



# MemBrain: A deep learning-aided pipeline for detection of membrane proteins in Cryo-electron tomograms



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## ABSTRACT

**Background and Objective:** Cryo-electron tomography (cryo-ET) is an imaging technique that enables 3D visualization of the native cellular environment at sub-nanometer resolution, providing unprecedented insights into the molecular organization of cells. However, cryo-electron tomograms suffer from low signal-to-noise ratios and anisotropic resolution, which makes subsequent image analysis challenging. In particular, the efficient detection of membrane-embedded proteins is a problem still lacking satisfactory solutions.

**Methods:** We present MemBrain – a new deep learning-aided pipeline that automatically detects membrane-bound protein complexes in cryo-electron tomograms. After subvolumes are sampled along a segmented membrane, each subvolume is assigned a score using a convolutional neural network (CNN), and protein positions are extracted by a clustering algorithm. Incorporating rotational subvolume normalization and using a tiny receptive field simplify the task of protein detection and thus facilitate the network training.

**Results:** MemBrain requires only a small quantity of training labels and achieves excellent performance with only a single annotated membrane (F1 score: 0.88). A detailed evaluation shows that our fully trained pipeline outperforms existing classical computer vision-based and CNN-based approaches by a large margin (F1 score: 0.92 vs. max. 0.63). Furthermore, in addition to protein center positions, MemBrain can determine protein orientations, which has not been implemented by any existing CNN-based method to date. We also show that a pre-trained MemBrain program generalizes to tomograms acquired using different cryo-ET methods and depicting different types of cells.

**Conclusions:** MemBrain is a powerful and annotation-efficient tool for the detection of membrane protein complexes in cryo-ET data, with the potential to be used in a wide range of biological studies. It is generalizable to various kinds of tomograms, making it possible to use pretrained models for different tasks. Its efficiency in terms of required annotations also allows rapid training and fine-tuning of models. The corresponding code, pretrained models, and instructions for operating the MemBrain program can be found at: <https://github.com/CellArchLab/MemBrain>.

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## 1. Introduction

Cryo-electron tomography (cryo-ET) is performed by acquiring projection images of a frozen sample at numerous different angles

using an electron microscope. Combining the information from all these images yields high-resolution 3D volumes. These molecular views provide a striking new perspective on cellular functions and can reveal important insights into both general biological phenomena [1] as well as human diseases including neurodegeneration and cancer [2,3]. About one third of human proteins are associated with membranes [4], which compartmentalize the cell. Membranes organize proteins into microdomains to direct cellular processes,

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including the bioenergetic reactions in mitochondria and chloroplasts, which produce the energy of life. It is thus an important challenge to identify protein complexes within their native membrane environment.

In cryo-ET, particle picking is commonly performed using template matching [5], i.e., a low-pass filtered model of the macromolecular complex of interest is fit to the entire tomogram by computing cross-correlation scores. Since this has to be done for all possible positions and orientations, this approach is computationally expensive and yields a noisy output that requires manual post-processing. For membrane-bound proteins, template matching is particularly challenging, as these complexes are often small, and large portions of their structures are buried within the membranes, which can reduce their correlation scores with the template.

As a more specialized approach, PySeg [6] is a template-free procedure for the detection of membrane-bound proteins. It uses discrete Morse theory to trace densities protruding from the membrane surface. These densities are then clustered using 2D rotational averages, followed by manual selection of reasonable classes. However, the use of PySeg is complicated by difficult parameter tuning and the requirement for human intervention.

Recently, several deep learning-based approaches have been proposed for the detection of macromolecular complexes. EMAN [7] detects various kinds of densities by creating segmentations based on a 2D CNN architecture that utilizes large convolutional kernels of size  $15 \times 15$ . Therefore, it requires large image patches for training, where all present objects of interest must be annotated with pixel-wise class labels in each of the 2D images. This is also the case for DeepFinder [8], which requires even more annotations, since it utilizes 3D convolutions with a large receptive field and therefore requires 3D voxel-wise class labels. However, given 3D center positions, DeepFinder can automatically generate coarse voxel annotations using its “sphere-based annotation” method. Another approach is implemented in crYOLO [9], which was initially developed for detecting single particles in 2D cryo-EM micrographs, but has since added the option to pick in 3D tomograms. It is based on the popular object detection framework YOLO [10]. Instead of creating a segmentation mask first, crYOLO predicts the bounding boxes of the particles directly. An advantage of crYOLO is that it requires only positive labels and uses adjustable penalty weights for false negatives and false positives to account for incompletely annotated regions. Nevertheless, we experienced that crYOLO still struggles to perform reliable predictions when trained with sparse annotations.

In current cryo-ET analysis workflows, manual particle picking is often performed to localize membrane-bound proteins. Even with the guidance of specialized software [11,12], the accurate annotation of particles in 3D remains a tedious task. Moreover, tomograms suffer from a low signal-to-noise ratio and anisotropic resolution from the missing wedge [13]. Thus, precisely localizing protein complexes remains a major challenge with existing methods, especially in large tomograms that involve thousands of proteins of interest. To enable more in-depth biological discoveries, it is necessary to develop automated tools that can be trained on a small number of high-quality annotations to reliably pick particles in extensive datasets of many tomograms.

Here, we present MemBrain: a generalizable deep learning-aided pipeline to detect membrane-bound protein complexes in cryo-ET. Its training can be performed annotation-efficiently, in that it requires only few particle annotations to reach a good performance. In contrast to other approaches, MemBrain utilizes the membrane geometry to extract and align subvolumes and thereby achieves model invariance to unseen membrane orientations. Furthermore, instead of classifying each subvolume into binary classes (i.e., particle vs. non-particle), we show that score assignment based on the regression of distance to the nearest particle can cope

better with imprecise ground-truth positions, which commonly occur in manual labelling. As an additional feature, MemBrain can extract particle orientations, in contrast to common detection networks that only provide particle positions. To our knowledge, this is the first deep learning-aided pipeline that is specialized for the detection of membrane-bound proteins.

## 2. Methodology

### 2.1. Overview of MemBrain

Fig. 1 illustrates the workflow of our pipeline. As an input, we use membrane segmentations from raw cryo-electron tomograms (Fig. 1A). For example, these segmentations can be generated using TomoSegMemTV [14], followed by manual curation, as demonstrated in [12]. In the first step, we sample points uniformly along the segmented membrane and identify their corresponding membrane normal vectors. Subsequently, subvolumes are extracted around each sampled position and rotated so that the membrane is parallel to the x-y plane (pre-processing step, Fig. 1B). These aligned subvolumes are then fed into a CNN, which assigns each subvolume a score indicating its distance to a particle center (scoring step, Fig. 1C). Finally, particle center positions and orientations are extracted using Mean Shift clustering [15] (post-processing step, Fig. 1D). We provide a detailed explanation of each step below.

### 2.2. Subvolume Sampling and Preprocessing

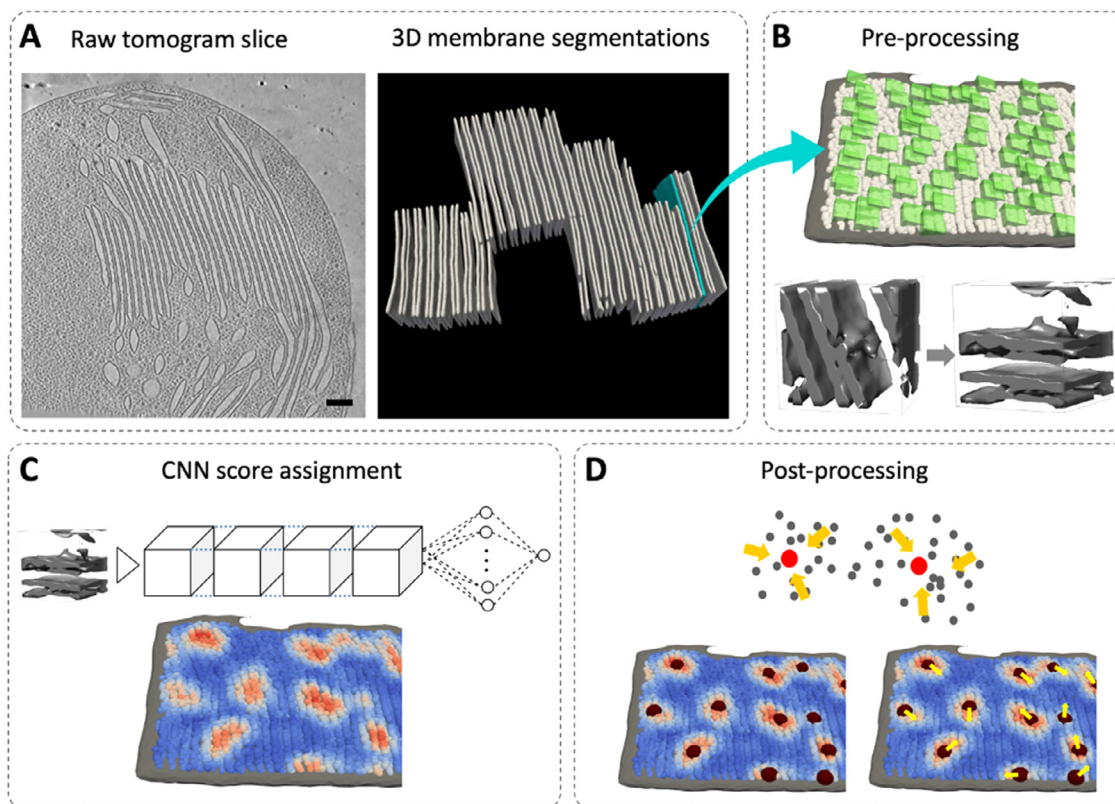
#### 2.2.1. Point Sampling and Normal Voting

First, we manually specify which side of the membrane should be picked. This is done by clicking on the desired side of the membrane segmentation (illustrated in Figure S1A). Next, MemBrain samples points all over the selected membrane surface (see sampled positions in Fig. 1B). More specifically, we compute the distance of any voxel in the tomogram to the membrane and threshold this distance to mask the neighborhood of the segmentation (see Fig. S1B; in all our experiments, we used a maximum distance of 15 voxels). Then, for each point in this neighborhood, we find its nearest voxel on the segmented membrane surface. These points on the surface represent our sampled points. The connection vector between them and the original points in the neighborhood serve as a membrane normal vector.

However, points in the membrane neighborhood that are very close to the surface tend to have non-reliable normal vectors. On the other hand, only considering points with large distances leads to non-uniform point sampling on the membrane surface. Therefore, we apply Normal Voting [16,17], which is an algorithm that corrects normal vectors via weighted averaging, while also taking the membrane curvature into account. By giving a higher weight to the reliable normal vectors (from long-distance points), we achieve both a uniform sampling of points on the membrane surface and a reliable estimation of normal vectors.

#### 2.2.2. Subvolume Extraction and Rotation

For each sampled position on the membrane surface, we extract a small subvolume. The exact size of the subvolume should depend on the size of the protein complex we aim to detect. In our experiments, we use a subvolume size of  $12 \times 12 \times 12$  voxels. We observed this size to be quite robust to different protein dimensions, but it can be adjusted if needed. Next, we rotate each subvolume using its corresponding normal vector so that the membrane contained in the subvolume is aligned to the x-y plane, i.e., the membrane normal vector is parallel to the z-axis (see rotated volume in Fig. 1B). This rotation step is critical to guarantee that our detec-



**Fig. 1. The MemBrain processing pipeline.** **A:** An example 2D slice of a cryo-electron tomogram (denoised using Cryo-CARE [25], scale bar: 100 nm) and corresponding membrane segmentations (3D view of all segmented membranes). **B:** Pre-processing step: **Top:** Points (white) are sampled, and subvolumes (green) are extracted around each point. **Bottom:** Subvolumes are aligned. **C:** Scoring step: The CNN predicts the distance of each subvolume to the nearest particle center. **D:** Post-processing: Particle centers and orientations are extracted using Mean Shift clustering.

tion is invariant to different membrane orientations, as we elaborate in Section 3.

### 2.3. Convolutional Neural Network

#### 2.3.1. Architecture

The preprocessing steps of MemBrain reduce the task of protein detection in the entire tomogram to the detection of densities protruding from the membrane. Since the context, i.e., the location of the membrane, is already given by the membrane segmentation, our network does not need to learn it. Therefore, we can neglect large-scale features and use a small network architecture, resulting in a tiny receptive field of the convolutional layers. In our experiments, we only used four consecutive 3D convolutional layers, followed by a single fully connected layer. The network outputs a single value to indicate the distance of the subvolume to the nearest protein center. The detailed network architecture is shown in Table S2.

#### 2.3.2. Label Assignment

For training, we assign labels to each input subvolume based on its center point's distance to the closest protein complex center. However, protein structures are generally not spherical. Therefore, instead of using the Euclidean distance to assign the distance values, we use the Mahalanobis distance [18], which weights distances in each direction based on a covariance matrix, thus taking the protein shape into account (visualized in Figure S3). The covariance matrix is extracted from the low-pass filtered structure that was also used for generating ground truth positions and orientations of the respective protein. This can, for example, be a struc-

ture acquired from the Protein Data Bank (PDB) or from a previous averaging experiment.

#### 2.3.3. Optimization Details

Even with substantial effort in manual annotation, our ground-truth labels are not perfectly accurate, as manually picked positions always deviate slightly from the exact particle locations. Moreover, it is almost unavoidable to miss some protein complexes. Therefore, we chose to optimize the smooth L1 loss function [19], which is more robust with respect to outliers compared to the commonly used mean squared error (MSE). We use the Adam [20] optimizer to minimize the loss function. To improve training stability, we incorporate several batch normalization layers [21]. Finally, as regularization techniques to make the training more stable and avoid overfitting, we use a combination of weight decay and data augmentation. In particular, we use random rotations around the z-axis and random flipping along the x- and y-axes to artificially increase the number of samples, as well as adding Gaussian noise to the subvolumes [22]. All of these augmentation methods are performed on-the-fly during training for each iteration.

### 2.4. Post-processing

#### 2.4.1. Mean Shift Clustering

We utilize the distance heatmap that results from our network predictions to extract particle positions. For this, we use only the points with a predicted distance less than a threshold (depending on the protein complex size) to perform our adapted version of Mean Shift clustering, where we have added a hierarchical cluster separation step. Mean Shift [15] is an iterative approach that re-

finds cluster centers based on a moving weighted average in each iteration. The only required parameter is the bandwidth, which specifies the radius of points considered for the weighted average. Using a large bandwidth leads to particle clusters that are merged, whereas a small bandwidth can cause one particle to split into two clusters. To avoid both of these errors, we implemented a refined version of Mean Shift: first, we choose a large bandwidth parameter, leading to relatively large clusters. If one of these clusters exceeds a certain size (depending on the protein complex size), we reprocess it using a lower bandwidth. Thereby, we split merged protein clusters hierarchically. Our version of Mean Shift also weights single points using the inverse network-assigned scores to guide the clustering algorithm towards the correct particle centers, since points close to the centers tend to have stronger (i.e., lower) distance values.

#### 2.4.2. Orientation Estimation

Besides the cluster center, Mean Shift also identifies each point that has converged to the respective cluster center. As the neural network cannot see a large context, it assigns distance scores to the points based on only the densities within the respective small subvolumes: small distances for subvolumes with high protein density and large distances for subvolumes with low protein density. By using the Mahalanobis distance and thus anisotropic distance assignments for training, this behavior is further amplified. After thresholding these distance scores, only those areas with high enough protein density remain. Thus, we assume that the converged cluster points resemble the rough shapes of the protein complexes. In cases of non-spherical proteins, MemBrain can use the cluster points to compute orientations of the detected protein complexes within the membrane. We perform Principal Component Analysis [23] to find the vector that best describes the cluster, i.e., minimizes the Euclidean distances between the cluster points and the line described by the vector. In combination with the previously extracted normal vector, we are able to compute all three Euler angles describing the protein's orientation in space. These Euler angles can then be used to initialize downstream tasks, such as subtomogram averaging [13].

### 3. Results

#### 3.1. Data Collection and Annotation.

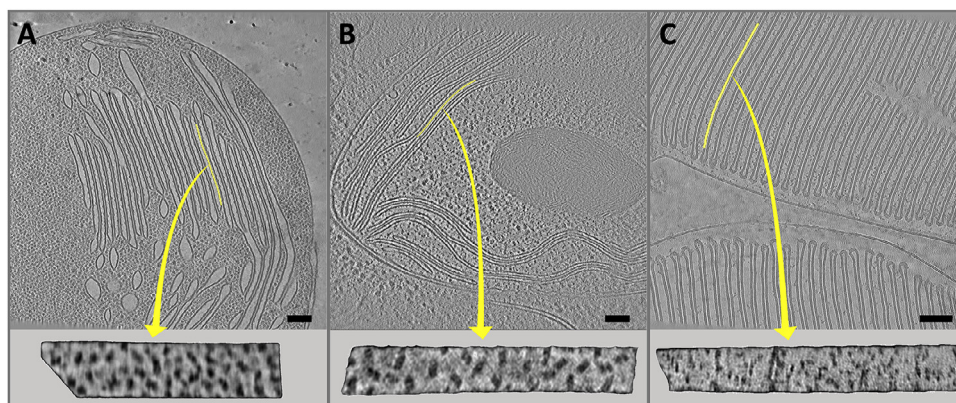
We evaluated MemBrain using three cryo-ET datasets of different biological samples that were vitrified on EM grids and then thinned with focused ion beam (FIB) milling [24]. Dataset

1 consists of nine tomograms of isolated *Spinacia oleracea* chloroplasts, acquired with defocus imaging and denoised with the deep learning-based Cryo-CARE program [25]. Dataset 2 contains four tomograms of *Chlamydomonas reinhardtii* chloroplasts inside native cells [12], acquired with Volta phase plate (VPP) imaging and not denoised. Dataset 3 is composed of five tomograms of isolated rod outer segments from wild-type mice [26], acquired without VPP and denoised with Cryo-CARE. Fig. 2 shows example 2D slices of all three datasets, as well as Membranogram views that display the different distributions of protein complexes within the membranes. More detailed information about acquisition of the datasets can be found in the supplementary S.1.1. In all tomograms, membranes were segmented using TomoSegMemTV [14], followed by manual curation. For Datasets 1 and 2, particle positions and orientations were manually annotated using Membranorama [11,12], whereas for Dataset 3, particle positions were generated semiautomatically by an expert using PySeg (see supplementary S.1.2). For Dataset 1, a total of 455 membrane segmentations were created, 45 of which were annotated with protein complex locations and orientations for 1641 Photosystem II (PSII) complexes, 471 Cytochrome b6f (b6f) complexes, and 757 unknown densities (UK). Dataset 2 contains a total of 31 segmented and annotated membranes, including 730 PSII positions, 379 b6f positions and 273 UK positions. For training and validation sets, we used 35 membranes from seven Dataset 1 tomograms. We trained and evaluated with PSII complexes, as the b6f complexes are so small that they are hard to visually identify in some tomograms, and therefore will require further adjustments to be reliably detected. The remaining two tomograms from Dataset 1, as well as all tomograms from Datasets 2 and 3, were reserved as test sets.

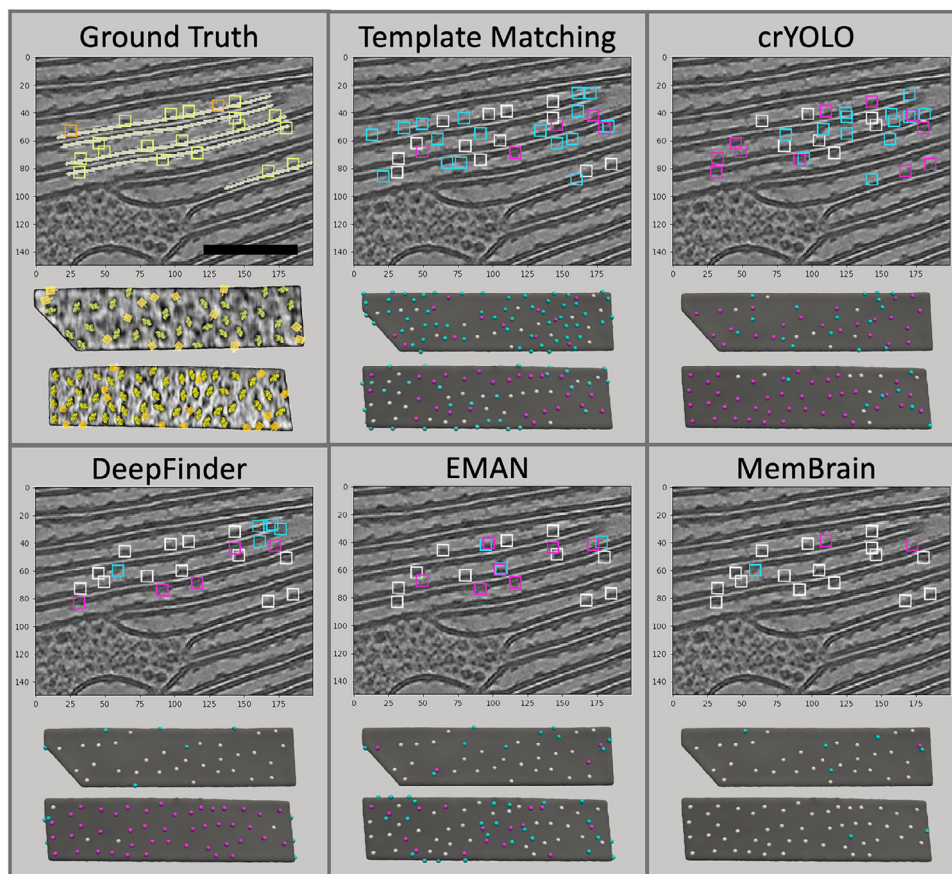
#### 3.2. Analysis of MemBrain's Performance

##### 3.2.1. Evaluation Metric

For evaluating MemBrain's performance with respect to ground truth particle positions, we compute precision ( $P$ ), recall ( $R$ ), and F1 score ( $F_1$ ) of our predicted particle coordinates. For the calculation of recall, we define a true positive ( $TP_R$ ) as a ground truth (GT) PSII position that has been *hit*, i.e., a predicted position is within a certain radius (in this case, 4.5 voxels). Correspondingly, a false negative ( $FN_R$ ) is a GT position that is not hit by a predicted position. For precision, a true positive ( $TP_P$ ) is a predicted position that hits a GT position (either PSII or unknown densities), and a false positive ( $FP_P$ ) is a predicted position that does not hit a GT position. The F1 score is computed as the harmonic mean of recall and



**Fig. 2. The three cryo-ET datasets examined in this study.** For each panel, **Top:** Example 2D tomogram slices (scale bars: 100nm), **Bottom:** Membranogram view of one membrane. The visualized membrane is highlighted in yellow. **A:** Dataset 1 – Chloroplasts isolated from *Spinacia oleracea*, acquired using defocus imaging and denoised with Cryo-CARE [25]. **B:** Dataset 2 [12] – Chloroplasts inside *Chlamydomonas reinhardtii* cells, acquired using Volta phase plate imaging [30], not denoised. **C:** Dataset 3 [26] – Rod outer segments isolated from wild-type mice, acquired using defocus imaging and denoised with Cryo-CARE.



**Fig. 3. Visual analysis of predicted positions.** For the ground truth panel, **Top**: 2D slice of a test set tomogram with annotated membranes highlighted in white (scale bar: 100 nm). Yellow boxes show PSII positions, orange boxes represent unknown density (UK) positions. **Bottom**: Membranogram views of two membranes from the test set. Mapped in are PSII protein structures (yellow) and UK positions (orange cubes). The five other panels show the analysis of predicted positions for all compared methods. True positives are highlighted in white, false negatives in magenta, and false positives in cyan.

precision:

$$R = \frac{TP_R}{TP_R + FN_R}, P = \frac{TP_P}{TP_P + FP_P}, F_1 = \frac{2 \cdot R \cdot P}{R + P}$$

### 3.2.2. Quantitative Analysis

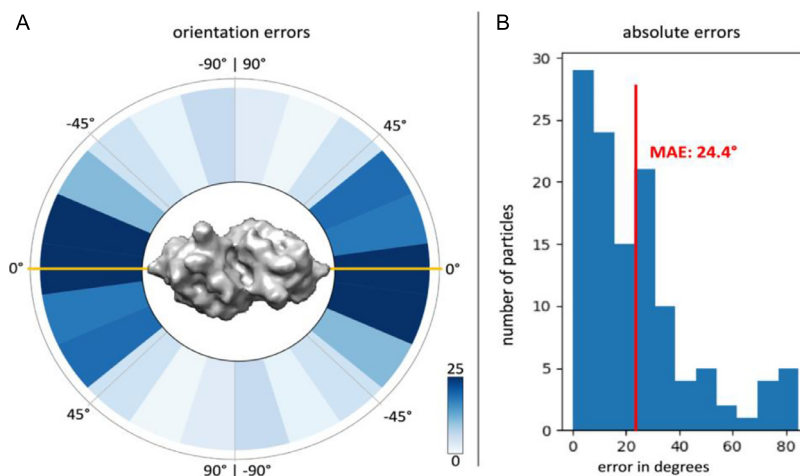
Table 1 shows the performance of MemBrain in comparison with other state-of-the-art deep learning particle picking algorithms, as well as the commonly used template matching approach (for more details about the generation of comparison positions, see supplementary S1.3). In addition, Fig. 3 shows how well the methods performed with respect to ground truth on a 2D slice (top views), as well as two membranes (bottom views). All deep learning-methods were trained using 28 membranes from Dataset 1 as the training set (7 membranes were used for the validation set), while template matching was performed using a native structure of PSII embedded in a membrane density [12] as the reference

**Table 1**

Benchmarking results on the test sets of Datasets 1 and 2 for Template Matching (TM) [29], crYOLO [9], DeepFinder [8], EMAN [7], and MemBrain.

Dataset	Dataset 1			Dataset 2		
	Prec	Rec	F1	Prec	Rec	F1
TM [29]	0.39	0.56	0.46	0.40	0.47	0.43
crYOLO [9]	0.22	0.18	0.20	0.25	0.04	0.07
DeepFinder [8]	0.54	0.61	0.57	0.28	0.55	0.37
EMAN [7]	0.63	0.64	0.63	0.47	0.39	0.42
MemBrain	<b>0.90</b>	<b>0.94</b>	<b>0.92</b>	<b>0.73</b>	<b>0.83</b>	<b>0.78</b>

template. For evaluation, we only considered those predictions that were close to an annotated membrane in order to enable comparison to the corresponding ground truth. MemBrain outperformed the other methods on the test set of Dataset 1 and even generalized well to Dataset 2, despite a considerable domain shift between these samples. In particular, we emphasize that the recall for MemBrain far exceeded the level of the other methods, which is an important advance to prevent missing ground-truth particles. In comparison, precision is less critical, as there are mature techniques to clean up false-positive picks, e.g., via subtomogram classification [27]. Although DeepFinder picks well in some regions, it misses proteins in other regions completely (Fig. 3, membrane views), conceivably because the training data does not cover all possible membrane orientations. EMAN already has a mechanism to compensate for the lack of particle orientations by performing random rotations on the training data. Nonetheless, it did not perform as well as MemBrain, demonstrating the importance of the subvolume rotation module and the focused detection in our pipeline. We conclude that all other methods have limitations in this specific context of membrane proteins, as all of them require regions in the tomograms that are richly annotated, and expectedly have problems in this setting of very sparse labels. Compared to deep learning-based methods, template matching is even more difficult to tune, because the peaks in the detection are mostly triggered by the strong membrane signal and often do not correspond to actual protein complexes. As a result, template matching leads to low recall and precision. Besides particle detection, MemBrain can additionally extract particle orientations, which is beyond the current capacities of other deep learning-based methods.



**Fig. 4. Analysis of particle orientations estimated by MemBrain.** Comparison of MemBrain's 120 true positive picks to the ground truth annotations in the Dataset 1 test set. **A:** Circular heatmap showing differences between ground truth in-plane angles and estimated angles. The long axis of the mapped PSII structure (0°) is plotted in yellow. Note that due to PSII's two-fold symmetry, the deviation cannot exceed 90°. **B:** Histogram of absolute differences between ground truth in-plane angles and estimated angles. The mean absolute error (MAE) is indicated in red.

Fig. 4 shows the distribution of MemBrain's predicted orientations with respect to the ground truth. We achieved a mean absolute error of 24.4 degrees (maximum possible deviation is 90 degrees due to PSII's C2 symmetry) on our Dataset 1 test set, which can serve as a good initialization for subvolume alignment and make the subsequent subtomogram averaging [5,28,29] more efficient. A comparison of the tracked times for training, prediction, and extraction of particle positions for all compared models can be found in Table S3.

### 3.2.3. Qualitative Evaluation on Dataset 3

For Dataset 3, we did not have ground truth protein positions to compute quantitative evaluation metrics. Instead, we assessed the picks from MemBrain and PySeg using subtomogram averaging (Fig. 5; for details about the averaging procedure, see supplementary S.1.4). First, we trained a MemBrain model using the ground truth data from Dataset 1 (the same model as for the previous section), which reliably picked PSII complexes in this spinach dataset (Table 1; Fig. 5A). Then, we applied this pre-trained MemBrain model to predict membrane-bound protein positions in the mouse rod outer segments of Dataset 3 (Fig. 5B). For comparison, we also predicted membrane-bound protein positions in Dataset 3 using PySeg (Fig. 5C). Subtomogram averaging of the MemBrain picks, PySeg picks, as well as intersection and difference sets between these picks revealed interesting differences between the two detection algorithms. In both Datasets 1 and 3, MemBrain consistently picks densities that are embedded in the membranes and appear as small bumps. In contrast, PySeg was configured to pick all densities over the membranes regardless of their shape. This initial picking was refined after the first cleaning step, where the expert selected automatically generated 2D rotational average classes that indicated a density on the membrane (PySeg<sub>clean</sub>, see supplementary S.1.2, and Figure S2). Thus, PySeg picks a wider variety of particles, resulting in a different average. Looking at the consensus analysis (Fig. 5D), we can see that PySeg picks often coincide with MemBrain picks, and the average of this intersection subclass looks very similar to the pure MemBrain average. In the subclass of MemBrain picks that were missed by PySeg, we observe a smaller bump on the membrane. On the other hand, the PySeg picks that MemBrain missed appear to be densities that are suspended above the membrane and not embedded within it. A further classification of this subclass can be seen in Figure S4, and the corresponding class numbers are given in Table S1. It is worth noting that this be-

**Table 2**

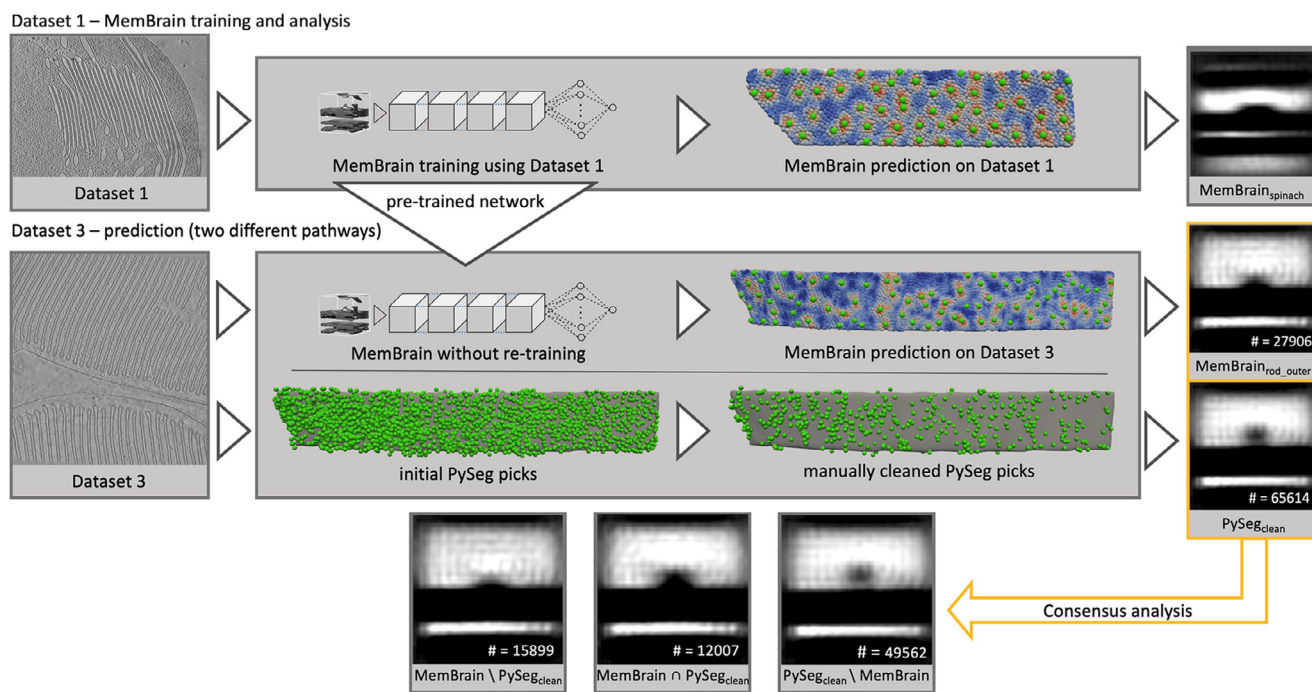
Ablation study: Effects of using a regression target (as compared to classification), denoised data, the rotational normalization module, and the Mahalanobis distance (as compared to the Euclidean distance) for 1, 8, and 28 membranes (mbs), respectively.

Method	F1 Score		
	1 mb	8 mbs	28 mbs
Default MemBrain	0.88	<b>0.91</b>	<b>0.92</b>
Classification	0.79	0.80	<b>0.91</b>
Non-denoised	0.78	0.80	0.85
No normalization	0.81	0.86	0.87
Euclidean Distance	0.86	0.89	0.90

havior of MemBrain is often desirable, since it has been trained to find exactly these bumps on the membrane (see the PSII average in the top row of Fig. 5), and one may not want to detect everything that is close to a membrane, but rather only specific membrane-embedded proteins. PySeg is a comprehensive data-driven workflow, but a specialized pipeline like MemBrain can save time and effort when the membrane proteins are visually recognizable.

### 3.2.4. Ablation Study

In our ablation study (Table 2) we show the results of MemBrain with varying experimental settings. First, we explored the minimum amount of training data that is required to train our model. Like for most biomedical images, data annotation requires human expertise and is generally difficult to obtain. In our experiment, we used 1, 8 or 28 annotated membranes in the training set, and we performed hyperparameter tuning using grid search for both learning rate (range  $3 \times 10^{-5}$  to  $3 \times 10^{-4}$ ) and weight decay parameters (range 0 to  $1 \times 10^{-3}$ ), although our pipeline was quite robust with respect to these parameters. The models were trained using a batch size of 1024 for up to 5000 epochs, with early termination in case the validation values stopped decreasing. As shown in Table 2, even with only one annotated membrane, MemBrain still achieved an F1 score of 0.88, which far exceeded EMAN, DeepFinder, and cryOLO (Table 1), even though these other deep learning networks were trained on the entire training dataset of 28 membranes. Furthermore, we explored the contribution of individual components in the MemBrain pipeline. We found that denoising the tomograms is vital to ensure good performance, as it simplifies the task by removing the necessity for the model to learn to cope with noise. In addition, using a CNN for a regression



**Fig. 5. Qualitative comparison of MemBrain and PySeg on Dataset 3.** **A:** MemBrain was trained using the ground truth data from Dataset 1. The trained program was used to predict particle positions (green) in the test set of Dataset 1. **B:** The same MemBrain program (trained on Dataset 1) was used to predict particle positions (green) in Dataset 3. **C:** PySeg was applied to generate particle positions (green) in Dataset 3. Visualized are the initial picks of PySeg (left) and the picks after cleaning using selection of 2D rotational averages in PySeg (right). Rotationally symmetrized subtomogram averages were generated from the picks of each pathway (right column). **D:** Consensus analysis using subtomogram averages to compare the MemBrain picks and the cleaned PySeg picks.  $\text{MemBrain} \setminus \text{PySeg}_{\text{clean}}$  = positions picked by MemBrain but not  $\text{PySeg}_{\text{clean}}$ .  $\text{MemBrain} \cap \text{PySeg}_{\text{clean}}$  = positions picked by both MemBrain and  $\text{PySeg}_{\text{clean}}$ .  $\text{PySeg}_{\text{clean}} \setminus \text{MemBrain}$  = positions picked by  $\text{PySeg}_{\text{clean}}$  but not MemBrain.

task rather than more commonly-used classification also improves the overall performance of the entire pipeline, particularly when the training dataset is small. We reason that the induced label noise from inaccurate manual labeling of particle center positions has a larger influence on classification than on distance regression, where the score assignment is smoother. Closely related to this, we also tested training our network using ground truth distances assigned using the Euclidean distance instead of the Mahalanobis distance (GT distances visualized in Figure S3). While MemBrain gives good results even without the Mahalanobis distance, we can still see that it is beneficial to also consider particle shapes. Finally, we explored the influence of our subvolume normalization module: The values for “no normalization” correspond to the results for MemBrain without normalized volumes, but trained with arbitrary subvolume rotations as data augmentation during training. Again, especially for the one membrane (1 mb) and eight membranes (8 mbs) settings, the results are worse than our fully trained MemBrain model. This corroborates the importance of our normalization module for simplifying the detection problem.

In addition to this ablation study, we performed several other experiments with varying settings (see Table S4), all of which confirm MemBrain’s robustness towards different pipeline parameters. Notably, when using no data augmentation during training, the performance does not drop. Nevertheless, we still recommend using data augmentation, as otherwise picking the best model may become less robust due to overfitting (see also Supplementary Figure S5 for an example of overfitting without data augmentation).

#### 4. Conclusion

In this study, we present MemBrain, a deep learning-aided pipeline that is specialized for automatic detection of membrane-bound proteins in cryo-electron tomograms. In the preprocessing step, MemBrain uses the membrane geometry and rotates to-

mographic subvolumes into a normalized orientation, which generalizes the trained CNN to membranes with different orientations than in the training set. Moreover, this rotation step reduces the complexity of the protein detection task, and thus, our network can be efficiently trained with a small dataset consisting of only one annotated membrane. This is experimentally practical, as the throughput of cryo-ET data acquisition is accelerating, but the manual annotation remains laborious. We evaluated MemBrain on three different datasets and showed that our pipeline outperforms other state-of-the-art methods (both conventional and deep learning-based) for particle picking by a large margin (recall: MemBrain >0.90 vs. other methods <0.65). In Dataset 3, where no ground truth annotations were available, we showed that MemBrain’s picks resemble membrane-embedded proteins. Furthermore, MemBrain is able to estimate protein orientations, which is beyond the current capacities of other deep learning-based methods. The particle positions and orientations extracted by MemBrain can be used to analyze the organization of protein complexes within membranes, revealing how they interact with each other to drive cellular processes. Since MemBrain is generalizable to unseen data domains, it will likely be applicable to investigating biological mechanisms in various kinds of membranes, ranging from protein production in the endoplasmic reticulum to the bioenergetic reactions in mitochondrial cristae and chloroplast thylakoids.

#### Declaration of Competing Interest

The authors declare no conflict of interest.

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## Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.cmpb.2022.106990.

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