Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 1, No.3, January : 2025

CONSTRUCTION PROJECT MONITORING MODEL BASED ON FASTER R-CNN ALGORITHM

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Abstract
In civil engineering, construction projects are very complicated and their success is dependent on various factors. In construction projects, there are numerous challenges such as delay, safety concerns and cost overruns. These issues are more complicated because of several issues like inefficient resource allocation, human error and ineffective planning. In order to minimise these challenges, artificial intelligence and machine learning algorithms are deployed in the construction project. Further, the deployment of these algorithms enhances labour efficiency, optimises resource allocation and increases the profits of the project. Artificial intelligence and machine learning are computer science fields that are currently deployed in different applications to design smart machines. These machines process the input data. Further, analyse and find out the various patterns in the input data and give appropriate data in the output. In civil engineering, artificial intelligence and machine learning are deployed for different purposes, such as concrete strength prediction, cost estimation, site monitoring, etc. In this research, the site monitoring model is designed for safety purposes because people are working on the site because, in construction projects, the maximum number of accidents happen due to safety issues. In the site monitoring model, helmets and harnesses are checked by detecting objects. In the site monitoring model, faster R-CNN is used to detect the objects. The simulation evaluation of both models is done in the MATLAB software. The simulation results of the site monitoring model are shown using the subjective and objective analysis parameters. The subjective analysis shows that the proposed model efficiently detects the objectives, whereas the objective analysis shows that the proposed site monitoring model achieves better accuracy, precision, recall and F1-score than the existing model.
Keywords: Classification, CNN, Construction, Helmet, Site Monitoring.

1. Introduction

According to surveys of workers throughout the world, the construction business has one of the highest injury rates (Zou et al. 2015). Manual supervision is now the most used method of construction safety monitoring. Continuous monitoring and manually determining all occurrences that have potential health and safety concerns is a significant challenge for safety inspectors. Construction sites need to be monitored in real time so that any potential hazards may be identified and eliminated before they cause harm. Therefore, in order to safeguard employees from injuries and fatal accidents, it is necessary to continuously monitor both the hazardous condition of surroundings 1and the dangerous behaviour of workers. When it comes to safety inspections, monitoring systems may incorporate a wide range of components and procedures, adapt to various settings and tasks and meet all relevant requirements. In the present scenario, machine learning algorithms are gained popularity for design automatic site monitoring model. In order to accomplish this goal, the machine learning algorithm, process the input dataset, extract the appropriate features and based on these feature, classify it.
The main contribution of this paper is to design a site monitoring model in which we have used the faster RCNN algorithm for detect the peoples on the site for safety purposes. In the safety, helmet and harness monitoring is done. The simulation evaluation is performed on the standard dataset which is available on the Github website. The evaluation is performed based on different factors like precision, accuracy, recall and F-score. The findings confirms that the proposed model provides superior performance over the existing models such as Resenet50, WRN, ALM, ViT, YOLOv5.

Industrial Engineering Journal
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The rest of the paper is defined as follows. Section 2 shows the related work is done in the site monitoring models. Section 3 explains the methodology in which database, R-CNN and performance metrics are explained. In Section 4 defines the proposed construction site monitoring model. Further, Section 5 shows the results and discussion part. Finally, conclusion and future scope is defined in Section 6.

2. Related Work

Li et al. (2023) suggested a convolutional neural network-based approach for determining whether or not employees are wearing head protection equipment. The SSD-MobileNet method was used by the model for this purpose. Then, to train and evaluate the model, a dataset of 3261 photos of helmets of different types is constructed and split into three sections. The model is trained using the TensorFlow framework. The helmet detection model is completed once training and testing have stabilized the mean average precision (mAP). The outcomes of the experiments show that the approach may be used to identify hard hats worn by construction workers. The trained model's 95% accuracy and 77% recall show that the suggested strategy is effective in detecting safety helmets. The provided technique provides an alternate approach to identifying hardhats, which may be used to enhance site-wide safety management.

Wu et al. (2022) established the significance of image processing on the basis of remote vision for the monitoring of head protection equipment on building sites. In this respect, autonomous safety helmets as well as harness monitoring systems based on computer vision have gained considerable interest for potential applications. Many issues with current computer-vision-based systems, such as a lack of safety helmets and harness monitoring datasets and unreliable detection algorithms, remain unresolved. In this research, researchers built a safety helmet and harness monitoring system using attribute-knowledge modeling, which allows us to elegantly translate safety status recognition into images semantic attribute identification, therefore addressing the aforementioned concerns. The goal of this study is to enhance attribute identification performance by introducing a unique transformer-based end-to-end network equipped with a self-attention mechanism. In order to do this, a security recognition system makes advantage of associations between visual characteristics and semantic properties. They built it by bringing together tracking, attribute identification and detection. The experimental findings for detecting safety helmets and harnesses show that the proposed transformer-based attribute recognition method clearly surpasses the state-of-the-art techniques in terms of accuracy and resilience. Furthermore, the provided approach is resistant to obstacles including position fluctuation, occlusion and a busy backdrop.

Hayat and Morgado-Dias (2022) Using real-time computer vision technology, this study introduces an autonomous safety helmet identification system based on the principle of "You Only Look Once" (YOLO) for use on a construction site. For real-time safety helmet identification, YOLO-based architectures are a viable option because to their high processing speed (45 frames per second). In this investigation, a benchmark dataset consisting of 5,000 images of hard helmets was employed and split into three equal parts for training (60 percent), testing (20 percent), and validation (20 percent). With a mean average accuracy (mAP) of 92.44%, the YOLOv5x architecture performed very well at recognizing safety helmets across a range of testing settings.

K. Han and X. Zeng (2021) In this research, they presented a deep learning-based approach to rapidly and accurately identify whether a safety helmet is being worn. In their approach, they started with YOLO v5 as a benchmark, then they augment it with a fourth detection scale to forecast more bounding boxes for tiny objects and they implement the attention mechanism in the network's backbone to build more informative features for subsequent concatenation operations. Inadequate data may lead to inaccurate predictions, but focused data augmentation and transfer learning can help fix that. The report discusses the enhancements brought about by each change. The final result of our model is a 3.0 ms detection time for a 640x640 image, with a mean average accuracy of 92.2% (an improvement of 6.3% over the previous technique). These findings show how practical and dependable our model is. The trained version of their model is just 16.3 m in size, making it very portable. After an acceptable model is obtained, they created a GUI to simplify their algorithm's operation.

Huang et al. (2021) presented a deep learning-based approach to the creation of a real-time detection system for helmet use. The general helmet colour pixels are determined by first locating the human head area using the enhanced YOLO v3 algorithm and then performing pixel feature statistics for the anchor box region. The confidence of the helmet standard wearing judgement is computed and the judgement is compared with the standard threshold to generate the final judgement result. This confidence is then compared to the standard threshold. The following are the results of this paper: First, they upgraded the original YOLO v3 in many significant ways. Then, they combined deep learning with traditional image processing methods and put it to use in a target identification challenge for protective headgear. With this, they can detect with more precision not only whether a safety helmet is there in the image and where it is located, but also if it is being worn on the head. The above efforts improved the effectiveness of the aforementioned algorithm for detecting safety helmets. In challenging construction site conditions, it enables real-time detection of whether or not employees are wearing helmets properly.

Wesam Salah Alaloul and Abdul Hannan Qureshi (2021) reviewed the material classification methods are proposed using artificial intelligence algorithms. In the literature, the most preferred algorithms are random forest, decision tree, k-nearest neighbour, artificial neural networks and support vector machine. Out of these algorithms, SVM and ANN is the most preferred method. In this approach, material images are collected from construction sites using drones or cameras. Further, pre-processing of the images is done using segmentation and feature extraction (color, contrast, corner, texture and compactness) algorithm. After that, based on the selected features, a machine learning algorithm is trained. On the other side, in the testing phase, classification of the material is done. Also, from their study, they have defined the 70:30 ratio to validate any machine learning algorithm performance. This means that 70% of data is trained and 30% of data is tested.

Farrukh Arif and Waleed Ahmed Khan (2021) designed a videography approach for construction progress monitoring by integrating a low-cost camera, MATLAB platform and building information modeling (BIM). Their approach is superior as compared to drone and laser scanning-based monitoring approaches due to complexity, high cos and human resource requirement. The main motive of their research was to monitor the vertical (column) and horizontal (beam) members and block masonry. In their approach, initially, video is read and processing of activity identification is determined by color detection. After that, image processing interfaced is used for comparing it as a planned model. The simulation evaluation is done by taking various case studies and performance evaluation is done by determining the RMSE and correlation coefficient value. The result shows that their approach achieves 0.287 and 0.172 RMSE values for the horizontal and vertical members. On the other side, 0.995 and 0.999 correlation coefficient values for the horizontal and vertical members.

Wang et al. (2021) Construction progress monitoring relies heavily on the ability to locate and identify precast components. In their approach, they have used vision-based methods to monitor construction progress over laser scanning, tag-based and manual methods. In their, initially, masked R-CNN and DeepSort algorithms are deployed for object detection, segmentation and tracking multiple objectives.

Martinez et al. (2021) developed an approach for detecting and tracking the construction operation. In the current scenario, due to the COVID-19 pandemic, the offsite construction approach is gained popularity. In this approach, the construction operations are performed in the manufacturing facilities. After that, pre-designed blocks are transferred to the construction sites. Thus, they have designed an approach using a deep learning algorithm and finite state machine to monitor the construction site. The data is collected from the installed camera on the sites. The dataset is collected from the floor panel manufacturing station. They have collected a total of 1069 images with a resolution of 640×480. The performance analysis is done based on the precision, recall and F-score. They have achieved superior results. Besides that, their approach can monitor the entire day and gives duration, resources and task efficiency parameters.

Wang et al. (2021), designed an approach to monitor the helmet and identity of the labor on the construction site by the You Only Look Once (YOLO) algorithm for safety purposes. The YOLO algorithm has numerous advantages such as it directly generating the class probability and position coordinate values. Due to the one-stage algorithm, the detection speed is very high and real-time monitoring is possible. In their approach, they have collected a large number of images in which sosme peoples wear a helmet and some do not. The performance analysis is done using various parameters such as robustness and recall. Worker and helmet recognition accuracy and detection speed are all demonstrated by the method in experiments. This method also resolves the issue of insufficient real-name channel supervision.

Based on the literature survey, following research gap is found.

In the construction site monitoring, the vision-based method gained popularity over laser-based and tag-based methods. In this method, low-quality cameras are used to capture the site images. The quality of the images is low. Thus, image pre-processing is required such as filtering, fusion, and enhancement of the images to select appropriate features from the images. Further, support vector machine, artificial neural network, deep learning, CNN and Yolo algorithms are deployed for classification/prediction purposes. However, existing systems face several unresolved issues, including a lack of sufficient datasets for training safety helmet and harness detection algorithms, as well as relatively low accuracy in detection.

3. Methodology

3.1 Database: In this research, standard database images of the construction project site is taken into consideration. This database is available on the Github website (https://github.com/njvisionpower/SafetyHelmet-Wearing-Dataset, accessed on 1 January 2023).

3.2 Faster R-CNN: The Faster R-CNN detector is an important part of the design and is in charge of finding objects in the region suggestions made by the Region Proposal Network. Let us examine the internal functioning of the Fast R-CNN detector in the Faster R-CNN (Faster R-CNN | ML. (2020, February 27)).

- **Region of Interest (RoI) Pooling:** The first stage involves applying ROI pooling to the area suggestions provided by the RPN. The process of Region of Interest pooling converts the variable-sized region proposals of the RPN into feature maps of a fixed size, which are subsequently utilized by the network's layers. In the process of RoI pooling, each area proposal is first divided into a grid of cells of equal size, and then maximum pooling is applied inside each cell. Through this approach, each area suggestion is converted into a fixed-size feature map that the network may analyse further.
- **Feature Extraction:** To extract useful features that capture object-specific information, the CNN backbone which is also used in the RPN for feature extraction-is fed the RoI-pooled feature maps. It uses region suggestions to extract hierarchical characteristics. The network can comprehend the content of the suggested areas because to these properties, which preserve spatial information while abstracting away small details.
- **Fully Connected Layers:** After that, the feature-extracted and ROI-pooled areas go through a number of completely connected layers. These layers are in charge of bounding box regression and object categorization.
- **Object Classification:** An object's class may be predicted by the network's class probabilities, which are shown for every region proposal. To conduct the classification, the shared weights of the CNN backbone are combined with the attributes derived from the region proposal.

- **Bounding Box Regression:** Every area suggestion has bounding box modifications predicted by the network in addition to class probability. These modifications improve the region proposal's bounding box's size and location, bringing it closer to the real object borders and increasing its accuracy.

To begin, there is a softmax layer with N+1 output factors, where N represents the number of class names and backgrounds. This layer guesses what the objects in the region suggestion will be. The second layer consists of N*4 output parameters and is a bounding box regression layer. This layer predicts the bounding box position of the item in the image.

- **Multi-task Loss Function:** The Fast R-CNN detector employs a multi-task loss function that includes both classification and regression losses. When calculating the classification loss, the disparity between the predicted and real class probabilities is taken into account. The regression loss calculates the difference between predicted and actual bounding box changes.
- **Post-Processing:** A post-processing step is used to improve the final detection results after the network has predicted class probability and bounding box modifications. Here, the most reliable and non-overlapping detections are kept while redundant detections are minimized by the use of non-maximum suppression (NMS).

3.3 Performance Metrics

To measure these performance metrics, confusion metrics is required. A detailed description of confusion metrics is given below (Gamil, Y. 2023).

- A confusion matrix summarizes the predicted and actual results for each application that involves classification problems. The comparison report is important for assessing the model's performance after data training.

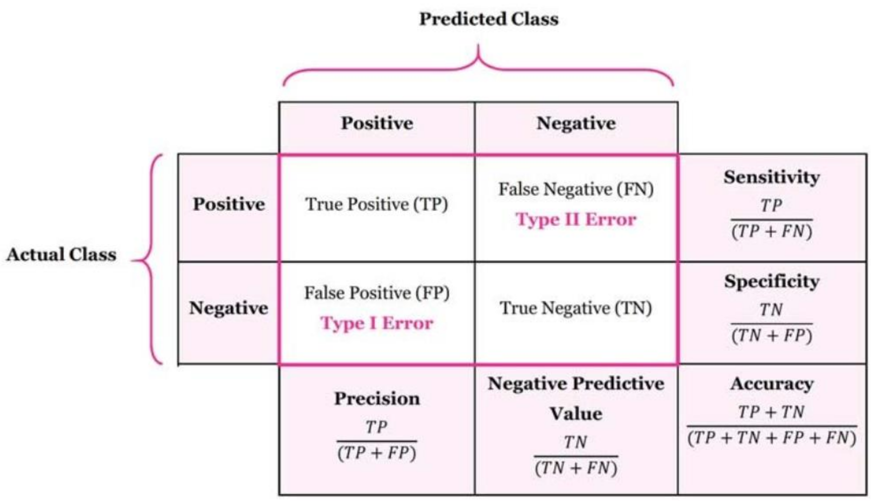

Figure 3.6: Confusion Matrix

A positive value in a binary result is represented by an Actual Class 1 value of 1, while a negative value in a binary result is represented by an Actual Class 2 value of 0.

Multiple parts are involved in creating a confusion matrix. Each part is detailed below.

- Positive(P): A favorable result is predicted. (For example, the image shows a cat.)
- Negative(N): An unfavorable result is predicted (For example: the image doesn’t contains a cat)
- True Positive(TP): It shows that the real and predicted values are both 1 (True).
- True Negative(TN): It shows that the real and predicted values are both 0.
- False Negative(FN): Here, FN indicates that the real value is 1, but the predicted value is 0 (Neutral). In this case, the two figures are contradictory.
- False Positive(FP): FP stands for "positive projection" when the predicted number is one and the real value is zero. The same problem is present here: the values are inconsistent.

Some of the common performance measures used to evaluate IDS are as follows:

- **True Positive Rate (TPR)**: It is calculated by taking the total number of attacks and dividing it by the number of correctly predicted attacks. If all intrusions are found, the TPR is 1, which is quite exceptional for an IDS. TPR is also known as the detection rate (DR) or sensitivity. The TPR may be expressed mathematically as

$$TPR = TP/ (TP+ FN) \quad (3.4)$$

- **False Positive Rate (FPR)**: Calculated by dividing the total number of normal events by the number of normal events that were mistakenly marked as attacks.

$$FPR = FP/(FP + TN) \quad (3.5)$$

- **False Negative Rate (FNR)**: A false negative happens when a detector misclassifies an anomaly as falling inside the predicted range. An example of a numerical representation of the FNR is:

$$FNR = FN /(FN + TP) \quad (3.6)$$

- **Classification rate (CR) or Accuracy**: The CR checks how well the IDS can find both normal and odd traffic patterns. The definition of this is the percentage of events for which the forecasts were correct in relation to all instances:

$$Accuracy =(TP + TN)/(TP+ TN + FP + FN) \quad (3.7)$$

4. Proposed Construction Project Monitoring Model

Remote-vision-based image processing plays a crucial role in ensuring the safety of workers at construction sites, specifically in monitoring the usage of safety helmets and harnesses. Computer-vision-based automatic monitoring systems for safety helmets and harnesses have garnered significant attention for their practical applications. However, existing systems face several unresolved issues, including a lack of sufficient datasets for training safety helmet and harness detection algorithms, as well as relatively low accuracy in detection. To tackle these challenges, we propose the implementation of a safety helmet and harness monitoring system based on attribute-knowledge modeling. In contrast to the widely used YOLOv5, our proposed approach utilizes Faster R-CNN Deep Learning for safety helmet detection. This shift is driven by the limitations of YOLOv5, which may struggle with accurately detecting small objects like safety helmets in complex scenes. In comparison, Faster R-CNN Deep Learning has demonstrated superior performance in tasks requiring object identification, especially when there are tiny and closely spaced items involved. By employing Faster R-CNN, we anticipate improved accuracy and robustness in safety helmet detection, leading to more effective monitoring of construction site safety. The proposed methodology for the attribute-knowledge-modeling-based safety helmet and harness monitoring system using Faster R-CNN Deep Learning involves several key steps:

- **Data Collection:** The first step is to gather a comprehensive dataset of images or video footage from construction sites. This dataset should include a diverse range of scenarios, lighting conditions and variations in safety helmet and harness appearances.
- **Data Annotation:** The collected dataset needs to be annotated to provide ground truth labels for training the Faster R-CNN model. Skilled annotators will mark the regions of interest (ROIs) in the images or frames of the video, specifying the location and class label (helmet, harness or background) for each ROI.
- **Pre-processing:** The annotated dataset undergoes pre-processing to normalize the images and reduce noise or artefacts. This step may involve resizing, cropping or applying image enhancement techniques to improve the quality and consistency of the data.
- **Model Training:** The Faster R-CNN model is trained using the annotated dataset. The two primary parts of the network design are a region-based convolutional neural network (CNN) and a region proposal network (RPN). The RPN produces region proposals by predicting potential

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 1, No.3, January : 2025

bounding box coordinates and objectness scores. The CNN then performs object classification and refinement of the proposed bounding boxes.

- **Model Evaluation:** The performance of the trained Faster R-CNN model is assessed using various evaluation metrics such as recall, precision and F1 score. The model is tested on a separate validation dataset to gauge its ability to accurately detect safety helmets and harnesses while minimizing false positives and false negatives.
- **Comparison with YOLOv5**: To validate the superiority of Faster R-CNN over YOLOv5, a comparative analysis is conducted. Both models are evaluated on the same test dataset, and their performance metrics are compared. This step aims to highlight the advantages of Faster R-CNN, such as improved accuracy, better handling of small objects and increased robustness in complex scenes.

5. Results and Discussion

This section shows the simulation results of the proposed construction site monitoring model on the standard dataset and comparative analysis with the existing models. The proposed model is simulated in MATLAB 2018a software. Table 1 shows the simulation setup configuration is initialized for the site monitoring model.

Table 1 Simulation Setup Configuration of the Site Monitoring Model

Parameter	**Values**
Image Format	.jpg
Object Annotation	'Rectangle'
Input Layer	[32 32 3]
Filter Size	[3 3]
Number of Filters	32
Fully Connected Layer	64

Table 2 shows the subjective analysis of the site monitoring model in which object is determined in the image.

Table 2 Subjective Analysis of the Site Monitoring Model

	


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ISSN: 0970-2555
Volume : 54, Issue 1, No.3, January : 2025

Table 3 shows the objective analysis of the site monitoring model in which various performance metrics are evaluated for it. The result shows that the proposed model achieves high accuracy (99.267), recall (99.267), precision (100) and F1-Score (99.632), as shown in Figure 1.

Table 3 Objective Analysis of the Site Monitoring Model

	Accuracy	Recall	Precision	F1-Score
Proposed Site Monitoring Model	99.267	99.267	100	99.632

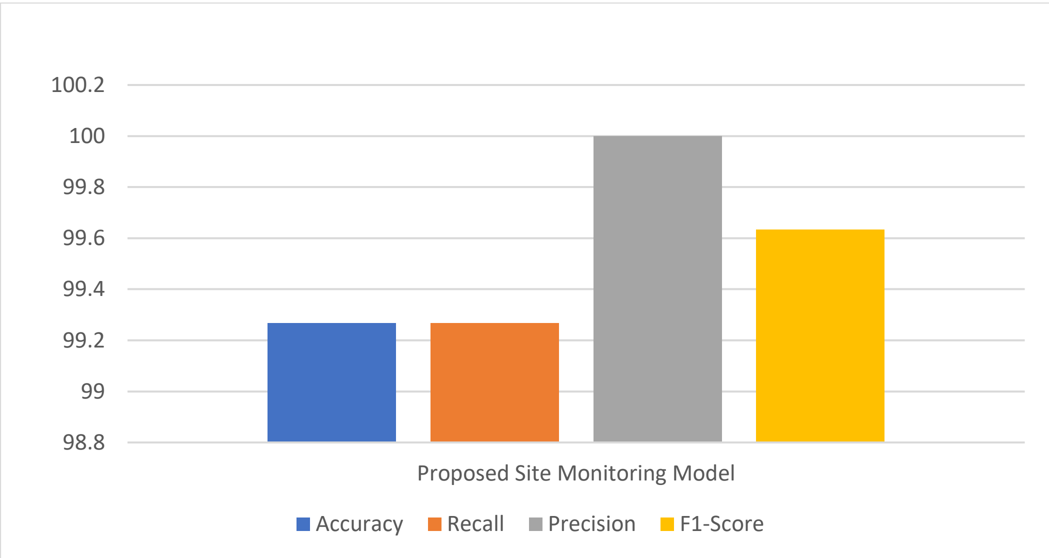

Figure 1 Performance Analysis of the Proposed Site Monitoring Model

Table 4 shows the comparative analysis of the proposed model with the existing site monitoring models (RESENET50, WRN, ALM, ViT and YOLOv5) [37]. The result shows that the proposed site

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ISSN: 0970-2555
Volume : 54, Issue 1, No.3, January : 2025

monitoring model gives the highest accuracy, recall, precision and F1-score over the existing models, as shown in Figure 2-5.

Table 4 Comparative Analysis

	Accuracy	**Recall**	**Precision**	**F1-Score**
Resenet50	73.78	75.78	74.38	75.08
WRN	73.89	75.62	74.88	75.25
ALM	82.11	83.1	82.77	82.94
ViT	82.91	83.93	83.3	83.61
YOLOv5	86.76	88.38	87.47	87.34
Proposed Site Monitoring Model	**99.267**	**99.267**	**100**	**99.632**

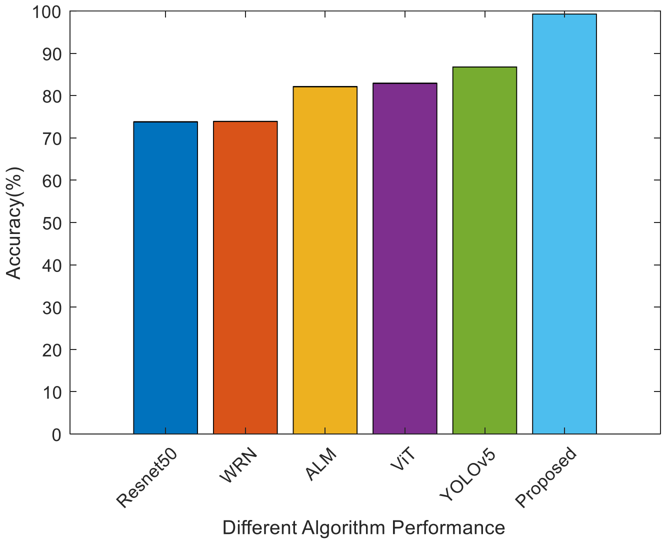

Figure 2 Comparative Analysis based on Accuracy Parameter

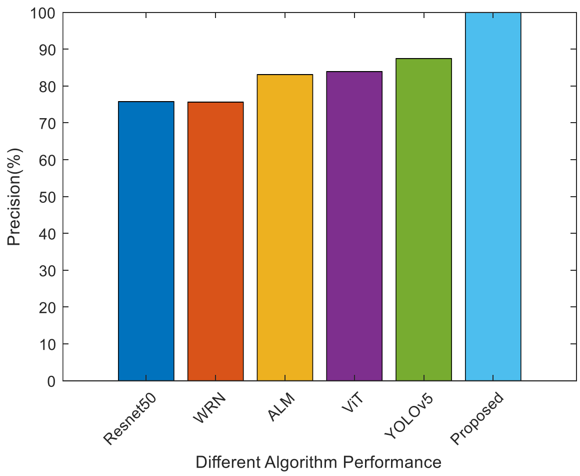

Figure 3 Comparative Analysis based on Precision Parameter

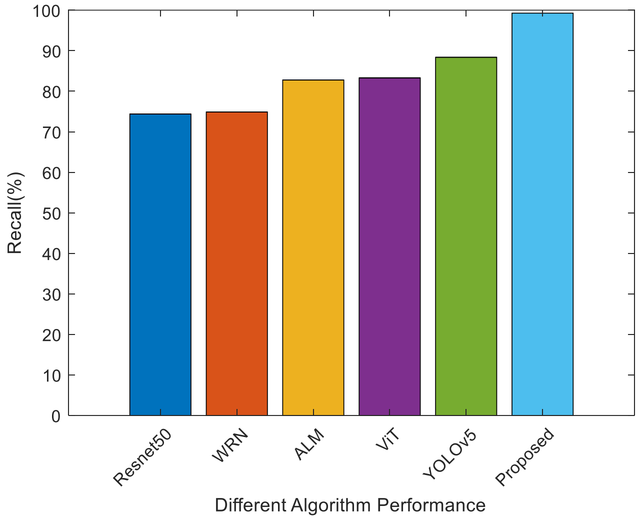

Figure 4 Comparative Analysis based on Recall Parameter

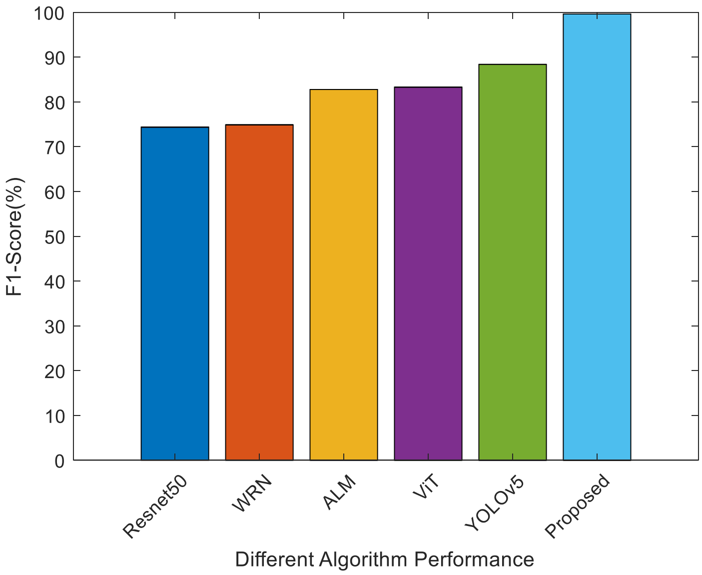

Figure 5 Comparative Analysis based on F1-Score Parameter

6. Conclusion and Future Scope

In the site monitoring model, we have used the faster RCNN algorithm for detect the peoples on the site for safety purposes. In the safety, helmet and harness monitoring is done. The simulation evaluation is performed on the standard dataset. The evaluation is performed based on different parameters such as accuracy, precision, recall, and F-score. The result shows that the proposed model provides superior performance over the existing models such as Resenet50, WRN, ALM, ViT, YOLOv5. On the other hand, site monitoring is efficiently measuring the helmet and harness on the site. To accomplish this goal, faster region convolutional neural network is deployed. However, this model has high time complexity because large amount of database is trained and tested using the site images. Next, how to enhance the site monitoring model in the future is explained. In the proposed site monitoring model, we have used the standard dataset images for train and test the model. In the future, we will perform data augmentation to generate new dataset images to evaluate the robustness of the proposed model. In the proposed method, conventional image enhancement method is used in the pre-processing stage. However, the image characteristics are different image to image. Therefore, in the future, we will design adaptive image enhancement method to enhance the images in the pre-processing step.

References

- Arif, F., & Khan, W. A. (2021). Smart progress monitoring framework for building construction elements using videography–MATLAB–BIM integration. International Journal of Civil Engineering, 19, 717-732.
- Faster R-CNN | ML. (2020, February 27). GeeksforGeeks. https://www.geeksforgeeks.org/faster-r-cnn-ml/
- Gamil, Y. (2023). Machine learning in concrete technology: A review of current researches, trends and applications. Frontiers in Built Environment, 9, 1145591.
- Han, K., & Zeng, X. (2021). Deep learning-based workers safety helmet wearing detection on construction sites using multi-scale features. IEEE Access, *10*, 718-729.
- Hayat, A., & Morgado-Dias, F. (2022). Deep learning-based automatic safety helmet detection system for construction safety. Applied Sciences, 12(16), 8268.
- Huang, L., Fu, Q., He, M., Jiang, D., & Hao, Z. (2021). Detection algorithm of safety helmet wearing based on deep learning. Concurrency and Computation: Practice and Experience, 33(13), e6234.
- Li, Y., Wei, H., Han, Z., Huang, J., & Wang, W. (2020). Deep learning-based safety helmet detection in engineering management based on convolutional neural networks. Advances in Civil Engineering, *2020*, 1-10.
- Martinez, P., Barkokebas, B., Hamzeh, F., Al-Hussein, M., & Ahmad, R. (2021). A vision-based approach for automatic progress tracking of floor paneling in offsite construction facilities. Automation in Construction, 125, 103620.
- njvisionpower. (2023, June 1). SafetyHelmetWearing-Dataset*(安全帽佩戴检测数据集)*. GitHub. https://github.com/njvisionpower/Safety-Helmet-Wearing-Dataset
- Wang, J., Zhu, G., Wu, S., & Luo, C. (2021). Worker's helmet recognition and identity recognition based on deep learning. Open Journal of Modelling and Simulation, 9(2), 135-145.
- Wang, Z., Zhang, Q., Yang, B., Wu, T., Lei, K., Zhang, B., & Fang, T. (2021). Vision-based framework for automatic progress monitoring of precast walls by using surveillance videos during the construction phase. Journal of Computing in Civil Engineering, 35(1), 04020056.
- Wu, X., Li, Y., Long, J., Zhang, S., Wan, S., & Mei, S. (2023). A remote-vision-based safety helmet and harness monitoring system based on attribute knowledge modeling. *Remote Sensing, 15(*2), 347.
- Zou, P. X., Xu, N., Yang, R. J., Ma, S. X., & Li, P. (2015). A REAL-TIME MONITORING SYSTEM FOR IMPROVING CONSTRUCTION WORKERS'HEALTH AND SAFETY. Proceedings CIB W099 Belfast 2015, 19.