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MACHINE LEARNING BASED IDENTIFICATION AND PRIORITIZATION OF ELECTRICAL CONSUMERS FOR ENERGY MONITORING

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Abstract

This paper presents a machine learning based tool for the automated analysis of circuit diagrams, identifying electrical consumers through computer vision. Detected technical information is extracted and summarized in a report. In a web-based interactive dashboard the identified consumers are prioritized for further actions. Based on their nominal power an ABC-analysis classifies the consumers into three groups. Within an energy portfolio they are divided into four distinctive categories. In both approaches the consumers' classification leads to specific strategies for energy consumption measurements in the subsequent detailed analysis.

Keywords:
Energy transparency; computer vision; decision support

1 INTRODUCTION

Due to rising energy costs, companies are facing the challenge of taking optimization measures to minimize the energy consumption of their production machines. Since 2022, the rise in energy prices in Germany has been further exacerbated by the geopolitical conflicts and the decisions to withdraw from Russian gas and oil. [German Association of Energy and Water Industries (BDEW) 2022] With the industry sector requiring around 45 % of Germany's electricity, companies also have a particular obligation to increase their energy efficiency and thus contribute to the transition to a climate-neutral economy [German Association of Energy and Water Industries (BDEW) 2021].

The lack of energy transparency is one of the main barriers to the successful implementation of energy efficiency measures. As a result, energy demands are not measured or known, and energy costs are not broken down to single cost centers based on the origin of effective energy utilization. Therefore, there is a strong need for appropriate methods and tools to support individual decision makers to implement energy efficiency measures through greater transparency. However, energy transparency is associated with personnel and investment efforts, and therefore requires appropriate strategies for decision support to prioritize metering points. [Posselt 2016]

Several analysis methods exist to identify hotspots in terms of energy use and energy efficiency in order to support the selection of promising metering points. However, these methods require time for initial skill adaption training and execution. [Weyand 2022] Furthermore, specific quantification of individual efficiency measures have the requisite of transparency on the unit process level. This requires meters to be directly attached to single machine components. [Kara 2011] Doing so demands expertise and time to analyze electrical circuit diagrams, and to extract information such as single components of the machine and associated technical information [Ioshchikhes 2022].

Against this background, this paper presents a machine learning based tool for automated circuit diagram analysis, to identify electrical consumers and prioritize them for measurements by applying different methods. Following this paper's introduction, Section 2 presents the fundamentals of electricity metering, electrical circuit diagrams, computer vision for reading electrical circuit diagrams, and different hot spot methods for prioritizing electrical consumers for further actions. Section 3 covers the overall method and its implementation in Python. The evaluation of the tool with an exemplary use case is provided in Section 4. Finally, a conclusion and outlook are given in Section 5.

2 FUNDAMENTALS

This section presents the fundamentals of electricity metering, electrical circuit diagrams, computer vision for reading electrical circuit diagrams, and different hot spot methods for prioritizing electrical consumers for further actions.

2.1 Electricity Metering

A basic prerequisite for achieving energy transparency in complex energy distribution networks in manufacturing is to measure, interpret, and visualize the consumed energy [Kara 2011].

Since the electricity consumption of the industrial sector accounted for about one third of the total industrial energy consumption in the European Union in 2020, it represents an important lever for improving energy efficiency [European Union 2022]. Furthermore, electrical energy can be converted into other forms of energy, such as mechanical torque, light, compressed air and many others, and can be metered with comparatively little effort [Kara 2011; Posselt 2016]. Metering electrical energy provides greater energy transparency, leading to potentially greater benefits at the cost of increased personnel and investment efforts [Posselt 2016]. Thus, to maximize the potential benefits and keep the measurement effort to a minimum, the following sections cover the fundamentals with which promising electricity consumers can be prioritized for metering.

2.2 Circuit Diagrams

According to [DIN ISO 1219-2:2019-01] circuit diagrams are defined as an aid to facilitate the understanding of the design and description of installations so that, by having unified representations, confusion and error can be avoided during planning, manufacturing, installation and maintenance. Circuit diagrams can be created individually or according to company-specific requirements. As a rule, however, nationally or internationally applicable standards are taken into account. These standards are, among others, developed by the German Institute for Standardization (DIN) and the International Organization for Standardization (ISO). The size and layout of preprinted technical drawings are specified in the international standard [DIN EN ISO 5457:2017-10]. The preferred sizes are A0 to A4 from the ISO-A series. For fast location of details, the sheets are subdivided by a grid reference system marked with capital letters (except I and O) from top to bottom and with numbers from left to right [DIN EN ISO 5457:2017-10]. The number of reference fields depends on the size of the drawing sheet. Title block formats containing information about the legitimate owner, the date of issue, or the title are, for example, defined by ISO 7200 [DIN EN ISO 7200:2004-05], which simplifies the exchange of documents. For the preparation of documents used in electrotechnology, general rules and guidelines for the presentation of information, as well as specific rules for diagrams, drawings, and tables, are established in [DIN EN 61082-1:2015-10]. Depending on the purpose, there are different types of diagrams such as overview diagrams, functional diagrams, and circuit diagrams. In this paper, the term circuit diagram is used as a general expression for all types of diagrams in electrotechnology. Graphical symbols for electrical circuit diagrams are drawn according to DIN EN 60617 [DIN EN 60617-2:1997-08]. Non-electrical components within the circuit diagram comply with ISO 14617 [ISO 14617-1:2005-07]. Symbols shall be drawn in such a way that they represent the flow of current. If necessary, they may be rotated or mirrored, assuming that this does not change the meaning of the symbol [DIN EN 61082-1:2015-10]. Technical information related to a symbol is indicated directly next to it, either to the left or above the symbol [DIN EN 61082-1:2015-10].

2.3 Computer Vision

Computer vision (CV), or also called machine vision, deals with the reverse path of an image from reality into the computer [Priese 2015]. As a field of artificial intelligence (AI), CV enables systems to extract relevant information from digital images or other visual inputs and, based on that information, make recommendations or take actions [IBM 2023]. Therefore, theories and techniques of *image acquisition* and *storage*, *image processing,* and *image analysis* are applied. *Image acquisition* and *storage* include the technology of sensors and cameras, as well as the storage of the images in various image formats and compressions for cost-effective mass storage. *Image processing* and *image analysis* can be divided into the following steps: *image pre-processing*, *feature extraction*, *segmentation*, *analysis*, and *object detection*. However, the transition between *image processing* and *image analysis* is fluent and does not allow for a strict differentiation between the two terms. The step of *image pre-processing* is mainly focused on preparing the raw image for the subsequent automated analysis by applying linear and non-linear local filtering and image transformation, e.g., Fourier-Transformation without giving any information feedback on the image [Priese 2015; Khan 2018]. *Feature extraction* means the localization of significant spots in the image which are characterized, for example, by edges, corners, or specific geometric shapes like lines and circles. The step of s*egmentation* tries to identify areas in the image that belong together by similarity of the pixels. The definition of similarity, however, can vary depending on the task applied to. While the previous three steps belong more to *image processing*, o*bject detection* belongs to *image analysis* where machine learning and AI algorithms are applied to detect and classify specific objects based on their appearance in the image [Priese 2015; IBM 2023].

In the case of the machine learning based identification and prioritization tool presented in this paper, the primary goal is graphical recognition of electric motor symbols in circuit diagrams. Most systems for graphical symbol recognition are based on two major steps: *data acquisition and preprocessing* and *data representation and recognition*, while [Santosh 1999] points out that the two steps are strongly correlated.

Convolutional Neural Networks

Because of the success seen in deep neural network learning, techniques of deep learning are currently seen as state-of-the-art for the detection, segmentation, classification, and recognition of objects in images. Specifically Convolutional Neural Networks (CNN), a category of deep neural networks, are very effective in areas like image recognition and classification [Khan 2018]. Artificial Neural Network models are inspired by the workings of the human brain, and can be understood as tightly interconnected basic processing units, operating on the given input and its information to generate desired outputs [Khan 2018]. CNN represent one of the most popular types of neural networks for high-dimensional data such as images. CNN belong to the feed-forward networks, where information is processed only in one direction [Khan 2018]. These networks can be considered as a graph with neurons as its nodes, which are connected directly without cycles or loops [Khan 2018]. Since the graph is deep and has many layers, this approach is called deep learning, and the networks are called deep neural networks respectively [Goodfellow 2016].

Convolutional neural networks employ a specialized kind of linear operation called convolution instead of matrix multiplication, where every input unit interacts with every output unit and each interaction is described by a separate parameter of the parameter matrix. CNN, in contrast, have sparse interactions, which is accomplished by a weight function called kernel. A kernel can allow for the detection of small meaningful features, like edges, that are represented by much fewer pixels compared to the original input image. This leads to fewer parameters needing to be stored, as well as reduced memory requirements and computing operations, hence resulting in a large improvement in efficiency. [Goodfellow 2016]

Optical Character Recognition

Besides graphical symbol recognition, Optical Character Recognition (OCR) and Portable Document Format (PDF) text extraction are also applied by the machine learning based tool in this paper to recognize and identify relevant information about the electrical consumers in form of text and symbols in the circuit diagram. Optical character recognition is a method to convert printed or scanned text images as well as handwritten text into editable text for further processing. This enables machines to recognize text automatically. The accuracy of OCR mainly depends on algorithms for text preprocessing and segmentation. Developing computerized OCR systems is related to two main problems. First, letters and digits of similar shapes with few visual differences, like *0* and *O*, are difficult to differentiate between. Second, texts of different styles, orientations, and sizes, or texts that are embedded into a dark background, overlaid by graphics and other words, might be difficult to extract. [Patel 2012]

The OCR engine Tesseract [Kay 2007], which is used by the tool in this paper, is based on a step-by-step method. The first step, *adaptive thresholding*, is used to convert the image into a binary image. The second step, *connected component analysis*, extracts character outlines. The character outlines are then converted into organized text lines and regions to be analyzed and divided into words by definite spaces and fuzzy spaces. The recognition of words is finally processed in two consecutive passes. Each word successfully recognized in the text by the first pass is then passed to an adaptive classifier that recognizes text in a more accurate manner, by using words from the first pass as training data for continuous adaptation. [Smith 2007; Patel 2012]

PDF Text Extraction

The PDF file format represents documents independent of the operating system, software, and hardware they are created with, as well as of the output device they are displayed or printed on. The appearance of the pages of a PDF document are described by a collection of objects, which can be any combination of images, graphics, and text. Due to the inclusion of identification and logical structure information in a document, its contents can be searched and edited or extracted for further use. [Adobe Systems Incorporated 2006] The usage of software applications, like Adobe Acrobat [Adobe Systems Incorporated 2006], can make use of this higher level of information to allow for an interchange between the document's contents and other applications. [Adobe Systems Incorporated 2006] These features are used in the presented tool for text extraction from PDF-based circuit diagrams.

2.4 Hot-Spot Methods

In industrial practice, the issue of insufficient energy data availability is widespread, especially on machine and component levels. In order to obtain an initial overview of the energy flows with low effort, and to estimate the electrical energy utilization on machine and component levels, it is necessary to allocate the energy consumption to the individual production machines and their components. For this purpose, dimensioning information from nameplates and electrical circuit diagrams is used. With suitable methods, the aggregated information can then be visualized and analyzed, from which further decisions for metering strategies can be derived. [Metternich 2021]

This paper focuses on two comparative methods: the ABC-analysis [Thiede 2012] and the energy portfolio [Posselt 2016]. According to the ABC analysis, which is also known as Pareto analysis, consumers are sorted and grouped based on their nominal power. Group A includes the main consumers, which account for 80 % of the cumulative nominal power, but often represent only about 20 % of the machines considered. Group B covers consumers, which together with Group A account for 90 % of the cumulative nominal power. Group C includes the remaining consumers. [Thiede 2012] The advantage of this method is the comparatively low time input for initial skill adaption training and execution [Weyand 2022]. On the other hand, the disadvantage of the ABC analysis is that the utilization time and the degree of utilization are not included. As a consequence, machines with a high nominal load and a low rate of operation are overweighted in the ABC-analysis [Thiede 2012; Posselt 2016]. The energy portfolio extends the ABC-analysis by including the utilization time, and it further separates consumers into a matrix with four quadrants and thus four classes [Blesl 2013]. Based on these classes, metering point recommendations can be provided. Class I consumers are highly relevant for continuous metering, as they have a large leverage effect on the total energy balance due to their high nominal power and utilization time. Consumers with low nominal power and high utilization time, or with high nominal power and low utilization time, belong to Class II or Class III, respectively, and have a medium-high and accordingly medium-low relevance for continuous metering. Class IV includes consumers with comparatively low nominal power and utilization time, which are therefore not relevant for continuous metering. [Posselt 2016]

3 METHOD AND IMPLEMENTATION

The following section covers the overall method and implementation of the machine learning based tool for automated identification and prioritization of electrical consumers in circuit diagrams as a further development based on [Keller 2019].

3.1 Method

The architecture and the workflow of the machine learning based tool for automated identification and prioritization of electrical consumers in circuit diagrams consists of five modules grouped and separated by four program sequences. As visualized in the program flowchart in Fig. 1, these are:

- Initialization and PDF Conversion
- PDF Text Detection and Preprocessing
- Image Detection
- Logic

Circuit diagrams are typically available in various common image formats as well as PDF files. In a first step, the input data is converted into a uniform format in the **Initialization and PDF Conversion Module** in order to standardize and simplify the following operations and calculations. Accordingly, all image files are converted into the Joint Photographic Experts Group (JPEG) format. PDF files are also saved as JPEG files on a page-by-page basis. The

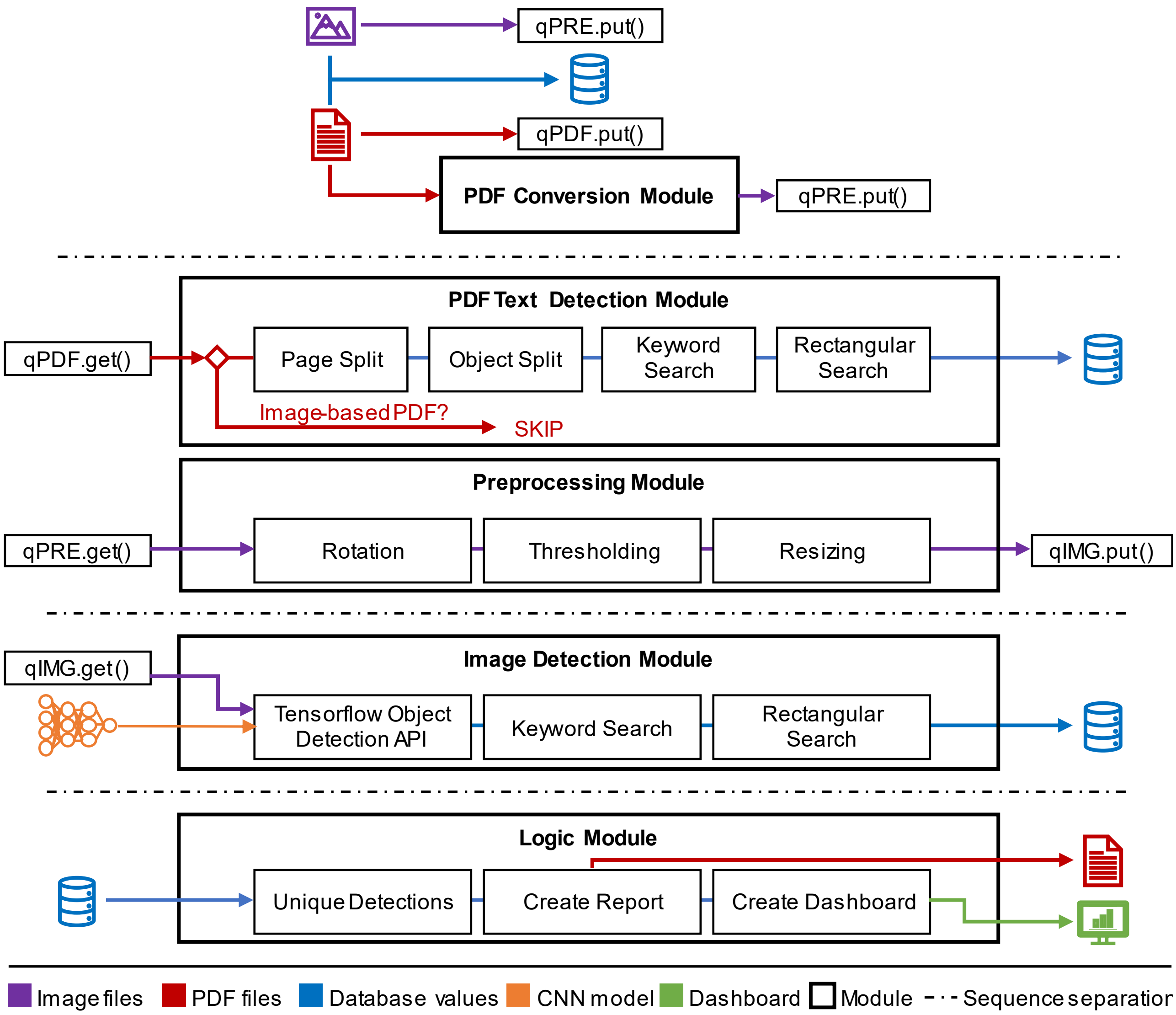

Fig. 1: Program flow chart (reading direction from top to bottom and from left to right).

reason for this is that the electric motor symbols are being implemented into text-based PDF files as graphical elements instead of text objects. Thus, they are only detectable by the Image Detection Module.

Circuit diagrams in the form of image files or image-based PDF files are created by scanning or photographing the original paper-based document. The quality of these files therefore depends on the quality of the creation of the files, as well as on the quality of the original document itself. Thus, the files are prepared for the object detection and the optical character recognition by the **Preprocessing Module** after conversion. First, rotations of twisted images against the horizontal axis are identified and corrected. Thresholding creates a binary image by converting pixels of grey scale images into black or white according to a threshold. The final step of the Preprocessing Module is the resizing of image files exceeding a predefined pixel length in order to reduce memory requirements and processing time.

In case of PDF files, the **PDF Text Detection Module** differentiates between text-based and image-based PDF files. The content of text-based PDF files is searched for electric motor symbols with keywords indicating electric motors. These keywords are different combinations of the letter *M* for *motor* and the phase descriptions *1~* and *3~*. Identified electrical consumers are surrounded by a bounding box. Based on the coordinates of the bounding box, a searching square is spanned around the identified electrical consumer to find technical information related to it, such as the identification number, the designation, or the nominal power which is usually positioned adjacently. Therefore, text objects that lie within the searching square are filtered for a minimum character length and saved in a database. Fig. 2 shows an identified electric motor in a text-based PDF file surrounded by a bounding box in red and identified text objects containing related technical information in green, all within the turquoise searching square spanned around the electric motor.

The workflow of the **Image Detection Module** is very similar to that of the PDF Text Detection Module. The difference is that electrical consumers are identified by a CNN which is trained on electric motor symbols. After successful detection of electric motor symbols and related technical information, the output data of the PDF Text Detection Module, as well as the Image Detection Module, is saved in several data tables in a Structured Query Language (SQL) database. Splitting the data into several smaller tables allows data to be connected through relations without duplication and creation of further tables. The structure of the data tables and the use of relational

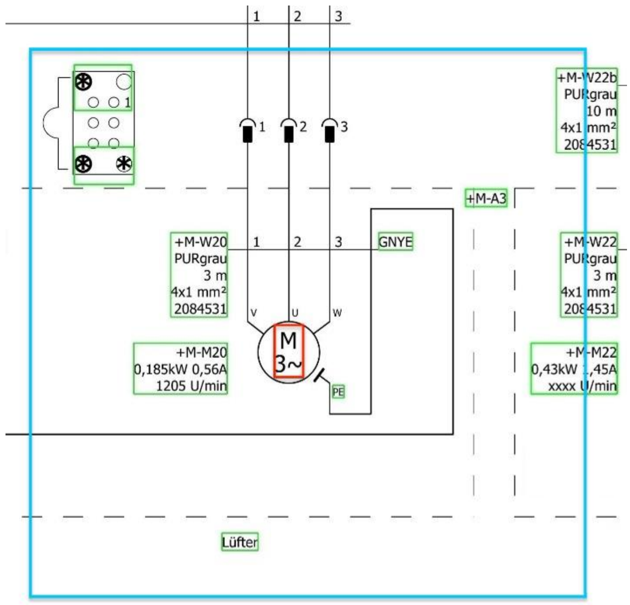

Fig. 2 Detected electric motor symbol surrounded by the bounding box in red, the searching square spanned around the bounding box in turquoise and identified text objects within the searching square in green.

items form the basis for the analysis of the data and the creation of both the final report and the dashboard in the **Logic Module**.

Since text-based PDF files are searched for electric motor symbols by both the PDF Text Detection Module and the Image Detection Module, there is redundancy in detected symbols in the database if both modules successfully detect them. To handle this redundancy, duplicates are filtered via positional matching of the bounding boxes. In that case, PDF detections are preferred, since their identification is based on text objects having a higher probability of being reliable against the object detection in the Image Detection Module. Filtered duplicates are saved in a new data table as unique detections.

Identified electrical consumers and their related technical information are summarized in a final report as a PDF file. The information contained in the report are the filename and the file type of the original circuit diagram file as well as the page numbers of tables of contents, structure indicator overviews, and parts lists in the original document, so long as any exist. Following this, the identified electrical consumers are listed with a consecutive detection identification number (ID), along with each detection containing a screenshot showing the identified electrical consumer surrounded by the bounding box and the searching square spanned around it. Furthermore, each listing contains the type of detection, which is either PDF or CNN detection, the page number of the detection in the original document, potential relevant power data like the nominal power and nominal current, potential functional designation, and potential measuring point designation. All the information is taken from the corresponding SQL tables in the data base. Relevant power data is identified through Regular Expression (RE) by searching for predefined patterns of numeric characters separated by dot or comma followed by alphabetic characters indicating physical units e.g., kW, W, V, A. The functional designation of the identified electrical consumer is found through keyword search in the detected text inside the searching square with a predefined list of keywords containing designations of electrical consumers typically used in circuit diagrams. This list can also be continuously expanded. The screenshot of each detection and its page number in the original document enable cross checking of the information between the report and the original circuit diagram.

Once the report has been generated, a web-based interactive dashboard is created to analyze and prioritize the identified electrical consumers based on the information contained in the report. The dashboard is structured in such a way that, in addition to the file name of the circuit diagram file for correct assignment, it first displays the original circuit diagram and the final report side by side. This allows for a quick and simple comparison of the documents and the information contained within them. It then shows a graphical ABC analysis of the electrical consumers and the results of the prioritization summarized in a data table containing the nominal power, the functional designation, and the detection ID of each electrical consumer. The default settings for the values of the three priority groups i.e., the cumulative share of the total nominal power and the cumulative share of all electrical consumers, can be interactively changed through sliders according to user's specific needs. Another interactive data table listing all the identified electrical consumers and their information allows the adding of the estimated degree of utilization, as well as the utilization time of each electrical consumer, to create an energy portfolio. The graphical representation of the matrix, which divides the consumers into four categories, is followed by a data table summarizing the categorization of the consumers together with the derived recommendations for continuous metering.

3.2 Implementation

For the programmatic realization of the process explained in section 3.1, the programming language Python in version 3 is used. Common libraries used for the specific tasks are specified in the following. For all tasks regarding CV, the library *OpenCV* is used. *pdfminer* is implemented for the processing of text-based PDF files, *pytesseract* for the Tesseract OCR engine, *pandas* for processing table data, *numpy* for processing mathematical matrix operations, and *sqlite3* for the use of SQL. The final report is created using the *reportlab* library. For the identification of relevant power data through Regular Expression, the library *re* is implemented. The web based interactive dashboard for analysis and prioritization of electrical consumers is implemented with *Plotly Dash*.

For efficient use of resources and saving of computing time, the modules run in parallel by multithreading. Python supports this via the program library *threading*. Separate threads allow the independent execution of the submodules. Threads can terminate themselves or be terminated by other threads. It is further ensured that threads wait for each other before they terminate themselves or others. These joins are represented by the dashed lines in Fig. 1, where the modules are divided into four phases: Initialization and PDF Conversion, PDF Text Detection and Preprocessing, Image Detection, and Logic. In order to provide data that is needed in a later phase and beyond joins, queues are used as intermediate storage, which is implemented via the program library queue. Queues can be filled by several producers (function .put()) and emptied by several consumers (function .get()), using the applied order of first in, first out. A total of three queues are used:

- qPDF: queue for forwarding file paths of all PDF files
- qPRE: queue for forwarding image file paths for Preprocessing
- qIMG: queue for forwarding image file paths for Image Detection

For the training of the CNN in the Image Detection Module *tensorflow* is used with the TensorFlow Object Detection Application Programming Interface (API). In the so-called *model zoo* of the TensorFlow Object Detection API [Huang 2017], pre-trained CNN models of different architectures are available. These are models that have already been trained to detect specific objects based on various data collections. The advantage of using such pre-trained models is that the CNN does not need to be trained from scratch, instead being tuned to the specific use case based on the available training images. This is possible because the first layers of neural networks often have similar structures regardless of the underlying training dataset [Yosinski 2014]. This approach, known as transfer learning [University of Stanford 2018], enables application to new problems and thus accelerates training. The architecture of the CNN model in the presented case is a MobileNet Single-Shot multibox Detection (SSD). For the training of the CNN, a total of 135 motor symbols from 14 circuit diagrams in PDF file format were used. The symbols were marked and labeled with bounding boxes using the labeling tool *LabelImg* [Tzutalin 2015] and divided into training and test data sets with 105 and 30 motor symbols, respectively. Of the 14 PDF files, four files with a total of 64 pages are image-based and ten files with a total of 896 pages are text-based. The image-based PDF files were created based on scanned circuit diagrams, while the text-based PDF files also contain circuit diagrams in which selected symbols have been implemented as graphics rather than text. Recognition of these symbols with the PDF Text Detection Module is not possible, although their detection by the Image Detection Module is nonetheless expected.

4 EVALUATION AND USE CASE

In this section the presented machine learning based tool for automated identification and prioritization of electrical consumers in circuit diagrams is evaluated and applied to an exemplary use case.

4.1 Evaluation

The evaluation of the tool in this section is focused on the accuracy of the detection of electric motor symbols by the PDF Text Detection Module and the Image Detection Module in the test and training dataset as well as an additional dataset for validation. This validation dataset consists of circuit diagrams with a total of 890 pages including 108 electric motor symbols in four PDF files with three of which being text-based. Regarding training and test data, the PDF Text Detection Module has an accuracy of 95.77 % with 68 of 71 detected motor symbols, while the Image Detection Module has an accuracy of 72.59 % with 98 of 135 detected motor symbols. On the validation dataset, the PDF Text Detection Module has an accuracy of 66.23 % with 51 of 77 detected motor symbols. The Image Detection Module has an accuracy of 73.15 % with 79 of 108 detected motor symbols and an average confidence score of 97.24 %. The discrepancy between the number of possible detections in the PDF Text Detection Module and the Image Detection Module stem from the motor symbols being implemented as graphical elements instead of text objects in the text-based PDF files. The comparatively low detection accuracy of the PDF Text Detection Module on the validation dataset results from electric motor symbols implemented without following the predefined pattern of searched keywords.

4.2 Use case: BvL OceanRC 750

This section shows the application of the machine learning based tool for automated identification and prioritization of electrical consumers on the circuit diagram of the cleaning machine OceanRC 750 manufactured by BvL Oberflächentechnik GmbH. The utilized circuit diagram consists of a total of 72 pages in a text-based PDF file and includes six electric motor symbols, whereof one is not specified with further information regarding nominal power and rated electric current. All six of the motor symbols are detected by the tool. They are listed in the final report, which provides a screenshot with the bounding box around the motor symbol and the spanned searching square, the page number in the original document, the nominal power and nominal current, the functional designation, and the measuring point designation inside the control cabinet. The entirety of the information is deemed correct. Furthermore, the report gives an overview about a total of eight page numbers in the original document containing tables of contents and one page number containing a structure identifier overview, both being correct as well. Based on the electrical consumers detected by the tool, they are first sorted by descending nominal power. Next, an ABC analysis is performed with the results being presented in the web based interactive dashboard. Since one of the six detected electrical consumers does not have any information about the nominal power, it is not included in the ABC analysis and the energy portfolio. The graphical ABC analysis is shown in Fig. 3. According to this, the electrical consumer with the highest nominal power, *hot-air drying* with 11 kW, is classified as Group A, possessing a share of 20 % of all electrical consumers and around 80 % of the total nominal power. With a cumulative share of around 90 % of the total nominal power, *washing pump* with 3 kW is categorized as Group B. The three remaining consumers, *exhaust fan*, *rotational drive*, and *oil skimmer*, belong to Group C. The dashboard also shows the results of the ABC analysis summarized in a data table, which is represented by Tab 1.

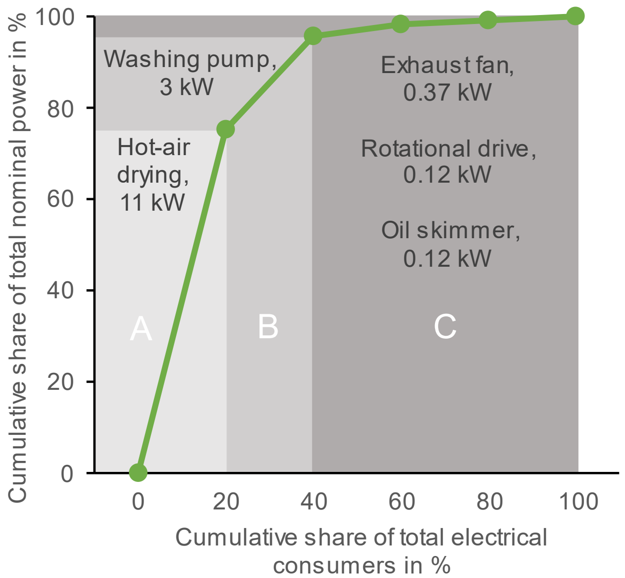

Fig. 3: Graphical result of the ABC analysis for the cleaning machine OceanRC 750.

By providing the estimated degree of utilization and utilization time of each electrical consumer in % through an additional interactive data table, an energy portfolio is created. The portfolio separates the consumers into a matrix with four quadrants and thus four classes of relevance for continuous metering. The matrix shown in Fig. 4 classifies *washing pump*, which has been assigned an estimated degree of utilization of 80 % and an estimated utilization time of 50 %, as highly relevant for continuous metering. With a utilization of 80 % and a utilization time of 20 %, *hot-air drying* has a medium-high relevance for continuous metering. While *rotational drive* has a medium-low relevance, *exhaust fan* and *oil skimmer* are irrelevant for continuous metering. The classification of the electrical consumers into the four groups, which leads to the specific relevance for continuous metering based on the estimated degree of utilization and utilization time of each consumer, is also summarized in a data table in the dashboard, which is represented by Tab. 2.

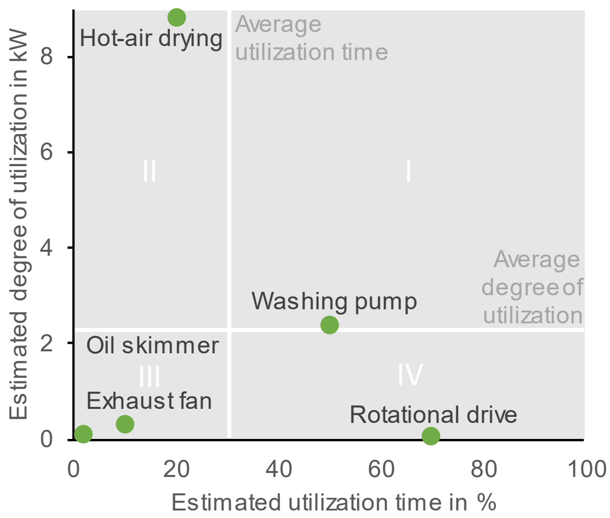

Fig. 4: Energy portfolio for the cleaning machine OceanRC 750.

5 SUMMARY AND OUTLOOK

This paper presents a machine learning based tool for identifying and prioritizing electrical consumers for energy monitoring. Therefore, CNN are applied to automatically analyze electrical circuit diagrams in order to identify consumers with associated technical information. By integrating established hot-spot methods, the technical information is then used to prioritize the identified consumers for measurements for the purpose of detailed energy analysis. In addition, other information, such as the estimated degree of utilization and the estimated utilization time, can also be included in an interactive dashboard to provide more accurate prioritization. The tool was successfully demonstrated using a cleaning machine as an example, detecting all motor symbols and associated information in the circuit diagram. Thus, the authors were able to show that the developed tool can significantly reduce the manual effort for an analysis of circuit diagrams and the manual prioritization of consumers for further actions.

In future research, the machine learning algorithms for image recognition will be extended to other frequently encountered symbols of electrical consumer in industrial circuit diagrams, such as heating elements. In addition, new methods will be developed and integrated into the tool to prioritize consumers for measurements across different machines.

6 ACKNOWLEDGMENTS

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Tab. 1: Results of the ABC analysis for the cleaning machine OceanRC 750.

Nominal power in kW	Detection ID	Potential functional designation	Share of total nominal power in %	Cumulative share of total nominal power in %	Share of total consumers in %	Cumulative share of total consumers in %	ABC prioritization
11	1	Hot-air drying	75.29	75.29	20	20	A
3	2	Washing pump	20.53	95.82	20	40	B
0.37	4	Exhaust fan	2.53	98.36	20	60	C
0.12	3	Rotational drive	0.82	99.18	20	80	C
0.12	5	Oil skimmer	0.82	100	20	100	C

Tab. 2: Results of the energy portfolio for the cleaning machine OceanRC 750.

Nominal power in kW	Detection ID	Potential functional designation	Estimated degree of utilization in %	Estimated utilization time in %	Matrix prioritization	Relevance for continuous metering
3	2	Washing pump	80	50	I	High
11	1	Hot-air drying	80	20	II	Medium-high
0.12	3	Rotational drive	60	70	IV	Medium-low
0.37	4	Exhaust fan	90	10	III	No relevance
0.12	5	Oil skimmer	100	2	III	No relevance

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