Automated Decision Support System Based on Quantification of Defective Tubular Steel Temporary Materials for Quality Circles.

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Abstract

Temporary materials are stored in construction warehouses after and before they are used in construction sites. Most of these materials are made of steel tubular sections such as square, circular, and rectangular sections. However, due to frequent reuse and their storage conditions they become subject to defects such as rust and bend which affect their quality for use in construction projects. Since these materials are stored in stacks or batches, checking the materials individually for defects can be time consuming making end point surface defect detection more efficient for construction workers. Deep learning techniques have proven to be more efficient than manual inspection. However, quantification of materials with defects for decision making on reusing, repairing, and disposing actions and documentation is still a challenge for construction workers. Hence, this paper quantifies temporary tubular steel materials; square hollow section, circular hollow section and rectangular hollow section with common cross section area defects using deep learning technique connected to a web platform for decision making by construction quality circle workers. The proposed system achieved an average precision of 84.9 percent with 105.2 GFLOPS and a speed of 20 seconds per inference.

Keywords –

Deep Learning, Decision Support System, Temporary Materials, Defects, Quality Circles.

1 Introduction

Construction projects use temporary materials to provide support and safe working platforms for the workers. The dominant materials used for these structures are tubular steel materials such as square hollow sections, rectangular hollow sections, and steel pipes. However, with frequent reuse and storage conditions of these materials, they become subject to surface defects such as rust and bend which has the potential of causing accidents. These materials are stacked in batches as shown in figure 1 which makes end point surface defect detection faster and productive method of judging their quality.

Monitoring these surface imperfections is done by quality circle workers. Quality control circles or simply quality circles encourages construction workers to actively participate in continuous improvement of material quality in construction [1]. However, these workers rely on manual inspection checklist and reporting which not only reduces productivity but also, is prone to human error. Computer vision techniques such as object detection are being employed to replace manual inspection and identification of defects in areas such as concrete cracks and anomalies in dimensions and misalignment, however, there exist a gap on quantification of temporary tubular materials with surface defects for decision making by construction workers in quality circles for quality control.

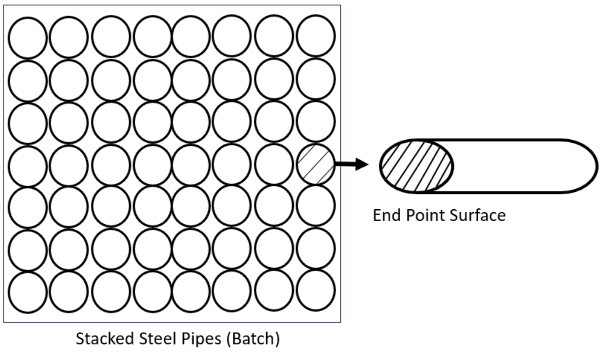


Figure 1. End point surface of stacked steel sections.

Hence, this paper proposes an automated decision support system based on quantified number of materials with surface defects; rust, bend and, rust and bend using deep learning object detection yoloV7 model. The model is deployed on flask web framework for visualization, with a rectification action and reporting of the results which can be used on mobile devices by quality circle construction workers. This is also visualized on local computer system by the management in real time.

2 Background

2.1 Tubular Steel Temporary Materials

Temporary materials are very important for the erection of temporary structures such as scaffolding, falsework and formwork systems. Metal temporary materials such as steel and aluminium are frequently used in the construction industry for these temporary structures due to their guaranteed strength, rigidity, and the ability to erect and dismantle quickly. Additionally, they are easy to reuse which makes them much cheaper compared to other alternatives such as timber based temporary materials. However, due to frequent reuse and exposure to varied environmental conditions, these metal-based materials become subject to rust which undermine their structural strength creating unsafe working condition on construction sites. Additionally, hollow steel sections such as square hollow sections experience global and local deformation under excessive loading especially when stored in batches creating a warp or bend on the cross-section area. This undermines the hollow steel section's aesthetic nature and their structural strength [2].

2.2 Deep Learning-Based Inspection

The quality inspection of these materials is mainly done manually, where workers or inspectors check these surface defects for quality control. However, use of deep learning techniques such convolutional neural networks (CNN) on identifying these surface defects have gained attention in the past decade. They involve extracting useful information from images and videos to reduce the involvement of human inspectors and construction workers. For instance, Hussein et al. [3] employed VGG-16, a convolutional neural network on images to detect and localize defects such as mold and stains in buildings. Sergio et al. [4] used convolutional neural network to detect defects such as cracks on structural members of bridges through images. In terms of steel sections, Zhaoguo et al. [5] introduced new modules on the deep learning neural network such as multiscale feature extraction to improve extraction process of features on images and efficient feature fusion to improve the fusion mechanism on the neck layer for accurate detection and localization of surface defects such as crazing and patches. However, though there exists extensive research on detection of surface imperfections using computer vision techniques, quantification of materials with these defects is still lacking.

2.3 Quality Control of Materials

Checking the quality standard of individual materials in a batch can be expensive and time consuming, especially where the lot size is very large. This has led to the introduction of sampling plans to decide whether to accept or reject a lot based on a defined sample size which is a representative of the lot. The whole lot is either rejected or accepted based on whether a specific threshold of the number of defective items in the sample has been observed or not. The two main sampling techniques used to determine the acceptance of materials in a batch are sampling by attributes and sampling by variables. Sampling by attributes is based on whether there is presence or absence of a particular characteristic of a material, for example, whether a material contains defective patch or not. It is computed on the probability of accepting or rejecting a lot using the defective aspect of the batch. For instance, assuming we have a lot of N size, where the sample size is n, and the actual number of defective materials is M, the probability of getting x number of defective items in the sample is expressed as shown in equation (1)

$$p(X = x) = \frac{\binom{M}{x}\binom{N - M}{n - x}}{\binom{N}{n}} \quad (1)$$

To compute the probability of accepting or rejecting the lot, we assume that the fraction of non-defective items in the lot to be q, and the fraction of defective items to be p. This is expressed in a binomial distribution equation as shown in equation (2).

$$g(p) = \sum_{x=0}^{r} p(x = x) = \sum_{x=0}^{r} \frac{\binom{N_p}{x}\binom{Nq}{n-x}}{\binom{N}{n}} \quad (2)$$

Sampling by variables on the other hand is more quantitative in nature and is focused on measurement of actual values such as length, height, and weight. It is a continuous process used to determine the overall acceptability of the batch. The main goal of the two sampling techniques is to control quality of materials in the most economical and efficient way [6].

However, this manual quality control system is prone to human errors and the documentation process is tedious for the workers especially when we have large number of materials.

2.4 Normal Distribution

Normal distribution or gaussian distribution is a probability distribution where an average distribution of random samples tends to converge towards the normal distribution creating a symmetric bell-shaped curve. This works under the concept of the central limit theorem. There are two broad techniques for monitoring quality in construction management: management techniques and statistical techniques. Management techniques involve quality control, quality assurance and total quality management concepts. Statistical techniques include gaussian distribution and hyperbolic distribution which use the 6-sigma concept on quality control. Gaussian distribution has been applied in many fields such as construction management, manufacturing, and civil engineering through estimation of statistical properties such as number of defects and defects per million opportunities [7]. For instance, Vivian et al. [7] compared the use of gaussian distribution and hyperbolic distribution on defect detection to improve the construction quality and the yield percentage. Diego and Peter [8] proposed gaussian process for predicting product quality based on defective products per unit (fault density). Silva et al. [9] employed the gaussian distribution to detect harmful conditions in aquatic life. The method used 2D image visualization on production of fish under three classifications: dangerous, warning, and normal conditions. Zhou et al. [10] solved the problem of clutters on 3D feature descriptors using histograms of gaussian normal distribution. This enabled capturing of conspicuous features creating a homogenous scene with the 3D model.

2.5 Web Framework

The era of information technology has seen a huge increase of data in the construction industry. However, the visualization of this data to help stakeholders make informed decision has always been a challenge. This is due to variations on the type of data produced which comes in different formats such as images, text and videos causing data driven decision making in the construction industry difficult. Additionally, the transfer of these data between project stakeholders has been slow affecting the project productivity. Hence, a cross integration platform such as a web framework system which can visualize and share construction information data in different formats rapidly has been of necessity.

In order to improve access and sharing of integrated construction data, Chassiakos and Sakellaropoulos [11] proposed a web framework connected to a relational database for managing construction information. Gurmu et al. [12] developed a dashboard for visualization of building defects from inspection reports through data mining using python libraries and natural language toolkit. Changyoon et al. [13] made a construction management system for real time site monitoring and construction information sharing with the aim of visualizing on mobile devices. Do-Yeop et al. [14] used web system framework to link defective data with BIM environment for visualization. However, there is still a gap on a web framework which can visualize quantified defective materials from a deep learning algorithm through mobile devices and local computer and, report the output for documentation.

3 Methodology

3.1 Overview of the Proposed Methodology.

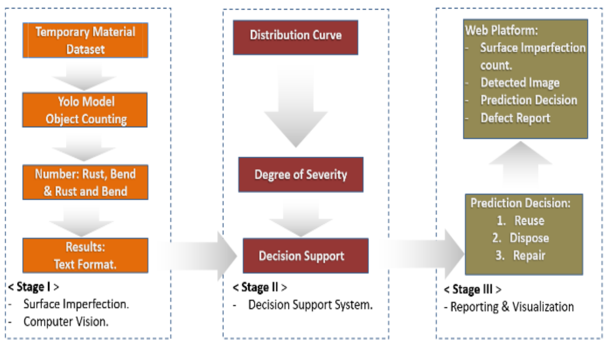


Figure 2. 3-Stage overview of the methodology.

The proposed methodology was divided into 3 main stages: computer vision, decision support and, reporting and visualization as shown in figure 2.

3.2 Stage I: Computer Vision.

3.2.1 Data Collection and Preprocessing

The first stage was collection of tubular steel temporary materials image dataset from two storage sites. The data collected consisted of circular hollow sections hereby referred to as steel pipes, rectangular hollow sections, and square hollow sections. The images taken focused on the temporary materials in batches as shown in figure 3. In the process a total of 500 images were collected for training the deep learning model.

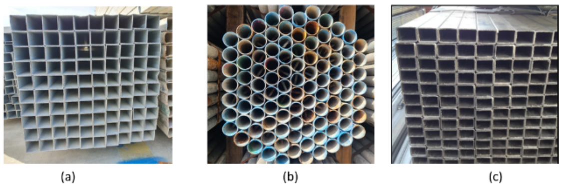


Figure 3. a). Square Hollow Sections, b). Steel Pipes, c). Rectangular Hollow Sections dataset collected in batches.

The image dataset obtained had varied size in terms of the height and width pixel. Hence, before training the deep learning model, the data was preprocessed using a fixed height and width of 640 x 640 pixels. A custom labelling process using LabelMe software was adopted as shown in figure 4 employing a 2-tier naming nomenclature where the first part represented the material type: steel pipe, square hollow section, and rectangular hollow section, and the second part separated by the hyphen represented the state of the material: rust, bend, rust and bend, and non-defective state.

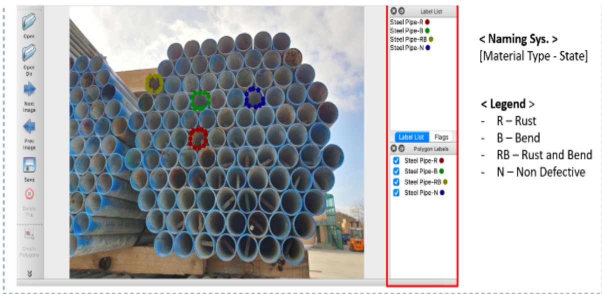
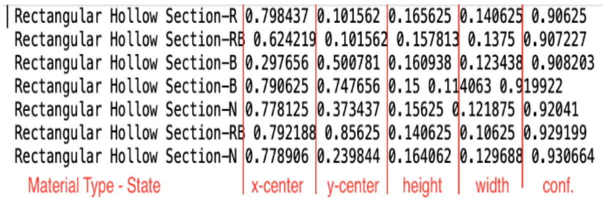


Figure 3. Labelling nomenclature using LabelMe software.

In the labelling process, occluded images such as those with concrete splatter on the cross-section area of hollow sections were included to make the model robust to occlusion. Additionally, before training, mosaic augmentation, mix-up augmentation and perspective transformation hyper parameters were adjusted to enable the model to generalize across various object configurations for occluded images.

During inference of the deep learning model, an image output of the detected object and text output are generated. The text output contains the class label, x-center, y-center, height and width of each detected box and confidence scores as shown in figure 4. A special python code was developed which converted the detected text results to python list. The listed results were separated using white spaces to extract the material type and the special hyphen character to extract the surface defect of the materials.



Material Type - State	x-center	y-center	height	width	conf.
Rectangular Hollow Section-R	0.798437	0.101562	0.165625	0.140625	0.90625
Rectangular Hollow Section-RB	0.624219	0.101562	0.157813	0.1375	0.907227
Rectangular Hollow Section-B	0.297656	0.500781	0.160938	0.123438	0.908203
Rectangular Hollow Section-B	0.790625	0.747656	0.15	0.114063	0.919922
Rectangular Hollow Section-N	0.778125	0.373437	0.15625	0.121875	0.92041
Rectangular Hollow Section-RB	0.792188	0.85625	0.140625	0.10625	0.929199
Rectangular Hollow Section-N	0.778906	0.239844	0.164062	0.129688	0.930664

Figure 4. Detection text results file.

3.2.2 YoloV7 Deep Learning Model

The dataset was then divided to a train set and validation set ratio of 4:1 and trained on the YoloV7 deep learning model. The model is typically made of three parts: backbone, neck and head as shown in figure 5. The backbone layer contains convolutional layers for feature extraction from an input image. Each convolutional layer has a kernel size, number of stride operation and the number of channels. The neck layer is used to fuse or connect the extracted features from the backbone layer while the head is used to make prediction using bounding boxes. The head is subdivided into 3 parts depending on the level of feature extraction on obtaining detection results for large, medium, or small objects [15].

Feature extraction process from the backbone layer is followed by a spatial pyramid pooling (SPP-net) layer in the neck layer. The SPP-net allows the use of input images with variable sizes which help maintain feature information from images without warping them. Additionally, the network contributes to improved accuracy on training [16]. There are additional plug-and-play modules which can be used in place of the SPP-net such as the Ghost-net layer and the Bottleneck layer. The Ghost-net layer is aimed at reducing the computational cost of the deep learning model enabling a lighter model. This is achieved by stacking the ghost modules [17]. Bottleneck layer uses pointwise convolutions to make bottlenecks for reducing parameters and increasing the depth, enhancing efficiency and computational performance [18].

However, these layers still have the problem of heavy inference computation especially when deploying them on mobile devices and web platforms. To mitigate this problem the SPP-net, Ghost-net and Bottleneck layer are concatenated with Cross-Stage Partial network (CSP-net). This improves speed of inference and accuracy when deployed on various platforms. For instance, when using the Dense network, the base layer is concatenated with the subsequent layers directly to map the output assuming a network with $\boldsymbol{k}$-layers of convolutional neural networks, with $\mathbf{F}$ as the mapping function using an input $\boldsymbol{x_0}$ to the target $\mathbf{y}$, an equation can be derived as follows:

$$y = F(x_0) = X_k. \tag{3}$$

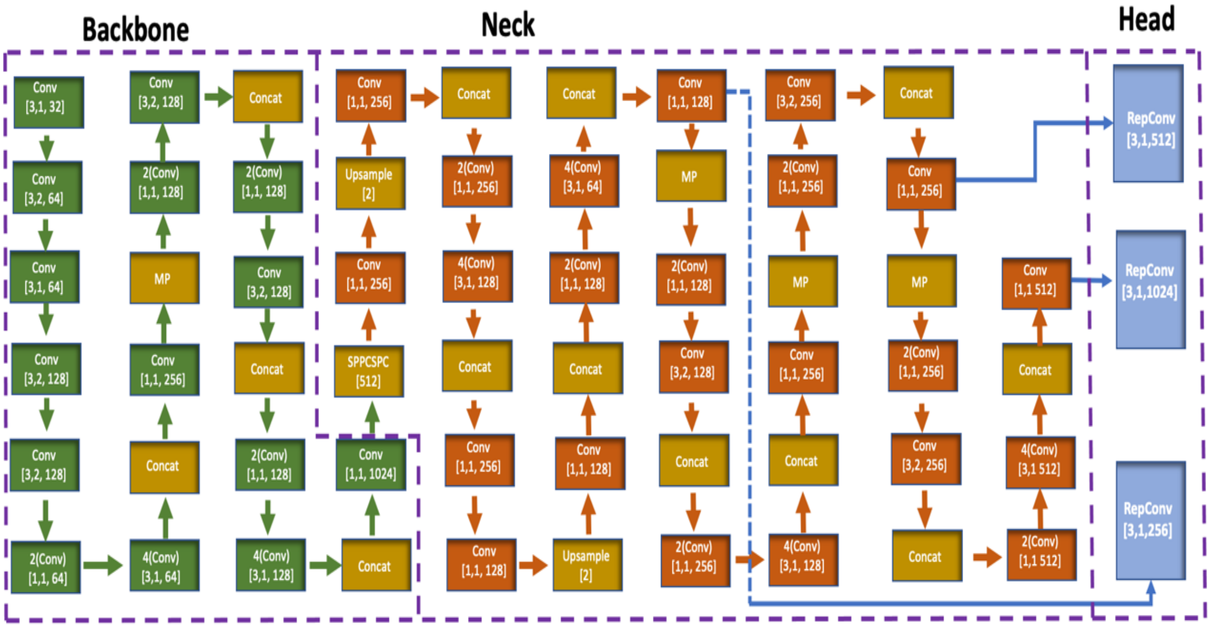


Figure 5. Internal architecture of the YoloV7 model.

However, the cross stage partial network relies on optimization by dividing the ***F*** function for the base layer ($\boldsymbol{x_0}$) into two parts:

$$x_0 = [\, x_{0'}, x_{0''} \,] \tag{4}$$

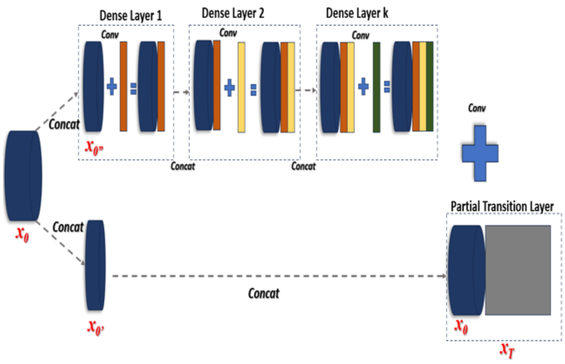


Figure 6. Cross stage partial network in the DenseNet.

Hence, to map the target y, x0' is connected to the end stage while the x0" undergoes the dense network operation under M transition function for combining the two separate parts of the network that is, F the mapping function and T the transition function from one layer in the dense network to another [19].

$$y = M\,([x_{0'},\ T(F(x_{0''}))]) \tag{5}$$

Hence, to obtain a model which can perform inference fast with high accuracy, three networks with cross-stage partial networks were evaluated: SPPCSP-net, GhostCSP-net and BottleneckCSP-net. Their performances were assessed using Giga Floating Point per second, mean average precision and recall in order to determine the best network that could be integrated into the web framework. The training parameters were a batch size of 16, 150 epochs with a 0.01 initial learning rate. The model was trained on the pytorch framework, CuDA 11.8, on the Tesla V100, 16GB graphical processing unit (GPU).

3.3 Stage II: Decision Support System.

To determine the threshold for different classification of batch materials based on whether to reuse, dispose or repair, a statistical distribution of the surface defects of different tubular steel materials in lots was performed on two storage sites. The equation for calculating distribution is normally based on two key parameters; mean (μ) and standard deviation (σ) with the normalization factor and natural logarithm base (e).

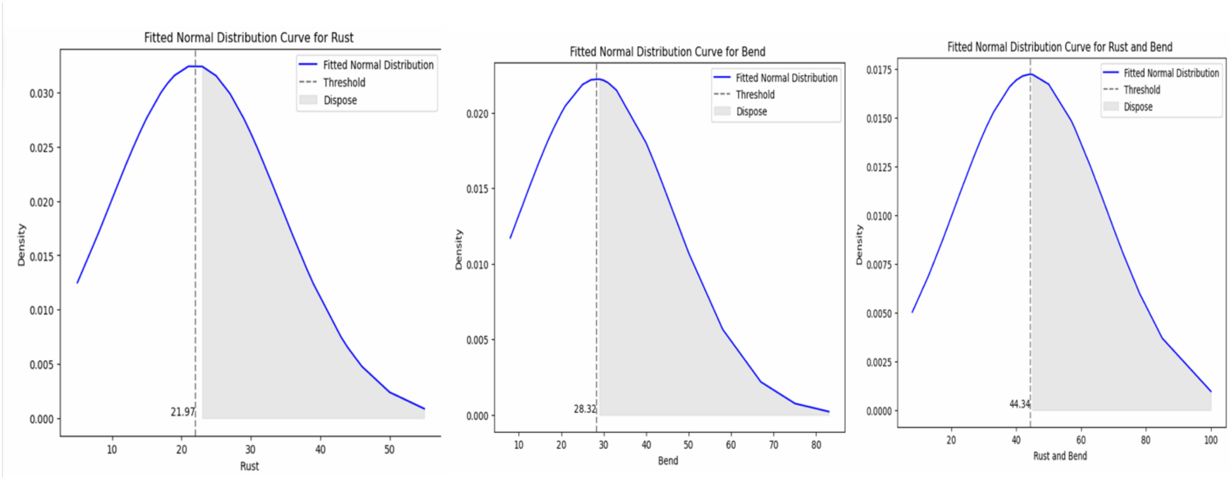


Figure 7. Normal distribution curves of different defective states of materials.

Hence, the mean and standard deviation of different batches was computed for statistical distribution.

$$f(x\mathrm{I}\mu\sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-u)^2}{2\sigma^2}} \quad (6)$$

The normal distribution curve of different condition of materials was plotted as shown in figure 7 and an assumption was made where percentage values greater than the curve threshold line indicated that the cost of repair is more than the cost of disposing the defective materials hence the dispose decision should be employed on the defective materials in the batch. On the other hand, when the percentage value falls below the threshold line but is more than zero, the cost of repairing the defective material in the lot is cheaper compared to the cost of disposing. Hence, the repair decision is employed.

Using the statistical distribution results, a degree of severity table was formulated to create a classification criterion as shown on table 1. The mean and standard deviation for the statistical distribution was based on the defective material count to total material count ratio expressed as a percentage.

Table 1. Surface Imperfection Degree of Severity Criterion

Defect	Critical Imperfection (Dispose)	Minor Imperfection (Repair)	Perfect (Reuse)
Rust	>22%	0%<R≤22%	0%
Bend	>28%	0%<B≤28%	0%
Rust and Bend	>44%	0%<RB≤48%	0%

**R – Rust, B – Bend, RB – Rust and Bend*

3.4 Stage III: Web Framework.

The final phase connected the computer vision model with the classification criteria from the decision support stage using flask web framework. The web framework was used to visualize the detected image, the total count of materials for each individual lot, the count for detected materials with defects, the decision to reuse, dispose or repair the materials in the batch and reporting the information for documentation. The quality circle leader or the user is required to take an image of the temporary materials in a batch using a mobile device, the image is sent to the cloud server which runs inference based on the trained deep learning model. From the detected results a text file is generated as shown in figure 5 containing information on the type of material and their corresponding defective state. Python code embedded into the flask framework computes the total number of materials in a batch and the total number of materials with specific defective condition expressed as a percentage. The percentage obtained is then compared to the degree of severity criterion table 1 where a decision on whether to reuse, dispose or repair the materials in the lot is obtained. The results are rendered on an interactive webpage using hypertext mark- up language. The user interface has an input field for the quality circle leader to enable reporting and documentation. The web framework plays a central role in connecting the front end which is the user interface and the back end which is the cloud server for hosting the deep learning model for inference and visualization on the actions to be applied on the defective materials. It ties almost all the nodes in the system which are illustrated in figure 8, creating a unified automated decision-making system for the management and the quality circle workers.

Table 2. Performance comparison of the selected deep learning neural network modules

Network	Epochs	GFLOPS	Precision	mAP@0.5	Recall	F1 Score
SPPCSP-net	150	105.2	82.4	84.9	74.8	78
GhostCSP-net	150	102.2	78.5	84.8	82.1	80
BottleneckCSP-net	150	100.3	82.4	82	76.3	78

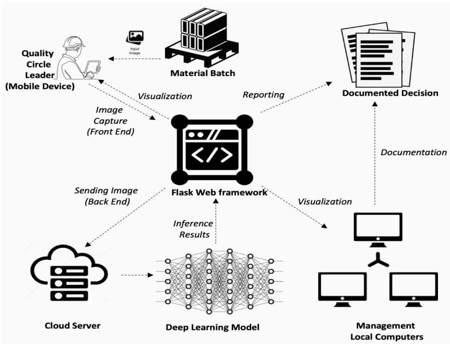


Figure 8. Web framework Concept.

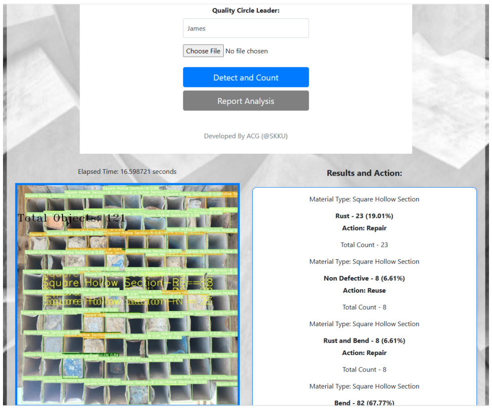


Figure 9. Visualization of the web framework user interface

4 Results and Analysis

Evaluation of the system was done based on average precision, precision, inference speed, Giga Floating Point per Second (GFLOPS) and the count accuracy of the materials. The spatial pyramid network with the cross stage partial network achieved the highest GFLOPS of 105.2, mean precision of 82.9, precision of 84.9 with a speed of 20 seconds per inference.

In terms of count accuracy, the material batches were divided into 3 classifications:

1. Small batches – batches with materials in between 1 to 100.
2. Normal batch – batches with materials between 101 to 250.
3. Large batch – batches with materials over 250

Different construction storage sites had specific number of materials to be stacked on an individual batch based on space availability. Hence, the classification was based on analysis of the stacking of materials at different temporary material warehouses and sites. Absolute error (Measured value – True Value) was calculated for each subgroup expressed as a percentage as shown in table 3.

Table 3. Measure of absolute error of average count of different batch size.

Batch Size	Detected Count	True Count	Absolute Error
Small	35	35	0%
Normal	105	105	0%
Large	300	500	40%

5 Conclusion

This research proposed an automated decision support system which can be used to determine whether to dispose, reuse or repair of tubular steel materials based on their end point surface defects. Additionally, the study contributed to quantification of temporary steel tubular materials using deep learning and integration of the deep learning model to the web framework for management of materials. This can be further used to calculate the cost of repair and disposal of steel tubular temporary materials.

However, through the study, a very high absolute error was observed on large batch material sizes. This is because the target objects appear smaller during the detection process. In order to improve the accuracy on large batches, it is recommended to customize anchor boxes responsible for detecting small objects in addition to adding dataset with large batches of materials. Hence, a robust deep learning model which is capable of accurately quantifying large batch size material is suggested as an area of further study.

Acknowledgement

This work is financially supported by Korea Ministry of Land, Infrastructure and Transport(MOLIT) as 「Innovative Talent Education Program for Smart City」.

This research was conducted with the support of the "National R&D Project for Smart Construction Technology (No. RS-2020-KA156488)" funded by the Korea Agency for Infrastructure Technology Advancement under the Ministry of Land, Infrastructure and Transport, and managed by the Korea Expressway Corporation.

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