FibeR-CNN: Expanding Mask R-CNN to Improve Image-Based Fiber Analysis

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Abstract
Fiber-shaped materials (e.g., carbon nanotubes) are of great relevance, due to their unique properties but also the health risk they can impose. Unfortunately, image-based analysis of fibers still involves manual annotation, which is a time-consuming and costly process.

We therefore propose the use of region-based convolutional neural networks (R-CNNs) to automate this task. Mask R-CNN, the most widely used R-CNN for semantic segmentation tasks, is prone to errors when it comes to the analysis of fiber-shaped objects. Hence, a new architecture – FibeR-CNN – is introduced and validated. FibeR-CNN combines two established R-CNN architectures (Mask and Keypoint R-CNN) and adds additional network heads for the prediction of fiber widths and lengths. As a result, FibeR-CNN is able to surpass the mean average precision of Mask R-CNN by 33% (11 percentage points) on a novel test data set of fiber images.

Source code available online.

Keywords: imaging particle analysis, automatic fiber shape analysis, carbon nano tubes (CNTs), region-based convolutional neural network (R-CNN), Mask R-CNN, Keypoint R-CNN

1. Introduction
Fiber-shaped materials, such as asbestos, carbon nanotubes (CNTs) and fiberglass, possess a janiform character. On the one hand, they exhibit unique and attractive material properties [1], so that they are of great scientific and commercial interest. On the other hand, they can have a severe toxicological potential, which impedes their environmental compatibility, especially when being delivered as aerosols [2]. Since both, the desired and the undesired properties, are often shape and size dependent, image-based fiber analysis is an important tool for the exploration and assessment of risks and chances of fiber-shaped materials [3–7].

There already exist automated online measurement methods for the determination of the length and width distributions of CNTs, e.g. via differential mobility analysis [8]. However, these methods always require a validation based on some form of image-based analysis. Unfortunately, automated annotation algorithms for images of fiber-shaped particles are scarce, especially for overlapping and occluded fibers.

The most notable and accessible of these algorithms is CT-FIRE [9], which is based on classical image processing methods and fast discrete curvelet transform (CT) [10], combined with the fiber extraction (FIRE) [11].

While having been successfully applied to high-contrast images of collagen fibers [9] and perfectly straight glass fibers [12], for more difficult data like the test data at hand (see Section 2.2), CT-FIRE produces insufficient results (see Figure 1), even if supplied with a priori information about the sample (e.g. minimum fiber length). Furthermore, it is extremely slow (~5 min per image on a single CPU core; see also Table A.1) and features many parameters that need to be carefully tuned – often on a per-image basis – to optimize the results. Due to these reasons, analyses of fiber length and width distributions still often have to be carried out manually. This practice is not only laborious, expensive and repetitive but also error-prone, due to the subjectivity and exhaustion of the operators [13].

To solve these problems, we propose a new approach to fully automated imaging fiber analysis, with help of convolutional neural networks (CNNs). Recently, CNNs have been applied successfully to particle measurement problems, such as the characterization of particle shapes and their size distribution [14] as well as the classification of the chiral indices of CNTs [15]. They are therefore promising candidates for the solution of the problem at hand. The main advantage of CNNs is that they require no user-tunable parameters, once they have been trained. Also, they are outstandingly robust to changes in imaging conditions. However, they require a set of already annotated samples for the training [14].

Our previously presented, Mask R-CNN-based, particle analysis method [14] works well for spherical instances, i.e. particles, even if they exhibit large amounts of occlusion and sin-
Figure 1: Example of the insufficient detection quality of CT-FIRE, when being applied to an image from the test data at hand. To reduce the number of false-positives, detections featuring a short fiber length were filtered with a threshold of 150 px. The remaining false-positive detections result from artifacts induced by the fast discrete CT used by CT-FIRE and could not be reduced any further through tuning of the associated parameters.

Figure 2: Example of the poor detection quality of Mask R-CNN, when being trained on and applied to fiber images from the test data at hand. However, Mask R-CNN yields quite ragged instance masks\(^2\), when being trained on and applied to fiber images (see Figure 2) and elongated objects in general [16]. The Mask R-CNN architecture is region-based. Contrarily to spheres, fibers contribute only little information to the extracted region of interest (ROI) feature maps, due to their thinness and curvature and therefore small area relative to the area of their associated ROIs. Apparently, the extracted features do not suffice to reliably reconstruct the instance masks of the fibers directly.

However, we hypothesize that the features may be meaningful enough to extract keypoints, as well as widths and lengths of fibers. While the latter are often sought-after measurands themselves, their combination with the extracted keypoints also allows a more complete reconstruction of instance masks.

In this publication, we therefore propose, implement and validate an extension of the Mask R-CNN architecture, hereby named FibeR-CNN, to extract keypoints, widths and lengths of fibers from images, thereby improving automatic fiber shape analysis.

2. Training and Test Data

The fiber images used in this publication are courtesy of the Institute of Energy and Environmental Technology e.V. (IUTA) and were created using a JEOL JSM-7500F field emission scanning electron microscope (SEM). The pictured fibers are CNTs, deposited from the gas phase (see Figure 3).

2.1. Ground Truth Generation

The ground truths\(^3\), used to train and test the CNNs utilized within this publication, have three origins: manual annotation, semiautomatic annotation and image synthesis.

2.1.1. Manual Annotation

A total of 1075 images, featuring 1935 fibers, were annotated manually, using an ad hocly implemented annotation tool\(^4\). The manual annotation was done by selecting keypoints for each fiber that were interpolated using cubic splines and adjusting the fiber width until an optimal coverage was achieved (see Figure 4).

2.1.2. Semiautomatic Annotation

For basic fiber images, featuring neither clutter, loops nor overlaps (see Section 2.2), a semiautomatic annotation can be carried out to avoid the laborious task of manual annotation. For the use case at hand, the semiautomatic annotation was implemented as follows (see also Figure 5):

1. The original image (see Figure 5a) is segmented using denoising and thresholding, yielding an instance mask (see Figure 5b).
2. The instance mask (see Figure 5b) is skeletonized\(^5\) (see Figure 5c).
3. To remove artifacts resulting from the skeletonization and to determine a correct order of keypoints, the longest connected path in the skeleton is identified via a path-finding method and all other pixels are discarded (see Figure 5d; pixels: kept, pixels: discarded).
4. The pixels of the longest connected path (see Figure 5d; pixels) are converted into keypoint coordinates (see Figure 5e).
5. To determine the fiber width (see Figure 5g), an Euclidian distance map\(^6\) (see Figure 5f) of the instance mask (see Figure 5b) is calculated. Subsequently, the Euclidian distances of the previously determined keypoints (see Figure 5e) are looked up, their average is calculated and the resulting value is multiplied by a factor of 2 to yield the fiber width.

\(^3\)In machine learning, the ground truth, while not necessarily being perfect, is the best available data to test predictions of an algorithm.

\(^4\)Available at: https://github.com/maxfrei750/FiberAnnotator

\(^5\)During a skeletonization, the outmost true pixels of a binary mask are removed repeatedly, until a further removal would separate previously connected regions. Effectively, a skeletonization reduces the thickness of a mask to 1 px (pixel).

\(^6\)In a Euclidian distance map, which results from the Euclidian distance transformation of a mask, each pixel represents the Euclidian distance of said pixel to the next background, i.e. false, pixel in the input mask.

\(^2\)An instance mask assigns a binary value to each pixel of an input image: false for background pixels and true for foreground, i.e. instance pixels.

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Figure 3: Example images of the utilized data sets (+/-/?: yes, no, random; 1/c/o: loops, clutter, overlaps).
6. The fiber length (see Figure 5h) is determined by integrating a cubic spline interpolation of the keypoints (see Figure 5e).

7. Finally, annotations with faulty keypoints or fiber widths are removed manually.

A total of 579 images, featuring 583 fibers, were annotated semiautomatically.

2.1.3. Image Synthesis

Using our synthPIC toolbox\(^7\), 500 images, featuring 760 fibers, were synthesized. The purpose of the synthetic images is to survey, whether they can be used to supplement or even replace real training data, thereby obliterating the need for a manual annotation.

2.2. Data Sets

So far, three data sets were distinguished: manually annotated, semiautomatically annotated and synthetic fiber images (see Section 2.1). However, the set of manually annotated images can be partitioned into subsets once again, based on the presence of potentially inhibiting factors for the automatic detection of fibers. A survey of the available images yielded three such factors:

- **Loops**: Self-overlapping fibers.
- **Clutter**: Agglomerates or aggregates of non-fiber particles which stick to fibers, e.g. nuclei that did not grow into long fibers.
- **Overlaps**: Multiple fibers which overlap each other. Fibers which are connected only by clutter are not considered overlapping.

The set of manually annotated images was therefore subdivided into eight subsets, representing all possible combinations of the three inhibiting factors (see Figure 3 and Table 1), to study their impact on the detection quality. Next, each real data set was partitioned once again, to yield training and test sets ([85%]/[15%]).

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\(^7\)Available at: https://github.com/maxfrei750/synthPIC4Python
for the proposed method (see Table 1, right side). Ultimately, due to the small number of images for data sets featuring loops, all loop data sets were aggregated into a single data set (see Table 1, gray rows).

3. Method

The focus of the proposed method lies on the modification of already existing R-CNN architectures (see Sections 3.1 and 3.2) and training schedules (see Section 3.5), to meet the requirements of imaging fiber analysis. Furthermore, the proposed extensions require changes with respect to the preparation of the utilized input data (see Section 3.3) and allow for custom-designed error detection and correction strategies (see Section 3.4).

3.1. Network Architecture

The FibeR-CNN architecture, presented within this publication, is an extension of the well-known Mask R-CNN architecture [17] (see Figure 6; box). It is therefore imperative to briefly elaborate upon the structure and general principles of Mask R-CNN. Subsequently, it will be expanded in two steps: Firstly, by adding a head for keypoint regression (see Figure 6; box), thereby yielding the Keypoint R-CNN architecture [17] and secondly, by adding two heads performing fiber width and length regressions, which ultimately yields the FibeR-CNN architecture (see Figure 6; box). As codebase for the implementation, the detectron2 framework [18] was used, which features PyTorch [19] implementations of Mask R-CNN and Keypoint R-CNN.

3.1.1. Region-Based Convolutional Neural Networks

Modern R-CNNs consist of three conceptual stages (see Figure 7): feature extraction, ROI proposal/extraction and instance property prediction.

**Feature Extraction.** The input image is processed by a CNN, referred to as backbone, thereby extracting a map of prominent features over the entirety of the input image. Compared to the other architecture parts, the backbone is usually a much deeper network, i.e. it has more layers. Therefore, the majority of calculations takes place within the backbone. It is easily interchangeable to adjust the number of operations and thereby the network speed. In this publication, the convolutional blocks 2 to 5 of the ResNet-50 network [20] are used as backbone.\(^8\)

\(^8\)For a more detailed, yet plain explanation please refer to [14]. An in-depth explanation can be found in [17].

**ROI Proposal and Extraction.** ROIs encompassing instances are identified and extracted from the feature map. The ROIs are selected so that each ROI represents exactly one instance. Additionally, for each ROI an objectness score, which quantifies the likelihood of the ROI to encompass an object, is output. Subsequently, the set of instance feature maps is passed to each of the downstream heads, each of which predicts a desired instance property (e.g. class, bounding box, instance mask, keypoints, etc.).

**Instance Property Prediction.** R-CNNs can be distinguished based on the presence of characteristic instance property prediction heads (e.g. the mask segmentation or the keypoint regression head). However, most modern R-CNNs share at least two such heads: The bounding box regression head, which determines a refined bounding box for the instance in each ROI and the instance classification head, which determines the class of said instance. For the given application, the latter head is obsolete, because there is only a single class of instances. However, due to its negligible computational cost, it was not removed to facilitate future multi-class applications.

All instance property prediction heads operate on the same shared set of instance feature maps. Therefore, the computational cost of adding additional heads is small compared to the

\(^9\)Neural networks can consist of multiple branches, which perform independent tasks. The final part of a branch, which produces an output meaningful to the user, is referred to as head.

\(^10\)In a machine learning context, the term regression refers to the prediction of continuous values, e.g. keypoint coordinates.

\(^11\)Contrary to ordinary maps, this map has more than two dimensions.

\(^12\)For an elaboration upon the reasoning behind this design choice, please refer to [14].

\(^13\)In a machine learning context, the term classification refers to the prediction of a discrete value, i.e. a class.
Table 1: Data set properties (+/-?; yes, no, random; l/c/o: loops, clutter, overlaps). Gray rows represent data sets before aggregation.

| Loops | Clutter | Overlaps | Annotation | Identifier | Number of Images | Number of Instances |
|-------|---------|----------|------------|------------|------------------|---------------------|
| yes   | random | random | manual     | [-1|-c|-o] auto | 579 | 492 | 87 | 583 | 496 | 87 |
| yes   | no     | no      | manual     | [+1|-c|-o]   | 425 | 425 | –  | 645 | 645 | –  |

backbone’s computational cost. This is beneficial for the use case at hand, since all extensions of Mask R-CNN within this publication come in the form of additional instance property prediction heads.

3.1.2. Mask R-CNN

The characteristic instance property prediction head of Mask R-CNN is the mask segmentation head (see Figure 6; box), which computes a binary mask representing the instance pixels, i.e. it answers the question, which pixels of the input image belong to a certain instance and which pixels belong to the image background or another instance. Figure 8 illustrates the functionality of the mask segmentation: Initially, each ROI feature map, resulting from the ROI extraction, is resized using ROI align. Subsequently, a CNN upsamples the low-resolution, high-depth feature map to a high-resolution, low-depth binary mask.

3.1.3. Keypoint R-CNN

The Keypoint R-CNN architecture was proposed along with Mask R-CNN by He et al. [17], with the task of human pose estimation in mind. Instead of a mask segmentation head, it features a keypoint regression head (see Figure 6; box). The functionality of this head (see Figure 9) is closely related to that of the mask segmentation head (see Figure 8), with the key difference being that multiple (keypoint) masks per instance are predicted, instead of just a single mask. In each keypoint mask, there exists only a single true pixel, which represents the keypoint position.

In the original implementation, the keypoint regression head outputs the coordinates of 17 keypoints, which is insufficient to describe the shapes of long and/or strongly curved fibers. Therefore, in the FibeR-CNN architecture, the keypoint regression head was altered to output 40 keypoint coordinates (see also Section 3.3.1), by increasing the respective dimension of its last layer.

3.1.4. FibeR-CNN

FibeR-CNN expands Mask R-CNN beyond Keypoint R-CNN by adding two additional instance property prediction heads (see Figure 6; box): the fiber width and length regression heads.

The architectures of these heads were inspired by the bounding box regression head of Mask R-CNN [17], i.e. they are implemented as fully connected neural networks, each consist of three rectified linear unit (ReLU) layers (see Figure 10). As inputs for the fully connected neural networks, resized and flattened versions of the input ROI feature maps are used. In contrast to the mask and keypoint prediction heads, the fiber width and length regression heads – just like the bounding box regression head – operate on lower-resolution versions of the utilized ROI feature maps, to reduce the size and complexity of the utilized fully connected neural network. During the flattening, each multidimensional ROI feature map is transformed into a vector by concatenating all of its elements. Subsequently, each element is being fed to a corresponding input neuron of the downstream fully connected neural network, which, as a whole, predicts the fiber width or length, respectively.

Due to the fact that the fiber width, as well as the fiber length regression head both only output a single quantity, each of them only features a single output neuron. While the prediction of a single length per fiber is intuitive, the prediction of just a single width per fiber is arbitrary and tailored to the utilized data, which features only fibers with various, yet constant widths. However, for fibers with inconstant widths, the architecture could easily be expanded, by adding more output neurons to the fiber width regression branch, to predict an individual width at every keypoint.

At first glance, the mask segmentation head inherited from the Mask R-CNN architecture and the fiber length head may

\[ x = \max(0, x) \]

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Figure 7: Illustration of the feature extraction as well as the ROI proposal and extraction, which are shared by most modern R-CNN architectures.

3.2. Loss Function

The loss function – sometimes also referred to as cost function – is an essential element of many optimization problems, such as the training of neural networks. It is a means to quantify the quality of a model, based on the deviation of its predictions from the ground truth, i.e., the desired target outputs. The higher the deviation, the higher the loss. Therefore, the goal of the training is to minimize this loss.

FibeR-CNN uses a multi-task loss $L$, which is equal to the sum of the individual prediction head losses:

$$L = L_{cls} + L_{box} + L_{mask} + L_{fw} + L_{fl}$$  

$L_{cls}$ and $L_{box}$ are the instance classification and bounding box regression head losses [21], whereas $L_{mask}$ and $L_{kp}$ are the mask segmentation and keypoint regression head losses [17]. The fiber width and length prediction head losses $L_{fw}$ and $L_{fl}$ are both based on the mean squared error (MSE):

$$L_{fw}(y,t) = w_{fw} \cdot MSE(y,t)$$  

$$L_{fl}(y,t) = w_{fl} \cdot MSE(y,t)$$  

where

$$MSE(y,t) = \frac{1}{n} \sum_{i=1}^{n} (y_i - t_i)^2$$

is the mean squared error, $y$ and $t$ are the prediction and target vectors$^{17}$ of the respective heads, $i$ is the index of each instance and $n$ is the number of dates, i.e., instances. The main difference of the losses are their weights $L_{fw} = 10^{-3}$ and $L_{fl} = 10^{-6}$, which were chosen so that $L$ is not dominated by the fiber width and length regression heads. Otherwise, the neural network would focus primarily on the improvement of these two heads during the training and neglect the other heads.

3.3. Data Transformations

To homogenize or augment the input and ground truth data of CNNs, it is often useful or even mandatory to apply transformations to it.

$^{17}$ROIs are usually processed in batches to take advantage of parallelization. Therefore, the properties of more than one instance are predicted simultaneously.
Figure 8: Illustration of the mask segmentation head.

Figure 9: Illustration of the keypoint regression head (white pixels in keypoint masks are oversized).

Figure 10: Architecture of the fiber width and fiber length regression head, respectively.
### 3.3.1. Number of Keypoints

As mentioned in Section 3.1.3, the number of keypoints per instance, predicted by the keypoint regression head of FibRe-CNN, had to be adjusted, to yield a high enough resolution of keypoints, to describe the shape of long and/or strongly curved fibers. Also, the calculation of the keypoint regression head loss requires a consistent number of keypoints in the ground truths.

While a higher number of keypoints yields a better resolution, as with all statistical models, it is undesirable to introduce more degrees of freedom (i.e. keypoints) than necessary. Therefore, approximations of the ground truth, using varying numbers of keypoints were tested and the resulting approximation qualities were assessed using the Bayesian information criterion (BIC)\(^{18}\).

According to Yaffee and McGee [22], the BIC (omitting the Bessel’s correction [23]) is defined as:

\[
\text{BIC}(y, t) = n \cdot \ln \left( \frac{1}{n} \cdot \text{SSR}(y, t) \right) + k \cdot \ln(n),
\]

where, for the case at hand, \(y\) and \(t\) are the coordinate matrices of the approximated and ground truth keypoints, respectively, whereas \(k\) is the tested number of keypoints, \(\text{SSR}\) is the sum of squared residuals and \(n\) is the number of dates, i.e. the arbitrary number of sampled squared residuals (for the study at hand: \(n = 200\)).

The sum of squared residuals (SSR) quantifies the error of the tested approximation. It equals the sum of squared distances of pairs of points, sampled from two uniform cubic spline interpolations, one through the ground truth keypoints and the other one through the approximated keypoints (see Figure 11):

\[
\text{SSR}(y, t) = \sum_{i=1}^{n} \sum_{j=1}^{2} (y_{i,j} - t_{i,j})^2,
\]

where \(i\) is the sampling point index and \(j\) is the coordinate index (i.e. whether the \(x\)- or the \(y\)-coordinate of the sampled point is used). The BIC rewards good approximations, while punishing the introduction of additional parameters. Therefore, lower BICs indicate better balanced models [22].

To determine the optimum number of keypoints per fiber, the ground truth keypoints of each fiber of the non-synthetic training data sets\(^{19}\) were interpolated using uniform cubic splines, having numbers of knots in the range from 4 to 100. Subsequently, the resulting BIC was calculated for each interpolation. The optimum number of keypoints of each fiber, was defined as the number of knots yielding the minimum BIC for each fiber. Figure 12 depicts the resulting distribution of optimum number of keypoints for the surveyed fibers. As overall optimum number of keypoints, the 90\(^{\text{th}}\) percentile of this distribution was chosen, which yields a number of 40 keypoints as optimum for the given data. Accordingly, the last layer of the keypoint regression head of FibRe-CNN was dimensioned to output the coordinates of 40 keypoints and all ground truths were transformed to have 40 keypoints, by using uniform cubic spline interpolation.

\(^{18}\)The BIC is a commonly used metric for the evaluation of statistical models.

\(^{19}\)The test data sets were excluded to prevent a possible bias.
3.3.2. Keypoint Ordering

The order of keypoints is crucial for the keypoint regression head loss, because the position of a keypoint within the list of keypoints has an implicit meaning, in form of a label. In human pose estimation, these labels are i.e. left hand, right hand, head, etc. Therefore, it is evident that a keypoint – even if it has the perfect spacial location – is plainly wrong, if it is mislabeled, i.e. it has the wrong position in the list of keypoints (see Figure 13). A keypoint labeled as left hand at the spacial location of a head is just as wrong as one labeled as left hand at another, e.g. random, spacial location\textsuperscript{20}.

For the use-case at hand, this brings about a problem with respect to the training data annotation. While during the annotation of human poses, each keypoint is unique and even similar keypoints such as left hand and right hand can be distinguished reliably (even if the human does not face the camera), this is no longer true for the annotation of fibers. To the human eye, both ends of a fiber are indistinguishable. Therefore, the annotations are inconsistent, which severely impedes the performance of FibeR-CNN. To solve this problem by establishing consistency, the keypoints need to be ordered according to a rule. Due to the fact that the relative keypoint order is already correct, the rule only has to address the fiber end keypoints.

A simple rule to order the fiber end keypoints, is to order them as if they were words in a book, i.e. from top to bottom and from left to right:

\textit{Choose the topmost end point of a fiber as the first keypoint. If there are two candidates, choose the leftmost candidate as first keypoint.}

3.3.3. Input Augmentation

A widespread augmentation technique, to artificially increase the amount of training data, is the flipping of images. Since Keypoint R-CNN is traditionally used for human pose estimation, it usually does only apply horizontal but no vertical flipping. However, since for microscopic images, there is no notion of up and down, FibeR-CNN offers the possibility to apply vertical as well as horizontal flipping. To have a consistent order of keypoints, independent from the flipping, the flipping takes place before the keypoint ordering (see Section 3.3.2).

To further increase the input data variance, the contrast and brightness of input images is varied randomly. An overview of the utilized input augmentation parameters is given in Table 2.

| Parameter | Description |
|-----------|-------------|
| Flip: left-right | 50 % chance |
| Flip: up-down | 50 % chance |
| Contrast | 0.5 to 1.5 |
| Brightness | 0.5 to 1.5 |

Table 2: Input augmentation parameters.

3.4. Error Detection and Correction

The creation of fiber masks (see Section 3.1.4) on the basis of fiber widths and keypoints is susceptible to misplaced keypoints, i.e. a single misplaced keypoint can lead to large errors (see Figure 13). However, as mentioned in Section 3.1.4, the retrieval of redundant information about the detected fiber instances enables the use of error detection and even correction strategies.

3.4.1. Error Detection

Since the fiber length prediction is much easier than the keypoint prediction, it is much more precise (see Section 4.4). Therefore, errors during the keypoint detection can easily be detected by comparing the length of the cubic spline interpolation of the predicted keypoints, to the length predicted by the fiber length regression head. Under the assumption, that the fiber length predictions are significantly more reliable than the keypoint predictions, this yields a possibility to reliably quantify the overall keypoint prediction quality.

An alternative error detection strategy is the comparison of the keypoint-based fiber masks with the masks output by the mask segmentation head, by calculating their intersection over union (IoU)\textsuperscript{21}. However, since the latter are usually quite ragged, i.e. imperfect themselves (see Figure 2), only relative statements about the prediction quality can be made: a higher agreement of both masks indicates a better prediction. However, in contrast to the fiber length based error detection strategy, this gives no absolute measure for the prediction quality.

3.4.2. Error Correction

As illustrated in Figure 13, misplaced keypoints can lead to large errors during the detection of fibers. Therefore pro-

\textsuperscript{21}Intersection over union is a measure to determine the likeness of a pair of two-dimensional objects, with respect to their size, shape and position (see also Figure 15). As the name implies, it is defined as the ratio of the area of intersection and the area of the union of the two objects.
pose an error correction strategy, hereby named keypoint pruning. During the keypoint pruning, individual keypoints are removed and it is tested whether the removal improves the detection quality (see Algorithm A.1). As measures for the quality, the strategies presented in Section 3.4.1, i.e. fiber mask IoU and length deviation, are used.

A drawback of keypoint pruning is its high computational cost, due to the large number of keypoint combinations to be tested and the repetitive calculations of the fiber mask IoU. Fortunately, it is possible to retroactively apply the error correction to an already trained FibeR-CNN, so that the training speed is not impeded by the error correction.

3.5. Training

The schedule, used for the training of FibeR-CNN\textsuperscript{22}, is based on the well-established 3× training schedule [17, 24], which was developed to train Mask R-CNN and Keypoint R-CNN on the Common Objects in Context (COCO) data set [25]. To adapt it to the simpler learning task and speed up the training, its step size and the training duration were reduced by a factor of 10.

Figure 14 depicts the learning rate schedule. The base learning rate is $\alpha_{\text{base}} = 0.02$. However, the training begins with a warm-up period of 1000 iterations, during which the learning rate is increased linearly from $0.001 \cdot \alpha_{\text{base}}$ to $\alpha_{\text{base}}$. After 21 000 and 25 000 iterations respectively, the learning rate is reduced by a factor of 10. The training ends after 27 000 iterations. A complete overview of all training hyperparameters can be found in Table 3.

To further speed up the training, transfer learning was utilized, by initializing the weights of the feature extraction network, with weights of a ResNet-50-based Keypoint R-CNN, which was trained on the COCO data set according to the 3× training schedule and is included with the detectron2 framework.

The training was carried out on a dedicated GPU server (see Tables A.1 and A.2).

4. Results

There are two kinds of results from the studies carried out for this publication. Firstly, there are the results and insights, produced during the design of the FibeR-CNN architecture (see Section 4.1). Secondly, there are the results and their implications with respect to the use of the FibeR-CNN architecture for imaging particle analysis applications (see Section 4.4).\textsuperscript{23}

Statistics Note. Each error bar in this section represents the 95 % confidence interval (CI) of a result, based on 3 repetitions, using varying random seeds during the training of the respective neural network.

4.1. Architecture Design

For the systematic design of the FibeR-CNN architecture, an additive approach was used. Starting with a basic implementation, as close as possible to Mask R-CNN and Keypoint R-CNN, the architecture was improved and enhanced piece by piece. After each addition, the new model’s quality was compared to that of the previous model version.

As quality measures, average precisions (APs) at multiple IoU thresholds were used, according to the COCO evaluation scheme [27]:

- mAP: mean of APs with IoU thresholds in the range from 50 to 95 % with increments of 5 %
- AP\textsubscript{50}: AP at an IoU threshold of 50 %

\textsuperscript{22}Whenever Mask R-CNN was used as a comparison during the design and evaluation of FibeR-CNN, both networks were trained using the same learning rate schedule, to maintain the comparability between both models.

\textsuperscript{23}The source code of the FibeR-CNN architecture, the final model and the data sets, used for its training and testing, are available via the following link: https://github.com/maxfrei750/FibeR-CNN/releases/v1.0 Additionally, the training and test data sets are part of the BigParticle.Cloud (https://bigparticle.cloud).

| Solver               | SGDM [26] |
|----------------------|-----------|
| Base Learning Rate   | 0.02      |
| Momentum             | 0.9       |
| Warm-Up Factor       | 0.001     |
| Warm-Up Period       | 1000 iterations |
| Learning Rate Drop Steps | 21 000 & 25 000 iterations |
| Learning Rate Drop Factor | 0.1       |
| Duration             | 27 000 iterations |
| Batch Size           | 64 (16 per GPU) |
• **AP75**: AP at an IoU threshold of 75%  

As test data, a collection of all available real test data sets was used. In case of conflicting quality indications from the different APs, the mean average precision (mAP) was used as basis for the final decision.

**Average Precision.** Since the AP is such a central concept for the evaluation of the architecture design, it shall be briefly elaborated upon. According to Padilla et al. [28], object detections can be grouped into four categories:

- **false positive (FP)**: erroneous detection that does not encompass a sought-after object  
- **true positive (TP)**: correct detection that encompasses a sought-after object  
- **false negative (FN)**: sought-after object that has not been detected  
- **true negative (TN)**: detection that has not been detected because there was no sought after object

To evaluate, which of these four categories a prediction belongs to, it is necessary to define a criterion to match pairs of detections and ground truths. A common criterion is the IoU (see Figure 15). Detections and ground truths that feature an IoU greater than or equal to a certain threshold (e.g. IoU ≥ 50%, which yields AP50 or IoU ≥ 75%, which yields AP75), are defined to be matches. For one-class detections like the application at hand, matching pairs of detections and ground truths are TPs. If there is no matching detection for a ground truth, then it is counted as a FN. Contrarily, if there is no matching ground truth for a detection, then it is a FP. If there are multiple matches for a ground truth, then the first match is counted as TP, while the rest is counted as FNs.

Two basic metrics for object detection applications are precision [28]:

\[
\text{precision} = \frac{\# \text{TPs}}{\# \text{TPs} + \# \text{FPs}} = \frac{\# \text{TPs}}{\# \text{detections}},
\]

i.e. the probability of the detector to yield a true positive, and recall [28]:

\[
\text{recall} = \frac{\# \text{TPs}}{\# \text{TPs} + \# \text{FNs}} = \frac{\# \text{TPs}}{\# \text{ground truths}},
\]

i.e. the chance of the detector to detect all ground truths.

When using an R-CNN, every detection comes with a score, which quantifies the confidence of the R-CNN in the detection. By setting a threshold for this score, the number of predictions can be effectively controlled. A higher threshold yields fewer detections, which are more likely to be correct and therefore results in a higher precision. Contrarily, a lower threshold yields more detections, which are less likely to be correct and therefore results in a higher recall.

This tradeoff between recall and precision can be represented by a precision–recall curve (see Figure 16). Due to its saw-tooth shape, precision–recall curves are often interpolated, by assigning each recall value the maximum precision value that can be found to the right side of it. After the interpolation, the AP is determined by sampling a fixed number of precision values at uniformly and linearly spaced recall intervals (see Figure 16) and calculating their average.

Ultimately, the mAP is the mean of multiple APs that result from the use of different IoU thresholds, usually in the range from 50 to 90% with increments of 5% [27].

### 4.1.1. Baseline

As starting point for the architecture design, it was necessary to establish baselines, against which all subsequent experiments could be evaluated. For the evaluation at hand, two such baselines were established:

1. A default Mask R-CNN implementation without input augmentation (see Section 3.3.3).
2. A basic FibeR-CNN implementation without mask segmentation head (see Section 3.1.3), keypoint ordering (see Section 3.3.2), input augmentation (see Section 3.3.3) or error correction (see Section 3.4.2).

Wherever possible, common hyperparameters (e.g. batch size) of the two baseline models were set to identical values to maximize the comparability between both models.

In Figure 17, the APs of the Mask R-CNN and the FibeR-CNN baseline models are being compared. The performance of
both models is quite similar with respect to mAP, with the Mask R-CNN model slightly outperforming the FibeR-CNN model. Interestingly, FibeR-CNN performs better than Mask R-CNN for higher IoU thresholds, while Mask R-CNN performs better than FibeR-CNN for lower IoU thresholds.

### 4.1.2. Mask Segmentation Head

As first addition, a mask segmentation head was added to the baseline FibeR-CNN model.

As can be seen in Figure 18, this does hardly affect its performance. However, the mask segmentation head was kept for the subsequent experiments, to allow the use of error detection and correction (see Sections 3.4 and 4.1.5).

### 4.1.3. Keypoint Ordering

As next addition, keypoint ordering according to the “top to bottom, left to right” rule, stated in Section 3.3.2 was implemented and evaluated.

Figure 19 depicts a comparison of the APs, resulting from the evaluation. Keypoint ordering significantly improves the performance of FibeR-CNN, so that for the first time, it is able to surpass the Mask R-CNN baseline model’s APs for all tested IoU thresholds.

The reason for this effect is presumably, that the start and end points of fibers are too similar to be distinguished, based on the intensity gradients in the input images alone. This leads to situations, where FibeR-CNN chooses an end point of a fiber as both start and end point, which leads to large errors with respect to the AP, as explained in Section 3.4 and illustrated in Figure 13. Therefore, it is essential to ensure a spatially consistent keypoint order, so that FibeR-CNN can make use of additional spatial information in the image.

### 4.1.4. Input Augmentation

As third extension, input augmentation was added to the FibeR-CNN architecture. Since Mask R-CNN can usually profit from input augmentation, it was also added to the baseline Mask R-CNN model (see Section 4.1.1), to maintain fairness with respect to the model comparison (see Figure 20).

Both Mask R-CNN and FibeR-CNN profit from the use of input augmentation. However, for FibeR-CNN the effect is more distinct, thereby making its APs surpass those of Mask R-CNN even further than with the previous model version.
4.1.5. Error Correction

As fourth and final extension to the FibR-CNN architecture, error correction was tested (see Section 3.4.2). As expected, error correction yields increased APs (see Figure 21). However, the improvement is rather small and comes at a high computational cost (see Section 3.4.2). The reason for the minor effect of the error correction is that the predictions quality of the FibR-CNN architecture without error correction is of rather binary nature: it is either excellent or bad, but much less often mediocre. Consequently, excellent results are hardly improved by the error correction, because there are only few errors. Bad results, however, are not improved enough to advance into the territory of IoU ≥ 50 % and are therefore – even with error correction – still not factored into the surveyed quality metrics.

4.1.6. Summary

Figure 22 summarizes the APs of all tested Mask R-CNN and FibR-CNN model variants. By systematically improving the FibR-CNN architecture, its mAP, AP50 and AP75 were increased by 14 pp (95 % CI = 12, 15 pp), 20 pp (95 % CI = 15, 25 pp) and 16 pp (95 % CI = 15, 17 pp) respectively, compared to the FibR-CNN baseline model. With these improvements, its mAP, AP50 and AP75 surpass those of the best tested Mask R-CNN model by 11 % (95 % CI = 10, 13 %), 12 % (95 % CI = 6, 18 %) and 18 % (95 % CI = 17, 19 %) respectively.

The final version of FibR-CNN, which was used for all subsequent experiments, included all presented extensions, i.e. a mask segmentation head, keypoint ordering, input augmentation and error correction.

4.2. Training Data Supplementation

For many applications, the accuracy of CNNs scales excellently with an increasing training data set size. Therefore, it was examined, whether the supplementation of the training data with synthetic images ([?l] +?c] +?o] synth.; see Section 2.1.3 and Table 1) was beneficial for the APs achieved by FibR-CNN.

Figure 23 compares the APs of FibR-CNN with and without training data supplementation. Within the margin of error, training data supplementation does not have any influence on the APs of FibR-CNN.

4.3. Lazy Annotation

Apart from trying to improve the performance of FibR-CNN by using synthetic images, just like semiautomatic annotation (see Section 2.1.2), they may also be used to circumvent the need for a manual annotation. Naturally, it is to be expected that the resulting APs will be lower than those achieved with the complete set of real training data used before. Nevertheless, it is interesting to examine what APs can be achieved with a “lazy” annotation.

Figure 24 compares the APs of FibR-CNN, trained with only synthetic data ([?l] +?c] +?o] synth.), only semiautomatically annotated data ([?l] +?c] +?o] auto.) and a combination of both.

The FibR-CNN model, trained only on synthetic data, yields a poor performance in comparison to the other tested models. This supports the supposition that the utilized synthetic images lack the necessary realism.

While better than only synthetic data, the use of only semiautomatic data still falls short of the use of the complete set of real training data, available for this publication. This observation is indeed plausible, because only fibers with simple shapes and neither loops, clutter nor overlaps can be annotated semiautomatically. Therefore, the set of semiautomatically annotated images does not cover the domain of the utilized test data sufficiently.

This also explains, why the combined set of both “laizily” annotated data sets performs slightly better than its individual components: While the semiautomatically annotated set contributes the necessary realism, the synthetic data set contributes the necessary complexity. However, also the combined data set still lacks the quality of the complete set of real training data.

4.4. Application

While the previous two sections concentrated on ways to improve the precision of FibR-CNN or to reduce the effort to manually produce annotations, this section will discuss what tasks FibR-CNN can be used for, how good it performs on these tasks and what possible inhibiting factors for a successful application to real world problems are.

4.4.1. Detection Quality

To get a first, qualitative impression on the capabilities of FibR-CNN, it is helpful to visually inspect a selection of example detections. Figure 25 shows four randomly chosen detections for each of the six test data sets (see Section 2.2).

Fibers with neither loops, clutter nor overlaps ([?l] +?c] +?o]) and ([?l] +?c] +?o] auto.) are not challenging for FibR-CNN and even fibers that could not be segmented semiautomatically, are detected reliably. Also, the presence of clutter ([?l] +?c] +?o]) or a combination of both ([?l] +?c] +?o])
does not impede the detection quality too much, as long as the degree of instance-instance or instance-clutter overlap is not too high and the size difference between overlapping fibers is not too small.

Contrarily, loops ([+1|?c|?o]) pose a greater challenge for FibeR-CNN, especially, when being combined with overlaps and clutter. Still, some loops can be detected flawlessly by FibeR-CNN.

### 4.4.2. Mean Average Precision

Figure 26 depicts the mAPs achieved by FibeR-CNN for each of the real test data sets. Just as indicated by the example detections presented in Section 4.4.1 (see Figure 25), loops ([1|c|+o]) pose the largest challenge to FibeR-CNN, while individual, isolated fibers ([1|c|o] and [1|c|o]auto) are much less problematic. Furthermore, the presence of clutter ([1|c|o]) impedes the mAP less than the presence of overlaps ([1|c|+o] and [1|c|+o]).

### 4.4.3. Fiber Width and Length Measurement

One way to evaluate the abilities of FibeR-CNN for applications featuring the measurement of fiber widths and lengths, is to carry out an instance based accuracy assessment, i.e. that predictions errors of the fiber width and length are determined for each instance. To perform this analysis, it is necessary to match predicted instances with ground truth instances. As criterion for this matching process the bounding box IoU was used, with an IoU ≥ 0.5 indicating a match. After the matching, the percentage error $\Delta y_{\%}$ for each match can be calculated:

$$\Delta y_{\%} = \frac{y_i - t_i}{t_i} \cdot 100\%,$$

where $i$ is the instance index, $t$ is the target value as determined via manual analysis and $y$ is the prediction of FibeR-CNN.

To characterize the prediction errors across multiple instances, e.g. across a complete data set, the mean absolute percentage error (MAPE) can be used, which is defined as [29]:

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} |\Delta y_{\%}|,$$
Figure 25: Example detections for each of the real test data sets (+/−/?: yes, no, random; l/c/o: loops, clutter, overlaps).
where $i$ is the instance index and $n$ is the number of dates, i.e. instances.

To reflect the requirements of different applications, two possibilities to handle non-matched instances were examined:

- **strict**: Non-matched instances were accounted for with $\Delta Y_{\text{st}} = 100\%$. This definition should be used for security-relevant applications and applications where the focus lies on the reliable detection of individual fibers (e.g. workplace risk assessments).

- **loose**: Non-matched instances were accounted for with $\Delta Y_{\text{lo}} = 0\%$. This definition can be used for non-security-relevant applications or applications where the fiber width or length distribution of an ensemble is of greater interest than the detection of individual fibers.

Figures 27 and 28 show the **strict** and **loose** MAPEs of FibeR-CNN with respect to the fiber width and length prediction, respectively, for the different real data subsets. In general, the fiber width prediction is more accurate than the fiber length prediction. In agreement with the analysis of the fiber mask prediction accuracy (see Sections 4.4.1 and 4.4.2), also for the fiber width and length prediction, fibers featuring neither loops, clutter nor overlap ([[-1|-c|o] and [-1|-c|o]auto) are least challenging. Interestingly, while loops ([+l|?c|?o]) are hardest for FibeR-CNN with respect to the fiber mask and length prediction, they are much easier with respect to the fiber width prediction. This observation is indeed plausible, considering the fact that for a fiber with a constant width, a partial understanding of the fiber structure suffices to make a correct prediction, while for the correct fiber length prediction, it is necessary to understand the fiber’s structure as a whole.

Another important factor with respect to the application of FibeR-CNN to fiber width and length measurement tasks, is its ability to reconstruct the underlying length and width distributions of an ensemble of fibers. Figures 29 and 30 compare the fiber width and length distributions of the ensemble of all real test data sets to the respective predictions of FibeR-CNN.26

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26 For the histogram creation, each prediction was weighted with its object-
Both the fiber width and the fiber length distribution are reconstructed accurately by FibeR-CNN, with no significant biases towards individual size classes. As indicated by the previous studies conducted within this section, the fiber width prediction is more reliable than the fiber length prediction. To quantify the accuracy of the prediction of fiber width and length distributions by FibeR-CNN, the Kullback–Leibler divergence – a common measure for the divergence of two probability distributions $P$ and $Q$ – can be used [30]:

$$D_{KL}(P \parallel Q) = \sum_x P(x) \log \left( \frac{P(x)}{Q(x)} \right),$$

(11)

where, for the case at hand, $Q$ and $P$ are the probability distributions of the predicted fiber widths (or lengths) and the associated ground truths, respectively.  

The Kullback–Leibler divergence yields values which range from 0 for identical to 1 for completely diverging probability distributions.

For the probability distributions at hand, Equation (11) yields the following Kullback–Leibler divergences:

- Fiber width: $D_{KL} = 0.006$
- Fiber length: $D_{KL} = 0.031$

both of which indicate extremely high degrees of similarity and further support the hypothesis that FibeR-CNN can predict fiber widths more reliably than fiber lengths.

5. Conclusion and Outlook

Within this publication, the well-known Mask R-CNN architecture was extended to yield an improved method for image-based fiber analysis. To do so, it was combined with a keypoint regression head, originally used for human pose estimation, to identify the “spine” of the analyzed fibers and supplemented with two novel heads for fiber width and fiber length predictions.

For the training and validation of the new architecture, a large data set of more than 1650 annotated SEM images, featuring approximately 2600 CNTs, divided into six subsets of varying difficulty, was used. With semiautomatic annotation and image synthesis, two possibilities to supplement the manually annotated data – or even avoid the laborious task of manual annotation as a whole – were explored. Unfortunately, neither of these strategies did yield APs comparable to those achieved with manually annotated data. Improved methods for the creation of more realistic synthetic training data may therefore be explored in the future.

The design of the novel FibeR-CNN architecture was optimized systematically, following an additive approach. Starting with a most basic implementation, the architecture was enhanced stepwise and reevaluated after each addition, based on the APs achieved on a test set of 401 fibers. The largest improvements were achieved by the introduction of a systematic ordering of ground truth keypoints during the training and the utilization of input augmentation. While the introduction of keypoint pruning as an error correction mechanism resulted in a significant improvement, it was not as beneficial as initially anticipated. Therefore, the study of other error correction strategies is advisable for future research.

In the course of the architecture design, the mAP was improved considerably, compared to both the FibeR-CNN and the Mask R-CNN baseline model.

To find possible weak spots and examine possible ways to improve FibeR-CNN in the future, its mAP was determined for a number of test data sets, featuring different kinds of inhibiting factors (overlap, clutter and loops). The evaluation showed that loops and large amounts of fiber overlap are especially challenging for FibeR-CNN. Future research should therefore concentrate on these types of fibers.

Unlike Mask R-CNN, FibeR-CNN can not only be used for the instance segmentation of fiber images but also for the prediction of fiber width and length distributions. The evaluation,
based on the complete set of available test data, yielded excellent reconstruction capabilities with respect to the underlying fiber width and length distributions, with the predicted fiber length and width probability distributions featuring only small deviations from the associated ground truths.

All in all, the FibeR-CNN architecture provides an effective tool for automatic image-based fiber shape analysis. It is likely that future research concerning FibeR-CNN in particular and R-CNN architectures in general will improve its reliability and precision even further.

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No carbon dioxide was emitted due to the training of neural networks for this publication, thanks to the use of renewable energy.

Acronyms

| Acronym | Description |
|---------|-------------|
| AP      | average precision |
| BIC     | Bayesian information criterion |
| CI      | confidence interval |
| CNN     | convolutional neural network |
| CNT     | carbon nanotube |
| COCO    | Common Objects in Context |
| CPU     | central processing unit |
| CT      | curvete transform |
| FIRE    | fiber extraction |
| FN      | false negative |
| FP      | false positive |
| GPU     | graphics processing unit |
| IoU     | intersection over union |
| mAP     | mean average precision |
| MAPE    | mean absolute percentage error |
| MSE     | mean squared error |
| SSR     | sum of squared residuals |
| R-CNN   | region-based convolutional neural network |
| ReLU    | rectified linear unit |
| ROI     | region of interest |
| SEM     | scanning electron microscope |
| SGDM    | stochastic gradient descent with momentum |
| SSR     | sum of squared residuals |
| synthPIC | synthetic particle image creator |

Symbols

| Symbol | Description |
|--------|-------------|
| $\alpha_{\text{base}}$ | base learning rate |
| $\text{AP}_{\text{50}}$ | average precision at IoU = 0.5 |
| $\text{AP}_{\text{75}}$ | average precision at IoU = 0.75 |
| BIC | Bayesian information criterion |
| $\Delta_{\text{Vig}}$ | percentage error |
| $D_{\text{KL}}$ | Kullback–Leibler divergence |
| $i$ | index |
| IoU | intersection over union |
| $j$ | index |
| $k$ | number of keypoints |
| $L$ | overall loss |
| $L_{\text{box}}$ | bounding box regression head loss |
| $L_{\text{cls}}$ | instance classification head loss |
| $L_{\text{fl}}$ | fiber length regression head loss |
| $L_{\text{fw}}$ | fiber width regression head loss |
| $L_{\text{kp}}$ | keypoint regression head loss |
| $L_{\text{mask}}$ | mask segmentation head loss |
| mAP | mean average precision at IoU = 0.5:0.05:0.95 |
| MAPE | mean absolute percentage error |
| MSE | mean squared error |
| $n$ | number of dates |
| $P$ | probability distribution |
| $Q$ | probability distribution |
| SSR | sum of squared residuals |
| $r$ | target |
| $w_{\text{fl}}$ | weight of the fiber length regression head loss |
| $w_{\text{fw}}$ | weight of the fiber width regression head loss |
| $y$ | prediction |

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Algorithm A.1 Keypoint pruning algorithm.

Input: keypoints  
> fiber keypoints, as predicted by the keypoint regression head
Input: fiber_width  
> fiber width, as predicted by the fiber width regression head
Input: fiber_length  
> fiber length, as predicted by the fiber length regression head
Input: mask  
> fiber mask, as predicted by the mask segmentation head

1: function PRUNEKEYPOINTS(keypoints, fiber_width, fiber_length, mask)
   2: number_of_keypoints ← GetNumber(keypoints)
   3: spline_mask ← GetSplineMask(keypoints, fiber_width)  
> spline fit through keypoints with width fiber_width
   4: iou ← CALCULATEIoU(spline_mask, mask)  
> intersection over union
   5: spline_length_error ← GETSPLINELENGTHERROR(keypoints, fiber_length)  
> see Line 24
   6: segments ← GETSEGMENTS(keypoints)  
> list of pairs of adjacent keypoints
   7: segments ← ORDERSEGMENTSBYLENGTH(segments)  
> misplaced keypoints cause long segments; should be checked first
   8: for segment in segments do
      9:   for keypoint in segment do
     10:      keypoints_new ← REMOVEKEYPOINT(keypoint, keypoints)
     11:      spline_mask_new ← GetSplineMask(keypoints_new, fiber_width)
     12:      iou_new ← CALCULATEIoU(spline_mask_new, mask)
     13:      spline_length_error_new ← GETSPLINELENGTHERROR(keypoints_new, fiber_length)  
> see Line 24
     14:      if iou_new ≥ iou and spline_length_error_new ≤ spline_length_error then
           15:         keypoints ← keypoints_new
           16:         spline_mask ← spline_mask_new
           17:         iou ← iou_new
           18:         spline_length_error ← spline_length_error_new
     19:      go to Line 7  
> start over with improved keypoints
     20:   end for
     21: end for
     22: keypoints ← UNIFORMSPLINEINTERPOLATION(keypoints, number_of_keypoints)  
> restore original number of keypoints
   23: return keypoints

24: function GETSPLINELENGTHERROR(keypoints, fiber_length)
   25: spline_length ← GETSPLINELENGTH(keypoints)  
> integrate length of spline fit through keypoints
   26: return |1−spline_length/fiber_length|

Table A.1: Relevant hardware of the utilized GPU server.

| Mainboard       | Supermicro X11DPG-QT |
|-----------------|---------------------|
| CPU             | 2 x Intel Xeon Gold 5118 |
| GPU             | 4 x NVIDIA GeForce RTX 2080 Ti |
| RAM             | 12 x 8 GB DDR4 PC2666 ECC reg. |
| SSD (OS)        | Micron SSD 5100 PRO 960 GB, SATA |
| SSD (data)      | Samsung SSD 960 EVO 1 TB, M.2 |

Table A.2: Relevant software of the utilized GPU server.

| OS (host)       | Ubuntu 18.04.3 LTS |
|-----------------|-------------------|
| OS (docker)     | Ubuntu 18.04.3 LTS |
| Python (docker) | 3.6.9             |
| PyTorch (docker)| 1.4.0             |

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