AI-POWERED WORKPLACE SAFETY: HELMET AND FACE DETECTION USING YOLO FOR ACCESS CONTROL

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Abstract - *The influence a hazardous workplace has on worker well-being and efficiency has led numerous companies to put extreme focus on workplace safety. Workers are continuously subjected to numerous hazards at all times and locations when laboring in today's large construction/manufacturing plants and other hazardous industrial sites. The accident occurrence is thus higher compared to other sectors because the number of variables of risk is higher, and it is also a requirement for employees to don personal protective devices (PPE) in order to protect their bodies against unsafe causes. The accidents that have occurred because employees failed to put on personal protection equipment, such as hard hats, are the most common types of safety occurrences at the worksites. In reality, most existing safety inspection processes rely on the manual observation and reporting of inspectors. Hand observation of construction sites can be time-consuming, error-prone, costly, and inappropriate for large projects with several simultaneous operations. There have been numerous publications of studies on automatic detection of helmet wearing and human identity recognition, which have been aimed at helping safety inspectors on construction sites in monitoring workers' safety. Another study asserts that the computer vision-based person identification could be combined with helmet wear. In other words, in helmet testing, we usually do not have the capability to recognize individual people, and vice versa. We propose a computer vision approach to automatically recognize workers' identity and helmet wear to resolve the issues discussed above. First, our method involves two applications: identification and detection of helmet wear. Second, we tested the accuracy and recall rate of the algorithm under different visual environments to establish its use in the real construction site conditions. This was carried out as per the differing visual conditions at the construction site.*

Key Words**: Accident Occurrence, Computer Vision, Helmet Detection, Personal Protective Equipment, Safety Inspection, Worker Identification**

1.INTRODUCTION

In order to reduce the risks involved with working under such circumstances, it is important to maintain worker safety on building and construction sites. It is advisable that all employees undergo extensive training programs regarding key standards and be given frequent refresher courses. Safety from exposure to a range of hazards can be provided by workers through the frequent use of Personal Protective Equipment (PPE), including hard hats, safety glasses, gloves, and appropriate footwear. Fall protection devices, including guardrails and personal fall arrest equipment, demand special attention, especially when undertaking work at heights. Routine maintenance and checks are necessary to ensure the safe usage of equipment and machinery. Training sessions that educate employees on proper use are also required. Proper hazard communication assists in enhancing awareness and ensures workers know about potential hazards. It can be attained through labelling, signage, and frequent safety meetings. Additionally, having a systematic approach to recording and fixing safety problems ensures a proactive safety culture on construction sites. Construction industry stakeholders could significantly enhance workplace safety and help minimize the probability of accidents and injuries by catering to these essential factors.

In most sectors, particularly construction where there is a high risk of head injuries, helmets are a critical part of employee safety. The primary function of helmets is to prevent the risk of severe head injury by serving as a protective barrier against possible threats such as falling objects, debris, or impact. Additionally, helmet usage is in line with occupational health and safety regulations in many locations, which demonstrates the importance as an obligatory protection measure. The helmets consist of a hard exterior, typically made from fiber glass or high-density polyethylene. This outer hard surface serves to spread force of impact across a bigger surface area, thereby making the helmet more effective. Suspension system, with straps and headband, is typically integrated in the interior in order to facilitate a comfortable as well as a secure fit around the head of the wearer. There are a variety of helmet types that exist and are created for specific sorts of work conditions. Industrial helmets, for instance, are manufactured to be able to withstand electricity conductivity, as well as brimmed construction helmets that help protect against sunshine and rain. Protecting workers from risks associated with heads, the combination of different helmets' features and designs together aims to provide an improved work condition. Fig 1 illustrates different colors of construction site helmets with code.

COLOUR	IMAGE	FOR
Yellow		Labourer, Heavy-duty operations, & Construction tasks
Grey		Site visitors
Red		Firefighters
Brown		Welders, high heat operations
Blue		Electricians and Technical operators
Green		Safety officers
Pink		female workers* *in some companies it is used as an additional helmet
White		Managers, Engineers, Supervisors, Foreman

Fig 1: Helmet with color codes (https://www.reddit.com/r/coolguides/comments/42safb/difference_between_different_safety_helmets_colors/?rdt=54588)

2. RELATED WORK

Desu Fu, et.al,…[1] A helmet detection algorithm based on improved YOLOv5 is put forward in this paper. First, the structure of the YOLOv5 network is changed. With the enlargement of the feature map size, one scale is added to the initial three scales, while also using the added 160*160 feature map to detect small targets. Second, K-means clustering is used to re-cluster the helmet data set to yield more suitable prior anchor boxes. It was observed from experimental results that the average precision (mAP) of the improved YOLOv5 algorithm is larger by 2.9%, reaching 95% as compared to the base model, while the mAP for helmet recognition is increased by 2.4%, reaching a level of 94.6%. The algorithm reduces the rates of missed detection and misdetection while theoretically supporting the hard to scale detection of small targets while being of high practicality with advanced features. It meets the demand for real-time detection and contributes significantly toward safety within the electrical industry. In realizing their daily activities, power workers are easily recognized by their safety helmets, whether it is sunny, rainy, or snowy. If the power worker fails to use such helmets during operations, he can be hit on the head by objects falling from above, suffer head injuries due to high falls, or get an electric shock on the head. Therefore, safety helmets serve as the safeguard for the staff in this industry. Safety helmets are mandatory for power workers to enter the operation areas. However, manual inspection is time-consuming and labor-intensive, with some work scenarios being risky in terms of close-range supervision. Hence, the development of the intelligent real-time safety helmet detection system for power workers has gained tremendous importance. This intelligent safety helmet detection system can not only bring the supervision and monitoring work of safety into automatic and digital practice but will also augment workers' safety in this industry, therefore having significance in practical developments.

Shuai Wang, et.al,…[2] The present work investigates a smart vision-based method for identification of workers, which in turn is developed on the GMM model for motion extraction, based on MHOG and SVM techniques for personnel recognition, and is further built upon OpenPose and transfer-learning CNN techniques for helmet identification. The method can very well identify the worker type in construction sites, factory workshops, power construction sites, and interior decorations, among many others. The method is applicable to small-scale datasets, and accuracy of worker identification does not suffer much for occluded helmets, varying sizes of workers, and lighting conditions. The results of the experiment performed on our self-collected dataset demonstrate that the accuracy values vary little under different types of identification-related circumstances, with one figure reaching 99.43% as the mean accuracy value. It is worthwhile to mention here that the visual characteristics of the self-collected dataset in the present study are rather ideal, and this explains the better identification result in this study. Our following, larger scheme of work would be to collect some worker videos in real industrial environments, including a careful analysis of the workers' images relative to application of vision-based identification of workers.

Yi-Jia Zhang, et.al,….[3] Design an algorithm for helmet-wearing detection for the construction workers, based on contour and color features. Image preprocessing involving image smoothing and image enhancement is adopted to eliminate interference in the image. The combination of face detection, skin color detection, and helmet contour detection procedures helps extract the two-stage ROI based on the result of image preprocessing. Safety helmet-wearing detection is implemented by color space conversion and color feature recognition based on the output from the region of interest extraction, stating whether the workers wear their helmets. The wearing of helmets does bear great significance in most contexts, thus rendering the detection of helmet-wearing a matter of some intérêt in providing safety in construction. The algorithm proposed here is realized mainly for batch image helmet-wearing detection that can satisfy some detection requirements, although some real-time detection is not covered in this study. In the direction of future research, real-time helmet-wearing detection, along with a prompt for non-wearing alarm, will be realized and assistance in constructing a safety helmet-wearing system that could be practically applied.

Ahatsham Hayat, et.al,…[4] developed machine and deep learning-based helmet detection systems, but few have focused on most helmet detection at construction sites. In this paper, the authors proposed a safe, real-time computer vision-based automatic safety helmet detection system on a construction site. The YOLO architecture is very fast, with the capability to process 45 frames per second, making it suitable to use it for real-time helmet safety detection. In this study, a benchmark dataset of 5000 images of hard hats, which was further subdivided in a ratio of 60:20:20 (%) for training, testing, and validation respectively, was used. Backed by experimental results, the YOLOv5x architecture scored the best mean average precision (mAP) of 92.44%, establishing excellent success in safety helmet detection under low-light conditions. The monitoring of construction workers' safety is of paramount importance. Monitoring the use of safety equipment is a critical component of safety management at construction sites. In most falling accidents, a worker may fall from a height and then hit his head on the hard ground. Safety helmets are designed to absorb and dissipate impact energy and minimize injury to the worker in case of a fall from a height. Hard hats are also designed to lessen the risk of shock from falling objects or cut by sharp objects or contact with electrical hazards. If hard hats are used properly, half of all deaths from falls might be avoided and most deaths from slips, trips, and being struck by falling objects.

Han Liang, et.al,…[5] GhostNet, a lightweight network, is proposed to be utilized as the backbone feature extraction network in the helmet detection network. It makes the model lighter overall through its cheap operation, while guaranteeing efficient automatic feature extraction. In the feature processing stage, we designed multiscale segmentation and feature fusion network (MSFFN) to improve the robustness of an object detection algorithm from different scales. On the other hand, the feature fusion network brings out the diversity of the helmet features that would help to increase the accuracy of helmet detection in the distance changes, viewing angle changes, and occlusion phenomena. The proposed lightweight residual convolutional attention network version 2 (LRCA-Netv2) is basically the improvement of an attention module of spatial features from LRCA-Net that we proposed in the previous work. The main idea of improvement is that by fusing the combined features, both horizontal and vertical, while using their weights for attention, this operation can establish dependencies between those features further apart with accurate location-based information. The improvement clearly shows better performance as compared to the previous module. The proposed lightweight helmet-wearing detection network, evaluated on the combined dataset, achieved mAP and FPS of 93.5% and 42, respectively, which improves our model in execution speed and accuracy compared to existing methods.

3. EXISTING METHODOLOGIES

Usually, conventional video monitoring techniques are used to supervise the wearing of safety helmets on construction sites. These techniques mostly rely on human judgment about final clearances. Essentially, conventional methods may not be as good a gauge in recording compliance to safety helmet use compared to fully automated versions. This is why conventional methods of object detection are multitudinous. They commonly use sliding window approaches to select regions, which involves conducting a meticulous pass over an entire image. Choosing the right aspect ratio and scales of a sliding window, however, may easily be difficult when dealing with helmets of various sizes and orientations. Also, sliding windows can cause navigational delays while scanning through the entire image for detection. Because of this, methods advanced by human management may experience issues of accuracy and efficiency. There is increasing interest in looking for more sophisticated technologies like automated visual processing systems coupled with machine learning techniques to address these challenges. Such technologies can immensely reduce human intervention for accurate real-time use detection of helmets; an efficient means of ensuring safety compliance in building sites. Embracing these automated systems could supply an excellent simmering solution for improving the efficiency of building safety monitoring procedures. Adoption of top-end technological solutions is becoming increasingly popular towards solving these challenges. Promising substitutes include automated computer vision systems that are driven by machine learning algorithms. In real time, these algorithms may be trained to identify safety helmets with accuracy, eliminating the need for human monitoring. Deep learning techniques, which acquire complex patterns from a variety of datasets, offer a more flexible method for helmet detection.

4. PROPOSED METHODOLOGIES

This model comprises helmet detection with facial recognition. This form of intelligent safety involves the merger of cutting-edge technology and attempts to provide reliable means by which surveillance and enforcement of safety procedures may occur simultaneously. Camera placements are made at critical locations in the operation through the Grassmann algorithm-a visual features extraction technique. This gives an essential and adroit foundation on which further identification can be built by extracting the features unique to the face. Then, comparison of identified face features for streaming data is made with an authorized personnel database to ensure real-time and accurate identification.

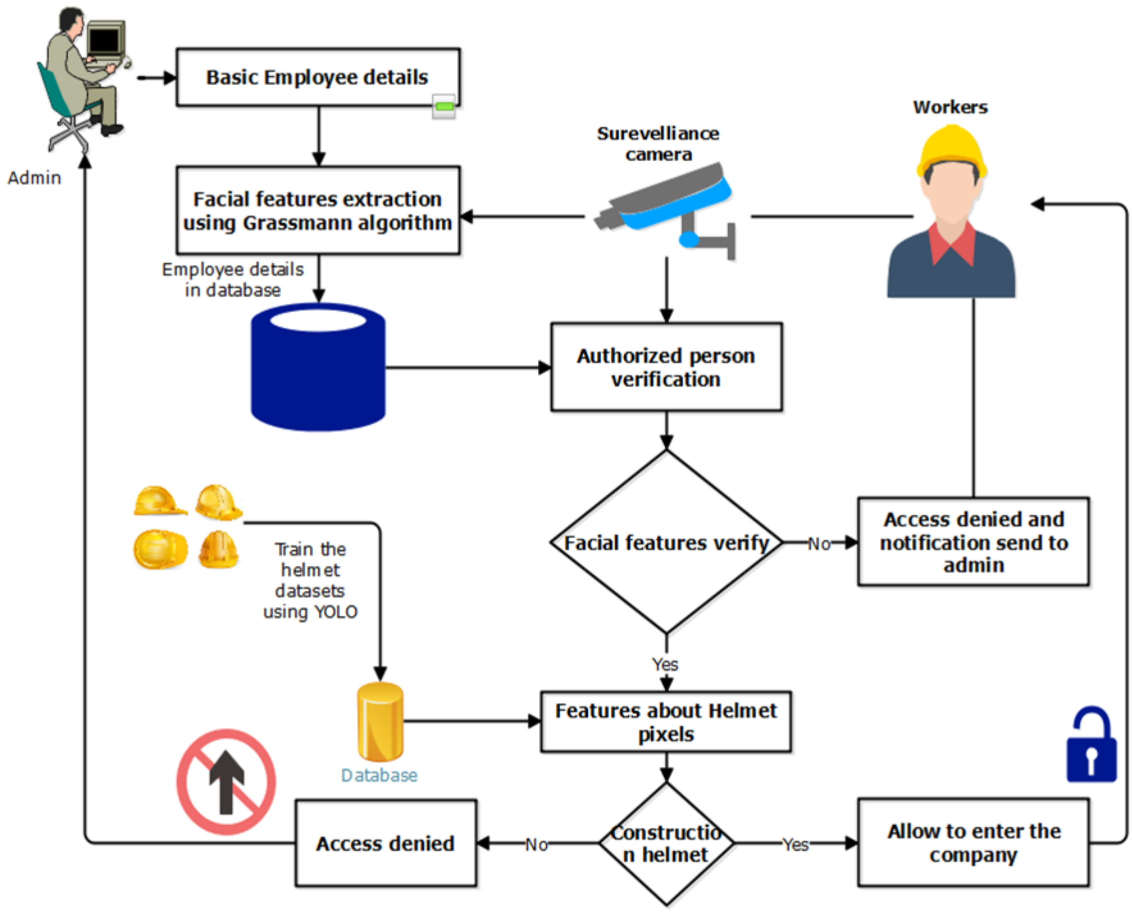

Fig 2: Proposed work

YOLO (You Only Look Once) algorithm enables helmet detection and further augments safety measures. This algorithm specifically aims to identify people not wearing helmets, allowing for fast and accurate object detection. By integrating facial recognition and helmet detection, the solution provides a holistic approach to ensuring helmet usage and access with an adherence to safety protocols. Upon identifying non-helmet use or unauthorized access, the technology is designed to sound alarms. The proactive alarm system allows for rectifying any deviation from safety requirements. The proposed technique enhances workplace safety through real-time monitoring and quick response in combination of both face recognition and helmet detection algorithms. The proposed framework is depicted in fig 2.

The diagram fig 2 illustrates a system for verifying workers' identity and construction helmet usage before granting access to a company. The process involves several stages:

Basic Employee Details: An administrator inputs basic employee details into the system.

Facial Feature Extraction: The system extracts facial features using the Grassmann algorithm and stores them in a database.

Helmet Dataset Training: The system trains a dataset of construction helmets using YOLO (You Only Look Once), an object detection system.

Surveillance Camera Verification: When a worker approaches, a surveillance camera captures their image.

Authorized Person Verification: The system verifies the worker's identity by comparing their facial features to the database.

- If verified, the system proceeds to check for a construction helmet.
- If not verified, access is denied, and a notification is sent to the administrator.
- Construction Helmet Detection: The system checks if the worker is wearing a construction helmet.
- If a helmet is detected, the worker is allowed access to the company.
- If no helmet is detected, access is denied.

This system aims to enhance security and safety by ensuring that only authorized personnel wearing appropriate safety gear can enter the company premises. The use of facial recognition and helmet detection technology automates the verification process, improving efficiency and reducing the risk of human error.

4.1 YOLO ALGORITHM

The YOLO (You Only Look Once) algorithm is a powerful real-time object detection system that works in a single forward pass of a neural network. Here's how it processes an image step by step:

Splitting the Image into a Grid

The input image is divided into a grid of cells. The size of the grid depends on the specific YOLO version—for example, YOLOv3 typically uses a 13×13 or 19×19 grid. Each cell in the grid is responsible for detecting objects that have their center within that cell.

Predicting Bounding Boxes

Each grid cell predicts multiple bounding boxes (usually two or three) that define the potential location of objects. These boxes include details such as width, height, and the (x, y) coordinates of the box's center. Additionally, each box comes with a confidence score, indicating the likelihood that an object is present.

Classifying Objects

For every predicted bounding box, the model assigns probabilities to different object categories (such as "person" or "car"). This is done using softmax activation, meaning the highest probability indicates the most likely object in that box.

Calculating the Confidence Score

To determine how reliable a prediction is, the confidence score is computed by multiplying the abjectness score (which indicates whether there's an object in the box) with the highest-class probability.

Removing Duplicate Detections (Non-Maximum Suppression - NMS)

Since multiple boxes may predict the same object, a filtering process called Non-Maximum Suppression (NMS) is used. The algorithm sorts the boxes based on their confidence scores and removes any overlapping boxes with lower scores to avoid redundant detections.

Filtering Low-Confidence Detections

Any bounding boxes with confidence scores below a predefined threshold are discarded, ensuring only the most reliable detections are kept.

Final Output

In the end, YOLO provides a list of detected objects, including their bounding box coordinates, confidence scores, and class labels. This allows us to see what objects are present in the image and where they are located.

By processing the entire image in a single pass, YOLO achieves real-time performance, making it a popular choice for applications like self-driving cars, surveillance, and robotics.

4.2 GRASSMANN ALGORITHM

Grassmann manifolds Gn,pis are sets of linear subspaces of Rn(p-planes in Rn), where

$0 < p \leq n$. This manifold has a natural quotient representation Gn,p

= Vn,p/ Op, where Vn,p is a Stiefel manifold (the set of n×p orthonormal matrices) and Op

is the orthogonal group. This means that two such matrices if and only if their columns span the same p-dimensional subspace. Thus, an entire equivalence class can be represented as the space spanned by the columns of some matrix Y.

$$[Y]=\{YQ\_p:Q\_p\in O\_p\}$$

In other words, a point on the Grassmann manifold is a linear subspace which may be specified by any arbitrary orthogonal basis.

- Use eye coordinates to determine the initial affine registration parameters for each image.
- Sample the affine registration manifold by perturbing the affine parameters
- Compute the k nearest neighbors from the registration manifold
- Apply color equalization and filter features values
- Construct the tangent space
- Embed the approximated tangent space and compute canonical angles
- Compute the subspace distance

5. RESULTS AND DISCUSSION

Obviously, in order to test the system some faces are required. There are so many standard face databases for testing and rating a face detection algorithm. A standard database of face imagery is essential to supply standard imagery to the algorithm developers and to supply a sufficient number of images to allow testing of these algorithms. Without such databases and standards, there will be no way to accurately evaluate or compare facial recognition algorithms. All the experiments described here have been executed mainly on the faces provided by the real time face database.

Accuracy

Accuracy (ACC) is found as the fraction of total number of perfect predictions to the total number of test data. It can also be represented as 1 – ERR. The finest possible accuracy is 1.0, whereas the very worst is 0.0.

ACC= (TP+TN)/(TP+TN+FN+FP) x 100

True positive (TP): number of true positives - perfect positive prediction.

False positive (FP): number of false positives - imperfect positive prediction.

True negative (TN): number of true negatives - perfect negative prediction

False negative (FN): number of true negatives - imperfect negative prediction

Table 1: Performance table

ALGORITHM	ACCURACY
PRINCIPAL COMPONENT ANALYSIS	65%
LINEAR DISCRIMINATIVE ANALYSIS	85%
GRASSMANN ALGORITHM	98%

From the graph given in Fig:3, proposed system provides improved accuracy rate than the existing PCA and LDA algorithm.

HELMET PERFORMANCE

The YOLO model demonstrated high accuracy in detecting helmets in various construction environments. Key performance metrics are as follows:

Precision: The system achieved a precision of **90-95%**, indicating that most of the detected helmets were accurate, with few false positives (incorrectly detecting helmets where none were present).

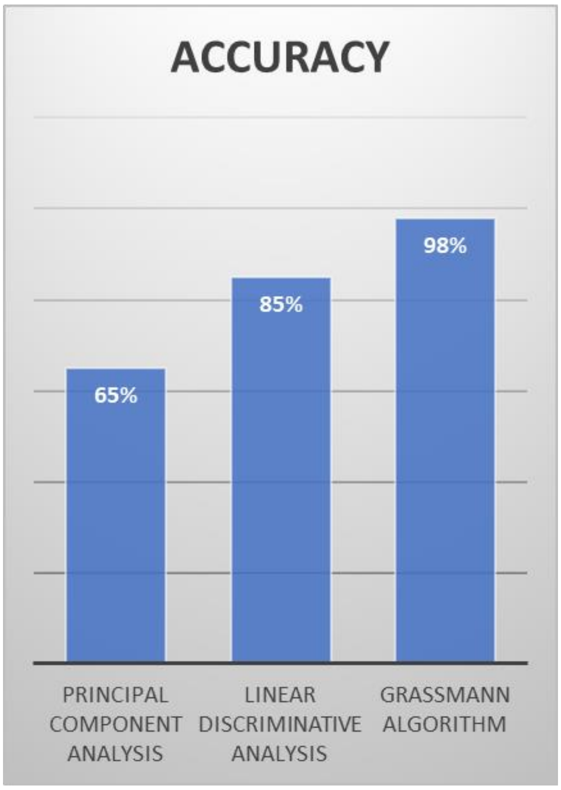

Fig 3: Accuracy graph

Recall: Recall ranged from **85-90%**, reflecting the model's ability to identify workers who were wearing helmets. Some minor false negatives were observed in cases where the helmet was partially obscured or in cluttered scenes.

F1-Score: The F1-score, a balance of precision and recall, was consistently above **0.87**, suggesting a well-balanced detection performance.

These results are promising and demonstrate that the

YOLO-based system is highly capable of detecting helmets with minimal errors. The system performed well under various lighting conditions, occlusions, and crowded environments, which are common in construction sites. The performance chart can be shown in following figures 4, 5 and 6.

The YOLO-based Helmet Monitoring system performs significantly better than Traditional Manual Monitoring in terms of Precision, Recall, and F1 Score, providing more reliable, accurate, and comprehensive helmet detection. Traditional Manual Monitoring is subject to human error and fatigue, leading to lower Precision, Recall, and F1 Score, which can affect the overall effectiveness of safety monitoring on construction sites.

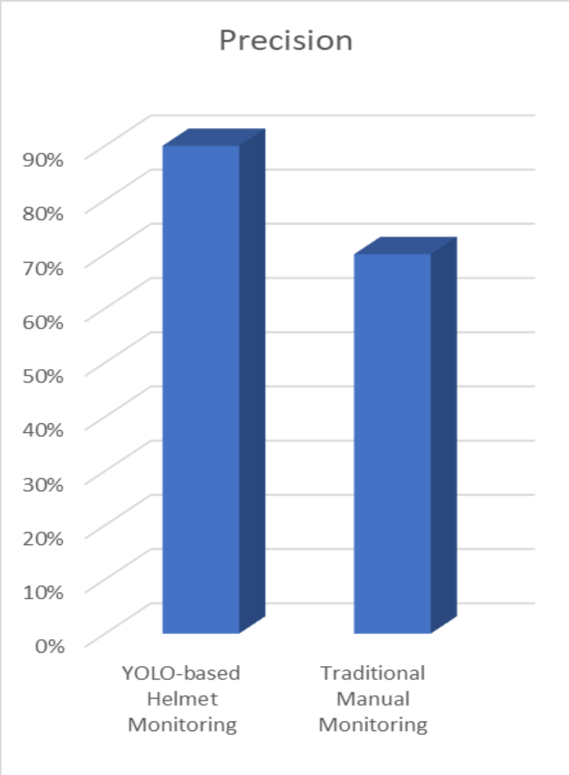

Fig 4: Precision chart

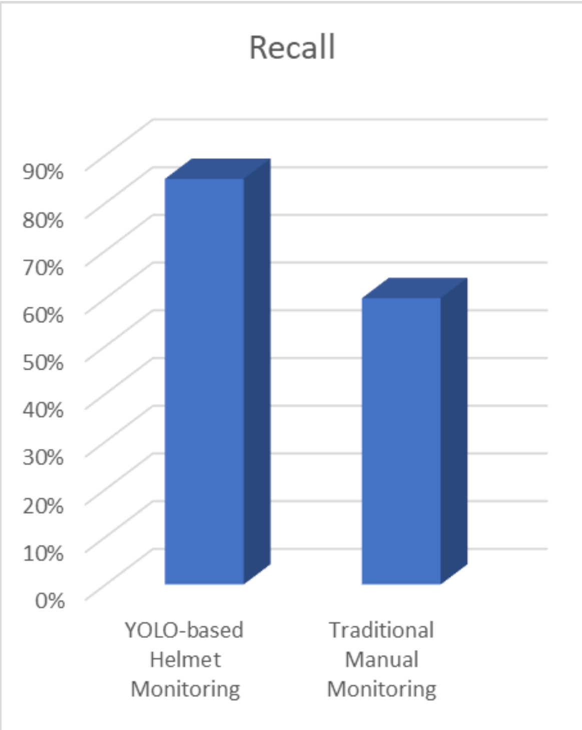

Fig 5: Recall chart

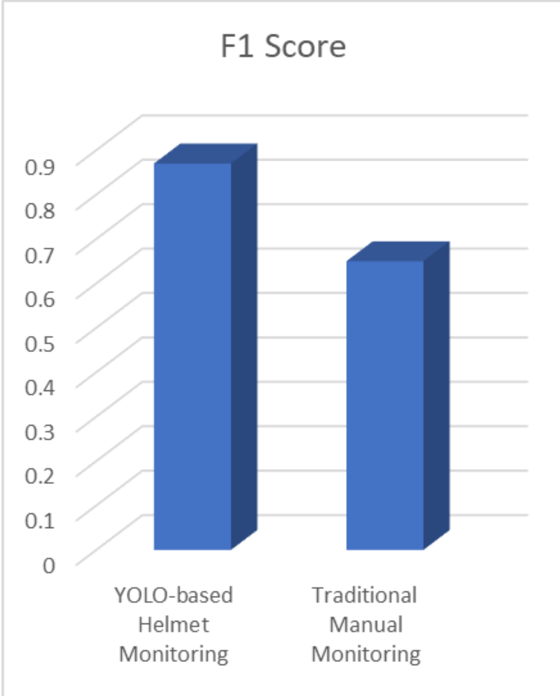

Fig 6: F1 score chart

6. CONCLUSION

To summarize, the technology transformed safety patterns in construction sites through compliance and surveillance. The system proposed utilizes the Grassmann and YOLO algorithms for helmet detection and face recognition to yield precise results. The system was able to not only check safety protocols for the use of safety helmets but also allow entry based on facial recognition with the help of real-time data processing and strategically positioned cameras. The YOLO algorithm tailored helmet detection efficiently while Grassmann realizes correct extraction of facial features and gives an apt step for identification. The combination of these advanced technologies affords a novel approach to workplace safety, allowing rapid responses to unauthorized entry and non-compliance with helmet regulations through proactive alarm systems. Its strong and flexible method of risk reduction puts the proposed system at the forefront of innovation in the construction industry, still highly centered on safety. Joining automated technology with traditional safety techniques realizes more accuracy and effectiveness, furthermore creating a safer working environment. The acceptance of such innovations is a pledge to improve workplace safety, protect employees, and minimize hazards on construction sites.

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