

**DEFORMABLE CONVOLUTION NETWORK AND  
DEFORMABLE ATTENTION IN YOLO11 FOR ORIENTED  
SMALL OBJECT DETECTION**

**A MASTER'S THESIS**

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In partial fulfillment of the requirements  
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BANDUNG  
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## **APPROVAL PAGE**

### **MASTER'S THESIS**

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## **SELF DECLARATION AGAINST PLAGIARISM**

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20<sup>th</sup> November, 2025

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## **ABSTRACT**

Quantum technology in recent decades is attracting great attentions, especially on the quantum computing, quantum communications, and quantum key distribution (QKD), which are candidates for the sixth generation of telecommunications (6G) in 2030 and beyond.

**Keywords:** CSS, Decoherence, Depolarizing Channels, Red-Muller codes, QWER.

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## PREFACE

Alhamdu lillahi rabbil 'alamin, praise to Allah, the most gracious, the most merciful, with the mercy and guidance, the author has successfully finished this thesis with the title of "**DEFORMABLE CONVOLUTION NETWORK AND DEFORMABLE ATTENTION IN YOLO11 FOR ORIENTED SMALL OBJECT DETECTION**". The author compiled this thesis to be filled in the graduation requirements in Program of Master of Electrical-Telecommunication Engineering, School of Electrical Engineering, Telkom University.

Some parts of this thesis also have been submitted to The 9th Asia Pacific Conference on Wireless & Mobile (APWIMOB) Conference 2024.

The suggestions for improving this thesis are highly appreciated. Hopefully, this thesis is expected to be improved and provided contributions for the reader and Indonesia especially for education and research of telecommunication on the future.

Bandung, 20<sup>th</sup> November, 2025

REYNALDHI TRYANA GRAHA

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## **LIST OF ABBREVIATION**

1G	: First Generation
2G	: Second Generation
3G	: Third Generation
4G	: Fourth Generation
5G	: Fifth Generation
6G	: Sixth Generation
CSS	: Calderbank-Shor-Steane
MDS	: Maximum distance separable
LUT	: Look Up Table
QECC	: Quantum Error Correction Codes
QKD	: Quantum Key Distribution
QWER	: Quantum Word Error Rate
RM	: Reed-Muller codes
SIP	: Simplectactic Inner Product
WP	: Work Packages

## **LIST OF SYMBOL**

- $\alpha$  Constant number complex
- $\beta$  Constant number complex
- $\rho$  The density operator
- $\rho'$  Evolution of quantum system

## **ACHIEVEMENTS**

1. AAAAA

# CHAPTER 1

## INTRODUCTION

### 1.1 Background

Object detection is a fundamental task in computer vision with numerous applications across various domains, including medical imaging [1], autonomous driving [2], security surveillance [3], and aerial imaging [4]. The primary objective of object detection is to identify and localize objects within an image or video frame by predicting bounding boxes and class labels for each detected object. Over the years, significant advancements have been driven by the development of deep learning algorithms, specifically Convolutional Neural Networks (CNNs). These advancements have led into two main categories of object detection methods: two-stage detectors and single-stage detectors. Two-stage detectors, such as Faster R-CNN, prioritize accuracy by first generating region proposals before classification [5]. In contrast, single-stage detectors, like You Only Look Once (YOLO) and Single Shot MultiBox Detector (SSD), optimize for speed by directly predicting bounding boxes and class probabilities in a single pass [6, 7]. The YOLO family, in particular, has undergone rapid evolution leading to the recent YOLOv11, which offers a superior balance between inference speed and detection accuracy [8].

Despite the impressive performance of single-stage detectors on general tasks, they frequently encounter difficulties when detecting small objects. Small objects typically defined as those occupying a minimal number of pixels present significant challenges due to limited visual information, susceptibility to occlusion, and background clutter [9]. This issue is particularly critical in aerial imagery analysis, where targets such as vehicles, buildings, and ships appear at varying scales [10]. The primary challenges include the loss of critical features during CNN down-sampling, the extreme class imbalance between small and large objects, and the difficulty in distinguishing small objects from noise. To mitigate these issues, researchers have explored techniques such as multi-scale feature fusion, context-aware modeling, and specialized data augmentation [11]. Additionally, architectural enhancements like Feature Pyramid Networks (FPNs) and attention mechanisms have shown promise in recovering details necessary for small object detection [12].

Beyond scale, another critical aspect in aerial object detection is orientation. Unlike traditional detection methods that utilize axis-aligned Horizontal Bounding

Boxes (HBB), oriented object detection employs Oriented Bounding Boxes (OBB) or polygons to capture objects more precisely. This capability is essential for aerial imagery, where objects often appear with arbitrary rotations due to the top-down perspective of the imaging sensor [10]. Standard HBBs often introduce excessive background noise when enclosing rotated objects, confusing the classifier. Consequently, oriented detection methods incorporate angle regression, rotation-invariant feature extraction, and specialized loss functions to effectively handle these geometric variations [13].

However, standard CNNs backbone of most modern detectors including YOLO possess inherent limitations when simultaneously addressing orientation and small scale. Standard convolution operations sample the input feature map using a fixed, regular grid. This rigid geometric structure lacks invariance to large geometric transformations such as rotation, scaling, or deformation [14]. Consequently, when a small object is rotated or appears in a non-standard pose, the fixed receptive field of a standard convolution may fail to cover the object of interest effectively [15, 16]. This limitation is particularly detrimental for small oriented objects, where semantic information is already scarce, and any misalignment in feature extraction can lead to detection failures [17].

To overcome these geometric and spatial limitations, advanced mechanisms such as Deformable Convolution Networks (DCN) and Attention Mechanisms have been proposed. Deformable convolution introduces learnable offsets to the regular sampling grid, allowing the receptive field to adaptively deform and align with the object's actual shape and orientation [14, 18]. Furthermore, attention mechanisms, specifically Deformable Attention, enable the network to focus dynamically on the most relevant features while suppressing irrelevant background information [19]. By adjusting the importance of different spatial locations, these mechanisms enhance the representation of small objects that might otherwise be overwhelmed by background clutter [15].

Therefore, this research proposes the integration of Deformable Convolution and Deformable Attention mechanisms into the YOLO11 architecture to enhance feature extraction capabilities for oriented small object detection. By leveraging the adaptive sampling of deformable convolution and the context-aware focusing of deformable attention, the proposed method aims to address the geometric variations and feature scarcity inherent in aerial imagery. This thesis explores the synergistic effect of these components within the YOLO11 framework, aiming to achieve superior detection performance compared to existing state-of-the-art methods on challenging aerial and remote sensing datasets.

## 1.2 Problem Identification

The primary problem addressed in this research is the main two challenges of detecting objects that are both tiny in scale and arbitrarily oriented within aerial imagery, which modern detectors struggle to handle due to the fixed geometric structure of standard Convolutional Neural Networks (CNNs).

Specifically, the technical problems are identified as follows:

1. **Geometric Rigidity of Standard Convolution:** Standard convolution operations rely on kernels with a fixed geometric shape. This rigid structure inherently restricts the network's ability to model complex geometric transformations. When objects in aerial imagery appear at arbitrary angles, the fixed receptive field of the convolution kernel fails to adapt, preventing the network from effectively capturing the features of rotated objects.
2. **Feature Loss in Low-Resolution Targets:** Small objects in aerial imagery typically possess low resolution and limited feature information. As these images pass through the downsampling layers of standard CNN architectures, the already scarce spatial details are often lost or ‘washed out’. Consequently, the detector fails to preserve the fine-grained information necessary to recognize these very small targets in deeper network layers.
3. **Interference from Background Noise:** Due to their small scale and limited features, small objects are difficult to distinguish from environmental background noise. Standard feature extraction mechanisms often lack the ability to focus exclusively on the object of interest, causing the weak feature signals of small targets to be overwhelmed by stronger signals from complex backgrounds, leading to missed detections.
4. **Inefficiency of Horizontal Bounding Boxes:** Traditional object detection relies on Horizontal Bounding Boxes (HBB). For oriented objects, HBBs are inefficient because they inevitably capture excessive background information along with the object. This inclusion of irrelevant background noise within the object proposal confuses the classification process and hinders the precise localization required for aerial targets.

## 1.3 Research Objective

The primary objective of this research is to develop an enhanced hybrid single-stage object detection framework based on YOLO11, specifically optimized for the

two main challenges of oriented small object detection. This is achieved by addressing the geometric rigidity of standard convolutions and the lack of context-aware focusing in current baselines through the integration of adaptive feature extraction mechanisms.

The specific objectives of this research are detailed as follows:

- 1. Integrate Deformable Convolution Modules for Geometric Adaptation:** Strategically modify the standard convolutional layers within the YOLO11 architecture by integrating Deformable Convolution modules. This modification aims to enable the network to adaptively adjust its receptive field based on the scale and orientation of target objects. By learning offset values for the sampling grid, the model will capture the geometric features of rotated objects more effectively than the fixed-grid convolutions used in the baseline model, directly addressing the issue of geometric rigidity.
- 2. Implement Deformable Attention for Robust Feature Fusion:** Enhancing the feature fusion process by incorporating Deformable Attention mechanisms. Unlike standard attention modules which often treat spatial locations uniformly, this mechanism is designed to focus computational resources sparsely on the most informative key points of small objects. This objective seeks to demonstrate that dynamic, sparse attention can effectively suppress the background clutter and noise inherent in aerial imagery, therefore preserving the weak feature signals of small targets.
- 3. Design and Validate a Hybrid Architecture While Balancing Accuracy and Speed:** Design and validate a cohesive hybrid architecture that synergizes Deformable Convolution and Deformable Attention to optimize Oriented Bounding Box (OBB) task. This objective involves benchmarking the proposed framework against state-of-the-art methods on large-scale aerial datasets (DOTA and SODA) to demonstrate a superior balance between detection accuracy (mAP) and computational efficiency (FLOPs), ensuring the model remains practical for real-world deployment.

## 1.4 Research Method

This research proposes a novel single-stage object detection framework that enhances the YOLO11 architecture by integrating two advanced adaptive feature extraction mechanisms: Deformable Convolutional Networks (DCN) and Deformable

Attention. These methods are selected to specifically address the two challenges of geometric variations in oriented objects and feature scarcity in small objects.

### 1.4.1 Deformable Convolutional Networks (DCN)

Standard Convolutional Neural Networks (CNNs) are inherently limited in modeling geometric transformations due to the fixed geometric structures of their building modules. A standard convolution unit samples the input feature map at fixed locations (e.g., a regular  $3 \times 3$  grid) and pools features with a static receptive field. This rigidity is suboptimal for oriented object detection, where targets may appear with arbitrary rotation, scaling, or deformation.

To overcome this limitation, this research employs Deformable Convolution, as introduced by Dai et al. [14]. The core idea is to augment the spatial sampling locations in the convolution modules with learnable offsets.

In a standard 2D convolution, the output feature map  $y$  at a specific location  $p_0$  is computed as:

$$y(p_0) = \sum_{p_n \in \mathcal{R}} w(p_n) \cdot x(p_0 + p_n) \quad (1.1)$$

where  $\mathcal{R}$  defines the regular sampling grid (e.g.,  $\mathcal{R} = \{(-1, -1), (-1, 0), \dots, (1, 1)\}$  for a  $3 \times 3$  kernel) and  $w(p_n)$  represents the weights.

In Deformable Convolution, the regular grid  $\mathcal{R}$  is augmented with offsets  $\{\Delta p_n | n = 1, \dots, N\}$ , where  $N = |\mathcal{R}|$ . The equation is reformulated as:

$$y(p_0) = \sum_{p_n \in \mathcal{R}} w(p_n) \cdot x(p_0 + p_n + \Delta p_n) \quad (1.2)$$

Here, the sampling is performed on the irregular and offset locations  $p_n + \Delta p_n$ . The offsets  $\Delta p_n$  are obtained by applying a separate convolutional layer over the same input feature map, allowing the deformation to be conditioned on the input features in a local, dense, and adaptive manner.

Since the learned offset  $\Delta p_n$  is typically fractional, the pixel value  $x(p)$  at an arbitrary location  $p = p_0 + p_n + \Delta p_n$  is computed via bilinear interpolation:

$$x(p) = \sum_q G(q, p) \cdot x(q) \quad (1.3)$$

where  $q$  enumerates all integral spatial locations in the feature map  $x$ , and  $G(\cdot, \cdot)$  is the bilinear interpolation kernel. This differentiability allows the offsets to be

learned end-to-end via standard back-propagation.

### 1.4.2 Deformable Attention

While DCN improves geometric adaptability, detecting small objects in cluttered aerial images requires a mechanism to focus on sparse, informative key elements. Standard Transformer attention modules suffer from slow convergence and high computational complexity because they look over all possible spatial locations in the image feature maps.

To mitigate these issues, this research integrates the Deformable Attention module proposed by Zhu et al. [19]. This mechanism combines the sparse spatial sampling of deformable convolution with the relation modeling capability of Transformers.

Unlike standard Multi-Head Self-Attention (MHSA) which has quadratic complexity relative to pixel numbers, the Deformable Attention module only attends to a small set of key sampling points around a reference point.

Given an input feature map  $x \in \mathbb{R}^{C \times H \times W}$ , a query element  $q$  with content feature  $z_q$ , and a 2-D reference point  $p_q$ , the Deformable Attention feature is calculated as:

$$\text{DeformAttn}(z_q, p_q, x) = \sum_{m=1}^M W_m \left[ \sum_{k=1}^K A_{mqk} \cdot W'_m x(p_q + \Delta p_{mqk}) \right] \quad (1.4)$$

where:

- $m$  indexes the attention head ( $M$  heads total).
- $k$  indexes the sampled keys ( $K$  keys total), where  $K \ll HW$ .
- $\Delta p_{mqk}$  and  $A_{mqk}$  denote the sampling offset and attention weight of the  $k^{th}$  sampling point, respectively.
- $A_{mqk}$  is normalized such that  $\sum_{k=1}^K A_{mqk} = 1$ .

Similar to DCN, the term  $x(p_q + \Delta p_{mqk})$  is computed using bilinear interpolation. This design allows the model to focus on a small, fixed number of keys for each query, significantly reducing computational complexity to  $O(2N_q C^2 + \min(HWC^2, N_q KC^2))$ , which is linear with respect to the spatial size.

## 1.5 Hypothesis

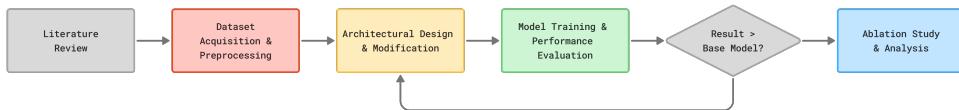
Based on the structural limitations of standard CNNs and the proposed architectural enhancements, this research posits the following hypotheses regarding the

performance of the modified YOLO11 framework:

1. **Improved Accuracy for Oriented Objects:** Integrating Deformable Convolution modules into the YOLO11 backbone will significantly improve the detection accuracy of oriented objects compared to the baseline model. This prediction relies on the ability of Deformable Convolution to learn adaptive sampling offsets, allowing the receptive field to align dynamically with the rotation and geometric variations of aerial targets [14].
2. **Enhanced Small Object Detection:** Implementing Deformable Attention mechanisms will measurably increase the detection performance for small objects in cluttered environments. By focusing computational resources on a sparse set of key sampling points rather than the entire feature map, this mechanism is expected to suppress background noise and preserve the weak feature signals of small targets more effectively than the baseline architecture [19].
3. **Synergistic Performance of the Hybrid Architecture:** The hybrid combination of Deformable Convolution and Deformable Attention is expected to yield a synergistic effect, achieving a superior balance between accuracy (mAP) and computational efficiency. The proposed architecture is expected to outperform both the baseline YOLO11 and single-modification variants on the DOTA and SODA datasets by simultaneously addressing geometric misalignment and feature scarcity without incurring the quadratic complexity of standard Transformers.

## 1.6 Research Methodology

The research methodology employed in this thesis follows a systematic experimental approach, structured around distinct Work Packages (WP). This structure ensures a logical progression from theoretical understanding to practical implementation and final evaluation. The overall flow of the research is visualized in Figure 1.1.



**Fig. 1.1** Research Methodology Flowchart

The specific Work Packages (WP) for this research are outlined as follows:

- **WP 1: Literature Review**

This work package involves an in-depth analysis of existing literature to establish a strong theoretical foundation. The review focuses on the evolution of the YOLO architecture up to YOLO11, the mathematical principles of Deformable Convolutional Networks (DCN), and the mechanics of Deformable Attention.

- **WP 2: Dataset Acquisition and Preprocessing**

This work package focuses on preparing the data required for training and evaluation. Acquiring standard aerial imagery datasets such as DOTA (Dataset for Object deTecTion in Aerial images) and SODA (Small Object Detection dAtaset). Then preprocess data annotation labels from polygon or complex formats into the YOLO OBB format (center-point, width, height, angle).

- **WP 3: Architectural Design and Modification**

This is the core development phase where the YOLO11 baseline is structurally enhanced. The modifications include:

1. **DCN Integration:** Replacing standard convolutional layers in the Backbone and Neck with Deformable Convolution modules to enable adaptive receptive field learning.
2. **Attention Integration:** Designing the replacement of the standard C2PSA block with the Deformable Attention mechanism to improve feature focusing on small targets.
3. **Hybrid Design:** Validating the two methods compatibility and ensuring that the combined architecture maintains computational efficiency while enhancing detection capabilities.

- **WP 4: Model Training and Performance Evaluation**

This work package include the implementation, training, and quantitative evaluation of the proposed architecture. The model is implemented in PyTorch within Ultralytics YOLO framework. Then the model is then trained and evaluated on a unseen test set using standard metrics, including Mean Average Precision (mAP) for Oriented Bounding Boxes (mAP50 and mAP50-95). Furthermore, computational efficiency is benchmarked via Number of Parameters (Params) and Floating Point Operations (FLOPs) to ensure practical viability against the baseline YOLO11.

- **WP 5: Ablation Study and Analysis**

To validate the individual contributions of the proposed enhancements, this WP involves conducting ablation studies. Separate models will be trained with single modifications (e.g., YOLO11+DCN only, YOLO11+Deformable Attention only) to isolate the performance gains attributed to Deformable Convolution versus Deformable Attention. The analysis will also include qualitative visualization of detection results to identify improvements in handling background clutter and rotation.

## 1.7 Timeline

The research activities are scheduled to be completed within a period of six months. The timeline is structured to ensure that each phase of the methodology is given sufficient time for thorough execution and analysis. Table 1.1 details the schedule of activities.

**Table 1.1** Research Timeline

No.	Activity	Month					
		1	2	3	4	5	6
1	Literature Review						
2	Dataset Acquisition and Preprocessing						
3	Architectural Design and Modification						
4	Model Training and Performance Evaluation						
5	Ablation Study and Analysis						
6	Conclusion and Thesis Writing						

- **Month 1:** Focus on understanding the theoretical background, reviewing related works, and finalizing the research proposal. Initial dataset acquisition begins.
- **Month 2:** Completion of dataset preprocessing. Start of the architectural design phase, identifying where to integrate DCN and Attention modules.
- **Month 3:** Finalizing the system design. Beginning the implementation of the modified YOLO11 model in code and starting initial training runs.
- **Month 4:** Intensive model training and tuning. Conducting the first round of evaluations on the validation set.

- **Month 5:** Performing comprehensive testing on the test set. Conducting ablation studies to isolate the effects of specific modules. Beginning the analysis of results.
- **Month 6:** Finalizing the analysis. Writing the complete thesis report, preparing for the defense, and drafting a paper for publication.

## CHAPTER 2

### BASIC CONCEPT

This chapter establishes the theoretical and architectural foundations requisite for understanding the proposed enhancements to the YOLO11 framework. It provides an exhaustive examination of the evolution of object detection paradigms, delineating the unique pathological challenges associated with detecting small, arbitrarily oriented objects in aerial imagery. Furthermore, this chapter presents a rigorous mathematical treatment of Convolutional Neural Networks (CNNs), the architectural specifics of YOLO11, and the adaptive mechanisms of Deformable Convolution Networks (DCN) and Deformable Attention, which constitute the core technical contributions of this thesis.

### 2.1 Object Detection

Object detection stands as one of the most fundamental and challenging problems in the field of computer vision. Unlike image classification, which assigns a single label to an entire image, or semantic segmentation, which classifies pixels without differentiating object instances, object detection requires the simultaneous localization and classification of multiple objects within a scene [20, 21]. The primary objective is to predict a set of bounding boxes—rectangular delineations of object boundaries—and associate a class probability score with each box. The complexity of this task is compounded in remote sensing and aerial surveillance domains, where varying altitudes, sensor angles, and environmental conditions introduce significant geometric variability [9, 20].

#### 2.1.1 Small Object Detection

The detection of small objects represents a specialized and pathological sub-domain within computer vision. While general object detection on datasets like MS COCO achieves high performance, accuracy degrades precipitously as object size decreases. This is particularly critical in aerial imagery, where the combination of high altitude and wide field-of-view results in targets of interest—such as vehicles, pedestrians, or small maritime vessels—occupying a minute fraction of the pixel space [11, 21].

## Defining “Small” Objects

The definition of a “small object” is contingent upon the application context and the dataset standards:

1. **Absolute Scale (MS COCO Definition):** The most widely accepted definition comes from the MS COCO evaluation protocol, which categorizes objects with a spatial area of less than  $32 \times 32$  pixels as small ( $area < 1024$  pixels) [11, 22].
2. **Relative Scale (SPIE Definition):** The Society of Photo-Optical Instrumentation Engineers (SPIE) defines small objects based on the image coverage ratio. An object is considered small if it occupies less than 0.12% of the total image area (e.g., roughly  $9 \times 9$  pixels in a  $256 \times 256$  image) [9].
3. **Aerial-Specific Scale (AI-TOD):** In specialized aerial datasets like AI-TOD, the definition is even more stringent, with the average object size often being around 12.8 pixels, significantly smaller than the COCO standard [23].

## Challenges in Feature Extraction and Representation

The difficulty in detecting small objects stems from fundamental limitations in the architecture of Convolutional Neural Networks (CNNs), specifically related to feature hierarchy and resolution.

- **Feature Vanishing and Dilution:** Deep CNNs rely on successive downsampling operations (strided convolutions or pooling) to increase the Receptive Field (RF) and abstract high-level semantic features. A standard backbone (e.g., ResNet or CSPDarknet) typically has a total stride of 32 ( $S = 32$ ). This means an input image of size  $640 \times 640$  is reduced to a feature map of  $20 \times 20$ . Under this transformation, a small object of size  $16 \times 16$  pixels in the input is theoretically mapped to an area of  $0.5 \times 0.5$  pixels in the final feature map [9, 16]. In practice, this sub-pixel representation means the object’s spatial information is effectively aggregated into a single feature vector mixed with surrounding background information, leading to severe feature dilution or complete vanishing of the signal [16, 17].
- **Low Signal-to-Noise Ratio (SNR):** Small objects possess very few constituent pixels, limiting the visual information available for the network to learn discriminative features. Unlike large objects that exhibit rich internal textures and clear geometric structures (edges, corners), small objects often appear as amorphous blobs [9, 16]. This feature scarcity makes them highly

susceptible to background clutter; a small rock or a patch of texture can easily be misclassified as a vehicle due to the lack of distinguishing details [10].

- **Occlusion and Dense Clustering:** In aerial imagery, small objects often appear in dense clusters (e.g., a parking lot full of cars or a flotilla of ships). The overlap between valid objects and the interference from the background complicates the bounding box regression. Standard Intersection over Union (IoU) metrics are highly sensitive to small positional shifts for small objects; a misalignment of just a few pixels can result in a zero IoU score, destabilizing the training process [9, 13].
- **Context Dependence:** Because intrinsic features are weak, the detection of small objects relies heavily on contextual cues (e.g., a car is likely on a road, a ship is likely in water). However, standard CNN operations with fixed receptive fields may fail to capture this global context effectively if the object is isolated or the background is heterogeneous [16, 17].

### 2.1.2 Oriented Object Detection

Traditional object detection systems rely on Horizontal Bounding Boxes (HBB), parameterized by  $(x_{min}, y_{min}, x_{max}, y_{max})$  or  $(x_c, y_c, w, h)$ . While sufficient for ground-level photography where gravity imposes a natural vertical orientation on most objects, HBBs are fundamentally inadequate for aerial and satellite imagery [21, 24].

**Geometric Mismatch and the HBB Limitation** In top-down aerial views, objects have an additional degree of freedom: rotation. A ship or vehicle can point in any direction, so axis-aligned bounding boxes either include excessive background or misalign the target, which makes IoU scores unreliable even when the localization is correct [24, 25]. The predominance of arbitrary orientations in aerial data renders Horizontal Bounding Boxes inadequate; instead, oriented rectangles—parameterized by center coordinates, width, height, and rotation angle—are preferred for tight localization.

### 2.1.3 Deformable Convolution

The output feature  $y(p_0)$  at location  $p_0$  of a regular convolution is the weighted sum of features sampled at a fixed grid:

$$y(p_0) = \sum_{p_n \in \mathcal{R}} w(p_n) \cdot x(p_0 + p_n) \quad (2.1)$$

where  $w(p_n)$  are the kernel weights and  $x$  is the input map [14, 26].

**Deformable Convolution (DCNv1)** Deformable convolution augments the regular grid  $\mathcal{R}$  with 2D offsets  $\{\Delta p_n | n = 1, \dots, N\}$ , where  $N = |\mathcal{R}|$ . The equation transforms to:

$$y(p_0) = \sum_{p_n \in \mathcal{R}} w(p_n) \cdot x(p_0 + p_n + \Delta p_n) \quad (2.2)$$

Here, the sampling is performed at the irregular locations  $p_n + \Delta p_n$ . These offsets allow the sampling points to shift to cover the semantic parts of an object—for instance, spreading along the wings of a rotated airplane rather than sampling the empty tarmac [14].

**Bilinear Interpolation** Since the learned offsets  $\Delta p_n$  are typically fractional (continuous values), the pixel coordinates  $p = p_0 + p_n + \Delta p_n$  do not align with the integer grid of the feature map. To compute the pixel value  $x(p)$ , bilinear interpolation is employed:

$$x(p) = \sum_q G(q, p) \cdot x(q) \quad (2.3)$$

where  $q$  enumerates the integral spatial locations in the feature map (e.g., the 4 nearest neighbors), and  $G(q, p)$  is the bilinear interpolation kernel:

$$G(q, p) = \max(0, 1 - |q_x - p_x|) \cdot \max(0, 1 - |q_y - p_y|)$$

This formulation ensures that the operation is fully differentiable, allowing the offsets  $\Delta p_n$  to be learned via standard backpropagation [14].

**Modulated Deformable Convolution (DCNv2)** While DCNv1 allows the sampling points to move, DCNv2 introduces a **modulation mechanism** to further enhance feature extraction capability. It adds a learnable scalar weight  $\Delta m_k$  to each sampling point, bounded between 0 and 1 via a sigmoid function. The formulation becomes:

$$y(p_0) = \sum_{p_n \in \mathcal{R}} w(p_n) \cdot x(p_0 + p_n + \Delta p_n) \cdot \Delta m_n \quad (2.4)$$

This modulation scalar  $\Delta m_n$  allows the network to adjust the “amplitude” or importance of each sampling point. Crucially, it enables the network to “turn off” sampling points that fall on irrelevant background regions or noise, acting as a local attention mechanism within the convolution kernel.

#### 2.1.4 Integration and Offset Learning

The offsets  $\Delta p_n$  and modulation scalars  $\Delta m_n$  are not fixed parameters; they are dynamic outputs of the network itself. They are generated by a separate, lightweight

convolutional layer (typically a  $3 \times 3$  conv) applied to the same input feature map  $x$  [14, 27].

- **Input:** A feature map  $x$  of size  $H \times W \times C$  serves as the shared source for both the detection head and the offset generator.
- **Offset Generator:** A convolution layer produces a tensor of size  $H \times W \times 3N$  (with  $N$  denoting the kernel size, e.g., 9 for  $3 \times 3$ ). The  $3N$  channels encode the  $x$ -offset,  $y$ -offset, and modulation scalar  $m$  for each kernel element, enabling the kernel to adapt to local geometry [14, 27].
- **Conditioning:** Because offsets are predicted from the same visual evidence they transform, the network can “look” at the object’s morphology (e.g., a ship’s elongated hull) and emit offsets that align the receptive field with that structure, achieving rotation and scale adaptability.

## 2.2 Attention Mechanisms

### 2.2.1 Fundamentals of Visual Attention

The concept of “attention” in computer vision draws inspiration from human cognitive systems, where the visual cortex selectively focuses on specific parts of a scene to process relevant information while ignoring the rest [28, 29]. In the context of Deep Learning, an attention mechanism is mathematically defined as a dynamic weight adjustment function. It computes a set of “importance scores” or weights based on the input features and applies these weights to emphasize informative regions (e.g., objects) and suppress irrelevant ones (e.g., background clutter) [28].

Standard attention mechanisms, such as the Self-Attention found in Transformers, compute the relationship between every pair of pixels in the feature map to capture global context.

$$\text{Attention}(Q, K, V) = \text{softmax} \left( \frac{QK^T}{\sqrt{d_k}} \right) V \quad (2.5)$$

While powerful, this global computation has a quadratic complexity of  $O(H^2W^2)$  with respect to the feature map size. For small object detection, which requires high-resolution feature maps to prevent feature vanishing, this computational cost is often prohibitive [19, 28].

## 2.2.2 Deformable Attention

Deformable Attention, introduced in Deformable DETR, addresses the computational bottleneck of standard attention by combining the sparse sampling principles of DCN with the relation modeling of Transformers. Instead of attending to all pixels in the image, each query element attends only to a small, fixed set of key sampling points learned from the data.

### Mathematical Formulation

Given an input feature map  $x$ , a query element  $q$  with content feature  $z_q$ , and a 2D reference point  $p_q$ , the Deformable Attention output is computed as:

$$\text{DeformAttn}(z_q, p_q, x) = \sum_{m=1}^M W_m \sum_{k=1}^K A_{mqk} \cdot W'_m x(p_q + \Delta p_{mqk}) \quad (2.6)$$

- **Sparse Sampling ( $K$ ):**  $k$  indexes a small set of sampling points (e.g.,  $K = 4$ ). This reduces the complexity from quadratic  $O(H^2W^2)$  to linear  $O(HW \cdot K)$ , making it feasible for high-resolution maps needed for small objects [19].
- **Reference Point ( $p_q$ ):** Unlike standard attention which is location-agnostic, Deformable Attention is grounded at a reference point  $p_q$ . In the encoder, this is the grid location; in the decoder, it is predicted from object queries [19].
- **Sampling Offsets ( $\Delta p_{mqk}$ ):** Similar to DCN, the network predicts offsets  $\Delta p_{mqk}$  from the query feature  $z_q$ . This allows the attention head to dynamically “look” for information in flexible locations relative to the reference point, adapting to the object’s scale and shape [19].
- **Attention Weights ( $A_{mqk}$ ):** These are scalar weights predicted from  $z_q$ , normalized via softmax such that  $\sum A_{mqk} = 1$ . They determine the contribution of each sampled point [19].

### Synergy with Small Oriented Objects

The Deformable Attention mechanism acts as a **spatial filter**. By restricting attention to  $K$  points, it inherently suppresses the vast majority of background noise pixels that would otherwise contribute to the weighted sum in global attention [18, 19]. For small, oriented objects, the learnable offsets  $\Delta p_{mqk}$  allow the model to concentrate its limited computational resources (“glances”) precisely on the object’s key features (e.g., the bow and stern of a ship), regardless of its orientation, while ignoring the surrounding water or land clutter. This significantly enhances the feature representation of small targets that are otherwise prone to being washed out in standard aggregation operations.

## CHAPTER 3

### THE PROPOSED CODES

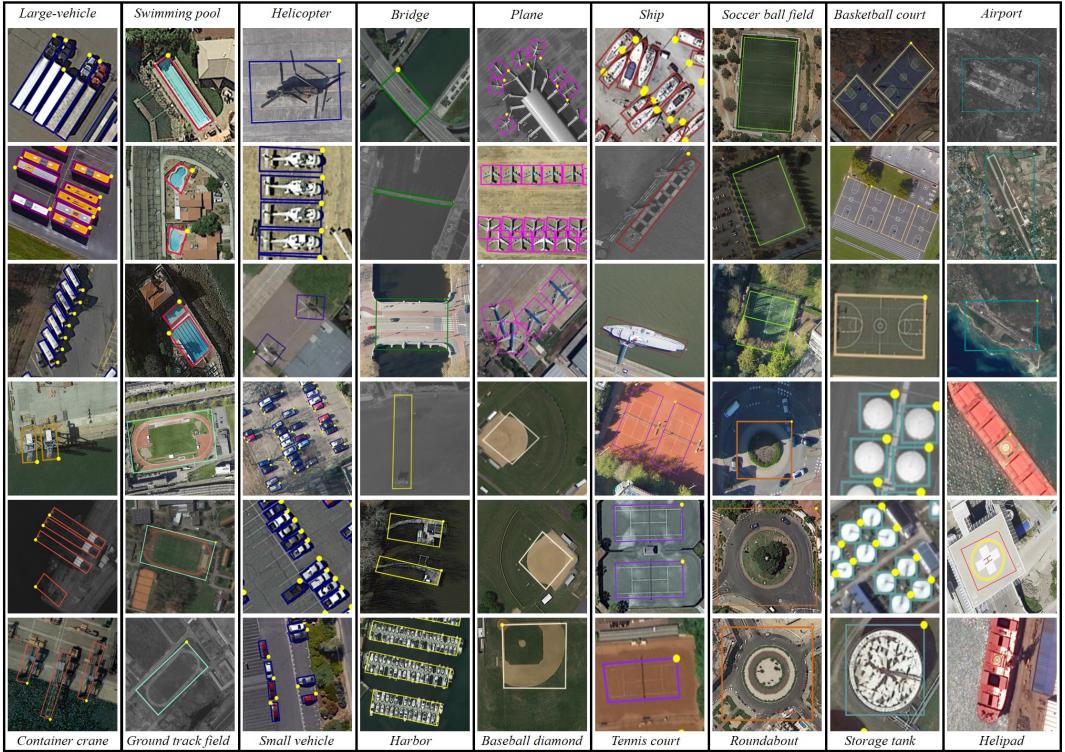
This chapter details the research methodology employed in this study. It includes descriptions of the dataset used, the overall system architecture, modifications made to the YOLO11 model, and the performance evaluation metrics applied to assess the effectiveness of the proposed approach.

#### 3.1 Dataset

This research utilizes two primary datasets for training and evaluating the object detection models: the Dataset for Object Detection in Aerial Images (DOTA) and the Small Object Detection dAtaset (SODA). Both datasets are specifically designed for aerial imagery and present unique challenges for object detection tasks.

##### 3.1.1 DOTA Dataset

The DOTA (Dataset for Object deTection in Aerial images) is a large-scale geospatial dataset widely used as a baseline for oriented object detection [25]. It is built from 2,806 high-resolution aerial images collected from different sensors and platforms, including Google Earth, to ensure a wide diversity of acquisition conditions. The images span from approximately  $800 \times 800$  to  $4,000 \times 4,000$  pixels, and together provide 188,282 annotated instances belonging to 15 common object categories such as plane, ship, storage tank, stadiums, harbor, bridge, large and small vehicles, helicopter, roundabout, and swimming pool. DOTA is split into training, validation, and test subsets with proportions of 1/2, 1/6, and 1/3 respectively, which facilitates standard benchmarking protocols. Each instance is annotated with an Oriented Bounding Box (OBB) defined by four vertices  $(x_i, y_i)$  arranged clockwise, which makes the dataset particularly suitable for aerial scenarios where objects appear at arbitrary rotations. The combination of extreme scale variation, dense object populations, and varying aspect ratios makes DOTA a challenging benchmark for evaluating object detection algorithms in aerial imagery. Figure 3.1 illustrates several instances from the DOTA dataset.



**Fig. 3.1** Instances from the DOTA dataset.

### 3.1.2 SODA Dataset

The second dataset used in this research is the Small Object Detection dAtaset (SODA) benchmark [11], which contains two subsets tailored for driving (SODA-D) and aerial (SODA-A) scenarios. SODA-D spans 24,828 high-resolution street-level images with 278,433 instances labeled with Horizontal Bounding Boxes, while SODA-A focuses on aerial imagery and is the subset used in this research.

SODA-A comprises 2,513 aerial images harvested from Google Earth, each at an average resolution of  $4761 \times 2777$  pixels to preserve the fine structure of tiny targets. The dataset contains 872,069 objects distributed over 9 classes, including Airplane, Helicopter, Small-vehicle, Large-vehicle, Ship, Container, Storage-tank, Swimming-pool, and Windmill. Data splits follow a 40% / 25% / 35% ratio for training, validation, and testing, respectively. Similar to DOTA, annotations use Oriented Bounding Boxes (OBB) to capture rotated objects, but SODA-A explicitly targets the small-object challenge: objects with area under 1024 pixels are considered small, and the average instance size is only 14.75 pixels, with many instances qualifying as "Extremely Small" (area  $< 144$  pixels). The dataset also exhibits extreme density, with some images containing over 11,000 instances, which compounds occlusion and background interference issues. These characteristics make

SODA-A a demanding benchmark for evaluating detection performance on small, densely packed aerial targets. Figure 3.2 shows several instances from SODA-A.



**Fig. 3.2** Instances from the SODA-A dataset.

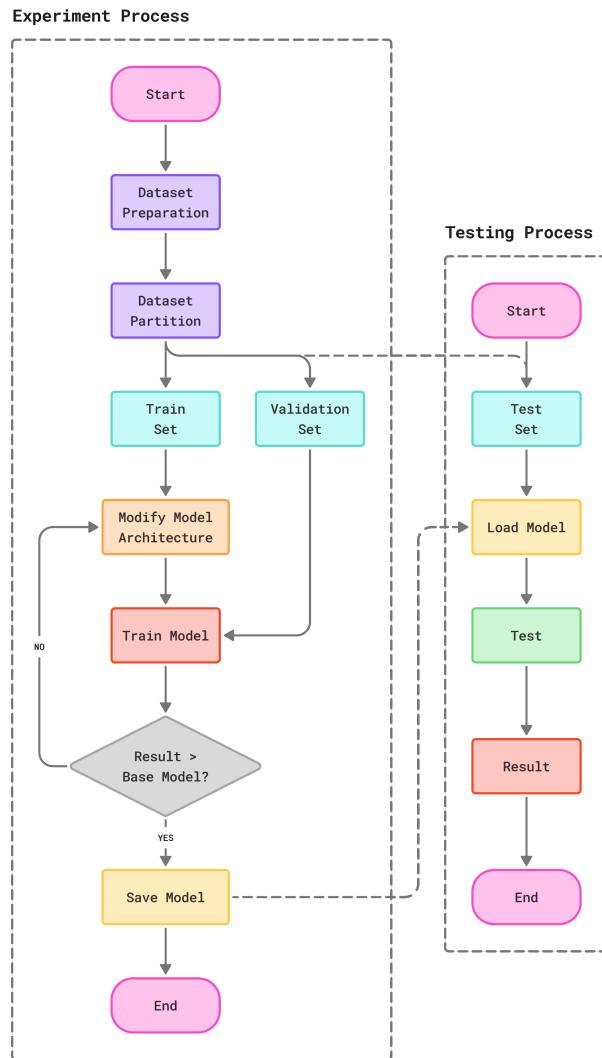
The following Table 3.1 summarizes the key features of both datasets used in this research.

**Table 3.1** Summary of DOTA and SODA-A Datasets.

Feature	DOTA	SODA-A
Domain	General Aerial Detection	Small Object / Dense Aerial Detection
Images	2,806	2,513
Instances	188,282	872,069
Categories	15	9
Annotation Type	Oriented Bounding Box (OBB)	Oriented Bounding Box (OBB)
Key Challenge	Scale Variation, Orientation	Extremely Small Objects, High Density

## 3.2 System Process Architecture

Figure 3.3 illustrates the overall Experiment and Testing flow used in this research. The process begins with dataset preparation, where images and annotations from DOTA and SODA-A are standardized and converted into the annotation format required by the Ultralytics YOLO framework. The prepared dataset is then partitioned into training, validation, and testing subsets according to each dataset's predefined allocation ratios.

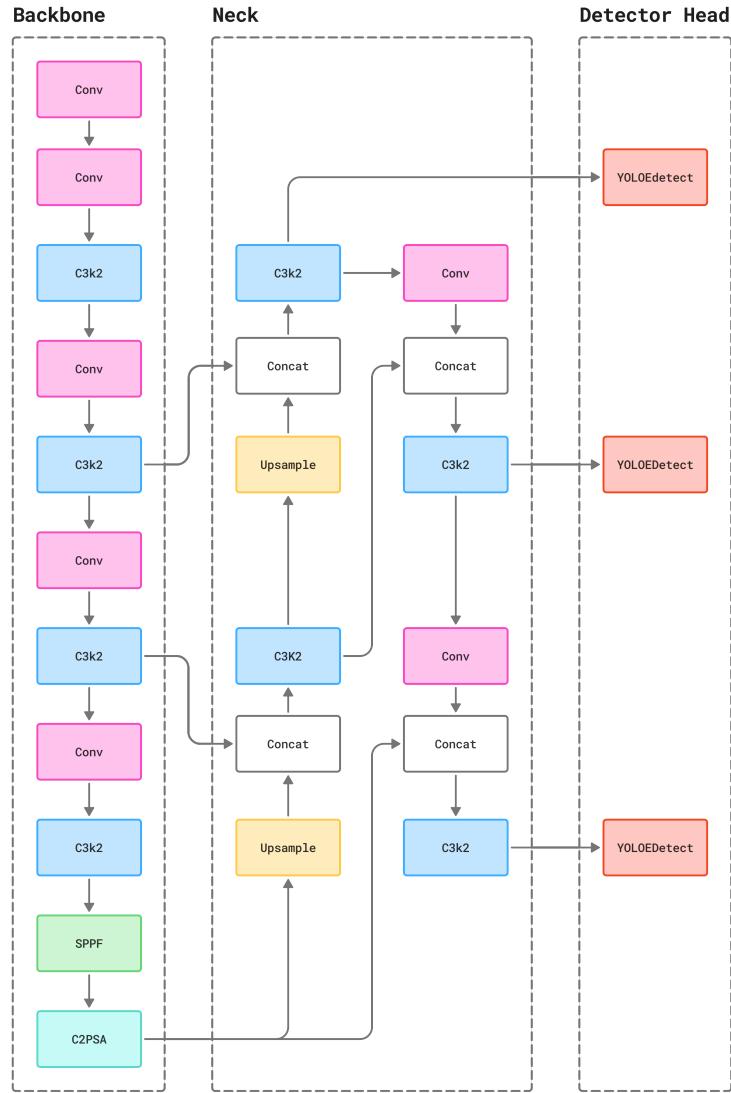


**Fig. 3.3** System Process Architecture.

Next, the modified YOLO11 model is trained on the training set while monitoring validation performance to guide early stopping or further architecture tuning. When a trained checkpoint surpasses the established baseline, it is saved for later testing; otherwise, additional architectural modifications or hyperparameter adjustments are applied and the training loop repeats. The saved model is eventually loaded during the testing phase, where inference is performed on the unseen test set and the predicted boxes are compared to the ground-truth annotations to compute the evaluation metrics in this research. This system-wide process ensures that data collection, model development, and evaluation are tightly coordinated, which is essential for improving accuracy and efficiency in detecting aerial objects.

### 3.3 Modified YOLO11 Architecture

The proposed modifications to the YOLO11 architecture focus on enhancing its capability to detect oriented and small objects in aerial images. The key changes include integrating Deformable Convolutional Networks (DCN) into the backbone and neck of the model, as well as incorporating Deformable Attention mechanisms in the detection head. Figure 3.4 illustrates the overall architecture of the modified YOLO11 model.



### 3.3.1 Deformable Convolution Networks (DCN)

### 3.3.2 Deformable Attention

## 3.4 Performance Evaluation Metrics

In this research, the performance of the modified YOLO11 model is evaluated using standard object detection metrics, primarily focusing on Mean Average Precision (mAP) at different Intersection over Union (IoU) thresholds. Others metrics such as Precision, Recall, and F1-Score are also computed to provide a comprehensive assessment of the model's detection capabilities, especially in handling oriented and small objects in aerial imagery. To quantify computational cost, we also track the number of model parameters (Params) and Floating Point Operations per Second (FLOPS), ensuring that accuracy improvements remain practical for real-world deployment.

### 3.4.1 Precision

Precision measures the proportion of correctly predicted positive instances (true positives) out of all instances predicted as positive (true positives + false positives). It reflects the model's ability to avoid false alarms.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (3.1)$$

where  $TP$  is the number of true positives and  $FP$  is the number of false positives.

### 3.4.2 Recall

Recall measures the proportion of correctly predicted positive instances (true positives) out of all actual positive instances (true positives + false negatives). It indicates the model's ability to detect all relevant objects.

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3.2)$$

where  $TP$  is the number of true positives and  $FN$  is the number of false negatives.

### 3.4.3 F1-Score

The F1-Score is the harmonic mean of Precision and Recall, providing a single metric that balances both aspects of model performance. It is particularly useful when the class distribution is imbalanced.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (3.3)$$

### 3.4.4 Mean Average Precision (mAP)

Mean Average Precision (mAP) is the primary metric used to evaluate the object detection performance of the model. It is calculated by averaging the Average Precision (AP) across all object classes. AP is derived from the Precision-Recall curve for each class, which plots precision against recall at various confidence thresholds. The mAP is computed at different IoU thresholds (e.g., mAP@0.5, mAP@0.50-95) to assess how well the model detects objects with varying degrees of overlap with ground truth boxes.

$$\text{mAP} = \frac{1}{N} \sum_{i=1}^N \text{AP}_i \quad (3.4)$$

where  $N$  is the number of classes and  $\text{AP}_i$  is the Average Precision for class  $i$ .

### 3.4.5 Number of Parameters (Params)

The number of parameters (Params) in the model quantifies its complexity and size. It is calculated by summing all learnable weights and biases across all layers of the neural network. A lower number of parameters generally indicates a more efficient model, which is beneficial for deployment in resource-constrained environments.

$$\text{Params} = \sum_{i=1}^L (W_i + B_i) \quad (3.5)$$

where  $L$  is the number of layers,  $W_i$  is the number of weights in layer  $i$ , and  $B_i$  is the number of biases in layer  $i$ .

### 3.4.6 Floating Point Operations per Second (FLOPS)

FLOPS measures the computational efficiency of the model by counting the number of floating-point operations required to process a single input image. It pro-

vides insight into the model's speed and resource requirements, which are critical for real-time applications.

$$\text{FLOPS} = \sum_{i=1}^L F_i \quad (3.6)$$

where  $L$  is the number of layers and  $F_i$  is the number of floating-point operations in layer  $i$ .

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