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Factory Inventory Automation using Industry 4.0 Technologies

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***Abstract*— Factory Automation using Industry 4.0 Technologies demonstrates how the upcoming industry technologies like Internet of things, Edge computing, Cloud, Artificial Intelligence, Deep Learning and Machine Learning could be used and integrated to create a use-case for implementation in Factories and other Industries. Nowadays, industries are researching in the lines of how a combination of these technologies could work. Concepts like Dark Factories, Digital Twinning, Robotic Automation for mass manufacturing, Datascience, and integration of AI with the above stated are being talked about and many product/ service based companies are already catching the bus for this revolutionthrough investment in research. Components and inventory logistics management is a challenging problem and this directly affects the efficiency in any industry. Theobjective of this paper is to provide some innovative solutions to factories and industries in tracking and managing various inventory resources. It aims to replace traditional methods of tracking inventory like register books, excel sheets etc. And instead focuses on how tracking and managing the status of inventory can be implemented in real-time that too remotely. The inventory data is tracked by deep learning systems and processed in an IoT platform that is deployed in a cloud service for ease of access in tracking and further analysis.**

Keywords*— *Raspberry Pi 3, Radio Frequency Identification, IoT, IIoT, smart inventory, TensorFlow, Deep Learning, Image Classification, Node-red, Camera, MQTT, AWS, Cloud, EC2 Console, Google Teachable Machine, Edge computing.

I. INTRODUCTION

Improve the efficiency of assembling and manufacturing in factories is of importance considered by companies. On referring various reports and practically experiencing hands- on work in a car manufacturing factory, we came to conclude that the condition as to how the tools and components are goes unnoticed or is ignored upon. This is due to lack of proper management and maintenance leading to a loss of industry grade equipment and tools, in terms of operability and quantity. This only results in a reinvestment of buying them again, which is drastic loss to the company with respect to financials [7]. A unique yet immediately implementable solution has been devised to overcome this problem. This paper suggests and demonstrates the cumulative use of booming technologies to generate a meaningful use-case for the ever-increasing complexity of inventory logistics management in the factories.

Using technologies like IoT, Image processing and classification, Edge Computing and Cloud Services, we monitor and track the inventory equipment in the entire factory to report their location, identity, stock data, dates and time of usage at any particular moment. All the above- mentioned domains will seamlessly interact and are also interdependent with each other for the required use-case. They are meticulously chosen to generate a bare minimal implementation of the idea to minimize as many redundancies or drawbacks as possible.

Internet of things (IoT) is a dynamic ecosystem that realises the power of internet access to primarily inanimate objects, which are then termed as edge devices or “Smart Things”. These devices can interact with each other by to a centralised IoT gateway or the edge computing devices deployed locally using MQTT [1], [5]. An IoT architecture can be further integrated with AI, ML or DL models to help in the analysis and warehousing of sensor and actuator data for visualization and triggering additional processes. In simple terms, it can be understood that IoT is an exciting and the current booming technology that will pick up stream as more and more devices are interconnected and in turn simplifying and automating our lives.

In this paper, each component is attached with an RFID tag, and it is placed in an inventory station which has been an integrated weighing scale [1], [8]. The weighing scale is to correspondingly report any change in weight whenever an object is taken out or placed inside the station and the tools are further monitored by a camera which uses a deep learning software called TensorFlow. Here we have used image classification as a part of deep learning for the detection of objects and thereby tracking and processing this data at an edge server, followed by forwarding this data to a cloud service. Integration with cloud has been done for remote access of this data. We use a Raspberry Pi 3 which serves as a centralized unit for implementing all of the above mentioned [4]. A user can access this data locally as well as remotely to deduce where a tool is located and with further enhancement like on integration with the personnel's credentials, the member using this tool can also be tracked. Data from tracked inventory will be remotely accessible, configurable, manageable and storable for further integration with data science and machine learning models. It can also be used generate information of current stock present with date- time stamp. The IoT platform deployed generates a dynamic webpage that corresponds to displaying live data of inventory location [1]. This makes it easy for the user to monitor items in a composite and consolidated view. In comparison to the current tracking methods used in the factories, this paper provides an efficient and a readily-deployable mechanism that industries can implement. One outcome of this process could be generating a huge employability scope in the respective fields mentioned above [7].

Edge computing is an amazing technology which brings computation and storage of the sensor and actuator data, closer to the sources that emit them. It is primarily used to minimize latency in data transmission to the cloud and take proactive decisions at the instant. Therefore, a lot of bandwidth is saved, and it is more optimized over cloud computing. Soon, it is going to play a crucial role as many devices need to proactively interact with each other and the internet. There is also a need to enhance the communication between devices without much latency, edge computing will be the specific technology for it.

Deep learning has been implemented with TensorFlow to deploy image classification and recognition of the objects in real time. TensorFlow is an open-source software library for deep learning and machine learning. It is mainly used for classification, discovering, prediction, and object detection. The classification and recognition of the components is done by training the model to identify each component in the inventory station or cabinet and to track it anywhere in the factory [3], [9]. A weighing scale is also integrated with the inventory storage station which continuously monitors the weight of equipment present in the station, so that any change in the weight of the system without scanning the component's RFID tag and the personnel's identity card, can be reported and corrected accordingly.

II. METHODOLOGY

The inventory logistics management system as a part of factory automation has been implemented in two interdependent parts, firstly by implementing a component's identity and quantity tracking mechanism in the storage stations/cabinets, where they are currently stored. Second, implementing a mechanism for overall tracking of the equipment and tools used by the factory personnel across different regions in the factory. A prototype model of the cabinet with inventory stacked in and a camera with an overview of it will be mounted and a weighing scale is used at the base of the station. When any user wants to take out any particular equipment then they would first have to scan his ID card which has a built RFID tag in it and then take therequired tool and scan the same with the RFID reader [5]. The camera which is overlooking all this, sends this live video feed to the Raspberry Pi which uses Tensorflow to monitor the inventory and reporting the same. Tensorflow is importedas a module in a python program which is continuously running in the RPi and it is available for open-source development. The video feed is fed as an input to this python program file which contains a model that has been trained to implement image classification [3], [4], and [6]. To train this image classification model, we used Google Teachable Machine to train the image dataset since the dataset for this project is unique. Google Teachable Machine is an easy to use, browser based deep learning application used to train and deploy AI models. After training, the "tflite" model with the labels file is generated by the application and it which needs to be imported into the RPi and followed by specifying the path of the model in the python program. Ideally, there shouldbe a another separate RPi for edge computing, but for the sake of ease of implementation, the python program forwards this data to an IoT service called Nodered which is deployed in RPi as well as an AWS EC2 Cloud based Instance hosting Ubuntu 18.0 LTS as shown in Fig. 3., This has been done forremote access and visualization of component's data. Additional integrations like AWS S3 for mass storage of data etc. can also be executed. Therefore, this RPi only imitates the case of edge computing. The Nodered service application also natively supports forwards data to the cloud server using MQTT Bridging. It generates a beautiful browser-based UI for the Visualization of data in the form of tables, graphs etc. [1]. Conveniently, visualization can be done at both levels i.e., locally with RPi, and remotely with the help of cloud. In a case, where imminent fault in the system and it is unable to track the components taken from the station, the weighing scale comes to the rescue by deducing the change in the weight of the station and creating an alert for the same, if that particular component was not tracked/scanned properly whiletaking or keeping it back in the station.

Once a component is taken out from the station and is used across the factory by the personnel, the movement of the component from one region to another is tracked and the same is updated in the RPi edge server and the cloud server. For the ease of understanding, a representational floor plan of the factory divided into regions has been implemented and a camera is placed in a way that it is overlooking the whole floor plan [5], [3]. This aids in tracking the tools and components across different regions of the factory. A block diagram that illustrates as to how all the devices are interconnected with the different technologies which were mentioned previously is located below. In the block diagram, we have the inventory storage station in which all the inventory is stored and can be accessed. In the station there is a camera that overlooks the inventory and the base that has an integrated weighing scale and an RFID scanner [8]. Aftera component is taken out for use in the factory which has been divided into different regions as A, B and C. These regions are being overlooked by another camera that keeps track of the component throughout the factory across all the regions [6]. This data is then sent to the edge server (which in this case, is the RPi itself) for processing, local visualization and pushing data to the cloud. This data is then displayed through an interactive webpage UI based dashboard generated by Nodered. Data sent to the cloud also for storage in database, future reference and further analytics of the information [1]. The block diagram of the smart inventory management system is show in Fig. 1. With all the different technologies integrated to build the system.

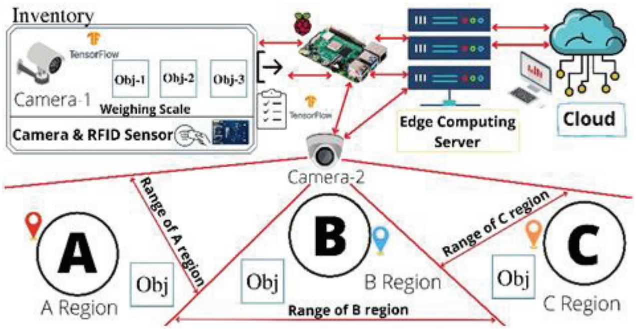

Fig. 1. Block diagram of the inventory management system.

The flow chart of the system explaining the different conditions and their respective cases is in Fig. 2.

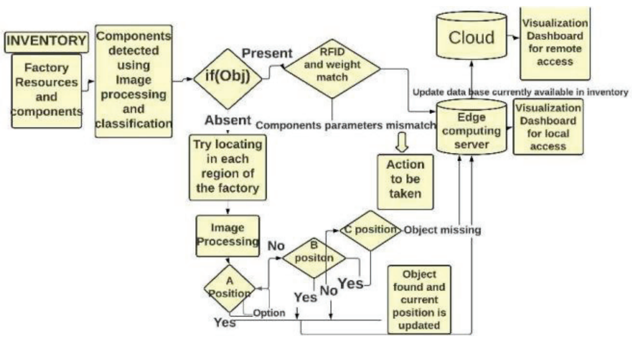

Fig. 2. Flow chart of the inventory management system.

This flow chart is an ideal representation of different states in the project implementation and it is a direct consolidated overview of the textual description given in the methodology.

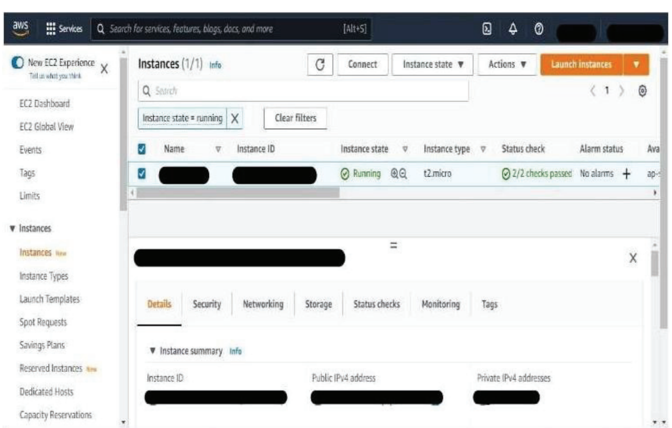

Fig. 3. AWS EC2 Console Instance hosting Ubuntu 18.0 LTS

III. RESULTS

Fig. 4. Is a setup of the inventory storage station, where there are 4 components present inside. The images are captured by a camera used during the training of the image classification model in Google Teachable Machine. This model is trained for multiple scenarios, two of which are shown here: when all the components are present and when a component is removed. The results are snapshots from Google Teachable Machine which showcases the model predicting the most likely result with percentages and bar graph for each scenario.

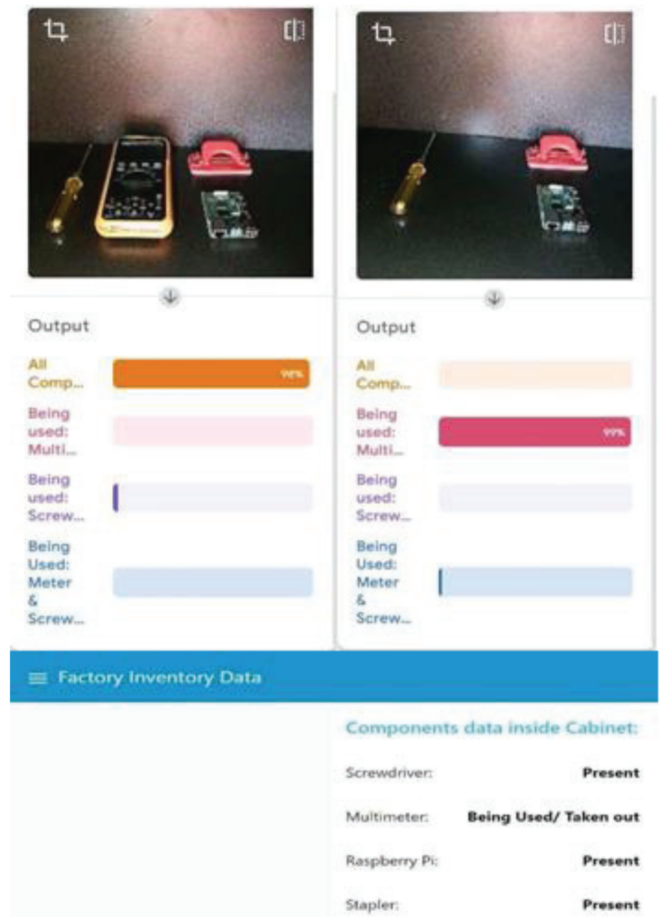

Fig. 4. Tracking the components inside the Storage Station

This model generated by Google Teachable Machine for the component specific image dataset, must be downloaded and imported to the python program running in RPi to derive the standalone result from a camera connected to RPi without Google Teachable Machine. But here, the results are taken from Google Teachable Machine running in a browser, for ease of demonstration purposes.

Additionally, Nodered application running on RPi as wellas Cloud, generates and displays this data in the Web UI upon receiving it from the python program. This UI Dashboard canbe accessed remotely as well.

RFID tag data and weight sensor data are not indicated in results. As this is a future scope of integration in the project. But it must be known that by using these components, manyof the above stated challenges can be averted. The inventoryinside the station must also be tracked based on the weight, as if any component is removed and suppose it is not being tracked by the RFID or the camera, then the change in weightwill indicate so, this logic must also be integrated in python program. The RFID scanner and Weight sensor must be integrated to the RPi via its GPIOs.

When an equipment is being used in the factory by personnel, the second camera overlooking the factory will monitor the location of the component and the data will be processed by RPi. To enhance the speed of processing, another RPi could be used, and these two RPi's should be connected in the same WiFi network for interaction.

Below in Fig. 5. We have a setup of a factory with 4 regions of A, B, C & N. The N region indicates a large number of possible regions in a factory. When a component is moved from one region to the other, the model is able to track it accurately and again display in the UI.

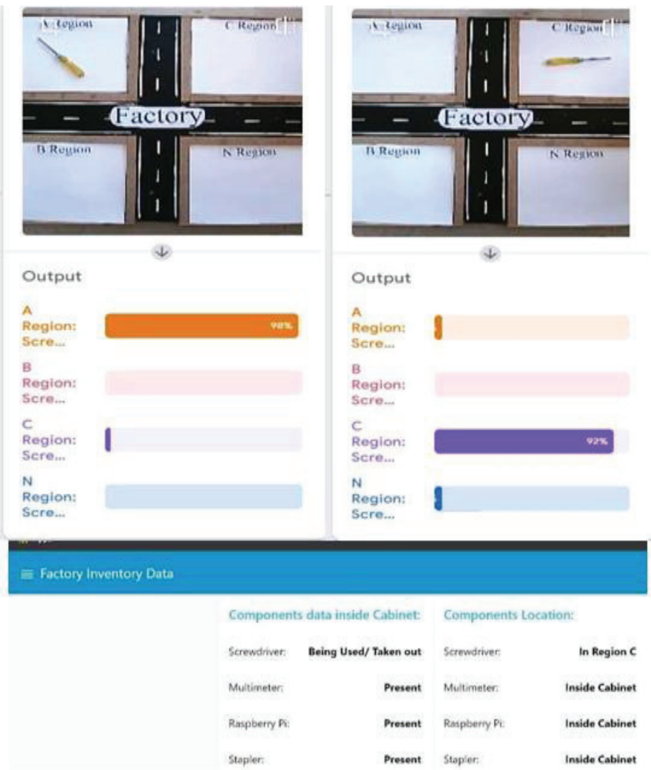

Fig. 5. Screwdriver's location in the factory.

In the above figure we can observe how a screw driver is monitored as it is kept in different regions of the factory and how accurate our model is in detecting the position in different regions of the factory. This way once the position isdetected it will send for processing the positions and reportingthe same to the user in the Dashboard and also send this to the cloud.

Now let's understand the model in detecting other components and their positions in the factory.

Below in Fig. 6. We shall see how our model will be monitoring a digital multimeter as it is moved across different regions in the factory.

Coming to the most realistic scenario, there will always be multiple components being used in the factory, in such a case our model is also able to accurately detect and monitor each component's position and report the same.

Fig. 7. Shows us how our model is able to monitor a multimeter and a screw driver and detect their locations as these components are used in the different regions of the factory.

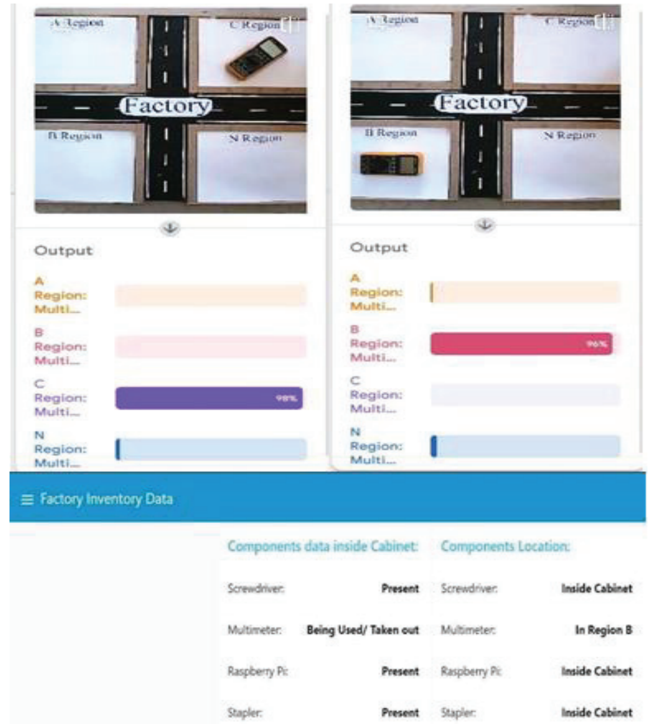

Fig. 6. Multimeter's location in the factory.

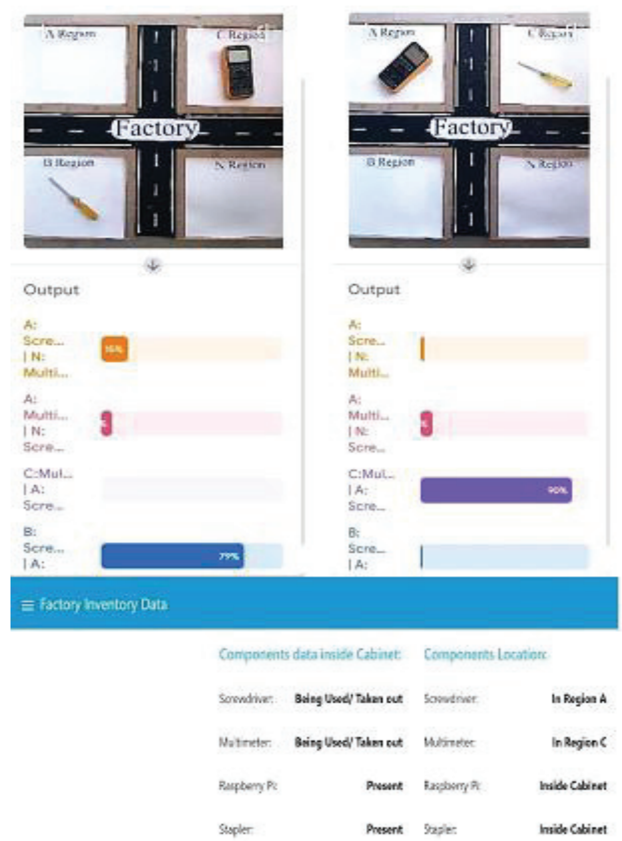

Fig. 7. Multimeter and Screwdriver's locations in the factory.

IV. CONCLUSION

Factory Automation for improved inventory logistics management has been successfully developed and implemented by integrating it with all the latest and trending technologies which will be able to effectively and accurately track and monitor the components anywhere in the factory and report the same. This way will be able to increase the efficiency in the factories by saving a lot of time, efforts, resources and capital. This paper foresees the idea as a disruptive possibility for industrial automation and many other sectors as well.

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