Journal of Asian Scientific Research
ISSN(e): 2223-1331
ISSN(p): 2226-5724
DOI: 10.55493/5003.v16i1.5867
Vol. 16, No. 1, 113-127.

URL: www.aessweb.com

YOLOv8-based detection of protection emblems for humanitarian safety applications

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Article History
Received: 19 September 2025
Revised: 24 December 2025
Accepted: 9 January 2026
Published: 2 February 2026

Keywords
Computer vision
Deep learning
Humanitarian aid
ICRC
Protection emblem detection
YOLOv8.

ABSTRACT

The research paper provides a novel application of YOLOv8 for the detection of protection emblems in the International Federation of Red Cross and Red Crescent Societies (IFRC), aimed at enhancing humanitarian safety in conflict zones. The authors created a dataset of 36 images from various sources, with 25 used as training data, 4 as test data, and 7 as validation data. Custom annotation was performed through Roboflow, and YOLOv8 was employed for detection. The findings revealed a maximum F1 score of 0.9 at a confidence threshold of 0.85. The confusion matrix indicated a detection rate of 0.91 on real positive cases, particularly in the successful recognition of the class of significance, which is IFRC_Symbols. This research implemented object detection in a sensitive humanitarian context, connecting artificial intelligence (AI) with humanitarian operations, thereby helping to reduce the risk of misidentification of symbols during relief operations. In the preliminary stage, the authors used a small dataset, creating opportunities for future researchers to expand the dataset and implement the model in real-time scenarios, including other environmental factors. The decision to enhance emblem detection facilities aligns with the mission of the IFRC to assist people in need safely and efficiently without jeopardizing the efforts of its diligent employees.

Contribution/ Originality: This work makes a significant contribution to the existing literature by integrating the concept of computer vision with humanitarian security applications through the implementation of an emblem detection system based on YOLOv8. It is among the relatively few studies that have explored AI-assisted identification of defense symbols, achieved robust detection rates and established a foundation for the development of real-time humanitarian aid solutions.

1. INTRODUCTION

Computer vision is the branch of AI that enables computers to work with and understand visual information collected from the physical world [1]. Computer Vision uses algorithms and pattern recognition to allow machines to process and interpret images or videos, which is the way that human beings perceive the visual world. It is used in a wide variety of fields, including face recognition, object detection, medical image analysis, and self-driving cars [2]. Computer vision focuses on enhancing machines in their ability to extract visual data with the view of enabling them to interact intelligently with the environment [3]. Our daily lives are now part of the omnipresence of visual information with this innovation in technology. Since surveillance cameras and medical imaging, the growth of Computer Vision technologies has already made a major shift in our perception and interaction with the world through applications of augmented reality. Nonetheless, this data flood of visuals also comes with new challenges regarding privacy, security, and ethical concerns like never before [4]. The Protection Emblem Detection project is a high-profile project targeting the multi-dimensional problems encountered concerning the security of civilians in a war-afflicted nation [5]. The given research paper examines the complexity of the how and why of the project, being interested in its importance to safeguard people, guarantee their safety, and provide rapid help to civilians in war-torn areas.

Going further into the topic of interest, the Protection Emblem Detection and its association with the Protection Emblem engage in ferreting and digging into the technologies, methodologies, and strategies used by the International Committee of the Red Cross (ICRC) to protect and locate persons in conflict areas [6]. Also, it is necessary to comprehend the importance of the Protection Emblem in this regard. The International Committee of the Red Cross (ICRC) is a humanitarian organization that operates worldwide, providing assistance and protection to victims of armed conflicts and other violent incidents. It was founded in 1863, and its headquarters are in Geneva, Switzerland [7]. The ICRC belongs to the International Red Cross and Red Crescent Movement that encompasses national Red Cross and Red Crescent Societies and the International Federation of Red Cross and Red Crescent Societies. Under the principles of humanity, impartiality, neutrality, independence, voluntary service, unity, and universality, the ICRC is committed to alleviating human suffering in wars and other violent events. Operating with strict neutrality, it provides humanitarian aid, including medical care and essential services, to victims regardless of affiliation. The organization plays a crucial role in protecting civilians, prisoners of war, and non-combatants by promoting adherence to international humanitarian law (IHL) and advocating for the rights of those affected by conflict. The ICRC strives to provide access to affected groups of people by making a commitment to dialogue with governments, armed forces, and non-state armed groups. Through partnerships with other organizations worldwide, notably the National Red Cross and Red Crescent Societies, the ICRC provides coordination and supplements humanitarian efforts in other parts of the world, with its headquarters located in Geneva, Switzerland [8]. The crucial points in the mission and the work of the ICRC are:

- **Humanitarian Action:** ICRC provides humanitarian assistance to people involved in armed conflicts and other violent incidents. This assistance includes medical services, food, water, shelter, and support in reuniting families divided by war.
- **Neutrality and Impartiality:** The ICRC focuses on the concepts of neutrality and impartiality, i.e., it does not intervene in disputes, and it does not offer its services selectively, regardless of the need.
- **Protection of Civilians:** The ICRC guarantees the safety and welfare of civilians, prisoners of war, and other people who are not involved in hostilities. This involves advocating for and enforcing international humanitarian law.
- **Promotion of International Humanitarian Law (IHL):** The ICRC has a significant role in facilitating awareness and compliance with international humanitarian law, which controls the behavior of hostilities and aims to protect civilians not involved in hostilities.
- **Visiting Detainees:** One of the unique roles of the ICRC is to monitor detainees' conditions in detention, ensuring that they are treated humanely and in accordance with international standards.

The group operates worldwide in the aftermath of natural disasters, war zones, and other humanitarian situations. The ICRC is an international law organization recognized as an independent and specialized institution, and its work is guided by the principles of universality, humanity, impartiality, neutrality, independence, and volunteer service [9].

ICRC is known to have iconic emblems, including the Red Cross, Red Crescent, and Red Diamond. The history of the development of these symbols is a chapter by itself, vividly presented in the geopolitical and ethnogeographical landscape of the world [10]. Figure 1 illustrates the ICRC emblems used by the organizations.

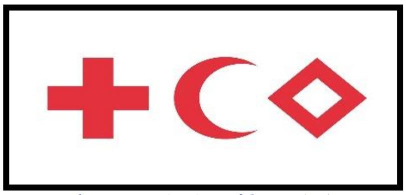

Figure 1. ICRC Emblems [11].

The growing use of technologies of AI and computer vision in the humanitarian context has created the prospects of improving safety, coordination, and situational awareness. However, protection emblem recognition in automated mode is not yet a thoroughly investigated research area, including the emblem use of the IFRC. The current literature in computer vision is mainly focused on generic object recognition, medical imaging, and surveillance, with little focus on emblem recognition in humanitarian settings. The current work aims to fill this gap by suggesting a YOLOv8-based emblem detection framework that would be able to identify IFRC symbols. In this way, the aim of the research is to illustrate the possibilities and outcomes of deep learning-based vision systems in emblem recognition and further the technical literature on AI-based detection and the practical purpose of improving safety measures in humanitarian activities.

1.1. Motivation

The motivation behind this exploration is founded on the fact that the pressure to strengthen the security of humanitarian workers operating in crisis areas is increasing. The rapid recognition of identified protection symbols is essential in field operations to prevent avoidable damage and ensure compliance with international humanitarian law. However, manual monitoring is often ineffective and prone to human error, especially in dynamic or risky environments. Therefore, AI-powered visual recognition systems are an attractive solution. Using YOLOv8 to identify emblems, this paper aims to demonstrate how automated recognition can enhance operational safety, improve decision-making, and assist organizations like the IFRC in addressing humanitarian missions with safety and technological advancement. The research paper seeks to highlight the positive aspects of human safety and the potential of technological progress to reduce the number of innocent lives at risk.

2. LITERATURE REVIEW

Robotic identification of symbols, logos, and protection emblems occupies the boundary between logo recognition, small-object recognition, and the proactive use of AI in its humanitarian applications [12]. The role of varied and heavily annotated datasets and custom architectures for small and highly varying targets is highlighted in surveys of logo and emblem recognition; these papers describe the nature of datasets, typical detection pipelines, and outstanding challenges such as occlusion, scale changes, and small training domains [13]. Studies that particularly examine the issue of small-object and symbol detection using contemporary YOLO variants are pertinent to the protection-emblem detection directly. There are a number of new works that have assessed or optimized YOLOv8 and its architectures to achieve better performance on small objects and real-time operation [14]. Indicatively, Khalili and Smyth [15] suggested SOD-YOLOv8, which enhances feature fusion in small-object detection directly and realistically overcomes the scale and feature-resolution dilemmas of emblem detection. In addition to pure detection, the literature on AI in humanitarian action and emblem policy indicates that essential ethical, legal, and operational issues are raised. Both the potential of AI to enhance situational awareness and the threats to the safety of the individuals under protection and humanitarian practitioners are addressed in the ICRC and International Review contributions, such as the misuse of symbol-detection systems and the need for privacy and governance. These policy-oriented writings highlight the importance of integrating technical development with control, regulation, and oversight to prevent misuse during the development of emblem-recognition tools that can be used operationally [16, 17]. The literature on logo detection and brand protection offers some useful ways to work with small datasets based on careful augmentation, synthetic data generation, transfer learning, and domain adaptation, which the authors suggest as directions for future research and as methods to enhance generalization to field data. Object detection is an ever-changing field that has seen the development of various deep neural networks with high precision and real-time performance. Previous versions like YOLOv3 and YOLOv5 provided effective single-stage detectors capable of achieving real-time detection with comparatively low computational burden. More importantly, two-stage detectors such as Faster R-CNN are more accurate with the use of region proposal networks, but at the expense of increased latency. Backbones based on ResNets have also been extensively used in feature extraction, offering strong gradient flow and depth scalability. Researchers have compared YOLO and Faster R-CNN in object detection tasks across various fields and noted that the latter is faster, giving it an advantage in real-life applications [18]. Likewise, architecture models of MobileNet and EfficientDet have been optimized for edge computing platforms. Nevertheless, the use of these models in the context of humanitarian or protection emblems is not extensive. A comparative summary of major object detector frameworks, including their accuracy, inference speed, and common usages, is shown below in Table 1:

Table 1. Comparative analysis with various models.

Model	Architecture type	Average mAP (%)	Inference speed (ms/frame)	Strengths	Limitations
YOLOv5	Single-stage CNN	86–89	~10–15	Fast, lightweight, high recall	Slightly lower precision in cluttered scenes
Faster R-CNN	Two-stage CNN	89–92	~60–120	High accuracy, region proposals	Computationally heavy
ResNet	Feature extractor	Varies	–	Strong feature hierarchy	Not a detector by itself
YOLOv8 (Proposed)	Single-stage CNN	90–94	~8–12	Balanced speed and accuracy, robust real-time detection	Limited validation in humanitarian contexts

3. METHODOLOGY

In order to meet the objectives of the study, the authors embraced the power of the latest computer vision technology that entails training machines to perceive and comprehend visual data. Specifically, the authors have applied the YOLO (You Only Look Once) technique, which is one of the state-of-the-art object recognition methods. YOLO is also recognized for its effectiveness and accuracy in recognizing and localizing objects in an image or video frame in real-time, which makes it a useful tool in our detection [19]. The authors had taken into consideration the following techniques to be adopted in this study. Figure 2 gives the proposed study methodology.

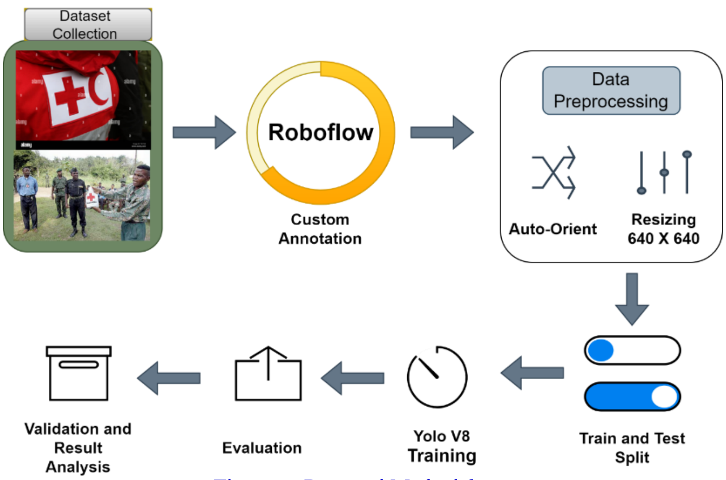

Figure 2. Proposed Methodology.

3.1. YOLOv8

A real-time object detection method called YOLO (You Only Look Once) was trained using the 80 classes found in the COCO dataset. It takes a picture and uses a grid to forecast the class probabilities and bounding boxes of each grid cell. YOLO achieves its results by using a single forward pass through the neural network to directly regress the bounding box coordinates and class probabilities from the full image. The nicest thing about YOLO is that the algorithm can be readily tweaked to forecast the class of your choosing, in this case, Protection Emblems. YOLOv8 is the latest iteration of the base YOLO model. The v8 stands for version 8 [20].

Backbone, Neck, and Head are the three main structural components of YOLOv8.

A backbone is the first element to be trained during the training of a neural network to extract features of an image as the input. A convolutional neural network (CNN) architecture, such as ResNet, Darknet, or MobileNet, is usually used to capture the hierarchical properties of the input image. It is essential when attempting to figure out the spatial properties of picture objects and contextual information. The neck is an intermediate component of the network that is after the backbone. It also performs fine-tuning of features that have been extracted by the backbone. It frequently adds more convoluted layers or other operations to provide a better representation of features and to represent more abstract information. The neck serves the purpose of merging and combining characteristics of various scales and resolutions and assists the network in making more accurate decisions regarding the locations and the classes of objects [21]. Finally, the network enters its head, which makes predictions based on the improved information that is retrieved by the neck. The YOLO head, typically consisting of either fully connected or convolutional layers, produces bounding box coordinates, object class probabilities, and the rest of the relevant information of each grid cell in the result. It yields a tensor that contains the final predictions, which are the object detection bounding boxes and classification scores. Figure 3 shows the YOLO version 8 architecture.

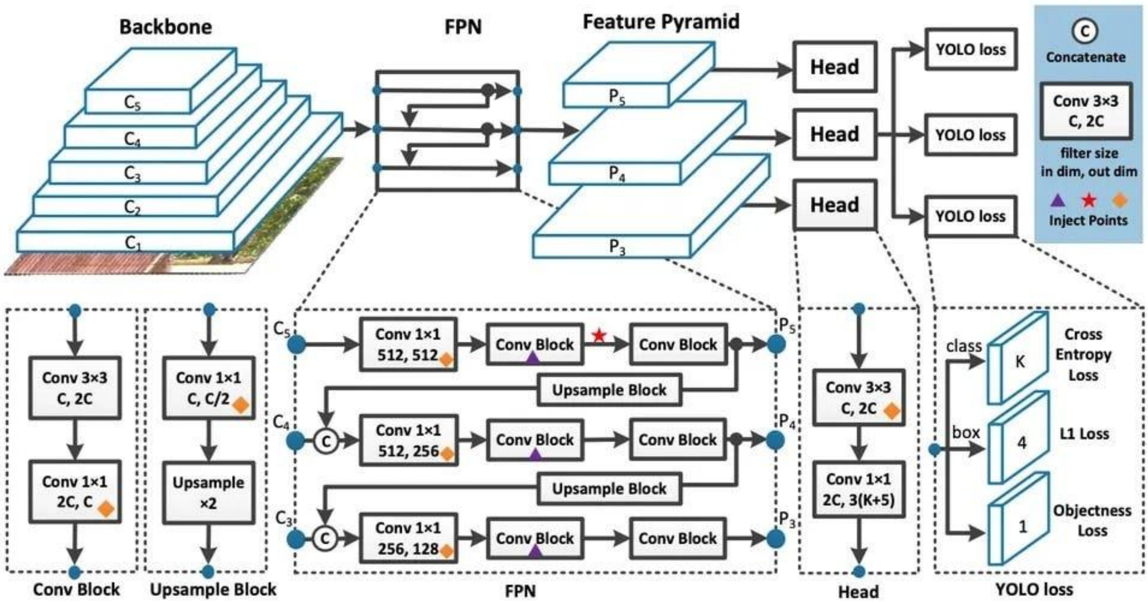

Figure 3. YOLO V8 Architecture [21].

3.2. Roboflow

Roboflow is a comprehensive Computer Vision platform that simplifies the training and deployment of machine learning models for image recognition tasks. It features a user-friendly interface that facilitates data preprocessing, annotation, and model training, making it an essential tool for Computer Vision researchers. Roboflow is an open-source system offering various services and tools to manage and prepare visual data for projects, owing to its efficient workflow and integration capabilities [22]. This research has been utilized by the authors to annotate classes and augment images. Clearly, augmentation is a method that involves numerous preprocessing and data preparation procedures for visual data. In this case, the authors resized all images to 640x640 pixels and auto-oriented the images. The customization was applied to only one class, designated as IFRC_Aid.

3.3. Dataset Creation

The dataset was meticulously curated by manually selecting specific images from Google that depicted individuals actively participating in humanitarian aid efforts associated with the International Committee of the Red Cross (ICRC). This selection process involved a hands-on approach, as there was no readily available consolidated image data about the desired criteria on the web. Each image was individually reviewed and selected to ensure the dataset accurately represented the context of people providing aid in ICRC-related activities. This manual curation was essential to guarantee the dataset's relevance and authenticity for the project's intended purposes. A glimpse of the images collected for the experiment is represented in Figure 4.

Figure 4. Glimpse of dataset images.

This research is currently a prototype with the potential to evolve into a larger initiative, but the authors have utilized only 36 images. Twenty-five (69%) of these images were used for training, while the remaining four (11%) and seven (19%) were used for testing and validation, respectively. The authors executed the YOLOv8 model for 70 epochs, meaning the learning and training were conducted over 70 iterations.

3.4. Preprocessing

During our preprocessing step of the image data, we have adopted considerable measure to boost the strength and effectiveness of our model. With the set of techniques of augmentation implemented, such as the highly-performing auto-orient method, we will be assured of having an array of views given to the data, which will improve the generalization capacity of our model. In addition, we have made the image sizes uniform by co-resizing them to 640x640 pixels [23]. This induces consistency in the dataset and speeds up the computation processes, making them faster in training and inference. The careful execution of these preprocessing procedures helps our machine-learning image-based model to achieve overall performance and reliability, enabling it to perform in a variety of situations with increased accuracy and speed.

The Figure 5 images provide a glimpse of how well our model performed in the training phase:

3.4.1. Training

Before **After**

Figure 5. Training Images [24].

It not only performed well on the training data with only 25 images, but it also performed exceptionally well on the validation data.

3.4.2. Validation

In the validation phase, the best.pt weights generated during training are used. Validation phase images are represented in Figure 6.

Before **After**

Figure 6. Validation Phase.

1. **Model Evaluation and Analysis**

- **F1 Score:** It is a harmonic mean of Precision and Recall. It ranges from 0 to 1, where one indicates perfect Precision and Recall, and 0 indicates poor model performance.

  F1 Score = 2 * Precision * Recall/Precision + Recall

- **Confidence:** We can set the Confidence Threshold for our model to detect the custom object. It indicates how much confidence we want our model to have while detecting the custom object. Its value ranges from 0 to 1, where 1 means it is sure that it is detecting the custom class. For example, if we set 0.5 as the Confidence Threshold, that will imply that it will detect the custom class only when it is equal to or more than (>=) 50% sure of its detection.

- **Precision (P):** Precision is the ratio of true positive predictions to the total number of positive predictions. It measures the accuracy of the positive predictions.

  P = True Positives/True Positives + False Positives

- **Recall (R):** Recall is the ratio of true positive predictions to the total number of actual positive instances. It measures the ability of the model to capture all the positive instances.
  R = True Positives/True Positives + False Negatives
- **mAP (Mean Average Precision):** It summarizes a model's precision-recall performance across multiple confidence levels. An increase in mAP reflects improved overall model performance.
  mAP=$n1\sum i=1nAPi$
  APi = Average Precision for class i
  n = Number of classes or categories of object

4. RESULT ANALYSIS AND DISCUSSION

The analysis of the implemented protection emblem detection system within the International Federation of Red Cross and Red Crescent Societies (IFRC) underscores the significance of this study in advancing the capabilities of automated recognition and localization in diverse environments. The system's robust performance is evident by leveraging the YOLOv8 architecture and a meticulously curated dataset of 36 images, comprising 25 for training, 4 for testing, and 7 for validation. Custom annotation through Roboflow and evaluation metrics such as F1 score, recall, precision, and mean Average Precision (mAP) provide a comprehensive understanding of its effectiveness. It is noteworthy that the system has the highest F1 score (0.9) with a threshold confidence of 0.85; thus, the system is better at identifying IFRC protection emblems. These major metrics are analyzed in the following discussion with a special focus on their implications for the successful deployment of the system in a humanitarian mission.

4.1. F1 Score VS Confidence

The given data is a line graph that describes the correlation between the Confidence Threshold and the F1 score of one category, namely IFRC_Aid. The optimal F1 score is found at a Confidence Threshold of approximately 0.85, and the value is almost 0.9. This implies that the model, under such circumstances, presents optimal performance with regard to the correct prediction of the instances of the IFRC_Aid category. The analysis of the results, F1 Score vs. Confidence, is depicted in Figure 7.

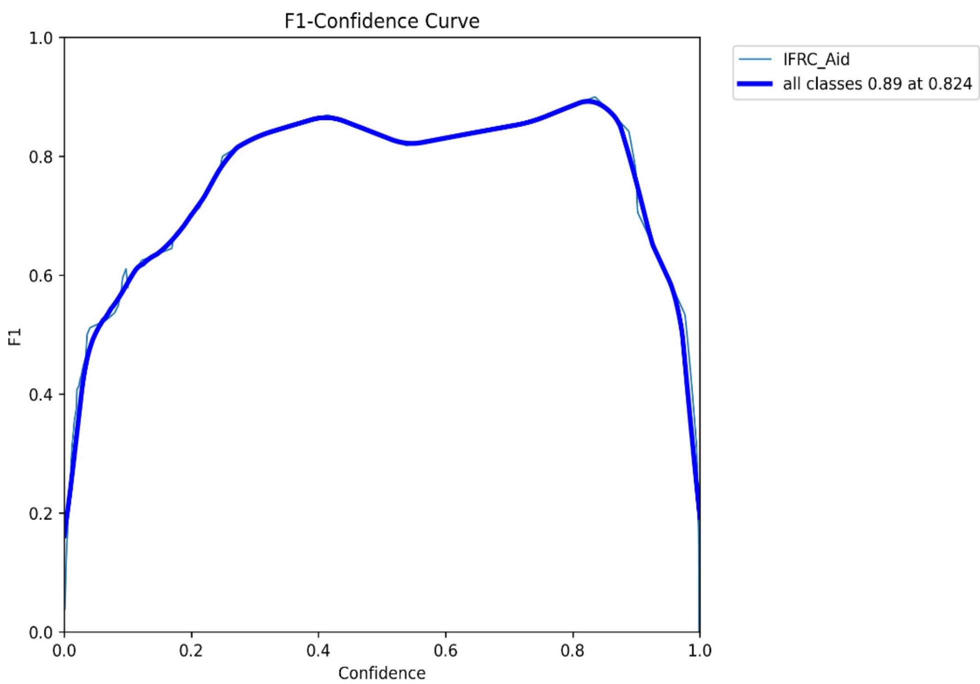

Figure 7. Result analysis of F1 Score vs Confidence.

4.2. Evaluation Metrics Analysis

The presented information is about a series of three graphs that illustrate the Precision, Recall, and mAP (mean Average Precision) metrics regarding the number of training cycles of a machine learning model. The key point to note is that as more epochs are taken, that is, there are more rounds of training on the data, a certain trend is observed in all the metrics. To begin with, the loss of the model is reduced, hence the model has an enhanced capacity to reduce errors. At the same time, Precision and Recall, the measures of the accuracy of positive predictions and the ability of the model to detect all the significant instances of a specific class, respectively, increase. Besides, the mAP, a single measure that is the overall indicator of precision and recall, has an upward tendency. This implies that as the model progresses through the epochs, it becomes more effective in minimizing errors, making accurate positive predictions, identifying relevant instances, and improving its performance, as displayed by Precision, Recall, and mAP values. Figure 8 shows the different evaluation metrics analysis.

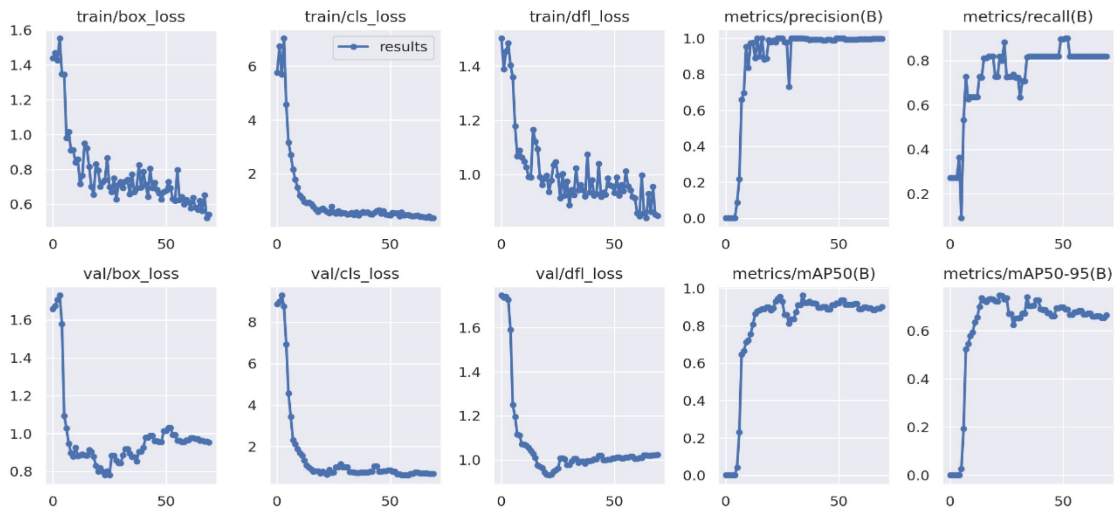

Figure 8. Summarization of Evaluation Metrics.

The given information implies that a heatmap of a confusion matrix has been analyzed, and the emphasis is on the particular class that is denoted as IFRC_Aid. The confusion matrix is a method applicable in classification functions to assess the efficiency of a machine-learning model by acknowledging its predictions and contrasting them with the true labels of the classes. The heatmap term suggests a graphical representation of this matrix, which tends to be color-coded to indicate various values.

In this respect, the heatmap indicates that the intersection of the class IFRC_Aid in the confusion matrix is 0.91. The value is linked to the number of True Positives, which is the number of cases when the model made a correct decision and categorized data points as belonging to the IFRC_Aid category. A True Positive, in this case, is when the model predicts a positive class, and the true class is also positive.

The 0.91 value indicates that the IFRC Aid category has a high proportion of correct identifications and demonstrates a high performance in recognizing instances of this category. The closer the value is to 1.0, the more accurate the model is in identifying positive instances. The heatmap representation can help evaluate and understand the model's performance across various classes quickly. In this example, the class is IFRC_Aid and the True Positive. Figure 9 shows the confusion matrix of TP of IRFC Aid.

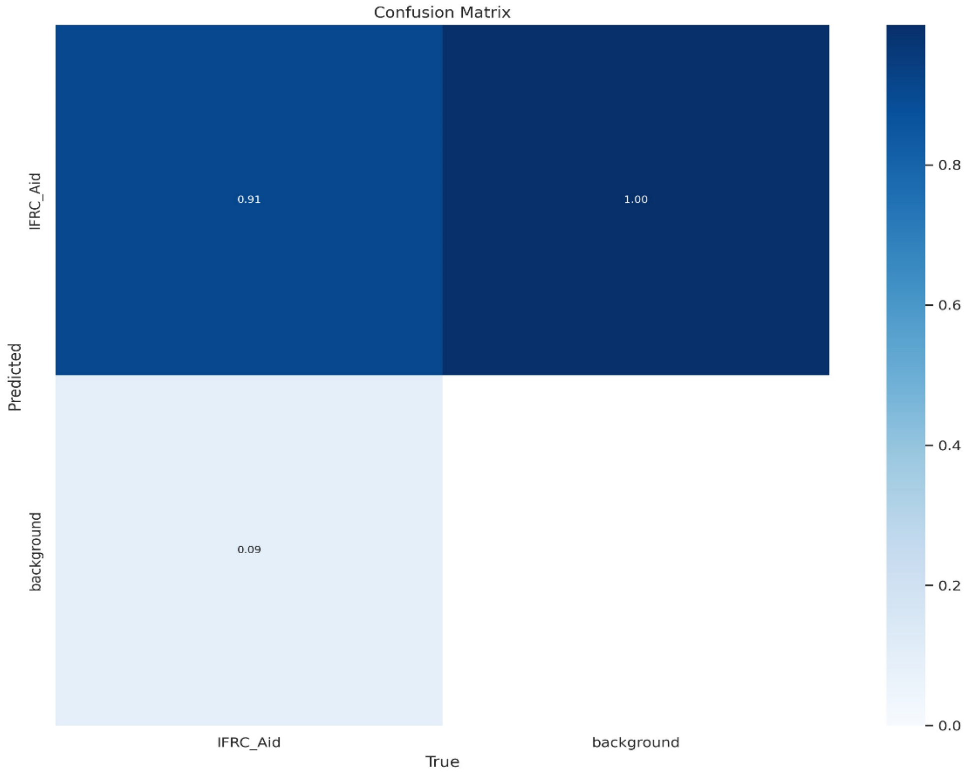

Figure 9. Confusion Matrix of TP of IRFC_Aid.

4.3. Overall Training and Validation Results

Its evaluation metrics showed that the model had high performance during the training phase. In particular, the model only had a small error of 0.99, which means that 99 percent of the positive predictions carried on throughout training were correct. The recall, which is the capacity of the model to recall positive cases correctly, was 0.81, and this means that 81 percent of the real positive instances were recalled successfully. The average precision (mAP), which is a holistic measure of precision over different levels of confidence, was achieved as 0.90 during training. This balanced performance indicates that this model was highly accurate and effective in differentiating positive instances throughout training.

During the next validation step, the robustness of the model continued. The accuracy remained very high, with 0.97 being an indicator that 97 percent of positive prediction instances made on validation were correct. The recall was the same as during training and was at 0.81, which shows that it has been used consistently to capture the actual positive instances. Moreover, the validation mAP of the model matched the training mAP of the model at 0.90, which supports the fact that the model is capable of supporting the balance in the precision-recall trade-off at some level of confidence. This performance measure consistency between the training and validation phases highlights the consistency and the generalization performance of the model outside the training data set.

5. LIMITATIONS

The Protection Emblem Detection project is one of the most unusual ones, as it represents a new way of implementing the idea of artificial intelligence for the well-being and security of war victims. However, there is an absolute necessity to examine the process of identifying some of the weaknesses that are inherent in the project. Despite the presence of the project-specific and highly motivated goals, it is possible to are certain limitations or limitations that cannot be neglected. These disadvantages can encompass numerous factors, such as technical, ethical, or unintended consequences of the application of AI to sensitive cases. Such issues as an inability to find protection emblems correctly or to adjust to dynamic and unpredictable conditions of the project war are examples of such issues.

Also, the ethical concern may be premised on privacy concerns, data security, or even the abuse of the technology. The comprehensive approach to the study of the positive and negative features of the Protection Emblem Detection project is essential to possess a balanced sense and manage all possible misgivings that might adversely affect its performance or ethical introduction.

The limitation of this is that it is on restricted data to train the model. The data employed is said to be small and not varied. It has comparatively little data, as well as the fact that it is not relevant in real time due to acquiring it via the internet. This will prove challenging given that learning of this model can only be done on a limited number of examples that may prove harmful to its ability to generalization and adapt to the dynamic and variable nature of a real-world scenario. Further, the data is not real-time, and the lack of responsiveness of the model to the changing conditions might result in poor performance and the credibility of the whole model.

The second significant shortcoming is associated with the fact that YOLOv8 is an undocumented framework. The fact that this model has not been recorded in a detailed manner also raises some concerns about its sustainability in the long term, since it may end up becoming obsolete or the authorities may become unwilling to support it. There are risks of the user being forced to use an older or less developed version of the YOLO model unless YOLOv8 is officially released. The potential switch to less popular versions would compromise the features, performance, and support by the community, and the sustainability of the project and its flexibility to changes in object detection technology in the future. It highlights the importance of good documentation to ensure the viability and availability of the chosen model for the Protection Emblem Detection project.

The third issue is to determine the effectiveness of the active Wi-Fi IP cameras that feature numerous cameras in a war-like situation. This fact is quite a setback since there are some difficulties in the process of keeping the operational Wi-Fi networks in such harsh conditions. Maintaining and installing a large number of IP cameras in war zones may be challenged by factors such as environmental and physical damage, as well as potential security threats. The probability of a stable and constant Wi-Fi connection under such scenarios raises doubts about the entire project implementation, since the solution relies on a network infrastructure that may prove challenging to implement and maintain in an environment that is hostile and unpredictable. This aspect also highlights the logistical and technical problems associated with the installation and servicing of the required camera infrastructure in war zones.

The fourth issue is that there exists a threat of the abuse of the AI-based Protection Emblem detection system that can be applied to locate the members of the International Federation of Red Cross and Red Crescent Societies (IFRC). Such abuse is life-threatening, and the possibility of the system being employed to trace the location of the IFRC workers is that it can be targeted by particular attacks. The fear is that a technology that is bound to enhance safety and protection shall be used against its target beneficiaries. It is dictated by the overpowering importance of the necessity to provide good security measures and ethical principles in designing and deploying AI systems, among them being the scenario where the misuse of this technology can lead to catastrophic consequences to the humanitarian operations and the well-being of aid workers. This issue must be addressed by a complicated solution to defend the system against any potential malicious intent and ensure the use of this system follows the moral principles and the purpose of humanity.

6. IMPLICATIONS OF THE STUDY

The Protection Emblem Detection project has serious implications for research as well as practical humanitarian operations. Technologically, this work demonstrates that it is possible to use advanced object detection architectures like YOLOv8 to identify humanitarian protection symbols with a high level of precision. The combination of visual recognition-based AI systems and humanitarian missions can help to enhance situational awareness, real-time safety evaluation, and adherence to International Humanitarian Law (IHL).

In practical terms, the given solution can benefit organizations like the ICRC and IFRC by allowing the swift recognition of protection signs within field operations, which could reduce incidental damage to civilians and humanitarian workers to a minimum. The model also has the potential to be used as a blueprint for the next generation of emergency response models that combine machine learning and computer vision to detect threats quickly.

Policy and ethics-wise, this study supports the need to create AI systems that can maintain the standards of neutrality, privacy, and security in the sensitive humanitarian setting. Such systems should be implemented under ethical guidelines that would help to ensure that technological tools are not used against humanitarian values.

7. CONCLUSION

In summary, the Protection Emblem Detection Project, which is an example of ICRC assistance and intervention, is guided by the concept of a developed algorithm. YOLOv8 is applied to enhance the process of recognizing and localizing protection emblems under varying circumstances. The prospects of such an innovative application of computer vision technology are immense and can improve the efficiency and effectiveness of humanitarian operations, particularly in conflict-afflicted and crisis-prone regions.

One of the positive aspects of this project is the potential to simplify aid activities. YOLOv8 enables quick and effective identification of protection emblems with the assistance of an automated system, which is impossible to achieve through human effort alone. Consequently, responses to situations where the safety and security of people are at risk can be provided much faster. This will help humanitarians dedicate more time to assisting and aiding those in need by automating this process, ultimately saving valuable time in critical situations. Additionally, the project aligns with the ICRC principles of upholding neutrality and impartiality. YOLOv8 will ensure accurate detection of emblems with a high degree of success and will reduce the likelihood of false positives or negatives. This precision will preserve the integrity of humanitarian operations, enhance the credibility of all stakeholders, and maintain the objectivity and impartiality of aid delivery.

However, it should be admitted that some disadvantages are associated with the Protection Emblem Detection Project. Among the challenges, the reliance on technological infrastructure and the availability of the latest information can be mentioned. The algorithm is unable to operate properly in areas of low connectivity or with outdated maps. Another fact is that the algorithm can be compromised by environmental factors such as lighting conditions, weather, and the quality of the image, making it difficult to work under specific circumstances.

Besides, it must consider the ethical factor, particularly regarding privacy and data security. One has to strike a balance between the application of new technologies in a humanitarian manner and respecting personalities and privacy. The most significant aspect of installing such systems is to ensure that robust measures concerning data handling are in place, which will make such systems transparent to the societies they serve. The Protection Emblem Detection Project is a significant step toward utilizing state-of-the-art technology in humanitarian work. Although it offers strong benefits in terms of efficiency and accuracy, there is an urgent need to address perceived challenges and ethical issues to ensure that the project aligns with the ideals of the ICRC and adds value to global humanitarian activities. The YOLOv8-based pipeline can easily identify protection emblems, as recent research has demonstrated that newer versions of the YOLO architecture can recognize small and emblem-like objects [25]. The results of studies like [15] demonstrate better accuracy in detecting small objects due to a better fusion of features and multi-scale refinement, which justifies our architecture and augmentation plan. On the same note, recent reviews of logo detection [13] also note that transfer learning and targeted augmentation are more effective in limited datasets, as well as in our studies. Nevertheless, there are conflicting pieces of evidence in the literature that point to significant shortcomings. Several studies with synthetic training indicate that a synthetic-to-real domain gap is consistently observed, with models fine-tuned on synthetic data demonstrating high validation accuracy but worse real-world generalization, without domain randomization or sensor-effect augmentation. This is the reason why only synthetic augmentation provided a small change in our experiments. Furthermore, in comparative tests, it is found that certain high benchmark detectors decline in performance under occlusion, blur, and very small target sizes, also reflected in our failures [25, 26]. In addition to accuracy, such studies by the International Committee of the Red Cross (ICRC)

[27] are policy-oriented and caution that automated emblem identification has to be governed, controlled by persons, and safeguarded against misuse. It is in line with our policy that verifying the deployment and controlling access to any field should be part of the deployment and coordination with authorized humanitarian organizations. In combination, recent supporting and contradictory literature indicate that YOLOv8 can be successfully used to detect emblems, although the real scene robustness may require enhanced domain adaptation, more comprehensive datasets, and safeguards surrounding the ethical aspects of implementation.

8. FUTURE DIRECTIONS

The research conducted in the future must address the limitations discussed above by working on a number of cruxes in developmental and methodological aspects. The most important one would be the further development of the dataset to consist of a much broader and more diverse set of images that describe different environmental conditions, angles of the camera, types of emblems, and situations in the field. The ideal form of such expansion is to collect real-world data by humanitarian operations and augment it with synthetic data created by generative adversarial networks (GANs) or diffusion models to increase diversity and boost generalization. Researchers need to use k-fold cross-validation, repeated random sub-sampling, and bootstrap confidence interval estimation to increase the statistical credibility and present the mean and standard deviation of the key performance measures, including mAP, Precision, Recall, and F1 score.

In terms of implementation, a future implementation should also be aimed at optimizing the model to be deployed in real time and on the edges, especially to small power devices to allow them to operate in the field with restricted resources. Lastly, it will be essential to incorporate the principles of ethical AI systems and work out governance rules along with the cooperation of international humanitarian organizations, which will guarantee the responsible introduction. With respect to these areas, future studies can be of much better benefit to the technical robustness as well as the ethical validity of AI-assisted emblem detection systems in humanitarian settings.

Funding: This study received no specific financial support.
Institutional Review Board Statement: Not applicable.
Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.

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