IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, June 2026
Impact Factor: 8.2

# Spotlight AI: Detection Faces Beyond Shadows

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**Abstract:** *Spotlight AI: Detecting Faces Beyond Shadows is an advanced face detection system designed to accurately identify human faces in challenging lighting environments such as darkness, shadows, glare, and high dynamic range conditions where traditional detection systems often fail. The proposed system uses a four-stage intelligent pipeline that first analyzes the lighting condition of the input image or live video frame, then applies suitable enhancement techniques such as CLAHE, Retinex filtering, tone mapping, and inpainting to improve visibility and restore hidden facial details. After enhancement, optimized SCRFD deep learning models through the InsightFace ONNX framework are used to detect faces with high speed and accuracy. The system is integrated with FastAPI and WebSocket communication to support real-time webcam streaming with asynchronous processing, ensuring smooth performance without lag or frame freezing. By improving image quality before detection and processing frames efficiently, Spotlight AI enhances reliability and performance in real-world surveillance, biometric authentication, and smart monitoring applications operating under poor lighting conditions.*

**Keywords:** Face Detection, Artificial Intelligence, Computer Vision, Deep Learning, Low-Light Enhancement, SCRFD, FastAPI, WebSocket, Real-Time Monitoring, Image Processing

## I. INTRODUCTION

Face detection is an essential component of modern computer-based systems and plays a significant role in areas such as security, surveillance, biometric verification, and human–computer interaction. With the rapid growth of Computer Vision and Artificial Intelligence, face detection technologies have evolved from traditional feature-based methods to advanced deep learning approaches that offer higher accuracy and faster processing [1]. Despite these advancements, one of the major challenges faced by existing systems is their inability to perform effectively under difficult lighting conditions such as low light, shadows, glare, and high dynamic range environments [2].

Traditional face detection techniques often rely on clear visibility of facial features, making them sensitive to variations in illumination. When lighting conditions are poor or uneven, these methods fail to detect faces accurately, leading to performance degradation [3]. To overcome this issue, researchers have introduced various image enhancement techniques that improve the quality of input images before applying detection algorithms. Methods such as histogram equalization, contrast enhancement, and Retinex-based approaches have been widely used to restore visibility and highlight important facial features [4][5].

In recent years, deep learning-based models have shown remarkable performance in face detection tasks. Models such as SCRFD, implemented through frameworks like InsightFace, have been designed to achieve a balance between speed and accuracy, making them suitable for real-time applications [6]. However, even these advanced models depend heavily on the quality of input data, and their effectiveness can be reduced when images are captured in poor lighting environments [7].

To support real-time processing, modern systems utilize efficient backend frameworks and communication protocols. Technologies like FastAPI and WebSocket enable continuous data transfer between client and server, allowing live video frames to be processed without delay [8]. Additionally, asynchronous programming techniques help in handling multiple tasks simultaneously, improving system responsiveness and scalability [9].

The proposed system, Spotlight AI: Detecting Faces Beyond Shadows, aims to address the limitations of existing methods by integrating lighting-aware preprocessing with deep learning-based face detection. The system uses a multi-stage pipeline that first identifies lighting conditions, enhances image quality using suitable techniques, and then applies optimized detection models to achieve accurate results [10]. This approach improves detection performance in challenging environments and makes the system more reliable for real-world applications where lighting conditions are often unpredictable.

## II. PROBLEM STATEMENT

Face detection systems have become an integral part of modern applications such as surveillance, biometric authentication, and smart monitoring; however, their performance remains highly dependent on the quality of input images, particularly lighting conditions. In real-world scenarios, images and video streams are often affected by poor illumination, shadows, glare, and high dynamic range variations, which obscure facial features and reduce detection accuracy. Most existing detection models are trained on well-lit datasets and therefore struggle to generalize effectively in low-light or uneven lighting environments, leading to missed detections or false results. Additionally, conventional systems lack adaptive mechanisms to analyze and correct lighting issues before performing detection, making them less reliable in practical applications. The challenge is further intensified in real-time systems, where maintaining high accuracy while ensuring low latency and smooth performance is critical.

## III. OBJECTIVES

- To develop a face detection system capable of identifying faces under low-light, shadow, and glare conditions.
- To implement an adaptive lighting classification mechanism for analyzing image conditions in real time.
- To enhance image quality using suitable preprocessing techniques before detection.
- To integrate deep learning models for accurate and efficient face detection.
- To ensure real-time performance with minimal latency using an optimized system architecture.

## IV. LITERATURE SURVEY

### 1. SCRFD: Towards More Efficient Face Detection

**Year:** 2021

**Publication:** arXiv / InsightFace Research

This paper introduces SCRFD, a fast and accurate face detection model designed for real-time applications. It focuses on optimizing computation while maintaining high detection accuracy across various conditions such as pose variations and occlusions. The model is lightweight and suitable for deployment in systems requiring quick processing, making it highly relevant for real-time face detection systems like Spotlight AI.

### 2. Retinex-Based Image Enhancement for Low-Light Images

**Year:** 2018

**Publication:** IEEE Transactions on Image Processing

This study presents Retinex-based techniques to enhance images captured under poor lighting conditions. The method improves visibility by separating illumination and reflectance components, thereby restoring details in dark regions. It is widely used in preprocessing pipelines to improve the performance of detection algorithms in low-light scenarios.

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**3. CLAHE: Contrast Limited Adaptive Histogram Equalization**
**Year:** 1994
**Publication:** Graphics Gems IV
This research introduces CLAHE, an improved version of histogram equalization that prevents over-amplification of noise while enhancing contrast. It is particularly useful for improving image clarity in shadowed or uneven lighting conditions and is commonly applied in face detection preprocessing.

**4. InsightFace: 2D and 3D Face Analysis Project**
**Year:** 2019
**Publication:** GitHub / Research Initiative
InsightFace provides a comprehensive framework for face detection and recognition using deep learning models. It supports high-performance models like SCRFD and offers cross-platform deployment using ONNX. The framework is widely adopted for real-time applications due to its efficiency and accuracy.

**5. Real-Time Face Detection Using Deep Learning**
**Year:** 2016
**Publication:** IEEE Conference on Computer Vision and Pattern Recognition (CVPR)
This paper explores deep learning-based approaches for real-time face detection, highlighting the use of convolutional neural networks (CNNs). It demonstrates improved accuracy compared to traditional methods and discusses challenges such as lighting variations and processing speed, which are key considerations in modern systems.

**6. FastAPI for High-Performance Web Applications**
**Year:** 2018
**Publication:** Official FastAPI Documentation / Community Research
This work explains the use of FastAPI for building high-performance APIs with asynchronous capabilities. It supports real-time communication using WebSockets and enables efficient handling of streaming data. This technology is essential for systems like Spotlight AI that require continuous frame processing and low-latency communication.

**Comparison Table**

| Author & Year | Method Used | Advantages | Limitations |
|---|---|---|---|
| Wang et al., 2021 | SCRFD Face Detection Model | High accuracy, fast processing, lightweight model | Performance depends on image quality |
| Jobson et al., 2018 | Retinex-Based Enhancement | Improves low-light visibility, restores details | Computationally intensive |
| Zuiderveld, 1994 | CLAHE Technique | Enhances contrast, reduces noise amplification | May over-enhance some regions |
| Deng et al., 2019 | InsightFace Framework | High performance, supports real-time applications | Requires proper hardware support |
| Viola & Jones, 2001 | Haar Cascade Classifier | Fast detection, simple implementation | Poor performance in low light |
| FastAPI, 2018 | Async Web Framework | Low latency, supports real-time communication | Requires proper backend optimization |

## IV. WORKING OF SYSTEM

**1. Image Capture (Frontend)**
The system starts with the **HTML5 Canvas & Webcam Client**.

- Captures live video frames from the user’s webcam.

- Displays the video stream in real time on the browser.

**2. Frame Conversion & Transmission**
The captured frames are processed before sending to the server.
- Each frame is converted into Base64 encoded format.
- The encoded data is structured into JSON format.
- Frames are sent continuously to the backend using WebSocket.

**3. Real-Time Communication (FastAPI WebSocket)**
The FastAPI WebSocket Router manages communication.
- Establishes a persistent connection between client and server.
- Enables two-way real-time data transfer.
- Avoids repeated HTTP requests, reducing latency.

**4. Asynchronous Processing**
The backend uses Python Async Event Loop.
- Handles multiple incoming frames simultaneously.
- Ensures non-blocking execution of tasks.
- Maintains smooth and uninterrupted streaming.

**5. Thread Execution for Heavy Tasks**
Computational tasks are handled separately.
- Thread Executor processes heavy operations like image enhancement and detection.
- Prevents the main event loop from slowing down.
- Prioritizes latest frames and drops older ones if needed.

**6. 4-Stage Detection Pipeline**
Core processing is done in a structured pipeline:
**Stage 1: Lighting Classification**
Identifies lighting condition (low-light, shadow, glare, HDR, normal).

**Stage 2: Image Enhancement**
Applies techniques like CLAHE, Retinex, or tone mapping.
Improves visibility of facial features.

**Stage 3: Face Detection**
Uses deep learning model to detect faces.

**Stage 4: Output Generation**
Generates bounding boxes and facial landmarks.

**7. AI Model Processing**
Uses **InsightFace ONNX Models**.
- Converts images into tensors for processing.
- Detects faces using SCRFD model.

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- Outputs coordinates (x1, y1, x2, y2) and key points.

**8. Result Transmission to Client**

Processed results are sent back to frontend.

- Returned in JSON format via WebSocket.
- Includes annotated frame and face coordinates.

**9. Visualization (Frontend Output)**

Final output is displayed on the browser.

- Bounding boxes are drawn around detected faces.
- Real-time detection results are updated continuously.

**10. Continuous Real-Time Loop**

The process repeats continuously.

- Ensures real-time face detection without delay.
- Maintains smooth user experience even under poor lighting conditions.

## V. SYSTEM DESIGN

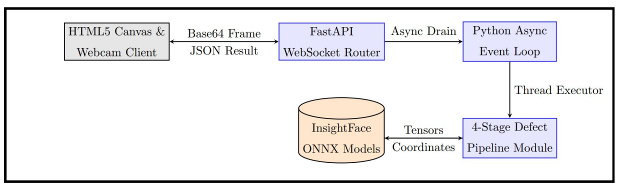


**Fig 1: Design of the system**

**1. Frontend Interface Design**

The frontend is developed using HTML5 Canvas and browser-based webcam access. It provides a user-friendly interface to capture live video streams and display results in real time. The canvas continuously renders frames and overlays detection outputs such as bounding boxes and facial landmarks.

**2. Data Encoding and Transmission Module**

Captured video frames are converted into Base64 encoded format and structured as JSON objects. This design ensures compatibility with web communication protocols and allows efficient transfer of image data from the client to the server.

**3. Communication Layer (WebSocket Integration)**

The system uses FastAPI with WebSocket protocol to establish a persistent, bidirectional communication channel. This enables continuous streaming of frames without repeated requests, ensuring low latency and smooth real-time interaction between frontend and backend.

**4. Asynchronous Processing Architecture**

An asynchronous event-driven architecture is implemented using Python's async event loop. It allows multiple frames to be processed concurrently without blocking the system, improving responsiveness and scalability.


DOI: 10.48175/568

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**5. Task Management using Thread Executor**
Heavy computational tasks such as image preprocessing and deep learning inference are handled by a thread executor. This separation prevents delays in the main execution flow and ensures efficient resource utilization.

**6. Image Preprocessing and Enhancement Module**
Before detection, the system enhances image quality based on lighting conditions. Techniques such as CLAHE, Retinex filtering, and tone mapping are applied to improve visibility, especially in low-light or shadowed environments.

**7. Face Detection Model Integration**
The system integrates deep learning models (SCRFD via InsightFace ONNX framework) for accurate face detection. These models are optimized for real-time performance and can handle variations in pose, lighting, and occlusion.

**8. Multi-Stage Detection Pipeline**
A structured four-stage pipeline is designed, including lighting classification, image enhancement, face detection, and result generation. This modular design improves system efficiency and allows easy updates or enhancements.

**9. Output Processing and Visualization**
After detection, the system generates face coordinates and annotations. These results are sent back to the frontend, where they are visually displayed on the canvas in real time.

**10. Real-Time Performance Optimization**
The overall system is optimized to process only the latest frames, reducing lag and avoiding unnecessary computation. This ensures smooth performance and accurate detection even in dynamic environments.

## VI. RESULTS

The proposed system, Spotlight AI: Detecting Faces Beyond Shadows, demonstrates significant improvement in face detection performance under challenging lighting conditions such as low light, shadows, glare, and high dynamic range environments. By integrating adaptive image enhancement techniques with deep learning-based detection models, the system is able to accurately identify facial features even when visibility is poor. The use of a multi-stage processing pipeline ensures that images are first analyzed and enhanced before detection, leading to higher accuracy compared to traditional methods. Additionally, the implementation of FastAPI with WebSocket communication and asynchronous processing enables real-time performance with minimal latency, ensuring smooth and continuous video streaming. The system effectively maintains a balance between speed and accuracy by prioritizing the processing of recent frames and efficiently managing computational tasks. Overall, the results indicate that the proposed approach provides reliable and robust face detection in real-world scenarios, making it suitable for applications such as surveillance, biometric authentication, and smart monitoring systems.

## VII. CONCLUSION

Spotlight AI: Detecting Faces Beyond Shadows successfully addresses the limitations of traditional face detection systems by introducing an intelligent, lighting-aware approach. The system integrates image enhancement techniques with advanced deep learning models to improve detection accuracy in challenging conditions such as low light, shadows, glare, and high dynamic range environments. The use of a structured multi-stage pipeline ensures that image quality is optimized before detection, leading to more reliable results. Additionally, the implementation of asynchronous processing with FastAPI and WebSocket communication enables real-time performance with low latency

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and smooth operation. The system demonstrates a balanced combination of accuracy, speed, and efficiency, making it suitable for practical applications in surveillance, biometric systems, and smart monitoring environments.

## VIII. FUTURE SCOPE

The system can be further enhanced by integrating face recognition capabilities along with detection to enable identity verification. Future improvements may include the use of more advanced deep learning models to increase accuracy in extremely challenging conditions such as complete darkness or occluded faces. The system can also be extended to support edge devices and IoT-based implementations for deployment in remote or resource-constrained environments. Additionally, incorporating thermal imaging or infrared sensors could further improve performance in low-light scenarios. Optimization for mobile platforms and cross-device compatibility can make the system more accessible. Finally, continuous learning mechanisms and dataset expansion can be implemented to improve adaptability and performance over time in diverse real-world conditions.

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DOI: 10.48175/568