

DEEP LEARNING BASED HUMAN OBJECT DETECTION IN FOG ENVIRONMENT FOR DEFENSE APPLICATION

Priya.K¹, Gayathri.M², Maha.S³, Mohitha sri.G⁴, Rani.S⁵,

¹Assistant Professor, Artificial Intelligence and Data Science& Bharathiyar Institute of Engineering for Women (Autonomous), Salem, Tamilnadu, India

^{2,3,4,5} UG Student, Artificial Intelligence and Data Science& Bharathiyar Institute of Engineering for Women (Autonomous), Salem, Tamilnadu, India

Abstract--Foggy weather conditions greatly affect the performance of vision-based surveillance systems used in sensitive defence areas such as borders, military bases, and ammunition depots. When fog is present, visibility becomes very low because fog particles scatter and absorb light. As a result, cameras capture unclear images with poor contrast and reduced details. Due to this, traditional computer vision systems often fail to detect human intruders accurately, which can create serious security risks in defence environments. To address this problem, this work proposes a deep learning-based framework for detecting humans in foggy environments, specially designed for defence surveillance applications. The proposed system combines a lightweight image enhancement module with an improved YOLO-based object detection model. In the first stage, the enhancement module improves the quality of foggy images by increasing contrast and restoring important visual details. This step helps make the objects in the scene clearer and easier to detect.

After the image enhancement stage, the improved images are processed by the YOLO-based detection model, which identifies humans in the scene by generating bounding boxes around detected objects. The use of YOLO allows the system to perform detection quickly while maintaining good accuracy, making it suitable for real-time surveillance applications.

The model is trained and tested using fog-specific datasets such as Foggy Cityscapes and RTTS, alongwith additional low-visibility surveillance videos. Experimental results showthat the proposed system improves mean average precision (mAP) compared with standard detection models, while still maintaining near real-time performance.

Overall, the results show that the system can effectively support continuous monitoring and early intruder detection in defence environments under foggy conditions. In the future, the system can be further improved by integrating thermal or infrared sensors, which can help detect humans even in verydense fog. The system can also be deployed on embedded devices to support large-scale defence surveillance operations.

Keywords--Deep Learning, Human Object Detection, Foggy Environment, YOLO, Image Enhancement,

defense Surveillance, Real-time Detection, Foggy Cityscapes, Intruder Detection.

1.INTRODUCTION

Security and surveillance play a vital role in protecting important defence installations such as international borders, military bases, airfields, and ammunition storage facilities. These locations are considered highly sensitive areas and therefore require continuous 24/7 monitoring to detect any unauthorized human movement or intrusion. Effective surveillance systems help security personnel respond quickly to potential threats and ensure the safety of national defence infrastructure.

However, surveillance systems often face challenges due to environmental conditions. Weather factors such as fog, mist, and haze can significantly reduce visibility, especially during winter seasons and early morning hours. In foggy conditions, cameras capture images with low contrast and blurred details because fog particles scatter and absorb light. As a result, objects in the scene become difficult to distinguish from the background. These conditions make it difficult for both conventional camera systems and human operators to accurately identify potential threats. In many cases, intruders may remain undetected until they are very close, which can create serious security risks in defence environments.

In recent years, deep learning-based object detection models have shown remarkable improvements in detecting objects and humans in images and video streams. Among these models, the YOLO (You Only Look Once) family of algorithms has gained significant popularity because it provides a good balance between detection accuracy and processing speed. YOLO-based models can detect multiple objects in real time and are widely used in applications such as smart surveillance systems, autonomous vehicles, traffic monitoring, and security systems.

Although these deep learning models perform very well in normal conditions, their performance decreases significantly in foggy environments. One of the main reasons for this limitation is that most object detection models are trained using clear-weather datasets, where images have good visibility and well-defined object features. When these models are applied to foggy scenes, the important visual features such as edges, textures, and shapes become unclear due to the scattering of light by fog particles. Because of this loss of visual information,

detection models may fail to identify humans correctly or may produce incorrect predictions.

To overcome this challenge, researchers have explored the use of image enhancement and dehazing techniques before performing object detection. These techniques improve the visibility of foggy images by increasing contrast, restoring lost details, and removing haze effects. When image enhancement methods are combined with deep learning models, the detection system can better recognize objects even in difficult weather conditions.

This research focuses on developing a deep learning-based human detection system for foggy environments, specifically designed for defence surveillance applications. The proposed approach combines an image enhancement module with a YOLO-based detection model to improve detection performance under low-visibility conditions. The main objective of this work is to accurately detect human intruders in foggy scenes while maintaining real-time processing capability, which is essential for practical surveillance systems.

The major contributions of this research include:

- Developing a deep learning pipeline that integrates fog-aware image enhancement with a YOLO-based human detection model.
- Training and evaluating the system using fog-specific datasets and surveillance videos that represent real-world low-visibility conditions.
- Analyzing the detection performance under different fog density levels to understand the system's effectiveness in defence surveillance scenarios.

By improving the ability of surveillance systems to detect humans in foggy environments, the proposed system can significantly enhance situational awareness, border monitoring, and automated security operations. This approach can help defence authorities maintain effective monitoring and respond quickly to potential threats even under challenging weather conditions.

II. LITERATURE REVIEW

In the early stages of surveillance system development, most detection methods relied on traditional image processing techniques to identify motion or human presence in camera footage. Common techniques included background subtraction, edge detection, and texture analysis. Background subtraction works by comparing the current frame with a reference background image to detect moving objects. Edge detection and texture-based methods were also used to highlight object boundaries and patterns in images. Although these techniques were useful in simple conditions, they have several limitations. They are highly sensitive to noise, lighting changes, and environmental disturbances. As a result, their performance decreases significantly in difficult conditions such as fog, haze, or low-light environments, where image quality becomes poor.

With the rapid development of deep learning and artificial intelligence, more advanced object detection models have been introduced. Deep learning models such as Faster R-CNN, Single Shot Detector (SSD), and YOLO (You Only Look Once) have become widely used in modern computer vision applications. Unlike traditional methods, these models can automatically learn important features directly from large datasets during the training process.

This ability allows them to detect objects more accurately and reliably, even in complex scenes.

Among these approaches, Convolutional Neural Networks (CNNs) have played a major role in improving object detection performance. CNN-based models are capable of extracting hierarchical features from images, such as edges, shapes, textures, and object structures. Because of this, they can recognize objects even when the background is complex or when objects appear in different positions or scales. For surveillance systems, CNN-based detectors have shown promising results in identifying humans in both images and video streams.

However, detecting objects in foggy environments remains a challenging task. Fog particles scatter and absorb light, which reduces image contrast and causes blurring. This effect hides important visual details such as object edges, textures, and shapes. When these features become unclear, even advanced deep learning models may struggle to identify objects correctly.

To address this issue, many researchers have proposed using image enhancement and dehazing techniques as a pre-processing step before object detection. These techniques aim to improve the visibility of foggy images by increasing contrast and restoring hidden details. Some commonly used methods include:

- Dark Channel Prior (DCP) – a widely used technique that estimates haze thickness and removes fog effects from images.
- Histogram Equalization – improves image contrast by redistributing brightness levels.
- Generative Adversarial Networks (GANs) – deep learning models that can learn to generate clearer images from foggy inputs.

By applying these techniques before detection, the visibility of objects can be improved, which helps deep learning models detect humans more accurately in foggy scenes.

In addition to image enhancement techniques, some recent research has explored multimodal approaches that combine visible camera images with thermal or infrared sensors. Thermal cameras detect heat emitted by the human body, which makes it possible to identify humans even when visibility is extremely low. By combining thermal data with visible images, surveillance systems can achieve higher detection accuracy and reliability.

For real-time surveillance applications, YOLO-based models such as YOLOv5 and YOLOv7 are commonly used. These models are popular because they provide a good balance between high detection accuracy and fast processing speed. This makes them suitable for applications such as security monitoring, border surveillance, and autonomous systems, where quick detection is very important.

Despite these advancements, detecting humans in dense fog conditions still remains a major challenge. In heavy fog, many important visual features become blurred or completely hidden, which makes it difficult for detection models to recognize objects correctly. Therefore, ongoing research in this field focuses on improving dataset diversity, developing better fog simulation techniques, and designing more robust deep learning architectures that can perform reliably under different weather conditions.

III. PROBLEM STATEMENT

Foggy weather conditions create a major challenge for surveillance systems used in sensitive defence areas such as international borders, military bases, and ammunition storage facilities. In these locations, continuous monitoring is essential to detect any unauthorized human movement or intrusion. However, when fog is present, the visibility of surveillance cameras is significantly reduced. Fog particles scatter and absorb light, which results in images with low contrast, blurred edges, and loss of important visual details. Because of this, objects and humans in the scene become difficult to distinguish from the background.

Due to these visibility limitations, many existing vision-based surveillance systems are not able to detect human intruders accurately in foggy environments. Traditional computer vision techniques depend heavily on clear visual features such as edges, textures, and shapes to identify objects. When these features become unclear because of fog, the performance of such methods decreases significantly.

Although deep learning-based object detection models have shown impressive performance in normal conditions, most of these models are trained using clear-weather image datasets. When these models are applied to foggy scenes, they often fail to extract reliable features because the image quality is degraded. This leads to several problems, including low detection accuracy, a high number of false negatives (missed detections), and delayed identification of potential threats. In defence applications, such failures can create serious security risks because intruders may remain undetected for a long period of time.

Another important challenge is maintaining real-time processing capability. Surveillance systems in defence environments must analyze video streams continuously and provide immediate alerts whenever suspicious activity is detected. However, many advanced image enhancement techniques require high computational power, which may slow down the detection process.

Therefore, there is a strong need to develop a robust and efficient deep learning-based human detection system that can operate effectively in foggy environments. Such a system should be capable of:

- Enhancing the quality of foggy images to improve visibility and restore important visual details.
- Detecting humans accurately even in low-visibility conditions, where traditional methods often fail.
- Maintaining near real-time performance so that surveillance systems can continuously monitor and quickly respond to potential threats.

Developing such a system can significantly improve early intrusion detection, situational awareness, and overall security in defence environments. By enabling reliable monitoring even in adverse weather conditions, the system can help defence authorities maintain better control over sensitive areas and respond quickly to unauthorized activities.

IV. METHODOLOGY

The proposed system follows a three-stage pipeline designed for real-time defence surveillance.

A. Fog-Aware Image Enhancement

The first stage improves the quality of foggy images captured by surveillance cameras. A lightweight image enhancement model is used to increase contrast and restore lost visual details while maintaining fast processing speed. The model is trained using both synthetic and real foggy image datasets.

B. Deep Learning-Based Human Detection

After enhancement, the improved images are passed to a YOLO-based object detection model. The model is initially pre-trained on large datasets and then fine-tuned using fog-specific datasets such as Foggy Cityscapes and RTTS.

Data augmentation techniques such as different fog densities, lighting conditions, and camera angles are used during training to improve robustness.

The detector predicts bounding boxes and confidence scores for human objects in each frame.

C. Post-Processing and Alert Generation

Finally, Non-Maximum Suppression (NMS) is applied to remove duplicate detections and refine the bounding boxes. If a human is detected in restricted areas or for multiple frames, the system can generate an alert for defence operators.

This design allows the system to be integrated easily with existing surveillance networks and multi-camera monitoring systems.

V. RESULTS AND DISCUSSION

The proposed human detection system was evaluated using fog-specific datasets such as Foggy Cityscapes and RTTS, along with additional low-visibility surveillance videos that simulate real-world defence monitoring conditions. These datasets contain images and video frames captured in different fog densities, lighting conditions, and urban environments, which helps in testing the robustness of the proposed model in challenging scenarios.

To analyze the effectiveness of the proposed method, the performance of the system was compared with a baseline YOLO detection model that does not include the image enhancement stage. This comparison helps in understanding how much improvement is achieved by introducing the fog-aware image enhancement module before the detection stage.

The evaluation of the model was carried out using commonly used object detection performance metrics, including:

- **Precision** – measures how many of the detected objects are actually correct detections.
- **Recall** – measures how many real human objects in the scene are successfully detected by the system.
- **Mean Average Precision (mAP)** – a standard metric used to evaluate overall detection accuracy by considering both precision and recall across different detection thresholds.
- **Inference Time per Frame** – measures the time taken by the model to process each image frame, which indicates whether the system can operate in real-time surveillance environments.

Experimental results show that the proposed system performs better than the baseline model, particularly in

moderate and dense fog conditions where visibility is significantly reduced. The image enhancement module improves the clarity and contrast of foggy images, allowing the detection model to extract better visual features. As a result, the enhanced pipeline is able to correctly identify human intruders that are often missed by the baseline YOLO detector.

In several test cases, the baseline model failed to detect humans because the objects were partially hidden or blurred by fog. However, after applying the enhancement stage, the proposed system was able to restore important visual details and successfully detect the human targets with higher confidence.

Another important observation from the experiments is that the system maintains near real-time processing performance, which is essential for practical surveillance systems used in defence environments. Even after including the enhancement module, the overall processing time per frame remains low enough to support continuous monitoring of video streams.

Overall, the experimental results demonstrate that the proposed framework significantly improves human detection accuracy in foggy environments while maintaining efficient processing speed. This indicates that the system can be effectively used for real-time defence surveillance, border monitoring, and early threat detection, even when environmental conditions reduce visibility.

VI. ADVANTAGES

- Improved detection accuracy in foggy environments.
- Better performance under different fog densities.
- Near real-time processing capability.
- Suitable for defence and border surveillance.
- Easy integration with existing surveillance systems.
- Reduced false alarms and missed detections.

VII. CONCLUSION

This work presented a deep learning-based human detection system for foggy environments, designed for defence surveillance applications. By combining a fog-aware image enhancement module with a YOLO-based detection model, the system improves detection accuracy without sacrificing real-time performance.

Experimental results demonstrate that the proposed approach can effectively detect human intruders in low-visibility conditions, making it suitable for border monitoring, military surveillance, and autonomous patrol systems.

Future work may focus on integrating thermal or infrared sensors, improving dataset diversity, and deploying the system on embedded edge devices for large-scale defence surveillance networks.

VIII. REFERENCES

1. S. Gupta et al., "Fog Guard: Guarding YOLO Against Fog Using Perceptual Loss," 2024.
2. Y. Zhang et al., "DSNet Enables Feature Fusion and Detail Restoration for Accurate Object Detection in Foggy Conditions," *Sci. Rep.*, 2025.
3. "YOLOv7-Based Moving Object Detection in Dense Fog Conditions," *Journal of Intelligent Systems*, 2024.
4. "Real-Time Object Detection in Adverse Weather Conditions Using Deep Learning," *IJECS*, 2025.
5. J. Gupta et al., "Robust Object Detection in Challenging Weather Conditions," *WACV*, 2024.
6. A. Silva et al., "Distributed Fog Computing System for Weapon Detection and Face Recognition," *J. Netw. Comput. Appl.*, 2024.
7. M. Khan et al., "A Real-Time Deep Learning-Based Smart Surveillance Using Fog Computing," *Procedia Computer Science*, 2023.