Equation 4) and (Equation 5).

$$P_i = \frac{TP_i}{TP_i + FP_i} \tag{4}$$

$$R_i = \frac{TP_i}{TP_i + FN_i} \tag{5}$$

Here, TP_i is the number of true positives for class i, FP_i is the number of false positives for class i and FN_i is the number of false negatives for class i.

On top of the standard metrics for classification, efficiency of the model is crucial for usability of the system on low-resource devices, such as mobile phones. For this reason, the **Inference Time** per sample is measured, the **GFLOPS** per predicted sample is computed and the **Model Size** is measured to assess the memory constraints imposed by the model.

Qualitative Experiments. Purely quantitatively assessing a model's performance may not be sufficient to truly determine the strengths and weaknesses of the model. For this reason, the models were also evaluated qualitatively by manually inspecting the misclassified samples and the predictions of the models on a sub-set of 20 test frames. Furthermore, the `GradCam` [7] algorithm was used to gain insights into the internal functioning of the model. GradCam is a technique that backtracks the activations in the convolutional filters of the model at some depth in the model's architecture and through the gradients of the model to the input image. This allows to visualise the regions of the image that were most relevant for the model to make its prediction. In this scenario, it is hoped that the highlighted regions can be used to understand what types of features the model is looking for in the image and what types of features it is not looking for. This can be used to identify potential issues with the model and to gain insights into how the model can be improved.

4 Experiment Setup

4.1 Best Model

The first experiment tries to find an answer for the research question: *"Which model architecture performs best?"*. To answer this question, the models listed in Table 3 are trained on the same data with the same set of training hyper-parameters and then evaluated as outlined in Section 3.5.

4.2 Data Efficiency

Approaching indoor localisation as a classification task, means to frame it as a supervised learning problem. Supervised learning requires human-annotated training data, which can be prohibitive to obtain in large quantities. For the proposed approach to be valid, minimal effort in the initial data collection and annotation should be required. For this reason, the second experiment tries to find an answer for the research question: *"How much data is necessary to achieve good performance"*. To answer this question, a single image and video classifier are chosen and trained on different subsets of the training data. The subsets include 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% and 100% of the training data. The models are then evaluated as outlined in Section 3.5 to find the natural drop-off in performance as the amount of training data decreases.

4.3 Problem Difficulty

The proposed approach is only really valid if it scales well to larger indoor spaces and if it can be used to localise a user in a large number of different locations. For this reason, the third experiment tries to approximate the performance to be expected when gradually increasing the number of locations and thereby the complexity of the problem. To answer this question, a single image and video classifier are chosen and trained on different subsets of the training data that only include samples from a subset of the locations, which are chosen at random. The models are then evaluated as outlined in Section 3.5 to estimate how the performance decreases as the number of locations increases.

5 Results

5.1 Best Model

6 Discussion

7 Conclusion

8 Remarks

8.1 Reproducibility

All code and data used in this project is available on GitHub at the following link: `https://github.com/mikasenghaas/bsc`. The project's `README` file contains detailed instructions on how to reproduce the results of this project.

Further, the precise configuration and results of the experiments that are reported here are publicly available on the Weights & Biases platform at the following link: `https://wandb.ai/mikasenghaas/bsc`.

8.2 Machine Specifications

Table 5 lists the specifications of the machine that was used for training and evaluation of the models. For training the `MPS` backend was used for accelerated training. However, for inference a single CPU core was used, to approximate latency and throughput on mobile devices.

	Specification	Value
System	Name	Darwin
	Node	Local MacBook Pro
CPU	Model	Apple M1
	Architecture	ARM64
	Physical Cores	8
	Frequency	2.4 GHz
Memory	Total Capacity	16 GB
	Avg. Used Capacity	$\sim$ 7.4 GB

Table 5: Machine Specifications

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