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FACIAL RECOGNITION FOR SECURITY SYSTEMS

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ABSTRACT

This study evaluates the performance of the Viola Jones and YOLOv3 algorithms for facial recognition under different conditions and highlights their strengths and weaknesses. Analysis focusses on facial emotions, angle recognition, lighting, and the effects of hidden facial features.

YOLOv3 outperformed the Viola-Jones algorithm in angle-based recognition with more robustness. Both algorithms performed exceptionally well in different lighting conditions, with 100% recognition rates in artificial, natural, high-contrast, and dark surroundings. This shows that they are highly adaptive to changing lighting conditions. When individual facial characteristics, such as the forehead or eyes, were concealed, the Viola-Jones algorithm showed excellent reliability. When the nose and eyes were concealed, however, its performance dropped to 77%. YOLOv3, on the other hand, consistently achieved a 100% recognition rate, indicating that it handled inadequate facial data better, even in scenarios where multiple significant attributes were concealed. Both algorithms proven their resistance to dynamic face changes by achieving 100% recognition rates over a wide range of expressions and proving that facial expressions had no effect on their recognition accuracy.

These algorithms should be improved in the future for extreme angles and partial occlusions, and their integration with other recognition methods should be investigated.

KEY WORDS

face recognition, Viola-Jones algorithm, YOLOv3 algorithm, angle-based recognition, facial expressions

CLASSIFICATION

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INTRODUCTION

Thanks to significant advancements, facial recognition technology is now widely utilized for a variety of purposes, including security, identity verification, and improving user experiences. Using facial feature analysis in images or videos, this technology recognises people.

Facial recognition is a key component of security. It assists in identifying suspicious persons and known offenders, hence enhancing monitoring at airports, border checkpoints, and public areas. This technology is also used by banks and other financial institutions to confirm the identity of its clients, which reduces fraud. Facial recognition is essential for personalising user experiences in addition to security. For example, facial recognition is used by tech businesses, especially those that make smartphones, to provide quick and easy access to gadgets [1]. This capability underscores the growing trend to integrate biometric authentication into everyday technology.

The preservation of human rights is also greatly aided by facial recognition technology. It assists organizations and activists in identifying vulnerable individuals and documenting cases of illegal arrests or persecution, providing a powerful tool for advocacy and justice.

Facial recognition technology, a fundamental component of machine learning, powers cutting-edge applications in a range of industries, including security and smart cities, with constant algorithmic advancements that dramatically increase accuracy and efficiency [2].

Several facial features are critical to the effectiveness of facial recognition systems. These include facial lines (such as the contours of the face, nose, lips, and chin), pupils and iris, eyebrows and eyelids, mouth and teeth, nose, and skin texture and tone [3]. Each feature offers distinct information that, when combined, creates a detailed profile of a person’s face, making identification and recognition more precise, Figure 1.

1) Facial lines: Recognizing different facial lines is one of the most important parts of face recognition. The chin, lips, nose, and cheek contours are among these lines [4].
2) Iris and pupils: Since the iris and pupils are distinctive to each individual and are essential for precise identification, facial recognition systems commonly use them to identify people [5].
3) Eyebrows and eyelids: By establishing facial shapes and expressions that are necessary to differentiate between various people, eyebrows and eyelids contribute significantly to face recognition [6].
4) Mouth and teeth: The features of the mouth and teeth, such as the arrangement of the teeth, the shape of the lips, and the presence of smiles, are often examined in facial recognition processes [7].
5) Nose: The shape and size of the nose, including its length, width, and curvature, are distinctive features that can aid in the identification of a face [8].
6) Colour of the face and skin tone: The colour and tone of the skin are considered in facial recognition, as these characteristics are unique to each individual and can improve the accuracy of identification [9].

Together, these distinctive points form the unique features of an individual’s face, which facial recognition systems use for analysis and identification. Algorithms and facial recognition can compare and identify faces in databases or in real-world settings using individual attributes.

There exist various methods for identifying objects. Figure 2 shows the main milestones in this field of science.

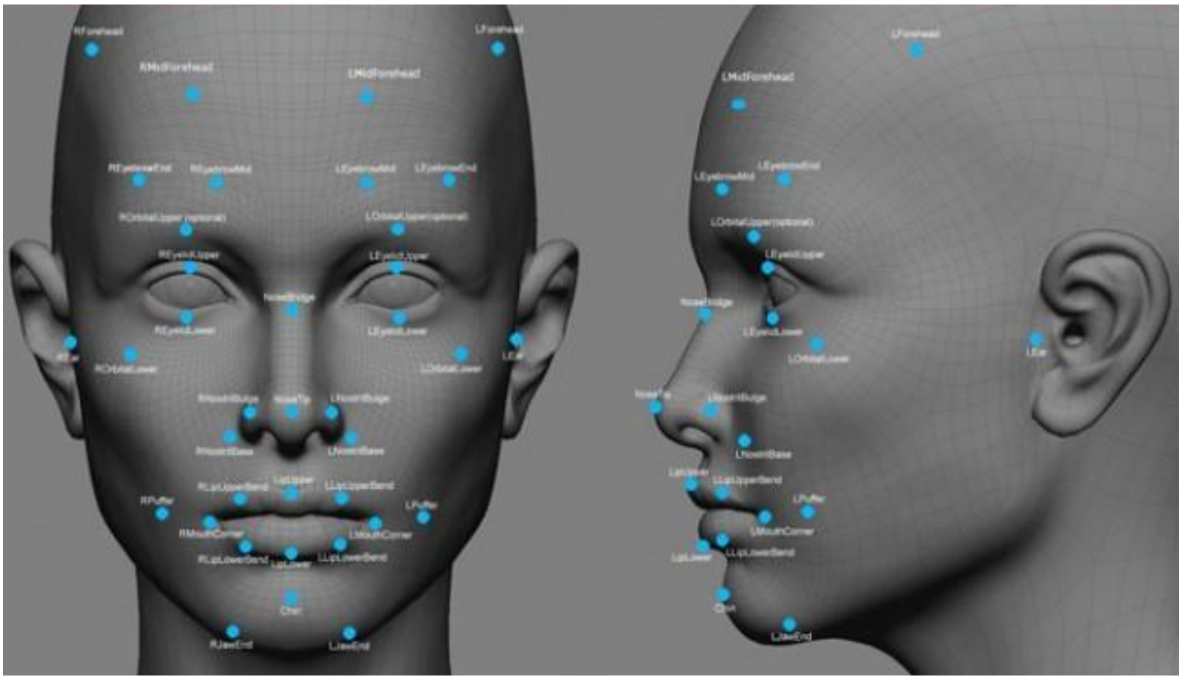

Figure 1. Points applicable to identification [10].

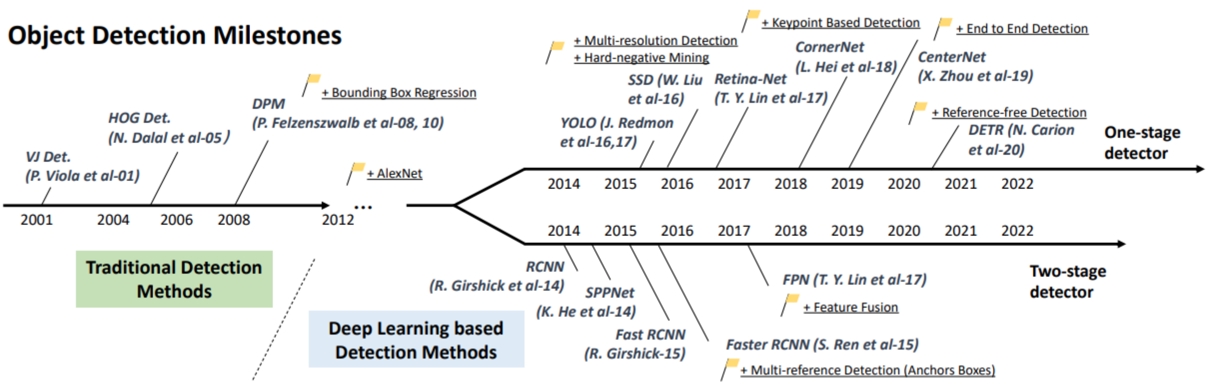

Figure 2. A road map of object detection [11].

In recent years, the practical application of facial recognition methods has raised questions about which techniques yield the most reliable and accurate results under specific conditions. This research is inspired by several publications that compare object identification algorithms [12-14]. Despite the various applications and benefits, the performance of facial recognition systems can vary according to the algorithms used. This research aims to compare the effectiveness of two algorithms: Viola-Jones and YOLOv3. The comparison will focus on their performance under different conditions, including various angles, lighting conditions, the presence or absence of characteristic facial points, and facial expressions.

OBJECTIVE OF THE RESEARCH

The objective of this research is to develop and evaluate a system that examines the capabilities of two algorithms used for face recognition. The system is implemented using freely available software tools and technologies. Throughout the study, we compare the two face recognition algorithms, highlighting their advantages and disadvantages. It is crucial to distinguish between face recognition and face identification: face recognition involves detecting the presence of a face in an image or video, while face identification involves recognizing the specific individual.

FACE RECOGNITION ALGORITHMS

Face recognition algorithms employ various methods to detect and identify faces. Here, we discuss the types of face recognition algorithms and briefly describe their operations.

1) Pre-trained face recognition models: These methods use deep learning models that have been pre-trained on extensive databases. Examples include convolutional neural networks (CNNs) trained with face recognition datasets such as VGG Face or FaceNet. This technology facilitates the recognition of individuals through their facial features in digital images or video recordings [15].
2) Face point-based algorithms: These algorithms identify the positions and proportions of the facial feature points, such as the eyes, nose, and lips. These points define the geometry and unique features of the face. Image processing techniques or facial line detection algorithms locate these points, which are then used for identification [16].
3) Curve-based methods: This method examines the contour and shape of the face. Algorithms determine facial contours and extract characteristics of the curves, such as convexity, length, and curvature. These curve features are used to identify and compare faces [16].
4) Two-dimensional statistical models: These algorithms construct statistical models of the face using techniques such as principal component analysis (PCA) or linear discriminant analysis (LDA). The models are used to project and compare face images [16].

ALGORITHMS USED IN RESEARCH

Viola-Jones Algorithm

The Viola-Jones algorithm, developed by Paul Viola and Michael Jones, is a machine learning and image processing algorithm designed for the rapid and efficient detection of objects, particularly human faces, in computer vision applications. They presented the algorithm in the 2001 paper "Rapid Object Detection using a Boosted Cascade of Simple Features", and it has since grown to be one of the most used techniques for object and face detection [17].

The Viola-Jones algorithm utilizes Haar-like features to detect objects. These features allow the algorithm to distinguish between the object of interest and the background. The object detection process in the Viola-Jones algorithm involves the following phases [17].

Selection of Haar Features: Human faces exhibit similar features, such as the eye region being darker than the bridge of the nose. This characteristic aids in identifying pixels that correspond to specific facial parts. Haar classifiers are used in the Viola-Jones algorithm to identify facial features. Using Haar functions, one may determine the density within a zone, potentially signifying a distinctive feature or attribute. These features show up as rectangles in the image. A feature will be defined using two or three rectangles. Figure 3 illustrates the characteristics identified by Haar functions [18].

Image integration: The objective is to minimise the quantity of pixel-based computations. The calculation of the integrated image from the pixel values is illustrated in Figure 4. Each point in the integrated image has a value equal to the sum of all pixels to its left and above, including the target pixel. Next, we use the formula (D –B –C + A) to determine the total number of pixels in the orange rectangle. As a result, the integrated image's value is 113 –81 –42 + 20 = 41 [18].

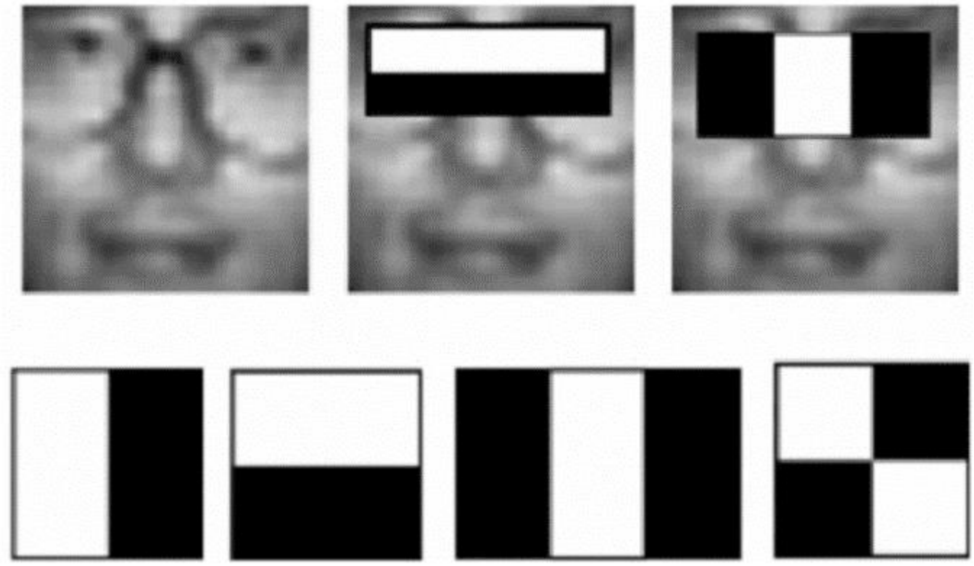

Figure 3. Haar characteristics [18].

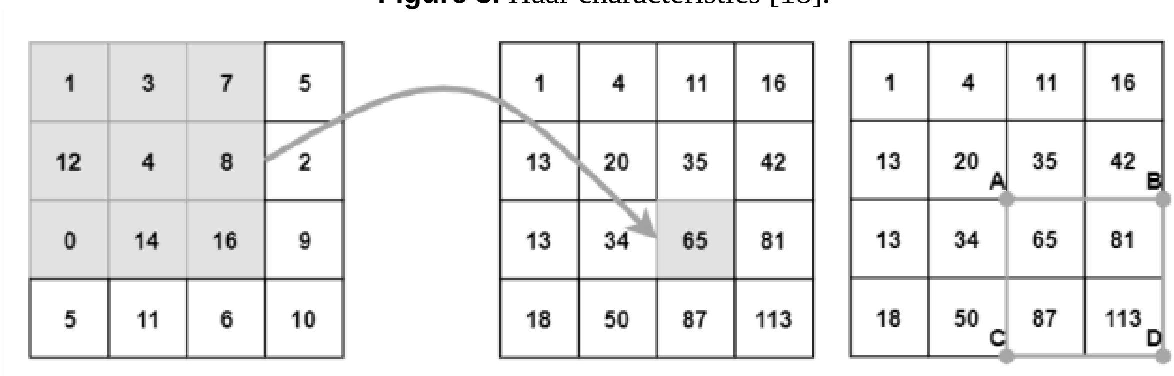

Figure 4. Integrated image [18].

The **cascading classifier** is a fundamental component of the Viola-Jones algorithm, pivotal for efficient object detection. It consists of multiple classifiers applied sequentially, each imposing increasingly strict conditions to identify objects in an image. The cascading classifier utilizes several classification layers to enhance detection accuracy. This multi-layer approach filters out non-objects progressively, focusing computational resources on regions of the image more likely to contain the target object. The operational principle of the cascading classifier is illustrated in Figure 5.

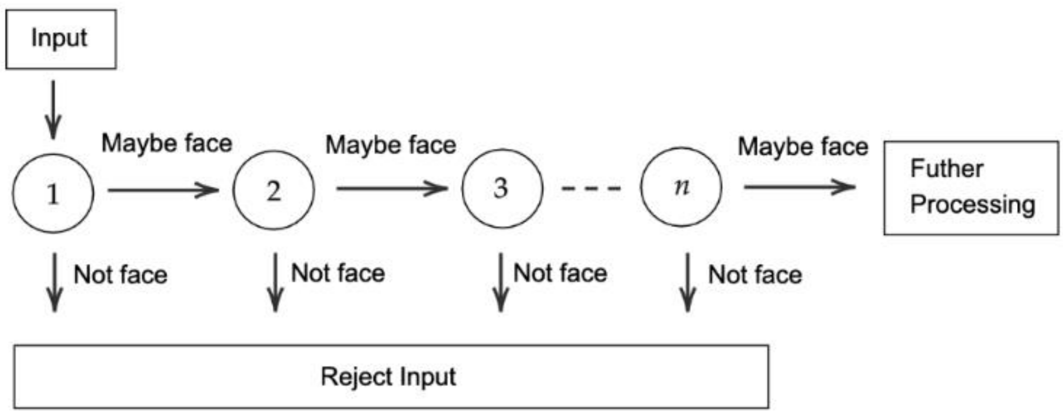

Figure 5. Cascading classifier [19].

The **Histogram of Orientated Gradients** (HOG) is a feature descriptor commonly employed in computer vision and image processing for object detection. This technique involves counting the occurrences of gradient orientations in localised parts of an image. HOG is computed on a dense grid of uniformly distributed cells, with overlapping local contrast normalization to enhance accuracy. Essentially, HOG represents an object as a single value vector, making it robust and effective for object detection tasks, Figure 6 [18].

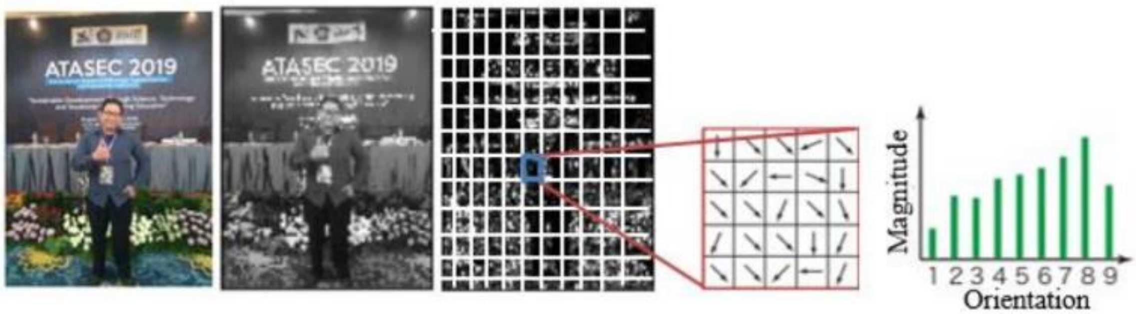

Figure 6. Histogram feature extraction of oriented gradients [18].

YOLOv3 Algorithm

YOLOv3 (You Only Look Once, version 3) is a real-time object recognition algorithm designed to identify specific objects in videos, live streams, or images. YOLO employs features learnt by a deep convolutional neural network (CNN) for object detection. Developed by Joseph Redmon and Ali Farhadi, YOLOv3 is an improved version of the earlier YOLO algorithms, offering higher precision [20]. The latest version, YOLOv7, was released in 2022, further enhancing the algorithm's capabilities. YOLOv3 is renowned for its reliability and speed in object detection, making it suitable for a wide range of applications, including vehicle recognition, video understanding, autonomous driving, and real-time object tracking.

The core mechanism of YOLO involves using a CNN to detect objects. A CNN is a classifier-based system capable of processing input images as structured data blocks and recognising patterns within them. Figure 7 illustrates object detection based on CNN [21].

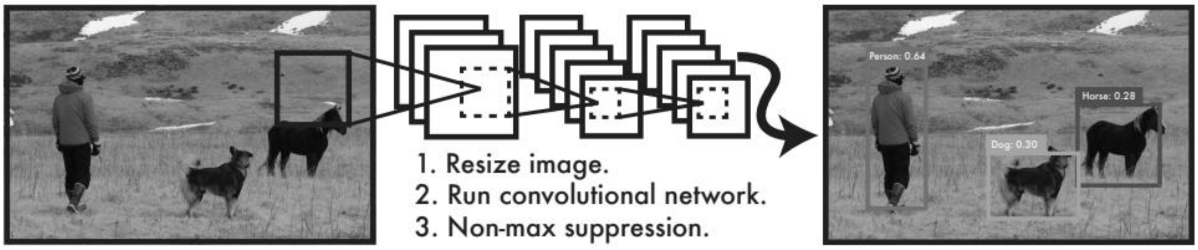

Figure 7. Detection strategy of YOLO [21].

The YOLOv3 algorithm processes the image through a simple CNN, which divides the image into a grid. It then generates bounding boxes for each grid cell and assigns class probabilities to them. These bounding boxes vary in size, allowing the detection of objects of different dimensions. YOLO scores regions based on their similarity to predefined classes; regions with high scores are recorded as positive detections and are classified according to their closest class match, Figure 8 [21].

Figure 9 shows the simplified architecture of YOLOv3.

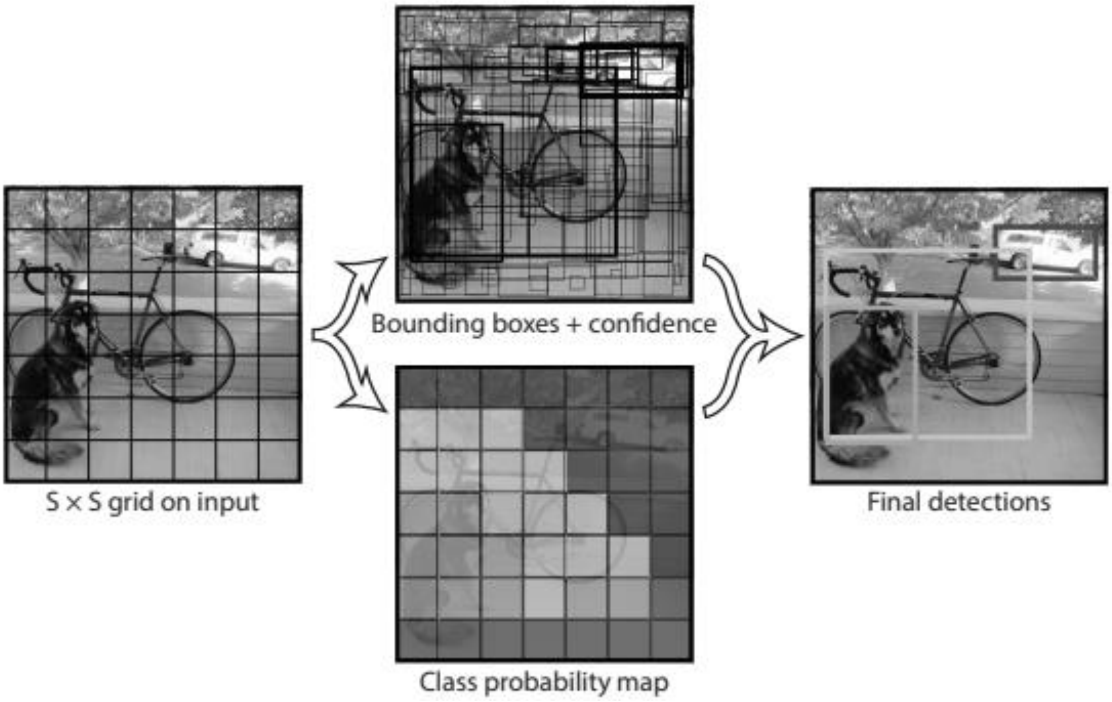

Figure 8. Predicting objects in the image [21].

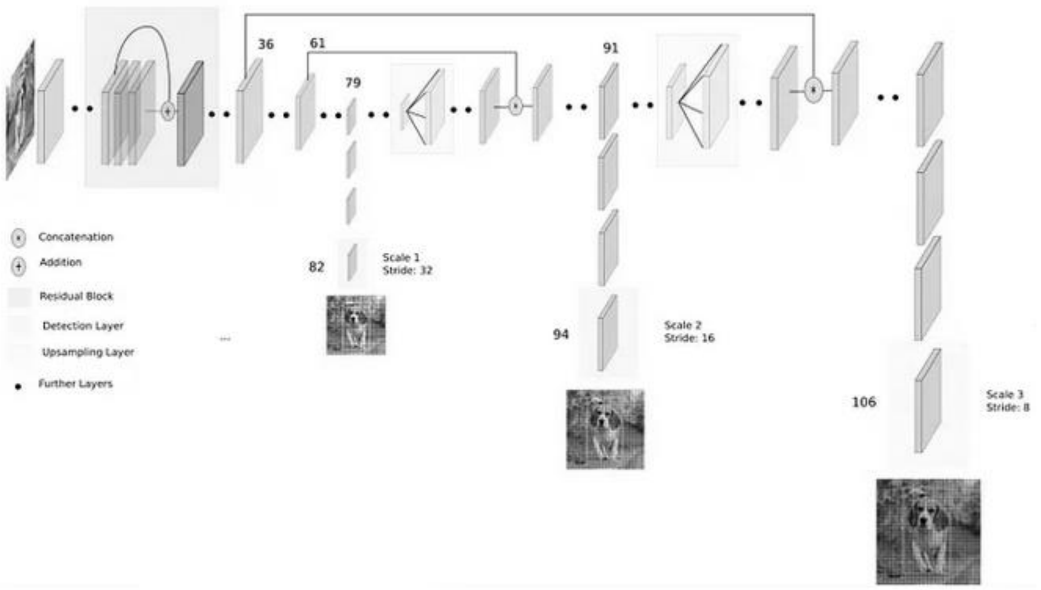

Figure 9. The CNN architecture used in YOLOv3 [16].

RESEARCH METHODOLOGY

The objective of this research is to establish a system to evaluate the capabilities of two face recognition algorithms. Viola-Jones and YOLOv3. The system was constructed using open source software tools and technologies and the study involved 210 images. These images were acquired with participants' consent, ensuring ethical compliance.

EXPERIMENTAL SETUP

The experiment was designed to test the algorithms under four specific conditions:

1) Different angles – images were taken with the head positioned at 0, 30, 45, and 90 degrees to the camera, as well as in an upward-facing position.
2) Lighting conditions – the images were captured under various lighting conditions, including low light, high light, and artificial light settings.
3) Absence of characteristic points – the images were taken with certain facial features obscured, such as the forehead, eyebrows, or eyes.
4) Facial expressions – the images were taken with different facial expressions, including smiling, frowning, and neutral expressions.

EVALUATION CRITERIA

The performance of each algorithm was evaluated based on the following criteria:

1) Recognition accuracy – the percentage of correctly identified faces under each condition.
2) Robustness – the ability to maintain high accuracy despite changes in angle, lighting, and expression.
3) Sensitivity to missing features – how the absence of key facial features affects the accuracy of recognition.

EXPERIMENTAL RESULTS

Viola-Jones Algorithm

Different angles. In our study, we investigated the impact of various angles on the performance of face recognition algorithms. Our findings reveal that in the case of the Viola-Jones algorithm, the angle at which an image is captured significantly affects the algorithm's recognition accuracy, Figure 10. At a 0-degree angle, which corresponds to a frontal view of the face, the Viola-Jones algorithm achieved a 100% recognition rate. However, this efficiency dramatically decreases with changes in the angle of the face.

When the face was tilted at a 45-degree angle, the recognition rate dropped to 80%. At a 30-degree angle, the efficiency dropped to 15%. Furthermore, when the face was positioned at a 90-degree angle, the recognition rate was a mere 10%. Interestingly, the algorithm showed a moderate recognition rate of 64% when the subject looked upwards.

Different light conditions. These observations are critical as they highlight the sensitivity of the Viola-Jones algorithm to the angle of image acquisition. The significant decline in recognition accuracy at non-frontal angles suggests that the algorithm is highly dependent on frontal facial features for accurate detection and recognition. This sensitivity can create challenges in real-world applications, especially when faces are not consistently aligned with the camera.

The performance of face recognition algorithms can be significantly influenced by varying lighting conditions. In this study, we evaluated the robustness of algorithms under different lighting environments. Our results indicate that the Viola-Jones algorithm exhibits exceptional performance across a wide range of lighting conditions, achieving a 100% recognition rate in almost all tested scenarios.

Natural light. The algorithm demonstrated flawless recognition capabilities in natural daylight. Faces were detected and recognized with complete accuracy, regardless of the intensity or direction of the sunlight. This suggests that the algorithm's feature detection process is highly effective in leveraging the sharp contrast and distinct shadows provided by natural light.

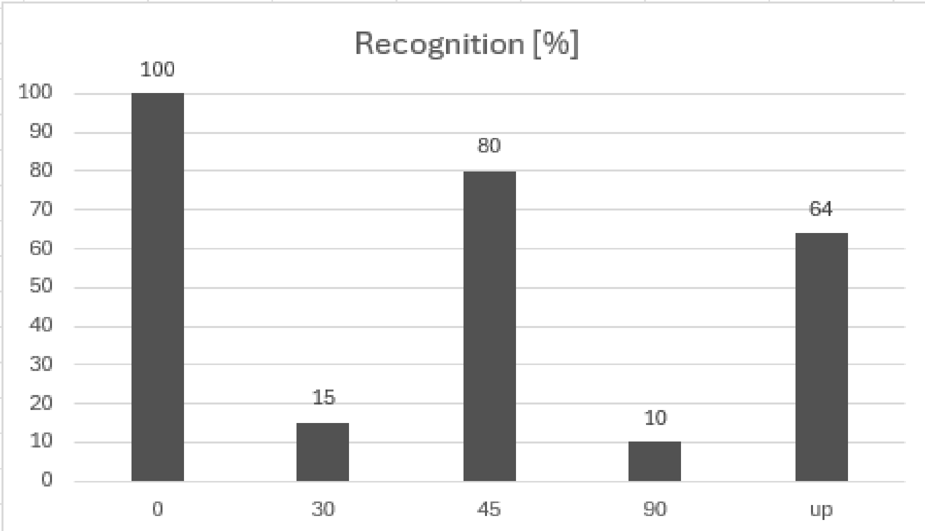

Figure 10. Face recognition for different angles for Viola-Jones algorithm.

Artificial light. Under artificial lighting conditions, such as those provided by standard room lamps and overhead lights, the Viola-Jones algorithm maintained a 100% recognition rate. This performance consistency indicates that the algorithm can effectively manage the uniformity and consistency of artificial light sources.

Dim lighting. The algorithm's robustness extends to low-light conditions as well. In environments with dim lighting, where details may be obscured and shadows are less pronounced, the algorithm still achieved perfect recognition accuracy. This suggests that the algorithm's feature extraction mechanism is sufficiently sensitive to detect facial features even when illumination is minimal.

Gray backgrounds. When evaluated against gray and uniformly lit backgrounds, the algorithm's performance remained impeccable. The lack of contrasting background elements did not affect its ability to recognize faces, highlighting the algorithm's focus on facial features rather than environmental cues.

Varied lighting conditions. The algorithm also performed consistently well in environments with mixed lighting conditions, such as those combining natural and artificial light sources or areas with uneven illumination. This versatility underscores the algorithm's robustness in real-world settings, where lighting conditions can be unpredictable and varied.

The results demonstrate that the Viola-Jones algorithm is highly resilient to changes in lighting conditions, making it a reliable choice for face recognition applications in diverse environments. The algorithm's ability to maintain high accuracy across different lighting scenarios can be attributed to its use of Haar-like features, which effectively capture the essential characteristics of faces regardless of external lighting variations.

Absence of characteristic points. When the forehead or eyebrows were not visible, the Viola-Jones algorithm maintained a high reliability rate of 98%. This indicates that while these features contribute to the overall recognition process, their absence does not drastically impair the algorithm's effectiveness. However, when the eyes were obscured, the reliability slightly decreased to 95%, underscoring the critical role that the eyes play in facial recognition. In contrast, occluding the nose or mouth had no adverse impact, with the algorithm achieving a perfect recognition rate of 100%, Figure 11. A more significant decline in performance was observed when both the eyes and nose were simultaneously obscured. In such cases, the recognition rate dropped to 77%. This finding emphasizes the importance of the eyes and nose as primary reference points for the algorithm. The decrease in accuracy suggests that the Viola-Jones algorithm heavily relies on these characteristic points to distinguish and identify faces reliably.

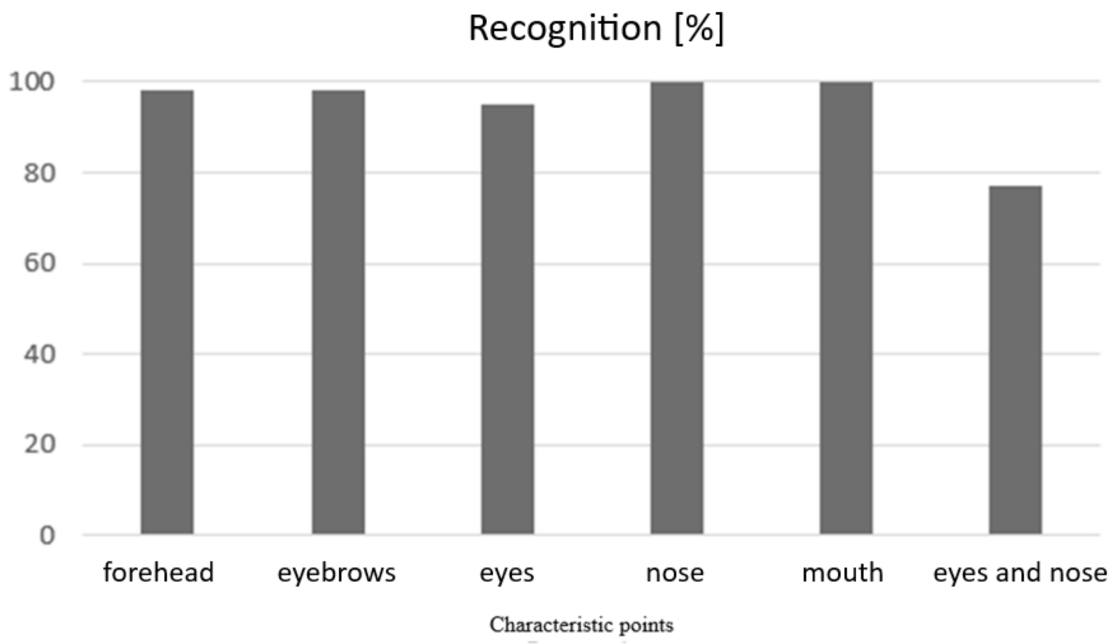

Figure 11. Results based on the absence of characteristic points for the Viola-Jones algorithm.

Facial expressions. Our study also explored the impact of various facial expressions on the performance of algorithms. We tested a variety of expressions, including smiles, glasses, surprised faces, sad faces, and grimaces. Remarkably, the Viola-Jones algorithm achieved a 100% recognition rate across all tests, indicating that facial expressions do not hinder its ability to recognize faces.

These results demonstrate that the Viola-Jones algorithm is robust against changes in facial expressions. The algorithm's invariant performance despite different expressions suggests that it effectively focuses on stable facial features rather than dynamic expressions. This robustness is beneficial for practical applications, ensuring consistent performance regardless of facial movements and expressions.

Figure 12. Evaluating the Viola-Jones algorithm.

YOLOv3 Algorithm

Different angles. The YOLOv3 algorithm demonstrated robust performance in face recognition across various angles, Figure 13. When capturing images from a frontal view (0 degrees), the algorithm achieved a 100% recognition rate. This high accuracy extended to angles up to 45 degrees of rotation. However, as the rotation increased to 90 degrees or decreased to 30 degrees, the recognition accuracy slightly decreased to 95%. For instances where subjects looked upwards, the efficiency varied, averaging around 80%, depending on the degree of head tilt.

These results underscore the YOLOv3 algorithm's strong capability in recognizing faces across different angles. The algorithm excels in frontal and moderate side views, maintaining high accuracy. However, extreme angles and upward views present more challenges, slightly reducing the recognition rate, though it remains notably high.

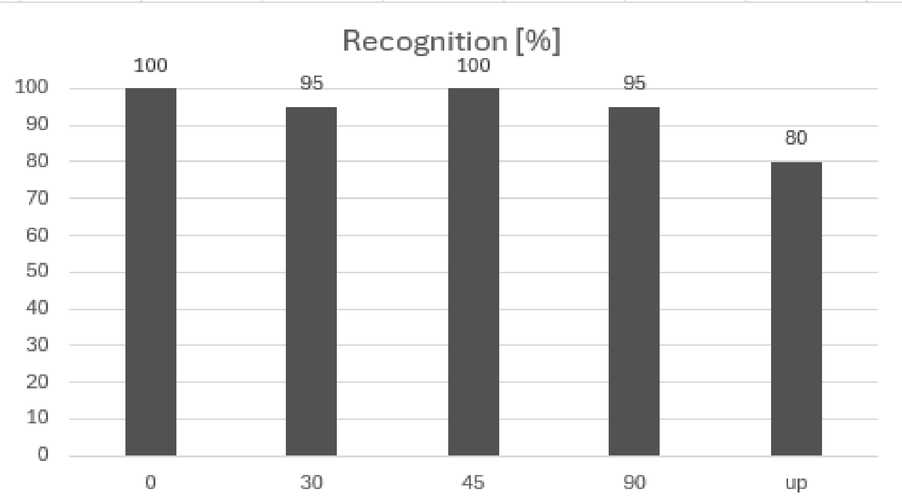

Figure 13. Evaluating the YOLOv3 algorithm for different angles.

Light conditions. The YOLOv3 algorithm also exhibited excellent robustness to varying lighting conditions. The face recognition rate was consistently 100% in different lighting scenarios, including natural light, artificial light from the lamp, sharp contrast settings, and dim environments. The algorithm maintained perfect performance even under artificial lighting conditions.

This robustness to lighting variations is crucial for real-world applications, where lighting conditions can be unpredictable and diverse. The ability of the YOLOv3 algorithm to perform reliably under various lighting conditions ensures its effectiveness in practical face recognition applications, providing consistent and accurate results irrespective of environmental lighting changes.

Absence of characteristic points. The algorithm was also evaluated for its ability to recognise faces when characteristic points were obscured. The absence of individual features such as the eyes, nose, forehead, eyebrows, and mouth did not significantly impact the recognition accuracy, which remained at 100% in all cases. Even when both the eyes and nose were obscured simultaneously, the algorithm maintained perfect recognition performance, Figure 14.

These findings highlight the YOLOv3 algorithm's advanced capability to manage incomplete facial data. This robustness makes the algorithm highly versatile and suitable for scenarios where certain facial features may be hidden or partially visible, thus broadening the potential applications of face recognition technology.

Facial expressions. In the final stage of our study, we evaluated the impact of various facial expressions on the YOLOv3 algorithm's performance. The tested expressions included smiling, surprise, sadness, and grimaces (Figure 14). The results showed that changes in facial expressions did not affect the recognition accuracy, which remained at 100% across all test cases. This finding indicates that the YOLOv3 algorithm is highly effective in recognizing faces regardless of facial expressions. This robustness to facial movements ensures that the algorithm can reliably identify individuals in dynamic real-life situations where expressions frequently change.

Figure 14. Testing the YOLOv3 algorithm.

CONCLUSIONS

The comparative analysis of the Viola-Jones and YOLOv3 algorithms in face recognition highlights distinct advantages and limitations for each algorithm. The Viola-Jones algorithm shows high sensitivity to facial angles, with notable performance drops at non-frontal views. However, it performs excellently under varying lighting conditions and is robust to changes in facial expressions. The algorithm's performance declines significantly when multiple key facial features are simultaneously obscured.

In contrast, the YOLOv3 algorithm demonstrates superior robustness across different angles, maintaining high accuracy even at moderate and extreme angles. It is highly resilient to various lighting conditions and facial feature occlusions, showing consistent performance regardless of facial expressions. In general, the YOLOv3 algorithm outperforms the Viola-Jones algorithm in terms of angle robustness and managing occluded facial features. Both algorithms exhibit exceptional performance in diverse lighting conditions and insensitivity to facial expressions.

Future research should focus on enhancing the algorithms' robustness against extreme angles and partial occlusions. Comparative studies with other state-of-the-art face recognition models could provide a comprehensive understanding of each algorithm's strengths and potential areas for enhancement. Viola-Jones and YOLOv3 may also be more applicable in a wider range of real-world circumstances if their integration with other recognition techniques is investigated as this could lead to additional gains in accuracy and reliability.

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