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Study on Development and Implementation of Safety Inspection Drones with Machine Learning Algorithms to Improve Construction Safety in Sri Lanka

DMNCT Dissanayake# and NDI Vithana

Faculty of Built Environment & Spatial Sciences, General Sir John Kotelawala Defence University, Sri Lanka

#34-qs-024@kdu.ac.lk

Abstract- Most of the construction sites in Sri Lanka work under unsafe conditions due to limited resources. Due to these unsafe conditions, human lives are in danger at times. The construction industry holds a major position in the development process of Sri Lanka, as it significantly contributes, not only for Gross Domestic Product but also for Gross National Product. Unfortunately, the Health and Safety factors have become a secondary concern though the construction industry holds a major portion in the economy of the country. The traditional inspection methods currently practised in the industry seem to be outdated, time-consuming, less efficient, less effective, and increase the workload of safety officers. It is impossible to perform observations in multiple locations at the same time by a single safety officer because some locations in the sites are hard to reach, and there may be blind spots too. This study proposes an automated safety inspection method to increase the safety levels of construction sites. For this, the study reveals a comprehensive experimental discussion on how to blend image processing techniques with unmanned aerial vehicles. Image processing is the technical analysis of images by using complex algorithms, and in this scenario, unmanned aerial vehicles (drones/quadcopters) act as a flexible image providing source that can fly over the construction sites by providing real-time videos for the algorithm to analyse for safety hazards. The study was concluded by achieving two objectives, developing an algorithm with YOLO v3 architecture to detect safety hazards through drones, and measuring the accuracy and reliability of the automated detections.

Keywords: *construction safety, Image processing, unmanned aerial vehicles*

I. INTRODUCTION

In Sri Lanka most of worksites are in under unsafe conditions, due this behaviour many pay from their lives every year. According to Department of labour Sri Lanka, annually 500,000-man days are wasted because of occupational health issues (Dissanayake, 2016). Moreover, Sri Lankan orthopaedic service of national hospital have records of 102,321 accidents treated in 2015. Among them 12% has been reported due to occupational health hazards. Within 12% of accidents, 50% fatalities are recorded from construction industry and most of them are preventable (Darshana, 2017). The construction industry owns a major role in development of Sri Lanka, it significantly appears not only in gross domestic product (GDP) but also in gross national product (GNP) of the Sri Lankan economy. The industry contributed 6.6% in 2009 overall GDP and 9% in 2019. Therefore, it contributes a considerable impact to the economy of Sri Lanka. While it is representing that much for the economy, one of essential factor, the health and safety has become the secondary concern in the industry. Managing a successful project means not only performing the construction operations within given time inside the budget but also considering the safety on site (Belel and Mahmud, 2012).

In Sri Lanka qualified safety officer will be employed for maintaining the occupational safety and health (OSH) performance in the site, but a study found that only 42% of construction sites are only able to employ a suitable safety officer to maintain the regulation inside the site. And the study also shows some barriers as high expenses and lack of qualified safety officers in the local industry (De Silva and Wimalaratne, 2012). Currently most of construction sites in Sri Lanka are still using traditional manual inspection methods. A study by Toole (2002) identified eight factors that result construction accidents. Absence of personal protective equipment (PPE), lack of proper training, lack of enforcement of safety, unsafe procedures, unsafe site conditions, poor attitude toward safety, lack of safety equipment and sudden deviation from prescribed behaviour. One of keyword used in his study to overcome above factors was "Observation", the safety officer has duty to frequently observe employees, compare actual methods and sequencing and current actual site condition (Toole, 2002).

We can define this task of observation as one of the main duties to frequently walk around the site and getting real time data on the ground through direct interactions and direct observations. The data gathered on observation are used as safety officer's decision-making process (Jalaei and Jrade, 2014).

These traditional methods are time consuming; it is sometimes impossible to make observations in multiple locations within the site at the same time and some locations are hard to reach. And there may be blind spots. As considering these facts, it is suitable to get assistance from other sources to increase the efficiency.

When it comes to assisting to the safety officers, we can utilize new technology to the construction grounds, drones are a very good flexible and cost-efficient option (Irizarry et al., 2012). Moreover, this study focusses on to implement safety inspection drones which are using machine learning algorithm to identify most common safety issues and provide assist when inspections going on. This will provide the construction safety managers to increase their quality of their duties reducing the workload within the site and the productivity will be improved by saving the time.

Machine Learning can be defined as a process of building computer systems that automatically improve with experience and implement a learning process (Zhang, 2012). This machine learning can learn theories automatically from data, through a process of model fitting, inference or learning from examples (Zhang, 2012). It has special reason to choose drones to use this developed algorithm, because instead of using closed-circuit television (CCTV) systems, drones are superior endurance, intelligence and flexible to fly over every aspect of the construction site and have ability to provide real time video feed to the decision making sever that running the algorithm.

The study includes a case study performed in a high-rise building construction site in Colombo 08, Sri Lanka. The following objectives were achieved during this case study.

(1) Develop a suitable algorithm to provide an artificial analysing capability to the program for an automated safety inspection process.

(2) Perform an experimental analysis consisted of using the drone as a tool to inspect real time videos from a typical worksite and measure the accuracy of hazard detections.

The study presents the abilities of the drone, what are the issues arisen when performing inspections. While these new technologies take the construction to new level, there are some flaws that attention needs to be given.

In near future, drones will take over the more complex tasks in massive construction projects. Contractors who rely on drones will get more benefits and involve in more ambitious projects and finish work on proper time in Sri Lanka with minimized construction hazards.

II. LITERATURE REVIEW

Construction safety on project site should pay significance high priority due to the hazardous nature of the construction industry. Construction industry is one of unpredictable industries that cause more deaths and injuries on worksites, construction industry is known as a hazardous industry that many components that are possibly risky to labours (Osei-Kyei *et al.*, 2019).

Safety has a secondary concern in a market driven society where the main objective is to obtain quality within minimum time and cost. This trend can be identified in most developing countries. Comparing to developed countries, Sri Lanka has less output of construction rather than developing countries but the magnitude of the accident rate is still large as reported in other developed countries such as United Nations of America (National Safety Council, 1997, cited in Chau et al., 2004; Bureau of Labour Statistics, 2008a, b), the United Kingdom (Health and Safety Executive, 2010; Bureau of Labour Statistics, 2008a, b; Sacks et al., 2009) and Singapore (Kartam and Bouz, 1998, cited in Chau and Goh, 2004; (De Silva and Wimalaratne, 2012).

Zhou, Goh and Li (2015) identified six research areas that should pay more attention to conduct in order to improve the safety on sites as follows,

(1) Lack of unsafe behaviour monitoring. Most of studies show that the priorities should pay to fatalities/ injuries occur from workers' unsafe behaviour (Choudhry and Fang, 2008).

(2) Lack of utilizing safety climate to improve construction safety. Safety climate and its relationship with safety performance has been

revealed in construction safety research (Siu et al., 2004; Mohamed et al., 2009).

(3) Ignorance of quantitative relationship study between project/company scale and safety of construction. Some of researchers have done research studies about construction safety in the perspective of scale of the project or the company. The results show that accident rates in small projects is higher than large scale projects (Jeong, 1998; Kheni et al., 2010).

(4) Lack of research studies about task level, as mentioned in 3rd point, more than 90% of research articles aimed on project or company level, task level studies are very rare, but tasks provide to build basic components of a specific project.

(5) Immoderate priority on building projects and lack of studies carried out for non-building projects, such as road projects, bridge, canal etc.

(6) Lack of usage of innovative technology in construction sites to overcome problem encountered and minimize the workload from safety officers (Zhipeng et al., 2013).

All above facts are relative to Sri Lankan construction industry. This study is based on the first and sixth factor that mentioned above as “Lack of unsafe behaviour monitoring” and “lack of innovation technology applications in construction sites”.

Due to the massive development of drone technology and real-time monitoring technologies, they are capable in assisting construction industry professionals to implement in house mass civil infrastructures capturing real-time images and videos and the most valuable benefit is the reachability of wide area of a site (Dastgheibifard and Asnafi, 2018).

One of study carried out by (Yong and Yeong, 2018) used a drone to human object detection with deep learning and deployed to forest surveillance purposes. This allowed to detecting existence of humans in forestry environment by saving time and cost. And the image detection results were categorized into three items as True Positive, False Positive, False Negative and tested them using F-score method. Hung (2020) performed another study using same F-score method, in his study he used Faster R-CNN deep learning module to detect pedestrian and searching for missing persons and illegal immigrants. In his results shows Faster R-CNN deep learning module was able to achieve acceptable decisions with 98% F1 measure.

III. METHODOLOGY

A comprehensive experimental case study was performed based on a high-rise building in Colombo. In this construction site, able to perform the sample tests to examine the hazard detection accuracy of the drone.

Also, in this scenario the accuracy of the drone was tested using F-score method. The F-score generally using in evaluation of information retrieval systems, machine learning models. The result is a value between, 0.0 for no F score and 1.0 for full or perfect F score.

The F-score also known as F1 score is a method of measuring model’s accuracy on a specific dataset of an algorithm. This method is ideal for classifying data into “negative” or “positive”. This method is ideal to evaluate binary classifications. F score or F1 score consists of “Precision” and “Recall”. And the harmonic mean of the algorithm is defined by the F score or F1 score (Goutte and Gaussier, 2005) (F-Score Definition | DeepAI, 2020).

In machine learning, pattern recognition and information retrieval, Precision (Also known as Positive Predictive Value) is the fraction of true positive cases among the combination of true positive and negative cases. Recall (also known as sensitivity) this is the fraction of True positive among the combination of true positive and false negative (Sokolova, Japkowicz and Szpakowicz, 2006).

Following confusion matrix shows the relation between the positive and negative identified data using algorithm.

		Predicted	
		Negative	Positive
Actual	Negative	True Negative	False Positive
	Positive	False Negative	True Positive

Figure 1: Confusion matrix

A. *Precision*

Precision factor reveals the relevant result percentage among all positive predictions. The fraction of true positive predictions and the combination of true positive and the false positive is the precision value.

$$\text{Precision} = \frac{True\ positive}{True\ positive + False\ positive}$$

Equation 1: Precision equation

Where:
True positive = Number of true positive predictions categorised by the model.

False positive = Number of false positive predictions categorised by the model.

B. Recall

Recall factor reveals the percentage of all relevant predictions correctly categorised by the algorithm. Recall is also known as sensitivity. The fraction of true positive by the combination value of true positive and false negative is the recall value.

$$\text{Recall} = \frac{True\ Positive}{True\ Positive + False\ Negetive}$$

Equation 1: Recall equation

Where:

True positive = Number of true positive predictions categorised by the model.

False negative = Number of false negative predictions categorised by the model.

C. F score/ F1 Score; (Sokolova, Japkowicz and Szpakowicz, 2006)

$$\text{F-score} = 2 \times \frac{Precision\ x\ Recall}{Precision + Recall}$$

Equation 2: F-score equation

IV. ANALYSIS AND DISCUSSION

The research concludes the data analysis done from the experimental case study and the assessment of the suitability of the algorithm in real world. The two objectives which are defined in the introduction were critically analysed on this chapter.

A. Experimental Case Study

Figure 2: Assessment area, 6.9104069,79.8837379

Source: <https://earthexplorer.usgs.gov/>

The core of this study is to design a suitable algorithm that can self-identify health and safety hazards by flying over construction job sites. For this scenario, a case study was carried out within a randomly selected high-rise building in Borella, Colombo area. The building was in structural stage at 11th floor when the study was initiated. The perimeter and the area of the enclosure is shown here,

B. Objective 01: Algorithm development

Machine learning inside the Computer Vision is a pair breakthrough that continues to energize the curiosity of start-up entrepreneurs, computer scientists and engineers for decades. It aims various application platforms to solve advance life problems basing algorithm from the human biological vision (Fullscale.io, 2019).

Both machine learning and computer vision anticipate bringing the human capabilities of sensing of data, understanding and processing data and take necessary actions based on previous and contemporary results into computers (Khan and Al-Habsi, 2020).

Solutions establishing from machine learning revolve around data obtaining, training the data set and make predictions using trained dataset (trained model) (Khan and Al-Habsi, 2020).

Development stage: In this case, the algorithm was developed and checked its capabilities according to following steps (an open-source python code was aided on following process under GNU General Public Licence v3.0),

1. Gathering data
2. Converting to YOLO V3 format
3. Setting Training Pipeline
4. Training model
5. Exporting weights file
6. Checking algorithm competences

1. Gathering data

Data gathering done through OpenImageV5 application, this was initially launched in 2016. It has high volume of image pool, about nine million images annotate with their labels which comprising of real-world object groupings.

On this study perimeters, 3 types of objects were downloaded (smoke, fire, PPE).

2. Converting to YOLO v3 format

"oid_to_pascal_voc_xml.py" was initiated for convert images into XML file format. After that "OIDv4_toolkit" used to perform conversion between XML files to YOLO v3 format.

3. Setting Training Pipeline

This stage's main purpose was to define the classes.

4. Training model

Training the data set (model) is the main step in an algorithm. Below were the computer specifications which were the model was trained.

Table 6: System specifications

GPU	NVIDIA GeForce GTX 1650 (4GB)
GPU Overclocking	N/A
CPU	Intel Core i5-9300H 2.4GHz
CPU Undervolted	N/A
Cooling	Stock Cooling (Nitro Sense Coolboost™ at max fan speed)
RAM	16GB DDR4
OS	Ubuntu 18.04

Data model testing stage: To understand the neural network accuracy, training epoch vs accuracy curve is an ideal method.

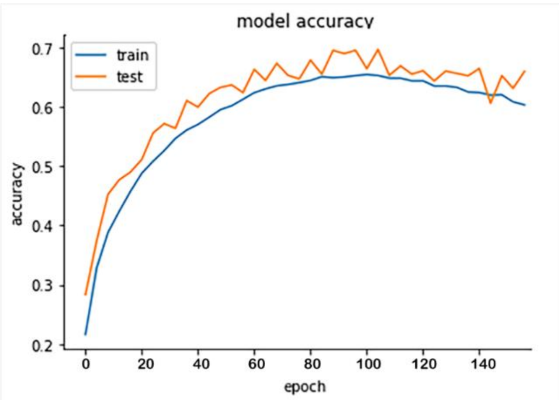

Figure 3: Accuracy vs epoch graph

This model consumed nearly 7 hours to train four objects with 100 epochs. (100 cycles through the full training datasets.)

5. Transferring the trained weights file to darknet format

After training of the specific model, final weight file needed to be converted to “darknet” format to test run.

6. Checking algorithm competences

Testing objects includes smoke, fire, and personal protective equipment presence. All below tests are executed after the special permission granted by the Assistant Operational Engineer of the site and collaboration with the Safety Officer on site.

Python code: The complete programming work has been uploaded to google drive, since it is open source, anyone has permission to modify it under GNU General Public License v3.0.

Use QR code to see above content.

Inside lab testing stage: The training has completed 100 epochs and gained a decent result as figure 3 for the internal testing purpose, the training model were examined with photos that took from construction personnel in the site, below are the results showing that the algorithm detects hardhats with higher rates of over 80% of accuracy.

Figure 4: Hard- hat detection accuracy

C. Objective 02: Accuracy of hazard detection

(1) Smoke detection accuracy test: To validate the smoke detection capabilities of the algorithm, the drone was tested on the site with artificially controlled smoke on 14^{th} slab of the building, while performing these, precautions were taken to prevent any other damage can occur to construction personnel or equipment. The selected area has approximately 200 m^2. The drone flew 0.4 m/s on a straight line holding 10 m of latitude from the 14^{th} floor of the building and above the tower crane, parallel to the routine straight lines covering the waypoints that planned before the flight. And 10 tests were carried out with maximum of six smoke points and minimum of zero. The test is as follows,

The control test: Manual count of the artificially made smoke points. (Accuracy 100%)
The experimental test: Count taken from the drone on smoke points.

Table 2: Smoke test- Drone counts vs. manual counts.

	Drone data	Manual data=actual data	True positive	False positive	False negative
Take 1	0	0	0	0	0
Take 2	3	3	3	0	0
Take 3	3	4	3	0	1
Take 4	6	6	6	0	0
Take 5	6	5	5	1	0
Take 6	2	3	2	0	1
Take 7	4	4	4	0	0
Take 8	5	4	4	1	0
Take 9	6	6	6	0	0
Take 10	4	5	5	0	1
	39	40	38	2	2

True positive =38
False positive =2
False negative =3

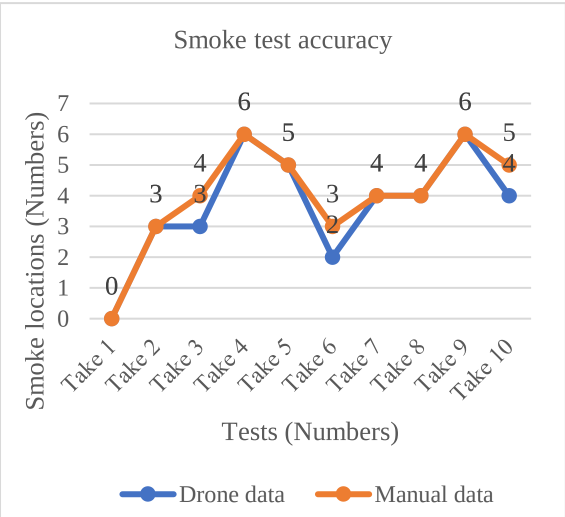

Figure 5: Smoke test accuracy test results

Using F score; (Rahman and Devanbu, 2013)

$$\text{Precision} = \frac{\textit{True positive}}{\textit{True positive}+\textit{False positive}} = \frac{38}{38+2} = 0.95$$

Equation 4: Precision equation

$$\text{Recall} = \frac{\textit{True Positive}}{\textit{True Positive}+\textit{False Negetive}} = \frac{38}{38+3} = 0.92$$

Equation 5: Recall equation

$$\text{F-score} = 2 \text{ x } \frac{\textit{Precision x Recall}}{\textit{Precision}+\textit{Recall}} = 2 \text{ x } \frac{0.95x0.92}{0.95+0.92} = 2 \text{ x } \frac{0.87}{1.87}$$

$$= \underline{0.93}$$

Equation 6: F-score equation

(2) Fire detection accuracy test: To demonstrate the Fire detection capabilities, the drone had to be tested with artificially controlled fire on safe parts of the construction site. The selected area has approximately 200 m^2. The drone flew 0.4 m/s on a straight line holding 10 m of latitude from the 14th floor of the building, parallel to the routine straight lines covering the waypoints. And 10 tests were carried out with maximum of six fire points and minimum of zero. The test as follows,

The control test: Manual count of the artificially made fire points. (Accuracy 100%)
The experimental test: Count taken from the drone on fire points.

Table 3: Fire test- Drone counts vs. manual counts

True positive =37
False positive =1
False negative =3

	Drone data	Manual data=actual data	True positive	False positive	False negative
Take 1	0	0	0	0	0
Take 2	4	4	4	0	0
Take 3	3	3	3	0	0
Take 4	5	6	5	0	1
Take 5	3	5	3	0	2
Take 6	4	4	4	0	0
Take 7	4	3	3	1	0
Take 8	4	4	4	0	0
Take 9	6	6	6	0	0
Take 10	5	5	5	0	0
	38	40	37	1	3

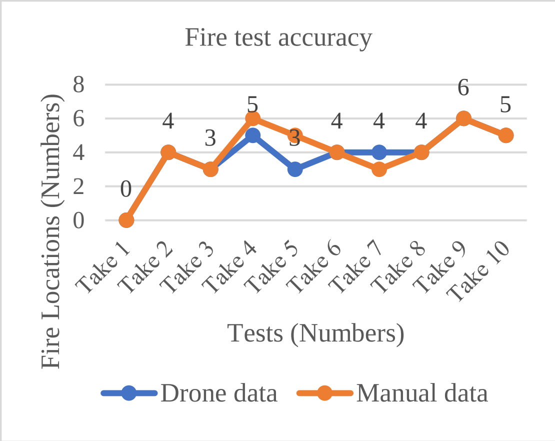

Figure 6: Fire test accuracy test results

Using F score; (Rahman and Devanbu, 2013)

$$\text{Precision} = \frac{True\ positive}{True\ positive + False\ positive} = \frac{37}{37+1} = 0.97$$

Equation 7: Precision equation

$$\text{Recall} = \frac{True\ Positive}{True\ Positive + False\ Negetive} = \frac{37}{37+3} = 0.92$$

Equation 8: Recall equation

$$\text{F-score} = 2 \text{ x } \frac{Precision\ x\ Recall}{Precision + Recall} = 2 \text{ x } \frac{0.97x0.92}{0.97+0.92} = 2 \text{ x } \frac{0.89}{1.89}$$

$$= \underline{0.94}$$

Equation 9: F-score equation

(3) PPE detection accuracy test: In this case hard hat detection accuracy was measured as for the PPE presence criteria. To test PPE presence capabilities, the drone was deployed on the construction site to detect PPE equipped construction personnel and alert on construction personnel who are not wearing hard hats.

For this scenario ten people were tested, two people from each colour as white, green, blue, yellow, red hard hats were deployed on the site in random places for ten times. The selected area was approximately 200 m^2.

The drone flew 0.4 m/s on a straight line holding 10 m of latitude from the 14th floor of the building, parallel to the routine straight lines covering the waypoints. The maximum count of hard hat is ten and the minimum count is zero.

The control test: Manual count of the labourers with hard hats. (Accuracy 100%)

The experimental test: Labourer count taken from the drone.

Table 4: PPE test- Drone counts vs. manual counts

	Drone data	Manual data=actual data	True positive	False positive	False negative
Take 1	0	0	0	0	0
Take 2	9	10	9	0	1
Take 3	6	9	6	0	3
Take 4	7	8	7	0	1
Take 5	10	10	10	0	0
Take 6	10	9	9	1	0
Take 7	10	9	9	1	0
Take 8	5	7	5	0	2
Take 9	8	8	8	0	0
Take 10	5	5	5	0	0
	70	75	68	2	7

True positive =68
False negative =7
False positive =2

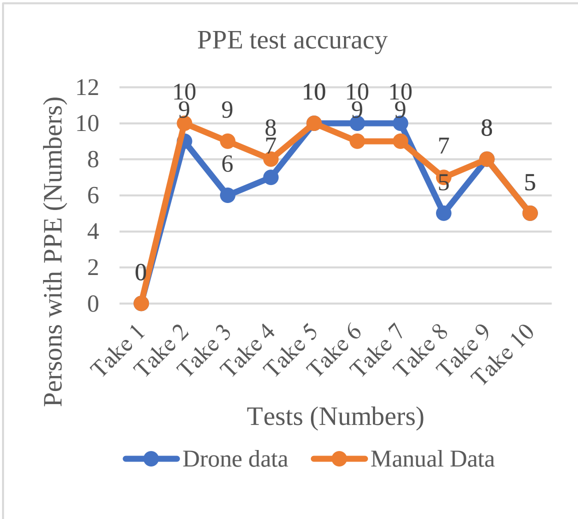

Figure 7:11 PPE test accuracy test results

Using F score; (Rahman and Devanbu, 2013)

$$\text{Precision} = \frac{True\ positive}{True\ positive + False\ positive} = \frac{68}{68+2} = 0.97$$

Equation 10: Precision equation

$$\text{Recall} = \frac{True\ Positive}{True\ Positive + False\ Negetive} = \frac{68}{68+7} = 0.90$$

Equation 11: Recall equation

$$\text{F-score} = 2 \text{ x } \frac{Precision\ x\ Recall}{Precision + Recall} = 2 \text{ x } \frac{0.97x0.90}{0.97+0.90} = 2 \text{ x } \frac{0.89}{1.89}$$

$$= \underline{0.94}$$

Equation 12: F-score equation

(4) Overall Accuracy of hazard identification

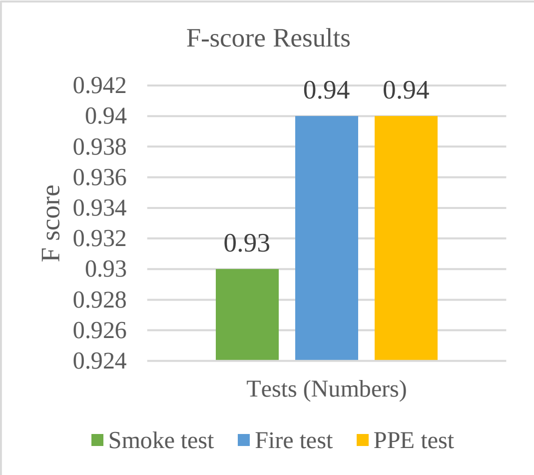

Figure 8:12 Overall accuracy of detection tests

$$\text{Overall accuracy} = \frac{(0.93 + 0.94 + 0.94)}{3} \times 100\%$$

$$= 0.94 \times 100\%$$

$$= \underline{94\%}$$

Overall accuracy of above three tests is higher than 90%, close to the best possible value of "1". A good data model produces high precision and high recall stated by Rahman and Devanbu (2013) and higher F-score (Sokolova, Japkowicz and Szpakowicz, 2006), the better predictive power given by the algorithm for the classification procedure. This automated system detected most of the site safety hazards including Smoke, Fire and PPE absence of labourers. Implementing this method will not be a wastage to a construction site, above real-world data are proving the capabilities of this automated safety drone is ideal to deploy to aid on safety inspections.

V.CONCLUSION

The main aim of the research is to show how to develop an algorithm to implement safety inspection drones in Sri Lankan construction sites.

A. Objective one

Develop a suitable algorithm to provide an artificial analysing capability to the program for an automated safety inspection process.

For the beginning, to make the foundation for this automated system, a suitable algorithm was developed. For this instance, YOLO v3 architecture was used and examined the accuracy of the data model and gain over 70% of accuracy (Redmon and Farhadi, 2018). After that, in lab test for image detection was performed prior to employing the drone in real world, in this test all the images were detected with over 80% of accuracy by achieving the first objective. The algorithm is only capable to detect smoke, fire, and PPE according to this study, it can be developed for detecting more safety related hazards by developing the code.

B. Objective two

To do an experimental analysis consisted of using the drone as a tool to inspect real time videos from a typical worksite and measure the accuracy of hazard detections.

Next step was employing the drone in real world scenario, for this instance a high-rise construction building in Colombo, Sri Lanka was selected to do an experiment by implementing the drone to assist the Safety Officers. In this assessment, three tests were performed to measure the accuracy of the drone's hazard identification capabilities. All three accuracy testes were scored above 90% of accuracy by proving that this automated inspection drone has a high accuracy of hazard detection and reliability to deal with real world situations while fulfilling the second objective of the study. All three tests were carried out under clear weather day. But to check drone's detections in the low light conditions, it is ideal to perform tests under low light weather conditions too.

C. Limitations and Further Directions of Research

This study was limited to automated inspection in above ground constructions, and only demonstrated with buildings which are high rise. For road constructions, the same waypoint method discussed in fourth chapter, can be utilized. But below ground constructions were not studied in this research. And this version of algorithm only capable to detect smoke, fire, and PPE, this can be developed to detect more safety related factors. Furthermore, other countries use drones for 3D underground infrastructure monitoring, underground mine explorations and 3D mapping, gas detection and underground atmosphere monitoring etc (Casos, 2018).
Moreover, there are some areas which can be addressed and developed.

- Develop the current algorithm to measure the construction personnel body temperature, this will be beneficial in pandemic situations such as Covid-19.

- Develop the current algorithm to measure sound level to keep the construction site at acceptable sound pollution level.

- Develop the current algorithm to detect unusual behaviours of the constructional personnel such as disputes, suicidal behaviours, drugs usage.

- Perform a study to implement safety inspection drone for underground constructions.

- Integrate algorithm with CCTV system for inside inspections in building projects.

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ABBREVIATIONS

CPU	Central processing unit
GDP	Gross domestic product
GNP	Gross national product
GPS	Global positioning system
GPU	Graphical processing unit
GTX	Giga texel shader eXtreme
PPE	Personal protective equipment
RAM	Random access memory
UAV	Unmanned aerial vehicle
YOLO	You Only Look Once

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AUTHOR BIOGRAPHIES

DMNCT Dissanayake is a graduated Quantity Surveyor from General Sir John Kotelawala Defence University (2017/2020). Now working as a proficient Quantity Surveyor in Sri Lanka. His research interests include

modern construction methods, building information modelling, construction safety and construction project management

NDI Vithana is a Lecturer (Probationary) attached to the Department of Quantity Surveying at General Sir John Kotelawala Defence University. She completed her first degree in Facilities Management at University of Moratuwa. Her research interests include construction project risk assessment and analysis, occupational health, safety and welfare and human comfort approach. 7.20.202