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Technical Paper

Machine learning-based real-time monitoring system for smart connected worker to improve energy efficiency

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ABSTRACT

Recent advances in machine learning and computer vision brought to light technologies and algorithms that serve as new opportunities for creating intelligent and efficient manufacturing systems. In this study, the real-time monitoring system of manufacturing workflow for the Smart Connected Worker (SCW) is developed for the small and medium-sized manufacturers (SMMs), which integrates state-of-the-art machine learning techniques with the workplace scenarios of advanced manufacturing systems. Specifically, object detection and text recognition models are investigated and adopted to ameliorate the labor-intensive machine state monitoring process, while artificial neural networks are introduced to enable real-time energy disaggregation for further optimization. The developed system achieved efficient supervision and accurate information analysis in real-time for prolonged working conditions, which could effectively reduce the cost related to human labor, as well as provide an affordable solution for SMMs. The competent experiment results also demonstrated the feasibility and effectiveness of integrating machine learning technologies into the realm of advanced manufacturing systems.

1. Introduction

1.1. Background and motivation

The advent of new technologies, as well as the rapid evolution of existing ones, are constantly reshaping the world. With the development of cloud computing, enterprises are able to access data storage and computing power with greater ease. The advancement of the Internet of Things (IoT) enabled a centralized network for the gathering and processing of information. Powerful machine learning (ML) algorithms have also been created in support of efficient data analysis and predictions. Yet, issues associated with training these algorithms and with propagating uncertainties from the inputs to the outputs still remain. As countries, industries, and institutions strive to improve their productivity with these new-born technologies, manufacturing systems that combine cloud-based information gathering with centralized data processing have been built. However, how to efficiently monitor sensors of different data inputs, while giving real-time feedback on state predictions remains a challenge.

Therefore in this study, the real-time monitoring system of manufacturing workflow for the Smart Connected Worker (SCW) was developed to address the aforementioned issues with centralized information gathering, accurate data predictions, and interactive user interfaces. The motivation and objective of this project include the following:

Energy Efficiency Focused. Since one of the primary objectives of this project is to track the energy profile of each machine in the small and medium-sized manufacturers (SMMs) through AI-assisted energy disaggregation, main attentions are focused on monitoring the human-machine interactions in real-time: that is, to synchronize and integrate the actions taken by the human operator with the response (i.e. machine state transactions and energy profiling) for analyzing how SCW can be involved and empowered to improve energy efficiency and productivity.

Worker Monitoring. The main objective of this project is to develop

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enabling technologies for establishing smart and connected infrastructure, as well as to improve energy efficiency and productivity in advanced manufacturing environments by empowering workers and operation supervisors in optimizing manufacturing workflow. Due to the developed system's flexibility of integrating visual data from cameras, worker monitoring based on the skeleton-detection of the global surveillance camera can be conducted to monitor the worker even beyond the cases of human-machine interactions. Therefore, worker monitoring is an essential part of this project to synchronize and integrate the actions taken by the human operator with the response, i.e. machine state transactions and energy profiling.

Addressing Industrial Needs. The SMMs typically lack the financial strength to deploy a fully connected and well-established smart manufacturing environment crave an affordable, cost-efficient, and easily deployable solution. While existing implementations, such as the usage of MTConnect protocol and Tera Term terminal emulator program, do enable the inter-communication and monitoring of devices from diverse manufacturers, the response time is unsatisfactory for a real-time system. This project aims to leverage the computing and feature extracting powers of machine learning algorithms to identify and analyze machine behaviors beyond the restrictions of data acquisition through the existing communication protocols, thereby supplying SMMs with a more flexible and affordable solution.

An Automated System. The processing and analysis of digital as well as visual information gathered from manufacturing systems are usually intricate. Therefore, the developed system aims for aiding users by providing a comprehensive graphical user interface for centralized control and monitoring of the entire smart manufacturing system. To further benefit manufacturing companies, this project seeks to reduce the need for human labor for monitoring, fault-detection, information gathering, and data analysis, all of which can be done autonomously in real-time.

In the developed manufacturing system, information gathered from human labor and automated machines are exchanged via wireless-connected networks, while high-level data processing, such as real-time energy disaggregation and machine state prediction for future optimizations, are conducted through a combination of various machine learning algorithms. Instead of solely depending on the output of the machines that rely on different communication protocols, the machine learning modules can be trained to identify the status of the machines, the interactions between operators and devices, as well as the profiling of the system's energy – this provides the SMMs with a possibly more affordable solution for establishing a smart connected manufacturing system with devices that do not support machine status indication. The machine learning-based energy disaggregation can further reduce the budget by predicting the energy consumption of multiple devices through the output of a single meter. This paper provides a detailed description of the real-time monitoring system, which includes the methodologies related to system architecture, data acquisition, machine learning algorithm implementation, experimental configuration, and result evaluation. After validating in a real-world working environment, the developed SCW system achieved competent accuracy and effectiveness in real-time data management and predictions.

1.2. Related works

Smart manufacturing has made the traditional manufacturing field more intelligent and efficient by combining technologies from the fields of data science, IoT, cloud computing, and artificial intelligence (AI) [1]. For example, in order to enhance work efficiency, Roda-Sanchez et al. [2] developed an algorithm to bring digitalization into factories and made a step forward in the wearable revolution. Tao et al. [3] implemented a method to recognize worker's actions during worker activities using CNN for the evaluation of their performances, obtaining a high model accuracy. Smart workers, referring to manufacturing systems that utilize assistive machine intelligence to create interactivity, collaboration, and workplace efficiency, have been widely used in different industries [4]. Park and Han [5] utilized smart worker ability subjects to design a learning curriculum, which significantly increased information utilization. The systematic literature review done by Mark et al. [6] also brought to view a rapid development of worker assistance systems during the fourth industrial revolution.

In order to establish a smart manufacturing system, machine state monitoring and analysis are indispensable elements. While many machines nowadays do provide application programming interfaces (APIs) to indicate their status, the various communication protocols supported by a diverse range of manufacturers are difficult to handle and synchronize. Therefore, researchers have been striving to develop efficient and robust machine state monitoring models. Edrington et al. [7] proposed a web-based machine monitoring system that utilizes MTConnect [8] to perform analysis of data collected from compatible machines regardless of manufacturer or brand. With the aid of the MTConnect protocol, Lynn et al. [9] proposed a local and a cloud machine tool monitoring system that enables the efficient collection, storage, and visualization of data in near real-time. In addition, characteristic data related to signals and positions could also be leveraged for condition and process monitoring. Bian et al. [10] proposed a YOLO-based model to identify the exact positions of the 3D printer's major components in real-time with promising efficiency and accuracy. Liu et al. [11] proposed an approach that identifies the condition of tools by comparing the target signal captured during application with a set of reference signals obtained from calibration via similarity analysis. Liu et al. [12] established a position-oriented machining process monitoring model that optimizes thin-walled part machining process through correlating monitoring signals with cutting positions. These approaches demonstrate the feasibility of monitoring machines through visual and digital information that may not be restricted by communication protocols.

In order to further enhance the robustness of the smart manufacturing systems, and to enable a synchronous analysis of data, numerous monitoring methodologies based on real-time detection algorithms have been developed. Hamzeh et al. [13] combined data acquisition modules, edge analytics, and software-based testbeds into one real-time monitoring system for welding quality control. Using the IoT applications, Mykoniatis et al. [14] was able to construct a real-time condition monitoring system that can both identify abnormal sensor inputs and record the data to a logging station via wireless connections. To achieve better efficiency and accuracy during processing, neural networks have been adopted by researchers for real-time data analysis. Convolutional Neural Network (CNN) for analyzing and classifying operational sounds was adopted by Kim et al. [15] to monitor the status of working devices in real-time. Miao et al. [16] also utilized CNN's feature-extraction functionality to achieve real-time detection and identification of weld defects.

Recent improvements based on traditional neural networks also led to the development of powerful object detection models. Leveraging CNN, the Region-based Convolutional Network method (R-CNN) [17] made remarkable progress in the field. The accuracy and efficiency of R-CNN were then pushed forward by fast R-CNN through the combination of a single-stage training algorithm and shared computations. Relation Networks for Object Detection [18] incorporated an object relation module that captures the mutual effect between objects, and further advanced the accuracy of object detection. Single Shot MultiBox Detector (SSD) [19] is another technology in this field, which has a default Bounding Boxes set before receiving the input. By processing the input channels through a single deep network, SSD gives each Box in the default set a score and determines the final output based on this score. The SSD also adjusts the selected Bounding Boxes based on the input to achieve a better fit. Because it is based on a single deep network, SSD is versatile and easy to train. Machine learning models based on these methods introduced new possibilities to manufacturing systems. For example, Chen et al. [20] combined an object detection model with the Convolutional Pose Machines [21] into a framework to recognize and analyze workers' assembly actions. The proposed work strives to further exploit the potentials of machine learning models by integrating them into the monitoring of machine states and human-machine interactions.

Furthermore, to keep track of energy consumption and detect unnecessary usage of energy, multiple techniques from the realm of machine learning have also been adopted for performing energy disaggregation and analysis in smart manufacturing. Deep Neural Network (DNN) with Convolutional Variational Autoencoder (CVAE) was used by Sirojan et al. [22] in Non-Instructed Load Monitoring (NILM) to perform energy disaggregation. Zico Kolter et al. [23] applied discriminative sparse coding in power and energy data to perform energy disaggregation. Cui et al. [24] adopted a Markov chain model to derive and capture coupled relationships between production rate and energy consumption. Long Short Term Memory (LSTM) [25] network was adopted by Abhiram [26] and Anawat Tonga et al. [27] for predicting the energy consumption of individual devices from the aggregated energy data collected by the smart meter.

Past researches have demonstrated the possibility and potential of adopting methodologies from machine learning to the realm of advanced manufacturing systems. Therefore, this research intends to present the framework and methodology for developing an automated real-time monitoring system that incorporates and centralizes machine learning methods of various kinds to improve and expand smart manufacturing functionalities.

1.3. Research contribution

The objective of the SCW project is to create affordable, scalable, accessible, and portable smart manufacturing systems (A.S.A.P. SM systems) through which advances in the Internet of Things (IoT) technologies can be effectively integrated into mobile sensor platforms to augment the intelligence of workers and supervisors with smart manufacturing principles and methods. This paper presents the real-time monitoring system of manufacturing workflow for the Smart Connected Worker. The major contributions in this work are:

With a carefully selected dataset from diverse experimental configurations, a You only look once (YOLO) [28] based object detection model was trained for the real-time identification of 3D printer components. Based on the output produced by the pre-trained machine learning model, a filtering algorithm was developed for supervising the status of the 3D printer, and for checking faulty behaviors during the 3D printing processes. By encapsulating the object detection model with the filtering algorithm into the first subsystem of the Smart Connected Worker, the developed work is able to achieve efficient and accurate behavior-supervision and status-monitor for 3D printers in real-time.

Building upon the Character-Region Awareness For Text detection (CRAFT) [29] text detection algorithm, a subsystem was developed for real-time finger position and text recognition. By feeding the real-time image frames acquired from a wearable camera into the algorithm, this second subsystem of the Smart Connected Worker is able to recognize both the texts that are displayed on the 3D printer panel and the position of the worker's finger over the panel buttons. By extracting the machine status from the text predictions and the human actions from the finger positions, the developed work is able to detect, record, and analyze both human interactions and automated machine processes in real-time.

Utilizing LSTM algorithms, Smart Connected Worker is able to disaggregate in real-time power signatures of individual devices from the total power collected and recorded by the smart meter. By training the LSTM model with digital data collected from authentic working conditions, the developed work takes advantage of the backtracking functionality of the Recurrent Neural Network (RNN) [30] and achieves energy disaggregation in real-time with competent accuracy and efficiency.

For visualization of the workflow, a web page-based graphical user interface (GUI) is developed to present both the raw data from the sensor devices and the processed high-level information from the Smart Connected Worker to the user in real-time.

Integrating all sub-components into one automated system, the developed Smart Connected Worker is able to detect and record data from various manufacturing devices, and perform real-time analysis, such as energy disaggregation or fault detection, via machine learning models and a web-based GUI. Since all components work in real-time and at low costs, the presented work would smoothly fit into existing advanced manufacturing systems, and serve as an auxiliary unit for advanced behavior monitoring, information analysis, and fault diagnosis. Furthermore, the proposed system, utilizing machine learning techniques instead of solely depending on the feedback from the machines, can accommodate devices regardless of their manufacturer or communication protocols, thus providing SMMs with a more scalable, deployable, and cost-efficient solution.

The detailed implementations are presented in the following sections.

2. System architecture

In this section, the architecture of the developed Smart Connected Worker, along with the general data acquisition and storage configurations are explained.

2.1. Framework

As shown in Fig. 1, the overall architecture of the developed SCW can be deconstructed into three main modules, each serving a dedicated purpose.

The first module is the data acquisition system, which is responsible for acquiring raw data from the multiple sensors that are installed in the lab. Specifically, two types of data are collected: the visual data from cameras, and the digital data from smart meters. The data collected are then delivered to the machine learning system (second module) for processing, and to the master device (the third module) to be fused together for real-time display. This module provides first-hand information of the running devices in the lab and serves as the preliminary channel that connects the real-world working conditions with the subsequent algorithm-based data processing methods. The detailed data acquisition methodologies and configurations are explained in Section 2.2. The high-level workflow for centralizing and displaying the collected data on a web-based graphical user interface is explained in Section 4.6.

The second module is the machine learning system, which is responsible for extracting features and making predictions based on the raw input from the first module. For the visual data, object detection and text recognition algorithms are implemented and utilized to predict in real-time the status of machines and workers. The timestamp associated with each specific machine motion and human action is aggregated to the main timeline of the digital energy streamline acquired from the smart meter. For the digital data, an energy disaggregation model is developed to extract device-specific power signals from the total aggregated signals. With the machine learning outputs, this module is also responsible for displaying the energy profile of both machine motions and human actions within the lab, which is the main goal of creating an affordable solution for SMMs to improve energy efficiency. The detailed machine learning methodologies, as well as the steps for processing the raw input images, are explained in Section 3.

The third module is the master device, which is responsible for controlling and monitoring the whole Smart Connected Worker facility in real-time. The master device records the processed data from the previous two modules into a database and provides a high-level GUI server for the control and monitoring of the entire smart manufacturing system. The detailed database selection considerations are explained in Section 2.3.

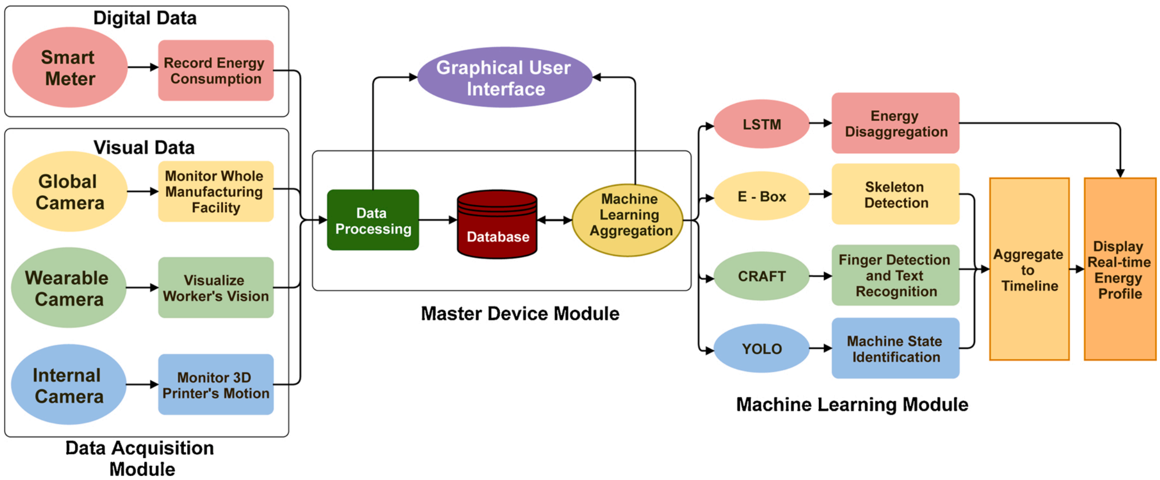

Fig. 1. Overall system architecture of SCW.

2.2. *Data acquisition*

The data acquired from the sensors and processed in the developed SCW system is of various types. In this subsection, a detailed description of the data acquisition process is presented.

2.2.1. *Digital data*

A smart meter is connected to the main functioning devices within the lab and is responsible for measuring the energy profile of the manufacturing systems. Specifically, each circuit of the smart meter is connected to a single device and is responsible for measuring the power, current, and energy consumption of that device in real-time. Using the Modbus protocol [31], the digital data acquired from the smart meter is transmitted via a wireless connection to the master device in real-time. The master device is responsible for processing the raw digital inputs, which include the calculation of accumulated energy consumption for each major device. Further processing and analysis steps in the machine learning module, such as energy disaggregation, can be achieved with these energy consumption data. The processed digital data of the smart meter is sent to the master device's server via the Asynchronous JavaScript and XML (AJAX) technique [32] and is displayed in real-time as a dynamic line chart on the dashboard of the web-based GUI.

2.2.2. *Visual data*

There are three cameras utilized to simulate a working environment by obtaining visual data from various angles. The internal camera is fixed to the inner side of the 3D printer case and is responsible for recording the movements of the printer's major components during a printing process. The wearable camera is fixed to the headset of the worker and tracks the vision of the worker in the manufacturing facility. The global surveillance camera is positioned on the ceiling of the lab and monitors the human behaviors and machine movement within the whole lab. In this configuration, each camera has a dedicated coverage scope, which compensates for the blind zones of others. In the common scenario of a worker walking inside the lab and interacting with the manufacturing devices, the wearable camera positioned on the headset captures the worker's vision, as well as the first-person view of the human-machine interaction process. The camera positioned inside the 3D printer records the activities of the running machine's internal components. The global surveillance camera monitors the movement of the worker, as well as the working condition of the lab as a whole. This acquired visual information will be processed in the SCW's machine learning module (detailed in Section 3) for further analysis and predictions.

2.3. *Database*

To store and manage the collected data, the following three database systems were considered as candidates: MySQL, developed and released by the Oracle Corporation, is an open-source relational database management system (RDBMS) [33] widely used for web-based applications; Microsoft SQL Server, developed and initially released by Microsoft, is a commercial RDBMS commonly used in industries and the Microsoft and Linux operating systems; MongoDB, developed and initially released by the MongoDB Inc., is an open-source document-oriented database that offers highly efficient data writing and retrieving service on numerous platforms.

Based on the characteristics of each candidate, as summarized in Table 1, MongoDB was selected as the database for the storage and management of data. MongoDB's open-source license, as well as its compatibility with numerous major operating systems, allow the developed SCW system to be deployed affordably for the SMMs. Since the data collected from the advanced manufacturing system often consist of various types, MongoDB, with a dynamic database schema [34] that supports flexible storage and retrieval of data with non-fixed structures, is the most ideal for the developed SCW. In addition, MongoDB's horizontal scalability [35] allows dynamic and elastic distribution of data across multiple computers and servers, which is suitable for dealing with the high throughput and large data sets of manufacturing systems.

3. Machine learning-based methodologies

In this section, the methodologies for utilizing various machine learning techniques to process visual and digital data are presented. Specifically, the object detection for machine state prediction, the finger detection and text recognition for 3D printer control, the skeleton detection for worker motion monitoring, as well as the energy disaggregation model are discussed. The web-based GUI is briefly mentioned

Table 1
Comparison of candidate databases.

	MongoDB	MySQL	Microsoft SQL Server
License	Open source	Open source	Commercial
Operating system	Linux, Windows, macOS	Linux, Windows, macOS	Linux, Windows
Database schema	Dynamic	Fixed	Fixed
Primary scalability	Horizontal	Vertical	Vertical

in this section, while more detailed illustrations are provided in Section 4.6.

3.1. Object detection for machine state prediction

The developed SCW combines a pre-trained YOLO-based object detection model with a filtering algorithm to predict the machine states of an operating 3D printer automatically in real-time, as illustrated in Fig. 2. Specifically, the raw images acquired from the printer's internal camera are processed by a pre-trained YOLO-based object detection model to extract the positions of each major component of the printer. A filtering algorithm is developed to predict the machine states of an operating 3D printer in real-time from the outputs of the object detection model. The predicted machine state as well as the processed images with bounding boxes are integrated into the web-based GUI for visualization and subsequent analysis.

In this submodule, three critical components are analyzed during the printing process of a 3D printer: the extruder, the motor axis, and the build plate. The extruder stores and ejects the raw printing material. When considering a right-hand coordinate system, the extruder can move in the x and the z-direction, which forms a horizontal planar activity space. The motor axis controls the z-position of the extruder. The build plate supports the whole printed model as a pedestal and can move in the y-direction.

In order to ensure a fully automated process for machine state prediction, object detection methods from the field of computer vision are adopted to identify the location as well as the movement of major printer components. YOLO [28], a state-of-the-art object detection algorithm built upon the single-shot detector method, is able to achieve competent accuracy with optimal efficiency by predicting both the location and class of bounding boxes within one evaluation via applying a single neural network. By feeding the raw images from the internal camera into a pre-trained YOLO model, the developed submodule identifies the absolute and relative coordinates of the printer's components in real-time, which are subsequently used by the filtering algorithm to extract the machine states of the 3D printer.

The developed submodule considers the following six sequential machine states during a full 3D printing cycle: the initialized state, where the printer receives the printing command and starts to operate; the testing state, where all components responsible for printing are initialized in position; the calibration state, where the extruder moves around and above the build plate to calibrate and find its starting position; the heating state, where the printing chamber and the ejection nozzle heats up; the printing state, where the extruder prints the 3D model by ejecting the support and model material upon the build plate; the ending state, where all components return to their initial locations. In each of these machine states, the positions of the fundamental components form a unique combination, as recorded in Table 2. The filtering algorithm checks the combination of the printer component coordinates against the criteria of all the possible machine states, and filters out the correct one that is predicted as the current machine state. In order to eliminate the error produced by individual frames that are falsely predicted by the object detection model, the filtering algorithm looks back at the past consecutive ten frames before making the prediction, thereby enhancing the accuracy and robustness of the real-time prediction model.

3.2. Finger detection and text recognition for 3D printer control

A CRAFT-based text recognition model is adopted and modified for monitoring the human-machine interactions in the lab in real-time. Specifically, to simulate the real-world scenario in which a worker operates the 3D printer with a control panel, the model identifies and recognizes both the texts and the worker's finger positions from images recorded by the wearable camera. The real-time human-machine interactions are displayed on the web-based GUI for visualization and monitoring. The workflow for capturing the displayed texts and the worker's finger positions during real-time human-machine interactions is illustrated in Fig. 3.

CRAFT [29] is a novel text detector that utilizes a CNN [36] to produce region scores for localizing individual characters in an image, and affinity scores to group individual characters into instances. Without the need for further post-processing, CRAFT achieves competent speed during the inference stage and is therefore suitable for text detection in real-time. In addition, CRAFT's high flexibility in detecting texts of complicated shapes and sizes allows it to be applied to dynamic manufacturing conditions. Therefore, for the first processing step of this

Table 2
Logical matrix of machine states and component position.

Machine state	Extruder position	Build plate position
Initialized	Left-back corner	Bottom
Testing	[No motion]	Elevates to top
Calibration	Moves around	[No motion]
Heating	Left-back corner	[No motion]
Printing	Moves around	Gradually descends
Ending	Left-back corner	Descends to bottom

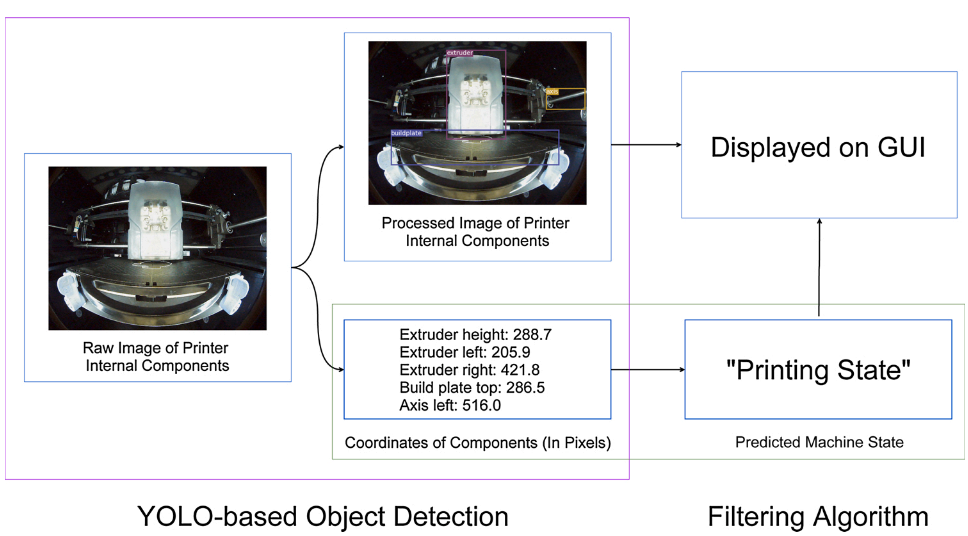

Fig. 2. Workflow of the object detection module.

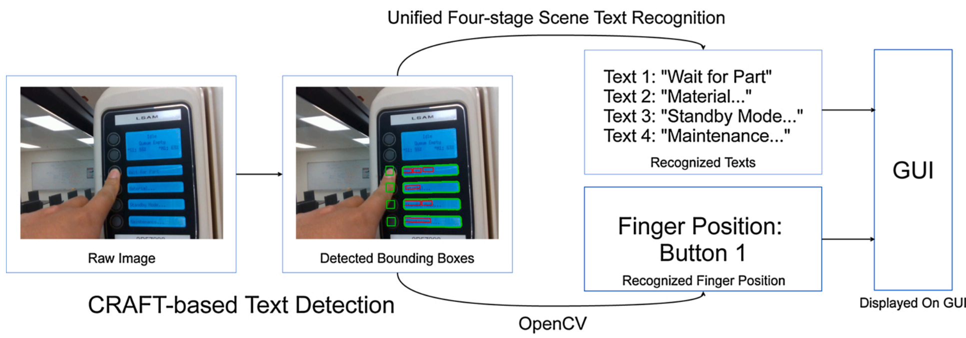

Fig. 3. Workflow of the finger and text recognition module.

submodule, the raw image acquired from the worker's wearable camera is fed into the CRAFT model, through which the locations of the displayed texts on the printer panel are identified and highlighted with bounding boxes.

In the subsequent step, a unified four-stage scene text recognition algorithm as developed by Jeonghun Baek et al. [37] is adapted to translate the bounding-box output from the CRAFT model into the corresponding text strings. Meanwhile, the contours of the display screen along with the location of the press-button blocks are identified and highlighted using the OpenCV library [38] functionalities. By calculating and comparing the average RGB value of each press-button block, the submodule recognizes which button the worker's finger is pressing on. Therefore, as a raw image acquired from the wearable camera is passed through this finger and text recognition submodule, the developed SCW is able to extract in real-time the texts and the finger positions from the panel of the device that the worker is interacting with. Finally, the processed image, as well as the predicted results, are displayed on the web-based GUI to monitor both vision and the working conditions of the worker.

3.3. Skeleton detection for worker motion monitoring

Deep learning-based RGB image-based skeleton estimation algorithms provide a novel and non-invasive method to estimate 2D or 3D body joint coordinates. In this study, OpenPose was applied, which is an open-source 2D skeleton estimation software with the capability to estimate the body, hand, face, and foot keypoints [39]. The advantage of Openpose is its capacity of maintaining a relatively constant processing speed at 20 fps to estimate multi-person skeletons even when there are over 20 people in the scene. Fig. 4 illustrates the data processing pipeline. In order to determine whether a worker interacts with a machine from the viewpoint of the global camera, the Body25 type skeleton is selected with the head and foot being removed as they are rather irrelevant to interaction gestures by hands. OpenPose predicts all the joints with x, y coordinates and scores in a single image and groups them to different people. A score-based filter is applied to the raw skeleton outputs to filter low-score less-convincible detections. After that, a tracking method is implemented based on the spatial consistency between adjacent frames to track a person continuously from the person entering the scene to leaving the scene. The intuition of spatial consistency is that between frames the skeleton from the same person should shift smoothly and subtly, which is used to set a threshold to identify the same person.

For the 3D printer use case, the worker machine interaction manifests as the worker's hand touches the control panel and the case door (or inside the case door), which are fixed at certain locations. Depending on this observation, we implemented an interaction detection module based on spatial relationships. The raw streaming video is partitioned into sliding windows with a window width equal to 60 (2 s). There is no overlap between adjacent windows. The averaged 2D positions of the right hand and left hand are calculated and compared with a pre-defined bounding box indicating the possible interaction region. The average over a window reduces the errors caused by unintentional hand movements during non-interaction periods.

3.4. Energy disaggregation

With a pre-trained LSTM model, the developed module is able to disaggregate the power of individual devices from the total power in real-time. The workflow is illustrated in Fig. 5.

The reason behind the developed energy disaggregation method can be summarized as a vector-valued function $F : R^k \rightarrow R^n$, where n is the number of appliances and k is the **look-back** parameter. The function F maps the total energy consumption of the past k moments to the current energy consumption of the n appliances. In other words, the input of F is a sequence X_i, $i = 1, \ldots, k$ of length k, where each element X_i is the total energy consumption at $k - i$ moment before the current moment. And Y_i, the ith element of the output $Y \in R^n$, is the current energy consumption of appliances i. In the developed methodology, the data is pre-processed by taking the interval between two moments as 0.5 seconds, and the look-back parameter k to be 100. Since this is a typical problem that deals with sequential input, LSTM, which is a well-established Recurrent

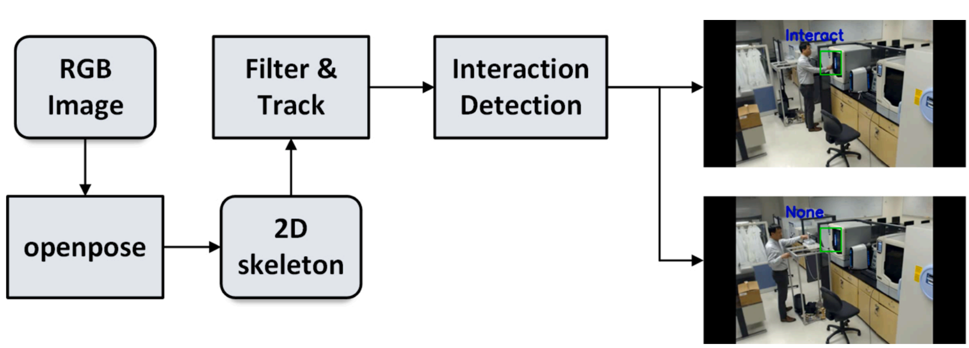

Fig. 4. Data processing pipeline for skeleton-based motion monitoring.

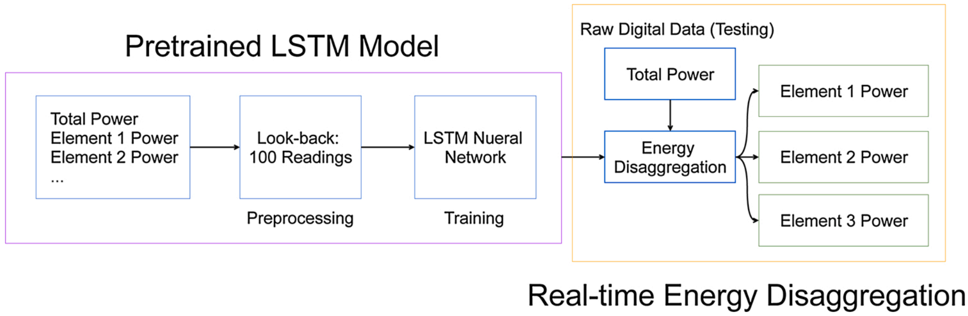

Fig. 5. Workflow of the energy disaggregation module.

Neural Network algorithm, is adopted to analyze the overall trend of past data and to produce the current predictions.

During real-time energy disaggregation, the raw digital data, which is the total power of all devices, is delivered into the pre-trained LSTM model, which predicts the current power of every single device. With this configuration, one single measuring meter will be sufficient to identify the power consumption of multiple devices, which helps in creating a centralized control system.

4. Results and discussion

In this section, the performance of the developed SCW is presented and analyzed with the instance of a worker operating a functioning 3D printer.

4.1. Experimental setup

4.1.1. Smart meter setup

The developed SCW adopted the PowerScout 48 HD Multi-Circuit Power Submeter as the smart meter that is responsible for acquiring the digital energy consumption data from the devices of the lab. Specifically, three of the smart meter channels were used, each connected to one of the following three devices: the 3D printer that is printing a model, a controlling PC, and a functioning assembly line. During the process of the experiment, the smart meter is configured to record the voltage (in Volt), current (in Ampere), and power (in kilowatt) of these devices.

4.1.2. 3D printer setup

In the experimental setup, the Stratasys uPrint SE 3D Printer was selected as the primary device that the worker interacted with. To test with a prolonged but continuous working process, a large and complicated model was chosen for printing. The SolidWorks Computer-Aided Design (CAD) of the 3D test model is shown in Fig. 6, and it took approximately 12 h to finish the entire printing process.

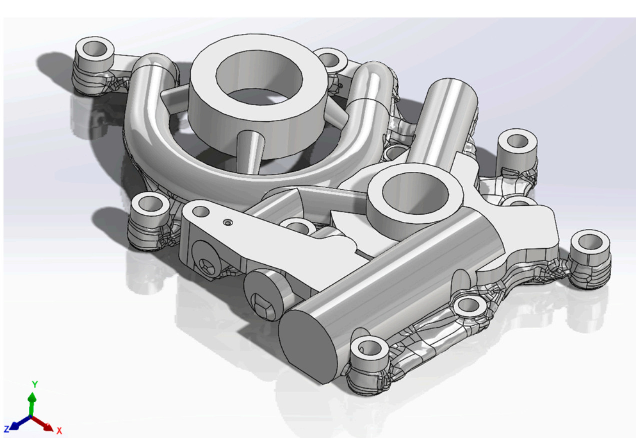

Fig. 6. SolidWorks CAD model of the tested 3D printing part.

4.1.3. Camera setup

A Logitech C922 Pro HD Stream Webcam with full 1920 × 1080 (unit: pixel) resolution and 30 fps frame rate was selected as the global surveillance camera to monitor the whole working condition of the experiment. An Intel RealSense Depth Camera D435i with 1280 × 720 active stereo depth resolution and 90 fps frame rate was chosen as the wearable camera to capture the vision of the worker during the experiment. Since the interior of a 3D printer can be heated up to about 70 during printing, a specially designed heat-resisting SVPRO Fisheye Lens camera with full 1920 × 1080 resolution and 30 fps frame rate was chosen and configured as the printer internal camera.

4.1.4. Master device setup

The master device adopted for the experiment was a workstation with the Windows 10 Enterprise operating system [40]. Specifically, the master device was equipped with an NVIDIA GeForce RTX 2070 GPU of 8GB memory, and an Intel Core i7-9700 CPU with 8 cores.

4.2. Object detection and machine state prediction

4.2.1. Training results

After setting up the camera and the 3D printer, the training dataset for the object detection model was acquired by utilizing the OpenCV package to capture the image frames at 5 fps during the printing process of a small sample model. For the 4400 collected images, the ground truth bounding boxes with labels were produced using the YOLO Visual Object Tagging Tool (VoTT) v1 software. 80% of the images were selected at random as the training set, while the rest was left as the validation set. After training for 200 epochs with an NVIDIA GeForce RTX 2070 GPU, the object detection model converged, and achieved an average IoU of 0.931 with an average validation accuracy of 0.998. This trained model was used for the real-time testing of the experiment.

4.2.2. Testing results

Of all the image frames collected by the internal camera during the 12 h and 27 min printing process of the complex model, 83,275 frames that covered all printing stages were chosen for testing. For each of these frames, the real-time output from the object detection model and the machine state prediction from the filtering algorithm were compared and validated against the ground truth. Among the total 83,275 test frames, 83,183 frames predicted all printer components correctly, achieving a competent accuracy of approximately 99.89%. The average inference speed of the test frames and the predicted machine states is 0.036 seconds per frame, which is an ideal efficiency for monitoring real-time working conditions. Due to the look-back functionality of the filtering algorithm that rules out the error produced by individual faulty frames, the predicted machine states achieved perfect (100%) accuracy during real-time testing, which confirms the feasibility of adopting object detection algorithms for machine states monitoring. The detailed test results of the object detection module are summarized in Table 3.

4.3. Finger detection and text recognition

During the whole process of the prolonged experiment, valid human-machine interaction only lasted for approximately 3 min. Specifically, 442 image frames that recorded the worker's entire operation on the 3D printer were collected by the wearable camera during the experiment. After the test images were passed through the pre-trained recognition model, the predicted texts and finger positions were compared with the ground truth. Among the 442 total frames, 381 produced totally accurate text recognition results, achieving a fair average accuracy of approximately 86.2%. Among the 174 total frames with the worker's finger in sight, 161 instances produced the correct position of the finger, thus achieving an average accuracy of 92.5%. The detailed test results of the finger and text recognition module are summarized in Table 4.

4.4. Skeleton detection

During the test, there are in total 12,120 frames captured from a global camera. Since interaction detection is based on sliding windows with a window width equal to 60, the 12,120 frames are grouped into 202 windows. 46 windows are interaction-related gestures and 156 windows are non-interaction gestures. By applying the developed method, 39 interaction windows are correctly detected and 152 non-interaction windows are detected. Table 5 shows the result with precision, recall, f1-score,and accuracy. In conjunction with other modules, the monitoring function can be achieved.

4.5. Energy disaggregation

4.5.1. Training results

The training data for the energy disaggregation model was collected by strictly following the configurations in Section 4.1. The smart meter measured and recorded the power of the three devices for 26 h, during which the 3D printer printed a sample model under the control of the PC. The collected data were then pre-processed according to the methodologies of Section 3.4 and was fed into an LSTM neural network for training. Specifically, the collected data was separated into the training and validation set using random shuffling and a train-validation split of 70/30. The LSTM model was constructed with the Adam optimizer [41] of learning rate 0.00001, and configured with a dropout rate of 0.3, hidden layers of sizes {64, 128, 256}, and a loss function that minimizes the mean square error between the predicted results and the ground truth. The model was trained with a batch size of 512 and converged within 200 epochs.

4.5.2. Testing results

In order to optimize the prediction accuracy, the configuration of the smart meter during the testing process strictly followed the setting during the collection of training data. Specifically, three devices were connected to the three circuits of the smart meter: device A was the 3D printer that printed the test model, device B was the PC that controlled the printing process of the printer, and device C was the assembly line. The smart meter measured and recorded the power of the three devices at a rate of two readings per second during the experiment process.

Table 3
Object detection module test results.

	Extruder	Build plate	Motor axis	Predicted machine state
Average accuracy	99.96%	99.90%	99.98%	100%
Average inference speed	0.036 (seconds per frame)			

Table 4
Finger and text recognition module test results.

	Text 1	Text 2	Text 3	Text 4	Finger position
Average accuracy	88.9%	95.2%	87.6%	91.4%	92.5%
Average inference speed	0.338 (seconds per frame)				

Table 5
Test results of the skeleton detection module.

Precision	Recall	F1-score	Acc (%)
0.907	0.848	0.876	96.5

Since it is relatively difficult to evaluate the accuracy of digital data in real-time, the predicted results and the ground truth produced during the experiment were compared and analyzed after the data collection process. Specifically for each of the three devices, the predicted power signature from the pre-trained LSTM model at each timestamp was matched with the corresponding ground truth power signature, while the Mean Square Error (MSE), as well as the Mean Absolute Error (MAE), were calculated to quantify the accuracy of the predictions. The detailed test results of the energy disaggregation module are summarized in Table 6. In order to better assess the results, the predicted power signatures of each device were also plotted with the ground truth. In Fig. 7, the energy disaggregation results for devices A (3D printer) and C (assembly line) are visualized, since they had more significant energy consumption during the experiment. The results demonstrated that the trained LSTM model is able to learn and predict the general trends of power signatures for individual devices by disaggregating them from the total energy data. Therefore, with this module, the developed SCW system can analyze and monitor the power and energy consumption of multiple devices with a single smart meter channel.

4.6. Web-based graphical user interface

The raw and the processed data from the modules of SCW is visualized on a web-based GUI. Specifically, the master device, connected to the smart meter via the Modbus wireless protocol, constantly obtains the meter readings and dumps the digital data in JavaScript Object Notation (JSON) format to the web page server for real-time visualization. Similarly, the master device uses the OpenCV package to obtain image frames from the cameras, and transmits the raw and processed visual data as NumPy array encoding to the server for real-time display.

The digital data acquired from the smart meter is recorded and displayed on dynamic line charts that update in real-time. Shown in Fig. 8 is an example that visualizes the accumulated energy consumption of individual smart meter circuits. By moving the cursor over the data points on the chart, the user may acquire the readings of the smart meter at any precise time stamp in the recorded time interval. By clicking on the legend icons, the user may display only the smart meter readings of interest, which allows for easier pattern analysis. The GUI also provides a zooming functionality, so that the user may zoom in and closely inspect the smart meter readings of a chosen period of time. Different line charts have different updating and recording intervals, ranging from seconds to days. Since all dynamic line charts are displayed and updated in real-time, the SCW web-based GUI provides the user with a convenient way to monitor and analyze the digital inputs from the smart

Table 6
Energy disaggregation module test results.

	Mean Square Error ($[kW]^2$)	Mean Absolute Error (kW)
Device A	9.88×10^{-5}	5.82×10^{-3}
Device B	2.42×10^{-4}	4.38×10^{-3}
Device C	2.68×10^{-5}	2.92×10^{-3}

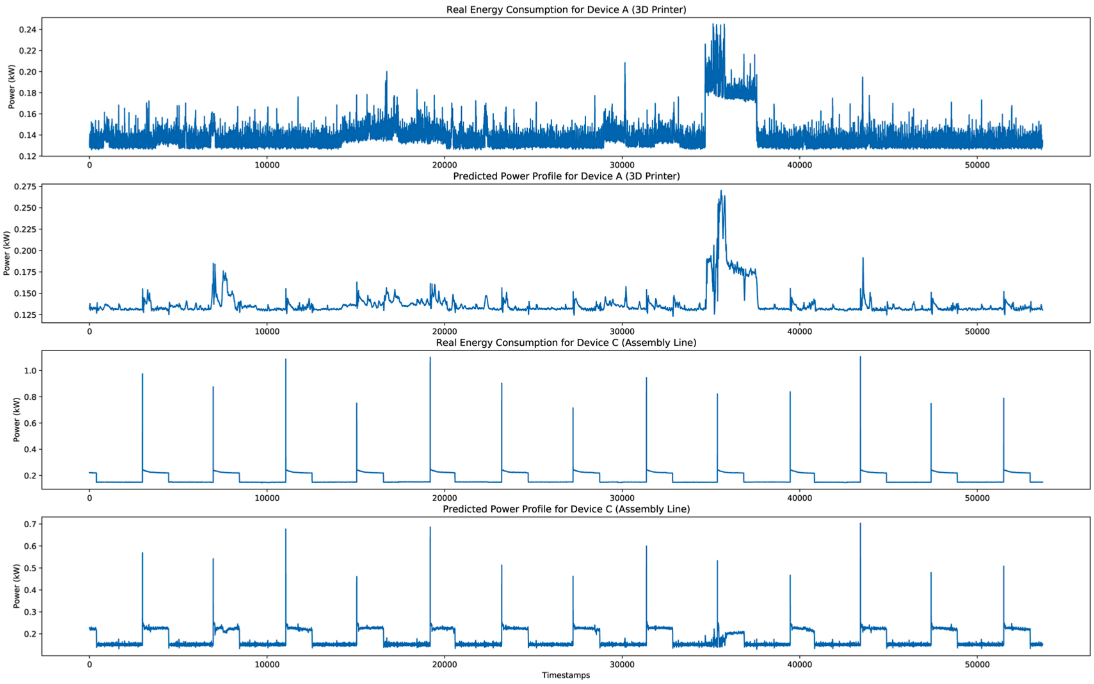

Fig. 7. Visualization of energy disaggregation results.

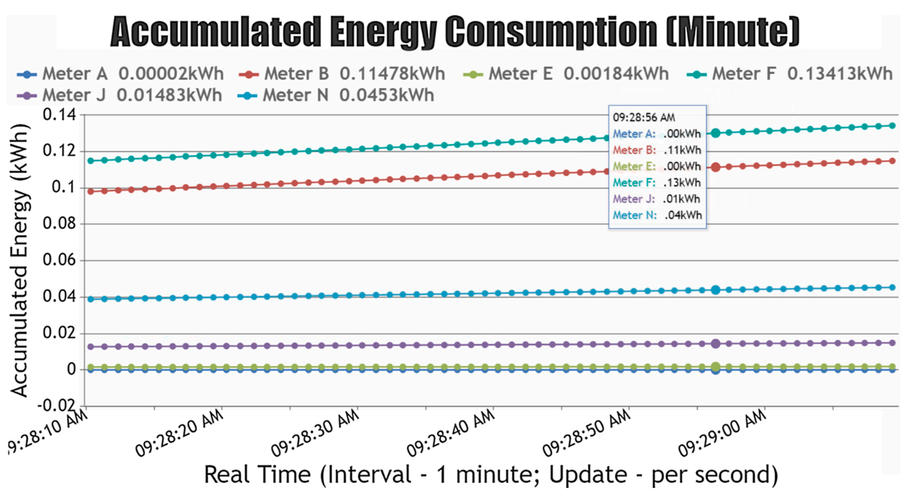

Fig. 8. Dynamic line chart of the GUI.

meters of the whole lab system.

Visual data from the cameras and the machine learning modules are also integrated into the GUI, as shown in Fig. 9. The raw images collected from the global camera, the printer internal camera, and the wearable camera are displayed in real-time on the web-based GUI for monitoring the entire working condition. For the object detection module described in Section 4.2, the processed image with highlighted bounding boxes and labels around each major printer component is visualized, while the predicted machine state is displayed underneath and updated in real-time. For the finger and text detection module described in Section 4.3, the processed image with highlighted bounding boxes around press buttons and text screens is visualized, while the predicted results of the text strings and the finger positions are displayed underneath in real-time.

4.7. Discussion

In this section, the proposed implementation is compared with several other approaches regarding real-world test cases. Specifically, the performance of the YOLO-based object detection model for real-time machine state identification is compared with that of Tera Term (an open-source terminal emulator program for multi-device communications) and Mask-RCNN [42] (a state-of-the-art region-based convolutional neural network for object detection). The filtering algorithm in Section 3.1 can significantly improve the robustness of machine state identification even if certain consecutive frames are not accurately processed by the machine learning models. Therefore in this testing stage, the average accuracy of identifying the machine state that each individual time frame belongs to is recorded. The test results for identifying/reporting machine states of each time frame during the printing of a sample model are summarized in Table 7. Mask-RCNN-based detection model, though achieving slightly better prediction accuracy, failed to exceed the performance of our implementation in terms of response time (i.e. inference speed). Even though Tera Term achieved perfect machine state identification by retrieving feedback directly from the 3D printer, its slow response time is unsatisfactory for real-time

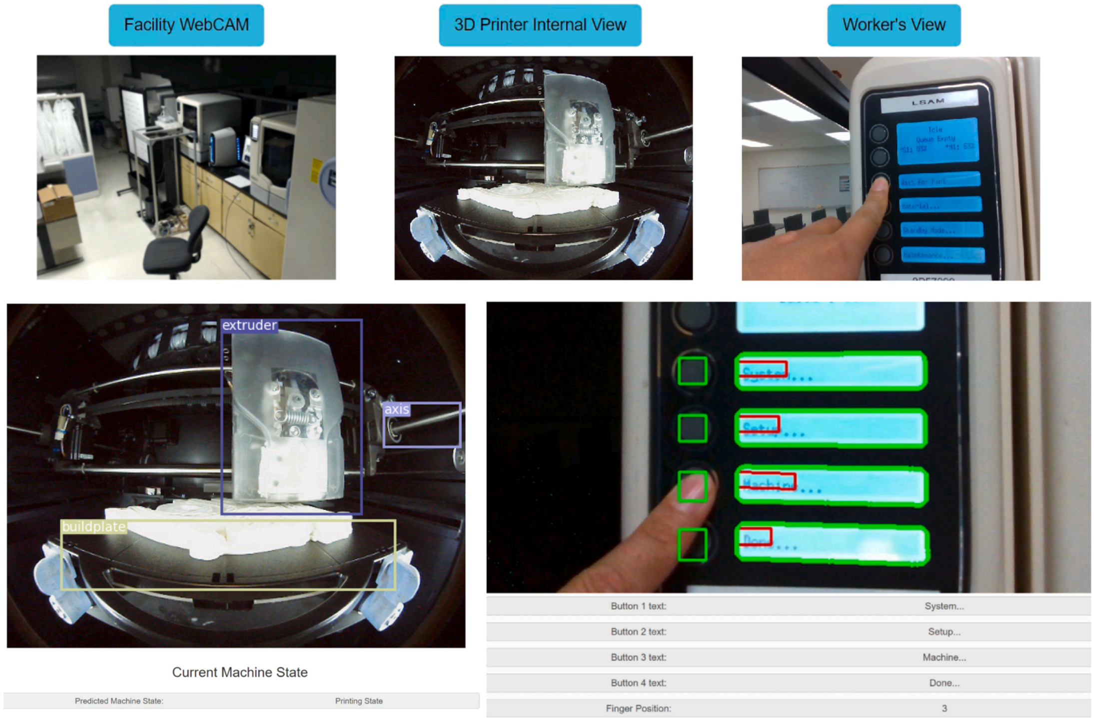

Fig. 9. Raw and processed visual data as displayed on GUI.

Table 7
Comparison of test results for machine state identification.

	YOLO-based	Mask-RCNN-based	Tera Term
Detection accuracy	96.81%	97.70%	100.00%
Response time (s)	0.041	0.16	3.81

inference. Considering the main goal of achieving a real-time system, as well as the presence of the filtering algorithm that can enhance the robustness of machine state identification, the optimization of response time and inference speed should be prioritized. If certain machines do not provide the feedback or indication of their machine states, the aid of machine learning algorithms is also more flexible and deployable. In practice (and also in most cases), when the detection accuracy of the machine learning modules is not 100%, the machine state identification's accuracy may be hindered as well. In these cases, the filtering algorithm's support of looking back at the predictions of several past consecutive frames can help improve the robustness of the system even if the predictions of few frames are faulty. If researchers would like to further improve the accuracy of the machine learning models, viable solutions would include training with a more diverse dataset from a wider range of environments, as well as fine-tuning the hyperparameters (such as learning rate and batch size) of the model.

4.8. User studies

The project also made substantial progress in deploying the user survey, through the partnership with the California Manufacturing Technology Consulting (CMTC) to facilitate communications with the NIST Manufacturing Extension Partnership (MEP) network and the Foundation for Manufacturing Excellence (FAME). With the support of CMTC for distributing the survey throughout the MEP network and NIST for feedback on the recruitment materials, we have launched the survey via Qualtrics and collected the results of this effort. The project team has completed the comprehensive literature survey to gauge the needs and readiness of SMEs to adopt and co-develop SCW technologies [43]. The user studies show that manufacturing companies can significantly reduce the need for human labor for monitoring, fault-detection, information gathering, and data analysis, all of which are done in real-time and automatically by using the developed system. Furthermore, the developed system may benefit the SMMs by providing a comprehensive graphical user interface, as well as a centralized smart-connected system that is cost-efficient.

5. Conclusion

This paper presents the real-time monitoring system of manufacturing workflow for the Smart Connected Worker that utilizes machine learning techniques to create an automated and intelligent manufacturing workflow. By passing the real-time digital and visual data into the dedicated modules of the system, SCW is able to extract high-level information, such as machine states, human-machine interaction status, and energy profile of individual devices, all of which are essential to further analysis and optimization. The evaluation process that took the 3D printing for plastic as one use case is being deployed into the metal additive manufacturing currently and may be extended to the use cases of robotics and assembly lines. The developed work, with an entirely automated workflow as well as a real-time GUI, should smoothly fit into existing advanced manufacturing systems and may serve as a supplementary unit or as a substitute for human labor.

Declaration of Competing Interest

The authors report no declarations of interest.

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