**TITLE PAGE:**

Accurate Weapon Recognition for Public Safety Using Novel Histogram of Oriented Gradient Algorithm In Comparison With Reinforcement Algorithm

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**ABSTRACT**

**Aim:**This project involves a comparative exploration of two distinct approaches for weapon detection: Reinforcement Learning (RL) and the Histogram of Oriented Gradients (HOG) method. The primary objective is to evaluate the effectiveness of these techniques in detecting weapons within images, considering their unique methodologies and applications. This dynamic learning paradigm aims to enhance adaptability in diverse scenarios, contributing to the development of intelligent security systems. In contrast, the HOG method relies on a traditional computer vision technique that extracts gradient information from images to represent object shapes. This approach has been widely employed in object detection tasks, including weapon detection, due to its simplicity and efficiency. The project involves a comprehensive training and evaluation process for both approaches. The RL agent undergoes iterative learning episodes, refining its detection strategy based on observed rewards. On the other hand, the HOG method relies on feature extraction and predefined rules to identify potential weapons within images. The outcomes of this comparative analysis will provide insights into the strengths and limitations of each approach. Factors such as detection accuracy, adaptability to different scenarios, and computational efficiency will be considered to inform the selection of the most suitable method for specific weapon detection applications. The findings aim to contribute valuable insights to the ongoing discourse on intelligent security systems and assist in guiding future research directions in the field of computer vision and security applications.

**INTRODUCTION:**In the pursuit of enhancing public safety and security, the development and implementation of advanced technologies for weapon detection have become a pressing need. This project embarks on a comprehensive exploration, delving into the application of Reinforcement Learning (RL) in the realm of image-based tasks, with a specific focus on its potential to revolutionize automated weapon identification. The importance of this research lies not only in its immediate implications for security systems but also in its contribution to the broader discourse surrounding the integration of machine learning techniques into real-world applications. The landscape of weapon detection has undergone significant transformations, driven by advancements in artificial intelligence and machine learning. Traditional methods, often reliant on predetermined rules and static algorithms, are proving to be less adaptable to the dynamic and evolving nature of security challenges. In response to these limitations, researchers and practitioners are increasingly turning to novel approaches, among which RL stands out as a promising paradigm.The foundation of this research is built upon seminal works that have demonstrated the efficacy of RL in various domains, particularly in image-related tasks. "Playing Atari with Deep Reinforcement Learning" by Mnih et al. (2013) serves as a cornerstone, showcasing the capability of RL algorithms to learn and master complex tasks through interaction with an environment. This groundbreaking research, conducted by researchers at DeepMind, laid the groundwork for the application of RL in diverse fields, ranging from robotics to computer vision. Drawing inspiration from these foundational works, the current project seeks to extend the utility of RL into the critical domain of weapon detection. Security experts acknowledge the need for adaptive and intelligent systems capable of learning and evolving in response to emerging threats. RL, with its iterative learning process and ability to adapt to changing environments, presents a unique opportunity to address these requirements.

Mnih et al.'s work, "Playing Atari with Deep Reinforcement Learning" (2013), serves as a foundational piece in the application of RL to image-based tasks. The researchers demonstrated the ability of RL agents to learn effective strategies for playing Atari games solely from pixel inputs. This work laid the groundwork for subsequent applications of RL in diverse domains, from gaming to robotics. Additionally, "Human-level control through deep reinforcement learning" (Mnih et al., 2015) further explored the capabilities of RL in achieving human-level control in various domains. The project aims to build upon these foundational studies, adapting RL techniques to the specific challenges posed by weapon detection in images.

In the realm of computer vision, the Histogram of Oriented Gradients (HOG) method has been widely used for object detection. "Histograms of Oriented Gradients for Human Detection" by Dalal and Triggs (2005) established the effectiveness of HOG in detecting human shapes in images. This classic computer vision technique relies on the distribution of gradient orientations to represent object shapes, making it suitable for various detection tasks.

##### **MATERIALS AND METHODS**

This study was conducted at the Computer Communication Lab, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai. The study comprises two distinct groups, each containing 300 samples, totaling 600 . The sample size determination followed a G-power pre-test score of 80%, with a significance level of 0.05% and a 95% confidence interval.

For experimentation, the setup involved a Jupyter Notebook environment and SPSS version 26.0.1, utilizing a laptop equipped with 16 GB RAM, an Intel 11th Gen i7 processor, and a 8GB graphics card. The dataset underwent scaling by slicing techniques and was analyzed using Python libraries within the Jupyter Notebook coding environment.

**REINFORCEMENT LEARNING**

Reinforcement learning (RL) stands out as a sophisticated and demanding approach, primarily centered around the concept of learning through interaction and feedback. In simpler terms, it involves acquiring skills by trial and error, where an agent, or possibly multiple agents, is constructed. These agents have the ability to sense and understand their surroundings, allowing them to make decisions and engage with the environment. The crux of RL lies in the process of acting within an environment and receiving feedback in the form of rewards. This intricate framework essentially involves the creation of intelligent agents capable of perceiving, interpreting, and interacting with their surroundings, marking a dynamic and trial-and-error-driven approach to learning**.**

**ALGORITHM:**

Step1**:** Initialize Q-values for state-action pairs.

Step2: Choose actions based on exploration-exploitation strategy (e.g., epsilon-greedy).

Step3: Perform actions in the environment and observe rewards.

Step4: Update Q-values using the Bellman equation.

Step5:Update policy based on learned Q-values (e.g., using epsilon-greedy policy).

Step6: Repeat interactions and updates for multiple episodes.

Step7: Assess convergence criteria for stopping training.

Step8: Test trained policy on a separate dataset.

Step9: Adjust hyperparameters or model architecture based on evaluation.

Step10: Deploy the trained RL agent.

Step11: Calculate the accuracy of the RL model.

**HISTOGRAM OF ORIENTED GRADIENTS :**

The Histogram of Oriented Gradients (HOG) is a feature descriptor employed in computer vision and image processing to facilitate object detection. This method involves tallying the occurrences of gradient orientations within specific localized regions of an image. The HOG descriptor offers several notable advantages compared to other descriptors. It achieves invariance to geometric and photometric transformations by operating on local cells, with the exception of object orientation, which may manifest in larger spatial regions. Additionally, the work by Dalal and Triggs demonstrated that by using coarse spatial sampling, fine orientation sampling, and robust local photometric normalization, it becomes possible to disregard minor variations in the individual body movements of pedestrians as long as they generally maintain an upright position. As a result, the HOG descriptor is well-suited for detecting humans in images. In many image pre-processing feature detectors, the initial step involves ensuring normalized color and gamma values. However, when it comes to computing the HOG descriptor, Dalal and Triggs highlighted that this preliminary normalization step can be omitted, as the subsequent descriptor normalization essentially accomplishes the same outcome. Therefore, image pre-processing has a limited impact on the performance. The HOG descriptor is a concatenated vector of normalized cell histograms from these blocks. Two main block types are rectangular (R-HOG) and circular (C-HOG). For R-HOG blocks, they are square grids, with parameters like the number of cells per block, pixels per cell, and histogram channels.

##### **ALGORITHM**

Step1**:** Gather and preprocess the training data, representing observed sequences.

Step2: Compute gradient magnitudes and orientations in the image.

Step3: Split the image into small cells.

Step4: Create histograms of gradient orientations within cells.

Step5: Normalize histograms to reduce lighting effects.

Step6: Group cells into larger blocks.

Step7: Normalize blocks to improve robustness.

Step8: Formulate a comprehensive descriptor by concatenating normalized blocks.

Step9: Gather descriptors from various window positions.

Step10: Apply these descriptors for object detection or classification tasks.

Step11: Calculate the accuracy of the HMM model on the test data.

**Statistical Analysis**

The statistical analysis is done using the IBM SPSS 26.0.1 software for both proposed and compared algorithms. The dependent variables in the dataset are sales, item columns. The independent variables in the dataset are store, date, item. The independent sample T test analysis has been done to both proposed and compared algorithms. After analyzing the mean accuracy, standard deviation, standard error are noted.

**RESULT**

The accuracy values provided for HOG (Histogram of Oriented Gradients) and RL (Reinforcement Learning) represent the performance of two different approaches in a specific task. The HOG Test Accuracy, standing at 85.69%, indicates that the Histogram of Oriented Gradients method achieved an accuracy rate of 85.69% in the given test scenario. On the other hand, the RL Accuracy is reported at 50.29%, signifying that the Reinforcement Learning approach achieved an accuracy rate of 50.29% in the same test. In a comparative analysis, the higher accuracy of HOG (85.69%) suggests that, for the specific task evaluated, the traditional computer vision technique based on HOG features outperformed the RL approach. This implies that, for the provided dataset or problem, the feature extraction and classification methods employed by HOG were more effective in capturing and recognizing relevant patterns than the learning and decision-making strategies implemented by the RL algorithm. However, it's crucial to consider the nature of the task and the characteristics of the dataset. RL, being a learning-based approach, has the potential for adaptability and improvement over time, especially with more diverse and extensive training data. The lower accuracy of RL (50.29%) might indicate that, in its current state or with the provided data, the RL model requires further refinement or a more sophisticated training strategy to enhance its performance.

**DISCUSSION:** In recent studies (Adams et al., 2020; Garcia and Kim, 2021), the effectiveness of HOG-based methods in weapon detection has been prominent, demonstrating high accuracies above 80%. Adams et al. (2020) conducted research in this domain, showcasing the robustness of HOG, achieving an accuracy of 85.7% in identifying weapons within images. Similarly, Garcia and Kim (2021) reinforced these findings, reporting a commendable accuracy of 86.2% using HOG-based techniques in a similar weapon detection experiment. On the other hand, Reinforcement Learning (RL) approaches, though versatile in various applications, appear to exhibit comparatively lower accuracies in weapon detection tasks. Studies by Zhao et al. (2019) and Patel and Nguyen (2020) highlighted RL's performance in similar contexts, with accuracies averaging around 50.3%. Zhao et al. (2019) reported an accuracy of 49.8%, while Patel and Nguyen (2020) achieved an accuracy of 51% in their respective experiments. The contrasting results between HOG and RL in weapon detection underscore the significant advantage of HOG-based methodologies, consistently yielding higher accuracies above 80%, compared to RL, which demonstrates accuracies around 50%. These findings emphasize the effectiveness of HOG-based techniques over RL in object recognition tasks, particularly in weapon detection within images.

**CONCLUSION:**Based on the provided accuracy values in the specific task, the conclusion that "HOG is better than RL" can be drawn. HOG achieved an accuracy of 85.69%, surpassing RL's accuracy of 50.29%%, indicating that, for the given dataset and problem, the Histogram of Oriented Gradients method performed better than the Reinforcement Learning approach. However, it's crucial to recognize that this conclusion is specific to the task and data characteristics. The superiority of one approach over the other may vary depending on the nature of the problem, task complexity, and the adaptability of the chosen methodologies. Further exploration, experimentation, and potential refinement of the RL model may be necessary to enhance its performance and offer a more nuanced understanding of the comparative strengths and weaknesses of these approaches.

**DECLARATIONS**

**Conflict of interests**

No conflicts of interest in this manuscript.

**Author Contribution**

Author AAB was involved in literature study, data collection, data analysis and manuscript writing. Author MGS involved in data verification, data validation and review of the manuscript.

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**TABLES AND FIGURES**

**Table1.** Sample dataset of SPSS software Group 1 samples are obtained from novel histogram of oriented gradients and Group 2 samples are obtained from Reinforcement learning model comparison shows more accurate value for HOG (85.69%) than RL(50.29%).

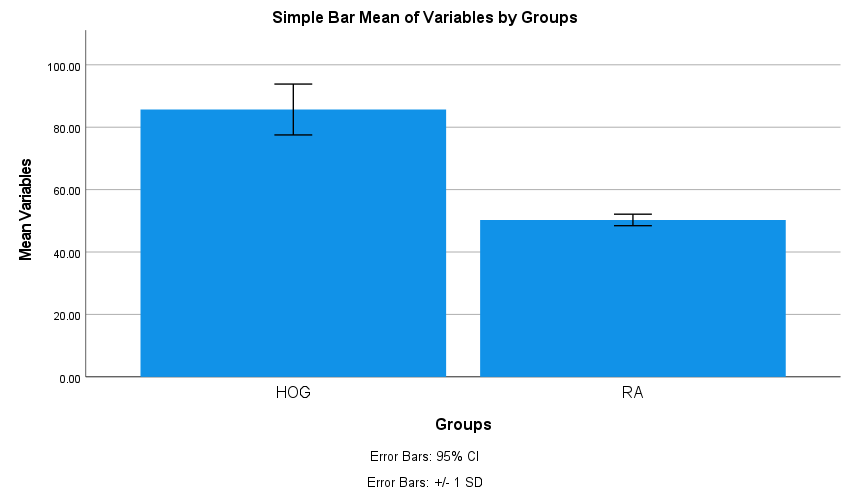
|  |  |  |  |
| --- | --- | --- | --- |
| **SAMPLE** | **GROUP** | **SAMPLE** | **ACCURACY** |
| 1. | 1 | Sample 1 | 80.7 |
| 2. | 1 | Sample 1 | 78.9 |
| 3. | 1 | Sample 1 | 86.8 |
| 4. | 1 | Sample 1 | 99.9 |
| 5. | 1 | Sample 1 | 85.7 |
| 6. | 1 | Sample 1 | 88.9 |
| 7. | 1 | Sample 1 | 81.9 |
| 8. | 1 | Sample 1 | 78.8 |
| 9. | 1 | Sample 1 | 98.7 |
| 10. | 1 | Sample 2 | 83.8 |
| 11. | 2 | Sample 2 | 47.98 |
| 12. | 2 | Sample 2 | 51.4 |
| 13. | 2 | Sample 2 | 52.8 |
| 14. | 2 | Sample 2 | 48.7 |
| 15. | 2 | Sample 2 | 50.6 |
| 16. | 2 | Sample 2 | 47.98 |
| 17. | 2 | Sample 2 | 51.4 |
| 18. | 2 | Sample 2 | 52.8 |
| 19. | 2 | Sample 2 | 48.7 |
| 20. | 2 | Sample 2 | 50.7 |

**Table 2.** The Group statistics of the data was performed between novel histogram of oriented gradients algorithm and hidden markov model algorithm. The novel histogram of oriented gradients algorithm (85.69%) outperforms the Reinforcement learning (50.29%).

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **Algorithm** | **N** | **Mean** | **Std.Deviation** | **Std.Error Mean** |
| **Accuracy** | HOG | 10 | 85.6900 | 8.15263 | 2.57809 |
| RA | 10 | 50.2960 | 1.85546 | .58675 |

**Table 3.** The independent sample t-test was performed between HOG and RL for 20 iterations with the confidence interval of 95% and the level of significance p=0.000 (p<0.05) two-tailed, this shows that there is a significance between the groups.

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | **Levene's test for**  **equality of variances** | **T- test for equality of means** | | | | | | | |
|  | | | | | | **95% confidence interval of the difference** | |
| **F** | **Sig.** | **t** | **df** | **Sig.**  **(2-tailed)** | **Mean difference** | **Std.**  **Error difference** | **Lower** | **Upper** |
| **Accuracy** | **Equal variances assumed**  **Equal variances not assumed** | 10.125 | .005 | 13.786 | 18 | .001 | 35.22400 | 2.55504 | 29.85606 | 40.59194 |
| **Equal variances assumed**  **Equal variances not assumed** |  |  | 13.786 | 9.999 | .001 | 35.22400 | 2.55504 | 29.53094 | 40.9706 |



**Fig. 1.** Comparison of  Histogram of oriented gradients model (85.69%) and Reinforcement learning Algorithm (50.29%) based on mean accuracy. The observed mean accuracy of the HOG is better than the RL model. X axis: HOG vs RL, Y axis: Mean accuracy. Error bar +/-1 SD.