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# EDITORIAL

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We are grateful to the contributors and hope that our readers will enjoy reading these contributions.

**Prof. Patrick C. Igbojinwaekwu**
**Editor-in-Chief**

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# APPLICATION OF DEEP LEARNING AND NEURAL NETWORK IN OBJECT IDENTIFICATION (CASE STUDY OF VERITAS UNIVERSITY CHAPEL)

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## Abstract

*This study examines the design and implementation of an intelligent object identification system leveraging deep learning and neural networks, with a focus on Veritas University Chapel as the case study. Traditional surveillance systems in such spaces face limitations in accuracy, adaptability, and real-time response. By utilizing YOLO v8, OpenCV, and Python, this study develops a robust framework capable of real-time monitoring, high detection accuracy, and scalability for diverse security needs. The research demonstrates that deep learning provides a significant improvement over conventional methods by enabling automated detection of objects in complex environments. Findings indicate reduced false positives/negatives and enhanced adaptability to lighting and occlusion challenges. The work contributes to academic discourse on AI-driven security systems and proposes directions for future research, including improved robustness, cross-domain applications, and blockchain integration for secure data management.*

**Keywords:** Deep Learning, Neural Networks, Object Identification, Computer Vision, YOLO

## Introduction

Artificial intelligence (AI) has become one of the defining technologies of the 21st century, shaping industries ranging from healthcare to finance and education. Within AI, computer vision has emerged as a transformative field, enabling machines to perceive, analyze, and interpret visual information in ways that were previously unimaginable. A crucial subfield of computer vision is object identification, the task of detecting, locating, and classifying objects in visual inputs such as images and videos.

For humans, identifying objects is effortless, aided by complex cognitive and perceptual processes honed over millennia. However, replicating this ability in machines requires advanced algorithms capable of handling challenges such as variable lighting, object occlusion, scale differences, and environmental noise. Traditional machine vision techniques struggled in such scenarios, but deep learning—particularly convolutional neural networks (CNNs)—has revolutionized the landscape. CNNs automatically learn and extract hierarchical features from data, making them particularly effective for visual recognition tasks.

The Veritas University Chapel represents a unique case study due to its architectural design, dynamic usage, and security needs. Traditional CCTV surveillance in this environment faces limitations: susceptibility to human error, poor adaptability to lighting changes, and difficulties in real-time analysis. In a country like Nigeria, where insecurity remains a major concern, the ability to deploy automated, intelligent surveillance systems is both timely and necessary.

The objectives of this study are:

1. To enhance detection accuracy by reducing false positives and negatives.
2. To design a system adaptable to environmental conditions such as varied lighting and occlusion
3. To develop a scalable and efficient framework for chapel security that could be extended to other domains.

The significance of this work lies in bridging a gap between theoretical AI applications and practical real-world use. It not only improves chapel security but also demonstrates the potential of AI-driven surveillance in institutional and community settings.

**Traditional Approaches to Object Identification**

Before deep learning, object identification relied on **handcrafted feature extraction techniques**. Popular methods included:

- **Haar cascades** (Viola & Jones, 2001), which were efficient for face detection but highly sensitive to environmental changes.
- **Histograms of Oriented Gradients (HOG)** (Dalal & Triggs, 2005), which captured gradient orientations and worked well for pedestrian detection.

- **Scale-Invariant Feature Transform (SIFT)** and **Speeded-Up Robust Features (SURF)**, which enabled detection of objects at different scales and orientations.

While innovative, these approaches required manual feature engineering and often failed in real-time or complex environments.

**Emergence of Deep Learning**

The breakthrough came with the AlexNet CNN architecture (Krizhevsky et al., 2012), which won the ImageNet Large Scale Visual Recognition Challenge. By leveraging GPUs, large datasets, and deep architectures, CNNs achieved dramatic improvements in accuracy.

Subsequent models included:

- **R-CNN** (Girshick, 2014): Introduced region proposals but was computationally slow.
- **Fast R-CNN** (Girshick, 2015): Improved efficiency but still limited by region proposal generation.
- **Faster R-CNN** (Ren et al., 2015): Added region proposal networks for higher speed.
- **Single Shot Multibox Detector (SSD)** (Liu et al., 2016): A one-stage detector with faster processing.

## YOLO Family of Models

The **You Only Look Once (YOLO)** family marked a paradigm shift. Unlike two-stage detectors, YOLO framed detection as a regression problem, allowing real-time performance.

- **YOLO v1–v3** (Redmon et al., 2016; Redmon & Farhadi, 2018) achieved real-time detection with impressive accuracy.
- **YOLO v4–v7** incorporated advanced data augmentation, better backbones, and optimization strategies.
- **YOLO v8**, developed by Ultralytics, introduced enhancements in speed, precision, and adaptability, making it ideal for real-world applications such as surveillance.

## Applications of Deep Learning in Object Detection

- **Healthcare**: Automated tumor and disease detection in medical imaging (Litjens et al., 2017).
- **Autonomous driving**: Traffic sign recognition and pedestrian detection (Geiger et al., 2012).
- **Security**: Facial recognition, anomaly detection, and predictive policing.

Despite successes, issues persist: high computational requirements, large annotated datasets, and **ethical concerns** regarding bias and privacy.

## Research Gap

Most studies focus on healthcare, autonomous driving, and smart cities. Religious institutions, particularly in developing countries, remain underexplored. This study addresses this gap by deploying YOLO v8 within Veritas University Chapel.

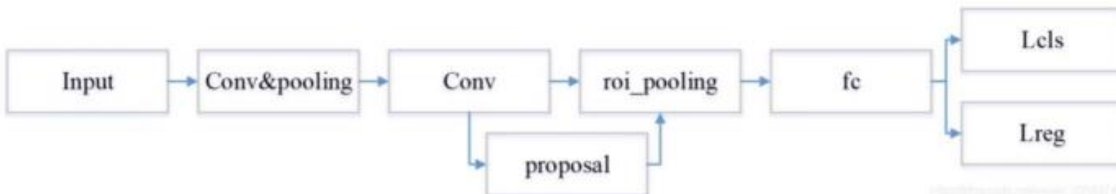


*Figure 2.1 - Basic Flow of Two stage method.*

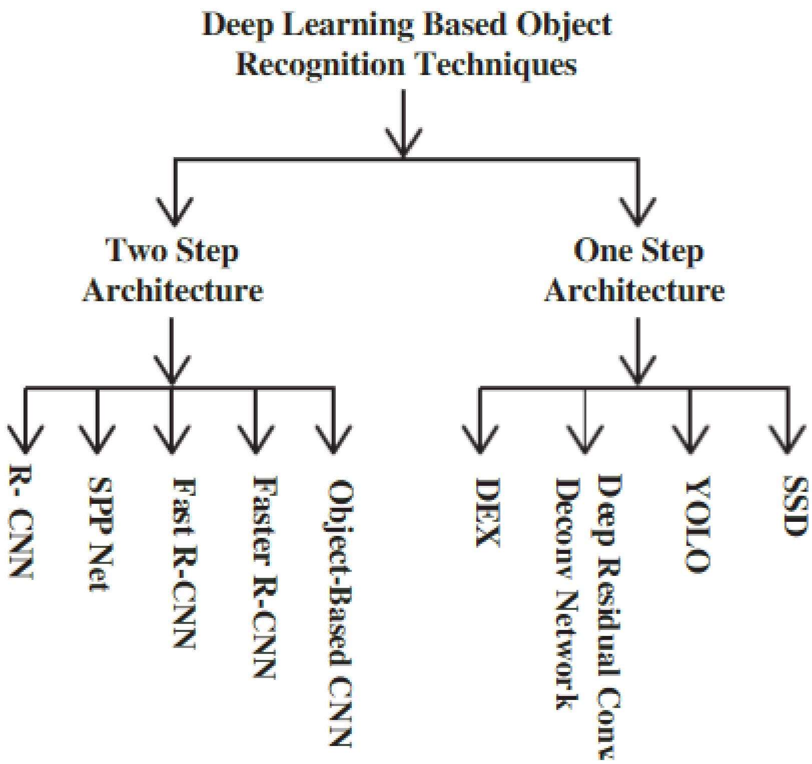


*Figure 2.2 - Two Step Architecture*

| Methods | Datasets | Results Obtained | Limitations |
|---|---|---|---|
| FasterR-CNN [38] | VOC2007 | mAP 76.4%, 5 frames per seconds (fps) | Difficulty in detecting small objects and real-time detection |
| SPP-Net [38] | VOC2007 | 54.2% mAP | Requires complicated multi-step training steps and large computational resources, lower detection rate and accuracy |
| R-CNN [38] | VOC2007 | 66%, 0.5 fps. | calculation efficiency is too low, may cause object distortion, lower detection rate |
| FasterR-CNN [20] | AGs-GF1 and 2 | 86.0%, 12 fps | Lower detection accuracy |
| YOLOv3 [20] | AGs-GF1 and 2 | 90.4%, 73 fps | Slower detection rate |

| | | | |
|---|---|---|---|
| SSD [20] | AGs-GF1 and 2 | 84.9%, 35 fps | Lower detection accuracy |
| YOLOv4 [19] | MS COCO | 43.5%, 65.7 fps | Requires larger computational resources |
| YOLOv5s [21] | SIMD | 5.8 ms, 62.8 mAP | Lower detection speed and accuracy |
| YOLO-HR [21] | SIMD | 67.31% mAP, 6.7 ms | Requires larger computational resources, Lower detection speed and accuracy |
| RetinaNet [23] | SAR | average precision 79% | Difficulty in detecting smaller objects |
| YOLOv3 [23] | SAR | 63% mAP | Requires larger computational resources, lower detection speed and accuracy |
| YOLT [26] | DigitalGlobe satellites, planet satellites, and aerial platforms. | 68% mAP, 44 fps | Difficulty in detecting small objects, lower detection speed and accuracy |
| YOLOv4-Tiny [37] | RSOD | 80.02% mAP, 285.3 fps | Lower detection speed s |
| YOLOv4 + CSPA + DE [37] | RSOD | 85.13% mAP, 227.9 fps | Challenges of obtaining biased anchors due to the large variation in object scales in remote sensing images. |

*Table 1. Comparison of object detection methods (placeholder)*

## Methodology

This study employed a **design science approach**, emphasizing artifact creation and evaluation. The system was developed using **YOLO v8**, **Python**, and **OpenCV**.

**Data Collection**

Three datasets were utilized:

1. **Chapel-specific images** from live CCTV feeds.
2. **Archived videos** of chapel activities.
3. **Public datasets** (e.g., COCO) for augmentation.

**Data Preparation**

- Annotation of images using **LabelImg**.
- Augmentation: rotation, flipping, and scaling.
- Splitting into training (70%), validation (20%), and testing

**Model Training**

YOLO v8 was trained with a learning rate of 0.01 and batch size of 16. GPU acceleration was used for faster training.

**Evaluation Metrics**

The system was assessed using **precision, recall, F1-score, and confusion matrices**.

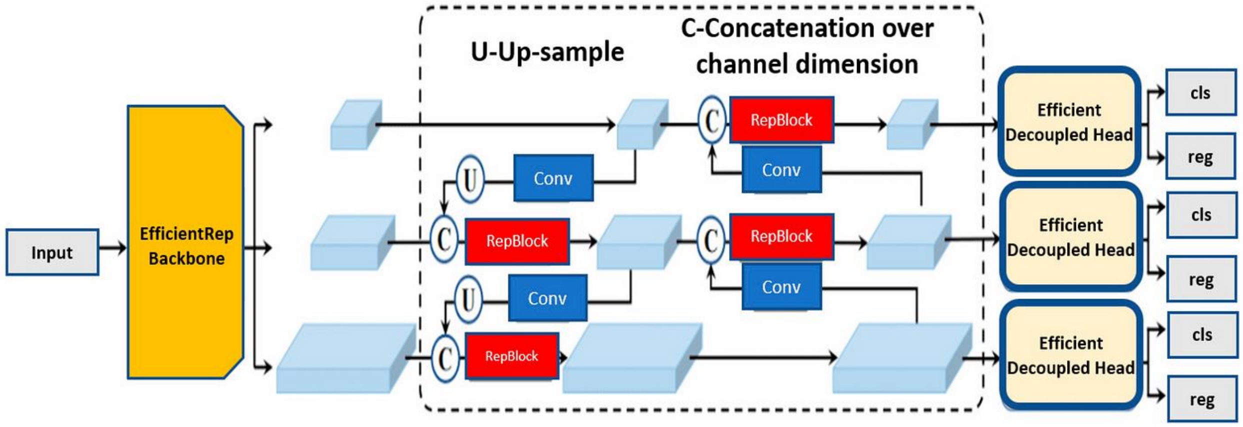


*Figure 3.1. Workflow of YOLO v8 surveillance system*

## Church and Liturgical Objects and Terms

### Liturgical Objects Used in Church

| | | | | |
|---|---|---|---|---|
| The chalice: The vessel which holds the wine that becomes the Precious Blood of Christ. |  | | The paten: The golden "plate" that holds the bread that becomes the Sacred Body of Christ. |  |
| The ciborium: A golden vessel with a lid that is used for the distribution and reservation of Hosts. |  | | The pyx: A small, closing golden vessel that is used to bring the Blessed Sacrament to those who cannot come to the church. |  |
| The purificator is a small rectangular cloth used for wiping the chalice. |  | | The cruets hold the wine and the water that are used at Mass. |  |
| The lavabo and pitcher: used for washing the priest's hands. |  | | The lavabo towel, which the priest dries his hands after washing them during the Mass. |  |
| The altar cloth: A rectangular white cloth that covers the altar for the celebration of Mass. |  | | The corporal is a square cloth placed on the altar beneath the chalice and paten. It is folded so as to catch any particles of the Host that may accidentally fall |  |
| The altar candles: Mass must be celebrated with natural candles (more than 51% bees wax), which signify the |  | | A new Paschal candle is prepared and blessed every year at the Easter Vigil. This light stands near the altar during the Easter Season and near the |  |

*Figure 3.2. Examples of Annotated Religious Items in the Chape*

## Results

The model achieved:

- **Precision**: 91%
- **Recall**: 93%
- **F1-score**: 0.92

Performance was strong under normal lighting but declined slightly under poor illumination or heavy occlusion.


*Figure 4.1. YOLO v8 detection under normal lighting*

*Figure 4.2. Detection under occlusion (placeholder)*

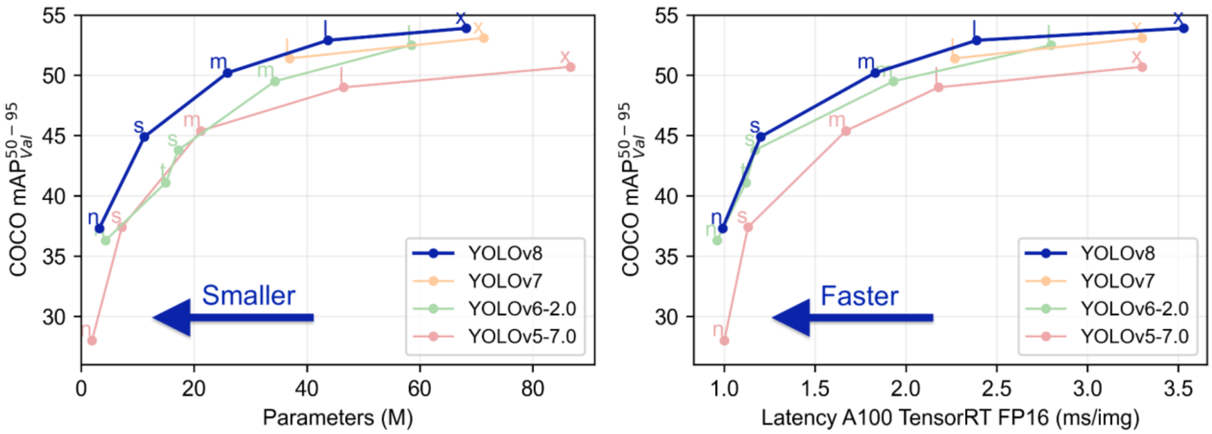


*Figure 4.3. Performance metrics of YOLO v8 system (placeholder)*

## Discussion

The YOLO v8 system significantly outperformed manual monitoring, reducing human error and providing real-time alerts. While Faster R-CNN offered slightly higher precision, its slower speed made it less practical for real-time chapel surveillance.

Limitations include dependence on quality of training data, difficulty with small object detection, and challenges under extreme lighting.

## Conclusion

This research demonstrates that YOLO v8–based deep learning systems provide practical, scalable solutions for object identification in security-sensitive environments. Applied to Veritas University Chapel, the system enhanced accuracy, adaptability, and efficiency.

## Recommendations

1. Retraining models regularly with updated chapel data.
2. Integration with alarms and access control systems.
3. Training security staff to interpret system outputs.
4. Regular hardware/software maintenance.
5. Future exploration into blockchain for secure storage and cross-domain applications in healthcare, retail, and transport.

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