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Development and verification of a System to identify Screws and Bits using a Neural Network

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Abstract: This study explores the use of machine learning and computer vision systems for object detection, specifically for identifying screws and their suitable bits. The system considers various parameters such as screw length and drive. It uses a neural network trained on pre‐established and labelled images of various screws. Different neural networks, YOLOv8 and YOLO‐NAS, are tested focussing on options that offers a higher accuracy and lower performance losses, neglecting versions that have a higher computational speed but less accuracy. YOLO‐NAS attained with mAP@50 0.982 and recall@50 0.995 higher values than YOLOv8. Result of a verification process showed that YOLO‐NAS detected 82,1% out of 952 real time images correctly while YOLOv8 achieved a detection rate of 76,1%. This technology could be used in next level of screw drivers for consumer applications helping unskilled persons to identify the correct screw‐bit‐combination. Another possible application is for improving the quality and time in manufacturing industry by choosing upfront the right tool and controlling pre‐defined screwing tasks for correctness.
Key Word: Screw Detection; Automation in Manufacturing; Computer Vision; Neural Network; YOLO‐Architecture.

I. Introduction

With more than 60% and billions of cases, screwing is the dominant method for detachable fittings in the automotive industry. [1, 2, 3] Also other industries like building constructions, electronics manufacturing or healthcare rely on this kind of connecting parts. [4] To automate the process of manufacturing, screw detection and the identification of the corresponding bits play a vital role. To achieve this, current industry uses either a manual labour process, automation tools or robotics to accomplish complex screwing tasks. In every assembly, two major objects need to be achieved:

1. The process is reliable and reproducible.
2. The process is efficient.

Reliability is especially crucial in safety relevant screwing tasks, like crash structures or airbag mounting in cars. The screwing must be according to given requirements. [5] Nowadays technologies like camera detection from KEYENCE [6] to identify the presence of a screw or supervised screwing devices like from Atlas Copco [7] are used to supervise the screwing process itself. The issues with these technologies are high costs, inflexibility of the location as they are not portable and time‐consuming to setup.

Based on the rule of ten, the earlier a failure is detected within a process the easier and cheaper the failure can be removed. [8] This especially applies to an assembly line, where screws may be covered or hidden behind other objects in later stage of assembly causing high rework costs or leading in a customer incident in the worst case. In an ideal process control, every screw will be checked and direct feedback after screwing will be given in case there is a deviation due to a missing or wrong screw. Due to high hardware costs and changing recognizable objects driven by car variants and evolving development, it's uneconomically to implement current technologies for every screw. Resulting only the before mentioned safety relevant screwing's are being deeply supervised nowadays.

To achieve a balanced load factor for the line workers, they typically have several different screwing tasks in the work area. This typically leads to a change of the necessary tooling, the so called "bit". Currently this is done manually or rule based as the workers adapt their procedure within their given cycle time individually. Rule based systems like described in [9], need to manually input the screw data and therefore additional effort nor are they for a general purpose and always tailor made. In a preferred solution, a system is "looking" at the screw, identifies it and decides which is the perfect fitting bit in near real time. This would remove the time for searching the bit, leading to a time reduction in manufacturing according to Methods‐Time Measurement (MTM). [10]

Bits are the tools which are used to drive the screw. [11] These bits can fit into drilling power tools and can be engaged to the contours of screw heads so that sufficient torque can be transferred to the screw for forward or backward motion. Except of special heads used in unique applications to avoid easy opening by customers,

e. g. automotive industry, five main classes for the bit profiles are used in DIY applications, construction or industry:

- Hexagon
- Phillips
- Pozidriv
- Slotted
- Torx

Figure 1.1 shows these main types. Bits are identified using the features extracted from the screw drive.

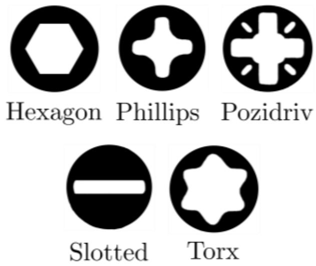


Figure 1.1: Overview of the five main classes of bit profiles [11]

Choosing the wrong bit, e. g. a too big or too small Phillips drive, that can be seen in figure 1.1, can still lead to a fixed screw, but the screw head gets damaged. [12] This is maybe not an issue in the first instance, but if the screw should be untighten later, e. g. in case of an maintenance, the unfitting can not be done properly. As there are no solutions currently existing, a newly developed guiding and supervising system could help to reduce these errors.

Using pick‐by‐light is a possibility to guide a worker to the correct object or to train them upfront. [13] Currently this is not working for identifying screws and their corresponding bits. Given an easy system as proposed, the pick‐by‐light could be extended for training purposes, enabling the worker to understand which bit would be the right one for future applications at the assembly location.

Another application is to lower the grade of necessary training for a user concerning the knowledge of screwing and perfect fitting bit. As the system could define the right bit in real time, the user of a screwing tool doesn't have to figure out which is the correct bit, especially in situations where it seems that different bits are fitting to the given screw. This would help also "unskilled" do‐it‐yourself (DIY) users to find the correct tools for their project.

Machine learning is therefor used to get one step further from rule based or expensive camera systems. To overcome these named issues of cost intensive, immobile and hard to configure solution, this study proposes a low cost and easy to setup system. Achieving this would lead to the possibility of a wider distribution of camera‐based screw detection systems in assembly or completely new use cases like in a guided screwing application. This leads to the goal of this research to develop and test a system that combines a low‐cost camera combined with a neural network which possesses the ability to detect various types of screws such as Phillips screws, Pozidriv screws, Slotted screws, etc. and identify the respective fitting bit for its fastening and unfastening. [14, 15] The neural network is build up by using the PyTorch. [16] The system should be suitable to be used in different industries and has the potential to be integrated with existing automation systems such as screw fastening/unfastening tools or robots in manufacturing facilities. This could improve the efficiency by:

- reducing times of wrongly chosen bits
- reducing screw damaging due to a wrong bit
- improving safety because of less slipping caused by a wrong bit selection
- time reduction by pre‐selecting the correct bit
- faster machine commissioning
- automated tool change
- quality improvements
- improving traceability by recording of the real chosen screw

This study also describes different methodologies of achieving the screw detection and bit identification tasks. Out of scope in this study is a later needed investigation for downsizing the model to use it in embedded systems.

One approach is shown by KIT (Karlsruhe Institute of Technology) using a Universal Robot UR5 e‐series with a neural network. [17] The KIT system consists of an eye‐in‐hand camera system to take a picture of a screw and detect the specific class of the screw as Pozidriv, Phillips, Torx, Hexagon, Hexagon socket and slotted screw. The robot is equipped with a screwdriver tool attached to its flange where the appropriate bit/tool can be inserted to perform the disassembly task. The screw localization and classification are being done using

YOLOv5 object detection architecture. Two models of YOLOv5 are implemented in this research and the results from both the models are compared. Siemens SIMATIC IPC227E [18] is used as an industrial edge device in the Universal robot UR5 e‐ Series to carry out object detection tasks. One of the limitations of this study is the lower computational power to achieve a desirable runtime and the limited number of screw types. Compared to this research, KIT is using YOLOv5 as architecture and a monochromatic and expensive industrial camera. Additionally in this study the focus is at identifying directly the correct bit and not just the screw.

System Setup

The screw detection task is achieved by using a computer vision system that utilizes a web camera. As web camera, a Logitech BRIO 4K Ultra HD with a maximum picture size of 4096 x 2160 and 13 megapixel is used. [19] The captured pictures are sent through a neural network to identify the screw. Based on the detected screw type and size, a respective fitting bit is identified and recommended to the user. [20]

Different neural networks where tested, named YOLOv8 (You Only Look Once) and YOLO‐ NAS (YOLO‐ Neural Architecture Search). [21] The systems utilizes computer vision techniques such as object detection to detect the type of screw using a pre‐ trained machine learning model based on the size and shape of the screw head and identifying the appropriate bit size which could be used for fastening/unfastening purposes. [22] Results will be compared, and the performance of each network analysed. Based on better performance parameters, such as accuracy, precision, learning rate and performance losses, a suitable neuronal network is selected. All these attributes contribute to the performance of the system.

To verify the feasibility, the system is tested with the 'Bit‐ Safe 61 BiTorsion kit' from Wera. [23]. The developed system is used with different testing parameters to verify its capability such as:

- different distances
- different backgrounds
- different light conditions

The so gained results are used to analyse how these parameters effecting the performance of this system. [20]

II. Material And Methods

A screw is device, which is used to convert rotational force into linear motion, and which varies in length and shape. [24, 25] There are five basic attributes as seen in figure 2.1 to describe different screws:

- head
- shank
- threads
- drive
- tip

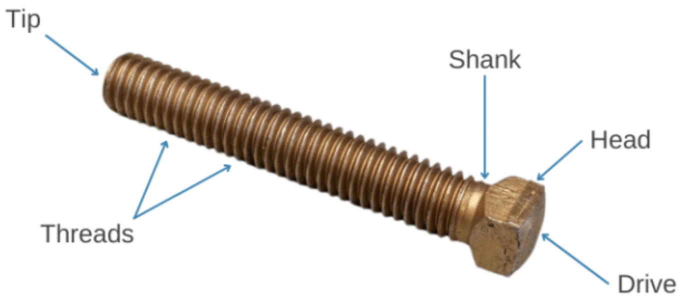


Figure 2.1: Overview of the main parts of a screw [24]

Based on the different types of shapes, styles and sizes, it is difficult to distinguish the exact type of screw. Due to the point of view, not all attributes of a screw are visible. For example, if the view is exactly from the top of the head, the shaft is covered completely by the head and the threads can not be identified. Because in most applications the point of view for fastening and unfastening is from the top or head side, this study focusses on identifying the single feature of the screw drive type and the screw drive size. Input images of the screws pass through multiple processing stages of a YOLOv8 or YOLO‐ NAS frameworks to produce the results. [26] Localization and segmentation are done using the neural network, so that the screw drive types, their dimensions, and visual attributes can be determined. [27]

Based on the combination of size of the screw drive and the drive types like the main drive types shown in figure 2.1 and some special drive types, the needed bits are classified into 30 different classes as shown in table 2.1.

Class ID	Bit Drive Type	Category	# of Images
00	Phillips PH1	main	210
01	Phillips PH2	main	300
02	Phillips PH3	main	196
03	Pozidriv PZ1	main	275
04	Pozidriv PZ2	main	233
05	Pozidriv PZ3	main	195
06	Combination of Phillips/Slotted	special	73
07	Combination of Pozidriv/Slotted, PlusMinus Screw	special	30
08	Torx TX10	main	218
09	Torx TX15	main	157
10	Torx TX20	main	256
11	Torx TX25	main	300
12	Torx TX30	main	244
13	Torx-BO/Torx-TR, Torx with safety pin	special	78
14	Torx IP, Torx Plus	special	67
15	Torx-IPR, Torx Plus with safety pin	special	54
16	Slotted 0.8	main	254
17	Slotted 1.0	main	283
18	Slotted 1.2	main	384
19	Hexagon 2,5	main	131
20	Hexagon 3	main	178
21	Hexagon 4	main	149
22	Hexagon 5	main	231
23	Hexagon-BO, Hexagon with safety pin	special	29
24	Robertson/Square	special	50
25	Torq-Set/Quad-Wing	special	41
26	Tri-Wing	special	33
27	Multi-point/Tripple Square/XZN	special	34
28	Micro Stix	special	26
29	Twin hole/Pig nose/Spanner 2-hole	special	43

Table 2.1: Overview of the used bit classes, category and distribution of images in the dataset [28]

Based on [29], following steps are implemented for the deployment of the model:

- model selection
- data collection
- data preparation
- data cleaning
- splitting the prepared data set
- annotating the data set
- model training
- model evaluation
- model deployment

Model Selection

There are many neural networks and algorithms that are used specifically for object detection purposes which include CNNs (convolutional neural network) like R‑CNN (region-based convolutional neural network), Fast R‑CNN, and YOLO. Based on results of [21] this project uses the YOLO architecture. Advantages of YOLO include typically a better processing speed, improved efficiency and accuracy and therefore it is not as computationally expensive as compared to other algorithms.

YOLO‑NAS (Neural Architectural Search) is a framework released by Deci AI in May 2023. [30] Three different models of YOLO‑NAS are available - small, medium and large. In this study the large version of YOLO‑NAS , is being used as necessary computational power is not the main factor in the first stage of development. YOLO‑NAS large can address challenges related to detection of small objects, enhancing localization accuracy and optimizing performance.

YOLOv8 is the latest framework released by Ultralytics in January 2023, when the development of this research was started. [31] Nowadays newer versions of YOLO are available. There are four different models of

YOLOv8 known as nano, small, large and extra‐ large. In this project the large version of YOLOv8 is used for the same reason as for the YOLO‐ NAS.
While the identification of the type is straight forward, the size identification is a limiting factor when using a simple picture. For example, a screw with a huge head but far away and a screw with a small head but close to the camera seem to be the same size of the head on the picture. Following options were identified to solve this issue:

1. Define a specific working range (distance from‐ to) and detect the screw drive type and size directly
2. Add to option 1 a size estimation model of the whole screw and use this additional information for the identification of the head or bit size in relation to the screw size
3. Add to option 1 the information of the length of the screw by getting a (partial) side view of the screw
4. Add to option 1 the distance of the screw from the camera by using a depth sensor of a camera

Because of the additional computational power needed for the options 2 and 3 and the additional hardware of option 4, only option 1 is chosen for the initial development, known of their disadvantages of a limiting working area.

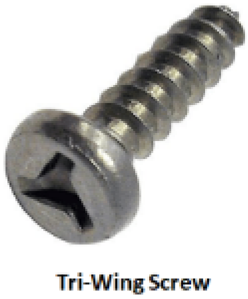
Data Collection, Preparation and Cleaning

To get a data set, two sources were used. Available screws in the laboratory of different drive types and drive sizes like the Pozidriv are photographed using a Logitech Webcam BRIO 4K Ultra HD. [19] The size of the self photographed images is 1920 x 1080 with 96 dpi. Images of not available screws in the laboratory like Tri‐ Wing (ID26) are collected from different forums such as Kaggle and from images searched by Google. This applies to the special screw head types 06-07, 13-15, 23-29 of table 2.1 that are only relevant for special applications like tamper proof. Figure 2.2 shows an example of images used in the dataset from webpages. As the physical availability of special screws is not given while this study, the number of images per class is varying significantly between the main type (see figure 1.1) of screws with 131‐ 384 images per class and the special screw head types with 26‐ 78 images per class. Reflecting this, a low recall or precision for the special classes can be assumed. In future studies, the dataset for these classes needs to be increased to ensure a balanced dataset. As machine learning models depend on high‐ quality images for better results, poor‐ quality pictures like fully blurred images which can make the model ineffective are identified and removed from the data set. [38] Duplicated images are removed. Result is a data set of 4752 images consisting of 80% self photographed and 20% images from internet sources. Images containing single screws but also several screws are shown in figure 2.2. All these images are sorted into the different classes of table 2.1 and prepared for labelling. While training, the image size is set to 640.


(a) PlusMinus (ID07) [32]

(b) Hexagon‐ BO (ID23) [33]


(c) Square (ID24) [34]



(d) Tri‐ Wing (ID26) [35]


(e) Micro Stix (ID28) [36]


(f) Twin hole (ID29) [37]

Figure 2.2: Example of screw pictures taken from the internet

Splitting the Prepared Data Set

By learning from noise or random fluctuations, the model can end up in an overfitting. This would cause a good identification of the training data but a bad performance or fail for unseen data. To avoid overfitting, it is important to split data sets into a training, validation and a test set. In this study the data is divided by 80% for training and validation data and 20% for test data. This results in 3800 training and validation images and 952 test images, which were taken in the lab as explained in section III. The training and validation data is split by 80% into training data and 20% validation data by using Roboflow. [39] The split is done class‑ sensitive to ensure that all classes are represented in each dataset. As the given amount of special screw images is too low, the test data set only consists of main type screws, while the training and validation dataset includes all 30 classes.

Annotating the Data Set

For supervised learning, the data set need to be annotated. The annotation enhances the image with the position of the object (location) within the image and the information of the kind of object (class). To achieve this, the given data set is manually annotated using Make Sense [40] to define the location of the screw drive and the corresponding class of table 2.1. In this project, the YOLO format is used that describes the bounding boxes by the values Class ID, x_centre, y_centre, width, height. The location of the centre defined by x_centre and y_centre, and the size of the bounding box defined by width and height are normalized by the size of the given image. The top left of the picture is defined as 0,0 coordinate. An example for an annotation of the dataset is given in figure 2.3.

(a) Square (ID24) [34] (b) Twin hole (ID29) [37]

Figure 2.3: Example of screw annotation [28]

Model Training, Evaluation and Deployment

GPUs (graphics processing unit) are commonly used for graphics processing tasks, rendering images and executing complex graphical calculations. Therefore, they are optimized for training of neural networks. For training purposes of the neural networks, a PyTorch based YOLOv8, and YOLO‑ NAS framework is running on a university GPU server with a GPU memory of 40 GB. [16] For training the following versions where used:

- PyTorch: 2.1.1+cu118
- Torchvision: 0.15.2
- Numpy: 1.26.2
- Ultralytics: 8.0.216
- Python: 3.10.12

Two different machine learning models, 'YOLO‑ NAS large' and 'YOLOv8 large', are trained on a GPU server. Both models are pre‑ trained with the COCO 2017 dataset. [41] Initially both run for test purpose for 500 epochs. It is observed that both models saturated after 200…300 epochs with the created dataset. The table 2.2 illustrates the adjusted and used hyperparameters for the machine learning model training.

	YOLO‑ NAS	**YOLOv8**
Epochs	200	300
Data set(No. of Images)	3800	
Batch size	16	
Classes	30	
No. of workers	8	
Image size	640	
Initial Learning Rate	0.0005	0.01
Weight Decay	0.0001	0.0005
EMA decay rate / Momentum	0.9	0.937

Table 2.2: Hyperparameters and training data [28]

For both models' classification loss, Distribution Focal Loss (DFL) and Complete Intersection over Union (CIoU) for box loss are used as error function. Table 2.3 shows the result of these losses, recall and Mean Average Precision (mAP) after the completed training.

	YOLO- NAS	YOLOv8
box loss	0.264	0.565
class loss	0.499	0.265
DFL	0.368	0.908
mAP@50	0.982	0.964
mAP@50-95	0.796	0.858
recall@50	0.995	0.973

Table 2.3: Training results of YOLO- NAS and YOLOv8 [28]

Figure 2.4 illustrate the loss curves for training and validation for both models. As soon as the training process started, the training losses drop down fast for YOLO- NAS and YOLOv8 models and start saturating indicating a good learning process. An exception can be identified for the validation of class losses of the YOLOv8. The losses dropping but fluctuating in the first 140 epochs and stay way higher compared to the YOLO- NAS curve. This indicates that the class identification for unseen data is for the trained YOLOv8 model worse compared to the YOLO- NAS.

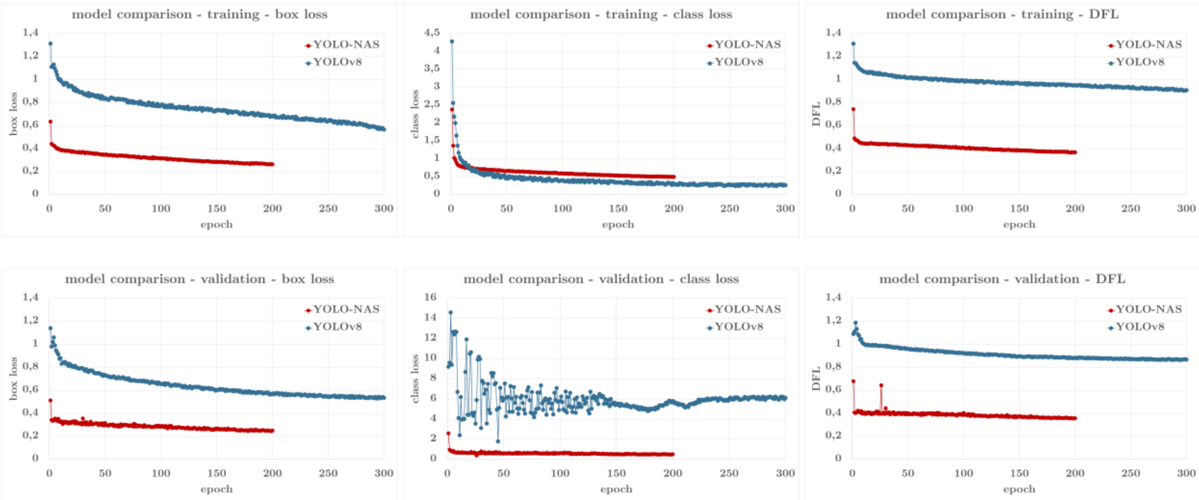


Figure 2.4: Training (top) and validation (bottom) loss curves for YOLO- NAS (red) and YOLOv8 (blue). From left to right: box loss, class loss, DFL [28]

mAP@50, mAP@50- 95 and recall@50 progress are shown in figure 2.5. They rise from 0 close to 1 which is the maximum value. YOLOv8 is run for 300 epochs while the mAP@50 value increases from 0 to 0.964, however, for YOLO- NAS, this value changed from 0 to 0.982 during the 200 epochs. The mAP@50 value rises initially fast when the training process started and with epochs elapsed more than 100 epochs, this value is getting saturated for both the models. As table 2.3 shows, mAP@50, recall@50, box loss and DFL performs better in the training phase for YOLO- NAS while YOLOv8 is performing better for mAP@50-95 and class loss.
Summarized YOLO- NAS indicating a higher detection accuracy and more precise localization while YOLOv8 is better in class identification for the specific training data set but worse for unseen data.

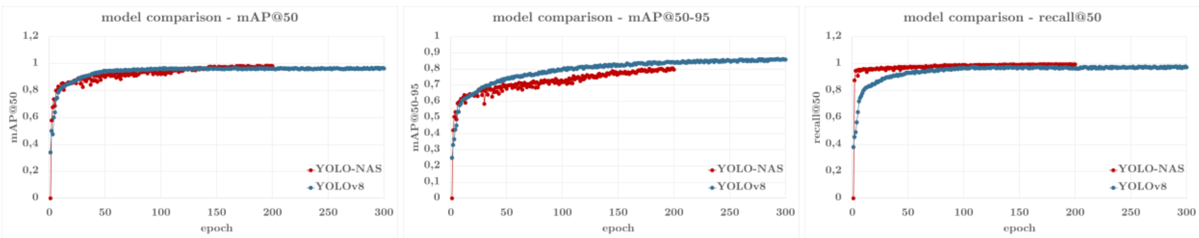


Figure 2.5: Performance values while training for YOLO- NAS (red) and YOLOv8 (blue). From left to right: mAP@50, mAP@50- 95, recall@50 [28]

After the training process these two models were deployed for real‐time live detection test on a laptop. As laptop a FUJITSU Workstation CELSIUS H760 with a NVIDIA Quadro M2000M 4 GB graphics card and 32 GB RAM (DDR4, 2133 MHz) and Intel i7 is used running with Windows 10. [42]

III. Result

To verify the functionality of the complete machine learning model of YOLO‐NAS and YOLOv8, the following tests were performed:

- **Test 1:** real‐time detection
- **Test 2:** impact factors

Test 1: Real-Time Detection

The purpose of this test is to verify the functionality of both models, YOLOv8 and YOLO‐NAS, for live detection/real‐world environment using the FUJITSU Workstation laptop. The test screws in the laboratory of the main classes (see figure 1.1) are placed in front of the Logitech BRIO 4K Ultra HD webcam to observe the performance of both models, resulting in the mentioned 952 images of the test data set. Table 3.1 shows the distribution of tested screws.

Class ID	Bit Drive Type	# of Images
00	Phillips PH1	58
01	Phillips PH2	60
02	Phillips PH3	69
03	Pozidriv PZ1	57
04	Pozidriv PZ2	39
05	Pozidriv PZ3	44
08	Torx TX10	43
09	Torx TX15	40
10	Torx TX20	45
11	Torx TX25	33
12	Torx TX30	43
16	Slotted 0,8	82
17	Slotted 1,0	53
18	Slotted 1,2	94
19	Hexagon 2,5	40
20	Hexagon 3	41
21	Hexagon 4	57
22	Hexagon 5	54

Table 3.1: Distribution of test image [28]

Positive test results of correct identified bit classes for the corresponding real‐world screws in the laboratory are shown for Phillips (ID01) size 2 in figure 3.1 for YOLO‐NAS and 3.2 for YOLOv8. A detection job is counted as correct if the system proposes the same bit as required by the real screw head. If several bits are identified the one with the highest confidence score is chosen and evaluated if it is correct or not. The location and size of the boundary boy is not relevant, as only the selected class and therefore bit is used in this application.

Figure 3.1: Correct identification of Phillips screw drive of bit size 2 with YOLO‐NAS [28]

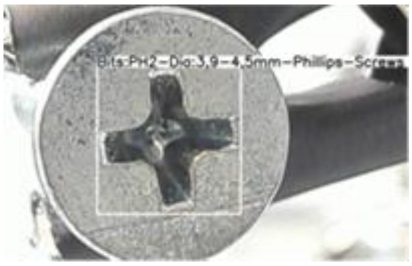


Figure 3.2: Correct identification of Phillips screw drive of bit size 2 with YOLOv8 [28]

Still bit types are identified wrongly as it can be seen in figure 3.3. In this case the YOLOv8 identifies the target class 16 ‘Slotted 0.8’ as class 01 ‘Phillips PH2’. Also, cases of no class detection happens like shown in figure 3.4 or identification of several classes in the same image as in figure 3.5.

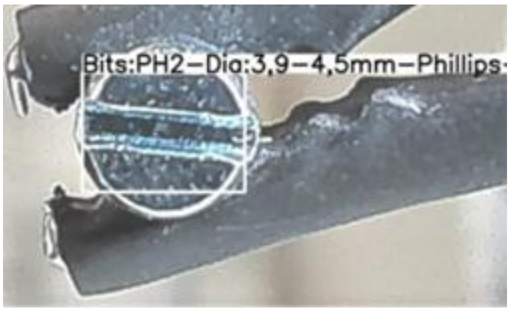


Figure 3.3: Wrong identification of Slotted 0.8 as Phillips PH2 with YOLOv8 [28]

Figure 3.4: Wrong identification due to no class with YOLOv8 [28]

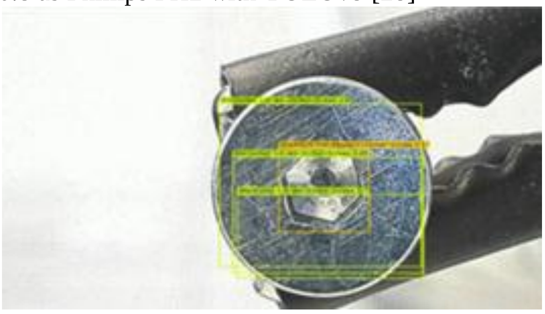


Figure 3.5: Wrong identification due to several classes with YOLOv8 [28]

Table 3.2 shows the result for the test data set of the 952 tested images. YOLO‑NAS has in this setup a higher rate for the correct bit class detection compared to the trained YOLOv8 model. The IoU was not taken in consideration as the location of the screw head is not relevant for the bit selection. YOLOv8 scores 0.0% for ID03. The model detects in these cases correctly the drive type as Pozidriv, but selects the wrong bit size PZ2 instead of PZ1. The same applies to ID09 and ID12 of YOLO‑NAS. ID16 shows bad results for YOLOv8 as here not only the size but also the drive type is identified wrong, or nothing is identified.

Class ID	YOLO-NAS	YOLOv8
00	65.5%	32.8%
01	98.3%	100.0%
02	100.0%	100.0%
03	73.7%	0.0%
04	100.0%	100.0%
05	100.0%	100.0%
08	81.4%	81.4%
09	5.0%	75.0%
10	100.0%	100.0%
11	100.0%	78.8%
12	18.6%	62.8%
16	70.7%	28.0%
17	100.0%	79.2%
18	100.0%	81.9%
19	55.0%	100.0%
20	100.0%	100.0%
21	100.0%	100.0%
22	79.6%	92.6%
overall	82.1%	76.1%

Table 3.2: Percentage of correct identified bits for each class and overall images [28]

Test 2: Impact Factors
While performing Test 1 it was observed in the laboratory that both models have a distance, angle and lighting dependency in real‑world environment.
To evaluate the models an experimental test setup is devised with a vice 'TOOLCRAFT ZD‑10H' [43] and optional lighting 'TOOLCRAFT TO‑7173471' [44] as shown in figure 3.6. The vice is used to place the screw

in different distances and angles. The vice can be moved in X‐ axis direction to change the distance between the screw and the camera system. To adjust the height of the screw in front of the camera, the holder of the screw can be moved in the Y‐ axis which is upward/downward direction. Similarly, a screw can be placed at different angles also in front of the camera by rotating the vice around the X‐ axis. To verify the distance between camera and screw assembly, a measuring scale [45] is placed which helps to maintain the specific distance. A protractor 'KS Tools 300.0700' [46] is used to measure the angle at which the screw is placed. The test was conducted using the following parameters:

- Screw: Hexagon 5 (ID22)
- Distance: 2 cm...10 cm, stepwise increased by 1 cm
- Lighting: on / off
- Angle: 0°, 10°, 20°, 30°, 45°

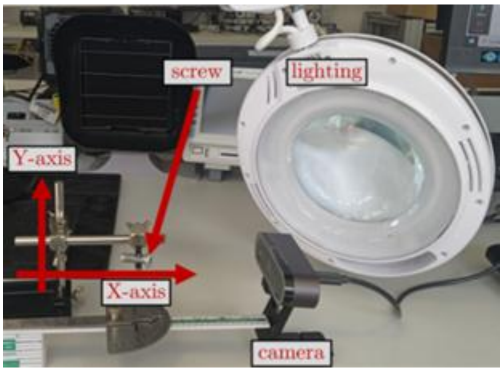


Figure 3.6: Experimental test setup of the screw in front of the camera along with a measuring scale, protractor, vice and lighting [28]

While the distance test, the angle was fixed to 0° and for each distance the detection was tested once with 'lighting off' and once with 'lighting on'. The confidence level at 3 cm is dropping to 0.73 while the peak is at 6 cm with 'lighting on' and a value of 0.92. For the used hardware‐ software combination, the neural networks are more reliable when the screw is placed at 6 cm from the camera. If the screw is getting closer than 3 cm, both models are not identifying any screw, as the image is getting to blurry due to the loss of the camera focus. If the distance is far, still the drive type is identified correctly, but the bit size is wrong (a far big screw looks like a close small screw for the models). If the distance is increased further than 10 cm, no or wrong drive types are identified as the area of interest in the image is getting too small.

When rotating the screw around the X‐ axis, the distance was fixed to 6 cm and the lighting turned on and off for each measurement point. While the corresponding bit is always detected correctly from 0° to 30°, the detection is starting to get wrong from 45° onwards for both models. This is caused as parts of the screw head are getting covered by the head itself and the distortion (closer parts of the head seems bigger). It is expected, that with an extended training dataset of tilted screws this problem can be partly solved and rotated screws with a bigger angle than 45° can be identified.

In general, under active lighting conditions the detection is better compared to a dark 'lighting off' setup, as the contours of the drive type are easier to identify.

IV. Conclusion

The objective of this study is to understand the development and testing of the neural network and performance of the object detection so that screw detection and bit identification tasks could be achieved. Screw detection is a complex task that is given labelled data sets of the chosen types of screws as an input to classify, localize and detect the screws based on their screw drive type and size. Appropriate bits were identified from the 'Bit‐ Safe 61 BiTorsion kit' of Wera. [23] This research explores YOLO‐ NAS and YOLOv8 architecture as neural networks used for object detection purposes. For the training a GPU server is used and afterwards the resulting model deployed on a laptop.

Detection results for both models in real‐ world tests are obtained which shows the successful deployment of models for fulfilling the task of bits identification and its requirements drawn initially. Real‐ time tests showed that YOLO‐ NAS with 82.1% correctly identified objects out of 952 images is better than YOLOv8 with 76.1%.

Different factors such as varying distance, illumination and angle affect the object detection. The system detects more reliable results when the test screw is placed at 6 cm from the camera with maximum area of work between 3 cm to 10 cm. Lighting conditions generally improve the performance while screws with an angle greater than 45° are not or wrongly detected.

The system builds the basis for further developments leading to an embedded solution into manufacturing facility and electric drilling tools. The use of upcoming YOLO frameworks and an increase in the volume of the data set can play a vital role achieving better mean average precision and lowering the performance losses for future improvements. Also, additional methods mentioned in this study should be investigated to solve the issue of the limiting distance corridor for the size detection for example by using a depth sensor. Another direction will be the downsizing of the model to create a lightweight embedded version.

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