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 Industrial Internet of Things(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.The workstation is a part of a larger assembly line whose purpose lies in the inventory selection. It consist of a 2-axis gantry mechanism with a gripper(Fig. 1). The gripper is equipped with a QR scanner which selects the inventory based on the operator's input and transfer it to the conveyer belt which is then further transferred to the next workstation. This paper detects the anomalies in gantry movements which are assumed to be an act of outside influence like a Cyberattack or an operational fault in the workstation.[1]

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. [2]

In a professional setting, it may occur that an external factor causes the workstation to select an inventory other than the one originally ordered. In such a scenario, any security or surveillance mechanisms can be circumvented by the hacker,and any anomlies can be easily masked. However, since the digital twin is resistant to tampering, it can serve as an effective means of detecting anomalies. By utilizing Deep Learning algorithms for computer vision over this data, a robust system for detecting anomalies can be established because the Deep Learning models are expected to run more ideally in a virtual space as compared to in the real world.

In order to detect the anomaly in the workstation, an entity that isn't part of the whole cloud network or the cyberphysical subsystems and which is outside the scope of control by the outside influence, has to be introduced [3]. This is where digital twin steps in for anomaly detection which implements the detection process through the virtual camera setup in the digital twin environment.[4]

Cameras are installed in the Digital Twin model which tracks the whole operation of the workstation with the help of Deep Learning algorithms. The results of the deep learning model are further analysed for anomalies [5]

Digital twin creates a virtual replica of a physical object or system, allowing it to simulate, emulate and analyze its behaviour in real-time which helps in the training and testing of various Deep Learning models for detecting anomalies and extraction of data for fine-tuning the multiple parameters in the model and analysis for anomaly detection.[6]

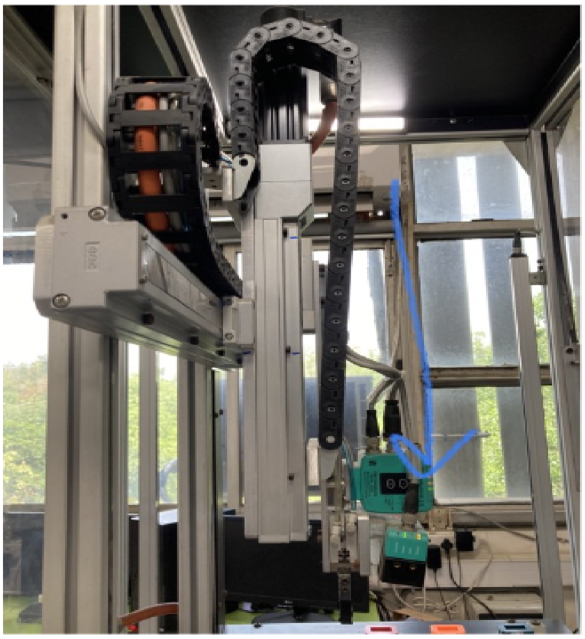


Fig. 1: Gantry in the Real Workstation

2. Methodology

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

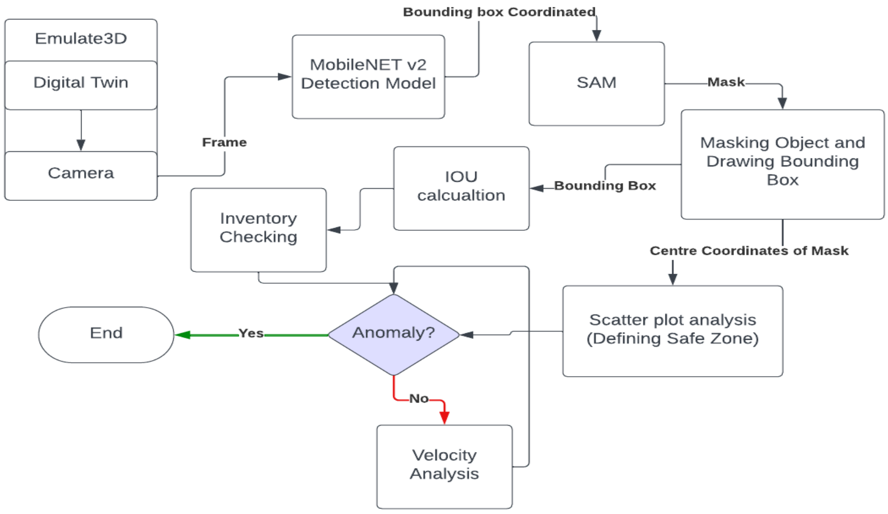
Two Cameras are installed in the digital twin workspace,each tracking one plane each(yz and xz). These are used for recording several sequences of the whole operation, including anomalous and non-anomalous sequences, which are used for training the models and for detecting anomalies during its operation. Once model is trained with considerable accuracy and minimal losses it can track the gripper movements from the camera feeds inside the Digital Twin.

The model tracks the movements of the gripper and log its movement in the yz and xz 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, forming a bounding box enclosing the gripper at all times

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 enclosing 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).
The data is logged in the form of CSV data of y, and z 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.



3. Digital Twin

Digital Twin plays a vital role by providing a virtual environment for simulating, emulating and testing the accuracy of the anomaly-detection model.
The digital twin model is assembled and emulated on the Emulate3D software.
The model(Fig. 2) is orderly divided into various subparts like the gantry, conveyor belts, inventory tray etc. so that their relative movements can be planned and executed. For this, it is equipped 2 different movement mechanisms like 2-axis linear movement for the gantry and 1-axis linear movement for the inventory tray. The gripper attached to the end is responsible for picking out the inventory from the inventory tray by scanning the QR codes of each item.

All of the inventory in the inventory tray is QR encoded like the real-time setup which plays a vital role in detecting anomalies based on inventory selection. Finally, two cameras are added to the scene to capture the whole operation, The first camera is responsible for providing a view in z-y plane which essentially covers the movement of the 2-axis gantry. The second camera provides a view in x-z plane which provides the video feed for inventory selection.

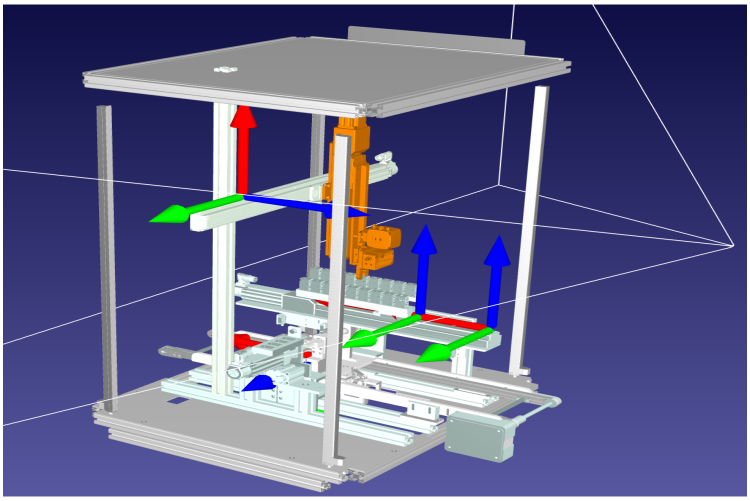


Fig 2: Digital Twin with Camera View

4. Gripper Tracking

For the sake of tracking the overall motion of the gantry, The model tracks the movement of the gripper as it is the core of the whole operation and all the movements can be estimated from it.

For object detection, there several viable pre-trained models like Yolo, RetinaNet [7] etc. After several testing, a bounding box regression model built on MobileNET V2 was used for training the model on the bounding box's annotations. In conjunction with it, the Segment Anything Model (SAM) developed by Meta is used for masking the gripper.
The bounding box regressor outputs the bounding box enclosing the gripper, but this box may include a lot of noise as well. To rectify this, the coordinates are fed to the Segment Anything Model(SAM) which reduces the noise and fine-tune the area of the bounding box

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.[8]
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 the model accuracy and smoothening the overall detection process.[9],

The model was trained on the video frames extracted from many sample operations in the digital twin workspace until considerable accuracy with minimal losses, it was then 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 Segment Anything Model.
For the Segment Anything 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, centre point of the mask is estimated as the mean of all the coordinates of the points enclosed within the mask. Then another bounding box is drawn (Fig. 3) 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. All of these operation are assisted with the help of Numpy library in Python.
To test the accuracy of the Segment Anything Model(SAM), 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 z-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. 4).

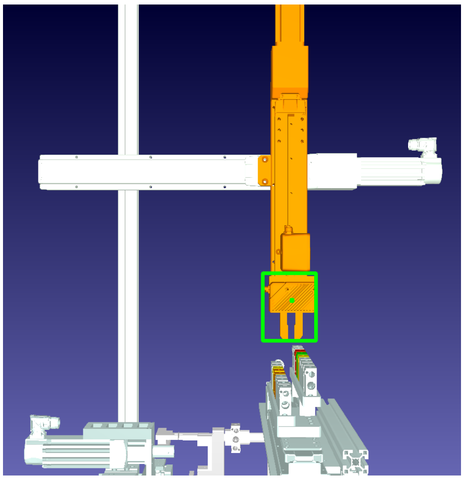


Fig. 3: Gripper Detection

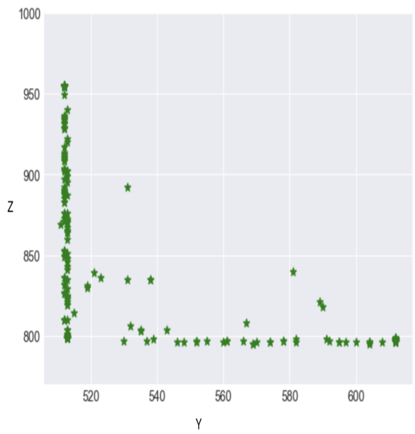


Fig. 4: Plot obtained for L-shaped path

5. Anomaly Detection

5.1 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 the 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.

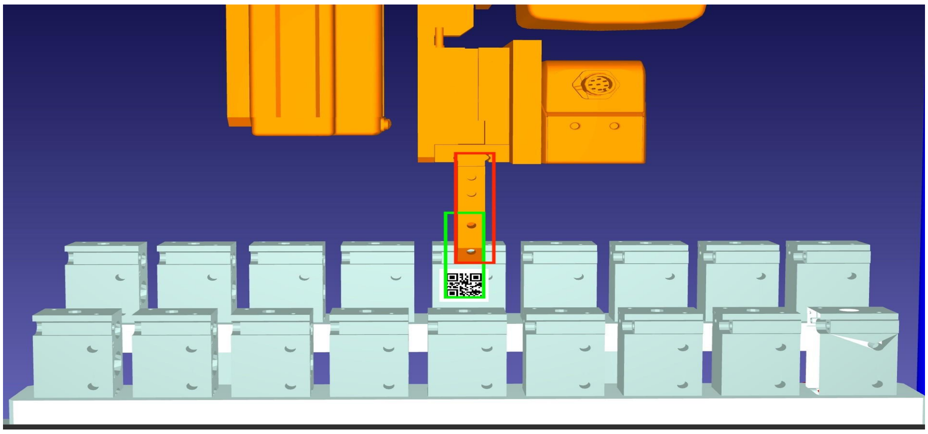


Fig 5: IOU value maximum for the holder encoded with QR

5.2 Gantry Path-Based Anomaly

It involves the anomalies based on the path traversed by the gantry. If the gantry traverses a path different from the pre-defined path between two points in space,or a path that disrupts the assembly line, it is then considered as an anomaly.
For this, the object tracker logs the z,y coordinates of the gripper, which is the centre of the bounding box, along with timestamps.
From this data, velocity and direction are calculated after the coordinates are calibrated according to the camera specification (can be modified). This done to check for velocity-based anomalies explained further.
To check whether the gantry follows pre-defined path, all the datapoints comprising the z-y coordinates of the gripper centre are plotted as a scatter plot.(Fig. 6)
Since the movement of the gantry can be evaluated from the scatter plot of the coordinates. To check any anomalous behaviour in the path of gantry, a safe region is demarcated on the plot initially by the operator (Fig. 6).This safe region is static during the operation of the workstation but can be modified according to the demand. Any scatter 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.

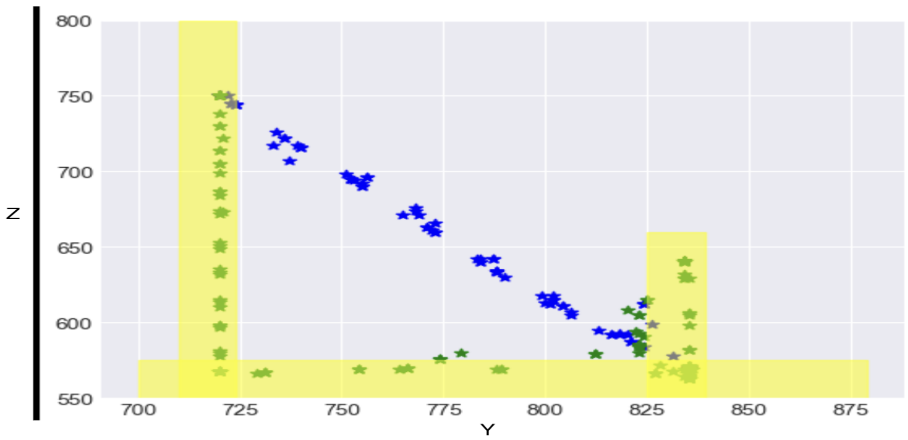


Fig 6: Yellow(safe zone), Blue(anomalous point), Green(non-anomalous)

5.3 Gantry Velocity-Based Anomaly

Velocity-based anomalies involves the non-uniformity in the velocity of the gantry which can damage the joints. A ideal gantry should complete all operation with a smooth velocity and minimum celerity.
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 dispersed and varying scatterplot as compared to a clustered scatterplot in the case of uniform, stable and smooth movements (Fig. 7).
Similar to the previous case in which a safe zone was pre-defined at the start of the process, Here, a dynamic zone is continuously updated based on the set of 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, considering no acceleration. Hence, linear regression is applied over the first 100 data points.
Then a safe region is defined about the line regressor (Fig.8). Similar to before, any data point lying outside of this region is considered anomalous and vice-versa.
But this is a dynamic process since this safe region keep on updating based after every 1000 datapoints. After 1000 thousand datapoint we establish a

linear regression about next 100 datapoints, if there is any change in the velocity of gantry movements the safe region shall be updated, else it shall remain immutable.
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.

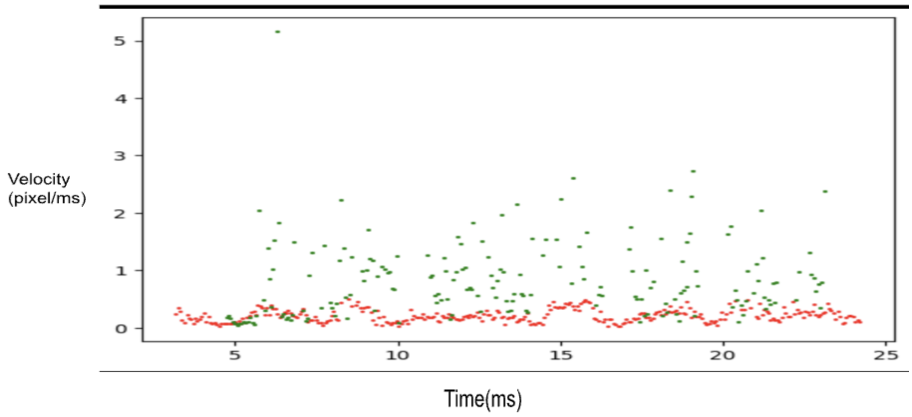


Fig 7: Red(non-anomalous); Green (anomalous)

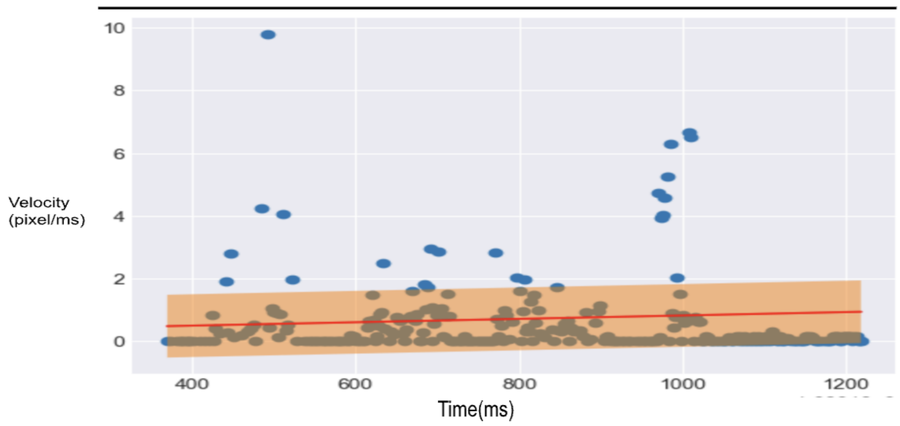


Fig 8: Safe region about the regressor

6. 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

.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 of the model, as well as revolutionising models like Segment Anything Model (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.

However, this approach of using combination of simple robust technique along with Deep Learning inside a Digital twin in detecting anomalies show satisfactory results and have a lot of scope for further development

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