# Multi-Resolution 3D Convolutional Neural Networks for Automatic Coronary Centerline Extraction in Cardiac CT Angiography Scans

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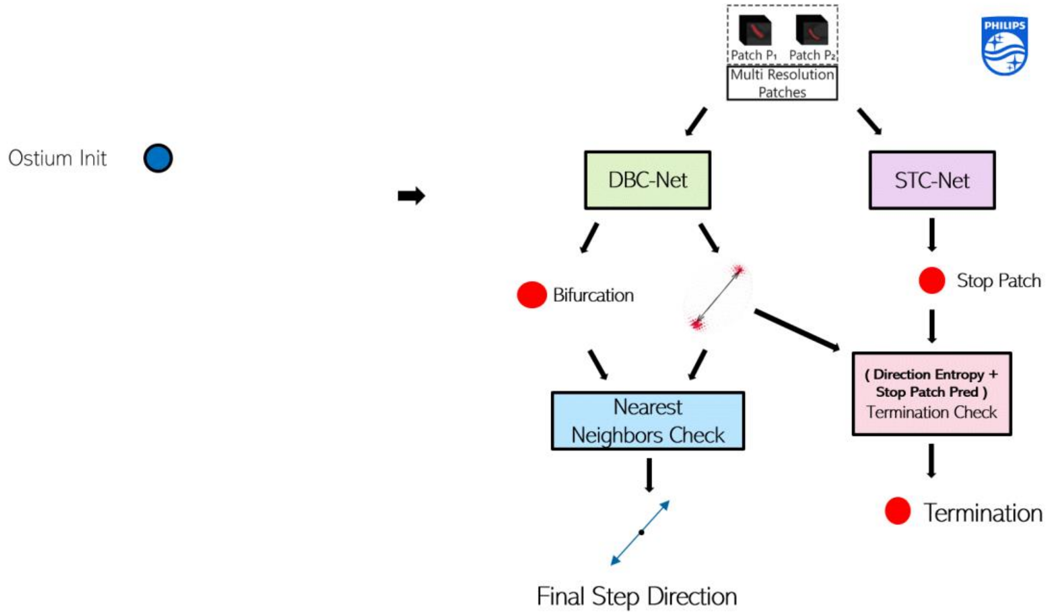


Ostium Init
Patch P1
Patch P2
Multi Resolution Patches
DBC-Net
STC-Net
Bifurcation
Stop Patch
( Direction Entropy + Stop Patch Pred )
Termination Check
Nearest Neighbors Check
Termination
Final Step Direction

# Introduction

- Coronary Artery Disease is a leading cause of death worldwide – 9.43 million deaths in 2016 (WHO, 2016).
- Coronary Angiography (CA) – invasive , non-negligible risk, lumen information only.
- Cardiac Computed Tomography Angiography (CCTA) – non-invasive , plaque information.

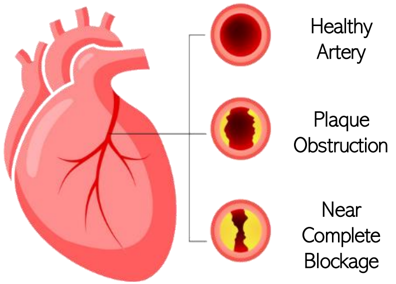



Fig 1 : Coronary Artery Disease [1]

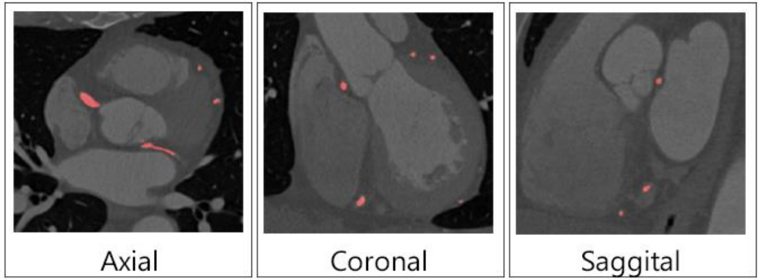



Fig 2 : Axial, Coronal and Saggital slices from a 3D CCTA Volume. Coronary arteries are difficult to visualize in a CCTA image.

[1] Modified from https://mplsheart.org/center-for-coronary-artery-disease/patients/

# Introduction

- Visualization Techniques such as sMPR and cMPR are based on centerline extraction.

- **Detection and classification of plaque type** and **determination of the degree of stenosis** can be done using sMPR and cMPR visualizations.

- Coronary centerline extraction is an important building block for diagnosis.

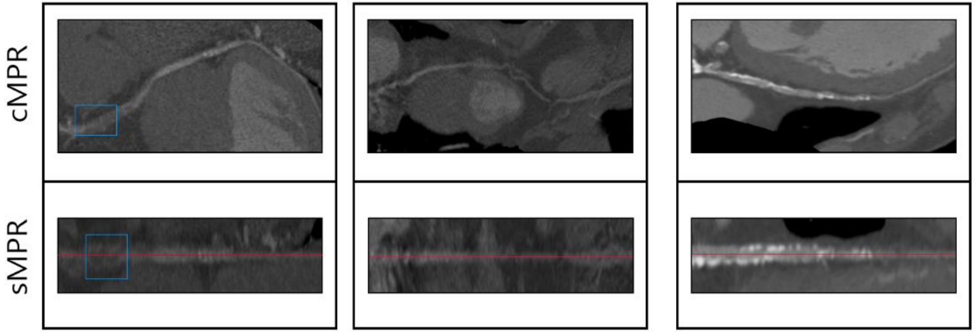



Fig 1: sMPR and cMPR visualization from extracted centerlines

Extracted Centerline —— Stenosis □

Problem Statement: Automatic Coronary Centerline Extraction in Cardiac CCTA Images

# Previous Work

**Interactive Methods – more than one point per vessel**

Friman - Minimal Path based method + vessel template ( 6 mins ) – 2008 → Shortcut Issues

**Semi-Automatic Methods – one point per vessel**

Krissian – Morphological operations and filters + voxel probability map ( 7 h ) - 2008 → Explicit filter construction

**Automatic Methods – no manually initialized points**

Zheng – Model driven approach based on segmentation mask ROI ( 60 s ) - 2013 → Trained on 108 cases

# Previous Work

## Wolterink's CNN approach – Interactive Method – 2019

1. **One or more** seed points per vessel are required.
2. The direction is predicted on a unit sphere with **N admissible** discrete directions.
3. The CNN predicts **two directions** only which track the vessel to the ostium.
4. The tracking is terminated by the **moving average of the entropy prediction**.

At-least one seed point per vessel

↓

Patch Extraction

↓

Convolutional Neural Network

↓

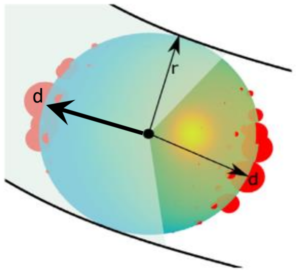
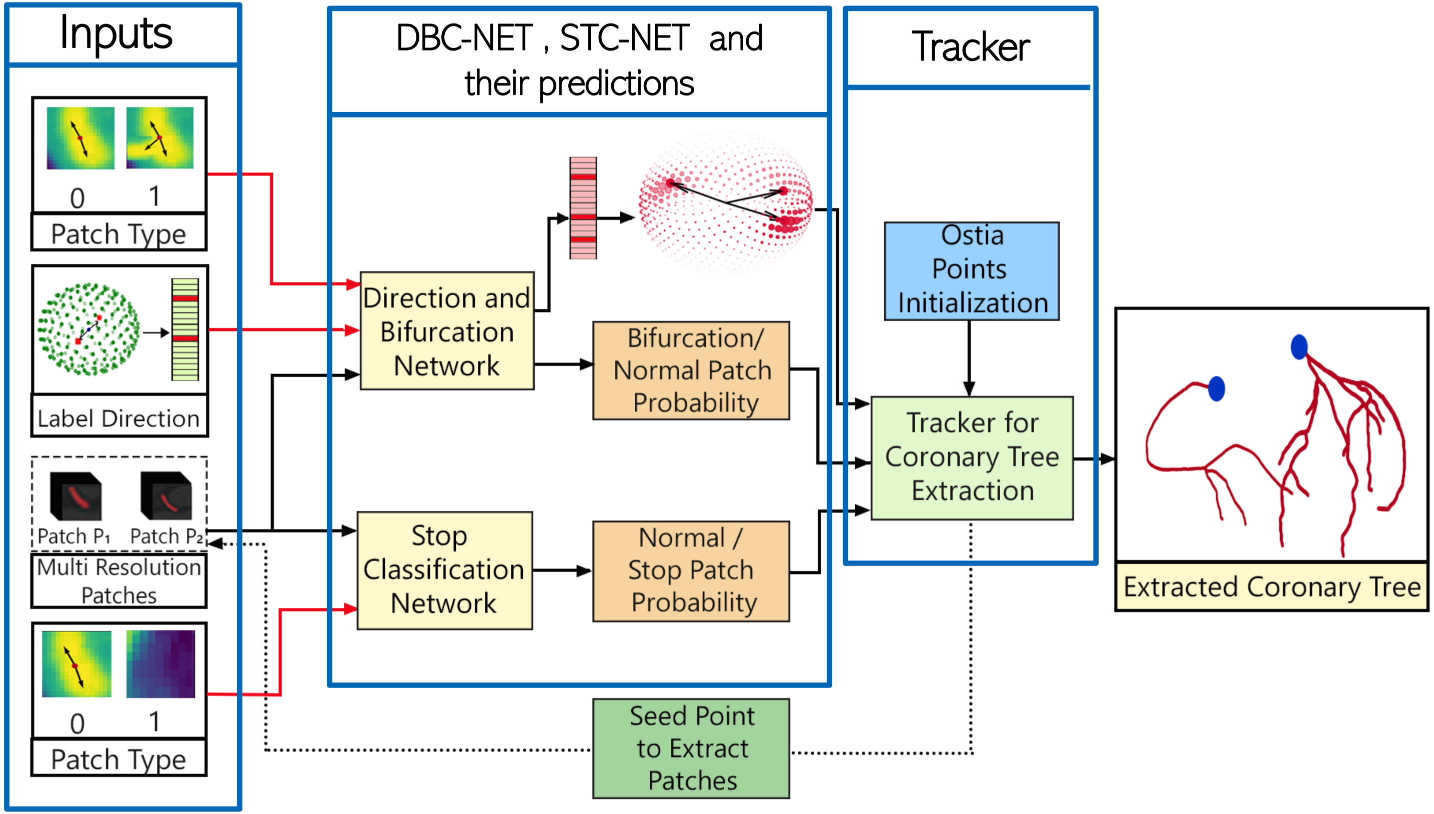
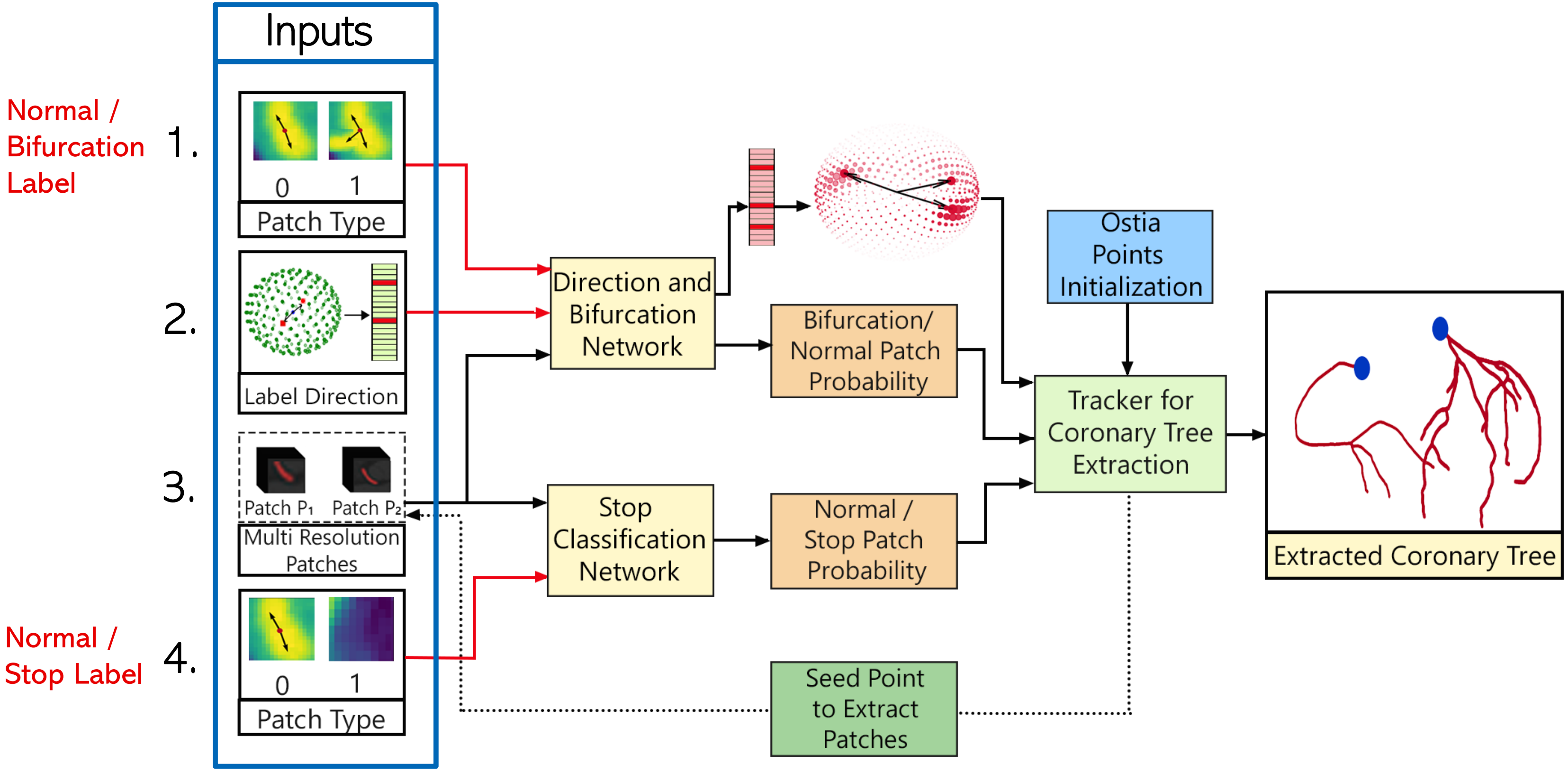



Fig 1: Wolterink's Approach

# Proposed Pipeline



# Input



Inputs
Normal /
Bifurcation
Label
1.
0
1
Patch Type
2.
Label Direction
3.
Patch P1
Patch P2
Multi Resolution
Patches
Normal /
Stop Label
4.
0
1
Patch Type
Direction and
Bifurcation
Network
Bifurcation/
Normal Patch
Probability
Ostia
Points
Initialization
Tracker for
Coronary Tree
Extraction
Extracted Coronary Tree
Stop
Classification
Network
Normal /
Stop Patch
Probability
Seed Point
to Extract
Patches

# Direction Label Assignment

1. Multi Resolution Patches of size = (19,19,19) extracted at patch center $c_p$.

2. The direction vectors are obtained by placing a sphere $S_d$ of radius R at patch center $c_p$ (Fig 1).

3. **Classification** problem on a unit sphere $S_u$ with N discrete points to obtain direction vectors (Fig 2).

4. Association of direction vectors obtained using sphere $S_d$ on unit sphere $S_u$. = 1 , = 0 in (Fig 2).

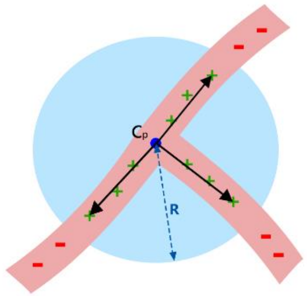



Fig 1: Obtaining direction vectors by placing sphere $S_d$ at center $c_p$.

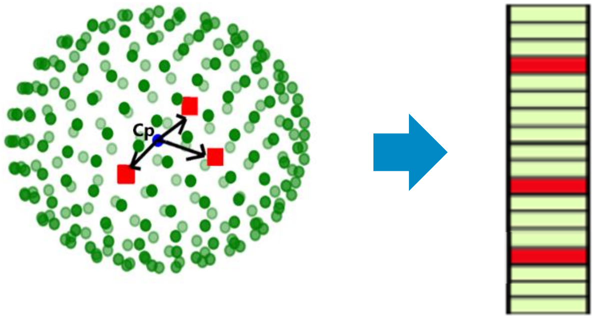



Fig 2: Direction label assignment on a discrete unit sphere $S_u$.

# Augmentation Strategy

- Translational Augmentation
- Rotational Augmentation

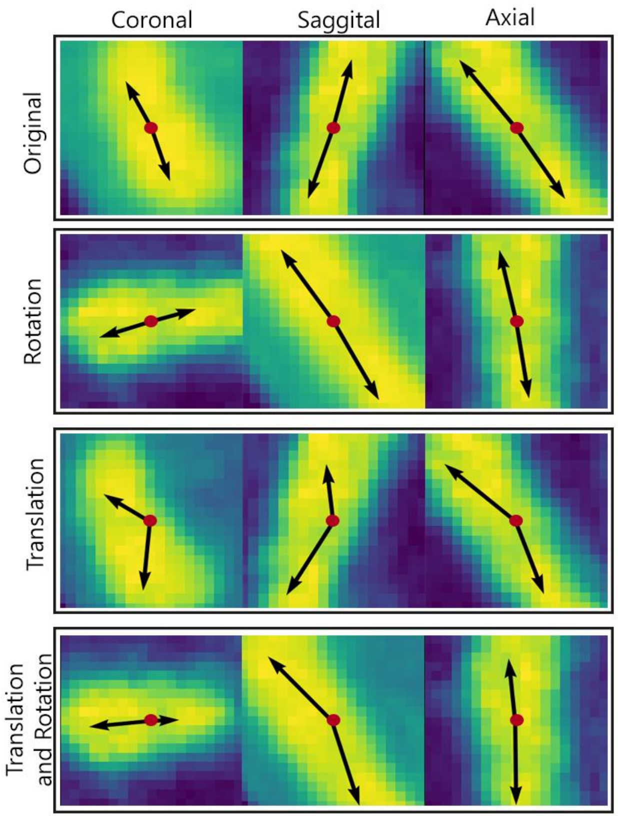
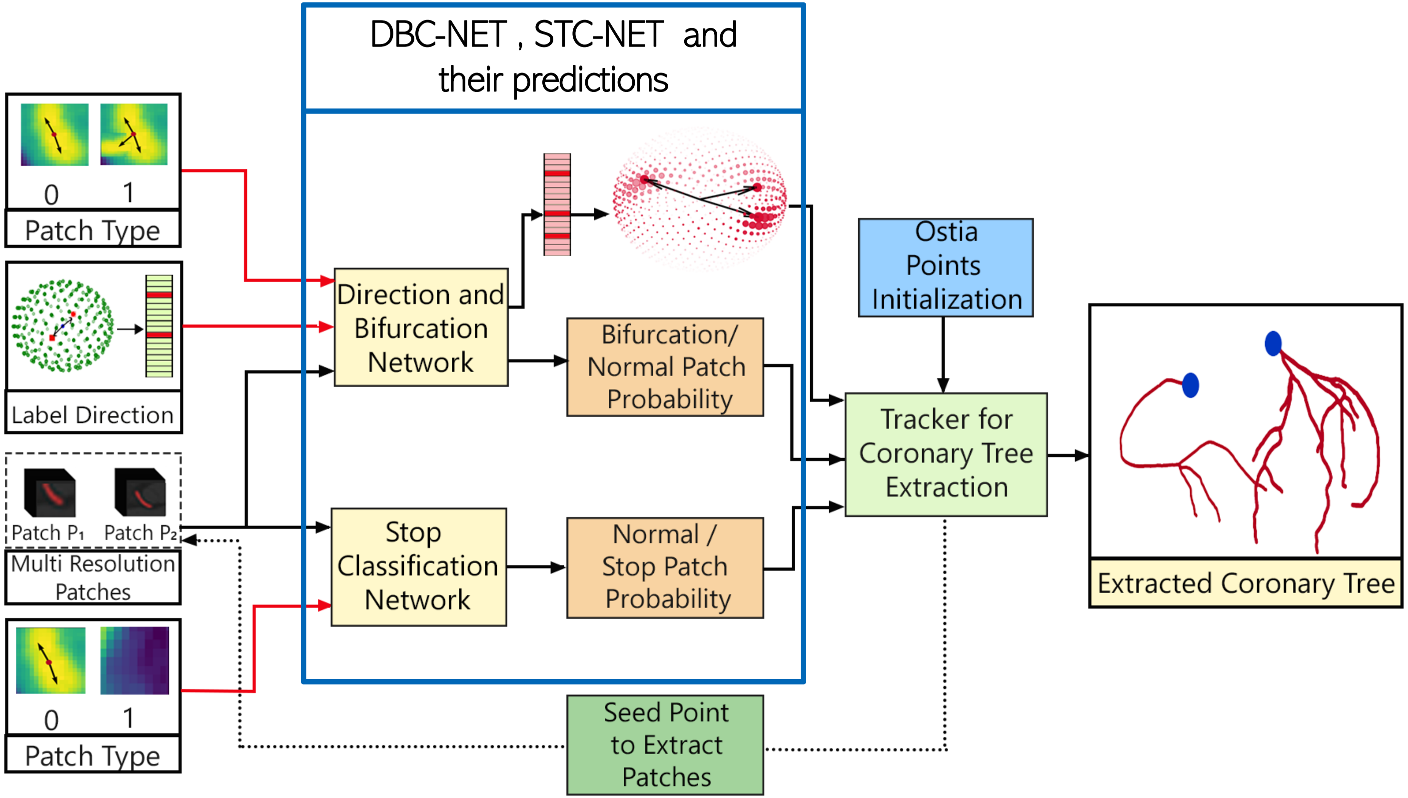



Fig 1: 3D Augmentation demonstration in **Maximum Intensity Projections (MIP)** of a 3D Patch.

# DBC-Net and STC-Net



# Direction and Bifurcation Classification Network (DBC-Net)

Fig 1 shows proposed network for simultaneous bifurcation detection and direction classification.

**Loss function :**

$$CE\ (\square) + \lambda_p * BCE\ (\square)$$

where $\lambda_p = 5$

**Data Imbalance :** Importance Sampling for bifurcation class.

Fig 2 shows typical predicted response in case of a normal patch and bifurcation patch.

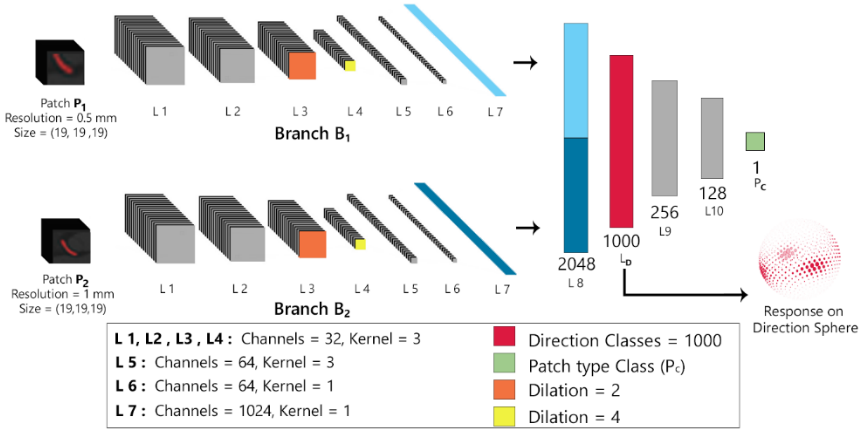



Fig 1: DBC-Net

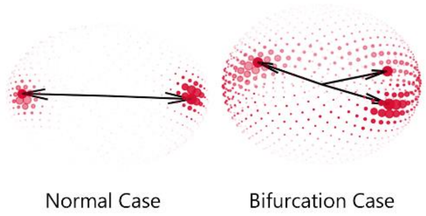



Fig 2: Response

# Stop Patch Classification Network (STC-Net)

Same network architecture as DBC-Net is employed except : **loss function** = BCE ( ). STC-Net is shown in Fig 1.

In Fig 2,
**Normal patches** ( ) = Patches on coronary arteries
**Stop patch** ( ) = Patches beyond the end point

**STC-Net prediction and entropy of direction response** is used as a combined criterion for termination.

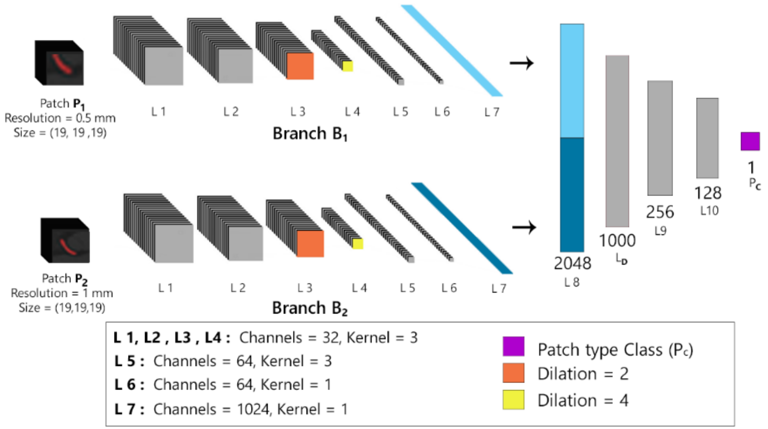



Fig 1: STC-Net

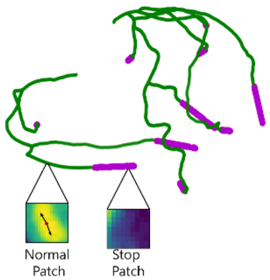
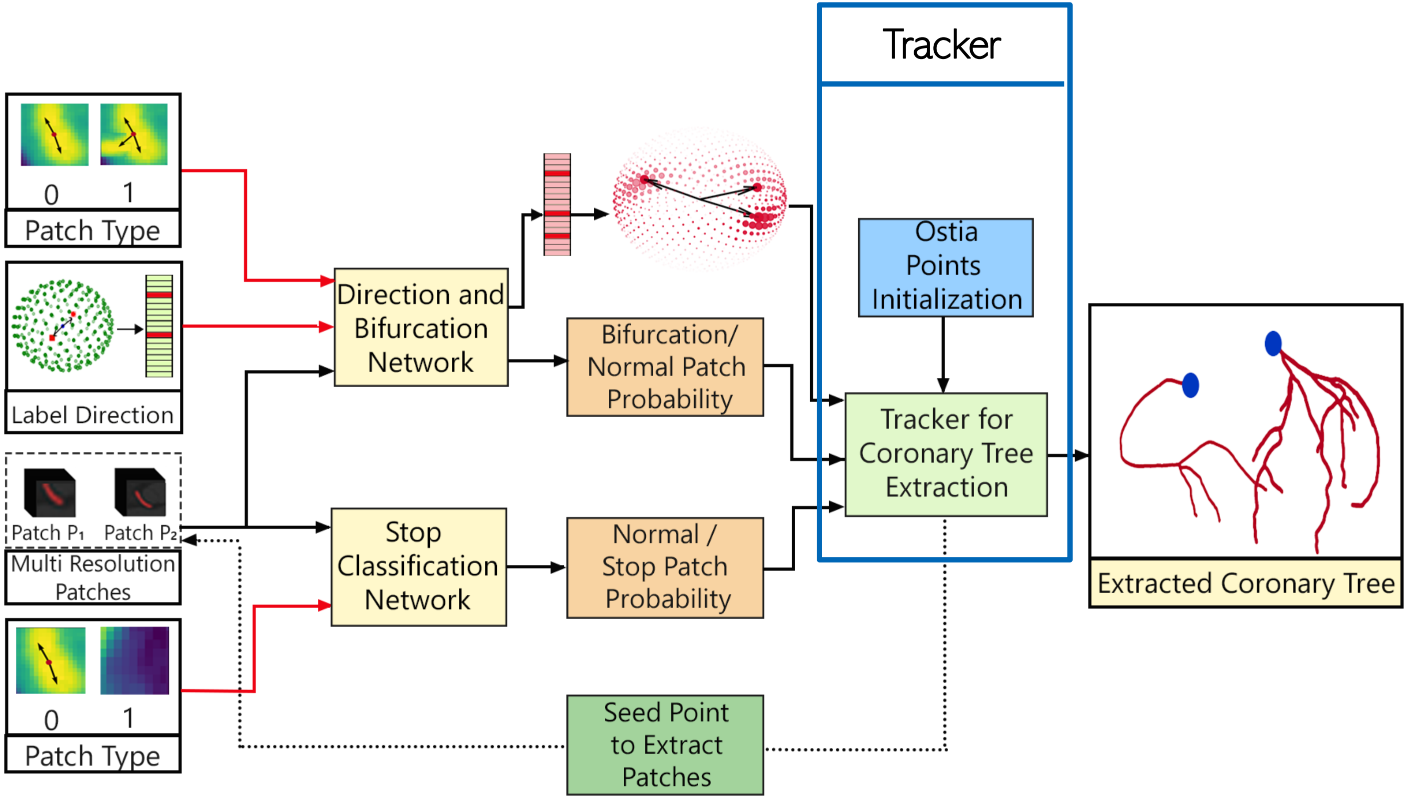


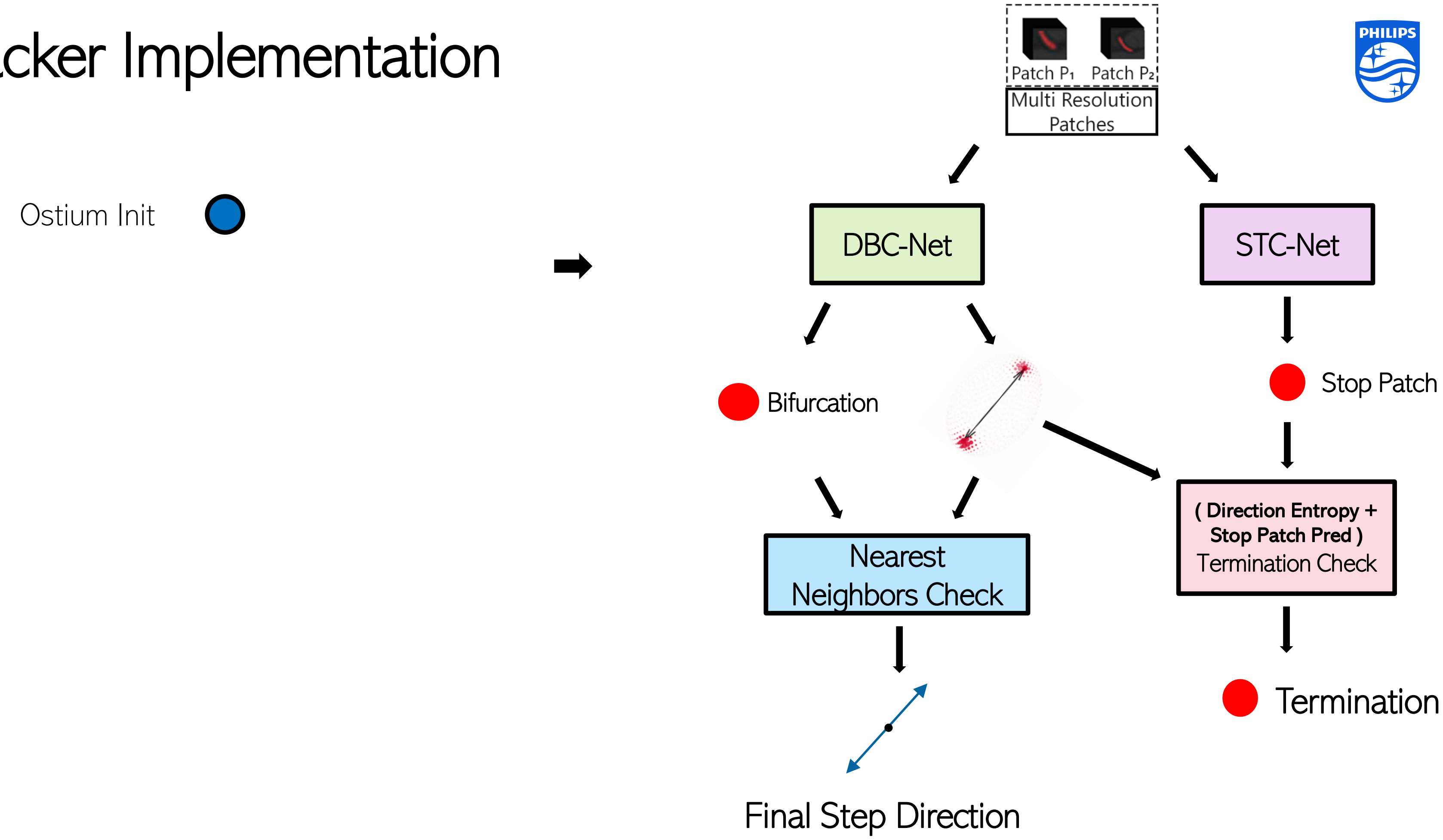

Fig 2: Patch type labelling for STC-Net

# Tracker



Tracker
0
1
Patch Type
Label Direction
Patch P1
Patch P2
Multi Resolution Patches
0
1
Patch Type
Direction and Bifurcation Network
Stop Classification Network
Bifurcation/ Normal Patch Probability
Normal / Stop Patch Probability
Seed Point to Extract Patches
Ostia Points Initialization
Tracker for Coronary Tree Extraction
Extracted Coronary Tree

# Tracker Implementation



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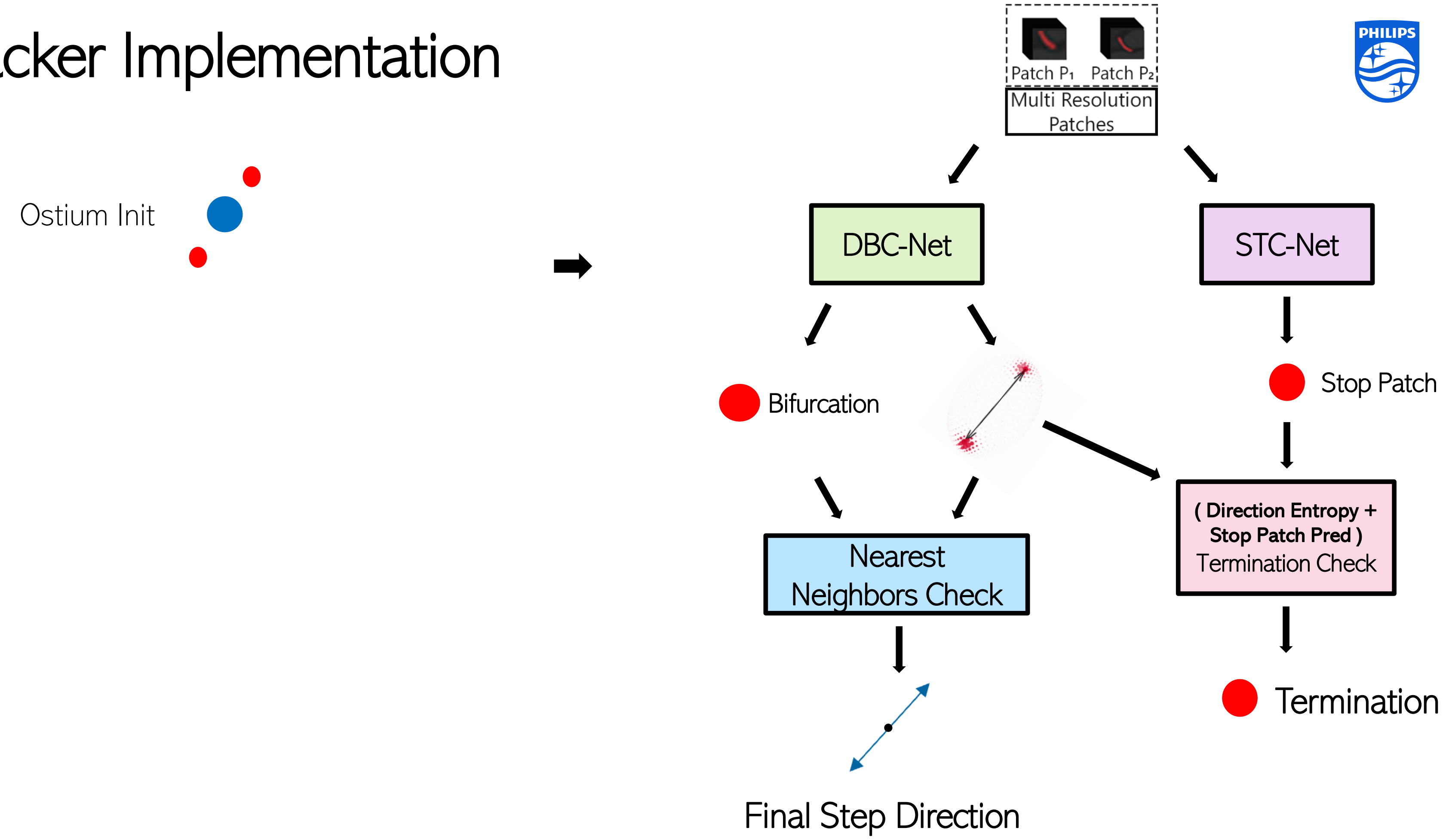

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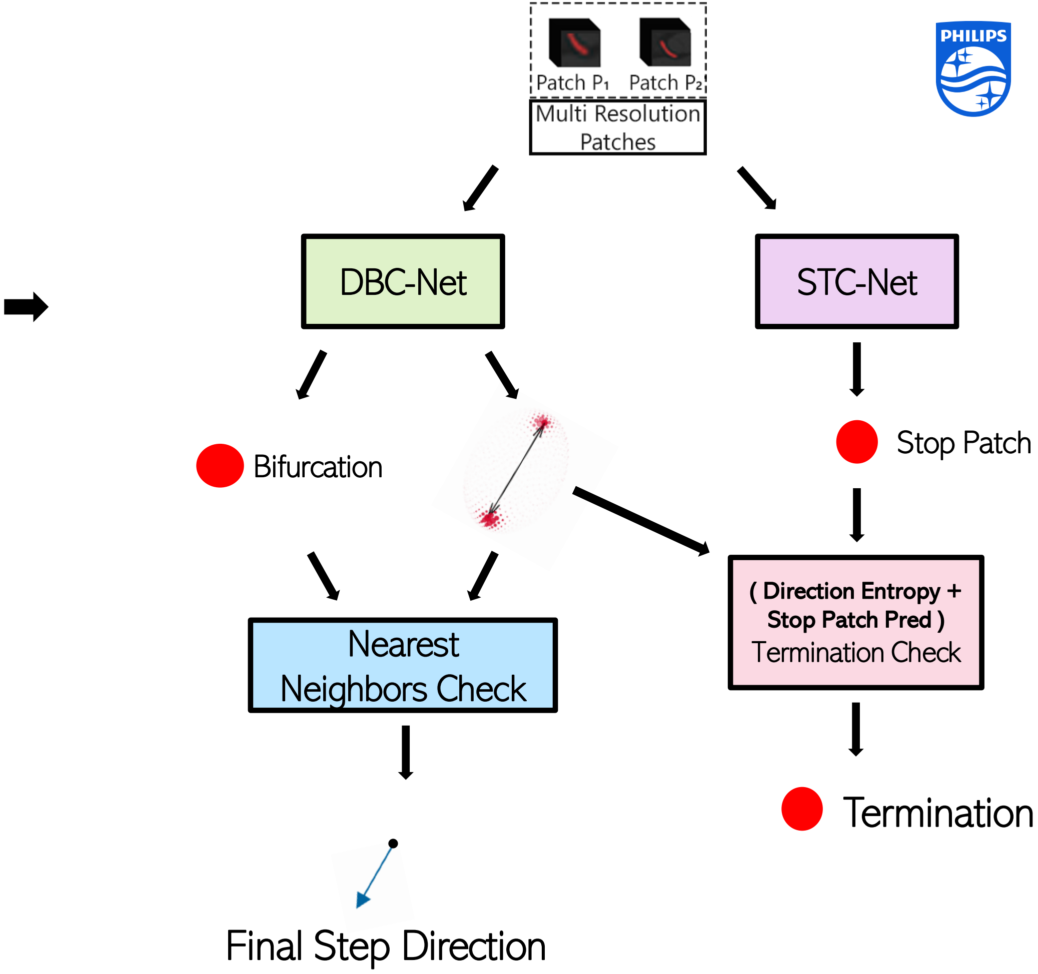

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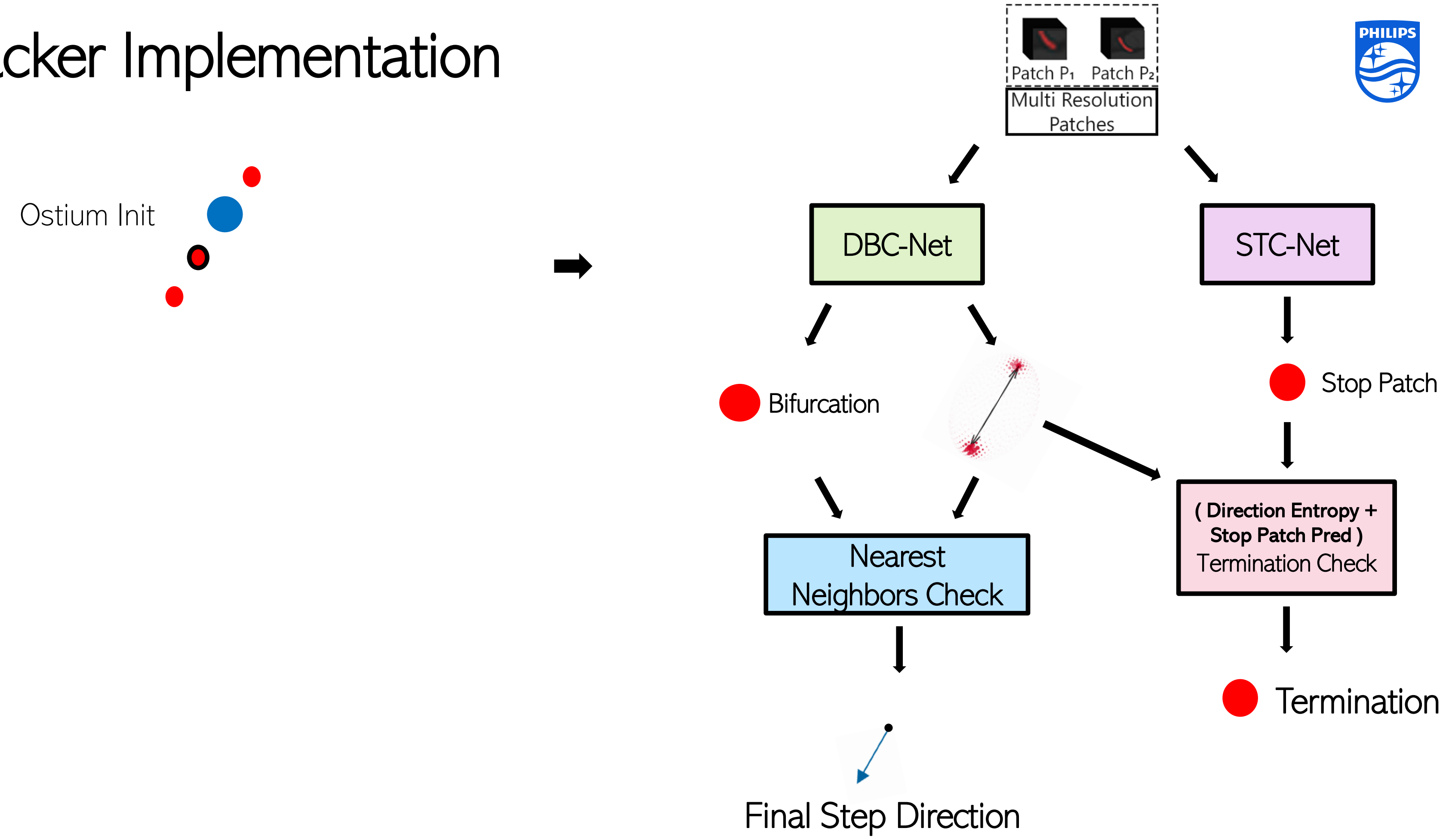
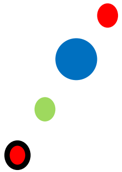
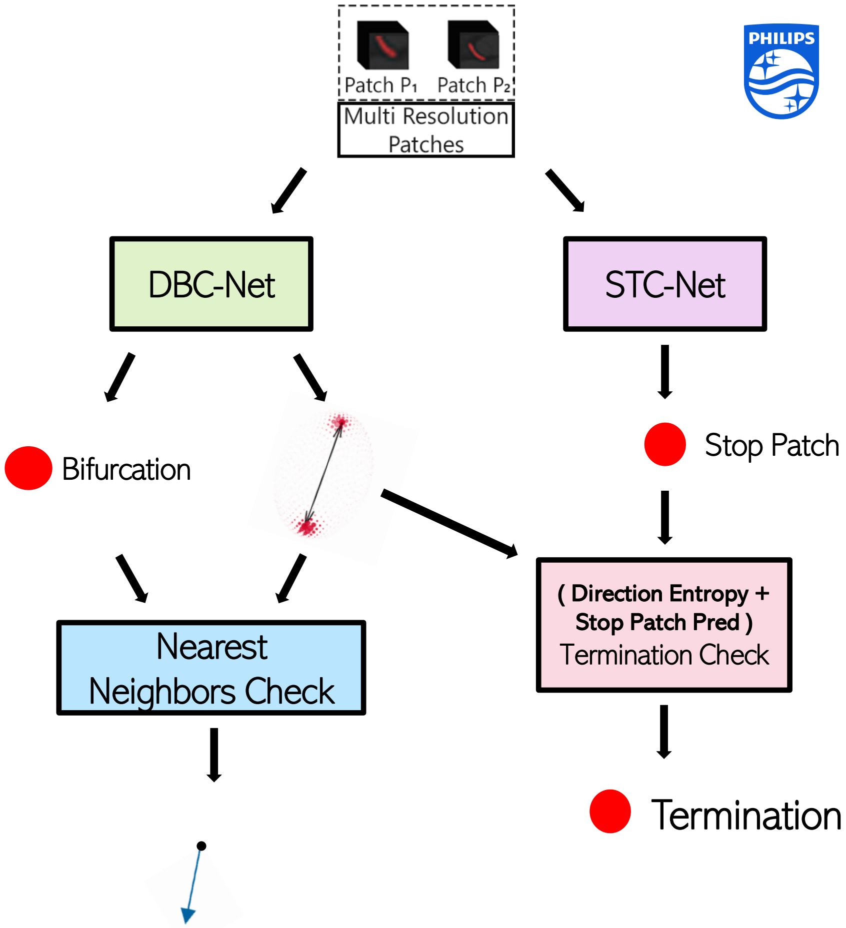


# Tracker Implementation

Ostium Init





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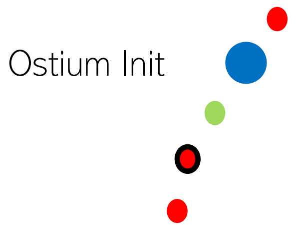
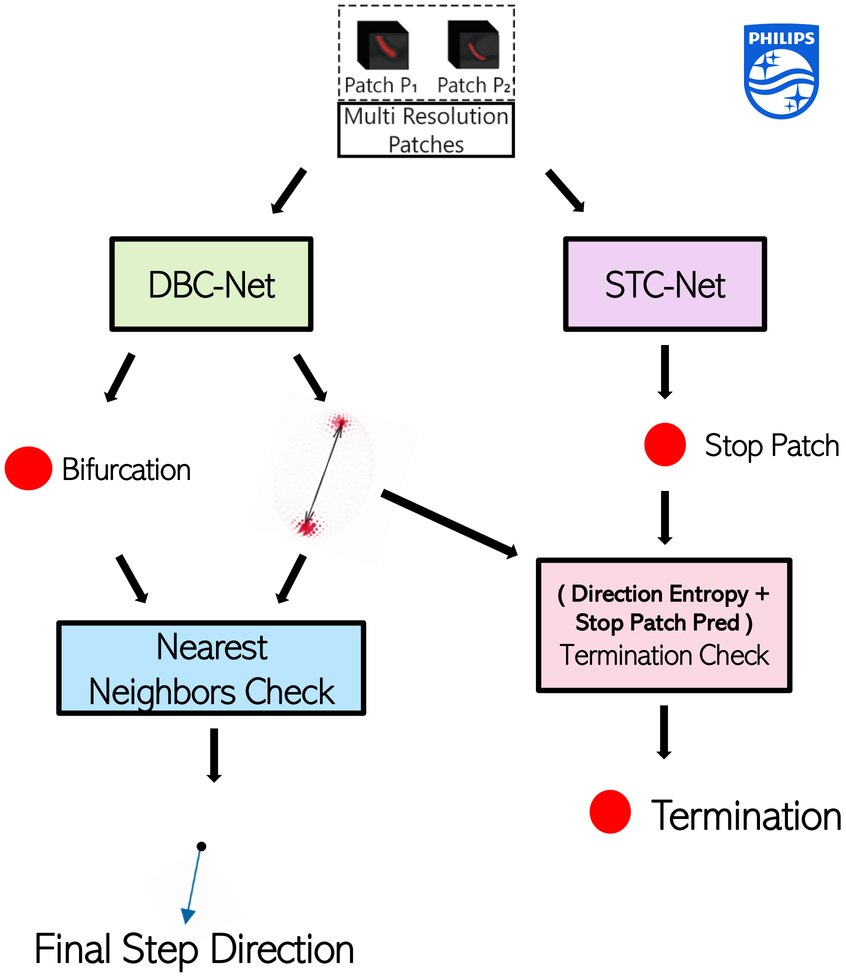
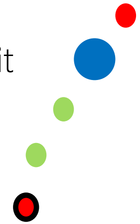
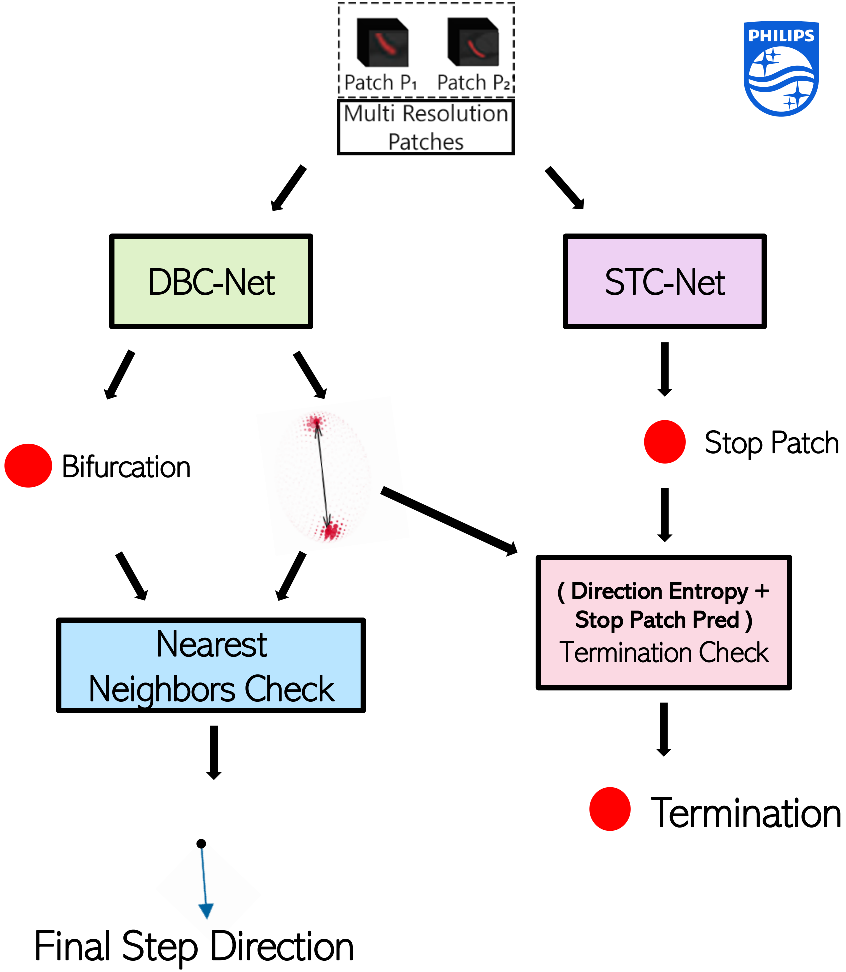


# Tracker Implementation

Ostium Init





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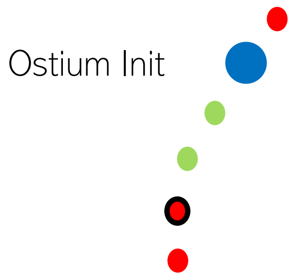


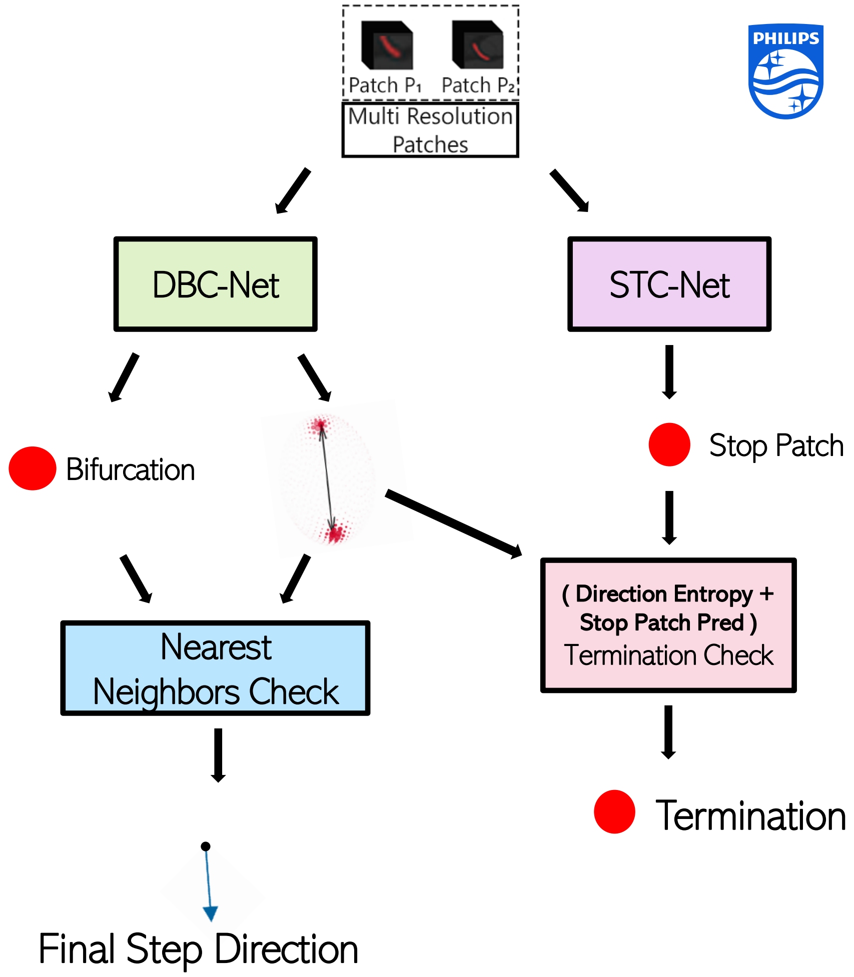

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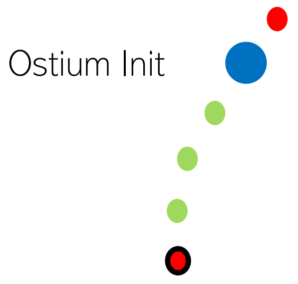


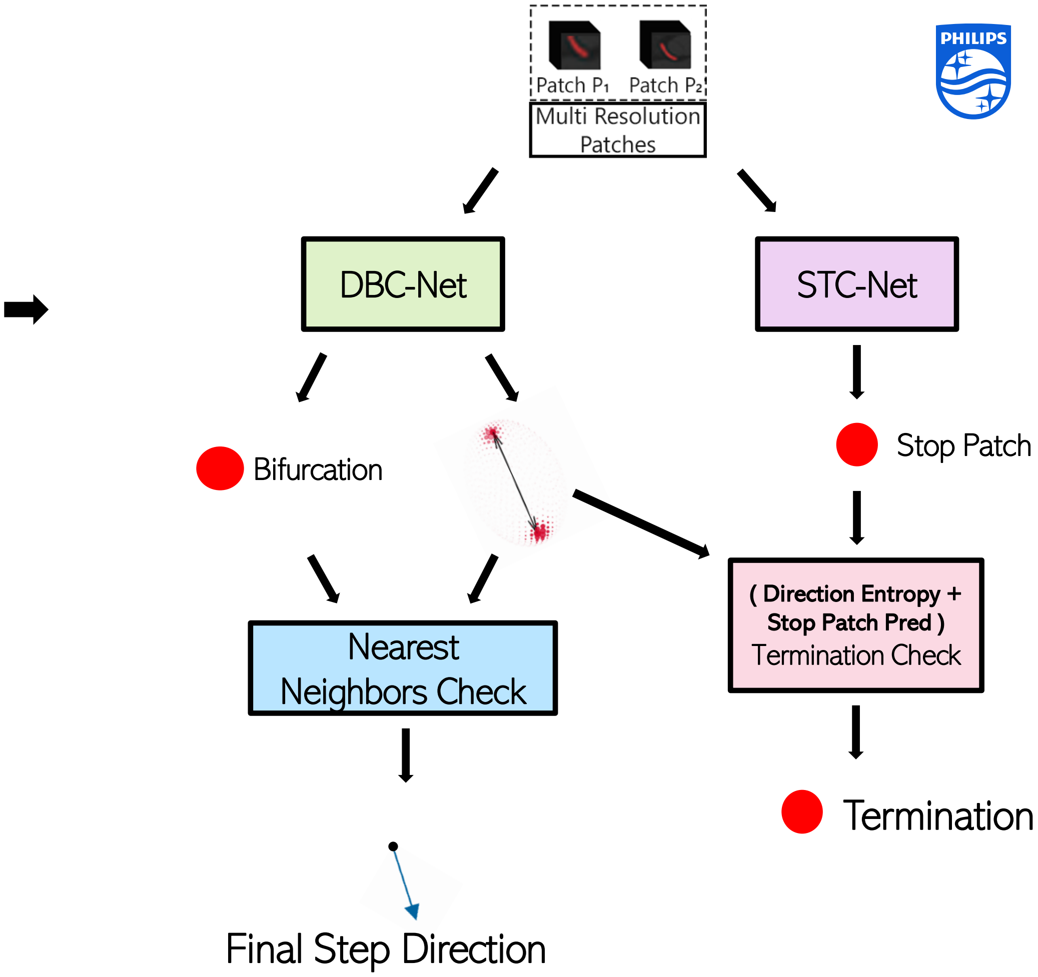

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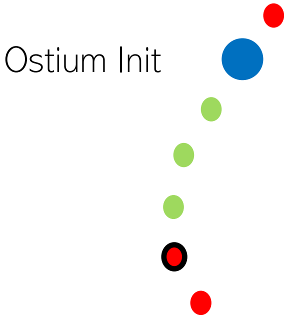


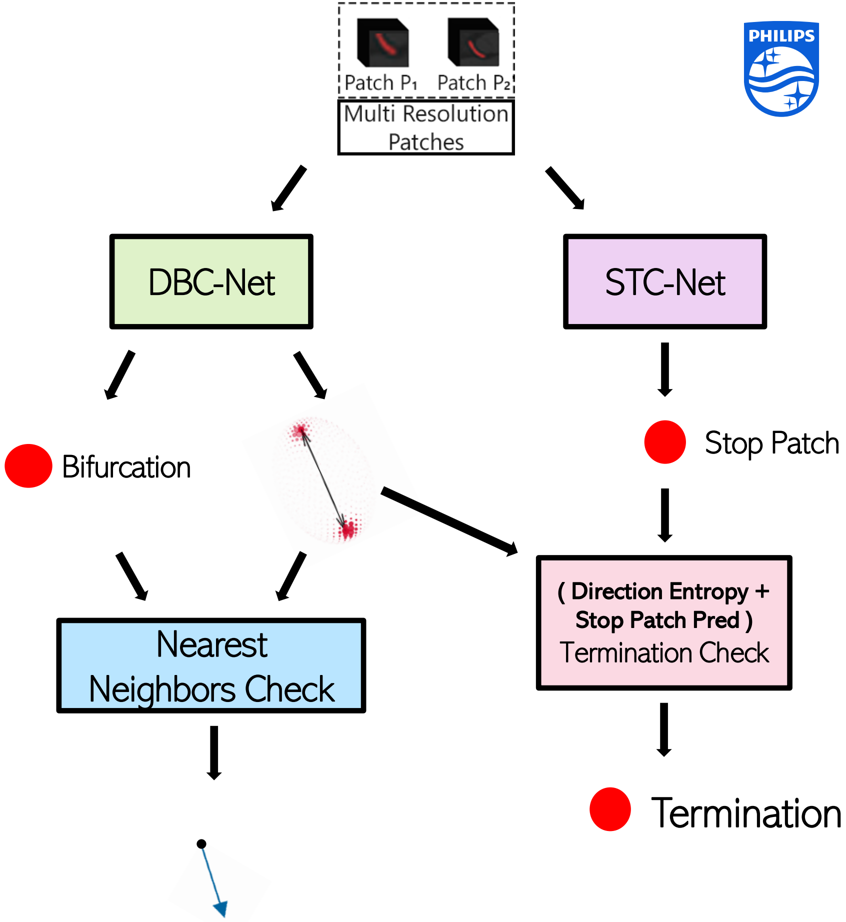

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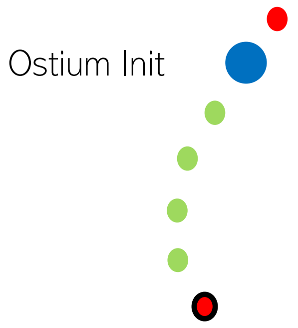


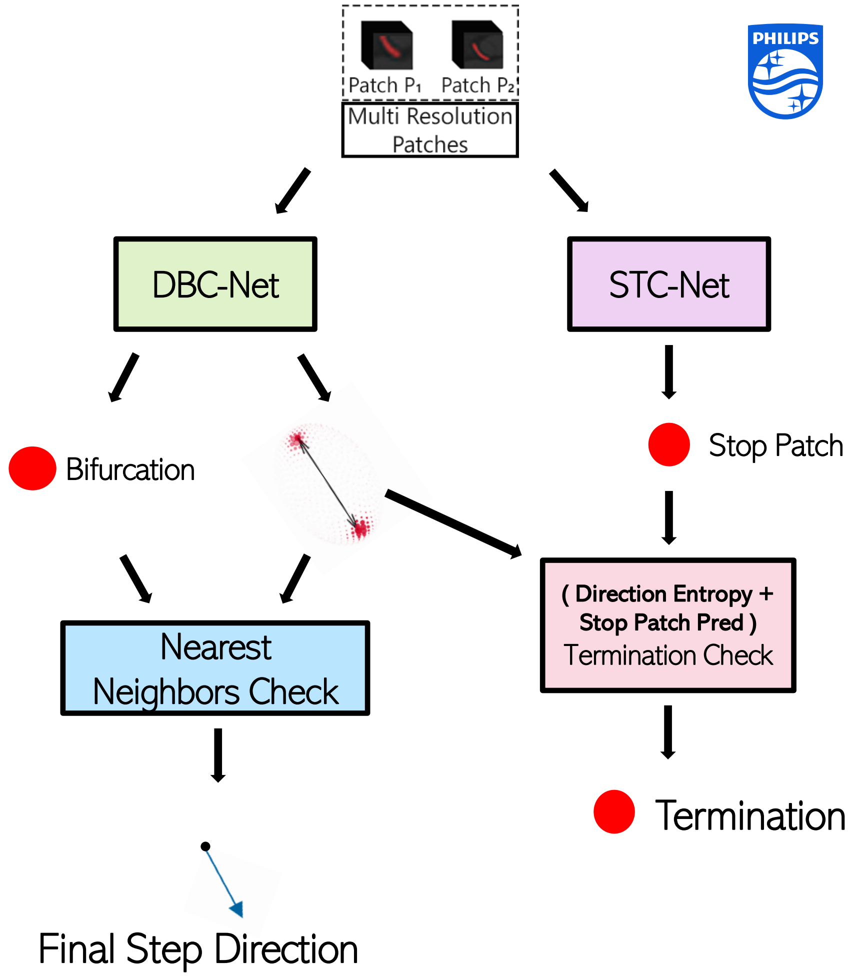

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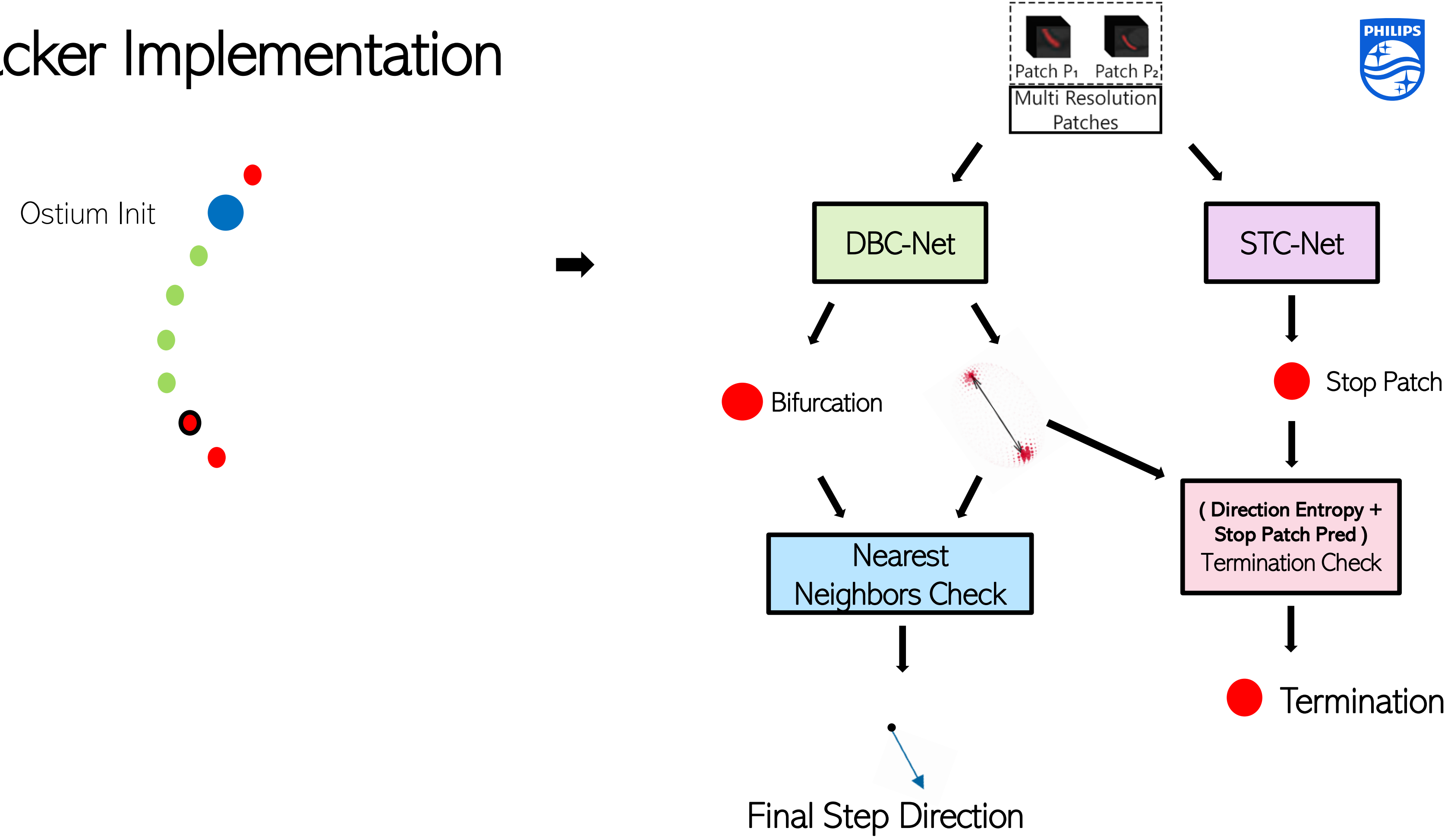

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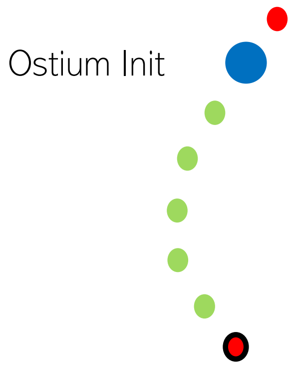


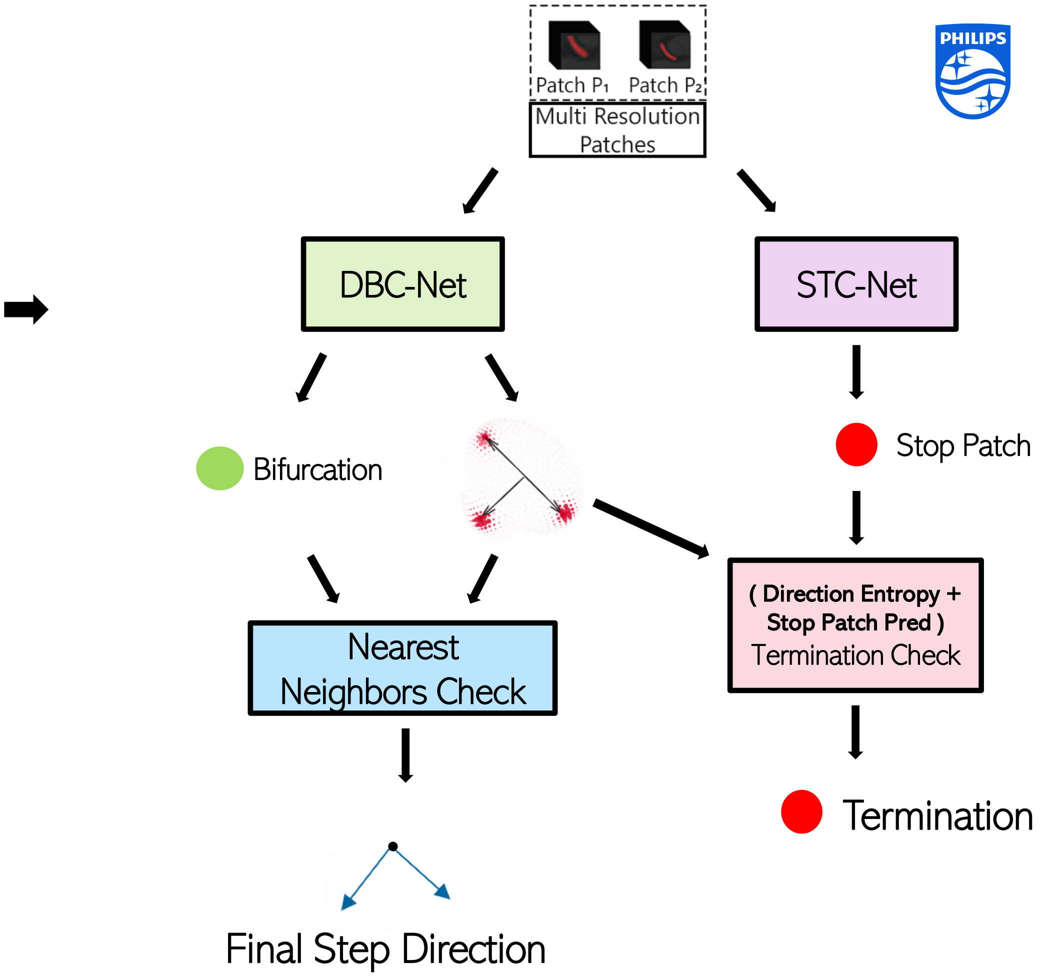

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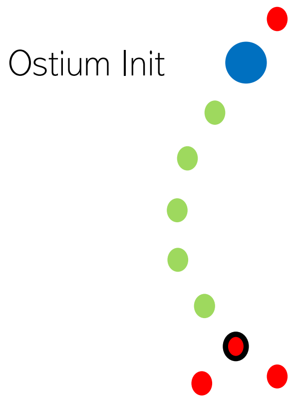


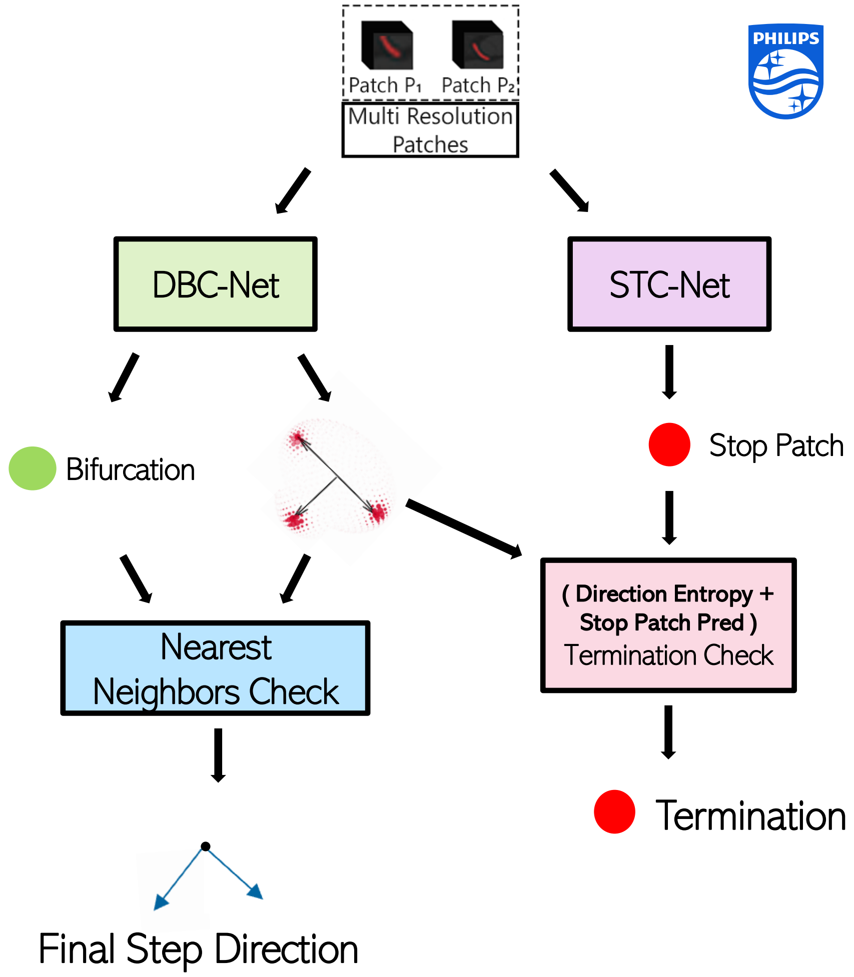

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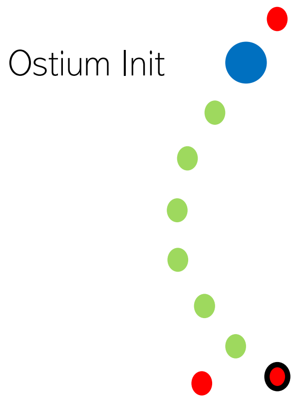


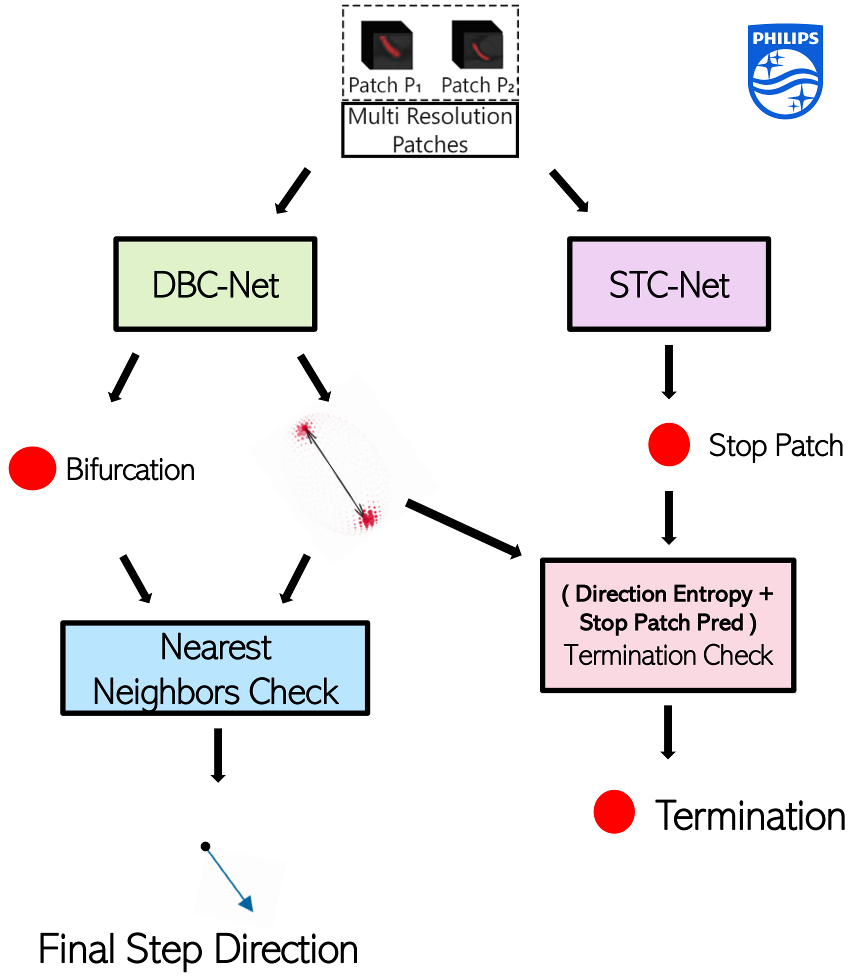

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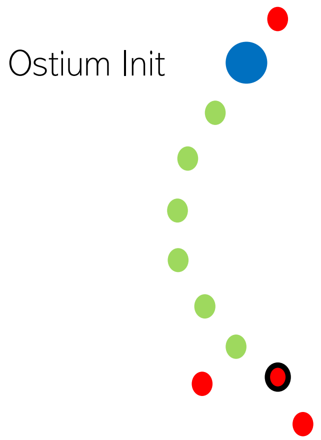


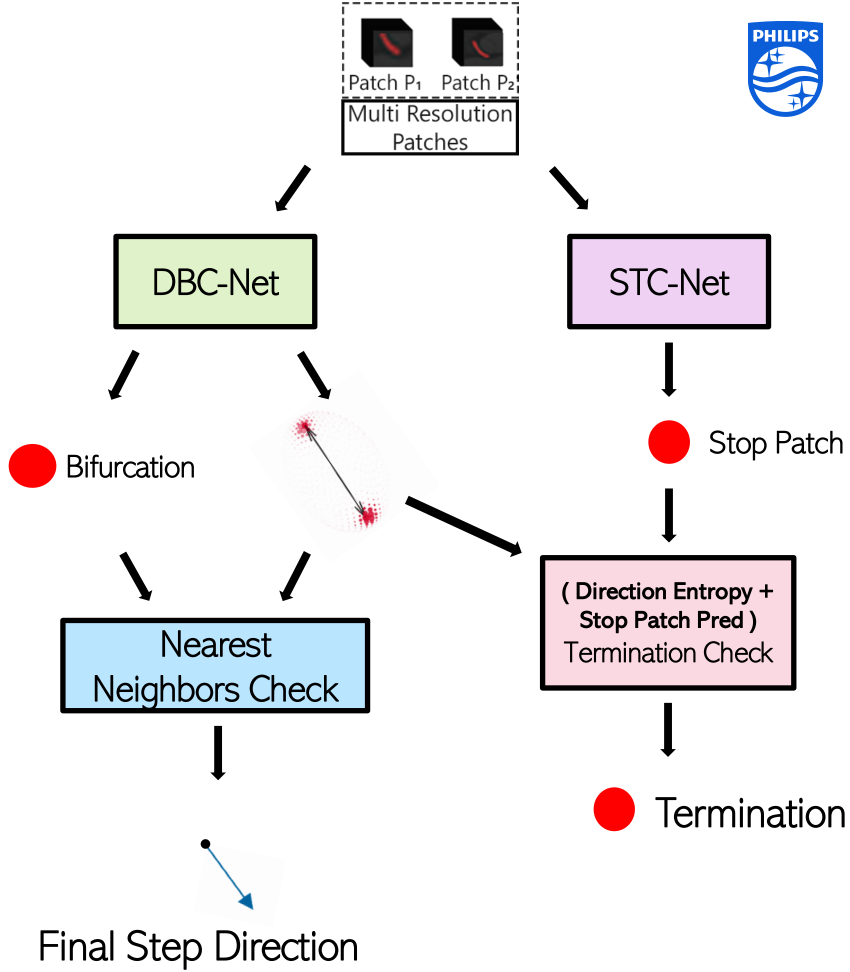

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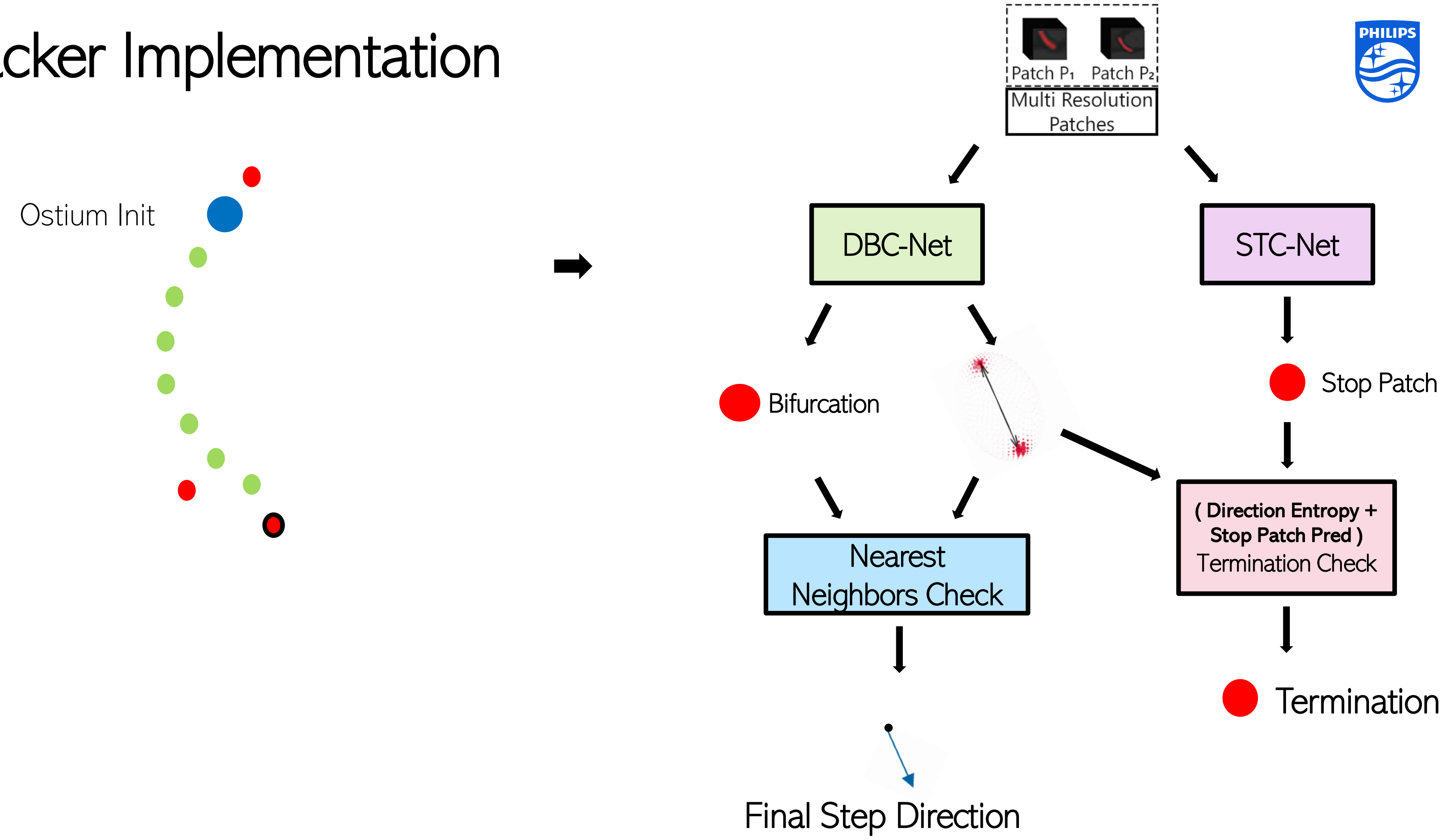

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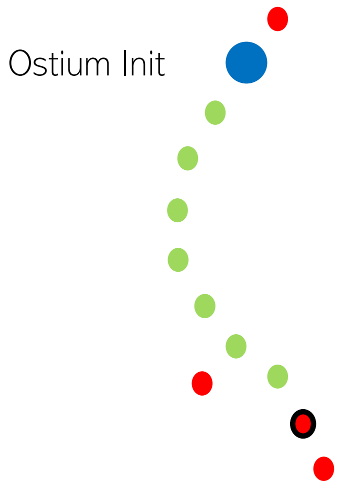


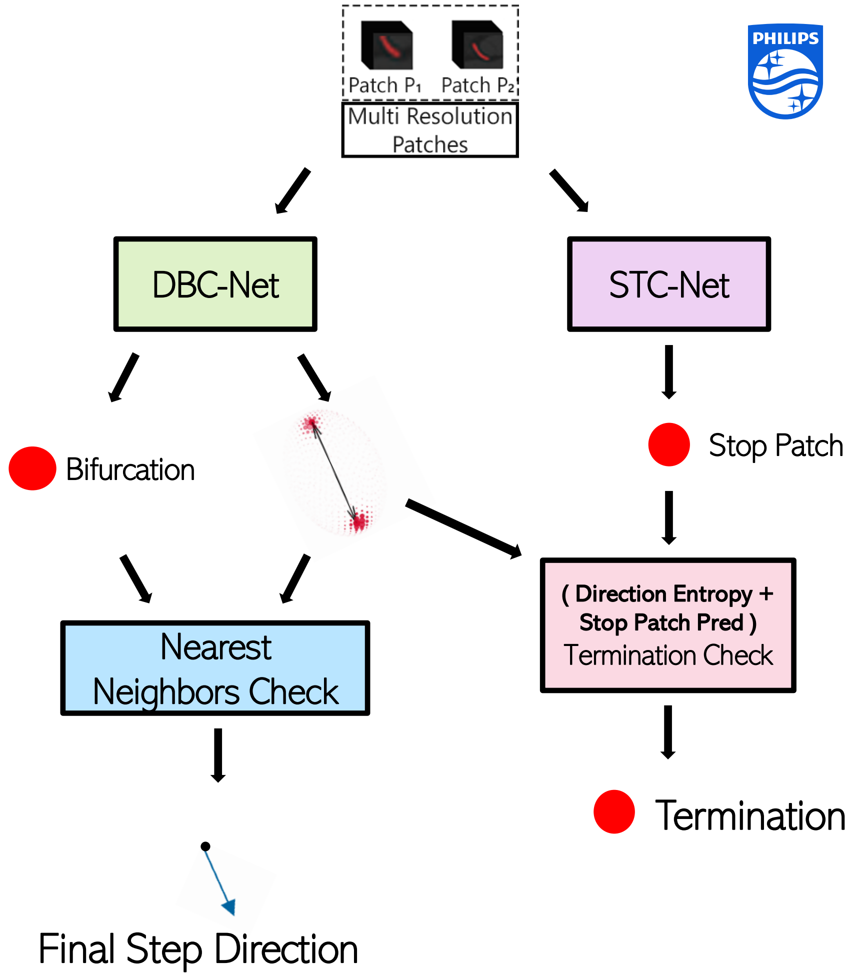

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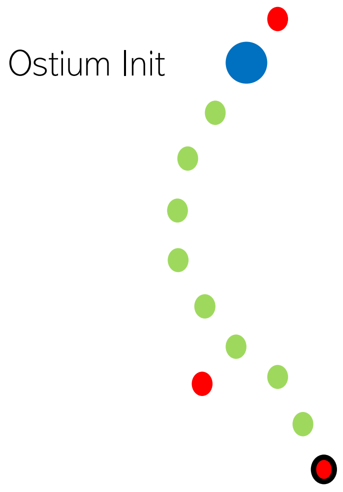


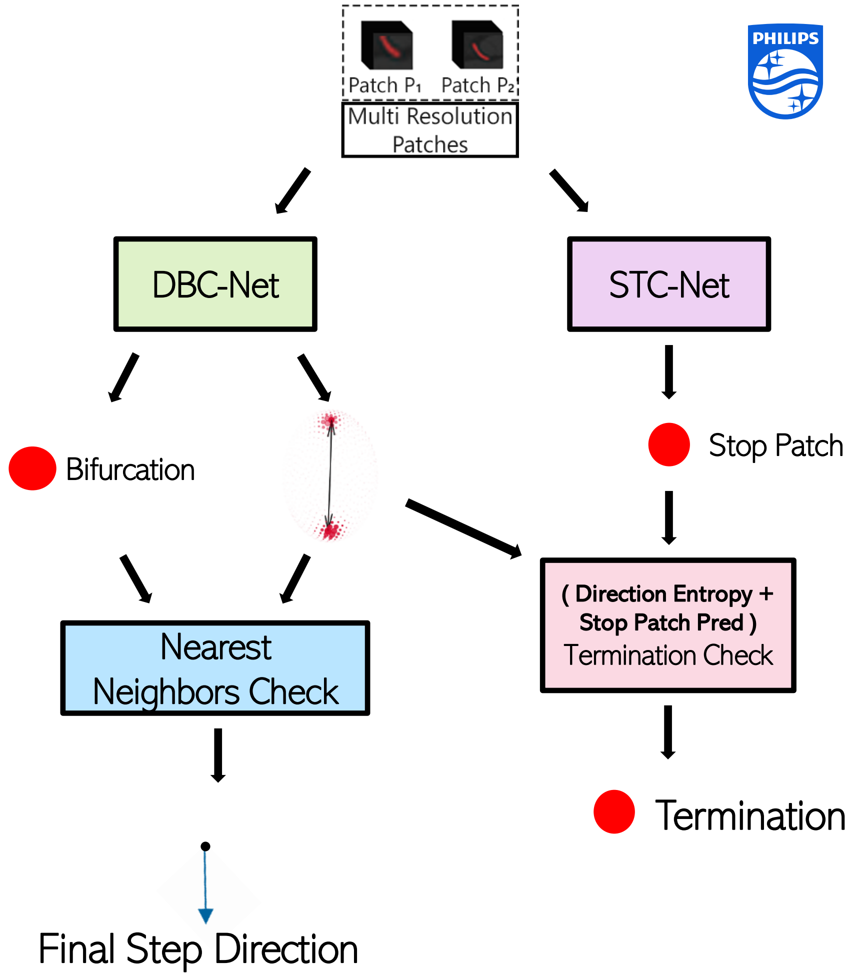

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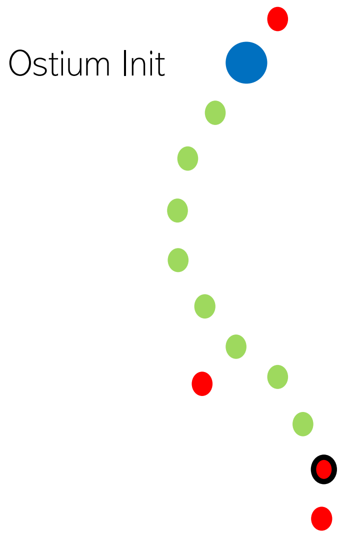


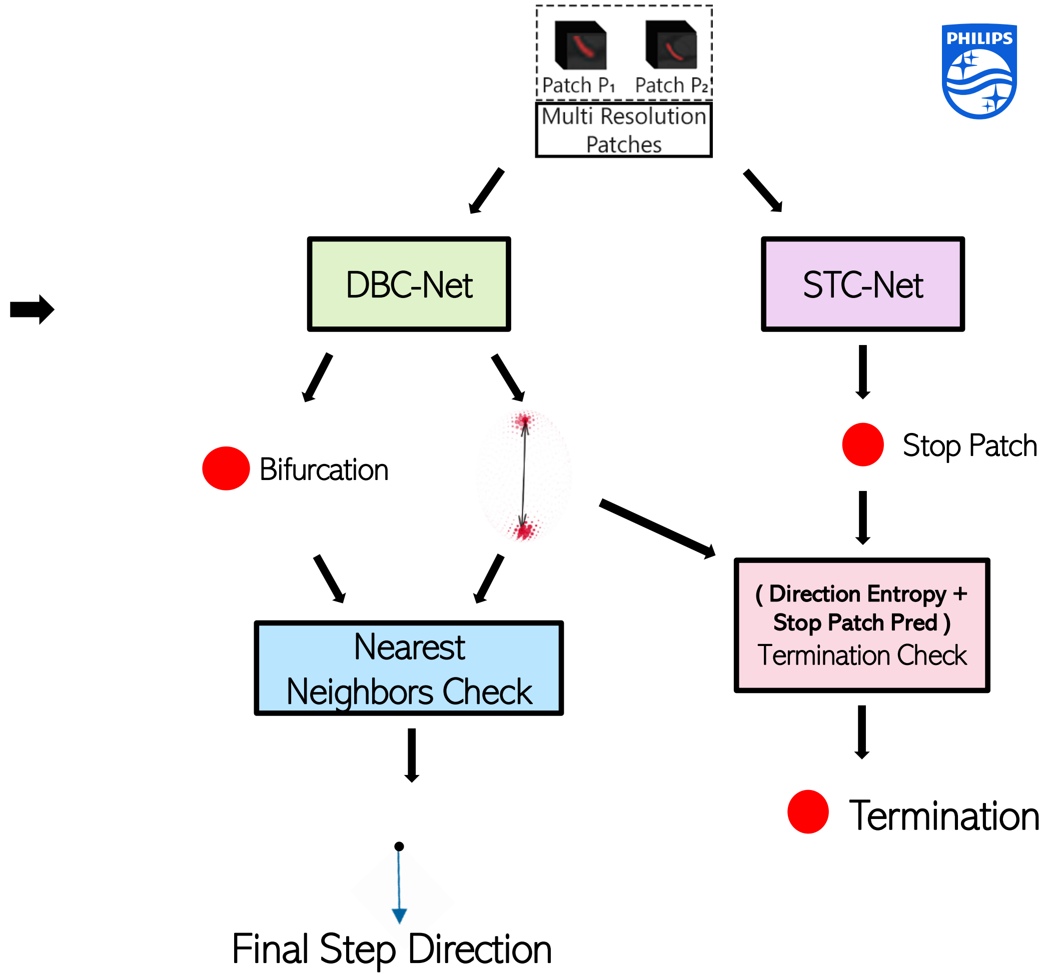

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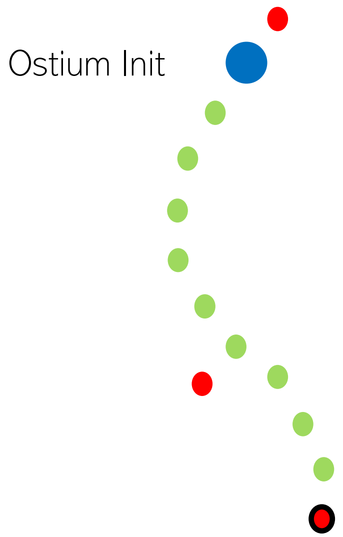


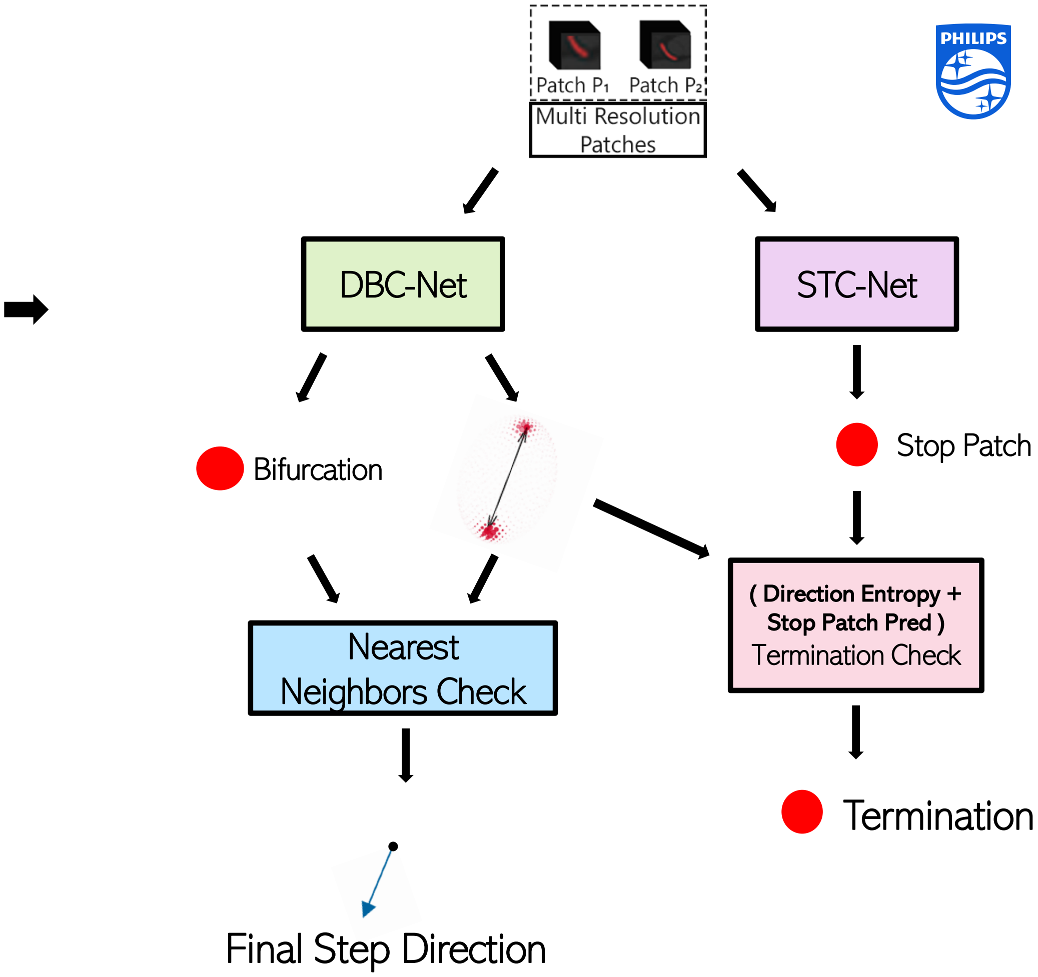

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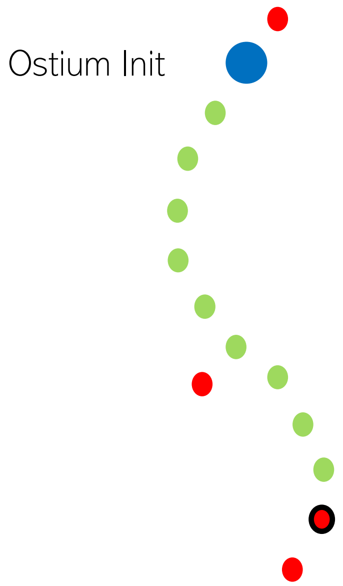


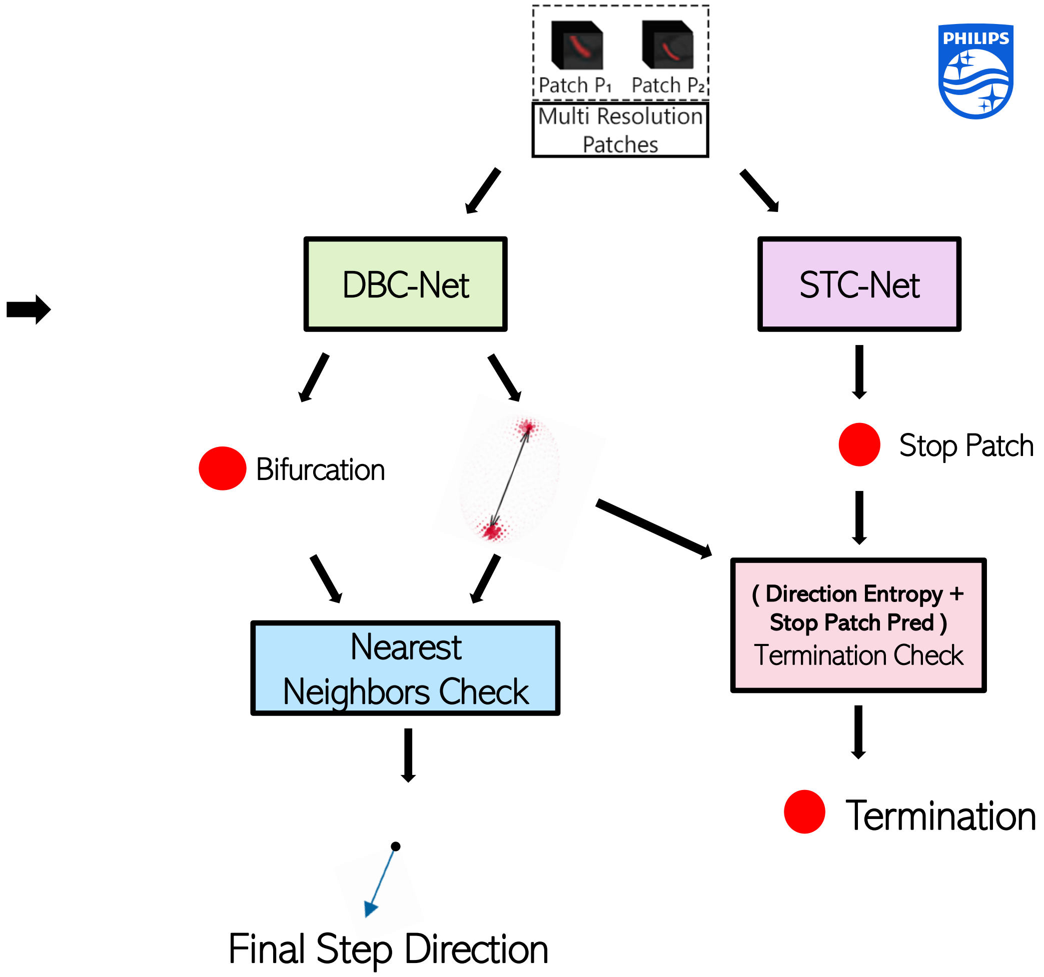

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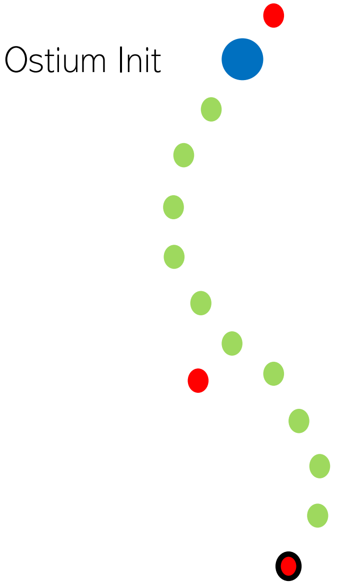


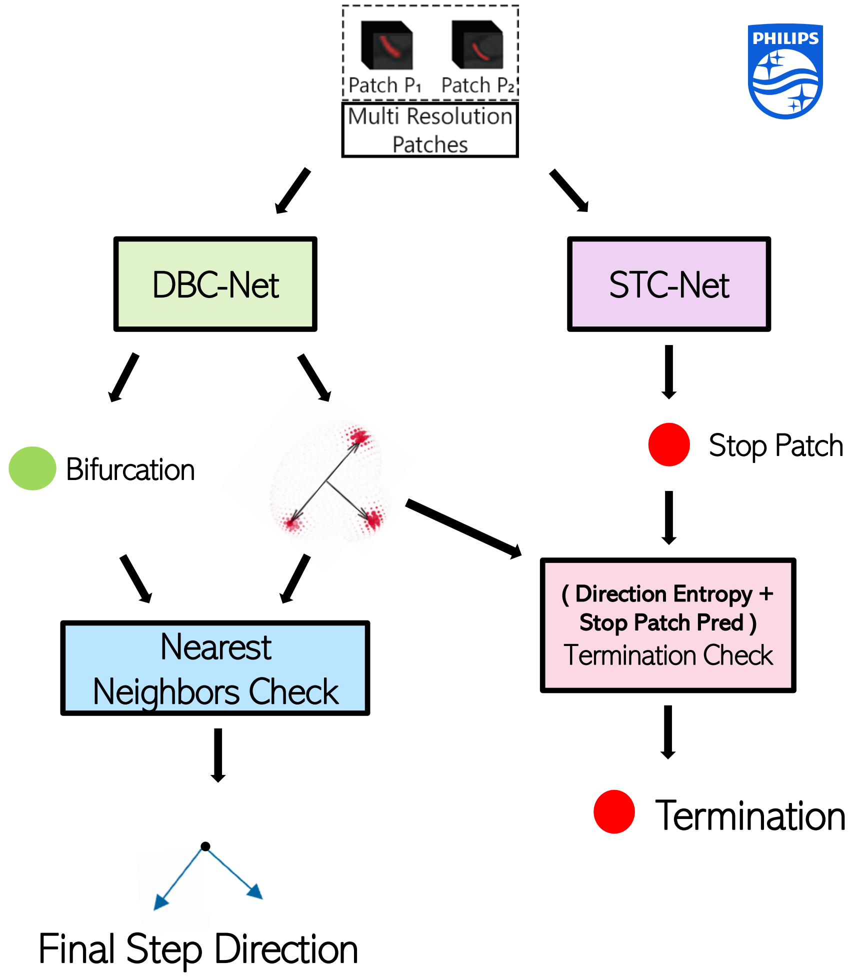

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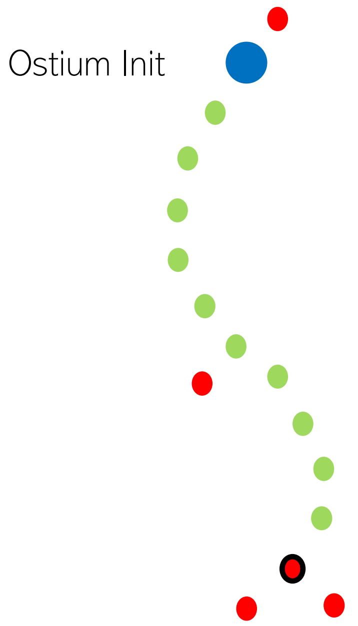


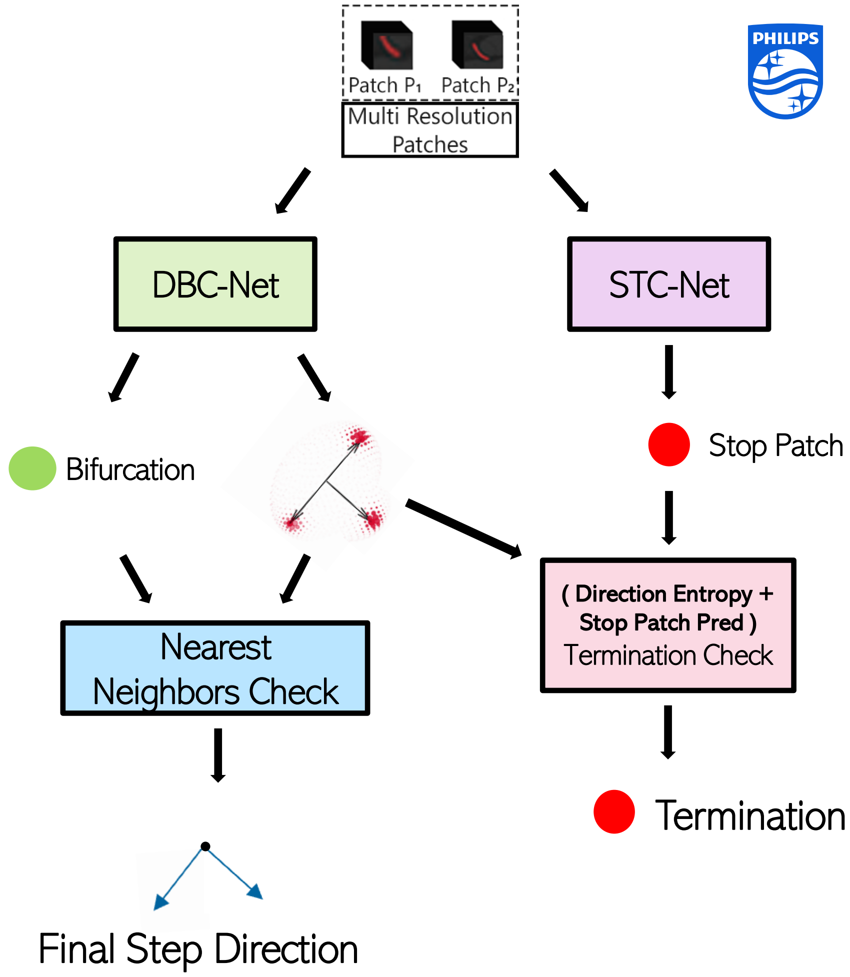

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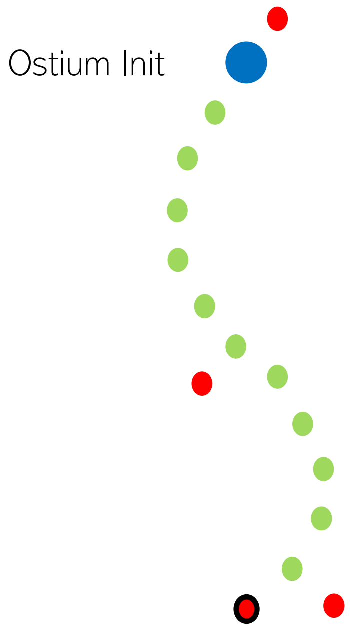


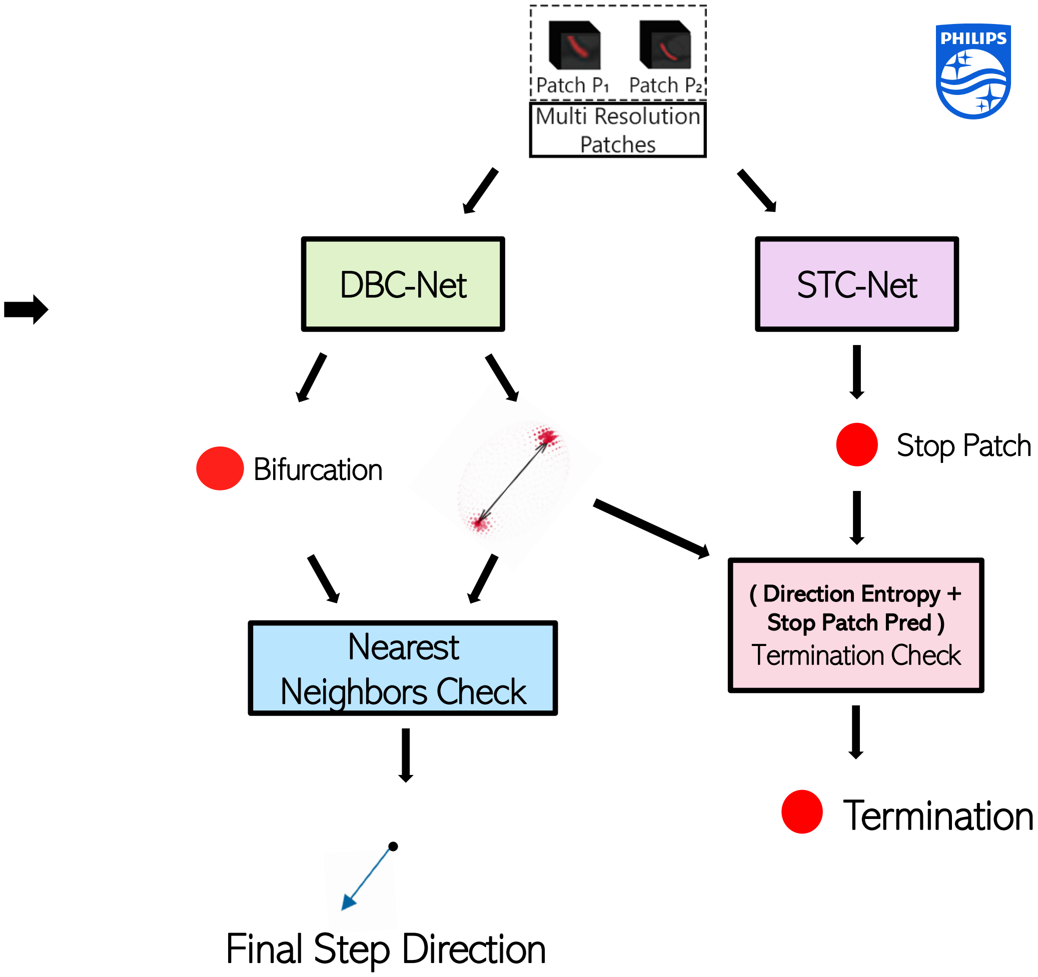

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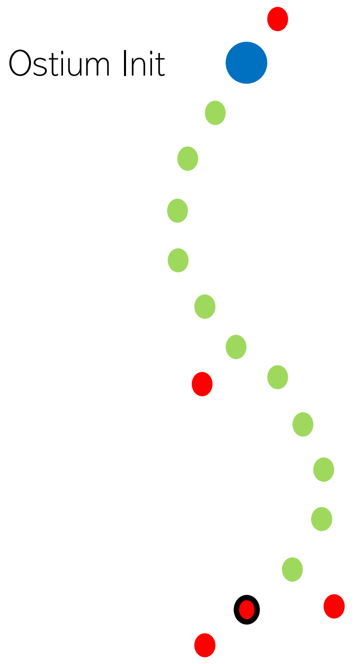
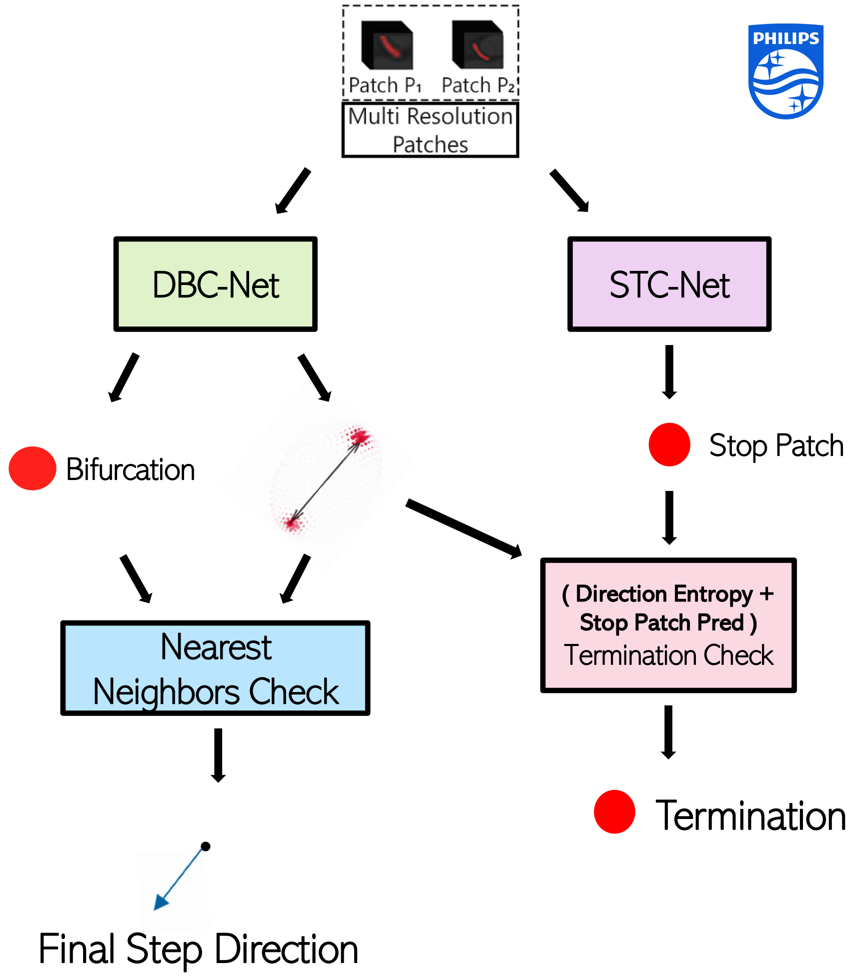
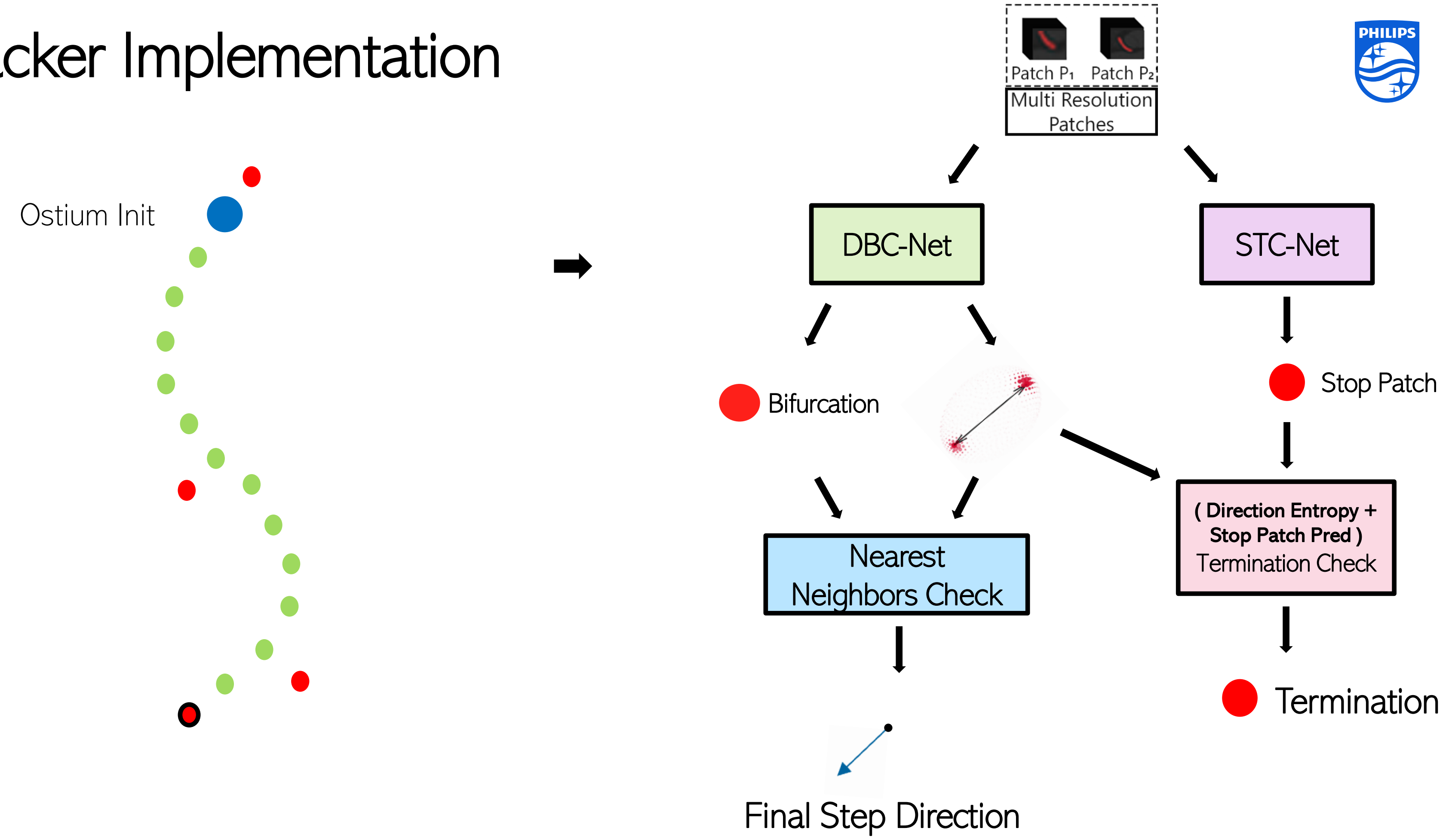


# Tracker Implementation



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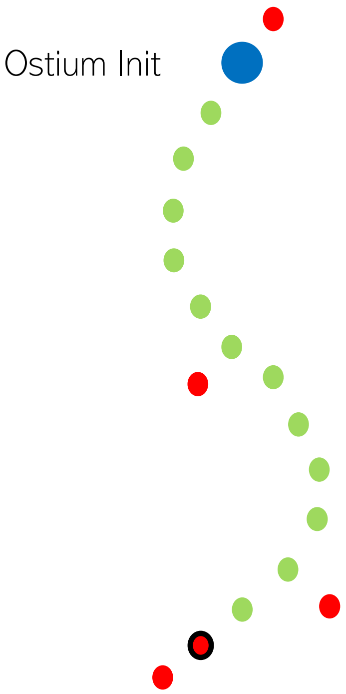


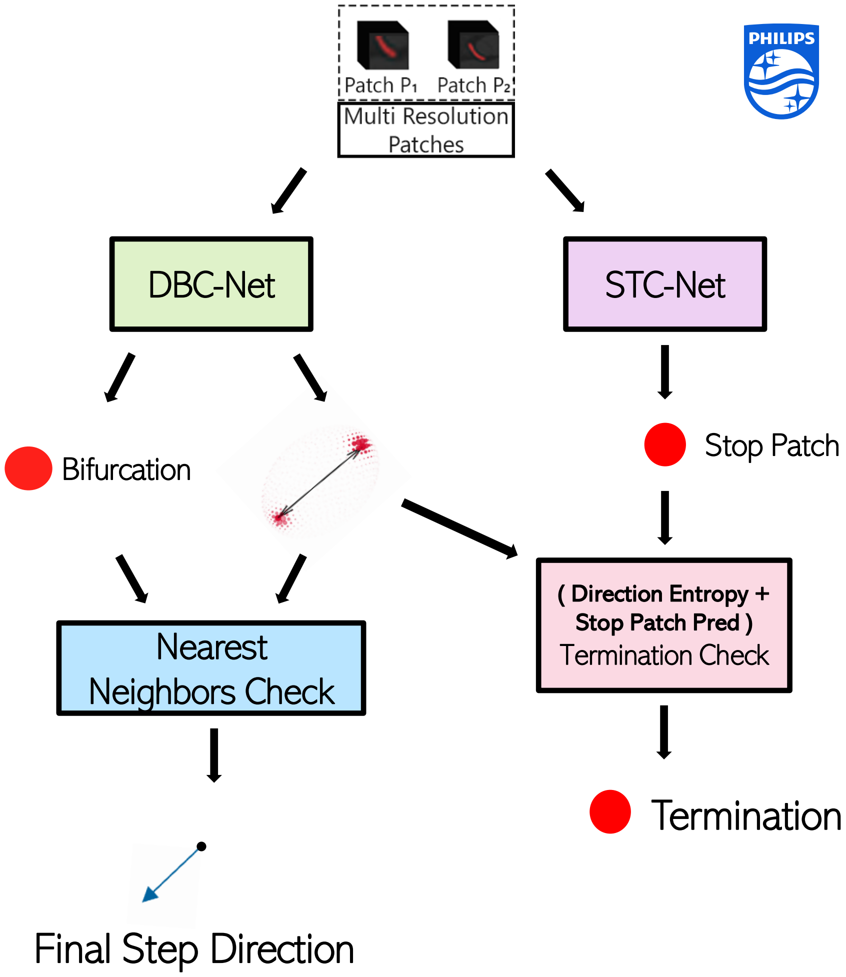

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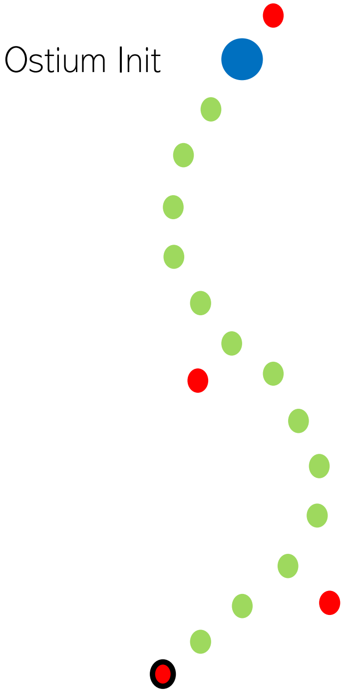


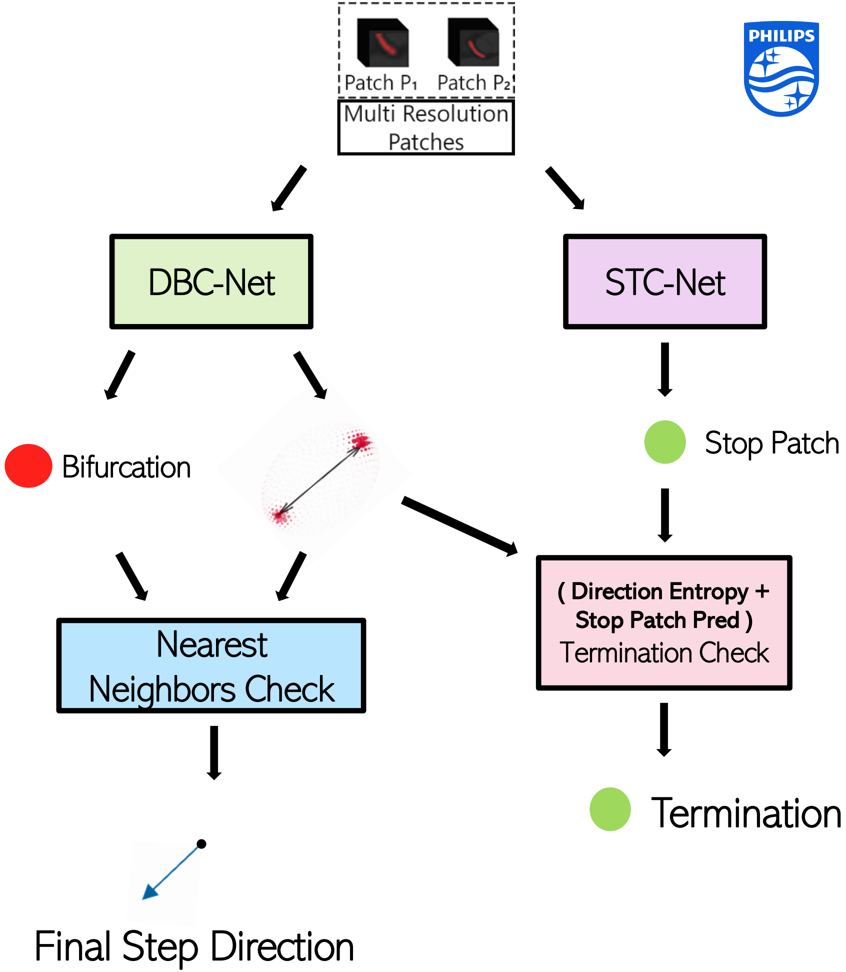

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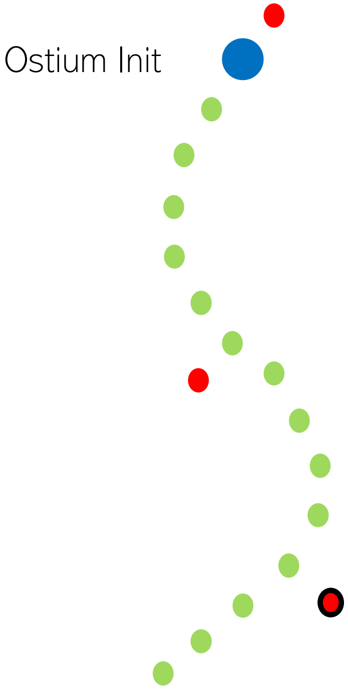


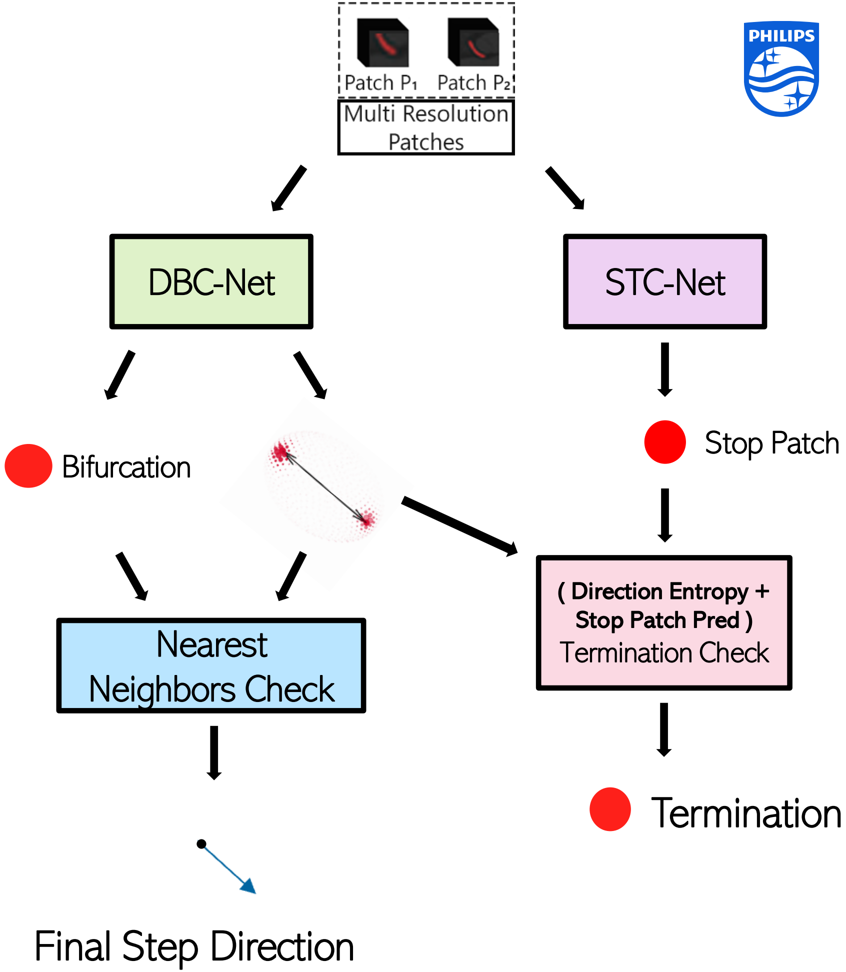

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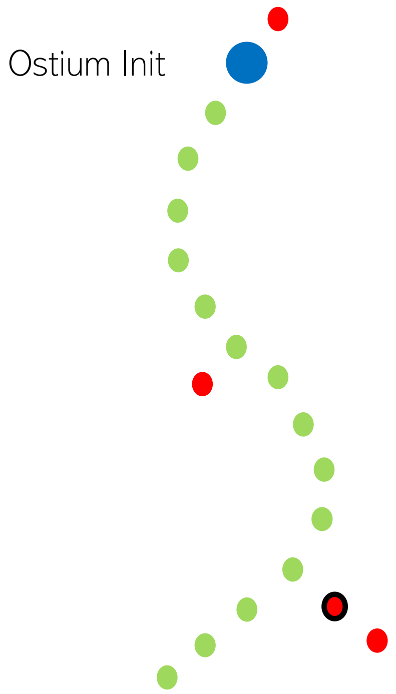


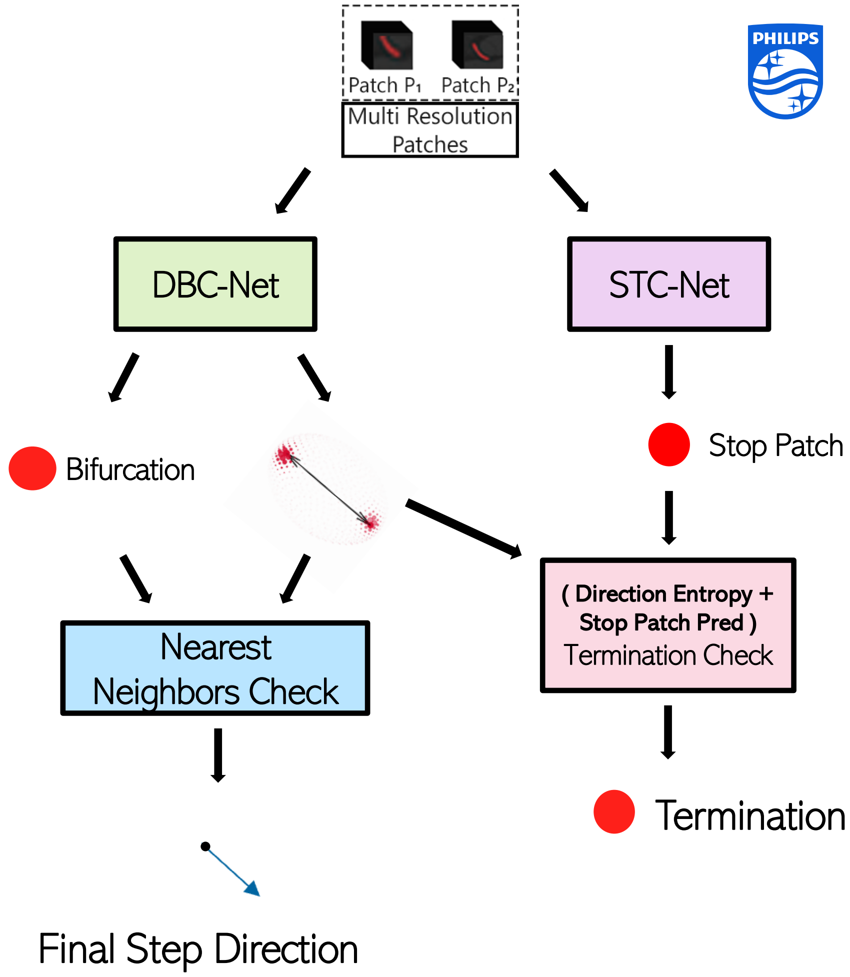

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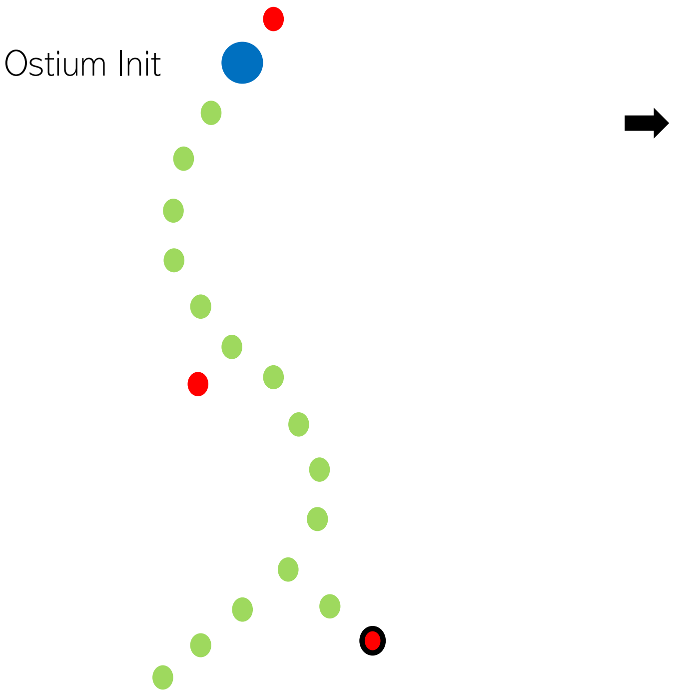


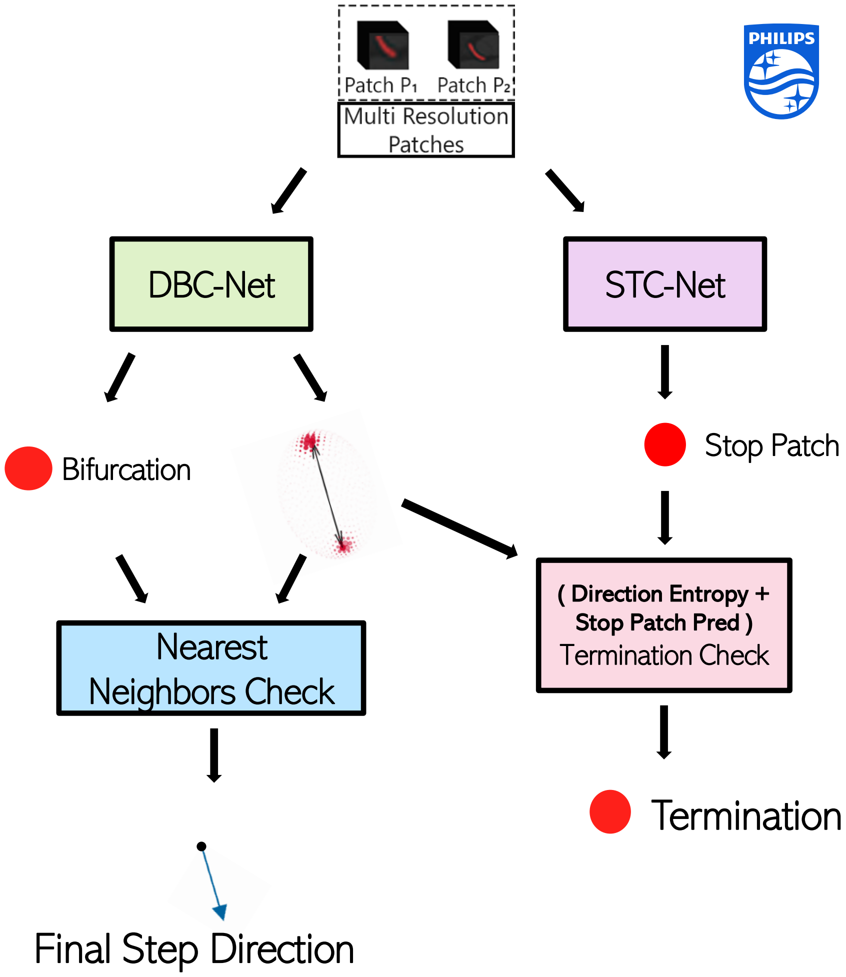

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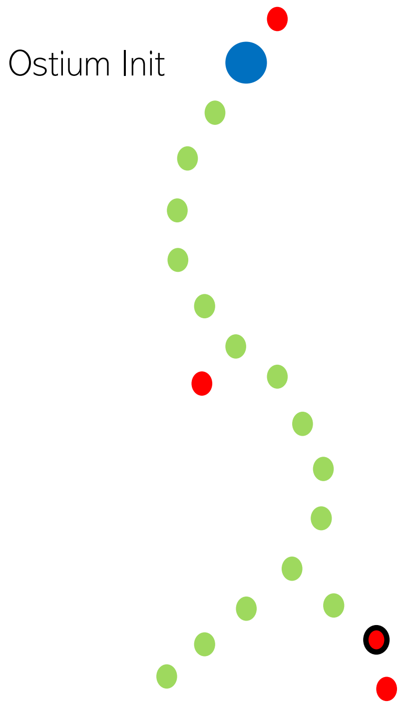


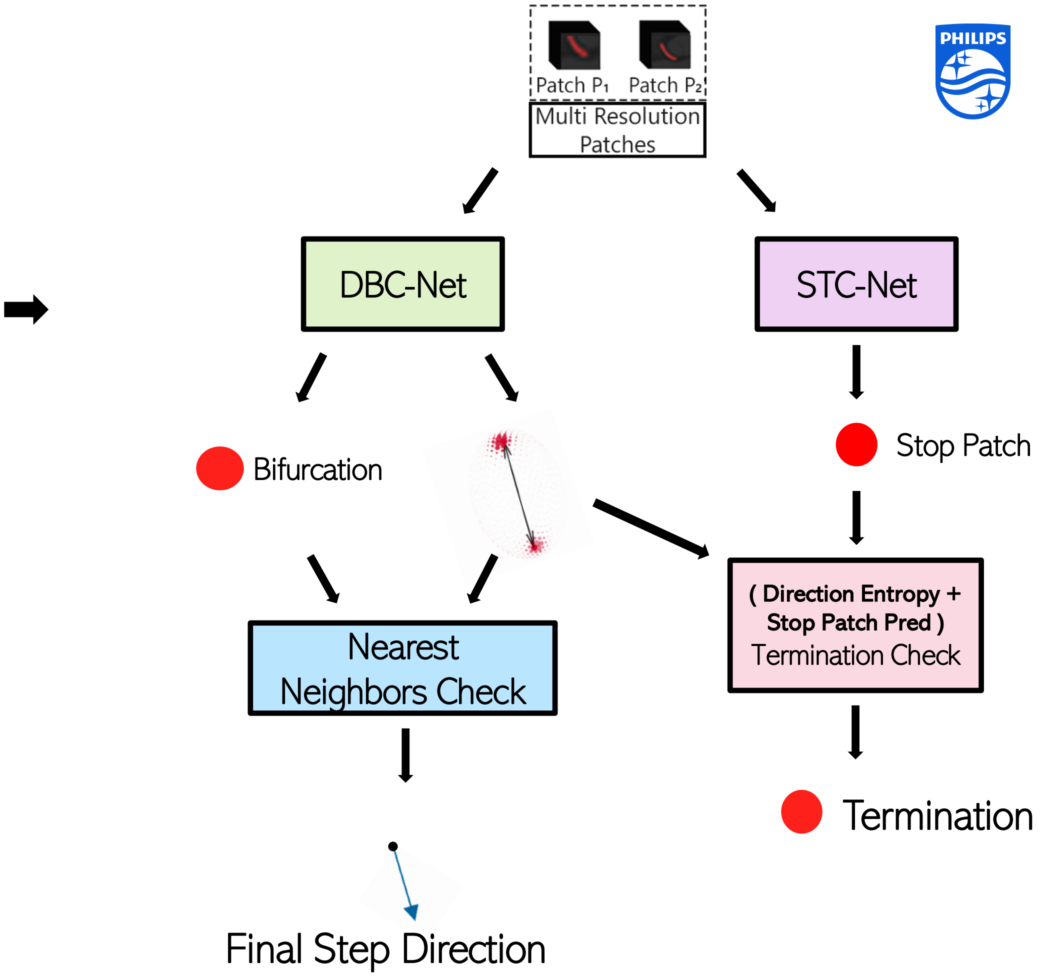

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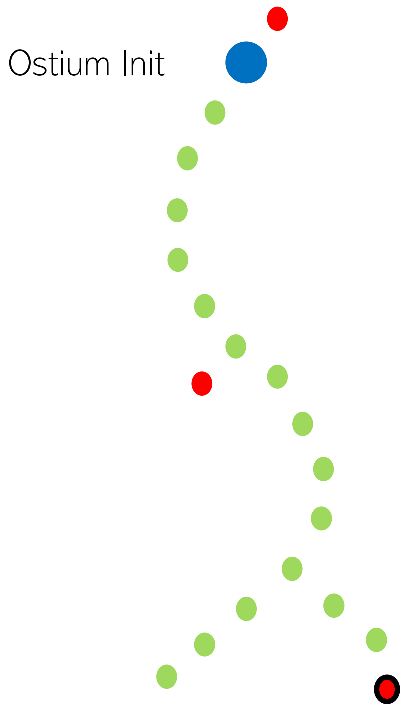


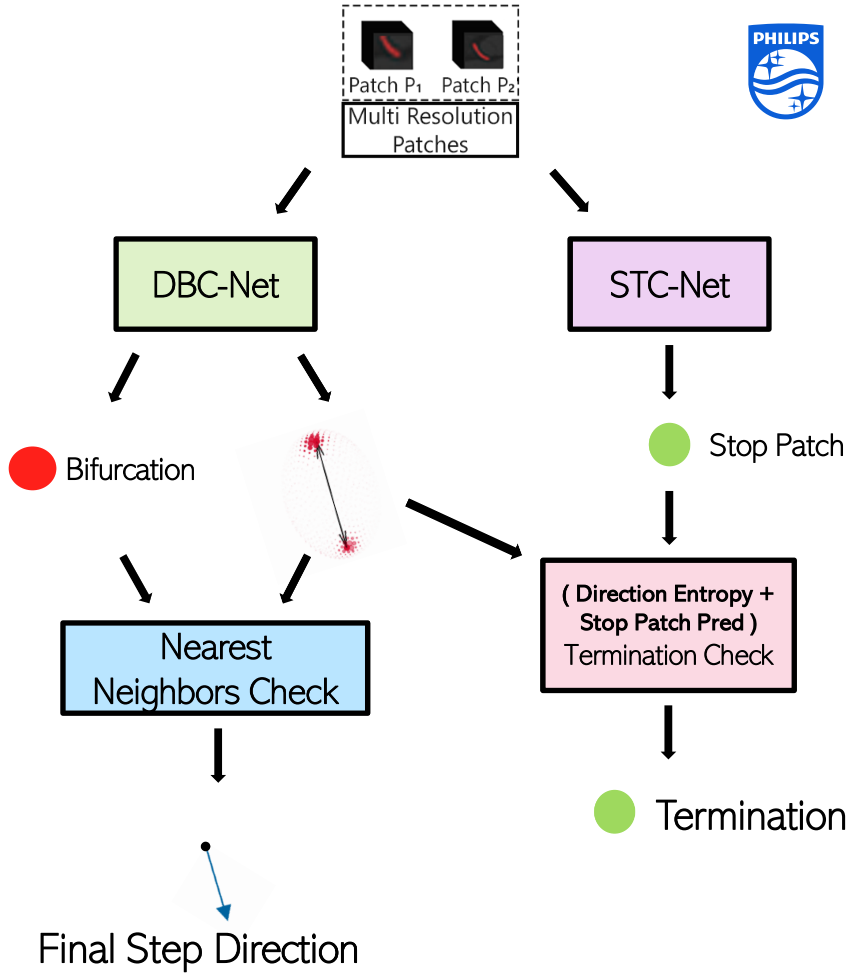

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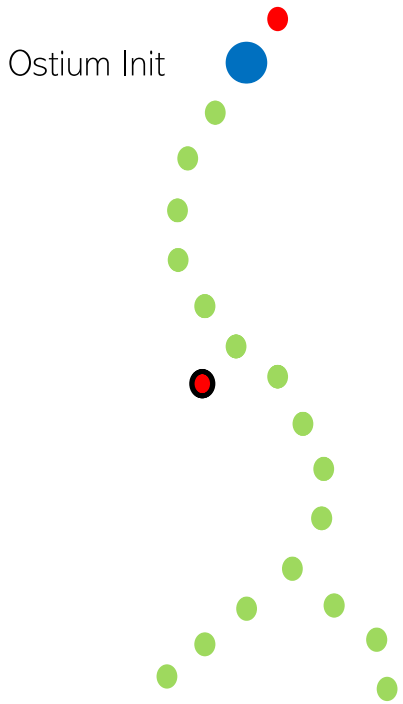


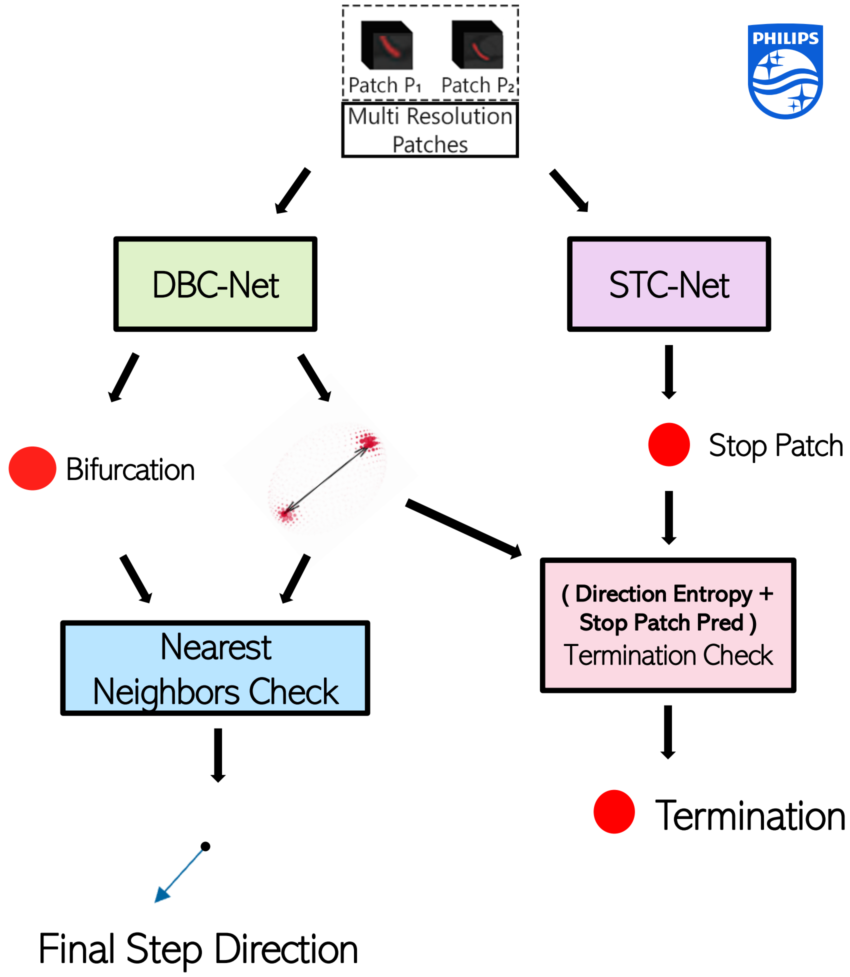

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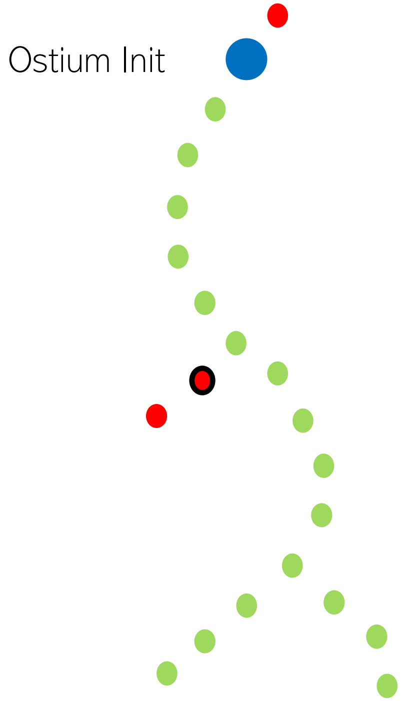


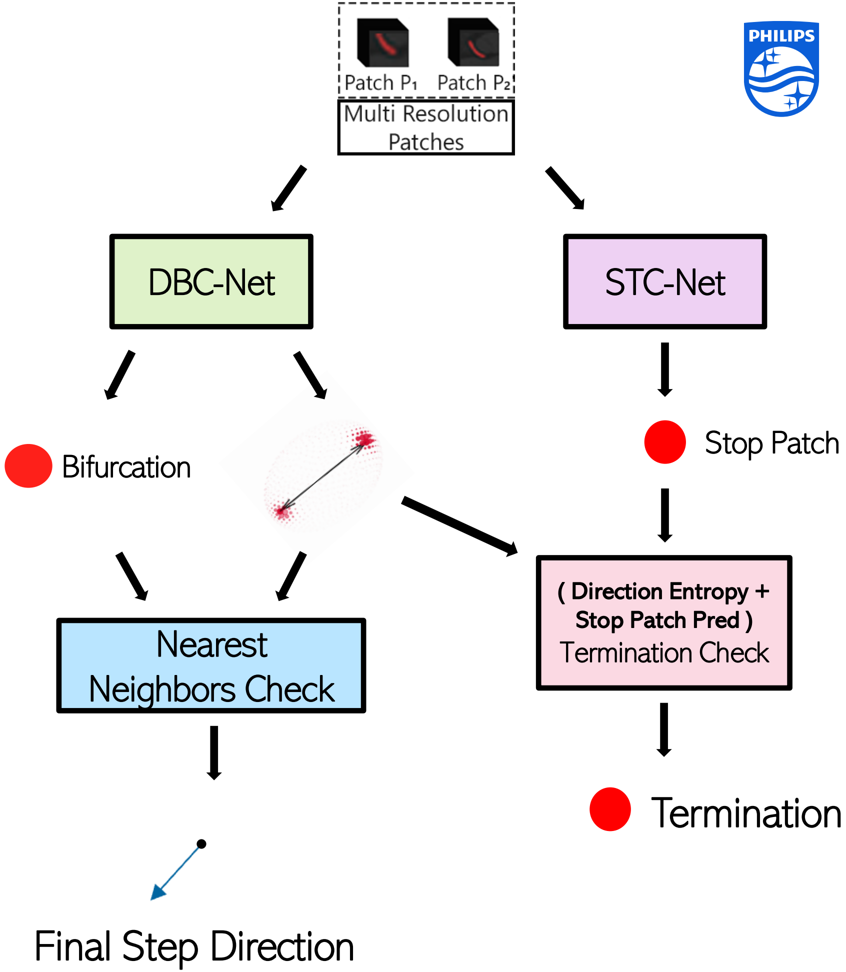

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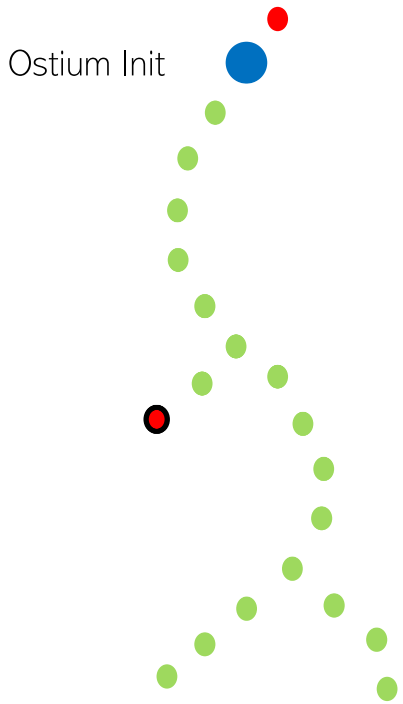


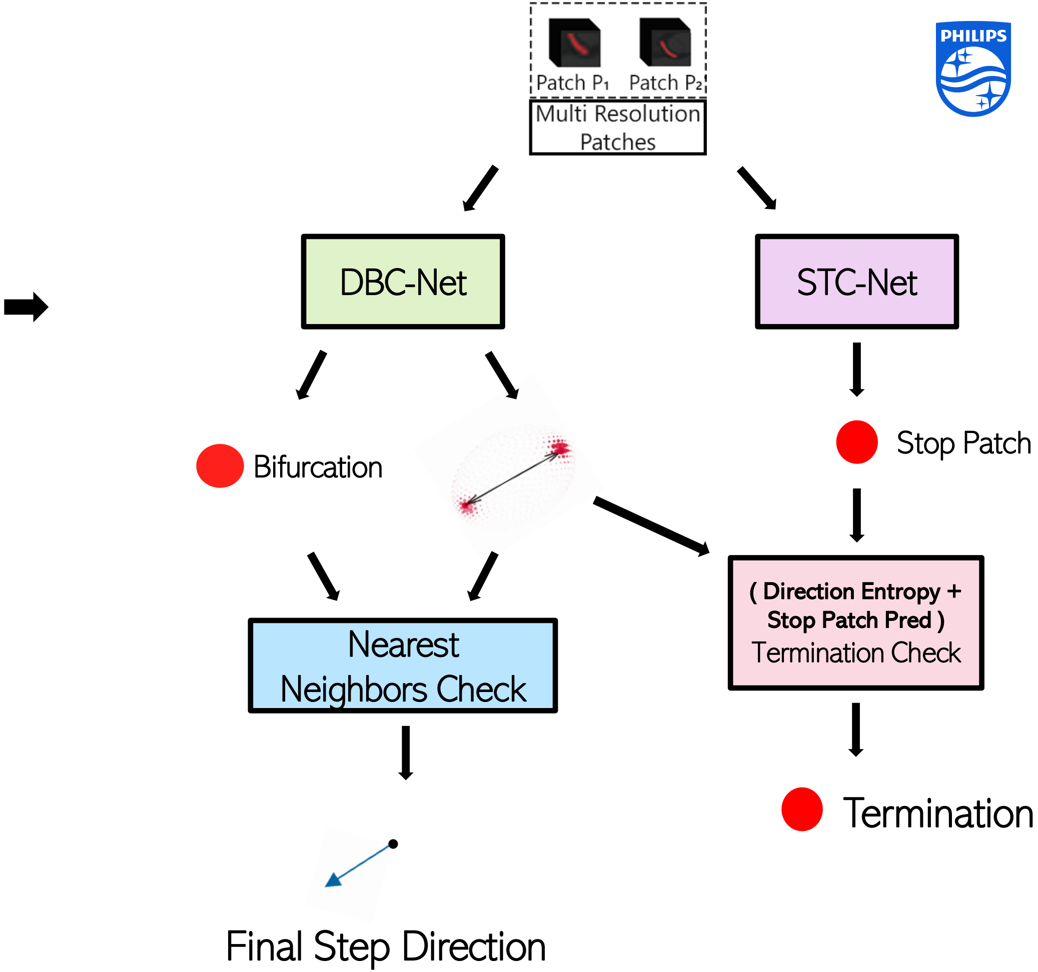

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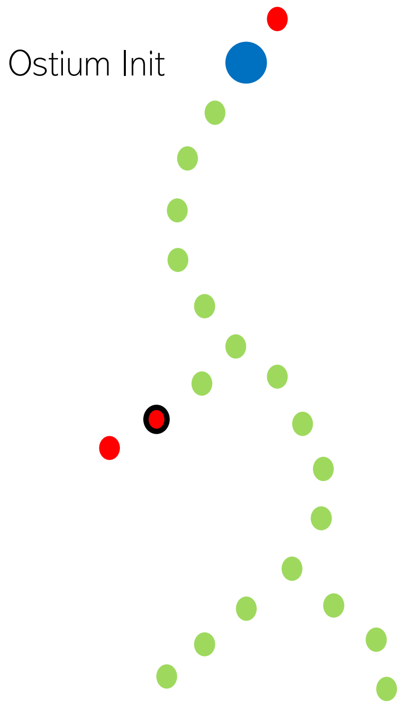


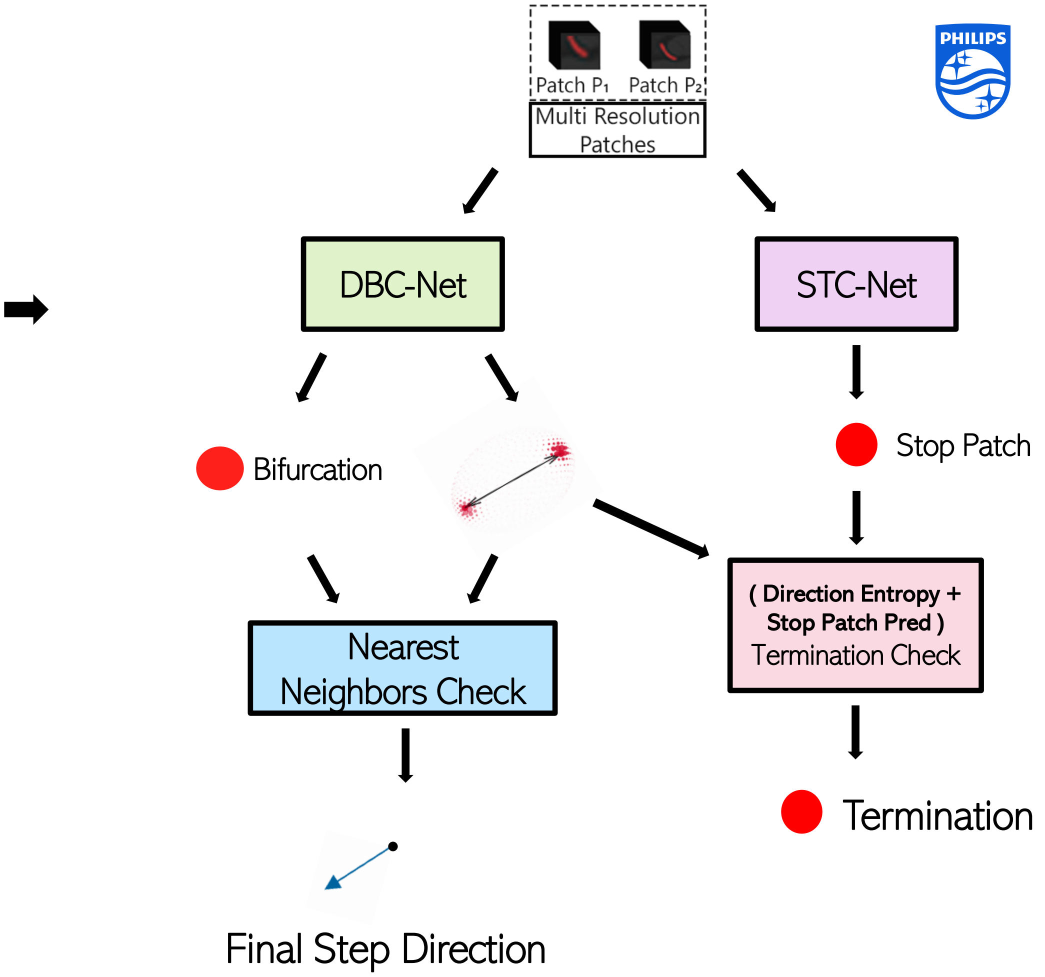

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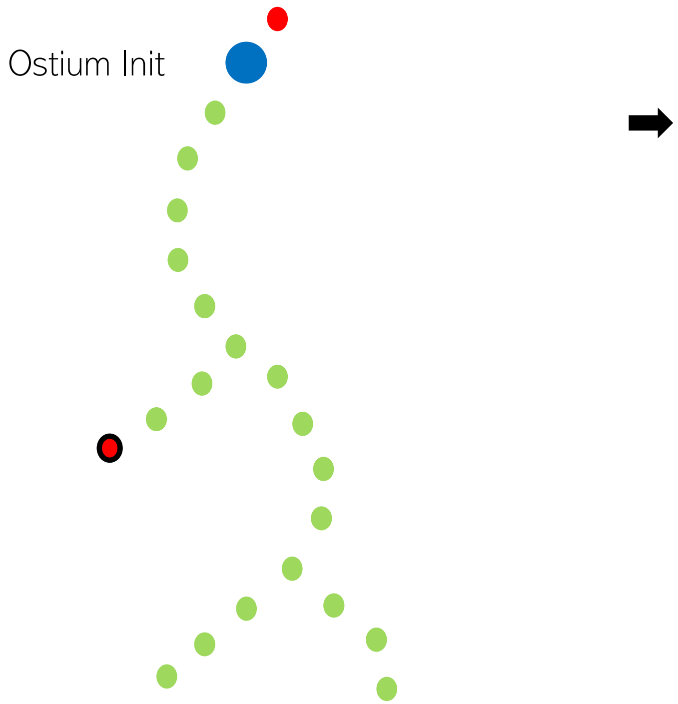


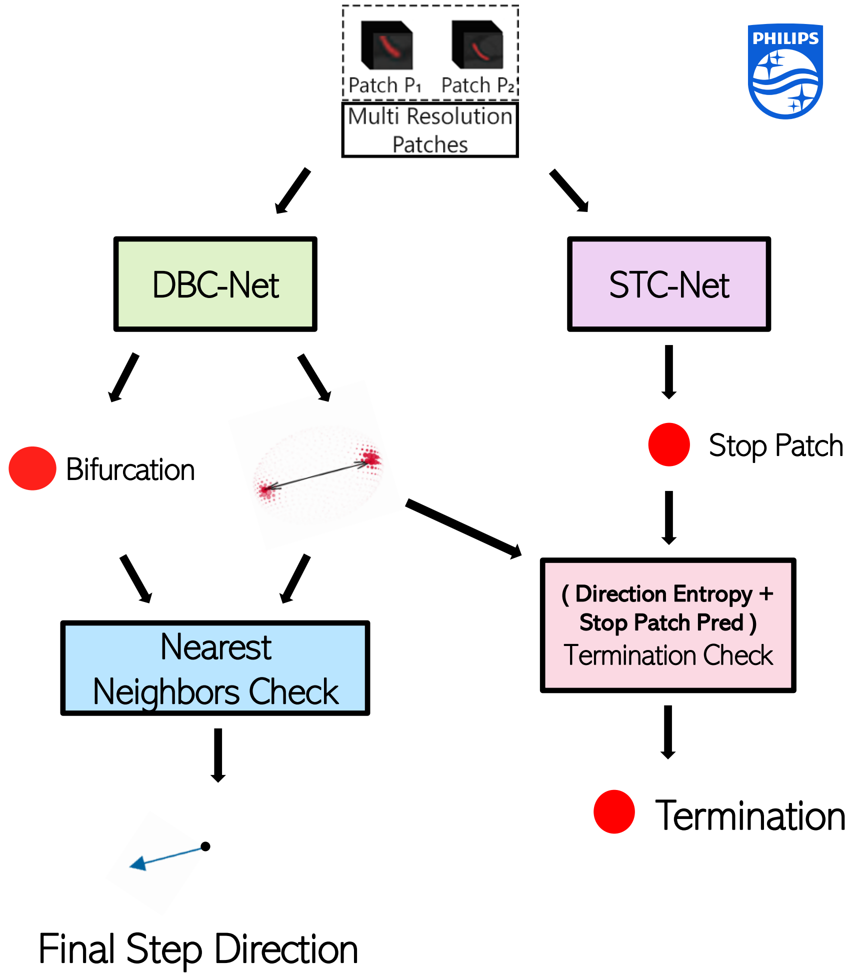

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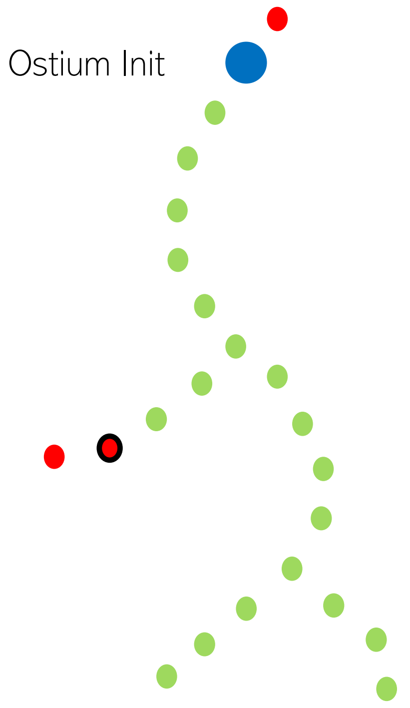


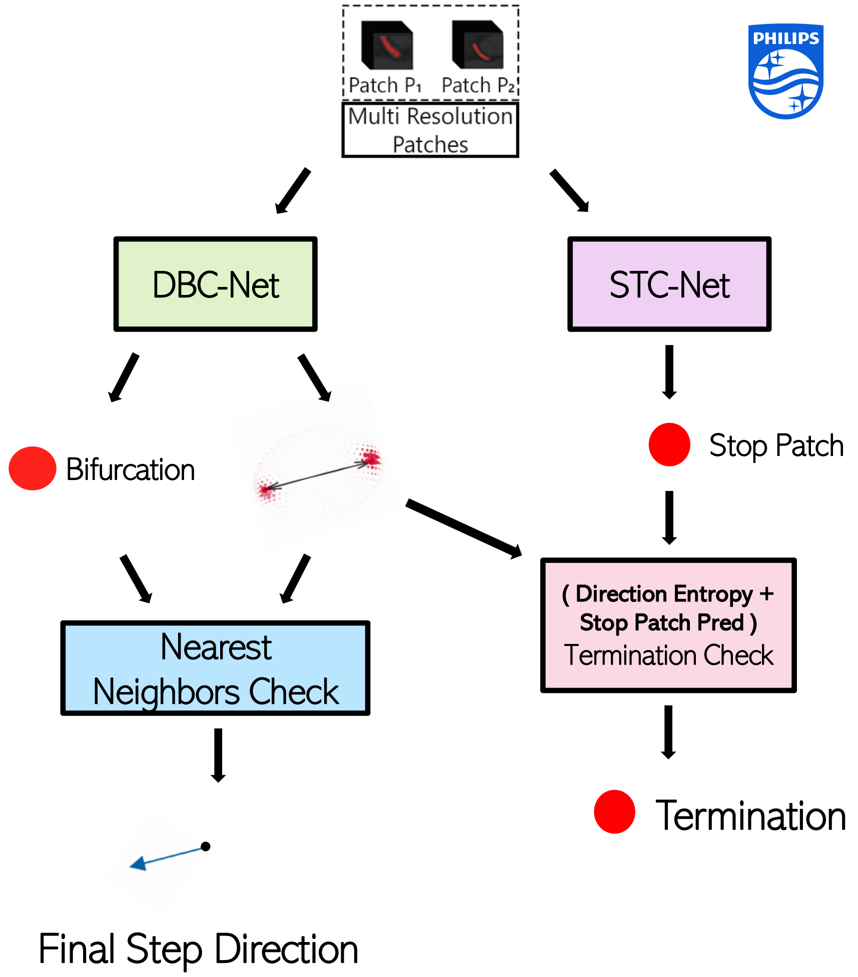

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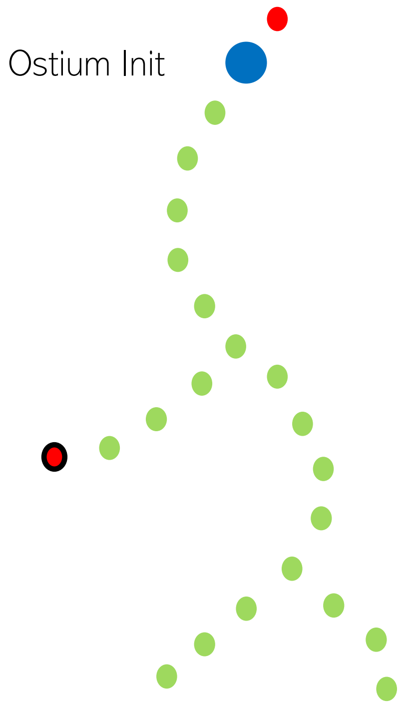


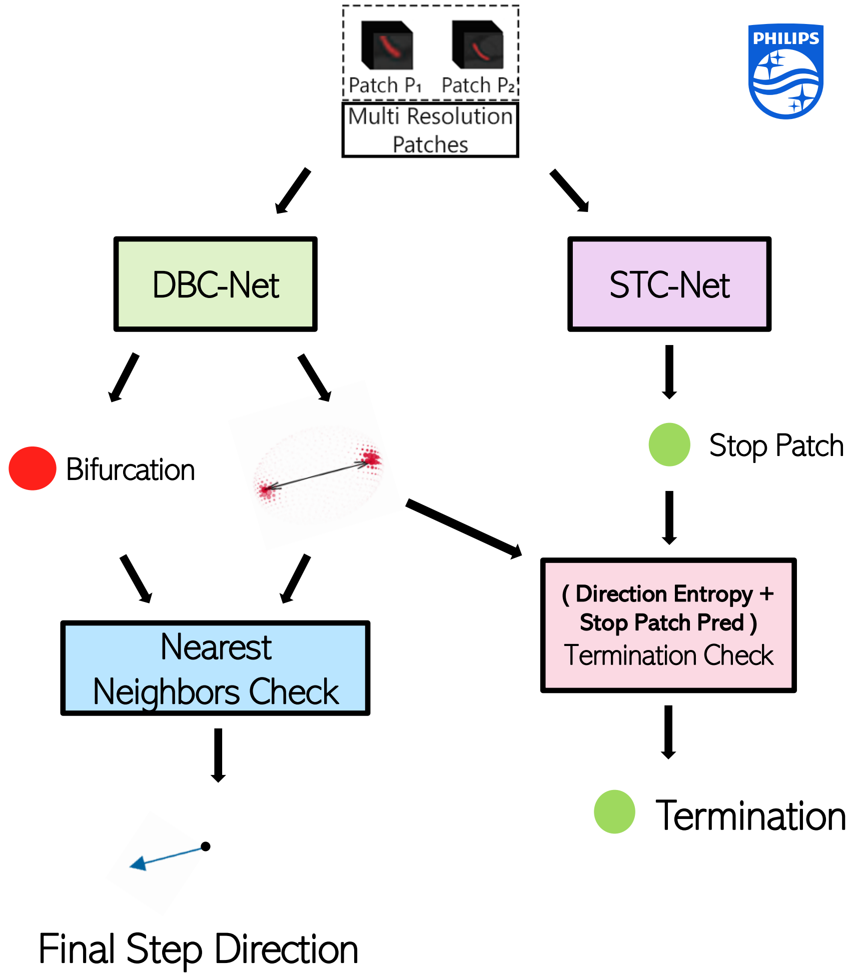

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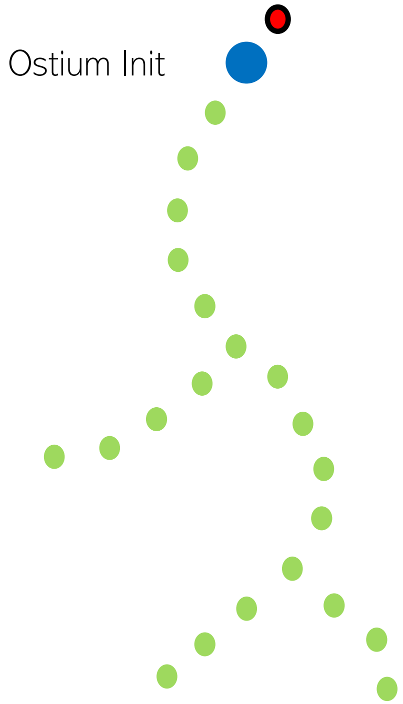
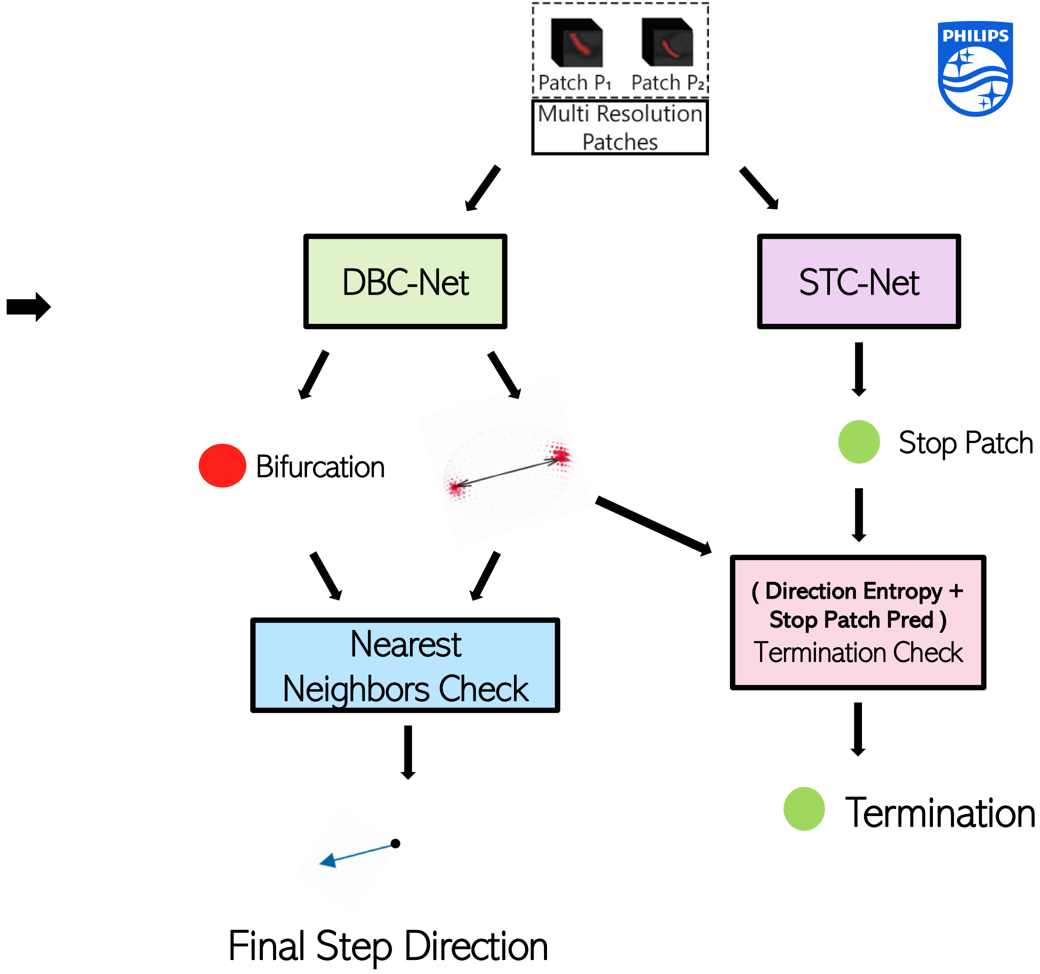
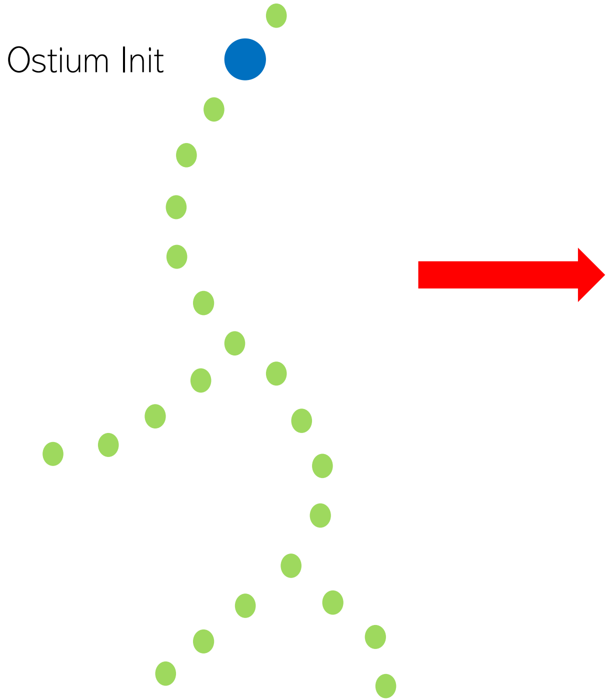


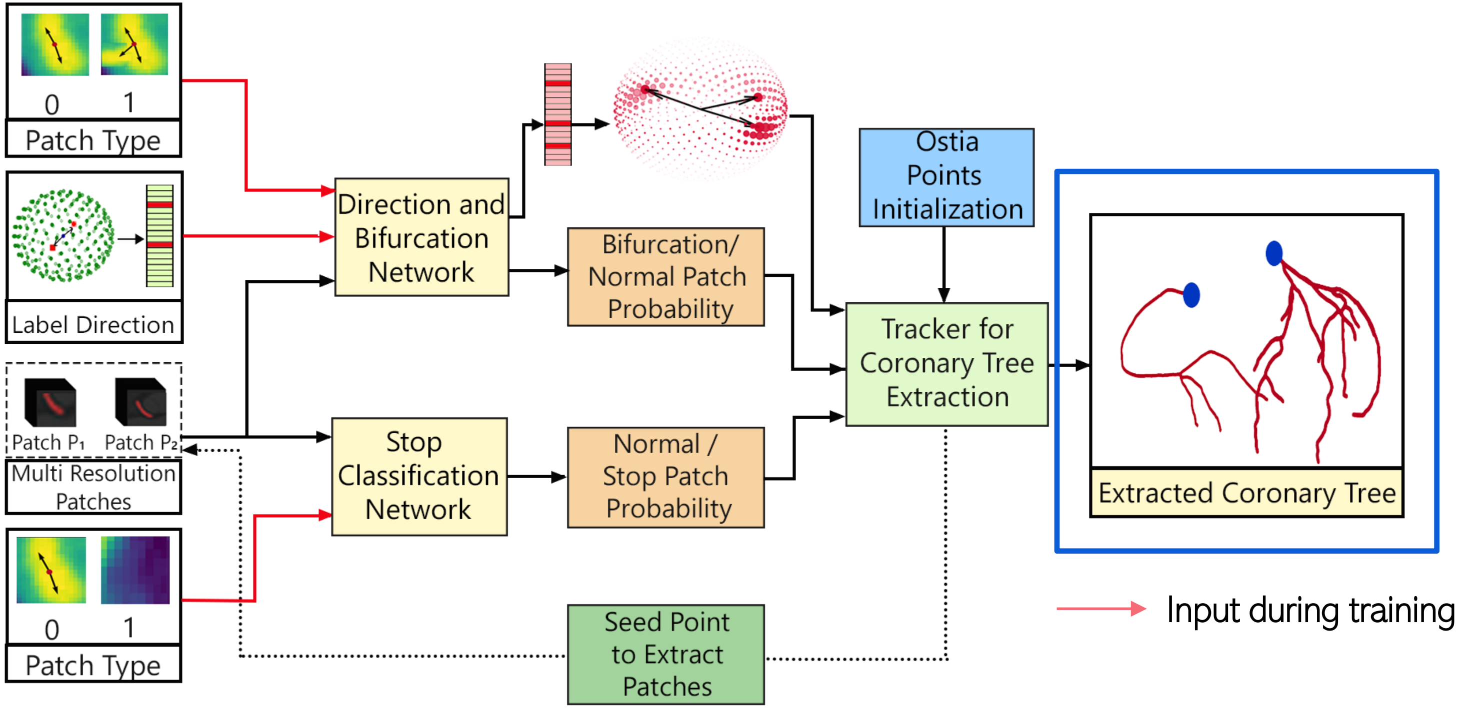



# Tracker Implementation




Final Extracted Coronary tree.

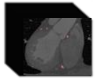
# Extracted Coronary Tree



# Dataset

## Philips in-house dataset

- **43** CCTA images, **9** different clinical sites.



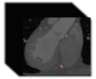
CCTA Image Volume

- **4 to 20** annotated arteries per CCTA image, mean = **9**.
- **428** annotated arteries.
- CCTA images from **Philips scanners**.

Annotated arteries

## MICCAI CAT08 Dataset

- CAT08 Training set, **8** CCTA images
- CAT08 Testing set , **24** CCTA images



CCTA Image Volume

- **4** annotated centerlines per CCTA image (**LAD , LCX , RCA and arbitrary**).
- **128** annotated arteries.
- CCTA images from **64-slice CT Siemens Scanner** and **dual source CT Siemens Scanner**.

Annotated arteries

# Evaluation Metrics

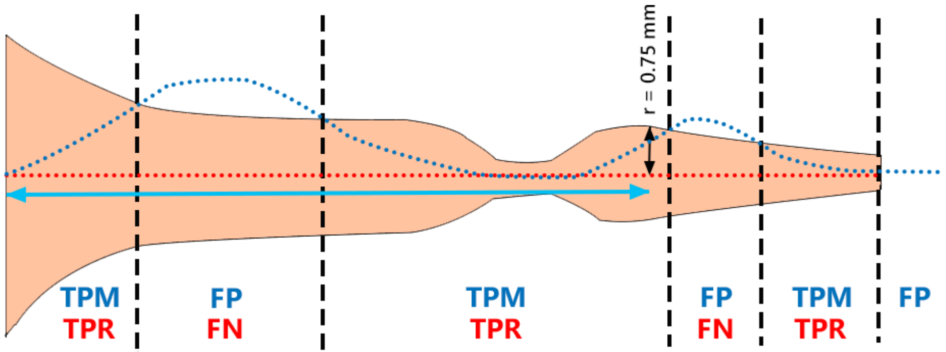
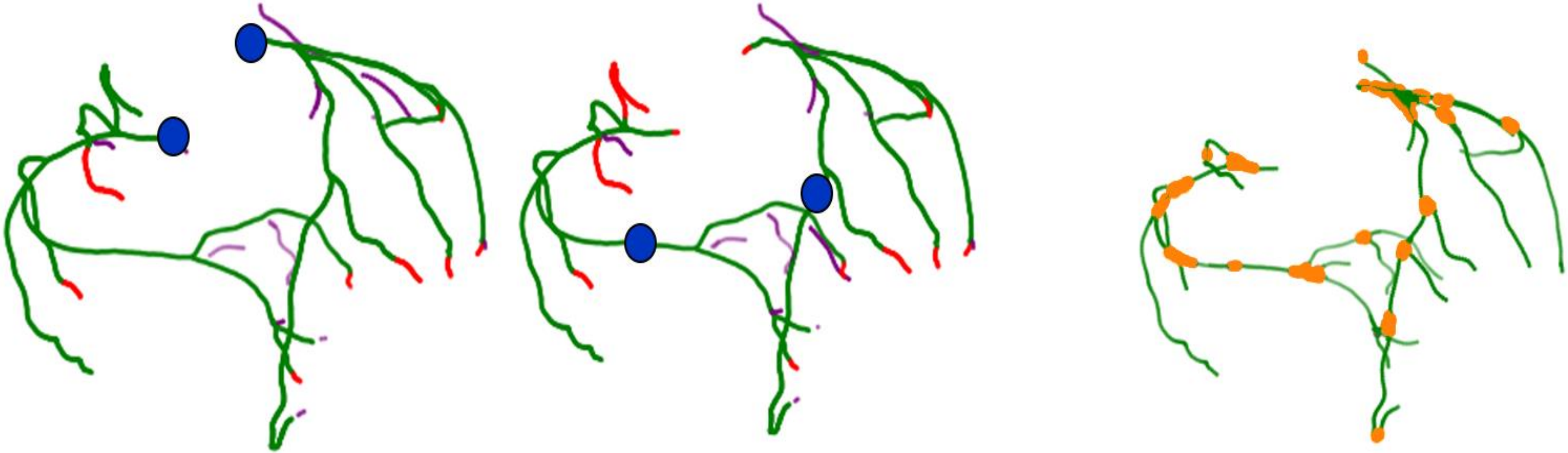



Fig 1: Metrics Calculation

| Threshold is set to 1mm | |
|---|---|
| Sensitivity (S) | $\frac{TPR}{TPR + FN}$ |
| False Positive Rate (FPR) | $\frac{FP}{TPM + FP}$ |

| Threshold is set to radius 'r' | |
|---|---|
| Overlap (OV) | $\frac{TPM + TPR}{TPM + TPR + FP + FN}$ |
| Overlap until first error (OF) | Percentage of overlap until the first error occurs |
| Clinically relevant overlap (OT) | Only clinically relevant part of the artery is considered |
| Accuracy Inside (AI) | Accuracy of points extracted only for TPR part |

# Results – Philips Dataset



(a)
Tracking initialized by seed points placed at the ostium

(b)
Tracking initialized by seed points placed in middle of LAD and RCA

(c)
Bifurcation detection overlayed on tracked result.

Fig 1: Qualitative Analysis of the Tracked Result

# Results – Philips Dataset

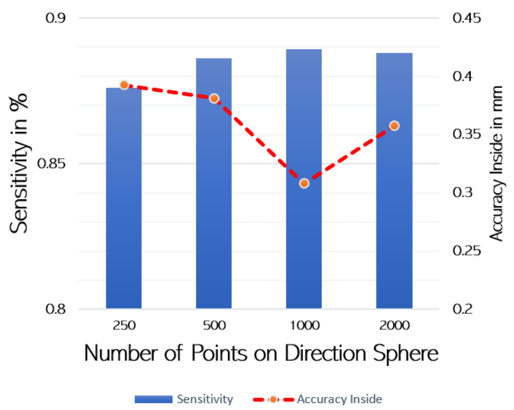



Fig 1: The effect of varying Discrete points on Direction Sphere

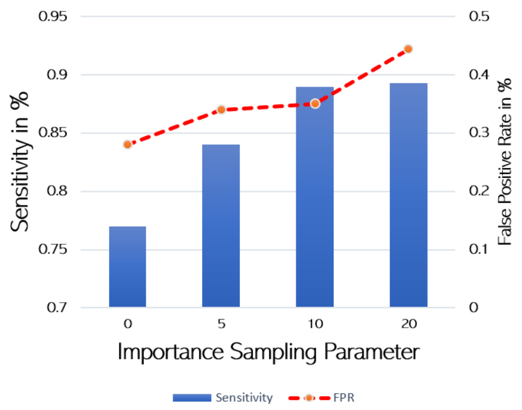



Fig 2: The effect of varying the importance sampling parameter in a minibatch of size 64.

| No of Resolutions Levels in Architecture | Sensitivity ( S, in %) | Overlap ( OV, in %) | Clinically Relevant Overlap ( OT, in %) | Accuracy Inside ( AI, in mm) |
|---|---|---|---|---|
| 1 | 82.3 | 76.4 | 85.9 | 0.37 |
| 2 | 88.9 | 81.2 | 87.4 | 0.32 |
| 3 | 87.4 | 78.6 | 86.5 | 0.34 |

Table 1: The effect of varying the number of resolution levels in the DBC-Net Architecture.

# Results – Philips Dataset

| Metric | Four Fold Cross Validation Result |
|---|---|
| Clinically Relevant Overlap (OT, in %) | 89.1 ± 2.3 |
| Sensitivity (S, in %) | 87.1 ± 3.2 |
| Overlap (OV, in %) | 80.4 ± 2.0 |
| Accuracy Inside (AI, in mm) | 0.34 ± 0.017 |

**Table 1:** Final Evaluation Metrics for the Philips Dataset.

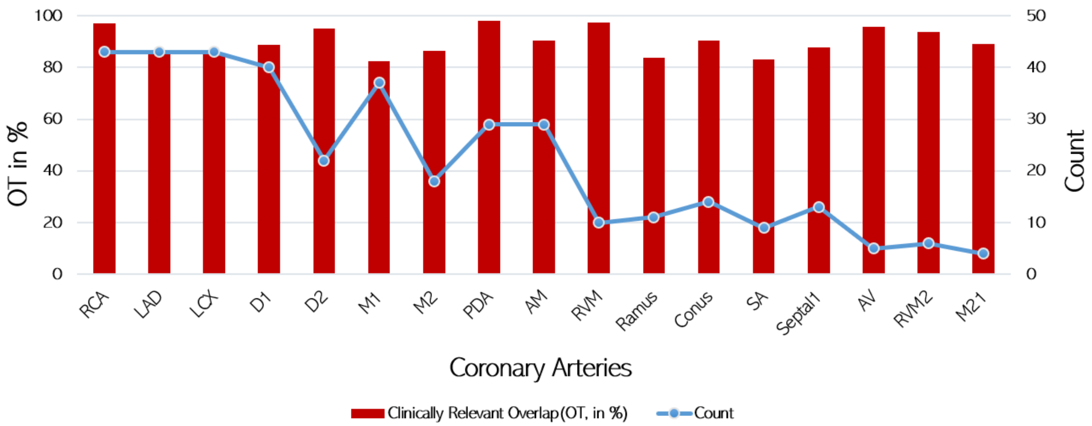



**Fig 1:** Clinically Relevant Overlap for all the arteries present in the Philips dataset that occur more than 4 times in 43 images.

# Results - CAT08 Training Dataset

- The model was trained on 33 CCTA scans from Philips dataset and validated on 10 CCTA scans from Philips dataset. **It was then evaluated on CAT08 training dataset to test generalization.**

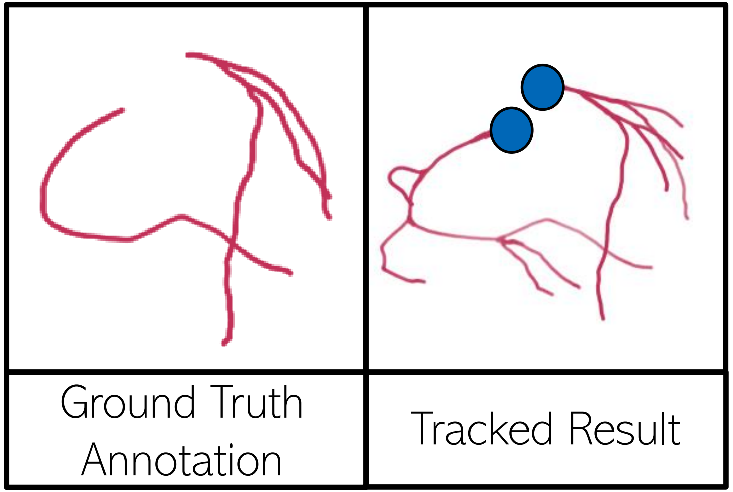



Fig 1: Ground truth and tracked result for Case 4 in CAT08 training set

| No. | Image Quality | Calcium Score | OV | OF | OT | AI | T |
|---|---|---|---|---|---|---|---|
| 0 | Moderate | Moderate | 94.2 | 77.7 | 95.1 | 0.4 | 55 |
| 1 | Moderate | Moderate | 97.3 | 99.4 | 99.6 | 0.32 | 39 |
| 2 | Good | Low | 98.3 | 99.7 | 100 | 0.31 | 43 |
| 3 | Poor | Moderate | 86.3 | 63 | 89.1 | 0.4 | 41 |
| 4 | Moderate | Low | 92.9 | 57.3 | 97.9 | 0.33 | 31 |
| 5 | Poor | Moderate | 97.6 | 77.5 | 99.7 | 0.43 | 33 |
| 6 | Good | Low | 96.7 | 87.2 | 99.6 | 0.3 | 36 |
| 7 | Good | Severe | 83.9 | 49.1 | 86.3 | 0.38 | 48 |
| **Avg** | | | **93.4** | **76.5** | **95.9** | **0.36** | **41** |

Fig 2: Results on CAT08 Training set

# Results - CAT08 Test Dataset

- The model was trained on entire **Philips (43 CCTA scans)** and **CAT08 training dataset (8 CCTA scans)**.

| Method | Overlap (OV, in %) | Overlap until First Error (OF, in %) | Clinically Relevant Overlap (OT, in %) | Overlap Rank | Accuracy Inside (AI, in mm) | Time (T, in s) | Number of Training Cases |
|---|---|---|---|---|---|---|---|
| AuCoTrack | 93.6 | 76.3 | **96.4** | **9.87** | 0.37 | **42.6** | **51** |
| Zheng et al | **93.7** | **76.5** | 95.6 | 10.43 | 0.21 | 60 | 108 |
| Kitamura et al | 93.5 | 70.9 | 92.5 | 13.81 | **0.2** | 160 | - |
| Yang et al | 90.6 | 74.2 | 95.9 | 10.55 | 0.25 | 120 | 58 |

Table 1 : Comparison of CAT08 test dataset (24 CCTA images) with other top automatic coronary centerline extraction algorithms.

# Results - CAT08 Test Dataset

CAT 08 Test set → 90/96 vessels automatically detected

6 vessels required an extra point.

3/6 vessels from Case 26 which has severe motion artifacts.

Detection rate on CAT08 = 95 %.

| Image Quality | Clinically Relevant Average (OT, in %) |
|---|---|
| Poor | 87.8 |
| Moderate | 95.4 |
| Good | 94.4 |

Table 1: Effect of Image Quality on CAT08 Test dataset.

| Calcium Scores | Clinically Relevant Average (OT, in %) |
|---|---|
| Low | 92.9 |
| Moderate | 94.0 |
| Severe | 94.2 |

Table 2: Effect of Calcium Score on CAT08 Test dataset.

# Conclusion

Automatic fast tracking algorithm based on local processing initialized by single point **e.g by MBS**.

Evaluated on Philips dataset that has **considerable variability** with high clinically relevant overlap of **89.1%.**

Good **generalization** demonstrated on **MICCAI CAT08 training dataset** using model trained on **Philips dataset** ; clinically relevant overlap of **95.9%.**

Better **overlap rank** on **CAT08 test dataset** than other automatic coronary artery centreline extraction algorithms.

**Missed vessels** can be retrieved by providing an additional seed point.

An **architecture** for **simultaneous direction classification and bifurcation detection** has been proposed which may used for other applications e.g. **centerlines in thorax CT images**

PHILIPS