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REAL-TIME OBJECT DETECTION, CLASSIFICATION, AND INTRUSION DETECTION TO PREVENT HAZARDS AND IMPROVE CONSTRUCTION WORKER SAFETY

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Abstract: Construction is a hazardous industry where workers are frequently exposed to fatal accidents. Construction safety regulations are frequently violated, and workers are exposed to incidents of injuries and fatalities. To overcome the limitations of manual efforts, automated safety monitoring is considered, but dependence on connected devices raises security issues and challenges for detecting real-time safety. The proposed model consists of two modules. The first module consists of three subsystems: image preprocessing, object detection, and object classification. The Non-Local Means (NLM) filter is applied for preprocessing images. Next, YOLO v8 is utilized for object detection, and MR-Net is employed for object classification. If the detected object is a person, it further classifies whether they are wearing, hard hat, a mask, and a safety vest. For attack detection, Maximum-Linear Normalization is used during the normalization process, and the Hiking Skill Optimization Algorithm (HSOA) is leveraged to train the hyperparameters for the Deep Max-out Network (DMN), which is responsible for detecting attacks. The results indicate that MR-Net achieved an accuracy of 94%, with a TPR of 95%, TNR of 95%, NPV of 96%, and PPV of 95%. In comparison, HSOA_DMN attained an accuracy of 92.5%, with a TPR of 91.9%, TNR of 93.9%, NPV of 90.4%, and PPV of 91.5%.

Keywords: Internet of Things (IoT), Construction safety, Intrusion detection, MR-Net, Hiking Optimization Algorithm

1. Introduction

The number of fatalities on construction sites has increased in recent years. The safety of individuals is not guaranteed in construction areas. The workers handled a lot of struggles and complexities in the work location due to the offensive equalization between work and their safety. In addition, it affects the individuals physically and mentally. Among all the other trades, the construction environment is situated as the foremost contributor to deaths. Based on the present Statistics, there is lakh of construction injuries that happen each year, and a major

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number of injuries are caused by falls or slips from heights.

The Internet of Things (IoT) is a physical object network sustained by combined technology for communicating data and sensors to communicate with states and environments of internal and external objects. For the past few years, the universe has transformed from fundamental services of the internet to social networks to the wearable web, which has led to a continuous upsurge in the requirement to interconnect wearable smart devices [1]. This exposure of wearable devices provides a new dimension to IoT by generating an intelligent fabric of body-worn or near-body sensors that communicate with one another or with the internet [2]. Workplace safety has become an essential issue for many industries since an insecure environment affects production and results in the loss of more workers. Construction is considered an extremely risky sector since workers often suffer from injuries while doing their job [3].

Object detection is essential for ensuring safety, preserving quality, and improving productivity at construction sites. This technology employs cameras, drones, and sensors to offer continuous surveillance of the environment, recognizing objects such as workers, equipment, safety gear, and possible hazards. Presently, object detection systems have been broadly employed in the construction industry for both safety management and the prevention of workers [4]. Detecting unauthorized entries, recognizing locations, and implementing alarms can essentially mitigate risks connected with incidents like electrical shocks, falls from heights, and the movement of heavy-duty equipment and machinery. In addition, these measures help to decrease adverse effects caused by glitches on project sites and prevent the integrity of projects and the complete design. Controlling the entry of unauthorized individuals helps evaluate the access levels of every person on-site against the required permissions for diverse, specialized work environments [5].

The proposed model is designed for Object detection and classification of objects in IoT-enabled construction safety monitoring named MR-Net. To overcome the problem of unauthorized access, an algorithm named Hiking Skill Optimization Algorithm (HSOA) is introduced for intrusion detection on the Internet of Things.

2. Literature Review

Mehata, K.M., et al. [6] created a smart wearable gadget that uses the Internet of Things (IoT) to help find workers who have fallen and send SMS warnings for immediate help. Additionally, the employees' heart rates and temperatures were recorded, revealing that aberrant health conditions made the workplace safer and more secure for workers by lowering the number of deaths. Also, this plan didn't include a GPS to show where the fall happened, so that others could get there faster and better.

Khan, M., et al. [7] developed a smart safety hook (SSH) monitoring system that utilizes computer vision and IoT-based technology to mitigate the risk of falls from height (FFH) accidents. This method assists site managers by promptly notifying them when staff engage in risky behavior. However, the system has restrictions, such as trouble in supervising a large

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number of individuals based on their location, and it does not enhance battery life when connected to IoT components.

Chang, H.K., et al. [8] created the portable and lightweight Lifting Safety Control Station (PLSCS), a real-time warning system for building construction lifting activities. This model minimizes employees' efforts by notifying them of safety hazards. The system's scope of supervision was limited by CCTV technology, which was not designed for remote oversight monitoring.

Shanti, M.Z., et al. [9] created an innovative monitoring method called the Personal Fall Arrest System (PFAS) for construction workers. This method combines a Convolutional Neural Network (CNN) approach with a standard safety protocol, which includes a designated security helmet. This method was able to achieve success in real-time applications. The model, however, did not explore the potential for AI to target and mitigate struck-by hazards in the construction industry and reduce fatalities.

Ahmed et.al. [10] created a deep learning model that utilized computer vision, integrated with advanced hardware, to provide accurate and near real-time identification of personal protective equipment. The detection system was a dual process, and it used a Fast Region-based Convolutional Neural Network (R-CNN) , which was built on 1,700 visual data points. His PPE detection system was able to target and predict mortal and non-mortal industrial incidents.

Khan et al. [11] implemented a Mask R-CNN-derived Object Correlation Detection system to streamline how training images were stored, optimize the assessment of the trained network, and lessen overfitting concerns. Still, the system was developed solely for a limited data set comprising 2D images and was hampered by occlusions.

Sa Jim Soe Moe et al. [12] developed a system that employs Federated Learning to enhance worker safety, particularly in outdoor construction sites. While this system has improved safety by diminishing false alarm rates, it has remained in the test phase with no real-world data, which hampers its efficacy in combative real-world scenarios.

Syed Farhan et.al. [13] presented a unique algorithm that employs temporal analysis to further reduce false alarms. The main emphasis of this study was to enhance the system's detection accuracy while working to minimize the false detection rates. This system has a limited operational range and is prone to hardware failures, and it does not sufficiently deal with the reliance on high-grade data.

Gutierrez et al. [14] released a new balanced dataset dubbed IDSAI, which currently features intrusions that were generated in real-world attack environments. This development partially resolved the issue of limited response capabilities, but fully leveraging the power of unsupervised machine learning and anomaly detection is still a goal.

Si Van et al. [15] Implemented a computer vision and 4D BIM approach for intrusion detection in dangerous areas. It delivers a warning message if there is an overlap between an on-site and a hazardous area object, but it does not study safety rules and regulations or incorporate contextual information to assist the 4BSP module.

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3. Methodology

The proposed model improves object recognition, classification, and intrusion detection in IoT construction safety monitoring systems. The monitoring of construction sites in real-time using IoT devices has transformed construction practices. This research merges two cutting-edge deep learning architectures to resolve these issues: MobileNet and Deep Residual Networks (ResNet). model utilizes MobileNet's rapid lightweight and real-time detection capabilities, while ResNet provides complex deep feature extraction for the precise identification of construction hazards, intrusions, and safety equipment in intricate construction environments.

This study also proposes the Hiking Skill Optimization Algorithm (HSOA) with a Deep Maxout Network (DMN) to optimize the model's intrusion detection task performance. HSOA achieves effective feature selection and parameter tuning, ensuring that DMN produces robust classifications with fewer false detections. This hybrid approach enhances detection precision, responsiveness to dynamic threat changes, and processing speed for real-time monitoring of safety in IoT construction systems. Figure 1 shows the architecture of the proposed Model.

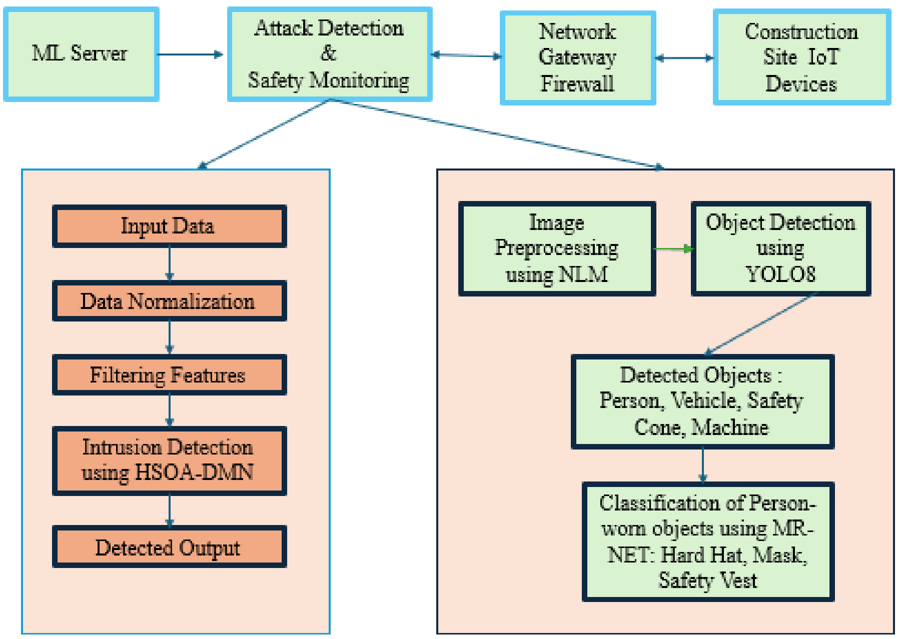

Figure 1: Architecture of the Proposed System Model

The following steps describe the architecture of the proposed model.

The ML server integrates various services and technologies to extract meaningful information from data collected by sensors and devices. The data is processed, and valuable insights are used for attack detection and safety monitoring. The sensors collect data from physical devices and transmit it to the router. The firewall is used to prevent unauthorized access. Construction site IoT devices connected to the network can communicate effectively. For safety monitoring, image preprocessing is performed by the NLM filter. Object detection is conducted using YOLO8. Object classification is performed by MR-Net, where the object is classified as a

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'Hardhat', 'Mask', or 'Safety Vest'. In attack detection, data normalization is carried out using Maximum-Linear Normalization. then, specific feature selection was conducted through City Block Distance

The attack detection is performed using DMN and trained using HSOA

3.1 Acquisition of Visual Data

The construction site image dataset from Roboflow [16] , is used for object detection. The annotated images are in YOLO format which provides good-quality photos. The dataset contains 10 object classifications that are aimed in accurate detection and categorization.

Equation 1 represents the individual sample and the total images from the database.

$$X = X_1, X_2, \dots\dots\dots\dots . X_{y\dots\dots\dots\dots,} X_k \tag{1}$$

where X denotes the database, X_y represents an individual image within the database, and the dataset contains a total of k samples.

3.2 Image Pre-processing

This step is intended for use on raw photos to remove noise and make them easier to analyze. As a result, a filter called Non-Local Means (NLM) [17]is used to pre-process the input image. The NLM filter uses the fact that similar patches are repeated across the image as data. Instead of using nearest neighbors, the processed picture gives each pixel a value based on a weighted average of the intensities of the surrounding pixels and the similarity of the pixel patches to all the pixels in the image. Equation 2 represents the working of non-local means filter with noisy and noise-free pixel values.

$$x(z) = p(z) + \lambda(z) \tag{2}$$

Here, x(z) and p(z) represent the noisy and noise-free pixel values at the λ^{th} pixel, respectively, while λ (z) denotes the noise sample.

3.3 Object Detection using YOLOv8

YOLOv8 [18], the newest version of YOLO, improves detection performance by using an anchor-free design, better regression heads, and a customizable network backbone that can be based on CSP-Darknet or other custom backbones. In this study, YOLOv8 is employed to perform object detection of a person, machine, vehicle, and safety cone on the preprocessed image.

3.4 Classification of person-wearable objects using MR-NET

MR-Net module is used for sorting wearable safety items. There are three categories of clothing worn by people on site: hard hats, masks, and safety vests. The proposed model includes MobileNet and Deep Residual Network (DRN) [19]. The Mobile Net Module [20] is a

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lightweight convolutional neural network that helps with feature extraction. The MRNet Module improves the classification process to make recognition more accurate. The DRN Module adds a deeper network as a residual learning scheme to improve feature representation for precise safety gear detection. The best thing about Mobile Net is that it is lightweight, which means it can be installed on edge devices with little computational capability. DRN, on the other hand, is designed to address the issues that arise during training of deep neural networks.

3.5 Intrusion Detection:

Intrusion detection is crucial for any unauthorized access that compromises the security system. If you detect these attacks at an early stage, construction sites can enhance safety and protect workers more effectively. In this situation, HSO_DMN is designed to quickly identify an attack. A Deep-Maxout Network (DMN) is used to identify objects, and its hyperparameters are improved with HSO.

3.5.1 Input Data Collection

The first step in identifying attacks in an IoT network is data collection. The Bot-IoT dataset [21]is utilized to do research in IoT Security. This dataset is used to detect various types of attacks on IoT Devices. This simulation is specifically designed to represent both normal traffic and botnet-generated traffic, providing a comprehensive foundation for evaluating attack detection models . Equation 3 represents the database and the total number of data samples.

$$D = \{ D_{1,} D_{2,} D_{3,} \dots \dots \dots \dots \dots . D_T \} \quad (3)$$

Here, D represents the database, and D_T denotes the total number of data samples.

3.5.2 Max-Linear Based Data Normalization:

It is a technique for normalizing numerical values to a designated range, commonly between 0 and 1. This approach not only accelerates convergence during model training but also improves data visualization. It also enhances the modeling of attacks and anomalies in IoT environments [22]. Equation 4 represents the computation of normalization.

$$X' = \frac{X - Xmin}{Xmax - Xmin} \quad (4)$$

X is the original data value, Xmin and Xmax are the minimum and maximum values in the data, respectively, and X′ is the normalized value, which lies between 0 and 1.

3.5.3 Feature Filtering using City Block Distance:

Feature selection using city block distance [23] identifies a subset of relevant features from a larger dataset to improve model performance, reduce overfitting, and enhance interpretability. The method measures the distance between candidate features and targets, which are provided in the dataset, and selects top features such as seq, sport, max, dport, standard deviation, state number, min, category, and subcategory based on low distance values. After computing the city block distances, features with the lowest distance values are selected. Equation 5 represents

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the computation of city block distance, which is defined as the sum of the absolute differences of their Cartesian coordinates.

$$\mathbf{U}\ (\boldsymbol{\alpha}, \boldsymbol{\beta}) = \sum_{p=1}^{v} |\boldsymbol{\alpha}\mathbf{k} - \boldsymbol{\beta}\mathbf{k}| \qquad (5)$$

Here, α represents a candidate feature, and β is the target.

3.5.4 Attack detection using Deep Maxout Network:

As IoT devices are more widely used in construction sites for real-time monitoring, it is crucial to ensure data integrity and protection. A Deep Maxout Network (DMN) [24], is used to identify attacks in the embedded Internet of Things. A DMN is an Artificial Neural Network (ANN) that maximizes representational capacity and model performance by utilizing the Maxout activation function. More flexibility in creating decision boundaries and better fitting intricate, non-linear relationships in the data is made possible by the Maxout function, which returns the maximum over a set of linear transformations. The performance of intrusion detection is improved by using HSOA algorithm.

4. Summary of the Findings

4.1 Evaluation of Mobile Net and Deep Residual Network for object detection and classification in IoT-enabled construction safety monitoring.

Roboflow provides the Construction Site Safety Image Dataset, which consists of ten classes ('Hardhat’, Mask’, O-Hardhat', 'NO-Mask', 'NO-Safety Vest', 'Person', 'Safety Cone', 'Safety Vest', 'machinery', 'vehicle') and YOLO-formatted 2801 images. The 73% images are used for training, 16% for validation, and 11% for testing.

This section elaborates on the evaluation of the proposed MR NET model's result for classifying objects in a construction safety monitoring system using the Internet of Things. It focuses on

the precision and reliability of MR Net's capabilities across different experimental perspectives.

The working of the model is analyzed using the evaluation criteria accuracy, TPR, TNR, and NPV.

4.1.1. Comparative model performance

To assess the efficiency of the MR Net model, it is compared with YOLOv5x [25], IoT JFML [26], ResNet [27] , and LSTM+MDN [28] architectures. It helps to identify strengths, weaknesses, and practical reliability. Figure 2 represents the performance assessment of MR Net model used for Object Classification.

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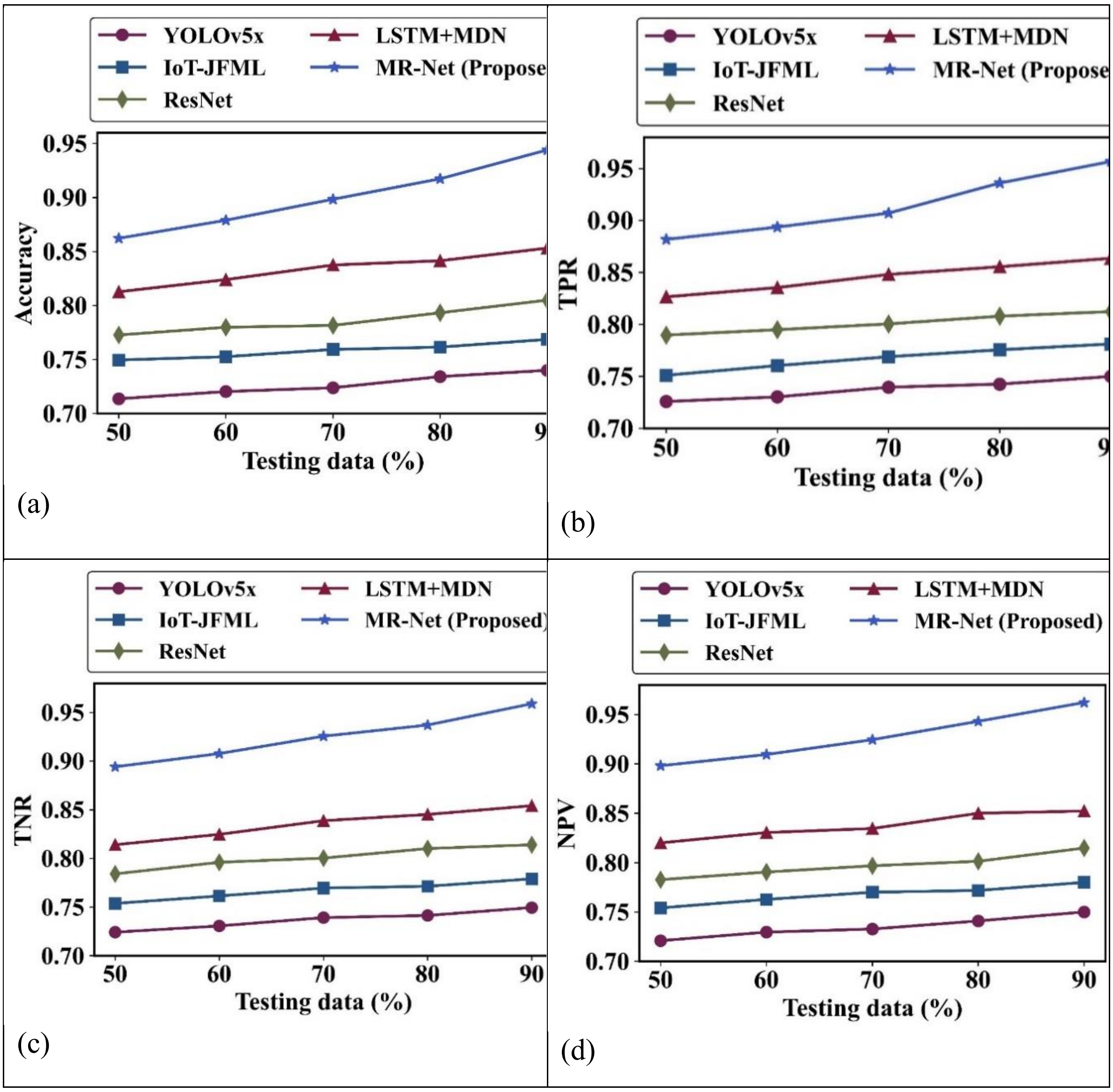

Figure 2. Performance assessment of the MR Net model for Object Classification

Figure 2 (a) shows the comparison of five models as the testing data increases from 50% to 90%. Then, MR Net achieves the highest accuracy, increasing from 0.86 to 0.94, while conventional schemes such as YOLOv5x, IoT-JFML, ResNet, and LSTM+MDN show improved performance, at 0.73, 0.76, 0.80, and 0.85, respectively. This demonstrates MR Net's strength when handling a large volume of data.

Figure 2 (b) illustrates the comparison of the True Positive Rates of five models, ranging from 50% to 90%. MR Net achieved the highest TPR from 0.88 to 0.96, while other models like YOLOv5x, IoT-JFML, Res Net, and LSTM+MDN showed improvements of 0.74, 0.78, 0.81,and 0.86 respectively.

Figure 2 (c) demonstrates the True Negative Rate of MR-Net. With 90% of testing data, MR-Net achieves 0.95, which is comparable to the performance enhancements of preceding

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strategies YOLOv5x, IoT-JFML, ResNet, and LSTM+MDN observed 0.74, 0.77, 0.813and 0.85%.

Figure 2 (d) represents the NPV of five models. By taking testing data=90%, MR-Net with NPV gained 0.96, while comparing the old models like YOLOv5x, IoT-JFML, ResNet, and LSTM+MDN accomplished 0.75,0.78, 0.81, and 0.85.

Table 1. Performance of MR- NET Models

Evaluation Conditions	Analysis Metrics	YOLOv5x	IoT-JFML	Res Net	LSTM+MDN	Proposed MR-Net
Testing data=90%	Accuracy	0.73	0.76	0.80	0.85	0.94
	TPR	0.74	0.78	0.81	0.86	0.95
	TNR	0.74	0.77	0.81	0.85	0.95
	NPV	0.75	0.78	0.81	0.85	0.96
	PPV	0.74	0.78	0.83	0.88	0.98

Table 1 compares the performance of five models: YOLOv5x, IoT-JFML, ResNet, LSTM+MDN, and MR-Net. These models were evaluated based on various metrics, including Overall Accuracy, True Positive Rate (TPR), True Negative Rate (TNR), and Negative Predictive Value (NPV). The assessments were conducted using testing data with a 90% confidence level. All performance measures consistently indicate that MR-Net outperforms the other models.

4.2 Performance Assessment of the HSOA-Enabled DMN Network for Intrusion Detection in IoT-Driven Construction Safety Monitoring

The Cyber Range Lab (UNSW Canberra) produced the Bot-IoT dataset, which is an open-source dataset for studying IoT security in botnet attacks and intrusion detection systems. The dataset contains realistic IoT network setups for recording both regular and malicious (botnet) traffic. It combines typical network behavior with numerous types of attacks, like DDoS, DoS, scanning, and botnet activities. It comes in several formats, including CSV, and organizing it by attack type or subtype makes it easier to label training ML models. Therefore, Bot-IoT is crucial for testing and evaluating IoT-based security models and algorithms that perform intrusion and anomaly detection.

4.2.1 Comparative Evaluation

This section compares different approaches to one another based on important performance measures. The examination of the methodologies will encompass 4D BIM-based, ML, NRO_SVM [29], EBWO-HDLID [30], and the suggested HSOA_DMN. The trials would employ training data sizes of 50% and 90% to examine the performance trends. Figure 3 represents the performance evaluation of the HSOA_DMN Model for Intrusion Detection.

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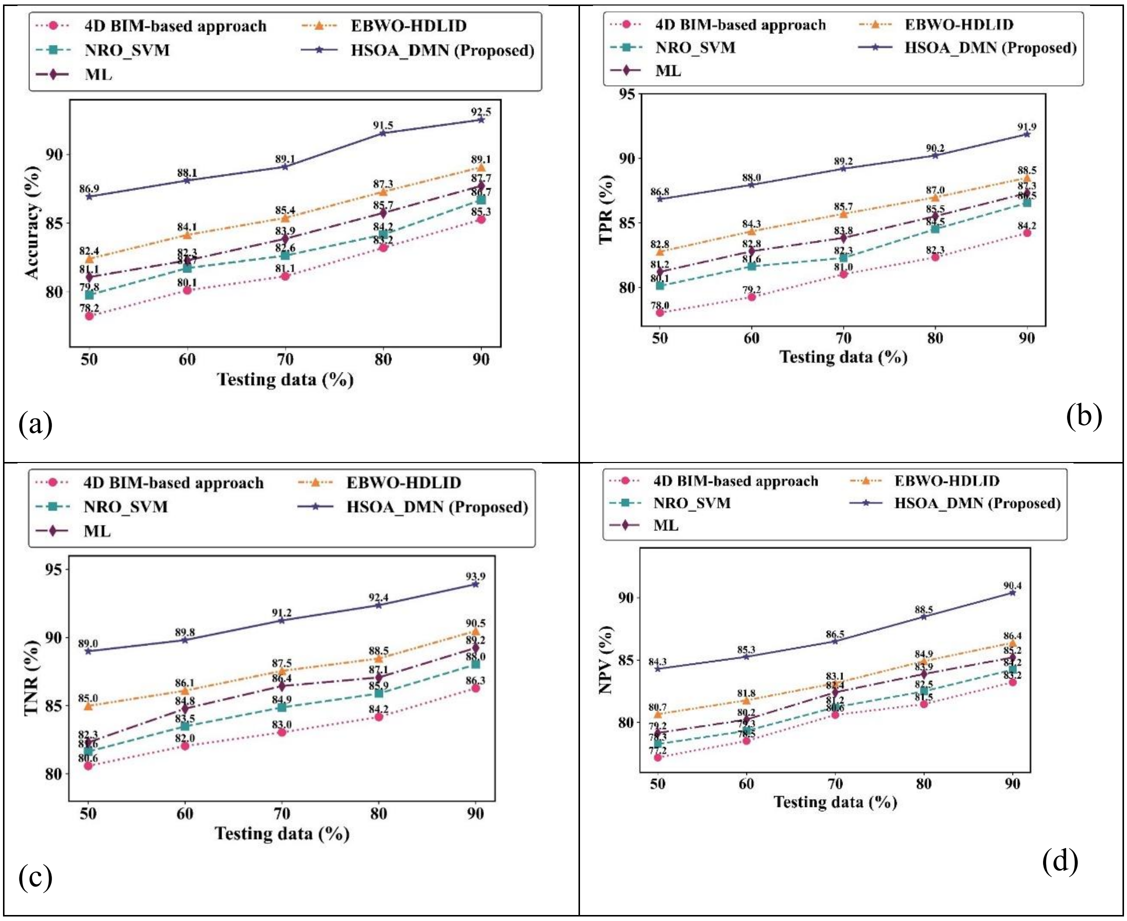

Figure 3. Performance Evaluation of HSOA_DMN Model for Intrusion Detection

Figure 3 (a) displays the performance of five intrusion detection models as testing data increases from 50% to 90%, with the proposed HSOA_DMN consistently outperforming the others. HSOA_DMN achieves 86.9% accuracy and increases to 92.5%, showing superior generalization, while EBWO-HDLID and ML peak at 89.1% and 87.7%, respectively.

Figure 3(b) indicates the TPR performance of five different methods as the percentage of testing data increases from 50% to 90%. The proposed HSOA_DMN approach consistently achieves the highest TPR, rising from 86.8% to 91.9%, outperforming all other methods across all test sizes.

Figure 3(c) illustrates the TNR performance across five different methods, where testing data ranged from 50% to 90%. When the data is 90%, HSOA_DMN with TNR achieves 93.9%, while conventional schemes such as 4D BIM, NRO-SVM, ML, and EBWO-HDLID gain performance of 86.3%, 88%, 89.2%, and 90.5%.

Figure 3(d) designs HSOA_DMN using NPV. When testing data =90.4%, HSOA_DMN with NPV achieved 88.53%, while conventional schemes like 4D BIM, ML, NRO_VSM, EBWO-HDLID, HSOA_DMN gained performance of 83.2%, 84.2%, 85.2%, 86.4% respectively.

Table 2. Performance of HSOA –DMN Network for Intrusion Detection

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Approaches	Metrics/ Methods	4D BIM-based approach	ML	NRO_SVM	EBWO-HDLID	Proposed HSOA_ DMN
Testing data =90%	*Accuracy (%)*	85.32	86.78	87.70	89.10	92.51
	NPV (%)	83.21	84.24	85.21	86.48	90.43
	PPV (%)	83.45	85.20	86.81	87.82	91.50
	TNR (%)	86.32	88.02	89.24	90.57	93.91
	TPR (%)	84.22	86.55	87.70	89.10	91.90

Table 2 highlights the performance of five alternatives (4D BIM-based approach, ML, NRO_SVM, EBWO-HDLID, and the proposed HSOA_DMN) across various metrics, evaluating their performance with two different sizes of testing data. When using 90% of the data, all approaches demonstrated improved overall performance. Among them, HSOA_DMN achieved the highest scores, with an accuracy of 92.56%, a negative predictive value (NPV) of 90.44%, a positive predictive value (PPV) of 89.77%, a true negative rate (TNR) of 93.90%, and a true positive rate (TPR) of 91.90%. This method consistently outperformed the others, particularly excelling in TNR.

4.3 Precision, Recall, and Confidence Curve Analysis

To evaluate the performance of the object detection model, various graphs are generated during the testing process. These visual representations help in understanding model accuracy, precision, recall, and error patterns.

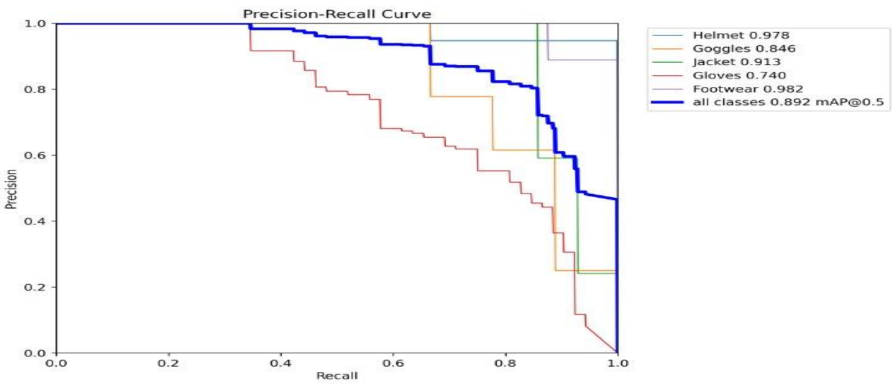

Figure 4: Precision-Recall curve for the construction worker dataset

Figure 4 represents the curve highlighting the precision and recall trade-off of an object detection model against different classes of PPE. It includes a helmet, goggles, a jacket, gloves, and footwear, among others. Each curve represents the precision-recall for individual classes, with associated Average Precision (AP) values specified in the legend. For example, the model has its best AP for the footwear (0.982) and helmet (0.978), indicating accurate detections in

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these categories. Jackets and goggles follow with AP scores of 0.913 and 0.846, while the lowest result, showing the minimum performance at 0.740, is for gloves.

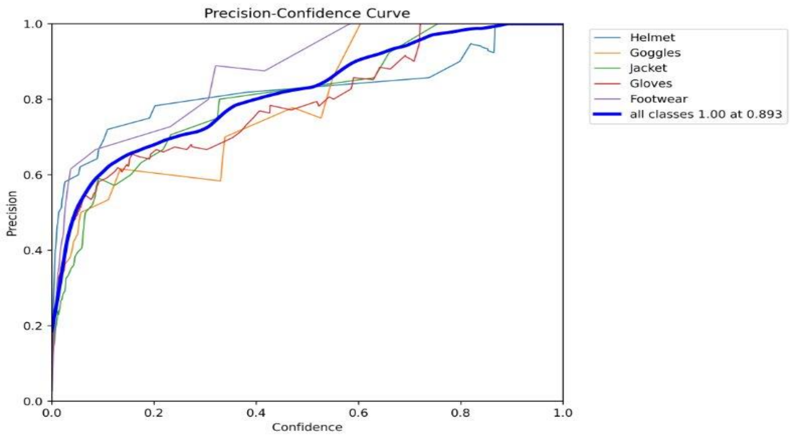

Figure 5: Precision-Confidence curve for the construction worker dataset

Figure 5 illustrates the curve highlighting the precision and recall trade-off of an object detection model against different classes of PPE. It includes a helmet, goggles, a jacket, gloves, and footwear, among others. Each curve represents the precision-recall for individual classes, with associated Average Precision (AP) values specified in the legend.

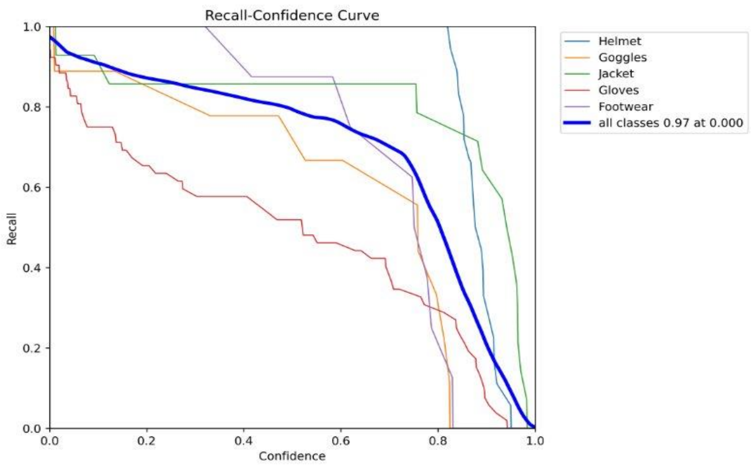

Figure 6: Recall-Confidence curve for the construction worker dataset

Figure 6 displays the Recall-Threshold curve, demonstrating the relationship between the recall of the object detection model and varying confidence thresholds across different PPE classes, such as helmets, goggles, jackets, gloves, and footwear. Every color line corresponds to a specific class, but the bold blue line presents the overall recall trade-off across all classes.

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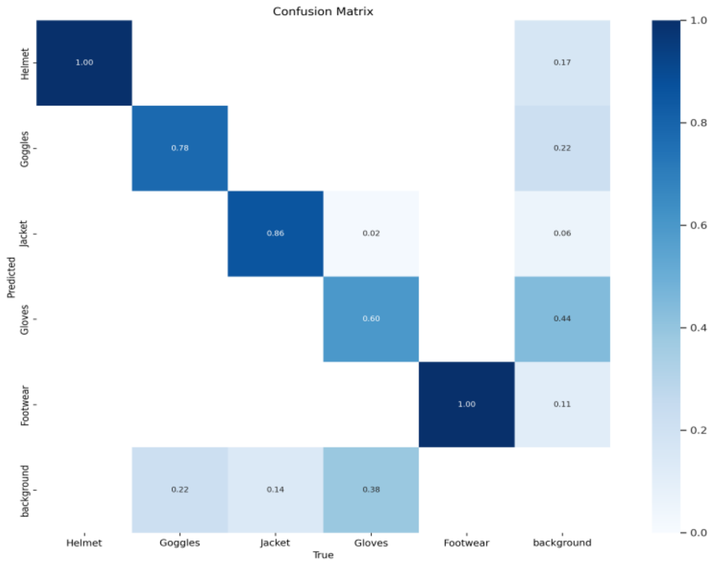

Figure 7: Confusion matrix on construction-site-safety-image-dataset

Figure 7 presents a Confusion matrix on the construction-site-safety-image-dataset. In a construction-site safety image dataset, the confusion matrix would most likely show how well the model can differentiate safety equipment or categories: helmets, goggles, jackets, gloves, and footwear, to name a few, from the images.

5. Conclusion

This research presents an IoT-enabled framework for construction safety monitoring, which employs MobileNet and a Deep Residual network for Object detection and classification of objects. The MRNet model is compared with already existing models, such as YOLOv5x, IoT-JFML, ResNet, and LSTM+MDN, using metrics like accuracy, TPR, TNR, PPV, and NPV. The comparison indicates that MR-Net consistently yields better results as compared to other models, signifying better accuracy, robustness, and generalization in older training data sets, thus making it very suitable for real-time IoT-enabled construction site safety monitoring and compliance enforcement.

This model also improves intrusion detection on construction sites using a Hiking Skill Optimization Algorithm (HSOA). Additionally, Deep Max Out Network (DMN) enhances feature extraction and increases classification accuracy. It has been identified that HSOA_DMN has accomplished an accuracy of 92.51%, NPV of 90.43%, PPV of 91.50%, TNR of 93.91% and TPR of 91.90%.

6. Future Scope

The performance of object classification models, such as MR-Net, can be improved using several advanced approaches within the complex setting of construction sites. The primary goal is to improve accuracy, flexibility, and real-time alertness for the different IoT-integrated systems. To improve the identification of small or overlapping safety gear, more sophisticated

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model architecture adjustments will use multi-scale feature fusion and attention mechanisms. Moreover, model design optimization for accuracy and device fit can also be achieved through Neural Architecture Search (NAS). The use of CutMix, MixUp, GAN-based synthetic data generation, and self-supervised methods will greatly improve a model's generalization and robustness.

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Conflict of Interest:

Authors here by declared that, there is no conflict of interest.

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