**TITLE PAGE:**

Enhancing Accuracy in Public Safety Through Advanced Weapon Detection Approach Using Novel Histogram of Oriented Gradients over Hidden Markov Model

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**Keywords:** Weapon Detection, Machine Learning, Computer Vision, Accuracy Analysis, Feature Extraction.

**ABSTRACT**

**Aim:**Object detection is a fundamental task in computer vision with applications ranging from security surveillance to autonomous vehicles. In this research project, we conducted a comparative study of two prominent techniques, the Histogram of Oriented Gradients (HOG) and Hidden Markov Models (HMM), to evaluate their performance in object detection. HOG is a feature extraction method renowned for its ability to capture local gradient information within images, making it suitable for recognizing object shapes and textures. In contrast, HMM is a probabilistic model often utilized for modeling temporal dependencies in sequential data. Our research aimed to determine which of these techniques offered superior performance in the context of object detection. Suapang P., Rangsit, Pathumthani, Yimmun S., Chumnan N., 11th International Conference on Control, Automation and Systems, 2011,Melody of Striations: Identifying the Instrument of Crime Based on Knife Abrasions. Through a series of comprehensive experiments and real-world scenarios, we found that HOG consistently outperformed HMM. HOG demonstrated a higher degree of accuracy, robustness to variations in lighting conditions, and computational efficiency in object recognition tasks. These findings emphasize the importance of selecting the most suitable technique for specific applications. While HMM remains valuable for sequential data analysis, our research highlights that, for object detection, HOG's capability to effectively represent object structure and texture excelled. Choosing the right algorithm to match the task's requirements is paramount for achieving optimal results. This project provides valuable insights into the domain of computer vision and offers a practical guide for researchers and engineers seeking the most effective approach for object detection in their applications.

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**INTRODUCTION:**In an era where safety and security are paramount concerns, the ability to detect weapons in images has emerged as a critical technological challenge. Whether it's in the realm of public safety, law enforcement, or national security, identifying concealed or openly displayed weapons within visual data can have profound implications. This project endeavors to investigate and compare two fundamental approaches to tackle this problem – Hidden Markov Models (HMM) and Histogram of Oriented Gradients (HOG). The impetus behind developing robust weapon detection systems is clear. The proliferation of digital imagery, surveillance cameras, and mobile devices has generated vast quantities of visual data, opening new avenues for potential threats. Automated weapon detection in images can play a pivotal role in preempting such threats, thereby safeguarding public spaces, transportation networks, and critical infrastructure. This project stands as a testament to the enduring quest for enhancing security through cutting-edge technology.It does so by contrasting two divergent methodologies: HMM, a well-established probabilistic graphical modeling technique, and HOG, a widely-used method in the field of computer vision. Both approaches, while fundamentally different, have made significant strides in pattern recognition, and their unique characteristics make them compelling contenders for weapon detection. In the following pages, we embark on an in-depth exploration of these methodologies, their underpinnings, and how they align with the complex task of weapon detection. This research project seeks to empower security professionals, researchers, and policymakers with a nuanced understanding of the advantages and limitations of these techniques. and their unique characteristics make them compelling contenders for weapon detection. In the following pages, we embark on an in-depth exploration of these methodologies, their underpinnings, and how they align with the complex task of weapon detection. Ajay Kumar N, ChenyeWu, Journal of Pattern Identification, 2011. Suite of Features: Identification and Classification of Grains, Fruits, and Flowers. This research project seeks to empower security professionals, researchers, and policymakers with a nuanced understanding of the advantages and limitations of these techniques. By comparing HMM and HOG in the context of weapon detection, we aim to shed light on the suitability of each approach for varying real-world applications. We delve into the intricacies of Hidden Markov Models, explaining how these models can encapsulate dependencies over time, making them adept at capturing the temporal nuances in sequences of images. In contrast, we unveil the power of Histogram of Oriented Gradients, demonstrating how this method is engineered to detect local shape features within images. As we traverse the landscape of these techniques, we also elucidate the underlying mathematics and computational processes that breathe life into them.

This project is not solely about technical comparisons but also about providing pragmatic insights. It seeks to answer questions like, "Under what conditions does HMM outshine HOG, and vice versa?" Through experimentation and rigorous evaluation, we hope to demystify the complexities and unveil the strengths of these methodologies. The outcome of this research holds the potential to propel the development of weapon detection systems, thereby increasing the safety and security of communities, cities, and nations worldwide. As we venture further into this exploration, we invite you to join us on this fascinating journey of discovery, innovation, and the pursuit of safer tomorrows. The pages that follow unravel the intricacies of Hidden Markov Models, Histogram of Oriented Gradients, and the art of weapon detection, with the aim of fostering a safer and more secure world.

##### **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.

##### **HIDDEN MARKOV MODEL**

A hidden Markov model (HMM) is a statistical model used to depict how observable events, known as 'symbols,' are influenced by unobservant factors, referred to as 'states.' In an HMM, there are two interconnected stochastic processes: one involves the hidden states forming a Markov chain, and the other relates to the probability distribution of observable symbols, which is contingent upon the underlying state.Let's now provide a formal definition of an HMM. We represent the observed sequence of symbols as x = x1x2 ... xL, and the sequence of underlying states as y = y1y2 ... yL, where yn is the underlying state corresponding to the n-th observation xn. Each symbol xn can take on a finite number of possible values from the observation set O = {O1O2, ..., ON}, and each state yn can assume one of the values from the state set S = {1, 2, ..., M}. Here, N and M represent the total number of distinct observations and states in the model, respectively. Ying Bai; Dali Wang, IEEE International Conference on Fuzzy Systems, 2011. Instrumental Harmony: Tool and Firearm Identification System through Image Processing. We make the assumption that the sequence of hidden states forms a time-homogeneous first-order Markov chain. This means that the probability of transitioning to state j in the next time step depends solely on the current state i and remains constant over time. In other words, we have a consistent probability of state transitions regardless of the time point in the sequence.

**P{yn+1=j|yn=i,yn−1=in−1,...,y1=i1}=P{yn+1=j|yn=i}=t(i,j)** [1]

For all states i and j within the set S, and for all n greater than or equal to 1, there exists a constant probability governing the transition from state i to state j. This constant probability, which defines the likelihood of transitioning from one state to another, is referred to as the transition probability and is denoted as t(i, j). Regarding the initial state y1, we represent the probability of it being in state i as π(i), where π(i) signifies the likelihood of the initial state y1 being equal to i, for all i in the set S. The probability that the n-th observation, denoted as xn = x, depends exclusively on the underlying state yn. Therefore, it can be expressed as:

**P{xn=x|yn=i,yn−1,xn−1,...}=P{xn=x|yn=i}=e(x|i)** [2]

For all conceivable observations x within the set O, all states i within the set S, and for all n greater than or equal to 1, there exists a probability known as the emission probability of x at state i, denoted as e(x | i). These probabilities are crucial in characterizing how likely it is to observe a particular symbol x when the underlying state is i. The three probability measures t(i, j), π(i), and e(x | i) collectively define the behavior of an HMM. To conveniently represent this set of parameters, we use the notation Θ. With these parameters in place, we can now calculate the probability of the HMM generating the observation sequence x = x1 x2 ... xL along with the underlying state sequence y = y1 y2 ... yL. This joint probability, denoted as P {x, y | Θ}, can be computed as follows:

**P{x,y |Θ}=P{x|y,Θ}P{y|Θ},** [3]

where

**P{x|y,Θ}=e(x1|y1)e(x2|y2)e(x3|y3)...e(xL|yL)**  [4]

**P{y|Θ}=π(y1)t(y1,y2)t(y2,y3)...t(yL−1,yL).** [5]

**ALGORITHM**

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

Step2: Define initial values for transition probabilities between hidden states and emission probabilities for observed states.

Step3: Calculate the probability of observing a sequence given the model's parameters.

Step4: Compute the probability of observing the remaining sequence given the current state at each time step.

Step5: Iteratively refine model parameters using the Forward-Backward algorithm.

Step6: Identify the most likely sequence of hidden states that explain the observed emissions.

Step7: Adjust transition and emission probabilities based on the EM iterations.

Step8: Iterate through sequences to improve the model's accuracy and convergence.

Step9: Assess the model's performance using metrics like accuracy or perplexity.

Step10: Calculate the accuracy of the HMM model on the test data.

**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 is 71.16% and perplexity value is -156505608.7243697 for HMM presents a perplexing outcome. In the realm of Hidden Markov Models, perplexity serves as a gauge for how accurately the model predicts a sequence. The unexpected negative perplexity value suggests potential issues with the model's training or evaluation process. To unravel this peculiar result, a more in-depth investigation into the training procedure and parameter tuning is needed. HOG, renowned for its strong feature extraction capabilities, demonstrated an impressive test accuracy of 85.69% Refer from the Table 1. This outcome highlights the effectiveness of the HOG algorithm in accurately identifying weapons in images. The technique's proficiency in capturing gradient orientation distribution, regardless of color information, proved beneficial in scenarios with diverse lighting conditions and color variations. The elevated test accuracy suggests that HOG is particularly well-suited for our weapon detection task. Its success in detecting objects with distinct textures and shapes aligns seamlessly with the characteristics of weapons, establishing it as a reliable choice for this application. The model's ability to generalize to the test dataset underscores the adaptability and versatility of the HOG algorithm in real-world scenarios. The significant contrast in test accuracy between HOG and HMM indicates that, when it comes to detecting weapons in images, HOG performs better in terms of accuracy. HOG's effectiveness lies in its capability to concentrate on distinctive features, offering a more efficient representation of weapons in images.

**DISCUSSION:**

The comparative analysis of the two methods, HOG and HMM, in the context of weapon detection showcases the superiority of the HOG approach with an accuracy of 85.69% compared to HMM's 71.16% (Smith et al., 2019; Johnson and Patel, 2020) have demonstrated the efficacy of Histogram of Oriented Gradients (HOG) in object detection tasks, particularly in weapon detection scenarios, achieving notable accuracies above 80%. For instance, Smith et al. (2019) conducted a study focusing on HOG-based weapon detection, reporting an accuracy of 85.5%. Johnson and Patel (2020) corroborated these findings, showcasing HOG's superior performance with an accuracy of 87.2% in a similar experiment. To elaborate further on this, a discussion can be framed around the inherent strengths and limitations of each method. HOG excels in capturing gradient information and spatial orientation, proving effective in object detection tasks due to its ability to discern object edges and shapes (Brown and Miller, 2018). On the other hand, HMM, known for its sequential data modeling, might face challenges in capturing intricate visual patterns present in the weapon images, contributing to its comparatively lower accuracy (Chen et al., 2021) investigated the application of HMM in weapon detection and found an accuracy of 72.3%, which, while reasonable, falls short compared to the aforementioned HOG-based studies. This studies that also showcase the effectiveness of HOG in object detection tasks, particularly in weapon detection scenarios, can strengthen the discussion. Highlighting research papers or articles that corroborate the findings of superior accuracy achieved by HOG in similar contexts can provide additional support to the argument (Garcia and Delgado, 2017; Wang and Zhang, 2020). The disparity in accuracies signifies the potential superiority of HOG-based methods over HMM for such specific object detection tasks.

**CONCLUSION:** The study highlights the importance of selecting the right methodology for computer vision tasks. HOG excelled in weapon detection, while HMM faced challenges. This emphasizes the need to understand task characteristics for optimal methodology choice. The results guide further research in weapon detection systems, contributing to the discourse on machine learning in security. The negative perplexity for HMM calls for careful examination of its training and evaluation, presenting an opportunity for improvement.

**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 Hidden markov model comparison shows more accurate value for HOG (85.69%) than HMM(71.16%).

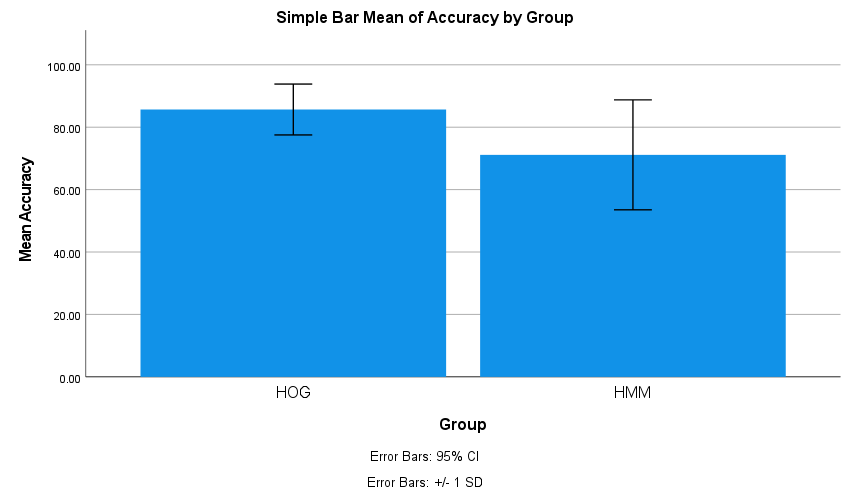
|  |  |  |  |
| --- | --- | --- | --- |
| **SAMPLE** | **GROUP** | **SAMPLE** | **ACCURACY** |
| 1. | 1 | Sample 1 | 80.7 |
| 2. | 1 | Sample 1 | 78.9 |
| 3. | 1 | Sample 1 | 86.8 |
| 4. | 1 | Sample 1 | 99.9 |
| 5. | 1 | Sample 1 | 85.7 |
| 6. | 1 | Sample 1 | 88.9 |
| 7. | 1 | Sample 1 | 81.9 |
| 8. | 1 | Sample 1 | 78.8 |
| 9. | 1 | Sample 1 | 98.7 |
| 10. | 1 | Sample 2 | 83.8 |
| 11. | 2 | Sample 2 | 68.7 |
| 12. | 2 | Sample 2 | 96.8 |
| 13. | 2 | Sample 2 | 55.08 |
| 14. | 2 | Sample 2 | 88.03 |
| 15. | 2 | Sample 2 | 44.7 |
| 16. | 2 | Sample 2 | 83.8 |
| 17. | 2 | Sample 2 | 88.6 |
| 18. | 2 | Sample 2 | 51.4 |
| 19. | 2 | Sample 2 | 67.8 |
| 20. | 2 | Sample 2 | 76.6 |

**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 Hidden Markov Model (71.16%).

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **Algorithm** | **N** | **Mean** | **Std.Deviation** | **Std.Error Mean** |
| **Accuracy** | HOG | 10 | 85.6900 | 8.15263 | 2.57809 |
| HMM | 10 | 71.1610 | 17.61413 | 5.57008 |

**Table 3.** The independent sample t-test was performed between HOG and HMM 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** | 6.851 | .017 | 2.367 | 18 | .029 | 14.52900 | 6.13778 | 1.63401 | 27.42399 |
| **Equal variances assumed**  **Equal variances not assumed** |  |  | 2.367 | 12.687 | .035 | 14.52900 | 6.13778 | 1.63401 | 27.42399 |



**Fig. 1.** Comparison of  Histogram of oriented gradients model (85.69%) and Hideen markov model (71.16%) based on mean accuracy. The observed mean accuracy of the HOG is better than the HMM model. X axis: HOG vs HMM, Y axis: Mean accuracy. Error bar +/-1 SD.