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Research Article

Development of Machine Learning Model for Detection of Ppe Kit

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ABSTRACT

Proper monitoring and detection of personal protection equipment is important for assuring societal health and safety, especially during emergencies concerning the health and wellbeing of the public. The aim of the research is to detect PPE using Detectron2 model in healthcare industry. This research concentrates on five classifications namely, goggles (safety glass), mask (face mask), face shield (helmet), coverall (vest/gown) and gloves. The research developed custom Detectron2 model and adopted the FAIR's base Detectron2 model to identify the PPE suits. The proposed custom model includes additional layers to the ResNet (backbone) architecture to heighten the performance of the model. From the outcomes of the research, classification accuracy of the model is identified to that of 92%.

Keywords: Personal protection equipment, detectron2 model, custom model, COCO evaluation method

INTRODUCTION

Personal protective equipment (PPE) ensures the workers safety in industrial environments (Zhao and Barati, 2023 and Lee et al, 2023). PPE entails different gears like masks, gloves, shoes, aprons and helmets are developed to protect staffs from biological, chemical and physical risks (Ji et al, 2023 and Monnikhof et al, 2023). Precise detection of PPE entails gloves, shoes, helmets, masks and aprons in workplace is important to protect staffs from possible hazards. Detecting PPE assures that staffs are prepared with needed gear, reducing the health issues and risk of injuries (Wu and Selvaganapathy, 2023). Health care sector plays a vital part in public welfare. Healthcare workers are giving their best to assure safety of the patient. Besides their efforts, infectious diseases could spread from one to another through different medium like body fluids, air, physical contact and others which put those works at high risk. Inappropriate use of medical PPE is one of the main sources in the transmission of the disease among healthcare sector. Medical PPEs are important for safeguarding healthcare workers from various infections like infected patient discharges, droplets, and contaminated surfaces. Improper use of such equipment could outcome in infection and cross-contamination of patients and healthcare professionals. Thus, it is important to continuously monitor whether these workers are using medical PPEs correctly. On contrary, manual monitoring of their accurate use is difficult and time-consuming process and not every worker in healthcare could monitor constantly. In order to address the issues linked with PPE enforcement and detection, artificial intelligence based outcomes have to be included (Aldossary et al, 2023)

World health organization (WHO) recommended some rules and regulations for frontline healthcare professionals, during COVID-19 like maintain distances, cleaning and disinfection in the workplace, use of disinfectants for reducing the transmission risk of virus in workplace, safe environment and assure that flexible healthcare system is maintaining during emergencies and public crisis. Major accidents are occurred due to unsafe behaviors of workers like neglecting safety codes and not properly using PPE and such unsafe behaviors are major issues to employee health and operational safety in the production. Protective masks, clothing, gloves and other equipment are vital as vital measure for safety to safeguard workers from infection and standardize use could directly minimize the virus transmission and assure the high safety among health care professionals (Dong, 2018).

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Research Article

Artificial intelligence (AI) capabilities were broken to introduce cost-effective, advanced and automated monitoring systems which could identify PPE and employees to choose whether the employees is following the rules and regulations in the safety or not; this assures safety of the worker. In particular, machines could detect and categorize by following the technologies of deep learning and computer vision. Subfield in the deep learning is machine learning that imitates the human brain, attractive ability of DL is its potential to learn and enhance by itself. Authority of computer vision created from CNN (Convolution neural networks) that automatically extracts the feature for the targeted objects. For supporting the model with abilities of decision-making, extracted features are given into deep learning model. Transfer learning could raise the solution consistency by including information of already trained models on relevant issues (Benedetto et al, 2020).

Further, detectors are categorized into two namely one-stage detectors and two-stage detectors. One-stage detectors carry both recognition and localization of needed objects in same phase therefore achieves the real-life detection. YOLO (You only lock once) family is one of the one-stage detector. RCNN (regional-based CNN) is famous two-stage detector which performs reliable and accurate outcomes by performing the procedure for detecting the object in two phases. Localization of the object comes in first phase to suggest regions with high possibilities to contain objects. Next phase detect objects from extracted features with respect to localized regions. Both one-stage and two-stage detectors intention to identify the targeted objects, at the same time, we can also notice trade-off between accuracy and real-time detection (Chen et al, 2020).

LITERATURE REVIEW

Nugraha and Rifai (2023) developed automatic system for identification which is assembled using CNN (convolutional neural network) to determine the use of PPE with specific reference to manufacturing technology laboratory. This study compared the CNN model with some algorithms namely YOLOv5 and YOLOv4. Three model scenarios were constructed in this study namely transfer learning (YOLOv4 and YOLOv5), train from scratch (YOLOv5). Performance of developed approach is estimated based on method and algorithm type used for obtaining the best performance with optimal CNN model. Overall performance of developed method showed good outcomes. It was found that transfer learning (YOLOv5) had the best performance with precision, recall and mAP.

Automated detection system was developed and implemented in real time for PPE using YOLO model. This model showed huge development in the area of occupational health, safety compliance and safety related protocols. Proposed system would enhance the competence and accuracy of PPE detection, reduce the non-compliance risk and elevate the overall well-being and safety of persons in different sectors. It reorganizes the resources allocation, leaving the process more accessible and cost-effective to wider users entails safety inspectors, industrial workers and healthcare professionals. The system preserves the safety standards by assuring precise compliance monitoring and PPE detection. Automated detection of PPE is transformative approach which improves the accessibility and precision of safety compliance in real life. Detected method would be more responsible, informed and safer to safety protocols which influence the domains of industrial safety, health care and public well-being (Kumar et al, 2023).

Pei et al (2024) developed an approach for identification that integrates detection of human keypoints with object detection of deep learning to monitor the standard PPE use for healthcare workers. For detecting PPE, YOLOv4 was used as baseline model and MobileNetv3 as the detector strength for minimizing the computational effort. HRNet (High-resolution net) was the strength for detecting keypoints, describing 25 key points coordinates in human body. GloU (generalized intersection over union) was adopted for expanding the relationship between key points and PPEs. Developed detector determines whether healthcare employee is using PPE with higher recall (96.88 percent), precision (95.81 percent) and F1-score (96.09 percent). It was noticed that model size and number of parameters are lightweight than other detectors. Proposed method gives a new solution for automated monitoring, management of protection in health care sector. Further it was added that modular design gives more useful applications for various scenarios in medical field.

A research was carried out by Wang (2024) to detect PPE using Anchor free-CNN. This research developed a model with deep learning adopting the YOLOv8 architecture, particularly developed to address the challenging real-time needs, non-destructive and accuracy. Model is trained on customized set of data and validated to assure extensive experiments, robust performance and evaluations of performance are carried out to show its effectiveness. Dataset is

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created with wide range of images which covers multiple scenarios related to PPE detection. From differing situations, lighting conditions and PPE types, dataset assures adaptability and robustness in training the algorithm. Its scalability allows vast testing and training, improving the generalization capabilities and accuracy of the algorithm. By entailing images from different PPE types and settings, dataset develops the process of learning, equipping algorithms for detecting PPE in real-life applications. Overall this dataset act as a potential resource to develop reliable and accurate algorithms for detecting PPE, important for workplace compliance and safety. From the evaluation of the performance and experimental results, it was found that developed method achieve best accuracy allow it a best solution for detecting PPE in industrial workplaces, fulfilling the rigid demands of non-destructiveness, accuracy and real-time functionality.

Madhu et al (2023) stated that PPE composes a main element in maintaining worker safety among unsafe environments within different industries. At the same time, assuring usage of PPE compliance would be challenging because of vital manual inspection by safety officers or supervisors. This research depends on the advance model in deep learning namely YOLOv8 to categorize and detect PPE objects particularly in the real-life applications. Transfer learning is adopted in already-trained deep learning model namely YOLOv8, solution could precisely determine different types of PPE like safety shoes, reflective vests and hard helmets. Developed approach for detecting PPE in real life was found to be effective. This is considered as valuable tool which help with supervising compliance to regulations of safety. Any needed corrective actions and measures are taken immediately in real-time application which reduces major injuries and accidents.

PPE could maximize the worker safety for assure by minimizing the severity and possibility of fatal incidents or injury at hazardous, chemical and construction sites. PPE is needed to provide a high level of safety for protecting from accidents and chemical hazards. For some negligence or reasons, workers don't follow exact rules while wearing the equipment. In such cases, manual monitoring is difficult and invalid; intelligent system needed for monitoring to provide the accurate and automated real-time detection of PPE safety. In this research computer vision and deep learning are carried out to provide accurate and real-time PPE detection. Safety glass, vests four colored hardhats dataset was adopted to train and estimate the proposed method performance. It was clear that proposed method could identify different type of PPE namely yellow, white, blue, red helmets, person, head, glass and vest. Two-stage detector was trained based on RCNN. Developed model achieved an acceptable mAP (mean average precision) of 96 percent (Ahmed et al, 2023).

Ali et al (2023) studied about the detection of medical PPE using YOLOv7 in healthcare sector. Inappropriate use of medical PPE could outcome in cross-contamination and contamination of infectious diseases, thus it is important for healthcare workers to use it properly. CPPE-5 dataset was adopted for training the model that includes 1029 images categorized into five namely goggles, masks, gloves, face shield, coveralls. From the findings of the research, it was noticed that proposed method performs well in terms of optimal maP at 90.93 percent. It was also observed that proposed method is promising to detect medical PPE in healthcare sector.

Zhang et al (2022) developed a model that automatically detects PPE donning for healthcare professionals using YOLOv4 that could adopt methods of deep learning to conduct intelligent detection of various PPE objects. This model are adopted to efficiently and stably monitor the situation of PPE donning among healthcare professionals and minimize the possible harm caused by consciousness of human in the process of management and protect medical resources. Medical PPE with YOLOv4 model is tested using dataset which is self-built and detection accuracy is up to 84.14 percent. Life safety of healthcare professionals is the base to fight infectious diseases and condition for safeguarding public health.

Ludwika and Rifai (2024) carried out a research to study about deep learning for detecting proper adequacy and utilization of PPE with respect to manufacturing teaching laboratories. Developed model detects the objects of PPE being used and at the same time evaluate their correct usage. In this research, seven PPE objects types are studied with these conditions namely improper usage and proper usage. Three algorithms were used namely YOLOv6, YOLOv5, YOLOv4 in this research for building detection models. 3 models were built for each algorithm with 100, 75 and 50 epochs. Developed approach performance was estimated based on selection of algorithm adopted to acquire the best-performing model for detection. From the findings of experimental results reveal that all developed models with deep learning could efficiently detect different PPE classes to review the correctness and completeness of their

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Research Article

usage with specific reference to manufacturing teaching laboratories. In addition to that, YOLOv5 revealed superior performance with 100 epochs compared to YOLOv6 and YOLOv4. Techniques or methods used for detection of PPE are depicted in Table 1.

Table 1: Techniques or methods used for detection of PPE

Author	Year	Techniques/methods	Findings
Nugraha and Rifai	2023	CNN, YOLOv5 and YOLOv4	Transfer learning (YOLOv5) had the best performance with precision, recall and mAP.
Kumar et al	2023	YOLO model	Automated detection of PPE improves the accessibility and precision of safety compliance in real life
Pei et al	2024	YOLOv4	Developed detector determines whether healthcare employee is using PPE with higher recall (96.88 percent), precision (95.81 percent) and F1-score (96.09 percent).
Wang	2024	Anchor free-CNN, YOLOv8	Developed method achieve best accuracy allow it a best solution for detecting PPE in industrial workplaces, fulfilling the rigid demands of non-destructiveness, accuracy and real-time functionality
Madhu et al	2023	YOLOv8	Developed approach for detecting PPE in real life was found to be effective.
Ahmed et al	2023	RCNN	. Developed model achieved an acceptable mAP (mean average precision) of 96 percent
Ali et al	2023	YOLOv7	Proposed method performs well in terms of optimal maP at 90.93 percent.
Zhang et al	2022	YOLOv4	Medical PPE with YOLOv4 model is

			tested using dataset which is self-built and detection accuracy is up to 84.14 percent.
Ludwika and Rifai	2024	YOLOv6, YOLOv5, YOLOv4	YOLOv5 revealed superior performance with 100 epochs compared to YOLOv6 and YOLOv4

DESIGN

Proposed Research Plan & Design

The research proposed identifies the objects classified (five classes) using the "Detetctron2" as computer vision based architecture. The study uses two models where the researcher adopts a base model and an advanced model (customized model to achieve more accurate identifications) with different neural layer. The plan and design for the current research includes gathering inputs (i.e. images as datasets), processing the data and cleansing for object identification in machine learning. Later using the machine learning (ML) algorithms, the research identifies the objects targeted by the investigator. In this research the base model "Detetctron2" is adopted with ResNet as its neural layer and object identification process without any customization, which is developed by FAIR (Facebook-AI-Research) as one of the original neural networks along with three main networking layers namely, Faster R-CNN (recurrent-convolutional neural networking), Fast R-CNN and Mask R-CNN.

The customization model includes customization to the existing neural network, to optimize the object detection's accuracy. The same datasets are used for both models to avoid ambiguity and unfairness of object detection. Once the models detect the pre-defined classes (five), the results are obtained and the respective data is bounded using the pre-defined classes. The results are then classified into respective folders as per their categories. Once the object identification is done by both models, the evaluation of their performance is measured using metrics and the accuracy and loss is evaluated (refer to Figure 1).

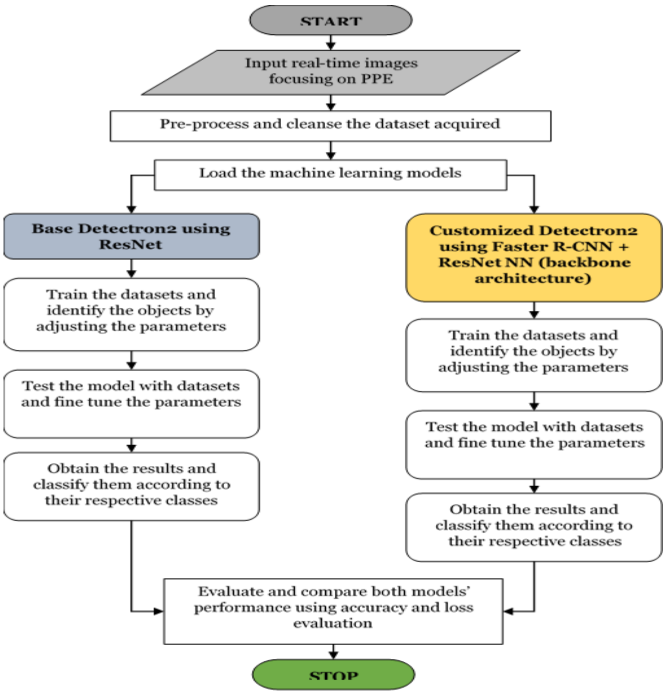

Figure 1: Proposed research plan

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Research Article

Thus, the current research encompasses of detection model using FAIR's Detectron2 to identify and discover people using the medical or protective equipment. In this research, a base and a custom detectron models are developed and compared for better outcome in detecting the protective equipment. As mentioned in the research plan, the custom model adopts the 'Backbone Network (ResNet)'. Generally FAIR developed the Detetcron2 model where the base model's network layers varies from R-CNN, RetinaNet, Mask R-CNN, Backbone Network like Region proposal network (RPN), and other networks as per the researcher's necessity.

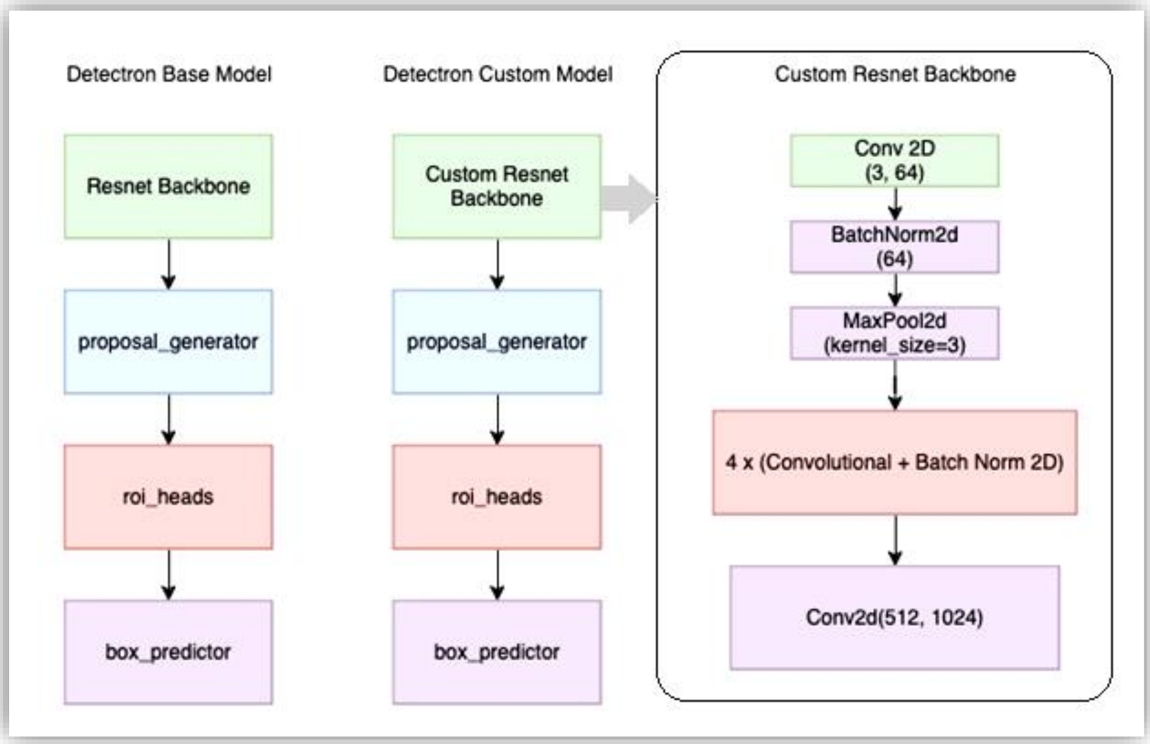

Figure 2: Proposed research design

The Figure 2 represents the basic architecture and the research design where the base model and custom model is explained. The base model has four layers where, ResNet based backbone networking layer as the first layer followed by regional proposal network (RPN). The ROI (Region-Of-Interest) head is the third layer where the targeted regions as data segmentation are carried out. Lastly, the segmented datasets are classified and bounded using the boundary-box under the box-predictor layer and the identified objects are then classified into respective folders, namely gloves, mask, coverall, face_shield and goggles.

Contrarily, the custom model includes a ResNet backbone layer as the first layer that has one 2D convolutional layer with batch-size of 3x64, followed by a batch-normalization layer with batch-size of 64. The max-pool is the third layer which has kernel-size of 3 is followed by four 2D batch-norm based convolutional layers. Finally, the ResNet layer is completed with a 2D convolutional layer with batch-size of 512x1024. The second to fourth layers of the custom model is similar to the base model where RPN, ROI and Box Heads are added.

Proposed architecture

Detectron2 by the FAIR group is the new model which has TensorMask, Cascaded R-CNN and panoptic FPN. The architecture includes ResNet as networking layer where the new Detectron2 model has an additional layer named Detectron2go. This study is unique where the architecture includes a customized model where in the Detectron2, ResNet is adopted (refer figure 3).

Journal of Information Systems Engineering and Management
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Research Article

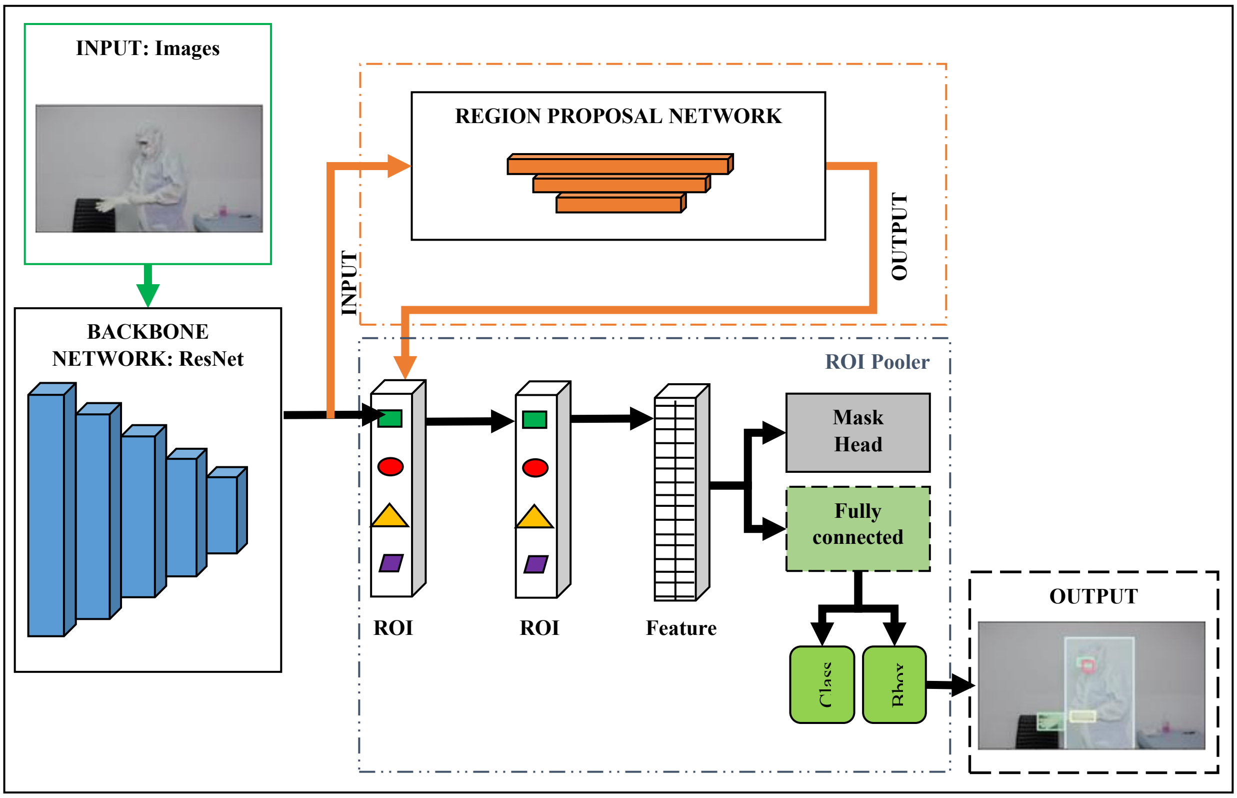

Figure 3: Proposed architecture of custom Detectron2 – PPE suit prediction model (PPESP)

The customized model obtains the personal-protective equipment based images as inputs and passes the data to the ResNet Backbone Network. The processed image is then passed onto the Faster R-CNN layers where the RPN layer processes the image for feature maps and passes the identified possible outputs with confidence score to the ROI pooler. The model detects regions of interest and bounds the identified areas using bound-box heads and classifies the identified objects into respective classes. Later, the detected and bounded areas are then passed on to the output layer, where the images are classified into classes of the identified objects. Once the model identifies the defined objects its performance is evaluated later using the classification accuracy and loss evaluation metrics (refer to Figure 3).

Materials and methodologies

The materials and methodologies in research focus on the data, procedures, techniques, methods and resources used. Here, the datasets, data used for training and testing, parameters and

Dataset

Data: The dataset is acquired from the internet resource “kaggle”, gathered and processed by the author Anil (2022). The dataset includes real-life CPPE (medical personal-protective equipment) images with high quality that are not available anywhere. The dataset includes 1029 images in .png format with two annotations folders for training and testing that has .json formats.

Training and testing: In this research the 1029 images are used for training and testing. 1000 images are loaded from “dataset/annotations/train.json” folder and remaining 29 images are loaded from “dataset/annotations/test.json”. The original images are acquired from the study conducted by authors Dagli and Shaikh (2021) by the author Anil where more than five data annotations were identified.

Parameters: The study uses the parameters namely, image size, batch size, iterations, learning rate, roi-heads, and classes. Since the current study focuses on PPE suits, only the most required data annotations are alone adopted. Here, the data annotations are not projected as texted-labels rather a boundary-box where the identified object is

Journal of Information Systems Engineering and Management
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Research Article

represented with different color boxes. The datasets resource has the annotations pre-processed in the databank and thus they are adopted and used here, they are:

i. **Goggles:** The goggles here annotated are the safety glasses or a protection eyewear that is used for protection of eyes and surrounding area from harmful chemicals, radioactive particles, medicines and other particulates;
ii. **Mask:** Masks here are annotated in the protective suits which prevents the infectious transmissions and other pathogens that are airborne from one-individual to another and causes respiratory diseases;
iii. **Face shield:** The face shields annotated here are the helmets worn in medical environment and laboratory setups to prevent hazards like chemical splashes, contagious blood smears, potentially-infectious particulates from being inhaled or from contact;
iv. **Gloves:** Gloves prevents the individuals in medical procedures and examinations from cross-contamination especially during patient-caregiver physical contact; and
v. **Coveralls:** The gowns or protective suits worn by the hospital employees are identified and annotated here as coveralls which cover the exposed skin like hands, feet and the entire body and acts as a barrier.

Generally, there are majorly more potential classifications than the five focused here in PPE classifications namely shoe covers, respirators, gowns, safety glasses and safety helmets. Since the classifications safety glasses, safety helmets and gowns are practically used in other fields like construction, adventures (outdoor activities), outdoor games, and more, the current study uses the most essential protective gears (PPE) in the medical setups. Thus, the five classes above are focused and used.

Algorithm

The software used here is the python for developing the models as open-source language. The research adopts the object detection algorithm in python where the images (medical protective suits) as inputs are pre-processed. Initially, the .json dataset from the resource are loaded and using the "extract data" functions for plotting, iterations, total_loss and clas_accuracy for metric evaluation. Simultaneously, to plot the loss-data and accuracy-data the figure size is set as 10x5 (length*width) with grid set to "true".

The pseudo-code for identifying the pre-defined classes in the input used here is written as:

Algorithm 1: Object detection and boundary box

Step 1: Initialize the process by loading the Detectron2 model with utilities and visualizer for plotting;

Step 2: Load the datasets from 'data.json' file under the head JSON and train the model;

Step 3: For the assigned images "1", "2" and "3" .png images respectively, estimate 'd';

Step 4: Read data (d) and using predictor for output file and meta-data for visualizer file assign the scale size of the image as 0.5 and instance_mode as ccolor_mode in training and testing with adjusted learning rate at 0.00025 in 2 batches of 300 iterations;

Step 5: To obtain results, the boundary-box is assigned as prediction on pre-processed image and the outcomes are stored under "instances" for evaluation in the CPU;

Step 6: The results are stored under five respective 'classes' and are represented as plots beside each other (i.e. as original and predicted with bound-box outputs);

Step 7: By utilizing the loss and classification-accuracy metrics, the performance of the Detectron2 models (base and custom) are evaluated.

The study just identifies and bounds the objects through the prediction model. Hence only the object identification algorithm is adopted.

Evaluation metrics adopted

Journal of Information Systems Engineering and Management
2025, 10(56s)
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Here coco evaluation metrics are adopted. The performances of the base and custom models are measured using classification-accuracy and total loss calculations. The classification accuracy is estimated using the precision, recall, intersection-over-union (IoU), average recall (AR) and average precision (AP) metric values, for object detection. The accuracy estimation includes following equation:

$$\textbf{Precision} = \frac{\textbf{Truepositives}}{\textbf{Falsepositives+Truepositives}} \text{..................................... (equation 1)}$$

$$\textbf{Recall} = \frac{\textbf{Truepositives}}{\textbf{Falsenegatives+Truepositives}} \text{..................................... (equation 2)}$$

$$\textbf{IoU} = \frac{\textbf{Overlapping Area}}{\textbf{Union Area}} \text{..................................... (equation 3)}$$

For instance segmenting process, the AP and AR are estimated by adding up the precision and recall scores and obtaining the average scores.

Similarly, the classification losses (background and foreground) of the classes are estimated by two approaches, where localization loss and classification loss. In this research the classification loss is adopted. Once the iterations are completed by the model, the results of the loss obtained are calculated by summing-up the 'loss_rpn_cls' in the RPN (region-proposal-network) during the training using the 'softmax cross-entropy' loss estimation.

IMPLEMENTATION AND RESULTS

System requirements

Software: The python is used for model development and object identification in the images as inputs. The models developed here are base model and customized model of Detectron2. Python is open-source language, easy to understand, user-friendly and works pretty-well across different languages like Java, C, C++, and operating systems like Mac, UNIX, Linux and Windows too.

Hardware: The researcher adopted the python software of version 3.6 and thus needs an Intel-Core of I5 processor (central processing-unit) for better performance. The memory usage for developing the model should be 4-8GB, where in this research 8GB is adopted. The disk-space in a model development is advisable to be more than the memory. Thus, here, 15GB as the hard-disk space is adopted. The clock speed for iteration used here is 1GHz. The current research uses Windows 10 Operating System.

Results

The model developed is trained and tested using the images obtained. The processes involved in detail are:

Training

For training and validation the following parameters are set, where: the batch size = 2, learning rate (lr) is 0.00025 and the total iterations are 300 with 256 batch size/image. The number of classes allocated is five, namely: gloves, goggles, mask, coverall and face_shield. The exist_ok in directory is set as "True" which is unlike the normal value set for exist_ok in python model, to create directory under "os.makedirs". The base and customized Detectron2 models are loaded and trained.

Journal of Information Systems Engineering and Management
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https://www.jisem-journal.com/
Research Article

Figure 4: Example dataset in training for object detection

The datasets used in this research by both the Detectron2 models are represented as sample images in Figure 4.

(a) **(b)**

Figure 5: Example of boundary-box in PPE object identified

Figure 5(a) shows the original raw image obtained from the internet as resource. The figure 5(b) shows the identified and boundary-box of the predictions made. In this image the mask and coverall as the identified objects are identified.

Once the model is trained using object identification method, the model identifies and classifies the pre-defined five categories, where the training results obtained are:

Journal of Information Systems Engineering and Management
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https://www.jisem-journal.com/
Research Article

Table 2: Object identification training

S. No	Category	Instances
1	Coverall	1152
2	Face_Shield	430
3	Gloves	1282
4	Goggles	375
5	Mask	1252
Total		**4491**

The Detectron2 models (base and custom) trained are loaded with real-time images to identify the objects classified under the protective suits category.

Testing

Post training the models, the images are loaded and passed through the neural networking layers where the image is processed, object id identified, bounded and classified.

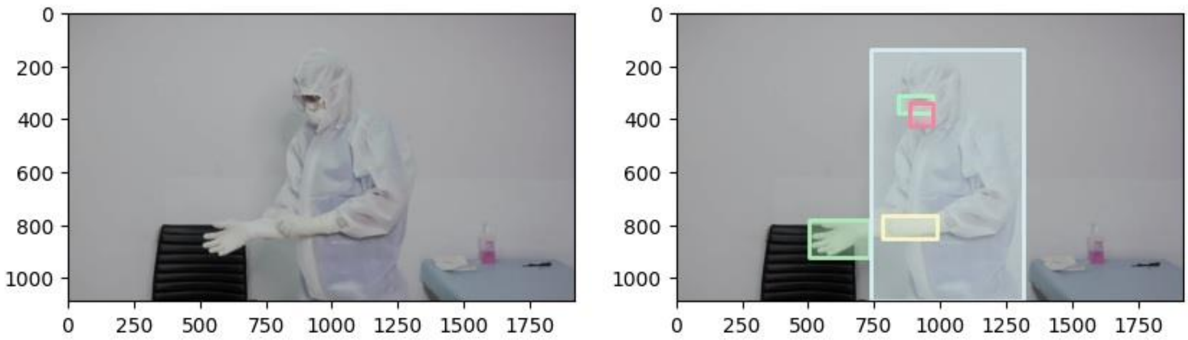

Figure 6: Testing result obtained - Example 1

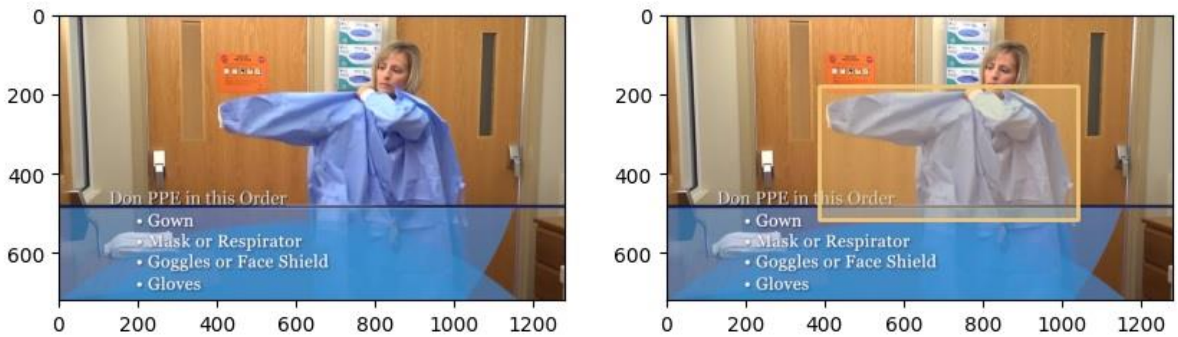

Figure 7: Testing result obtained - Example 2

Journal of Information Systems Engineering and Management
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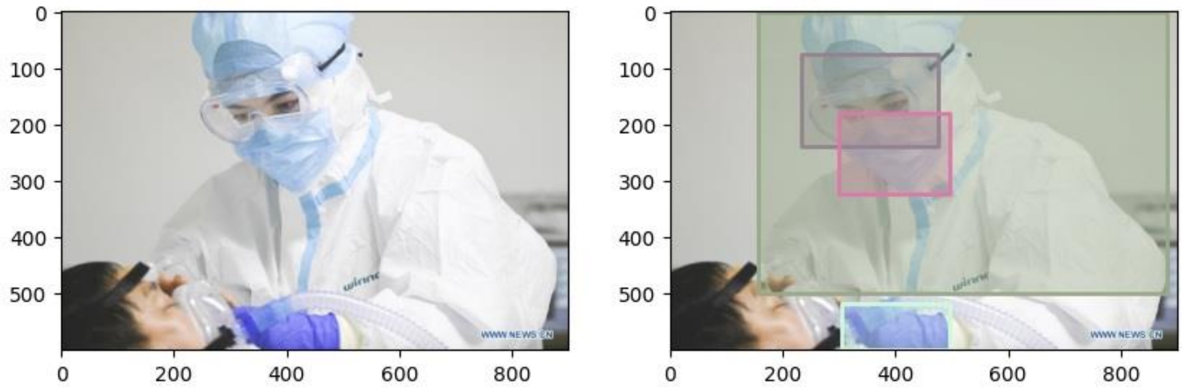

Figure 8: Testing result obtained - Example 3

Inference: From figure 6, 7 and 8, it is evident that the models are able to identify the objects classified as mask, gloves, goggles, coverall and face-shield. The example 1 identified all five categories accurately. In example 2 of figure 7 it is observed that only the coverall object identification is found by the model since the object "gown" is identified. Whereas in figure 8 it can be seen that the model identified only four categories (mask, gloves, goggles and coverall) where the face-shield was not identified by the model accurately.

Thus the custom model is trained and tested efficiently and the loss and accuracy of the model is obtained and the results are compared between the base model and the custom model.

Base model

The model is trained, tested and validated using the learning rate as parameters with 300 iterations.

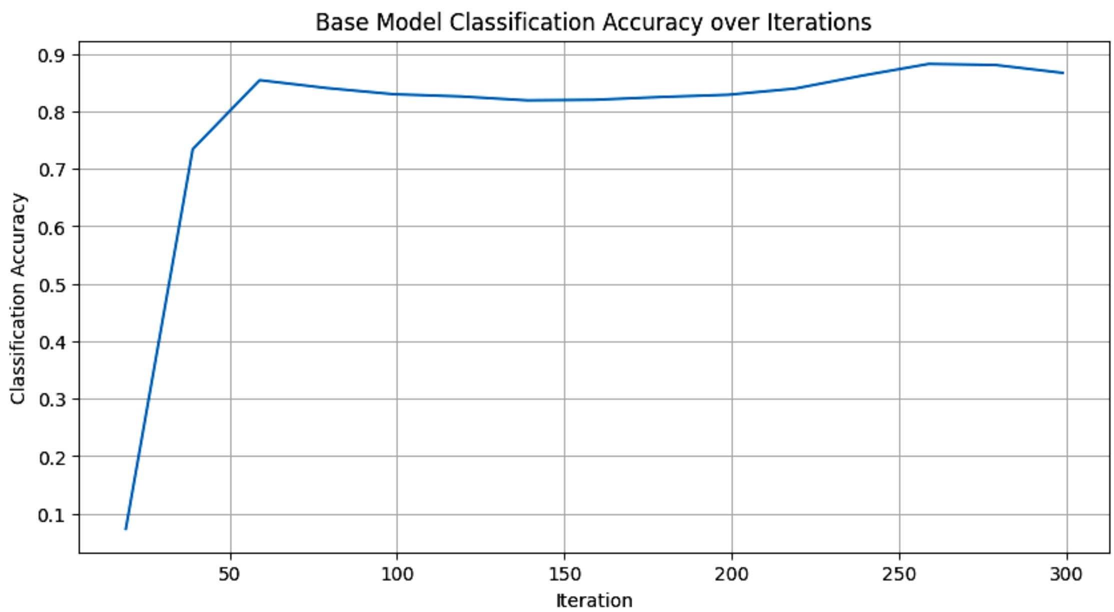

Figure 9: Base model's accuracy classification

Inference: The accuracy rate of the base model obtained and represented in figure 9 shows that from first iteration till 60th iteration the model's performance gradually increased and reached 85% accuracy. From 101st iteration till 250th iteration the performance remained same where the accuracy rates fluctuated slightly falling to average of 82%. From 260th iteration, the model's performance increased to 89% and gradually sloped down at the 300th iteration at 85%. Thus the base model achieved 85% accuracy.

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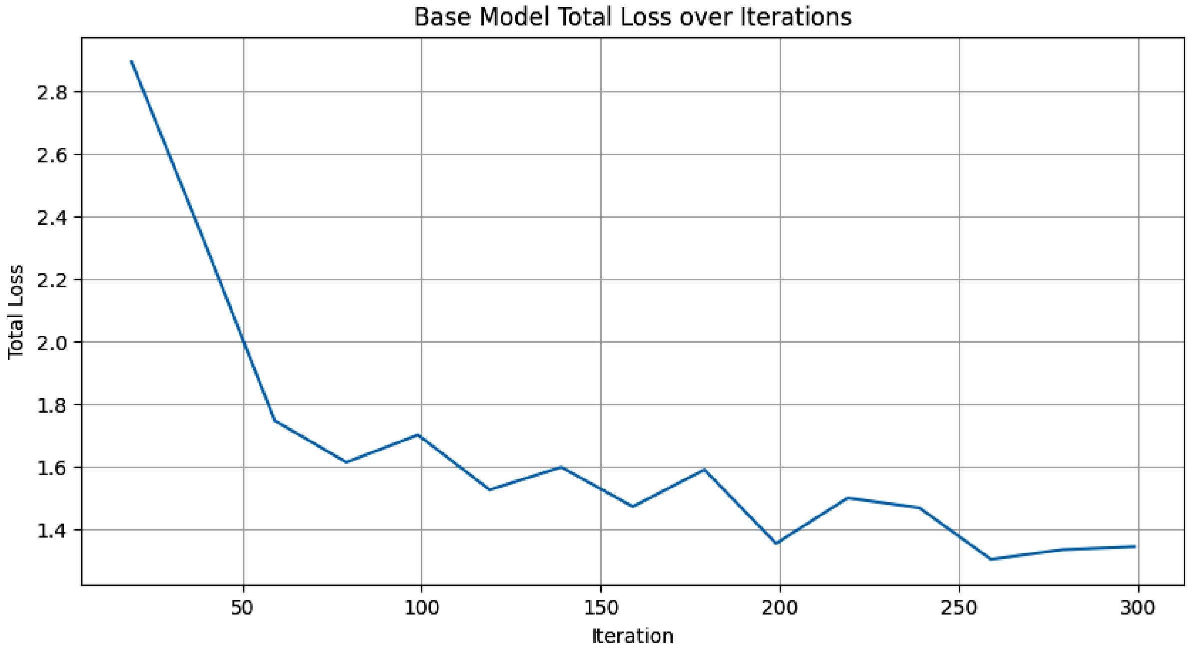

Figure 10: Base model's loss classification

Inference: From figure 10 the loss of the base model is observed at the first iteration, which is high at 3.0 as value. It gradually sloped down from 3.0 to 1.6 at 78th iteration. Then, the loss value fluctuated at 100th, 120th, 140th, 160th, 175th, 200th 220th, and 260th respectively where the loss value gained is 1.2 at the 300th iteration the loss value gained is 1.3 as value for the base model.

Custom model

The custom PEE-SP model after testing the images procured the following values for accuracy (refer to Figure 11) and loss (refer to Figure 12) estimation, which are represented as graphs below:

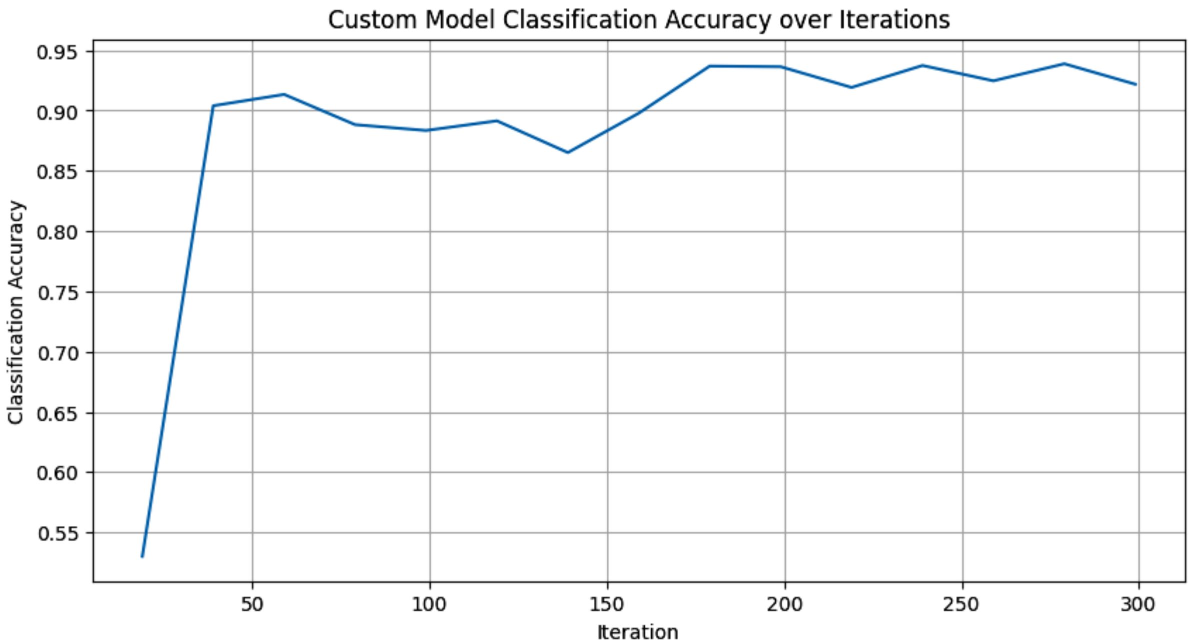

Figure 11: Custom model's accuracy classification

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Inference: The accuracy graph of the custom PEE-SP model shows that, initially the model acquired 91% accuracy rate at 35th iteration, which gradually fluctuated and decreased to 87% at 140th iteration. Then the accuracy rate increased rapidly till 175th iteration and fluctuated slightly till 300th iteration, where the accuracy rate obtained is at 92%. Thus the custom PEE-SP model obtained 92% accuracy.

Figure 12: Custom model's loss classification

The PPE-SP model's loss was initially high at 5.6, where it decreased rapidly till 4.4 at 60th iteration. Later, after fluctuations the model achieved loss value of less than 3.0 at 175th iteration, which again increased rapidly at 200th iteration with loss value around 4.0. Then the model performed significantly in which the loss value decreased rapidly from 4.0 to 2.2 at 300th iteration.

COMPARATIVE ANALYSIS AND PERFORMANCE EVALUATION

The research compares few different machine learning based architectures and algorithms that detects PPE suits in healthcare and also in other sector like, construction sector.

Comparative analysis

Table 3: Comparative analysis of different algorithms in PPE detection

S. No	Author	Year	Model	Accuracy/ Precision
1	Wang	2024	F-RCNN	92%
2	Wang	2024	SSD	89%
3	Wang	2024	YOLO-V5s	88%
4	Marquez-Sanchez	2021	CNN (Helmet)	92%
5	Vukicevic et al	2022	ResNet-50 (Overall/ Coverall)	91%
6	Gallo et al	2022	DNN_ResNet	70.17%
7	Nath et al	2023	YOLO+ResNet-50	77.80%
8	Proposed PPE-SP Detectron2 model	2024	F-RCNN + ResNet (backbone)	92%

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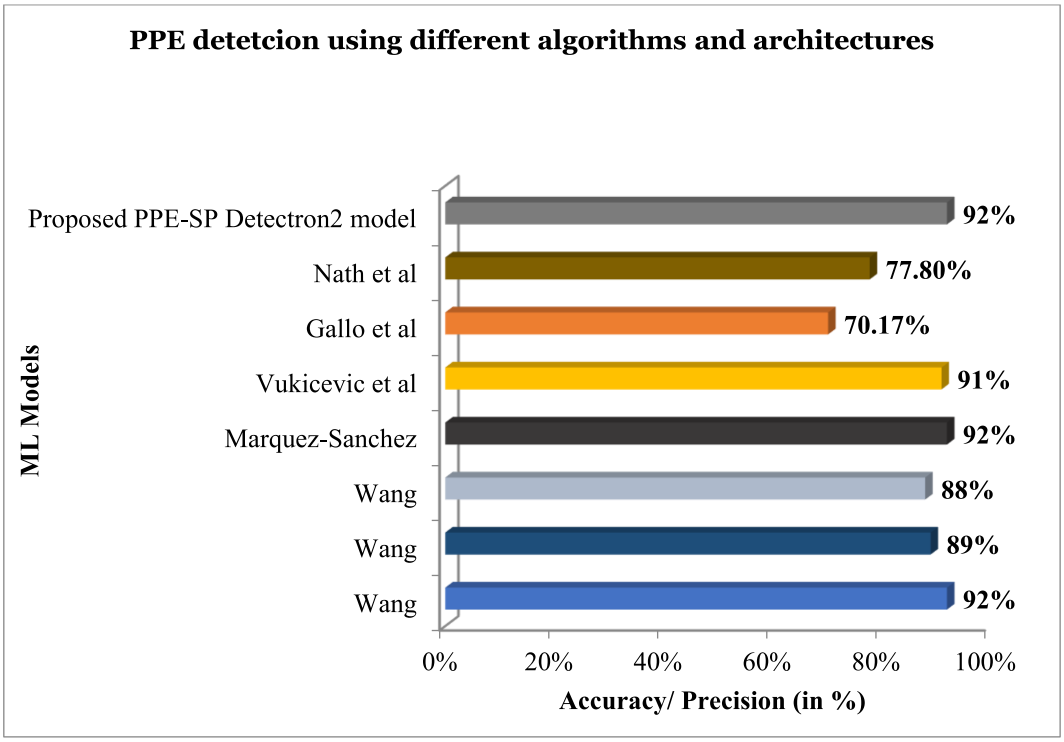

Figure 13: Comparative analysis of PPE detection

Inference: From table 2 and figure 13 it is evidently proven that, the developed model detects PPE suits significantly than other models with DNN, YOLO, CNN, SVM and SDD based algorithm and architectures. The current model ResNet (backbone architecture) gained 92% which is also similar to Wang's Marquez-Sanchez RCNN and CNN model. This proves that CNN based architectures are efficient.

Performance evaluation

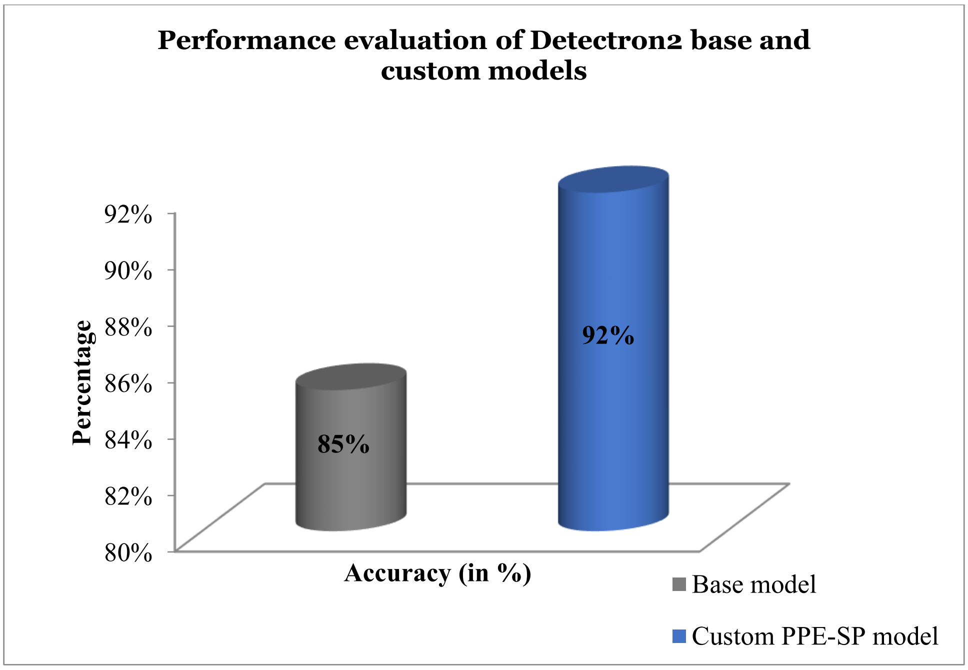

Figure 14: Performance evaluation

From figure 14 of performance metric based evaluation it is observed PPE-SP model (custom Detetctron2) detected 7% more accurately than the base Detectron2 model.

DISCUSSION AND CONCLUSION

Findings and discussion

The findings from the study are:

i. The base Detectron2 model obtained the accuracy rate of 85%;
ii. The base Detectron2 model acquired a total loss at value of 1.3;
iii. The custom Detectron2 PPE-SP model acquired the accuracy of 92%; and
iv. The custom Detectron2 PPE-SP model acquired a total loss at value of 2.2.

Though the loss value obtained in the custom model is bit higher than the base model, the accuracy of the custom model is higher (92%) than the base model. Thus, in future by optimizing and fine-tuning the model, the researcher aims at gaining more than 95% accuracy with minimal loss or '0' loss.

The existing models as reviewed in literature and comparison majorly adopted RCNN and YOLO based architectures for objected detection, where the usage of Detectron2 in PEE identification is not found. Thus, the current study is novel approach and first-of-a-kind.

Conclusion

The current research aims at detecting Personal Protection Equipment in the healthcare industry, using the Detectron2 model which is the main purpose. The study focuses upon the five classifications namely, goggles (safety glass), mask (face mask), face shield (helmet), coverall (vest/gown) and gloves. The study developed custom Detectron2 model and adopted the FAIR's base Detectron2 model to identify the PPE suits. The custom model developed includes additional layers to the ResNet (backbone) architecture to heighten the performance of the model. To evaluate the performance classification accuracy and loss is estimated using the COCO evaluation method, where the custom model obtained 92% accuracy which is 7% more than base model with loss value of 2.2.

Limitation

The current study is limited to medical PPE suits and apart from comparison purposes, other industry based models are not studied or analyzed. The current study is strictly based on ResNet based Detectron2 model and thus other neural networks are not analyzed in-depth.

Future scope

In future the researcher aims to reduce the loss to minimal or '0' loss with higher accuracy. Different sectors will also be focused in the future research. Different dataset and multi-class (more than five classifications) will also be focused in the near-future researches.

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