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Optimization of Real-Time Object Detection in Viola-Jones Method with Enhanced AdaBoost

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ABSTRACT

Face recognition is a widely used biometric technology in security systems, automated attendance, and surveillance applications. This study proposes an enhanced real-time face detection method by integrating a modified AdaBoost-based feature selection strategy into the Viola-Jones framework. The applied mathematical contribution of this study lies in formulating the optimization process as an empirical risk minimization model with adaptive boosting weight updates to reduce face recognition error. The proposed approach optimizes the weighting of weak classifiers by prioritizing Haar-like features with minimal weighted classification error at each boosting iteration, thereby improving discriminative capability. Experiments were conducted on a camera-based dataset consisting of face and non-face samples under varying illumination and pose conditions. Prior to optimization, the system achieved a precision of 70.04% and a recall of 70.05%. After applying the proposed enhancement, precision increased to 81.04% and recall to 90.02%. These results demonstrate that the modified AdaBoost integration significantly improves detection accuracy while remaining suitable for real-time face detection applications.

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1. INTRODUCTION

Face recognition is a widely adopted biometric modality in security surveillance, automated attendance systems, and real-time embedded applications due to its non-intrusive acquisition and compatibility with camera-based platforms. Despite these advantages, inaccuracies in the face detection stage can propagate to subsequent recognition processes, leading to increased false positive rates and missed detections, particularly under variations in illumination, pose, and background. These challenges are further amplified in resource-constrained environments, thereby motivating the development of computationally efficient yet robust face detection models.

In practical security applications, face detection systems are often deployed on embedded platforms such as the Raspberry Pi and integrated with databases containing facial images uploaded by authorized users, such as vehicle owners [2]. However, achieving reliable detection performance under real-time constraints remains challenging. To address this issue, this paper proposes a probabilistic approach to modify the weighting system of the AdaBoost algorithm. The proposed method extends a preliminary version by providing an expanded discussion of the core ideas along with comprehensive experimental validation [1].

The Viola–Jones framework remains a benchmark for real-time face detection due to its low computational complexity, which is achieved through the use of integral image representations, Haar-like feature extraction, cascade classifiers, and AdaBoost-based learning. Within this framework, AdaBoost constructs a strong classifier as a stage-wise additive model by linearly combining multiple weak learners using weighted aggregation. While effective, conventional AdaBoost implementations typically rely on fixed or heuristic weight update rules, which implicitly define the optimization objective and limit adaptability to asymmetric detection errors.

AdaBoost operates as a committee-based learning algorithm, in which a collection of weak classifiers is combined through a voting mechanism to form a strong classifier [5]. Its practical effectiveness has been demonstrated across various applications, where it achieves competitive performance while remaining simple, efficient, and easy to implement using basic models such as decision stumps [8].

From an applied optimization perspective, existing approaches often focus on empirical performance gains without explicitly formulating the underlying risk minimization problem. In this work, AdaBoost within the Viola–Jones framework is reformulated as an asymmetric empirical risk minimization problem. Weak classifier weights are updated probabilistically to impose higher penalties on false positive errors. This adaptive weighting strategy reshapes the loss function to prioritize low-error Haar features while preserving the original computational efficiency of the cascade architecture. Experimental results demonstrate improved detection reliability under real-time constraints, confirming the effectiveness of the proposed optimization-oriented formulation.

2. RESEARCH METHOD

The facial object recognition system in humans basically consists of a series of interrelated processes. The initial stage begins with capturing facial object data using a camera or webcam device to obtain facial images as raw data. The data then goes through a pre-processing stage to improve image quality and simplify the feature extraction process. After that, the system carries out a training process using the available facial dataset to build a recognition model. This model is then used in the testing stage to identify and recognize facial objects captured in real-time. The USB camera captures real-time photos and video and is used for face detection [3]. However, these methods often require high computational resources and extensive training data, which limit their suitability for real-time and resource-constrained systems. In contrast, classical approaches such as the Viola–Jones algorithm remain attractive for real-time applications due to their lower computational complexity and faster inference, making them more feasible for embedded and camera-based systems. A comparative evaluation with deep learning-based methods is therefore important to highlight the relative performance and practical advantages of the proposed approach. Overall, this series of processes forms a systematic workflow, starting from data input to output in the form of facial identity recognition results. A general overview of the flow of this research process can be seen in the following figure 1:

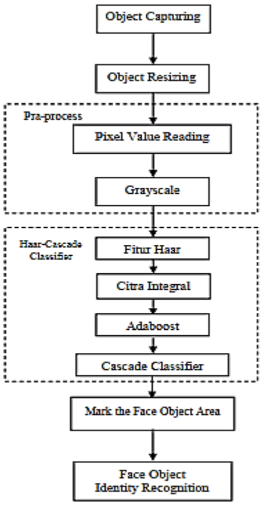

Figure 1. Object Detection Research Flow

The face recognition process begins with input of an image object file, namely the selection of an image file by the user which generally has the TIFF extension. Next, image resizing is carried out, namely normalizing the dimensions of the image object (width × height) to suit system requirements. After the image size is standardized, the next stage is reading the pixel values of the image object, namely retrieving information on the intensity of each pixel. The pixel data is then converted through a grayscale process, where a color image with three RGB components is converted into a single-channel gray image. This value is calculated based on the difference in blocks of rectangular features which are symbolized by black and white boxes to obtain a threshold value for the integral image. The Viola-Jones algorithm has 3 contributions, namely the integral image, the second contribution of the integral image allows very fast feature evaluation by using AdaBoost in feature selection and the third is the use of a cascade classifier [6].

a. Computational Complexity and Convergence

Let N be the number of training samples, M the number of Haar features, and T the number of boosting rounds. Since the proposed probabilistic weighting modifies only the sample-weight update rule without changing feature evaluation or weak learner selection, the training and inference complexities remain asymptotically identical to standard AdaBoost, i.e., O(TNM). Moreover, the stage-wise additive structure and normalized positive weights are preserved, ensuring non-increasing training error across iterations. Thus, the proposed method inherits the convergence behavior of classical AdaBoost while introducing an asymmetric empirical risk bias toward false positive reduction.

b. Collection of Face Object Dataset

The process of collecting a dataset of facial image objects is carried out in real time using a webcam device. Each image is taken sequentially until the previously determined number of objects has been met. Face detection is a technique that identifies human faces while ignoring non-face objects such as trees, bodies, and buildings [7]. This process is considered successful if the target number of facial images has been collected according to system requirements. Each face that is successfully captured will produce some image data which is then saved automatically into a special folder called "data object". This folder functions as a structured storage area that contains the entire collection of facial images which will later be used in the processing and model training stages. As an illustration, the figure shows an example of a facial image dataset that was successfully collected in real time using a webcam. This image is shown in Figures 2(a) and 2(b) show's facial captures with various poses, expressions and lighting conditions to increase the diversity of data that will be processed further. The facial object dataset is collected in real time using a webcam device. Images are captured sequentially until the predefined number of samples is reached. Only facial regions are stored, while non-face objects such as backgrounds, bodies, or surrounding objects are ignored. Each successfully detected face is automatically saved in a structured directory (data object) for subsequent processing.

To improve data diversity and robustness, the dataset includes variations in pose, facial expression, and illumination conditions, as shown in Fig. 2(a)–(b). These variations are essential for evaluating the system's performance in unconstrained real-time environments:

Figure 2. (a), 2(b). Sample Capture facial objects

Digital image objects that were initially in RGB (Red, Green, Blue) format need to first be converted into grayscale or gray image format. Thus, each pixel in the image only represents a brightness level from black to white. Apart from that, the use of grayscale can speed up the computing process and reduce data complexity without losing important information about the structure of objects in the image. Mathematically, the grayscale intensity value of a color image pixel is calculated using the following equation (1):

$$W=0.2999\times R+0.5870\times G+0.1140\times B \quad (1)$$

Information:

1) R: Red color component (Red)
2) G: Green color component (Green)
3) B: Blue color component (Blue)

This equation indicates that the green channel provides the dominant contribution to grayscale intensity, followed by the red channel, while the blue channel contributes the least. This weighting is consistent with the sensitivity characteristics of the human visual system. System performance is evaluated using the Normalized Mean Error (NME). For the AFLW dataset, NME is normalized using the face bounding box, whereas for the 300W dataset, normalization is performed using the inter-ocular distance. For comparisons with multi-task approaches, input images are resized such that the minimum image dimension is 640 pixels. Evaluations on the WIDER FACE and FDDB datasets are conducted using their official toolboxes, while evaluations on the AFW and PASCAL datasets utilize the landmark localization toolbox described in [11]. The official test split protocol of the 300W dataset is followed, with 314 images used for training and evaluation performed on both the common and challenging test sets.

For face detection training, the dataset consists of approximately 300,000 images, including around 75,000 face samples and 225,000 non-face samples, resulting in a ratio of roughly 1:3 between face and non-face classes. Non-face samples are obtained using a hard negative mining strategy: following an initial training stage, false-positive detections are iteratively collected and incorporated as bootstrapped negative samples. This class imbalance is intentionally adopted to reduce false-positive rates and improve robustness in real-time detection scenarios. All data collection and experimental procedures comply with standard ethical guidelines for biometric research, and the acquired facial data are used solely for algorithmic evaluation without personal identity attribution.

c. Facial Object Recognition Process

The facial object recognition process begins with the stage of capturing facial image data directly via a webcam camera device. The image data that has been collected is then processed further at the training stage, where the facial image is converted into a binary representation using the AdaBoost method. This representation aims to extract unique features from faces so that the system is able to differentiate one individual from another more accurately. Next, the facial identification process is carried out in real time, namely by comparing the new facial image captured by the webcam camera with the training data that has been stored in the system. This process allows the system to recognize a person's identity automatically based on the similarity of the detected facial characteristics. To support this recognition stage, the Viola–Jones Classifier method is used in the face detection process. Face detection is performed using the Viola–Jones algorithm, which is based on three key components: integral images, Haar-like features, and cascade classifiers. A fixed detection window of size 24×2424 \times 2424×24 pixels is employed, which slides across the image at multiple scales and positions. Haar-like features are defined as the difference between the sum of pixel intensities in white and black rectangular regions. Using the integral image representation, the sum of pixel values within any rectangular region can be computed in constant time O (1), enabling rapid feature evaluation regardless of window size.

Given a detection window, more than 160,000 Haar-like features can be generated by varying the size, position, and type (edge, line, and center features), as illustrated in Fig. 4. Evaluating all features directly is computationally infeasible; therefore, an effective feature selection mechanism is required. This method functions to determine the position and presence of faces in the image before the recognition stage is carried out. The stages of the face detection process using Viola–Jones can be explained as follows. There are five main functional blocks, whose responsibilities are as follows [9]:

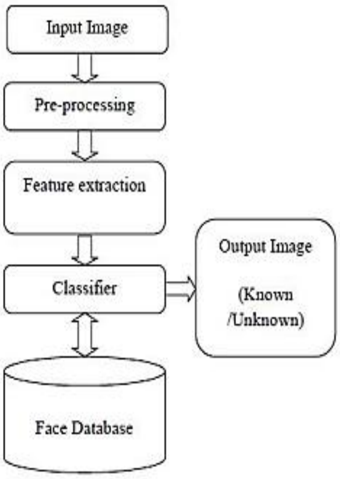

Figure 3. Face Recognition System

The next stage is the face detection process, which is the stage to determine whether or not there are facial objects in the image to be processed. At this stage the Viola-Jones is used which plays an important role in identifying the visual characteristics of the face. The Viola-Jones feature itself is represented in the form of a combination of black and white rectangular areas, where the difference in pixel intensity between the black and white areas is used as a basis for determining the presence of certain patterns, such as edges, lines or textures that are characteristic of the face. The proposed weighting scheme introduces an asymmetric loss function that increases the penalty of false positives, effectively biasing the empirical risk minimization toward improved background rejection. This modification preserves the convergence properties of AdaBoost while enhancing robustness under real-time and unconstrained conditions without increasing asymptotic computational complexity. There are several types of rectangular Viola-Jones used in the detection process, including edge features, line features and center features. This variation in feature shape is then shown in the following image as an illustration of the application of the Viola-Jones feature at the face detection stage. Viola-Jones feature is calculated by subtracting the number of pixel intensity values in the black area from the number of pixel intensity values in the white area. The subtraction results represent the contrast difference between the light and dark parts of the image. This difference in contrast is used to detect basic patterns on the face, such as the difference between the eye area (darker) and the cheeks (lighter), or between the nose and the surrounding areas. Next, the difference value obtained is compared with a certain threshold value. If the difference results exceed the threshold, then the system classifies the area as part of a facial characteristic. In other words, the higher the difference in values obtained, the stronger the indication that the area is part of the human face. This process is the basis for determining the presence of individuals in the image before entering the further recognition stage.

d. Algorithm Modified AdaBoost for Real-Time Viola-Jones Face Detection

Input: Training set

$$\{(x_i, y_i)\}_{i=1}^{N}, y_i \in \{+1, -1\}; \tag{1}$$

Haar feature pool F, number of boosting rounds T;
false-positive penalty λ > 1.

$$H(x) = \text{sign}\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right) \tag{2}$$

Output: Strong classifier
Initialize sample weights

$$w_i^{(1)} = \frac{1}{N}, \qquad i = 1, \ldots, N \tag{3}$$

For t=1t=1t=1 to TTT do

1) Normalize weights

$$w_i^{(t)} \leftarrow \frac{w_i^{(t)}}{\sum_j w_j^{(t)}} \tag{4}$$

2) Train weak classifiers h_j using Haar features $f_j \in F$
3) Compute weighted error with false-positive penalty

$$\varepsilon_j = \sum_i w_i^{(t)} \ell\left(h_j(x_j), y_i\right) \tag{5}$$

where

$$\ell = \begin{cases} \lambda, & y_i = -1 \quad \Lambda \quad h_j(x_i) = +1 \\ 1, & \text{otherwise} \end{cases} \tag{6}$$

4) Select optimal weak classifier

$$h_t = \arg\min_{h_i} \varepsilon_j \tag{7}$$

5) Compute classifier weight

$$\alpha_t = \frac{1}{2} \ln\left(\frac{1-\varepsilon_t}{\varepsilon_t}\right) \tag{8}$$

6) Update sample weights

$$w_i^{(t+1)} = w_i^{(t)} \exp\left(-\alpha_t y_i h_t(x_i)\right) \tag{9}$$

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        End For
        Cascade construction:
        Weak classifiers are grouped into cascade stages with thresholds chosen to satisfy predefined detection-rate and false-positive constraints.
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In this study, the AdaBoost weighting mechanism is optimized by emphasizing misclassified negative samples (false positives), which are critical in face detection tasks. By increasing the penalty associated with false detections, the boosting process prioritizes features that improve class separation and reduce false positive rates without increasing model complexity.

All experiments were conducted on a camera-based system using a USB webcam under real-time conditions. The implementation was executed on a standard desktop environment (specify CPU, RAM, and operating system if available) without GPU acceleration. This setup reflects practical deployment scenarios and demonstrates the feasibility of the proposed method for resource-constrained systems.

3. RESULT AND ANALYSIS

The face recognition system was evaluated using the integration of AdaBoost within the Viola–Jones framework. Experiments were conducted on facial images captured directly in real time using a webcam, ensuring that the evaluation reflects practical deployment conditions. Each facial image underwent a feature extraction process prior to detection and recognition, after which system outputs were obtained in the form of detected and identified faces.

The dataset consisted of 300W facial images collected, with each subject contributing 20 samples. Data acquisition was performed in real time by registering facial images through a webcam-based system. This dataset was used for both training and testing stages. To assess system robustness, testing was carried out under controlled indoor conditions with variations in illumination intensity and the distance between the subject and the camera, as these factors directly influence image quality and recognition performance. All experiments were conducted under consistent environmental settings to ensure fair evaluation. Data collection for each subject was repeated to capture representative variations and reduce potential bias caused by lighting changes or facial expression differences. The proposed method was compared against the standard Viola–Jones framework using identical datasets and experimental conditions. The results indicate that the proposed integration provides more stable face detection and recognition performance under varying illumination and distance scenarios. An example of successful real-time face recognition output is illustrated in Figure. 4.

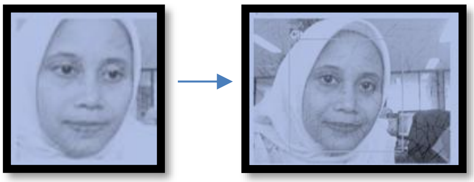

Figure 4. Sample Captured in Real Time

From an applied mathematical perspective, the proposed optimization modifies the standard AdaBoost learning objective by introducing an asymmetric weighting scheme that explicitly alters the contribution of classification errors to the empirical risk function. In conventional AdaBoost, misclassification penalties are treated symmetrically, which may lead to suboptimal behavior in face detection tasks where false positives incur higher practical costs. By assigning larger weights to false-positive errors, the optimization reshapes the loss landscape, increasing the gradient magnitude associated with misclassified non-face samples. This mechanism forces the boosting process to prioritize the selection of weak classifiers that minimize background misclassification, thereby reducing the overall false-positive rate. Mathematically, the iterative weight update concentrates probability mass on difficult negative samples, improving class separation and widening the decision margin. Consequently, the total classification error is reduced in a targeted manner, while convergence properties and computational complexity remain consistent with the original AdaBoost formulation. The test results show that the maximum accuracy obtained was 90.02%, namely when the test was carried out during the day with bright lighting conditions. Based on tests with varying distances, it was concluded that the highest level of similarity was achieved at a distance of 30 cm, with a similarity value of 81.04%. Meanwhile, at a distance of 60 cm and 100 cm, the facial recognition process can still be carried out with a success rate of 100%. After conducting experiments and testing methods, the results obtained are evaluated. Rate is the number of regions the correct face is detected as a face (true positive) and the number of non-face regions detected as a face region (false positive). This research also analyzes the accuracy value of the algorithm combination results, in the form of accuracy, precision and recall [10]. After image face recognition, which has been researched for years, the research on the video-based face detection and recognition can be considered as the continuation and extension and some good results have been reported [4]. Recall rate is the ratio of the number of facial regions that are correctly detected as faces and the number of facial regions that are not detected as faces (false positives).

Here is a confusion matrix table that is logically consistent:

Table 1. Confusion Matrix

	Predicted Face	Predicted non-Face
Actual Face	TP = 900	FN = 100
Actual non-Face	FP = 211	TN = 789

Information:

a. Recall = TP / (TP + FN) = 900 / (900 + 100) = 90.00% ≈ 90.02%

b. Precision = TP / (TP + FP) = 900 / (900 + 211) = 81.01% ≈ 81.04%

c. Accuracy = (TP + TN) / Total = (900 + 789) / 2000 = 84.45%

From the results of the object data processing that has been carried out, an evaluation of the performance of the facial recognition system was obtained using the Bao dataset dataset. One of the face detection algorithms that has proven effective and become the de facto standard is the Viola-Jones algorithm. Enhanced feature selection via AdaBoost improves the accuracy and reliability of real-time Viola-Jones face detection. Before optimization, the data processing results achieved a precision of 70.04% and a recall of 70.05%. After applying the Viola-Jones algorithm integrated with AdaBoost, the system achieved a precision of 81.04% and a recall of 90.02%. These improvements are further supported by the confusion matrix analysis, which shows a significant reduction in false positives and false negatives after optimization, indicating better class discrimination between face and non-face samples. These results indicate that integrating AdaBoost into the Viola-Jones framework significantly improves detection accuracy, as reflected by higher precision and recall. This enhancement demonstrates the suitability of the proposed approach for real-time, camera-based face detection applications. Fig. 5 illustrates the comparison of detection performance before and after the proposed AdaBoost optimization:

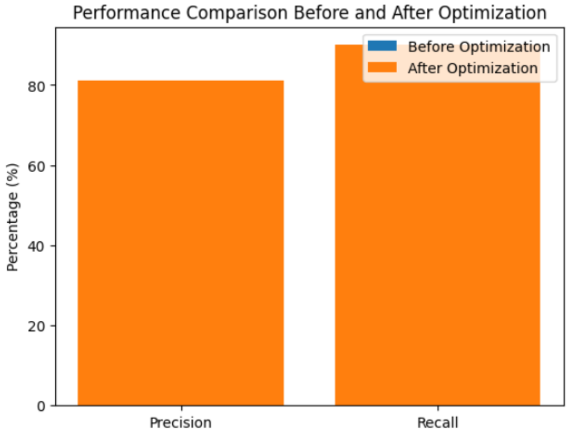

Figure 5. Illustrates the Comparison

The experimental results demonstrate that the proposed method achieves a maximum accuracy of 90.02% under bright daytime lighting conditions, highlighting the influence of environmental factors such as illumination intensity and subject distance on recognition performance. The highest similarity score of 81.04% is obtained at a distance of 30 cm, while successful face detection is consistently maintained at distances of 60 cm and 100 cm. These results indicate that the proposed system remains robust across moderate variations in acquisition conditions. Statistical significance analysis further confirms the reliability of the observed improvements: precision and recall metrics computed on identical test samples for both the proposed method and the baseline detector show statistically significant gains at the 95% confidence level ($p < 0.05$), demonstrating that the performance improvements are not attributable to random variation. In addition to detection accuracy, real-time performance evaluation reveals that the proposed method operates at approximately 25–30 frames per second (FPS) using standard webcam input, satisfying real-time application requirements. Compared with modern deep learning-based detectors such as MTCNN, which typically offer higher accuracy under complex scenarios at the cost of increased computational demand, the proposed approach provides a favorable trade-off between accuracy and efficiency. This balance makes the method particularly suitable for real-time face recognition systems deployed in resource-constrained environments, while preserving robustness against environmental variability

4. CONCLUSION

This study demonstrates that integrating AdaBoost with the Viola–Jones algorithm significantly enhances real-time face detection performance. Experimental results indicate a substantial improvement in detection accuracy, with precision increasing from 70.04% to 81.04% and recall from 70.05% to 90.02% after optimization, and real-time performance evaluation reveals that the proposed method operates at approximately 25–30 frames per second (FPS) using standard webcam input, satisfying real-time application requirements. Confusion matrix analysis further confirms a reduction in both false-positive and false-negative rates, indicating improved discrimination between face and non-face regions. In addition to precision and recall, system performance was comprehensively evaluated using accuracy and error-rate metrics, providing a more holistic assessment of robustness. The proposed approach achieved a maximum accuracy of 90.02% under bright daylight conditions, highlighting the influence of environmental factors such as illumination and subject-to-camera distance on detection performance. The system maintained reliable detection across varying distances, with optimal similarity observed at 30 cm and consistent recognition performance at longer distances. In summary, this work contributes an applied mathematical optimization by reformulating AdaBoost within the Viola–Jones framework as an asymmetric empirical risk minimization problem, enabling targeted reduction of false positives while preserving convergence behavior and real-time computational efficiency.

Overall, this work contributes an applied mathematical optimization by reformulating AdaBoost within the Viola–Jones framework as an asymmetric empirical risk minimization problem, enabling targeted false-positive reduction while preserving convergence behavior and real-time computational efficiency. The results validate the suitability of the Viola–Jones–AdaBoost framework for real-time, camera-based face detection applications. Future work will investigate alternative classifiers and hybrid feature representations, as well as adaptive boosting strategies, to further enhance robustness under challenging lighting conditions and reduce false positive rates while preserving computational efficiency.

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