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Abstract of the bachelor thesis with the title:

Development of a KI-supported process monitoring using machine learning to detect fiber damage in the oxidation process

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1 Abstract

With a global carbon fiber demand of 92,000 tons in 2021 and a compound annual growth rate (CAGR) of 9.77%, carbon fiber is the driver for innovative products in lightweight industries such as aerospace and wind power [SS22]. The use of carbon fiber as a reinforcing element offers enormous lightweight construction potential [JH10]. Carbon fibers have very high tensile strengths of up to 7.5 GPa and Young's moduli of up to 900 GPa at a ring density of 1.8 g/cm³ [GVW19].

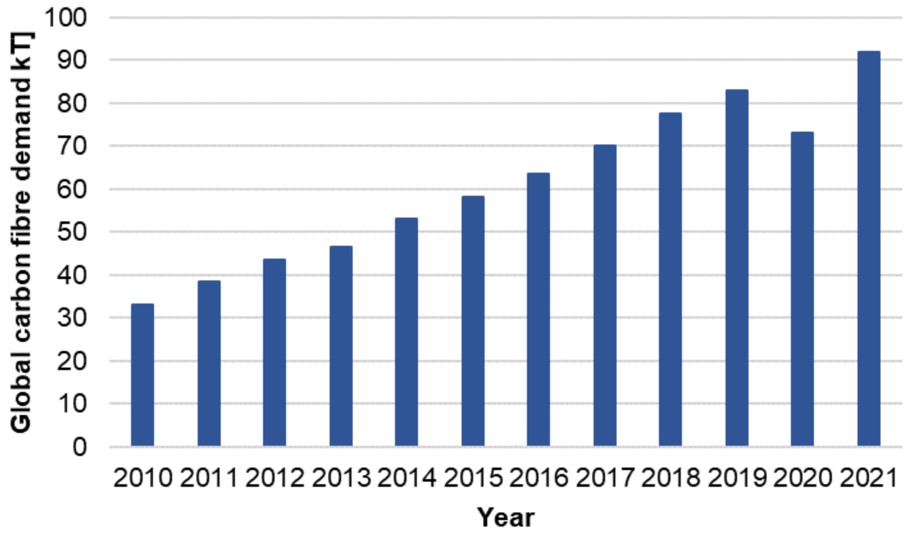

Fig. 1: Global carbon fiber demand from 2010 – 2021 [SS22]

In the field of fiber production, carbon fiber manufacturing is considered one of the most complex, but also most conservative processes. During production, up to 300 fiber strands of individual filaments are chemically converted simultaneously [FSI+14]. The strong exothermic reactions must be carried out as economically as possible without damaging the fiber or even causing fiber burn. At present, monitoring is only carried out optically by specialist personnel. Despite large safety factors in the process design, purely manual monitoring isn't sufficient. Plant failures and fiber fires are the results. In addition, fiber pieces with minor fiber defects are often not noticed by personnel and thus reach the end customer. However, carbon fibers can only develop their full potential if they aren't damaged during production and subsequent processing.

In many areas of industrial manufacturing, automated and computerized control systems are already providing faster and more reliable production monitoring. Market analyses conducted by McKinsey & Company, New York, predict an increase in productivity of visual process monitoring of up to 50% by using artificial intelligence (AI) and advanced image recognition technology [BBR+17].

The aim of the present work is therefore the development of a system suitable for carbon fiber production to detect fiber defects in the process independently and to classify them with the help of an AI.

State of the art:

The manufacturing process of PAN-based carbon fibers is divided into three thermal production steps:

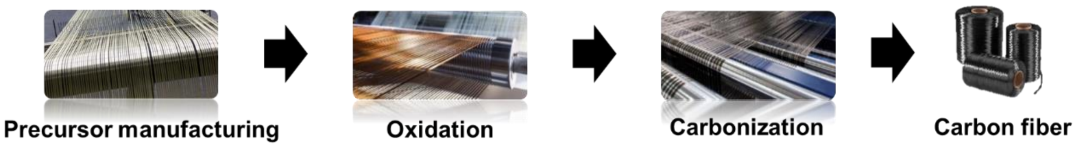

Fig. 2: Carbon fiber manufacturing

In a first step, a polyacrylonitrile fiber (PAN fiber) is spun out. In the subsequent oxidation stage, the PAN fiber is converted into a thermally stable state in several temperature zones from 200°C to 300°C, so that it can be carbonized at temperatures of up to 1500°C in the subsequent carbonization stage. In the production ovens, up to 300 fiber strands are converted simultaneously with a small distance between them [LMA19]. This is followed by the application of a sizing, which protects the fragile carbon fiber from damage during processing and increases the adhesion of the fiber with the matrix in the composite [JH10].

Oxidation of the PAN fiber is carried out in four to eight convection ovens, each with isothermal temperature profiles. The fiber is passed through the oven zones several times. The temperature of the individual zones is successively increased from approx. 200 °C to up to 300 °C [War14]. Visually, the color of the fiber changes from white to yellow and brown to black [LMA19]. In particular, the oxidation process step is considered to be the most crucial process step for successful carbon fiber production. The strong exothermic conversion reactions and the correct setting of the stretching require a high degree of process understanding and process control [FSI+14]. Incorrect parameter settings will result in fiber damage or equipment failure. Despite the higher temperatures of up to 1500 °C, carbonization is not very susceptible to failure and is easy to control [DDA90].

The process is monitored manually and visually by specialist personnel. Due to the size of the ovens and many fiber strands, fiber defects often cannot be identified at an early stage in industrial production. This results in severe fiber damage, which can lead to plant downtime. To optimize the process in the most resource-saving and economical way, automated visual process monitoring is unavoidable.

In the context of advancing digitization and automation, artificial intelligence (AI) can be integrated into industrial production processes [SN18]. Machine learning (ML) is the best-known subfield of artificial intelligence and pursues the goal of intelligently linking data, recognizing correlations in data sets and making predictions based on this [LEH+17]. In the field of visual object detection, computer vision can extract meaningful information from digital images, videos, and visual inputs. The basic goal of computer vision is to mimic human vision by using camera systems to automatically complete predefined tasks [LPK+20]. Artificial intelligences are integrated into production processes according to the concept of intelligent augmentation to optimize productivity, quality, and efficiency [BPO19]. These processes form the basis for energy- and resource-saving production in industrial companies and are important for operating economically and remaining competitive [HGA+21].

Solution approach:

The aim of the bachelor thesis is the development of an automated optical monitoring system for carbon fiber production. The oxidation, which is difficult to control, is initially selected as the relevant monitoring area. The application-related methodology for implementing visual monitoring in the carbon fiber manufacturing process is visualized in Figure 3.

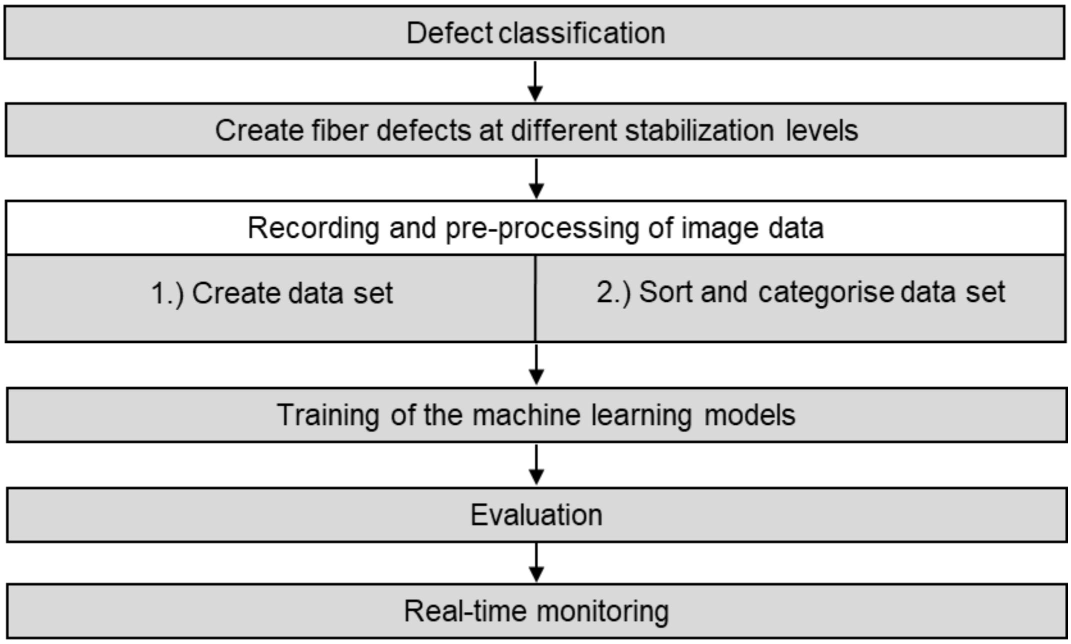

Fig. 3: Methodical procedure

Based on literature research and in consultation with experts in the field of carbon fiber production, different defect classes are selected, which can also occur in the oxidation process under real conditions. Then PAN fibers of different oxidation states are marked with defects and images of the fiber in the process are taken. It is then necessary to sort and categorize the image data according to their defect category. The resulting image data set is divided into a training, validation and test data set. The machine learning models are trained based on training data and evaluated on the basis of validation and test data. Finally, the most accurate ML model is integrated into carbon fiber manufacturing process.

Create image database:

To take the image of the PAN fiber, the fiber guide is slightly changed and a camera is installed outside the oxidation oven. The setup of the camera system and the fiber guide is shown in Figure 4.

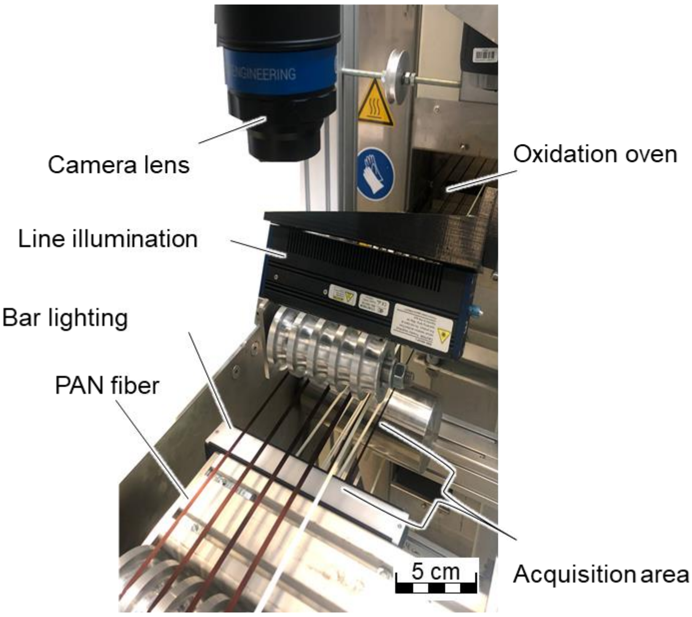

Fig 4: Assisting System in carbon fibre manufacturing

Afterward, it is necessary to assign a defect to fibers of different oxidation states and to classify them. The classification is necessary to train the algorithm to the predefined defect classes. The underlying error catalog consisted of five fiber defects and one defect-free fiber as a reference for the ML models (see Fig. 5). The error classes are:

1. Error-free
2. Light damage
3. Severe damage
4. Constriction
5. Splitting
6. Trembling

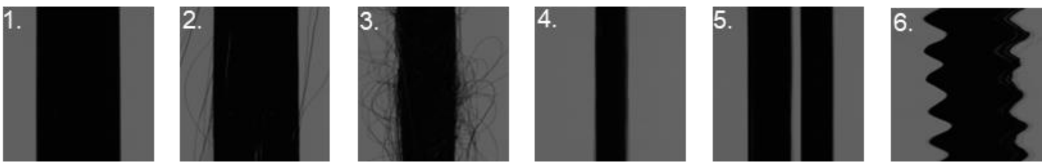

Fig. 5: Image recording of the different error classes

The division of the image captures are subdivided into a training, validation and test data set according to the general methodology of machine learning. The set of training images is set to 60%, the validation dataset is set to 30% and the test dataset is set to 10%. In total, four different image data sets are assembled to capture different oxidation states. The first image dataset depicts only oxidized black fibers. The second image database is composed of about 6,000 images and contains only white precursor fibers. The third image dataset is a combined dataset of about 12,800 images. This doesn't differentiate between the oxidation state and is sorted by error category only. The fourth image dataset distinguishes between the oxidation state of the PAN fiber in addition to the known six error classes and is intended to allow a subdivision between oxidized black fibers and white PAN-fibers.

Four different ML models are used to detect and classify the fiber defects, which have been specifically designed for object detection applications and can extract relevant identification features from the image frames. Although all four models have been tested and evaluated, the focus is on the ResNet-50 and VGG16 models due to their higher performance.

Model training:

Model training is based on supervised learning. In this process, the group into which an image acquisition is to be classified is determined in advance. During the training phase, the algorithms recognize special features of the error classes to enable the assignment of unknown image data. The training phase of the machine learning models comprises a total of 50 epochs. In each epoch, the algorithm performs a change of parameters and records the difference between the predicted classification and the actual classification, the loss factor. The loss factor becomes small when the predicted classification is close to the specified classification. After performing the specified epochs, the algorithm adopts the parameter configuration with the smallest error deviation.

Model evaluation:

The evaluation of the trained machine learning models is based on the validation and test data. According to the principle of machine learning, the validation data is used to verify the trained models against unknown image data. The model testing phase is considered as the last instance of performance evaluation of the used ML models and is a crucial procedure to test the performance of the trained ML models before integrating them into production workflows.

The performance of the algorithm used can be evaluated using different performance metrics. The most important metrics in the field of classification are Accuracy and Precision. Accuracy defines the precision of the classification and indicates the percentage of correct predictions of a model. Precision, on the other hand, indicates the accuracy of a single classification class.

To obtain the accuracy, the correct predictions, true positive (TP) and true negative (TN), are divided by the total number of all predictions made. False positive (FP) and false negative (FN) are misclassified predictions of the model.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Precision measures the ratio of positively assigned classifications to the total number of positive assignments.

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

Oxidized PAN fibers of the validation data set are correctly classified by the ResNet-50 with a recognition accuracy of over 99.9%. The VGG16 model correctly recognizes all image data of the validation set and achieves an accuracy of 100%.

White Precursor fibers are detected by the ML models with lower detection accuracy. The ResNet-50 model achieves 99.4% accuracy in the validation phase, while the VGG16 model achieves 99.2% accuracy. The color change of the fiber only slightly affects the accuracy of the models.

The combined image data set without identification of the oxidation state classifies the unknown validation data with an accuracy of 99.6% for the ResNet-50 and 99.4% for the VGG16. The values in the validation phase of the combined image data set are comparable to the accuracies for white Precursor fibers but achieve lower accuracies than the accuracy for oxidized black fibers.

With an accuracy of 99.6% for the ResNet-50 model and the VGG16 model, the recognition rates of the combined image dataset in the validation phase are almost identical to the combined image dataset with the advantage of distinguishing the oxidation state.

The evaluation of the validation data shows high accuracies in error classification of over 99% for each configuration. In particular, the VGG16 model for the oxidized fiber data set stands out with a detection accuracy of 100% and provides the highest detection accuracy for oxidized fibers. For white fibers, the ResNet-50 model achieves the best results in the validation phase with an accuracy of 99.4%. For the combined image data set without identification of the oxidation state, the ResNet-50 model achieves high detection rates with an accuracy of 99.6%. Also the extension of the oxidation state of the fiber confirms the high accuracies for the ResNet-50 and VGG16 models with an accuracy of 99.6 % each. Due to the high assignment accuracies, the used models describe an accurate approach for AI-assisted visual process monitoring in carbon fiber manufacturing.

The final test phase confirms the results of the validation phase. For oxidized fibers, the VGG16 model achieves the highest detection accuracy with an accuracy of 100 %. For white precursor fibers, the ResNet-50 model is the most reliable with an accuracy of 99.4%. The combined image dataset is classified in the test phase by both machine learning models with an accuracy of 99.3 %. When the combined dataset is extended to include the distinction of the oxidation state, the VGG16 model achieves the highest accuracy of 99.6 %. Figure 6 summarizes the results of the ResNet-50 and VGG16 models in the test phase.

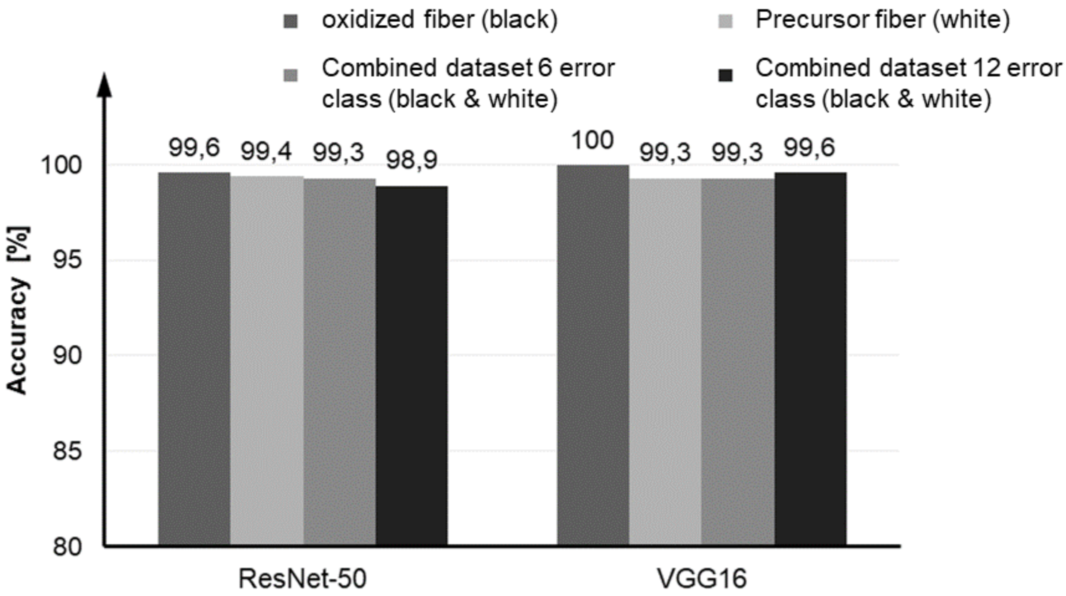

Fig. 6: Accuracy of test data set

In summary, the highest detection accuracy for black fibers can be achieved with the VGG16 model at 100%. To represent the holistic process, the VGG16 model is the best choice in the fourth model configuration and achieves high accuracies for oxidized and non-oxidized fibers. With an accuracy of 99.6 %, the model achieves high assignment accuracies in the test phase. The decisive advantage of this configuration is that the monitoring of the entire oxidation process can be realized with one model and the integration into the process is simplified. The relevance of the installation position of the visual monitoring in the oxidation process is eliminated, thus avoiding application problems.

Process integration:

The process integration is realized in cooperation with our industrial partner Heinen Automation GmbH & Co. KG. As part of the process integration, machine learning algorithms are adapted to classify defects in the PAN fiber in the oxidation process. The main difference to the models used so far is that the images aren't pre-classified. The algorithm classifies unknown images based on learned models. For this reason, no known evaluation metrics can be used to evaluate the assignments.

The algorithm used is adapted to classify unknown images based on prediction. The algorithm assigns a previously defined and learned defect class to each input image based on known defect characteristics. To make the complete decision processes of the classification more comprehensible for the user, as well as to identify uncertainties and a decreasing fiber quality, an output of the defined probabilities is required. For this purpose, the algorithm is optimized to output the class-specific assignment probability in addition to the defect class. An exemplary classification output with a probability output is visualized in table 1.

Tab. 1: Classification output

filename	**prediction**	Error-free [%]	Light damage [%]	Severe damage [%]	Constriction [%]	Splitting [%]	Trembling [%]
image_1.bmp	Error-free	92,92	6,68	0,11	0,12	0,07	0,11
image_2.bmp	Error-free	95,85	3,88	0,07	0,09	0,05	0,07

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