Anomaly Detection in Workstation Using Deep Learning Techniques

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Abstract.

Industry 4.0 has led to the development of smart manufacturing with control systems for data collection, optimization, and fault detection and diagnosis (FDD). However, buildings and setup, with regards to assembly lines, controls etc., contribute to significant global energy consumption. Digital Twin (DT) technology offers a sustainable solution for facility management and predictive maintenance of machinery. For this, Data-driven methods are gaining popularity due to their ability to handle large amounts of data and improve accuracy, flexibility, and adaptability. Also, Deep learning methods can analyze large and complex datasets, making them a promising area for further investigation in anomaly detection and other fields of Industry 4.0. This paper will be focussing on anomaly detection in the Workstation-1 present at the IAFSM Lab at IIT, Delhi. The workstation is integrated with many prime fields of Industry 4.0 like IIOT. Though this helps in increasing productivity, Data Collection, reducing operational costs as well as helping with predictive maintenance, at the same time makes it susceptible to an external attack over the cloud, in other words, makes it vulnerable to cyber-attacks. This can be proved very detrimental to the whole workstation, as an external attack (hacking) can influence various factors of the total operation, like changing the direction of the assembly lines, changing the inventory(using the incorrect raw material), or increasing/decreasing the pace of the whole process. All this can increase the overall operational cost and manipulation of the product's quality. To counter this, this paper introduces a combined approach of Digital Twin and Deep Learning to detect anomalies in the movements of the gantry, as well as inventory control.
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Keywords: Industry 4.0, Smart Manufacturing, Digital Twin, Deep Learning, Robotics

1. Introduction

This paper is going to be focussing on the detection of anomalies in workstation-1 located at the FSM Lab at IIT, Delhi. These anomalies are assumed to be an act of outside influence like a Cyberattack[1], or an operational fault in the workstation.

The list of anomalies that this paper talks about includes the selection of the correct inventory and uniform and correct movement of the arm along the predefined path to the assembly line without any irregularities or deviations from it.
In order to detect the anomaly [2] in the workstation due to the outside influence, an entity that isn't part of the whole cloud network [3], which is outside the scope of control by the outside attack, has to be introduced. This is where digital steps in for anomaly detection [4] which implements the detection process through the virtual camera setup in the digital twin environment.
Hence, for the sole purpose of the integration of Digital Twin [5] and Deep Learning algorithm, Cameras are installed in the Digital Twin model which tracks the whole operation of the workstation with the help of Deep Learning algorithms.

Digital twin creates a virtual replica of a physical object or system, allowing it to simulate, emulate and analyze its behaviour in real-time.
Thus adding a camera inside for tracking the operation is equivalent to adding a camera in the real-time setup.
This also helps in the training and testing of various Deep Learning [6] models for detecting anomalies and extraction of data for fine-tuning the multiple parameters in our model and analysis for anomaly detection.

2. Workflow

Firstly, A Digital Twin is assembled within the Emulate3D software with proper orientations and planning scenes for the workstation operation.

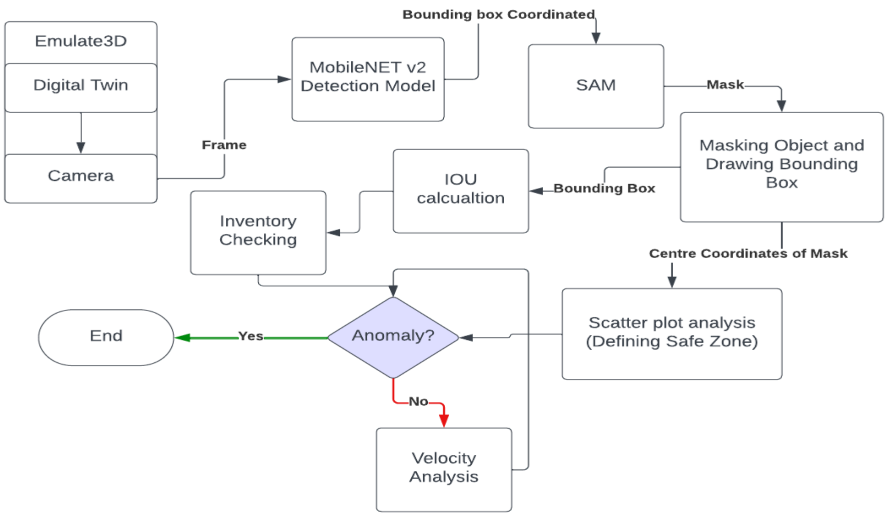
Two Cameras are installed in the digital twin workspace. One is used for recording several sequences of the whole operation, including anomalous and non-anomalous sequences. These are then used as a reference for training our models and for detecting anomalies during real-time operation. The second camera tracks the inventory and the gripper when it selects the inventory.

Once our model is ready it can be directly deployed with the help of Digital Twin. Our model would be consisting of an object tracker, which as the name suggests would track the movements of the gripper and log its movement in the X-Y plane. This can later be used for comparing the followed path with the pre-defined path of the gripper/arm and determining whether the coordinates lie in the safe zone(s) of the graphs.

The model is based on a bounding box regressor, hence forming a bounding box enclosing the gripper.
The bounding box is used for ensuring the correct selection of the inventory which is QR encoded by calculating the Intersection of Union (IOU) value between the bounding box enclosing the QR and the box formed around the gripper. The IOU score is a concept that helps in estimating the extent of the intersection of the area between the two boxes(rectangle).

Apart, From all this, Data is obtained in the form of CSV data of x, and y coordinates which are then used for ensuring that, the Gantry followed a safe and pre-defined path as well as estimating its velocity and directions for checking whether there were any irregularities in its movement(speed) or not.

All this combined, helps in classifying the operation as anomalous or non-anomalous.



2.1 Digital Twin

Digital Twin plays a vital role by providing a virtual environment for simulating, emulating and testing the accuracy of our anomaly-detection model.
The digital twin model is assembled and emulated on the Emulate3D software.
Emulate3D is a software developed by Rockwell automation platform enabling users to create virtual models of industrial automation systems, saving time and money while reducing the risk of errors at the same time. It offers various features such as virtual commissioning, simulation, 3D visualisation etc., allowing users to test and commission control systems offline and further test them in real-time.

The model is orderly divided into various subparts like the gantry, conveyor belts, inventory etc. so that their relative movements can be planned and executed. For this, it is equipped with different movement mechanisms like 2-axis linear movement for the gantry and 1-axis linear movement for the conveyor belt.

Finally, two cameras are added to the scene to capture the whole operation, for tracking the inventory selection and gripper movements.

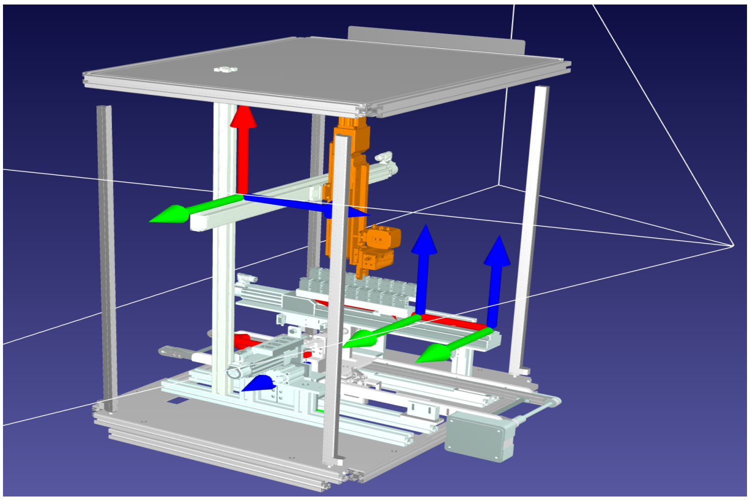


Fig: Digital Twin with Camera View

2.2 Object Tracking

For the sake of tracking the overall motion of the gantry, it required that we track the movement of the gripper as it is the core of the whole operation and all the movements associated with it.
Object Tracking requires a synergy between the detection model and tracking.

2.2.1 OBJECT DETECTION MODEL

There are several approaches and algorithms that can be deployed for object detection models like Yolo, RetinaNet [7] etc. But for this, a bounding box regression model built on MobileNET V2 [8] has been used for the training model on the bounding box's annotations. In conjunction with it, the SAM model [9], developed by Meta is used for masking the gripper.

MobileNet-v2 is a convolutional neural network that is 53 layers deep. The pre-trained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images and thus can improve the overall process of detection of custom models with MobileNET V2 as its head, as a result of transferred learning.

Segment Anything model developed by MetaAI is a revolutionary model that has achieved near-perfection in masking objects. It accepts a bounding box or a point's coordinates as prompts and masks the object enclosed in it. This capability has been utilised for perfecting our model accuracy and smoothening the overall detection process.

2.2.2 OBJECT TRACKING

After the model reaches considerable accuracy, it is deployed in the digital twin workspace. During real-time simulation of the digital twin, the frame recorded through the camera in the same workspace is fed into the MobileNET V2 as input after appropriate modifications.

Once the bounding box regressor predicts the gripper location in the frame, it sends the bounding box coordinates as xyxy format to the successive SAM model.

For the SAM model to work accurately and efficiently, it requires a prompt in the form of a point or bounding box coordinates. Here it is fed the bounding box coordinate from the bounding box regressor.

In the masks with the gripper enclosed, some mathematical operations are applied with the help of Numpy functions to obtain the centre point of the mask. Then another bounding box is drawn with the centre point of the mask as the centre of the rectangle. It extends to the extreme-most point present in the mask located on either side.

To ensure the accuracy of our model, The Intersection Over Union (IOU) score between the bounding box from the regression model and the mask of the SAM model is calculated. If It is greater than the threshold value of 0.7, only then it is considered, otherwise, the initial bounding box from the regressor is drawn over the image.

The x-y coordinates of the centre point of the gripper's bounding box are logged and used for further inventory selection monitoring, and graph analysis.

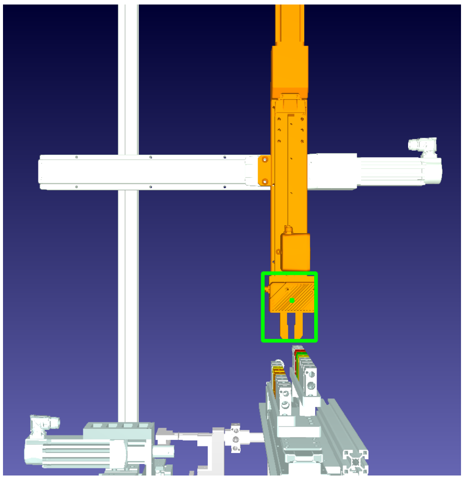


Fig: Gripper Detection

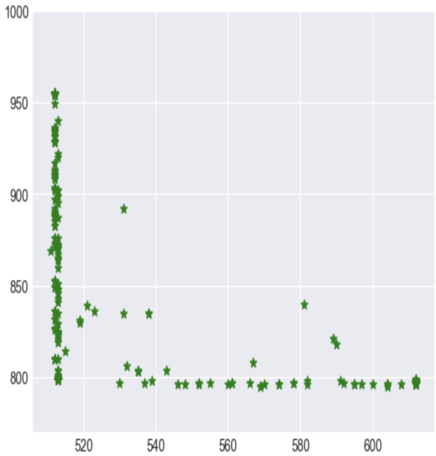


Fig: Plot obtained for L-shaped path

2.3 Inventory Selection

Inventory selection is a primary task in any assembly line as it directly influences the end product and its manipulation can lead to incorrect product, poor quality and manufacturer’s dissatisfaction.

To ensure accurate inventory selection, all the inventory which is QR encoded is monitored with the help of a camera which has its field of view covering the inventory tray and the gripper.

Frames from the video sequence are inputted into our detection model which draws the bounding box enclosing the gripper. Simultaneously all QR codes are enclosed within slightly elongated bounding boxes.

Whenever an inventory order is given, the gripper goes above the required holder and picks it up. In case, It picks up the incorrect holder; this scenario is categorised as an anomaly.

All the holders are QR-encoded and are bound within an enclosed box with proper ID, with respect to the camera monitoring the process of inventory selection. Whenever the gripper comes into the camera view, it gets bounded in a box as a result of the detection model.
To ensure the gripper goes over the correct holder, the Intersection Over Union (IOU) score is calculated between the bounding box of the gripper and all QR codes. Whichever produces the greatest score indicates its selection which can further be checked, whether it matches the initial inventory order or not.

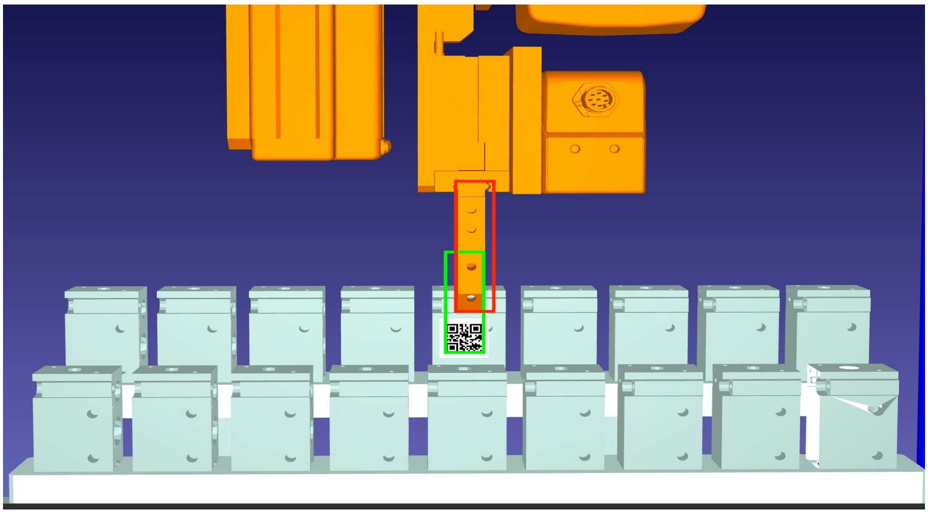


Fig: IOU value maximum for the holder encoded with QR

2.4 Data Extraction and Irregularities Detection

The object tracker logs the x,y coordinates of the gripper, which is the centre of the bounding box, along with timestamps.
This is then later imported into a Python script with the help of the Pandas library.
From this data, velocity and direction are calculated after the coordinates are calibrated according to the camera specification.

2.4.1 PATH FOLLOWING

To make sure the gantry follows a pre-defined path which, at the same time doesn't damage the joints or some other component, all the datapoints comprising the X-Y coordinates of the gripper are plotted as a scatter plot. Since one can make out the path followed by the gantry by looking at the X-Y plot of the gripper. In order to ensure, the gantry follows the pre-defined path, a safe region is defined on the plot. Any data point that lies outside of this region is considered anomalous. [10]
The total number of anomalous data points are counted for the whole operation, if this figure exceeds the threshold value of 20, the whole process is considered anomalous.

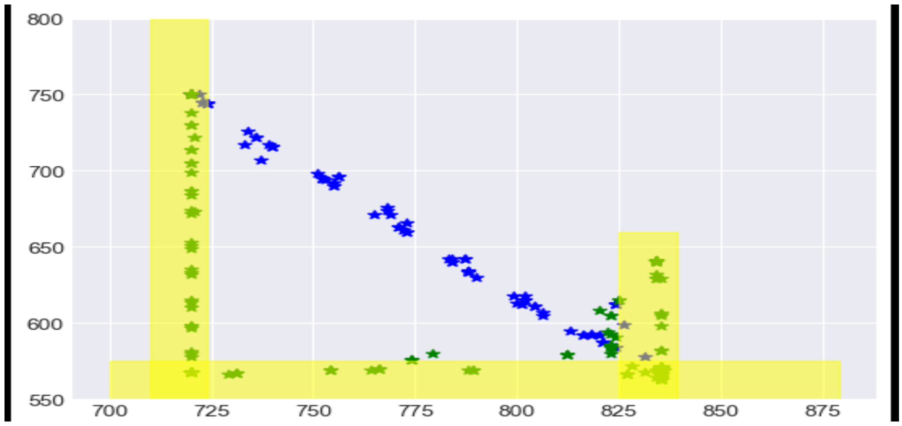


Fig: Yellow(safe zone), Blue(anomalous point), Green(non-anomalous)

2.4.2 UNIFORM VELOCITY

The velocity data is also analysed with the help of a scatter plot.
As a general observation, it is seen that a non-uniform movement i.e. movement consisting of varying unstable velocity tends to produce a more scattered scatterplot as compared to a clustered scatterplot in the case of uniform, stable and smooth movement.
Similar to the previous case in which a safe zone was pre-defined at the start of the process, Here, a custom zone is established based on the set of initial data points.
The velocity is extracted and plotted for the first 100 frames. Naturally, assuming a non-anomalous operation initially, all the data points are expected to form a linear regression. Hence, linear interpolation is applied over the first 100 data points(say).
Then a safe region is defined about the line regressor as produced as the result of linear interpolation. Similar to before, any data point lying outside of this region is considered anomalous and vice-versa. Hence the total number of anomalous points are counted for the whole process, and if this figure exceeds the threshold value, it is then classified as an anomaly.

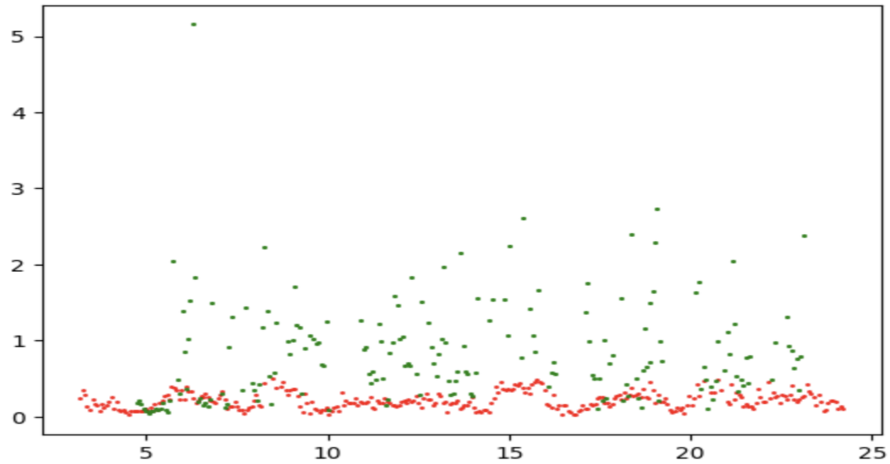


Fig: Red(non-anomalous); Green (anomalous)

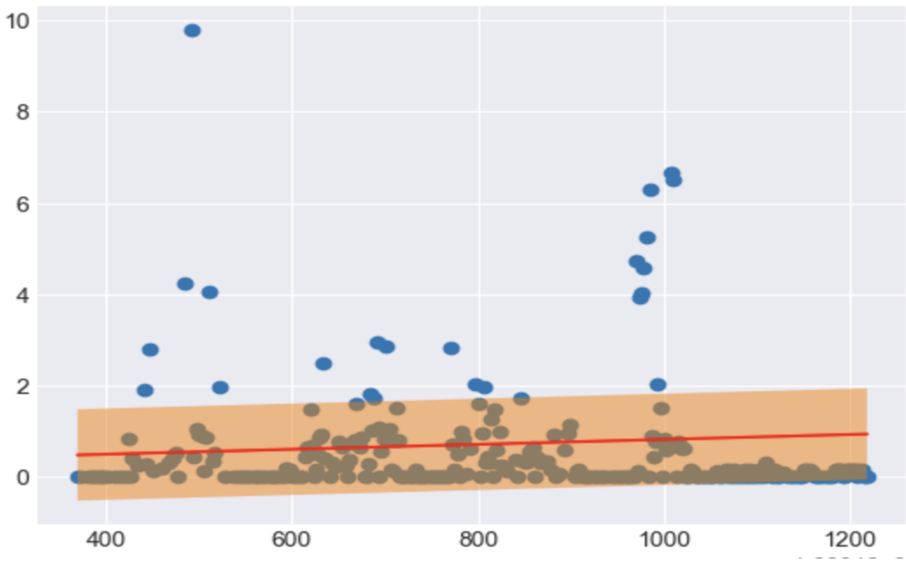


Fig: Safe region about the regressor

3. Conclusion

This proves to be an effective way of detecting anomalies in workstations that are well integrated with the aspects of Industry 4.0 and vulnerable to outside attacks. Integration of digital twin with deep learning techniques provides a reliable source of observation and data collection without being influenced by foreign attacks or manipulation

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A workstation that is integrated over the cloud network provides a possible path for foreign manipulation or in simple terms, hacking. However, using a virtual camera inside a Digital Twin workspace provides a backup that is outside the influence of the cloud and thus immune to foreign cyber attacks. Using Deep Learning algorithms, which is another field introduced in Industry 4.0, in conjunction with the digital twin provides a more modern and smart approach for data analysis that would have been tedious and out-of-human bounds.

Using famous and accurate pre-trained models like MobileNET as head in building our model, as well as revolutionising models like SAM which has brought object masking to a whole new level, serves as insurance against any mathematical and analytical errors, encountered while building custom Deep Learning models.

These models have robust architecture and have undergone plenty of training and testing for them to be used in real-life applications and in the area of Industry 4.0. They show satisfactory results in terms of feature detection and optimised results.

Hence, this bounteous combination of Digital Twin and Deep Learning in detecting anomalies can prove beneficial in the area of Industry 4.0 and is worthy of attention.

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