

Towards Simplifying Electrical Machine Design with Automated CAD Component Identification using Mask RCNN

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The state-of-the-art design processes for electrical machines (eMachine) are template-based methods and design from scratch approaches. Over the past four decades, significant advancements have been made to make these methods effective in terms of electromagnetic performance. However, these techniques cannot provide information on the topology and the components of an eMachine from a given CAD drawing. This information is imperative for the automatic selection of an appropriate simulation profile to meet the required KPIs, enhancing the numerical computation of electromagnetic fields, and improving the user experience through an improved user interface. This paper uses object detection to identify the components of an eMachine and uses that information to classify the topological category.

Index Terms— Computer aided manufacturing, Electric machines, Machine Learning, Software Methodologies.

I. INTRODUCTION

THERE ARE two different approaches for the design process of an electrical machine (eMachine) i.e. the template-based method and the design from scratch approach. Both methods are commonly found in leading eMachine design software i.e. Siemens Simcenter, ANSYS, COMSOL, etc. [1–3]. The former method allows users to choose different components from a given library to construct an eMachine but has limitations. When a user imports a design, he/she must specify the simulation profile according to the required KPIs and the topology of the eMachine. On the other hand, design from scratch requires users to construct the whole eMachine from the beginning. The knowledge of the components and the topology of the eMachine must be specified by the user. Hence, there is room for improvement in both these approaches. This paper proposes a novel approach that uses a Mask RCNN (Region-based Convolutional Neural Network) to classify the components of an eMachine from a sketch in a CAD file. This will accelerate the preprocessing stage of an eMachine design. Lastly, a neural network will identify the topology of the eMachine [5]. This will be used to properly select the appropriate simulation profile, enhancing the user experience.

II. METHODOLOGY

The Mask RCNN is the state of the art in the computer vision community for object detection and semantic segmentation [4]. On each region of interest (ROI), it predicts segmentation masks. The framework of this model consists of three specifications. First, a deep convolutional neural network, ResNet-50 is used as the backbone network of this model. Second, another neural network, i.e. a Region Proposal Network, is used to generate a region of interest based on scores for the specific object. Third, a segmentation branch is used for each ROI through fully connected layers to achieve pixel-level segmentation masks [4]. Figure 1 shows the flowchart for the generation of the dataset and training approaches for the segmentation and classification. For this work, the Simcenter

E-Machine Design (EMD) software is used to generate the design files for different electrical machines. An image labeler is used to create and label the bounding boxes for different objects. Lastly, an image segmenter tool is used to create labels and binary masks of each component of an eMachine. For this work, the necessary functions are implemented using MATLAB's image labeler and image segmenter tool. This data is used to localize the segments of different objects and classify the topological category of a given eMachine design.

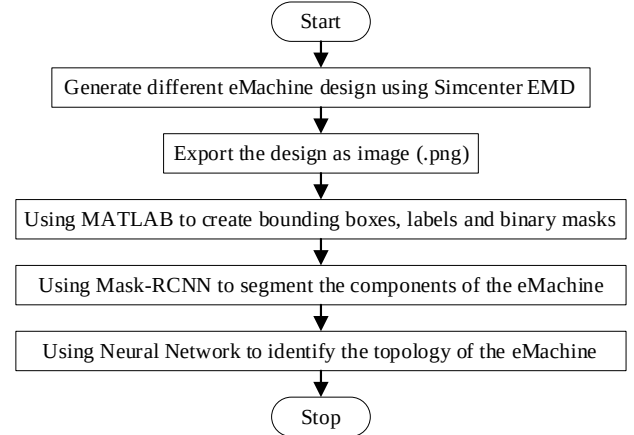


Fig. 1. Flowchart of the approach

III. COLLECTION AND PREPROCESSING OF THE DATA

To achieve better results from an AI model, the training set must be built meticulously. Through Simcenter EMD, around 500 CAD designs are generated for each class of an eMachine i.e. BLDC, IPM, SynRM, IM, etc. Afterwards, different components such as stator and rotor core, air gap, winding, permanent magnets, etc. need to be located. For that, the CAD files are exported to a .png file format. Later, for each image, bounding boxes are placed on each object and labels are given to them accordingly. Similar to the bounding boxes, the objects need to be segmented and labeled. For each object in an image, a binary mask is generated. These masks are stored under their corresponding labels.

IV. PREPARATION OF THE DATASET

After assigning the bounding boxes, binary masks, and their corresponding labels to the source image, these data are combined to make a complete dataset. One instance of the dataset is shown in the following figures.

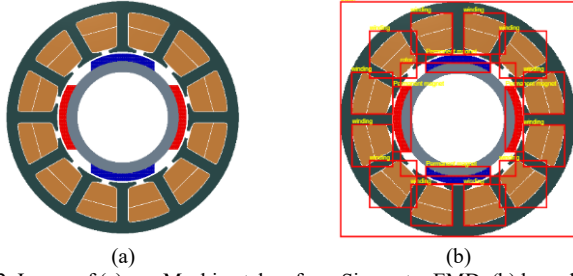


Fig. 2. Image of (a) an eMachine taken from Simcenter EMD, (b) bounding boxes enclosing different components of the design.

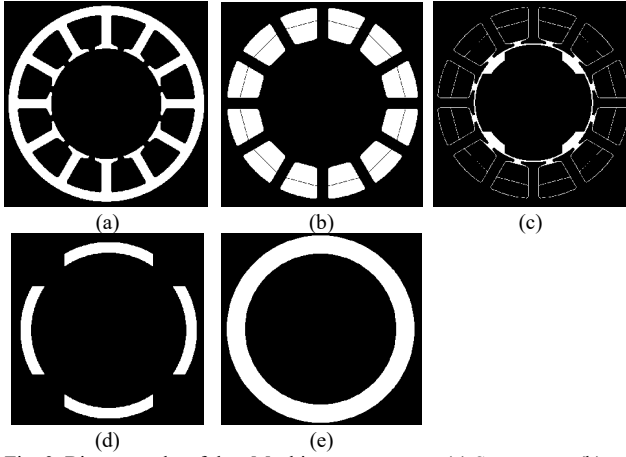


Fig. 3. Binary masks of the eMachine components. (a) Stator core, (b) stator windings, (c) air gap, (d) permanent magnets, (e) rotor core. Size of the images is not to scale.

Figure 2(a) illustrates the image of a surface mounted permanent magnet three phase machine. It has 4 poles and 12 stator winding slots. The bounding boxes encapsulating the components are depicted in figure 2(b). Binary Masks of each component are shown in figure 3.

V. TRAINING PHASE

A. Training Mask RCNN

The Mask RCNN model is trained using the newly generated dataset, specifically curated to accommodate various and representative samples of CAD images from eMachine components. The ratio of training, validation, and test set is 70%, 15%, and 15%, respectively. The training process includes fine-tuning the Mask RCNN architecture to effectively learn to recognize and segment the objects. Utilizing the capabilities of convolutional layers, the model can identify and segment previously unseen CAD images with high precision. The output will include bounding boxes, which encapsulate the detected objects, and binary masks that represent the exact regions filled by these objects.

B. Training the Neural Network

A dedicated neural network is developed and trained to classify the topology of eMachines based on their CAD representations. This network will extract features from the segmented images provided by the previously used Mask RCNN model. The classification task requires categorizing eMachines into predefined classes, considering factors such as the rotor-stator arrangement, winding configurations, permanent magnet placement, and other structural attributes. For high accuracy and effectiveness, the network architecture is optimized through batch normalization, dropout, and advanced activation functions to reduce overfitting and improve its efficacy. This classifier plays a vital role in automating the identification of eMachine topologies. This will reduce the time and effort required for manual analysis while ensuring consistency and reliability.

VI. CONCLUSION

In this digest an approach is presented to simplify the traditional methods of designing an eMachine with the help of Mask RCNN and Neural Networks. In the full paper, detailed results will be provided. The system provides a significant enhancement of the pre-processing work needed to set up and solve an electromagnetic field problem to generate the requested KPI's. It could be applied to other electromagnetic devices such as transformers, actuators, inductors, sensors, etc., to streamline the whole process.

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