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Article Title: Analysis of Job Site in Construction using Artificial Neural Network

Analysis of Job Site in Construction using Artificial Neural Network

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ABSTRACT
This paper proposed a model for the analysis of construction that is based on personal protective equipment (PPE). In this context, this study explores the application of Artificial Neural Networks (ANNs) in conjunction with the You Only Look Once (YOLO) architecture for the analysis of job sites in construction projects. Traditional methods of job site analysis often rely on manual monitoring, which is labor-intensive, time-consuming, and prone to errors. The proposed approach harnesses the real-time object detection capabilities of YOLO within an ANN framework to automate the monitoring and analysis process. Through the deployment of YOLO, the system is swiftly identify and track various elements present on the job site, including workers, equipment, materials, and potential hazards. This enables construction managers to obtain timely insights into job site activities, facilitating informed decision-making and proactive risk management.The number of co-workers on a job site might make it difficult to physically do a safety check yet, it is the authority's primary responsibility to ensure that the workers on the working site are as protected as possible. Because of its high processing speed 45 frames per second YOLO architecture makes real time safety applications possible. The Accuracy Comparison of the YOLO-ANN is 93%, Specificity Comparison of YOLO-ANN is 93.5% and Sensitivity Comparison of YOLO-ANN is 92.5% respectively.
Keywords: PPE, ANN, YOLO, CNN and Job Site.

1 Introduction

It is crucial to protect workers' safety on building sites in order to avoid mishaps and injuries. PPE is essential for protecting employees from the many risks that exist at construction sites. PPE is still available, but incidents of employees neglecting to wear the appropriate safety gear intentionally or accidentally remain an issue [1]. This study uses the novel YOLO architecture to present a model for the analysis of building sites based on PPE detection in order to handle this difficulty. Because of the nature of the work, the construction sector has inherent dangers, such as exposure to heights, heavy machinery, electrical hazards, and more [2, 3]. The proper use of PPE in these kinds of settings greatly lowers the risk of accidents and lessens the degree of injuries. However, it is impossible to physically check adherence to PPE rules, especially on large-scale construction sites with several workers. The persistence of worker failure to wear PPE in the face of strict safety regulations underscores the necessity for automated safety monitoring systems [4, 5].

With a 45 frames per second processing speed, the YOLO architecture offers a practical solution for real-time object identification workloads. Applications like PPE detection in construction situations are a good fit for it because of its great speed and precision [6]. The goal of this paper is to create a real-time safety PPE identification system that recognize different kinds of safety gear that employees wear on building sites automatically by utilizing YOLO-based architectures [7, 8]. The need to give construction site workers the best possible protection and the realization of the shortcomings of manual safety inspections are the driving forces behind this study. Conventional safety monitoring techniques depend on manual observations or recurring inspections, which are prone to human error and miss real-time non-compliance incidents. The proposed computer vision-based method, on the other hand, provides a proactive way to identify PPE usage, allowing for prompt actions to guarantee worker safety [9, 10]. This paper's implementation entails using deep learning methods and computer vision techniques to train a YOLO model to identify and categorize various PPE, such as hard helmets, safety vests, goggles, gloves, and boots. A collection of annotated photos of workers in various PPE combinations and construction conditions is used to train the machine. The creation and deployment of models are done with Python software [11, 12].

This article is important because it improve worker safety in the construction sector by using automated PPE detection. Construction site managers and safety staff may swiftly detect non-compliance and eliminate dangers by implementing a real-time monitoring system built on the YOLO architecture [13]. Moreover, the proposed system's flexibility and scalability allow it to be used on building sites of different sizes and complexity [14, 15].

The primary objective of construction management is to oversee and regulate the advancement of construction projects. From beginning to end, the Construction Manager oversees, plans, organizes, and allocates funds for the project. They manage the project from start to finish on the owner's behalf. To create company plans, optimize profitability, maintain quality, encourage personal growth, boost efficiency, and lower risk.

2 Recent Works

Marjan Ilbeigi *et al* [2020] have focused on an Iranian research center building in order to provide a dependable strategy for optimizing energy use in buildings. The building's energy usage are simulated by developing, training, and testing a robust artificial neural network (ANN) utilizing a multi-layer perceptron model. The primary conclusions showed that system improvement might cut energy use by about 35%. Furthermore, the results of the sensitivity analysis showed that the number of occupants had the greatest influence on energy usage, with

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wall U-value which is related to wall insulation coming in second. In addition, the building's energy usage is precisely anticipated by the trained MLP model. The method's disadvantage is that it might provide difficulties due to the artificial neural network's intricate training process and the genetic algorithms computationally demanding optimization, which is demand a large amount of processing power.

Md. Ferdous *et al* [2022] have made a study on alarming number of deaths in the construction business even after a variety of remedies have been put in place. A great deal of study has been done to identify the underlying factors that lead to these deaths and to create practical risk-reduction plans. Research continuously point out a number of critical elements that contribute to construction-related deaths, such as electrocutions, falls from great heights, and being trapped in or between incidents. Construction sites are dynamic and complicated environments where personnel from different backgrounds share workspaces with many contractors and subcontractors, making safety management measures even more challenging. The fact that deaths in the construction sector remain despite these measures emphasizes the necessity of ongoing research and innovation to solve this pressing problem and provide safer working conditions for construction workers. One possible limitation of the YOLO architecture-based PPE detector is its inability to reliably identify PPE items in a variety of climatic conditions and intricate building site settings.

Wang, Z *et al* [2021] have proposed a unique method for training and evaluating eight deep learning detectors across six classes (e.g., helmets with four colors, person, and vest) using YOLO architectures. In addition, a carefully created high-quality dataset called CHV is presented. It consists of 1330 photos with backdrops that are actual construction sites, a variety of actions, perspectives, and distances, as well as different PPE classes. On similar datasets, the proposed detectors perform better than competing deep learning methods, having been trained on the CHV dataset. The drawback of Fast Personal Protective Equipment Detection for Real Construction Sites using Deep Learning Approaches is the potential loss of detection accuracy, particularly on blurry faces, despite overall greater performance.

Nipun D Nath *et al* [2020] have made a study on building sites, sensors and reality capture equipment are commonplace; the most common type of sensor is vision-based. On the other hand, human analysis of gathered picture and video data is difficult and resource-consuming. Using the large-scale dataset Pictor-v2, which comprises over 3,500 photos and over 11,500 examples of typical construction site items, this work explores YOLO-based CNN models for construction object detection. In addition, the YOLO- based CNN has the ability to accurately forecast the relative distance of objects that have been identified, which paves the way for technology-assisted systems that improve human interpretation of visual data in complicated contexts. The possible trade-off between detection accuracy and processing speed is a limitation of lighting or congested situations.

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Li-Wei Lung *et al* [2023] have proposed manual work is the most common form of labor on construction sites because of their broad areas and complexity. However, the use of physical lab or to manage the field and advance construction frequently results in ineffective job site oversight. A building activity picture identification system is proposed as a solution to this problem. It makes use of deep learning methods, namely CNNs, for automatic image extraction and recognition. The system enhances the overall efficiency and efficacy of construction management procedures by making construction-related objects easier to recognize through the use of CNNs for feature extraction and training. The limitations due to the potentially complicated and resource-intensive nature of training and inferring models, which is affect scalability and real-time deployment.

3 Proposed Work Explanation

The dataset used as training input for YOLO model fine-tuning is frequently a refined subset of the original data used in the first training stage. This improved dataset have more annotated examples that are particular to classes or situations that the model had trouble with at first. Furthermore, the model's resilience are increased by applying augmentation techniques like data synthesis or perturbation to increase the dataset's size and add variability. With more targeted and varied training examples, the model's performance is further optimized, improving its capacity to recognize items of relevance in certain situations. The pretrained YOLO model is improved to better fit the intended application by means of this fine-tuning procedure, which also helps the model adapt to new activities or settings.

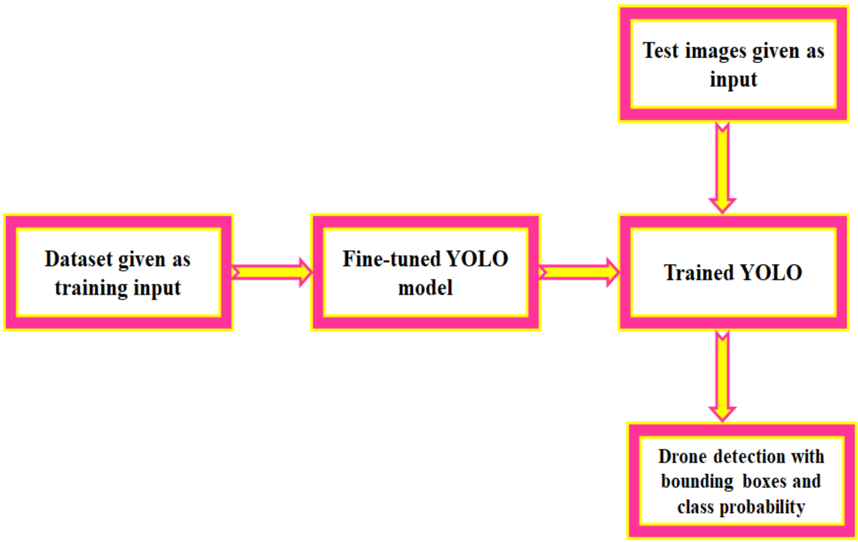

Figure 1: *Proposed block diagram*

The YOLO model receives test images as input and uses its parameters and learning characteristics to recognize objects. Bounding boxes around objects are created by the YOLO

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model as it analyses each test image. It then gives each bounding box a class probability, which represents the chance that the item belongs to a specific class. YOLO's model locates and recognizes drones in test photos by surrounding them with bounding boxes and assigning class probabilities confidently the drones are classified. This procedure makes it possible to identify drones quickly and precisely in a variety of environmental settings, which offers insightful information for uses including security, surveillance, and airspace monitoring. Decision-makers respond quickly to possible drone-related to the bounding boxes and class probabilities generated by the YOLO model.

3.1 YOLO Architecture

In order to concurrently forecast bounding boxes and class probabilities, YOLO proposed using an end-to-end neural network. It is not equivalent to past object identification algorithms that detected objects using classifiers. A deep learning model architecture called YOLO is used for object detection in images and videos. Good real-time object identification accuracy is achieved with this single neural network configuration. With a series of convolutional layers, the YOLO architecture first extracts features from the input image in order to forecast bounding boxes and class probabilities for each object in the image. A feature pyramid network is used to recognize items of different sizes, and a prediction module is used to improve item detection results. YOLOs reputation for accuracy and speed makes it a popular choice for a wide range of applications, including as autonomous cars, robotics, and surveillance systems. The YOLO approach uses a simple deep convolutional neural network as its input after obtaining an image to recognize items in the image.

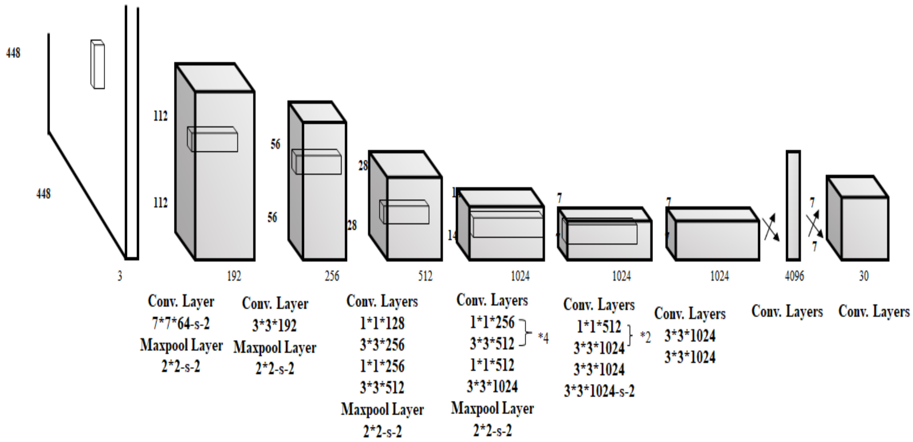

Figure 2: *YOLO Architecture*

By adding a temporary average pooling and fully connected layer, Image Net is used to pre-train the model's initial 20 convolution layers. Then, as it has been shown in earlier studies that including convolution and linked layers into a pre-trained network enhances performance, this

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pre-trained model is adjusted to conduct detection. The final fully connected layer of YOLO predicts bounding box coordinates in addition to class probabilities. An input image is divided into an S × S grid by YOLO. A grid cell is responsible for recognizing an item whose center lies inside it. For every grid cell, the anticipated B bounding boxes and confidence ratings for those boxes are given. These confidence ratings reflect the correctness of the projected box as well as the model's degree of confidence that the box contains an item. YOLO produces several bounding box predictions for every grid cell. YOLO assigns a predictor the title of "responsible" predictor for an item based on whose forecast has the highest current IOU with the ground truth. The bounding box predictors consequently grow more specific. Through improved prediction of specific item sizes, aspect ratios, or classifications, each predictor contributes to an overall increase in recall score.

3.2 ANN in Construction

This article summarizes the applications of artificial neural networks (ANN) in the construction industry, which include application forecasting, soil mechanics, energy usage and efficiency, structural evaluation, building supplies, smart city and BIM systems, structural design and optimizing, and building construction.

Energy Efficiency and Energy Consumption

Building energy consumption and efficiency activities make extensive use of neural network technology. ANNs are first utilized for energy consumption analysis, electricity consumption forecasting, and load forecasting for heating and cooling systems. The study of materials' thermal and heat insulation qualities as well as the characteristics of building walls is another area in which neural networks are employed.

Construction Materials

Among the many applications of neural networks in the construction industry for predicting characteristics of building materials are the following: determining the composition of cement-stabilized rammed earth; analyzing adiabatic increases in temperatures that represents the degree of concrete hydration; anticipating the compressive strength of cement-based materials subjected to sulphate attack; and anticipating the diffusion of sodium chloride in cement. These applications include, but are not limited to, calculating the amount of water in volume at different times and points during water consumption inside porous building materials.

Safety in Construction

Neural networks are used in research on the fire resistance of building materials as well as other aspects of construction safety, including megaproject safety assessments, evacuation plans, building structure safety forecasts, preventing different types of injuries at construction sites, and more.

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4 Results and Discussion

This paper is implemented using python software. In Result section Train Valid Split Distribution, Worker's behavior on site and Agents' Behaviors are discussed as follows

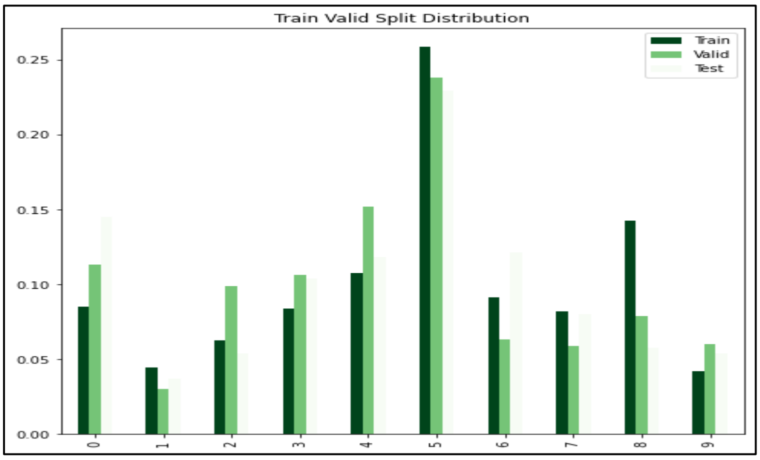

Figure 3: *Train Valid Split Distribution*

Figure 3 shows the Train Valid Split Distribution. A train-valid split distribution is created by splitting a dataset into two subsets: a validation subset and a training subset for a machine learning model. In order to avoid bias and over fitting and to facilitate reliable evaluation and generalization of model performance, the distribution makes sure that representative samples from each class are included in both subsets. In order to preserve dataset integrity and model performance, this split is usually stratified while maintaining class proportions.

Figure 4: *Worker's behavior on site.*

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The actions of the worker during labor are depicted in Figure 4. Numerous instances of focused attention areas in the head and upper body are displayed in this study. The data indicates which personnel on the job site have worn and have not worn safety gear.

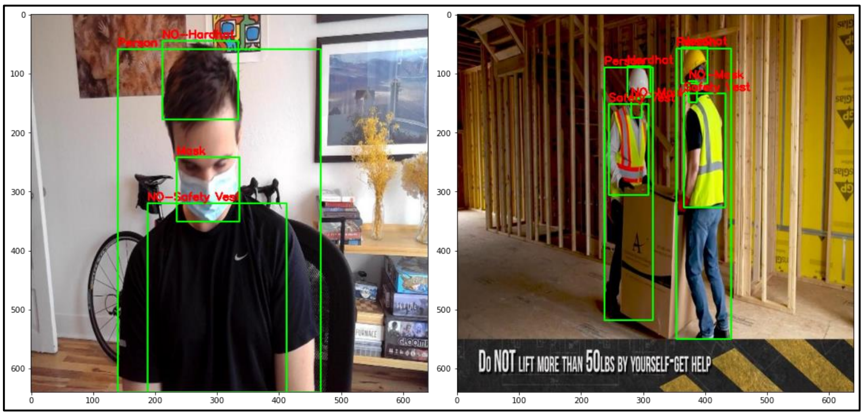

Figure 5: *Agents' Behaviors*

Figure 5 shows the agents behave. The agent wearing a mask but not a hardhat in the first photograph, which shows a vest item that is not recognized. Workers are seen in the second shot with a yellow vest and hardhat, but not a mask.

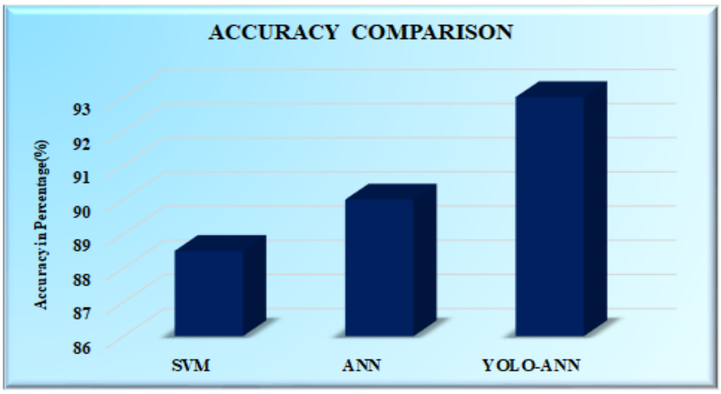

Figure 6: *Accuracy Comparison*

Figure 6 presents the Accuracy Comparison of the Classification values. The results for the SVM, ANN, and YOLO-ANN Classier are, respectively, 88.5%, 90%, and 93%.

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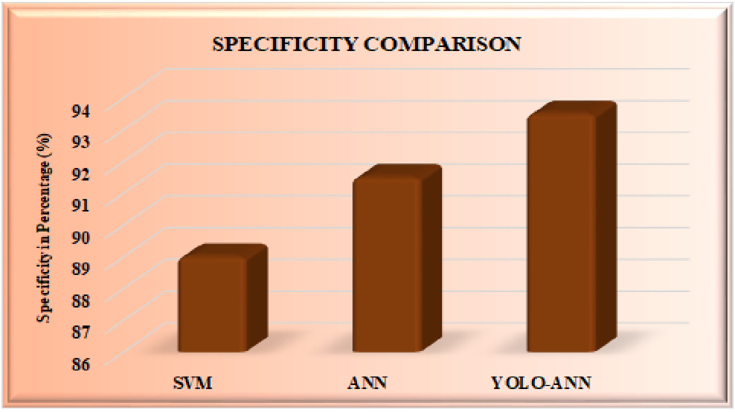

Figure 7: *Specificity Comparison*

The Specificity Comparison of the Classification values is presented in Figure 7, where the values for the SVM, ANN, and YOLO-ANN Classier are, respectively, 89%, 91.5%, and 93.5%.

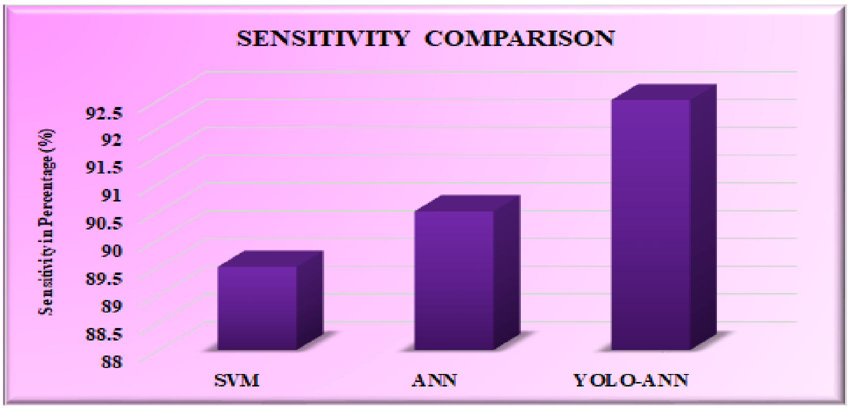

Figure 8: *Sensitivity Comparison*

Figure 8 presents the Sensitivity Comparison of the Classification values, which are, respectively, 89.5%, 90.5%, and 92.5% for the SVM, ANN, and YOLO-ANN Classier.

5 Conclusion

This research offers a proactive strategy to solve safety risks on construction sites. The research circumvents the drawbacks of human monitoring techniques by combining ANNs with the YOLO architecture to automate job site inspection. ANN is used to leverage YOLO's real-time object detection capabilities, it becomes possible to quickly identify and track a variety of critical components for safety management, such as personnel, equipment, materials, and potential dangers. By facilitating the quick and precise identification of various PPE kinds, the deployment of an automated PPE identification system based on CV reinforces safety precautions. All things considered, the automation of PPE identification using CV and the integration of ANN and YOLO architecture in building site analysis mark a major advancement in raising safety standards in the sector. Through the provision of prompt insights into job site activities and the guarantee of optimal worker protection, this strategy exhibits potential for risk mitigation and accident prevention, therefore cultivating safer and more efficient work environments. The Accuracy Comparison of the YOLO-ANN is 93%, Specificity Comparison of YOLO-ANN is 93.5% and Sensitivity Comparison of YOLO-ANN is 92.5% respectively.

References

1. Yiqun Xie; Jiannan Cai; Rahul Bhojwani; Shashi Shekhar; Joseph Knight, Year: 2020, "A locally-constrained YOLO framework for detecting small and densely-distributed building footprints", International Journal of Geographical Information Science, Vol: 34, no: 4, pp. 777 – 801.

2. Shidan Sun; Shijia Zhao; Jiachun Zheng, Year: 2021, "Intelligent Site Detection Based on Improved YOLO Algorithm", In 2021 International Conference on Big Data Engineering and Education (BDEE), pp. 165 – 169, IEEE.

3. Md Ferdous; Sk Md Masudul Ahsan, Year: 2022, "PPE detector: a YOLO-based architecture to detect personal protective equipment (PPE) for construction sites", PeerJ Computer Science, Vol: 8, pp. e999.

4. Fangli Mou; Hao Ren; Bin Wang; Dan Wu, Year: 2022, "Pose estimation and robotic insertion tasks based on YOLO and layout features", Engineering Applications of Artificial Intelligence, Vol: 114, pp. 105164.

5. Tausif Diwan; G. Anirudh; Jitendra V. Tembhurne, Year: 2023, "Object detection using YOLO: Challenges, architectural successors, datasets and applications", multimedia Tools and Applications, Vol: 82, no: 6, pp. 9243 – 9275.

6. Piyush Singh; V. M. S. R. Murthy; Dheeraj Kumar; Simit Raval, Year: 2024, "Enhancing dragline operations supervision through computer vision: real time height measurement of dragline spoil piles dump using YOLO", Geomatics, Natural Hazards and Risk, Vol: 15, no: 1, pp. 2322492.

7. Hongmin Huang; Zihao Liu; Taosheng Chen; Xianghong Hu; Qiming Zhang; Xiaoming Xiong, Year: 2020, "Design space exploration for yolo neural network accelerator", Electronics, Vol: 9, no: 11, pp. 1921.

8. Zijian Wang; Yimin Wu; Lichao Yang; Arjun Thirunavukarasu; Colin Evison; Yifan Zhao, Year: 2021, "Fast personal protective equipment detection for real construction sites using deep learning approaches", Sensors, Vol: 21, no: 10, pp. 3478.

International Journal of Advanced Trends in Engineering and Management (IJATEM)
Vol. 3(01), January 2024, pp. 28-38

9. Shilei Lyu; Zhen Li, Year: 2023, "YOLO-SCL: a lightweight detection model for citrus psyllid based on spatial channel interaction", Frontiers in Plant Science, Vol: 14, pp. 1276833.

10. Seong-Eun Ryu; Kyung-Yong Chung, Year: 2021, "Detection model of occluded object based on YOLO using hard-example mining and augmentation policy optimization", Applied Sciences, Vol: 11, no: 15, pp. 7093.

11. U. Sirisha; S. Phani Praveen; Parvathaneni Naga Srinivasu; Paolo Barsocchi; Akash Kumar Bhoi, Year: 2023, "Statistical analysis of design aspects of various YOLO-based deep learning models for object detection", International Journal of Computational Intelligence Systems, Vol: 16, no: 1, pp. 126.

12. Mingshuo Liu; Miao Yin; Kevin Han; Ronald F. DeMara; Bo Yuan; Yu Bai, Year: 2023, "Algorithm and hardware co-design co-optimization framework for LSTM accelerator using quantized fully decomposed tensor train", Internet of Things, Vol: 22, pp. 100680.

13. Muhammad Hussain, Year: 2023, "YOLO-v5 Variant Selection Algorithm Coupled with Representative Augmentations for Modelling Production-Based Variance in Automated Lightweight Pallet Racking Inspection", Big Data and Cognitive Computing, Vol: 7, no: 2, pp. 120.

14. Muhammad Hussain, Year: 2023, "YOLO-v1 to YOLO-v8, the rise of YOLO and its complementary nature toward digital manufacturing and industrial defect detection", Machines, Vol: 11, no: 7, pp. 677.

15. Dong-Jin Shin; Jeong-Joon Kim, Year: 2022, "A deep learning framework performance evaluation to use yolo in nvidia jetson platform", Applied Sciences, Vol: 12, no: 8, pp. 3734.