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Wireless Power Transfer System for the Intelligent Video Monitoring and Analysis Based on the Safety of Power Grid Construction Site

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Abstract: - This study describes a power grid construction site surveillance system that includes wireless power transmission and an improved Yolo V3 detection model. An artificial intelligence and wireless power transfer methodology is employed used for continuous monitoring. Improved Yolo V3 detection is optimized using Hierarchical Particle Swarm Optimization (HPSO) for enhanced efficacy in detecting power grid development threats. The methodology is compared to existing methods in terms of precision, accuracy, recall, and speed. The findings indicate that the proposed method is achieved a real-time and accurate power grid development site monitoring. Experiments on test sets in various situations improved the detection accuracy, and indicate that the proposed technique is quite robust. Also the detection accuracy and speed of the proposed method have improved over existing approaches, indicate that the strategy provides superior detection efficacy. This method considerably improves risk source detection, that's critical for assuring safety on power grid building sites.

Keywords: Power grid construction site, wireless power transfer (WPT), artificial intelligence, video monitoring system, RF-based wireless power transfer, Improved Yolo V3 detection model, Hierarchical Particle Swarm Optimization (HPSO), Histogram equalization, Gabor filtering

INTRODUCTION

Power is transferred using electromagnetic fields via inductively linked coils in wireless power transmission. During the transition of power, metallic or magnetized items, as well as active items (like animals or human parts) between or around the coils, represent a risk to the platform's security, efficacy, and functioning. Live items might well be injured by contact with the field because metallic or magnetized items absorb the energy from the field and heat up.

The electric power grid, which transports electricity from major power plants to clients, has become an integral section of everyday life. Even though it is presented for a lengthy duration, the existing electricity grid is nearly entirely created and run using theories and technologies from 100 years ago, which have been demonstrated to be insufficient to find the requirements of current society. Among the most essential elements of the power grid configuration, regular monitoring of the power grid construction site, for instance, continues to use the conventional physical monitoring design, resulting in several concerns like ineffectiveness, difficulty checking in off-work periods, and inability to offer a real-time observation.

As a consequence, collapse or blackout and grid failure have been common in the power grid in recent years, posing safety and annoyance concerns and also a significant financial loss for both power producers and users. WPT methods have progressed in two ways. When transferring energy across short distances, non-radiative methods like inductive or magnetic resonant coupling are used. For long-distance power transmissions, however, radiative approaches utilize the electric field of electromagnetic waves, most often radio frequency (RF) waves. Other benefits of RF-based WPT are its broadcast nature, little difficulty, size, and price of the energy receiver apparatus, and applicability in transportable elements. It can provide energy to several receivers at the same time. Low-power implanted elements including sensors and RFID tags may now be charged in practice using RF-based WPT. Many embedded devices, such as wireless cameras or sensors, may need them in the future due to improvements in energy transfer efficiency [1].

Weather forecasting is significant as it determines the way weather patterns are going to develop in the future. Using latitude, we can assess the probability of rain and storms reaching the earth. We can calculate the amount of thermal energy providing the sun exposes a region area. Weather prediction enables building site operations to be adjusted accordingly. Construction site safety assessments are an important aspect of any industry's accident-preventative measures. Despite advancements in secured teaching and standards, the regular-increasing need for increased output that having a negative influence on construction site safety. In the United States, for instance, over 20% of serious accidents happen on construction sites, even though construction crews make up less than 10% of the total workforce. Environmental damage, object contact, and body part damages are common outcomes of resistance with sufficient precautions and wrong equipment usage. In 2017, 145 people died as a result of

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exposure to hazardous substances or conditions, while another 133 died as a result of contact with objects or machinery [2].
In power grid construction activities, security surveillance is of the utmost significance, particularly when the workplace location is complicated and exposed to severe weather. Protection guards must do routine manual inspections and screenings as part of the conventional method of safety monitoring, which results in a significant burden and poor performance. Therefore, safety threats on power grid building sites cannot be eradicated [3]. The conventional manual monitoring, paper media documents, and other working methods could no longer fulfill the criteria of infrastructure management and control due to the characteristics of multi-faceted construction sites, numerous construction respondents, dispersed machinery, and superficial regulations. Despite the widespread utilization of Building Information Modeling (BIM) in construction projects, there are still certain issues with power grid infrastructure project operation and supervision [4].
Due to a shortage of competent power construction firms, some firms' low quality and capability results in inadequate safety monitoring, failure to administer, and a slew of improper failures. Currently, the firm has set up a development location safe monitoring scheme dependent on mobile video supervision (surveillance) that may be used to perform distant video supervision from the industry's head office. Nevertheless, to the enormous amount of development locations and several simultaneous video feeds, the monitoring, detection, and analysis of illegal activity requires a significant amount of manual labor. When there is a shortage of people, effectiveness suffers and failures are more likely to occur. As a result, it is critical to conduct intelligent secured monitoring of power grid development locations [5]. The proposal's primary goal is to improve the rate of hazard source detection, which is crucial for guaranteeing the security of power grid construction sites.

Contribution to the work

- ➢ Images of various types of helmets, safety gloves, and labor suits are gathered for the dataset.
- ➢ Enhancement of images using histogram equalization
- ➢ Image De-noising is done by Gabor Filtering
- ➢ Improved Yolo V3 detection model with HPSO for intelligent video monitoring and analysis for the safety of power grid construction site
- ➢ The performance was evaluated with various metrics and analyzed the proposed effectiveness.

Hence, in this article, we present intelligent video monitoring and analysis for the safety of power grid construction sites using the Improved Yolo V3 detection model with HPSO. The further part of this article was structured as: Section II provides the related works and the problem statement. Section III demonstrates the flow of the presented work. Section IV examines and compares the performances of our presented technique with the existing techniques. And, finally, section V summarizes the complete research.

Related Works

Sunindijo et al (2017) [6] recognized four essential components for enhancing construction safety standards: 1) Surveys for competent builders, 2) Experiment development and relationships with coworkers as well equipment, 3) Approaches for improving workers' awareness of security, and 4) Collaboration of universities to promote safety awareness. Although fundamental security instruction meets the legal requirements, experts argue that extra processes such as information exchange are as important in enhancing security knowledge and awareness.
Chung et al (2020) [7] created an Internet-of-Things (IoT)-dependent novel safety framework that allows for real-time surveillance of development locations humans and the setting. The suggested framework not just detects real-time employee security issues, such as near misses, to minimize injury rates, but it also saves digitized information to enhance future training and the arrangement itself. The suggested approach in this study offers users a price-effective alternative for improved construction security. However, this method is still in the planning stages. More advantages will become apparent after the system was executed throughout an actual project. It is a complex framework.

A detailed assessment of the applications of wearable technology for tailored construction security surveillance was published by **Awolusi et al (2018) [8].** Wearable device features and security regulations that are considered to impact security performance and management strategies are investigated. According to the study, current wearable technologies that have been employed in further companies could be employed to observe and evaluate a broad range of security performance metrics in the development firm. Different wearable sensors may be mixed based on attributes for multi-parameter security analysis. Regarding the outcome of this study, more investigation could include creating models of construction-specific wearable components as well as evaluating their usefulness.

Sun et al (2020) [9] build a smart management and control system that enables surveillance, early warning, control, and emergency reaction using UAV remote sensing, geographical information structure, 3D virtual model, IoT, smart sensors, and other technological means. To create the groundwork for precise dynamic analysis, smart extensive forecast, and thorough and reliable project tracking, it is required to delve deeply into the possibilities of project monitoring and administration, as well as enhance the surveillance system.

Depending on PSO-SVM, **Zhu et al (2020) [10]** presented a power grid construction safety early warning framework. The classic Support Vector Machine (SVM) security early warning technique's mathematical approach has limits in parameter tuning. Since it cannot acquire a stronger early warning impact, the PSO technique is preferable to the previous technique in parameter tuning. It searches for improved parameter combinations and achieves an improved early warning impact by combining information from the entire group and mutual collaboration between people. Yet, the detection speed is low in this method.

Gao et al (2021) [11] created the ID-Net framework, which is an upgraded context-aware mask region-based convolutional neural network (Mask R-CNN) concept for intrusive recognition of objects in power grid surveillance systems. The core network includes a modified flexible convolutional operation for training resilient feature representations from geometric fluctuations in construction devices. A self-attention-based element is employed for distant context connections models by assessing the relationship among elements and their contexts. A data integrating component includes multi-scale feature fusion for micro item detection. In addition, a transmitted coarse-to-fine area suggestion network is built to enhance boundaries location regression. However, as time passes, this method gets less accurate.

Niu et al. (2019) [12] developed a grid emergency capability estimation methodology with 4 major and 14 supplementary parameters. A unique fuzzy evidential reasoning approach connecting entropy weight is developed because the previous assessment process cannot handle with loss of data and has high sensitivity. The weight of each parameter can be accurately described using entropy weight. Yet, the fuzzy evidence reasoning technique may combine multiple criteria for a more thorough examination.

Based on a common case base update technique, **Shen et al (2019) [13]** established a standardized management framework in power grid crises. The emergency information transmission method is enhanced based on the categorization and level of urgency. The case matching method and the case updating technique is presented using a standard case architecture that includes basic characteristics, feature attributes, processing pattern, and assessment attributes, and the implementation of the H-law algorithm considerably enhances the effectiveness of case matching. The benefits of a standard case base include a great hit rate and ease of extension that can be useful in the realm of power urgent situation supervision.

Rong et al (2019) [14] developed a smart safety monitoring framework for the electric power construction scheme to notice if employees are wearing their helmets properly. The data for the electric power construction scenario is fine-tuned using the YOLOv3 objective detection algorithm. The helmets and the head are the primary targets for identification. The laborer's helmet and head are examined to see if he or she is wearing one. The efficiency of helmet identification after the testing is over 90%. The technique substitutes the traditional technique with an automated process, saving a significant amount of both human as well as material assets. This strategy could be used in real-world production. However, when compared to other methods, the technique's efficiency is lower.

To assess the usage of a safety helmet, **Ouyang et al (2020) [15]** suggested the Improved Faster R-CNN method. The Retinex image enhancement is utilized to increase image quality for external complicated matters in power stations, based on real-world circumstances. For improved adaption to the tiny size helmets, the K-means++ method is used. The experiments show that, when contrasted to the Faster R-CNN algorithm, the suggested technique's mean average accuracy is increased, and real-time automatic detection of safety helmet usage is achieved. The detecting speed, on the other hand, is quite slow. The next phase is to increase detection speed while maintaining high accuracy.

Wu et al (2019) [16] introduced a real-time helmet identification program depending on YOLO (You Only Look Once) v3 and wrapped it into a real-time identification software with alarm functionality and easy effective functioning, which has been effectively developed for numerous construction sites. The YOLO v3 method performed well when it comes to identifying personas. To begin, the YOLO v3 design is used to identify and identify the employees in the video, and positive and negative samples are taken. The employee in the dataset is then recognized, whether or not they are wearing helmets. However, when compared to traditional approaches, the accuracy is lower.

Conventional manual examinations and video monitoring techniques to recognize the use of workers' helmets have inadequate reliability and miss assessments due to the difficult backgrounds of the development location and the varied kinds of construction people. **Tan et al (2021) [17]** presented a deep learning-based approach to resolving the challenges mentioned above. Initially, a functionality recognition scale was introduced depending on YOLOv5, allowing it to get smaller objects; second, rather than using NMS, it uses the DloU-NMS, which takes into account the overlap region and center distance of the two boxes, building it additional consistent in repressing the predicted bounding box. The investigational findings reveal that the suggested approach outperforms the YOLOv5 network model in terms of accuracy, and the recognition speed is 98 frames per second which satisfy the requirements of real-time identification. Yet, the efficiency could be improved further for this approach.

Nath et al (2020) [18] proposed 3 deep learning (DL) methods that rely on the You-Only-Look-Once (YOLO) framework for verifying employee PPE adherence in real-time, such as whether a person is wearing a secured helmet, jacket, or both. The algorithm recognizes workers, helmets, and jackets in the first method, and then a machine learning design confirms that every discovered employee is appropriately wearing a helmet or jacket in a second way. With the second technique, the system utilizes a single convolutional neural network (CNN) design to identify individual workers while also verifying PPE adherence. The algorithm in the third technique first recognizes just those employees in the input picture that were trimmed as well as categorized using CNN-based classifiers depending on the existence of PPE apparel. All of the algorithms are trained on in-house picture data compiled through crowd sourcing and web mining. This technique has a minimum efficiency and detection rate.
Kansal et al. (2018) [19] are a group of researchers that came up with a novel way to solve In this study, a novel unsharp mask filtering approach with histogram equalization is utilized for general-purpose pictures, which optimizes the image's entropy while controlling over and under enhancement by clipping the image's histogram. It is very time-consuming.
Benyang et al (2020) [20] Presents a helmet identification approach based on improved YOLO v4 suggested to avert protection mishaps caused by wearing helmets. Employing the K-means method to cluster self-created data of on-site development location video to gain more focused edge information and a suitable a priori frame dimensional center.

Jin et al (2020) [21] The VGG-16 network is used to develop a glove-detecting system. Cameras capture real-time photographs of employees and send them to a glove detection system for analysis.

Zhou et al (2021) [22] present a safety helmet identification approach based on YOLOv5 and annotate the 6045 gathered dataset sets to create a digital safety helmet surveillance structure. Furthermore, for testing and training, we employed the YOLOv5 model with varying factors. The four models are evaluated and contrasted.

Sengar and Mukhopadhyay (2020) [23] Adaptive thresholding-based optical flow methods are used to separate the foreground moving objects from the background in the suggested approach. The contour of the segmented foreground areas is then determined using the Freeman chain code. Then, utilizing versions of particle swarm optimization, block-based motion estimates and compensation is calculated.

Chen et al (2019) [24] present a model parameter update strategy to achieve model synchronization of the global DL model. Furthermore, to tackle the inequity of workload and processing capability of edge nodes, a dynamic data movement strategy is presented.

Liu et al (2016) [26] For RF-based WPTNs to operate efficiently and reliably, this study examined the privacy and protection issues raised by WPTNs. Recent research possibilities are highlighted in this burgeoning field.

Akbal and Tuncer (2022) [27] Monitoring the activities on the building site is a crucial duty to assess, quantify, and track them. This paper suggested utilizing noises to classify construction vehicles and identify automated activities using a BTPNet2 modality. The complicated structure dataset for monitoring cannot be processed.

Koc et al. (2022) [28] even though security administration systems are always becoming better, industrial injury rates in construction sites are typically greater than those in other sectors in most nations. By combining discrete wavelet transform (DWT) and other machine learning (ML) techniques; this work intends to advance the field of architecture security administration by predicting the frequency of industrial incidents using time series information. It takes a lot of time to estimate.

S.No	Reference	Objective	Limitation
1	Sunindijo et al (2017) [6]	This study created an Internet-of-Things (IoT)-dependent novel safety framework that allows for real-time surveillance of development locations humans and the setting.	This method is still in the planning stages. It is a complex framework.
2	Zhu et al (2020) [10]	This study presented a power grid construction safety early warning framework. The classic Support Vector Machine (SVM) security early warning technique's mathematical approach has limits in parameter tuning. So, they proposed PSO for parameter tuning.	The detection speed is low in this method
3	Gao et al (2021) [11]	This paper ID-Net framework, which is an enhanced context-aware mask region-based convolutional neural network (Mask R-CNN) prototype for intrusion object recognition in power grid surveillance systems.	This strategy becomes less accurate
4	Niu et al. (2019) [12]	This paper developed a grid emergency capability estimation methodology with 4 major and 14 supplementary parameters.	It cannot handle the loss of data and has high sensitivity
5	Kansal et al. (2018) [19]	In this work, general-purpose images are processed using a unique unsharp mask filtering technique with histogram equalization, which controls over- and under-enhancement by clipping the image's histogram and optimizes the image's entropy for construction safety management.	It is very time-consuming.
6	Jin et al (2020) [21]	The VGG-16 network is used to develop a glove-detecting system for construction site security management.	Detection accuracy is low.
7	Akbal and Tuncer (2022) [27]	This paper suggested utilizing noises to classify construction vehicles and identify automated activities using a BTPNet2 modality.	The complicated structure dataset for monitoring cannot be processed.
8	Koc et al. (2022) [28]	By combining discrete wavelet transform (DWT) and other machine learning (ML) techniques; this work intends to advance the field of architecture security administration by predicting the frequency of industrial incidents using time series information.	It takes a lot of time to estimate.

Problem Statement

For analyzing and enhancing the power grid construction site's continuous wireless camera current backup, safety, prompt, efficient, and precise safety inspections are critical. Overcoming power issues WPTNs use rf waves to transmit power to hardware platforms. Researchers have been working hard to create WPTNs that enhance collected power, energy unavailability, and charge latency. Also, for the safety Manual monitors often conduct safety tests and write biweekly or monthly official news. The frequency with which this operation is carried out makes it difficult to identify and eliminate dangers quickly. Moreover, text-based written safety reports frequently fail to adequately explain safety threats. Machine learning approaches are unable to reduce the time-consuming, complex operation of data augmentation and expensive cost in the security of power construction sites. To overcome those disadvantages in practice, actions are needed to automate safety tests on enormous volumes of data that are wealthy in facts and understandable by humans. For this aim, visual information from development locations is a possible option. Hence, an intelligent video monitoring and analysis system for the safety of power grid construction sites using an improved Yolo v3 detection model with HPSO is presented in this article.

PROPOSED WORK

The HPSO is a significant optimization technique that improves the detection model's performance, especially in recognizing potential safety hazards. The technique refines the parameters of the Improved Yolo V3 detection model by utilizing the hierarchical structure of particle swarm optimization, then contributing to increased accuracy and efficiency in identifying dangers connected with power grid development. This usage of HPSO emphasizes its value in improving complicated detection structures and demonstrates its function in enhancing comprehensive security procedures for power grid development environments. This part discusses the procedure of the presented technique. The diagrammatic illustration of the presented methodology is shown in figure1. Throughout this paper, technical using RF-based wireless power transfer and an upgraded Yolo V3 detection model, a power grid construction site wireless surveillance camera power transfer and video monitoring system is built. Wireless power transfer technology was used here for continuous monitoring. The input dataset is then preprocessed using histogram equalization and Gabor filtering techniques for image enhancement and de-noising, respectively, to analyze the security of the personnel. The Improved Yolo V3 detection model's detection performance is improved using Hierarchical Particle Swarm Optimization (HPSO). HSPO is an artificial intelligence technique.

A WPTN is a network of specific WPT nodes that transmit adequate power to adjacent energy receiver (ER) gadgets over the air as RF-based WPT systems are becoming more significant in practical applications. To charge various ERs, WPTN energy transmitters can control their transmission power, time/frequency, and waveform. To charge the built-in batteries, every ER has an RF harvester circuit. The researchers have spent a lot of time and effort designing WPTNs that improve collected power, energy outage, and charging delays, among others.

The YOLOv3 method is an improvement over the YOLOv1 & YOLOv2 techniques since it provides the advantages of high classification accuracy, accurate location, and quick reaction. This has been a current study focus since it can identify tiny objectives and has significant resilience to surrounding conditions, especially if multi-scale estimate approaches are applied. When the fundamental backbone system was changed from Darknet-19 to Darknet-53 to remove characteristics and gather extra comprehensive characteristic data, the residual network was commonly deployed to enhance the feature removal approach. We use the "You Only Look Once" strategy ("YOLO") throughout this work to detect the mobile telephone target in a single step. This series of such strategies use a solitary CNN strategy to provide entirety target recognition.

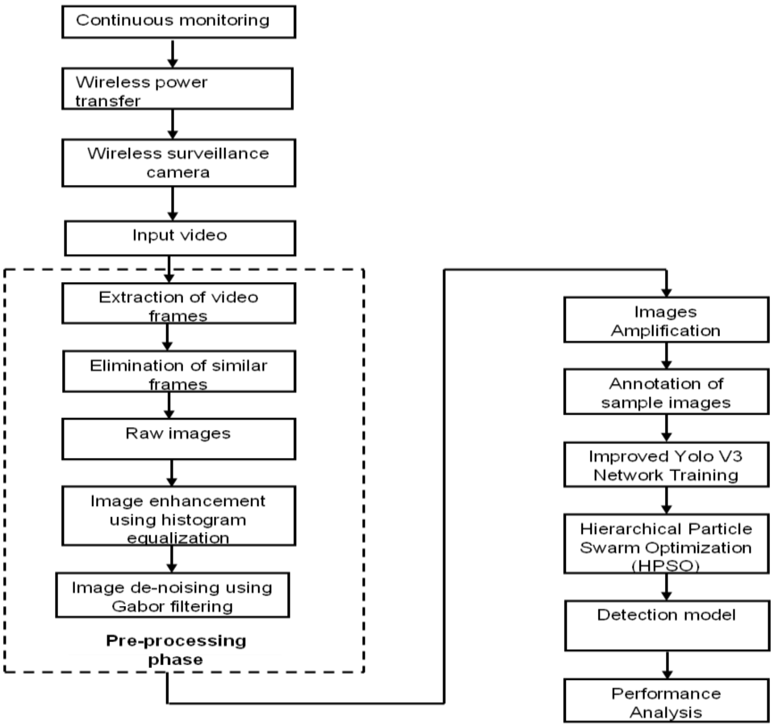

Figure 1: Diagrammatic illustration of the presented methodology

A. Dataset Description:

First, picture models of safety gloves, helmets, and labor costumes in multi angle & multi form in the site's surroundings must be collected for smart identification of illegal behavior in the power distribution network's construction site. Employees on the power grid construction site gather videos of operations that comply with security requirements or are in violation of safety laws. The image obtained from the video sequence was separated into frames from the video sequence. To create a standard data set, images of various types of helmets, safety gloves, and labor suits are gathered.

B. Image Enhancement using histogram equalization:

A histogram is the evaluation of the probability distribution of a definite kind of data generally. An image histogram is indeed a sort of histogram that displays the spectrum distribution of grayscale levels in digital images graphically. We may assess the frequency of the presence of the distinct grey levels present in the image by looking at the histogram.

Histogram Processing:

A discrete function is the histogram of a digital image with intensity degrees in the range [0, M – 1]. It is given by,

$$h(r_j) = n_j \tag{1}$$

Here r_j denotes the jth various intensities and n_j indicates the computation of image pixels with an intensity of r_j. Normalizing a histogram is done by splitting each of its elements because it's general number of image pixels, which is represented as a result of the item XY, wherein X and Y are the image's column and row measurements, respectively. As a result, a normalized histogram is equal to,

$$p(r_j) = n_j/XY, \quad \text{for } J = 0,1,2, \ldots \ldots, M - 1 \tag{2}$$

In a nutshell, $p(r_j)$ is probability estimation because of its presence of such fervor r_j in an image. A normalized histogram's total elements are equal to one. Poor images' histograms are generally small, but quality images' histograms are broad. The histogram is thus changed to transform a poor image into a quality one.

Histogram Equalization:

Histogram equalization is used to increase the contrasts of an image by distributing its brightness rates throughout the entire spectrum. The grid equivalence approach is unable to be used for images having non-uniform ambient brightness since it only adds pixels to the image's light parts and subtracts pixels from the image's dark sections, resulting in an increased dynamics range in the last images. The goal of grid equivalence is to split a certain image's contrast consistently across in full range of values that in the present instance is from 0 to 1.

The probability density function (PDF) customized in spectrum equivalence approach. The images' PDF can be computed as follows [18]:

$$P_J(F_k) = \frac{n_J^k}{n_J} \tag{3}$$

Here j = 0, 1..., s, and n_J denotes the overall calculation of pixels from F_0 to F_s intensity levels.

$$P_U(F_k) = \frac{n_U^k}{n_U} \tag{4}$$

Here= (s + 1), (s + 2), (J − 1), and n_U denotes the overall the number of squares across F_{s+1} to F_{J-1} strength level. Cumulative density functions (CDFs) are subsequently stated as,

$$C_J(F_s) = \sum_{j=0}^{s} P_J(F_k) \tag{5}$$

$$C_U(F_{J-1}) = \sum_{j=s+1}^{J-1} P_U(F_k) \tag{6}$$

Modify measures with respect to continuous concentration values:

$$T_J(F_k) = F_0 + (F_s - F_0) * C_J(F_k) \tag{7}$$

$$T_U(F_k) = F_{s+1} + \left(F_{J-1} - F_{s+1}\right) * C_U(F_k) \tag{8}$$

The image convert method is supplied by “Transform Function (TF)”:

$$TF = T_J(F_k) \cup T_U(F_k) \tag{9}$$

The aforementioned TF is then developed by employing a Gabor filter for de-noising, resulting in a final improved image.

C. Image De-noising using Gabor Filtering:

The Gabor filter (GF) is intended to reduce joint ambiguity in frequency along with spatial orientation. It recognizes frequencies components of an image with a certain orientation inside a confined region surrounding a given point or area of evaluation. The GF frequency and orientation properties are quite reminiscent of the human visual system. The GF, which is primarily used for texture characterization and separation, that is extremely excellent at catching subtle features within images. The GF is an effective instrument for image analysis and feature extraction that used in terms of safety at power grid building sites. GF were originally designed for signal processing and image analysis, while it is exceptionally effective at collecting texture and frequency information in images. GF is able to use with security camera footage or other visual data sources to improve safety at power grid building sites.

The Gabor filter, which uses frequency and directional representation to distinguish and characterize image texture, is useful for describing image energy distribution and de-noising. Employing Gaussian kernel operation (a, b) of pixels position (a, b) modulated through a sine wave, the Gabor filter of x_1th scale and y_1th direction is expressed by,

$$g_{x_1 y_1}(q', w') = v^{-x_1} g(q, w), \quad v > 1, x_1 = 1,2, \dots\dots, x_0, y_1 = 1,2, \dots\dots y_0 \tag{10}$$

In which, v=scale factor, x_0, and y_0 represent the overall scales and directions, correspondingly. Next, the low-frequency element may convolve with the GF to attain the Gabor coefficient,

$$B_g(q, w, x, y) = \iint L(q', w') g(q - q', w - w')\, dq' dw' \tag{11}$$

Here (q, w)=lower frequency element’s input matrix. Currently, the Gabor energy of every scale x_0 and direction y_0 shall be computed as,

$$E_g(q, w) = \sum_{x=1}^{x_0} \sum_{y=1}^{y_0} \left|B_g(q, w, x, y)\right|^2 \tag{12}$$

D. Image Amplification:

In this phase, the training sample is amplified as depicted in **Janson and Middendorf (2004) [24]**. All training images are turned by ±10° and ±20° to account for the differences in images with helmets, safety gloves, and labor suits. Furthermore, the safety gloves images are horizontally inverted. The image's center has been intercepted. When the object nearer the image’s edge partially or entirely vanishes after rotation processing, the labeling is discarded. Image amplification is critical for improving safety at power grid building sites. Image amplification provides a comprehensive perspective of the construction environment by utilizing the modern imaging technology including high-resolution cameras and powerful image processing methods. This improved visibility allows for the early discovery of possible hazards, resulting in improved safety for construction workers.

E. Annotation of sample images:

After the image amplification stage, the image can be extricated by annotating the picture. It's difficult to annotate a huge and diversified image collection. Although the annotation process is generally slow, an hourly compensated tiny grouping of annotators with construction information may offer trustworthy observations. Annotation jobs are distributed among many more annotators using crowd sourcing, and each annotator is compensated based on the several tasks performed. This method enables quick and gainful task achievement, although it necessitates a lot of quality control. In this work, the image is standardized to a similar size since the size of the picture database is not consistent, and afterward the standardized picture database is annotated. The PASCAL VOC structure of an information collection is compatible within annotation style. The VOC database contains the standard picture database style goal identification and the capability to access. A collection of solutions for accessing the database and comments, with the XML document in the database's comment folder, serve as the image analysis. It's difficult to annotate a huge and diversified image collection. Though the annotation process is likely to be slow, an hourly compensated tiny group of annotators with construction expertise is able to provide reliable annotations. After gathering the images, the next step is to manually annotate them with the graphical image annotation application Labeling. Image annotation is necessary for improving safety measures on power grid construction sites. Various safety-related features is detected and shared successfully by integrating extensive annotations into images acquired at these sites. Annotation is used to highlight potential hazards, indicate safe zones, and locate safety equipment. This visual data enhancement guarantees that workers and stakeholders comprehend safety measures and guidelines. Present safety gear detection, which consists of images with responses for safety equipment such as helmets, suits, and gloves.

F. Improved Yolo V3 Network Training:

Since it offers the benefits of large classification accuracies, precise positioning, and fast response, the YOLOv3 technique is indeed an upgrade over the YOLOv1 & YOLOv2 approaches. This could detect small aims and has strong robustness to surrounding scenarios, particularly if multi-scale estimation techniques are used, and as a result, it's become an existing research focus. Figure 2 sketches the YOLOv3 method's network model. The residual network is typically employed to advance the feature removal technique, whenever the essential backbone system was modified from Darknet-19 to Darknet-53 to remove characteristics and collect additional comprehensive characteristic data.

To recognize the mobile telephone target throughout this work, we apply the YOLO (“You Only Look Once”) technique in a single-stage technique. To accomplish end-to-end target recognition, this sequence of such techniques employs a single CNN approach. The necessary phases are used to execute the entire methodology: To begin, the given image is resized to 448x448 pixels. They are then placed in the CNN training phase. Lastly, the network is examined to accomplish the predictive performance and the identification target. It is a unified framework when compared to the R-CNN algorithm. It also has a faster pace. Yolo's training has been completed from beginning to end. One YOLO network seems to be the progenitor of the YOLOv3 network throughout this article. The YOLO network doesn't require region formation and instead returns the forecast objective across the entire input image, considerably speeding up identification. The system divides the repaired data provided across S*S(S=7) meshes and predicts two boundary elements for every weave, containing C (C=2) forms. To produce the final goal projection structure, conditional probability is employed to sift out boundaries frames with low criterion utilizing a non-maximum reducing method. A multi scale guidance technique is used in YOLOv3 training. YOLOv3 creates Darknet-19 and Improved Yolo V3 network topologies that simply have a convolution layer and a pooling layer to enhance the recognition rate. On the VOC2007 test set, improved YOLOv3 within 416*416 outperforms Faster RCNN, SSD, and YOLO.
The network causes layer by layer data leakage throughout the transfer, making it unable to create proper use of multi-layer features and lowering detection accuracy. To achieve multi-layer feature reuse as well as fusion while avoiding the computational burden introduced by the new framework, this article utilizes Huang et alidea's of intensive connection, embedding intensive components just in the dense coating of an improved Yolo V3 network feature map through minimal resolution, effectively substituting the Yolo V3's 7th convolution layer with intensive components. The 8^{th} convolution layer may accept multilayer convolutions and also dense link block outcomes owing to an improved Yolo V3 structure with dense connections (quality 16*16).
Conv layer 1×1×64 3×3×128 Residual unit ×2 1×1×N

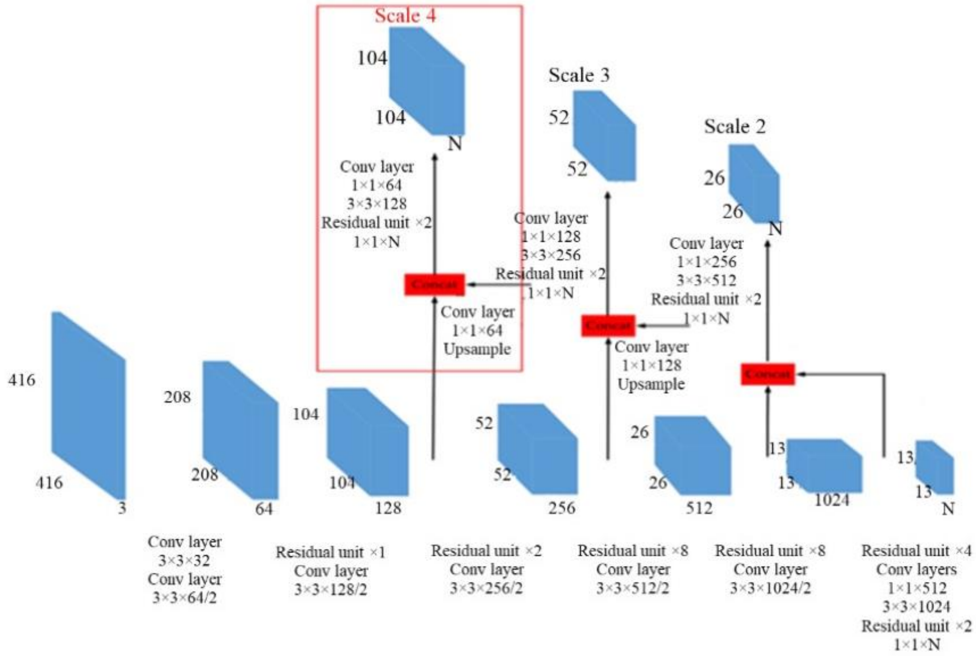

Figure 2: Architecture of Improved Yolo V3 model

G. Hierarchical Particle Swarm Optimization (HPSO):

The iterative approach of Particle Swarm Optimization (PSO) is depending upon the search behaviors of a swarm of n particles in a search area [22]. The velocity and position of the particles are modified with each repetition. The velocity vector $v_j$of each particle j is modified as per equation (13). The prior velocity's impact is controlled by the inertia weight g > 0. where x_j represents the particle's current location. The effect of the particles' personalized best position at the moment y_j, which corresponds to the position that its particles have identified the lowest functional values currently considering that the desired function needs to be lowered is regulated by the variable p1>0.
The influence of the best position identified thus far by every one of the particles in the corresponding vicinity, $\hat{y}_j$ is determined by parameter p_2. Here, we employ the so-called $_{best}$ neighborhood, in which every one of the particles was present. The scoress $_1$ and s_2 are chosen at random with an identical probability from the range [0, 1].
The particles travel with their updated velocity to their fresh locations 2 after the velocity modification. The objective function f_or is then assessed for each particle j on its present location. Qualification $f_o(x_j(t+1)) < f_o(y_j)$ the private preferred place v_j was upgraded correspondingly, that is,y_j be position toward $x_j(t + 1)$.

$$v_j(t+1) = g.v_j(t) + p_1.s_1.(y_j - x_j) + p_2.s_2.(\hat{y}_j - x_j) \quad (13)$$

$$x_j(t+1) = x_j(t) + v_j(t+1) \quad (14)$$

The neighborhood network in H-PSO is defined by the arrangement of all particles inside a hierarchy. Every particle throughout the hierarchy was surrounded by its neighbors, including the parent. Hierarchies were investigated in which the base structure is indeed an (almost) normal tree with all internal nodes having the same out-degree and then only the deeper level's internal nodes having a lesser out-degree. Upon that deepest level, the largest distinction between the out-degrees of internal nodes would be one. The framework is established by the height h, the degree d, i.e. the highest speed of the innermost nodes, and all nodes m of the linked tree.
Molecules proceed across the structure, delivering a powerful impact to the right people within the swarm. Following assessments of the objective functions at the particle's real locations in all repetitions, the new positions of the elements within the hierarchy are determined as follows. The most effective solution derived from each particle j within a tree node was matched to the best solution identified by the particles within the child nodes. Assuming the most effective among these fragments, particle$i$, outperforms(f_o (yj) $< f_o$(yk)), components j and k swap places in the hierarchy.

Such matches are beginning at the highest level and work down the structure in a breadth-first manner. It's worth noting that the top-down strategy indicates that a person may come back down numerous levels throughout the hierarchy in a single iteration, but only up one level. Therefore, after most h stages, the current global optimum particle would be at the highest level - until a proper result is discovered in the meantime. Throughout HPSO, a particle's velocity is changed according to its current best position in relation to the greatest position of the individual, particularly those higher up in the hierarchy. This means that the value of $\widehat{y}_j$ in Equations 13 equals y_j for particle *i* while *j* is the component in the previous nodes of particle *j*. HPSO utilizes $\widehat{y}_j = y_j$ whenever component *j* occurs in the root. Similarly to PSO, the target computation in HPSO is conducted at the new location once the particle speeds have been updated but they have travelled. The new position was saved in y_j unless the function score is higher than the individual best position thus far.

PERFORMANCE ANALYSIS

Simulation settings:

In this paper, the Improved Yolo V3 algorithm is established within Darknet, as well as attendant system constructed as Intel R Xeon (R), Table 1 depicts the system configuration. The scheme employed for this research is Ubuntu 16.04. Table 2 contains the model parameters.

Table 1: System configuration

Features	Value
CPU (E3-1245-v3)	3.40 GHz
Run storage	16 GB
Hard disk	2TB
1080Ti graphic card	12 GB

Table 2: Simulation parameters [4]

Parameters	Value
Momentum term	0.9
Initial learning rate	0.001
Attenuation coefficient	0.0005

In this study, there are 211 test images with the situation using a protective glove, 182 for the scenarios containing the protection helmet, and 133 in favor of the labour suit. As illustrated in Figure 3, the suggested approach is capable of detecting safety gloves, safety helmets, and labor suits. Table 3 shows the detection effectiveness of the presented approach.

Table 3: Detection performances of the presented approach

Scenario	Accuracy (%)	Precision (%)	Recall (%)	Detection speed (frames per second)
Safety glove	97.88	96.54	94.22	60
Safety Helmet	98.99	99.78	96.54	60
Labor suit	97.13	96.36	95.57	60

(a)

(b)

(c)

Figure3 :(a) Detection samples of safety glove (b) safety helmet (c) labor suit

The presented approach was related to the standard approaches regarding measures like accuracy, precision, recall, and detection speed. “True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN)” are the four ideas to consider for this assessment (Figure 3).
The algorithm successfully classifies positive pixels as TP. TN stands for negative pixels that the system accurately identifies.FP stands for positive but not accurate pixel numbers. FN denotes pixels that are regarded as negative but are not exactly negative.

Accuracy:
It determines the number of samples that can be identified. Results are judged on how nearly they reflect what was predicted in the beginning.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{15}$$

Precision:
Recalling only those aspects of an object that are critical is called precision. It is the percentage of optimistic forecasts that are correct.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{16}$$

Recall:
To be efficient, models must be able to identify only the most important features. It's the percentage of true positive predictions.

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{17}$$

Detection speed:
A vital measure of detection speed is necessary for the detection method, in addition to the evaluation metric of detection accuracy. For various appliance scenarios with high real-time needs, speed is far more important than accuracy. The most prevalent speed measurement is Frames per Second (FPS), which refers to the number of pictures, which was processed per second.
Figures 4, 5, and 6 show the comparison graph in expressions of “accuracy”, “precision”, and “recall” for the recognition about safety helmet, gloves, and labor suit respectively. Figure 7 depicts the comparative examination of detection speed for the existing and proposed techniques. The graphs reveal that the presented technique has better accuracy, precision, recall, and detection speed when compared with the traditional approaches. Figure 8 shows the frequency deviation concerning the relative error of training sets 5, 10, and 18. And figure 9 shows the WPT efficiency concerning different values of distance for both the theoretical and experimental performances.

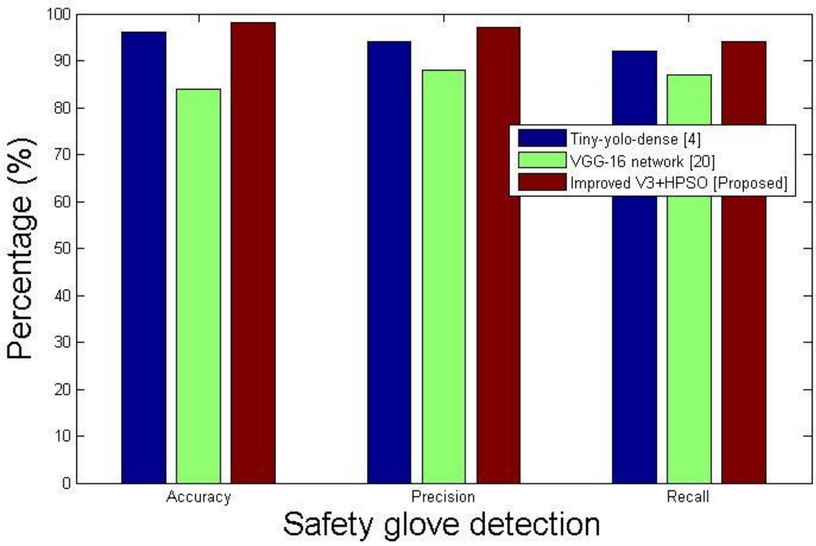

Figure 4: Relationship of accuracy (%), precision (%), and recall (%) for safety glove detection for existing and present techniques

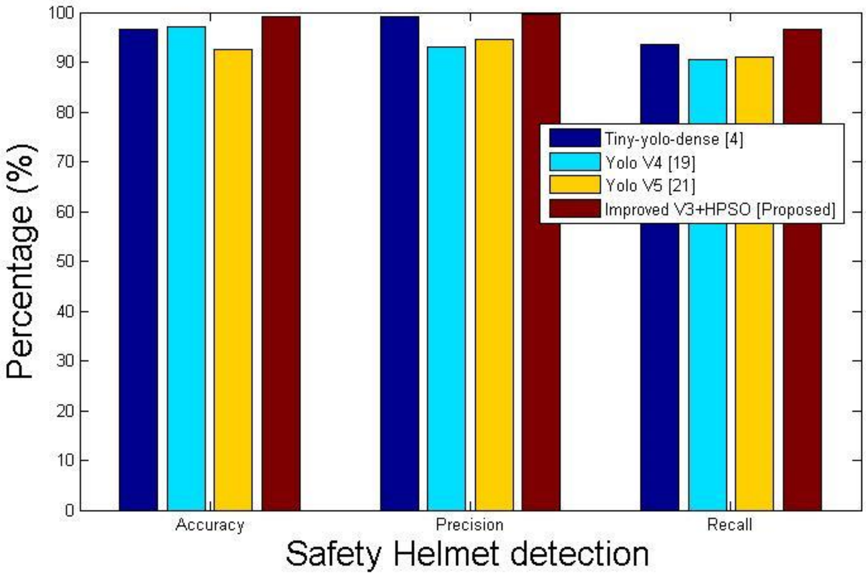

Figure 5: Comparison of accuracy (%), precision (%), and recall (%) for safety helmet detection for existing and proposed methods

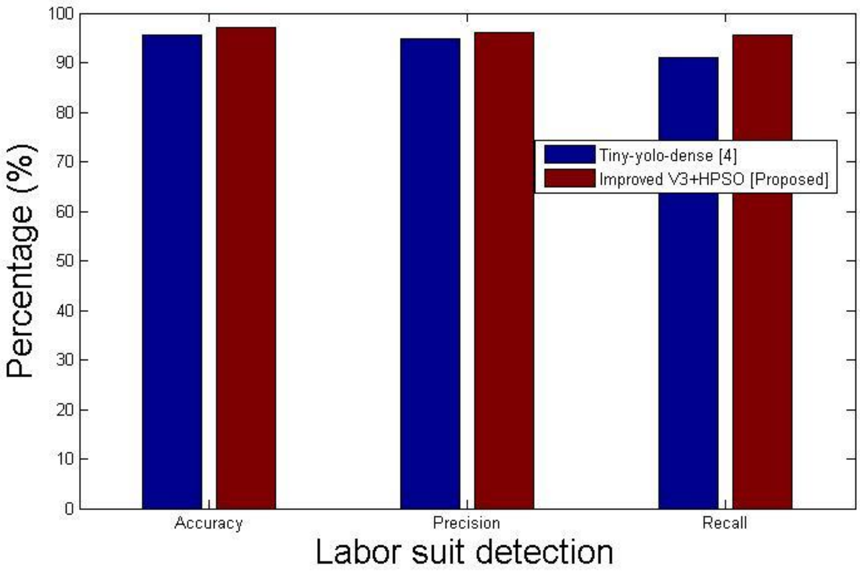

Figure 6: Comparison of accuracy (%), precision (%), and recall (%) for labor suit detection for existing and proposed methods

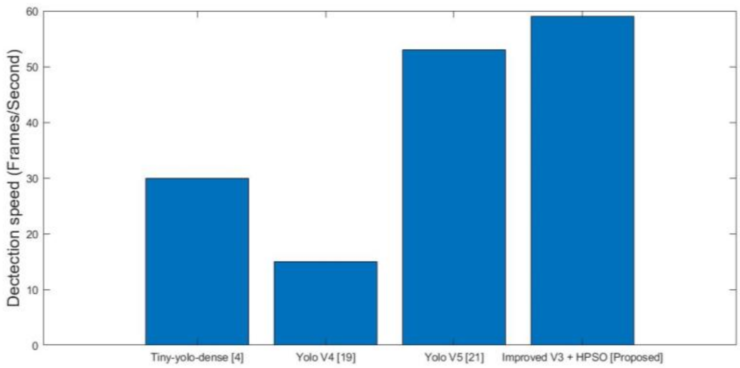

Figure 7: Comparative analysis of detection speed (frames/second) with existing and proposed methods

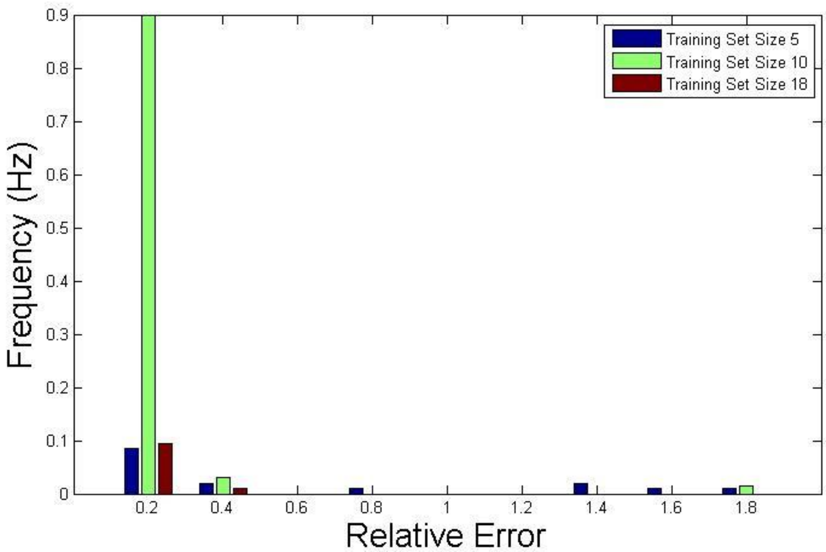

Figure 8: Frequency deviation w.r.to relative error training set 5, 10 and 18

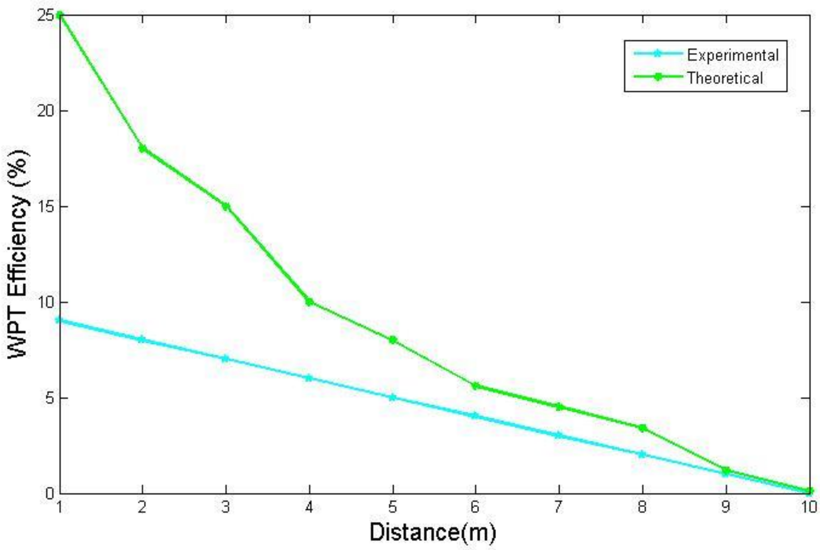

Figure 9: WPT efficiency (%) of theoretical and experimental performances

CONCLUSION

The RF-based charging system for efficient wireless power transfer systems was proposed. The improved YOLO-V3 method is proposed in this research to handle the difficulties of power grid development located on the foundation of the original YOLO-v3 model. Wearing a safety helmet, gloves, and labor suits is required on the construction site of the distribution system. As a result, great accuracy and real-time recognition are required. Different designs must be trained independently due to the variation in the recognition mechanisms of safety helmets, work gloves, and labor suits. Furthermore, the systems must ensure network camera recognition in real-time. Because of this, assuring the surveillance system's usefulness requires a high degree of precision and real-time. The improved Yolo-V3 framework is utilized in this work to provide a violation monitoring system at a power grid construction site. The HPSO technique was used to improve the system's detection performance. In deep learning, our proposed technique performs better in real-time. Three states are listed as infractions in this paper: no gloves, no helmet, and no labor suits. Those circumstances are then turned into the discovery of gloves, helmets, and work suits, all of which are routinely employed on power construction sites. The system provides better recognition accuracy and guarantees reliability by providing real-time monitoring. The safety system achieved high accuracy rates for safety gloves (97.88%), safety helmets (98.99%), and work suits (97.13%).The safety system obtained exceptional precision rates for safety gloves (96.54%), safety helmets (99.78%), and labor suits (96.36%).The safety method obtained high recall rates for safety gloves (94.22%), helmets (96.54%), and labor suits (95.57%). The spacing among the security camera and the power source is limiting the effective wireless power transfer. Wireless transmissions are susceptible to interference, and impacting the dependability of each power transfer along with video monitoring. The intricacy of the upgraded Yolo V3 detection model is requiring significant processing resources, consequently compromising real-time performance. Future research intends to effectively combine the power supply and monitoring technology, to develop a symbiotic relationship that is considerably to improve building site productivity and safety standards.

DATA AVAILABILITY STATEMENT: For anyone interested, the corresponding author can provide access to the simulated results that supported the study's findings.

CONFLICTS OF INTEREST: The authors claim no potential conflict of interest.

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