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Lightweight YOLOv5s Model for Early Detection of Agricultural Fires

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Abstract: Agricultural fires significantly threaten global food systems, ecosystems, and rural economies, necessitating timely detection to prevent widespread damage. This study presents a lightweight and enhanced version of the YOLOv5s model, optimized for early-stage agricultural fire detection. The core innovation involves deepening the C3 block and integrating DarknetBottleneck modules to extract finer visual features from subtle fire indicators such as light smoke and small flames. Experimental evaluations were conducted on a custom dataset of 3200 annotated agricultural fire images. The proposed model achieved a precision of 88.9%, a recall of 85.7%, and a mean Average Precision (mAP) of 87.3%, outperforming baseline YOLOv5s and several state-of-the-art (SOTA) detectors such as YOLOv7-tiny and YOLOv8n. The model maintains a compact size (7.5 M parameters) and real-time capability (74 FPS), making it suitable for resource-constrained deployment. Our findings demonstrate that focused architectural refinement can significantly improve early fire detection accuracy, enabling more effective response strategies and reducing agricultural losses.

Keywords: lightweight model; agricultural fire detection; early fire detection; smart farming; fire monitoring systems



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1. Introduction

Agricultural fires are increasingly recognized as a major environmental and economic threat, driven by a combination of natural events and anthropogenic activities. Unlike large-scale forest fires, agricultural fires often begin with subtle indicators—thin smoke trails or brief flame flashes—which are difficult to detect using conventional or general-purpose fire detection systems [1]. These early-stage signatures are particularly challenging to capture in real time due to their weak spatial features, variable lighting conditions, and often open or low-contrast environments. The urgency for accurate early detection systems is growing, particularly in the face of climate change, which has increased the frequency and severity of agricultural fire outbreaks [2]. Traditional fire surveillance technologies—including thermal sensors, manual monitoring, and satellite imaging—suffer from latency,

limited spatial resolution, or infrastructure dependence, making them less suitable for timely responses in dynamic rural settings [3]. Early detection and timely intervention are crucial to mitigating these risks, highlighting the need for advanced, efficient, and reliable fire detection technologies [4].

In the wake of increasing agricultural fire incidents [5], the imperative for innovative technological solutions has never been more critical [6]. Traditional methods of fire detection, often reliant on manual surveillance or basic sensor networks [7], are no longer sufficient given the rapid scale at which these fires can spread and the extensive damage they cause [8]. This has spurred the necessity for a transformation in how agricultural fires are monitored and managed [9]. Advancements in deep learning and computer vision offer a promising pathway to revolutionize this domain [10]. Among the potential solutions, the YOLO (You Only Look Once) [11] series of models have emerged as leaders due to their ability to perform real-time object detection with high levels of accuracy and speed [12]. Specifically, the YOLOv5s model [13] has been identified as particularly adept due to its optimized architecture that balances computational efficiency with robust detection capabilities [14]. However, despite its strengths, there remains room for enhancement, especially in the context of detecting the early stages of agricultural fires which present unique visual features that are often subtle and easily overlooked [15].

Our research aims to address these challenges by tailoring the YOLOv5s model to better suit the specific needs of agricultural fire detection. By augmenting the model's architecture, particularly through the modification of the C3 block, we seek to heighten its sensitivity to the early indicators of fire and smoke. These indicators include slight changes in color, sporadic movements of smoke, and other minute details that standard models might miss. The enhanced model is designed to capture these features by deepening the layers within the C3 block, thus allowing for a more granular analysis of the input images. Moreover, the implications of such technological advancements extend beyond the mere technical realm. The ability to detect agricultural fires early can drastically reduce the economic strain on farmers, protect wildlife habitats from extensive damage, and ultimately, contribute to the sustainability of agricultural practices. Thus, the enhancements detailed in this paper are not only a testament to technological progress but also an essential step towards a more sustainable and secure agricultural future. The main contributions of this study are as follows:

- We propose a modified C3 block within YOLOv5s, incorporating a deeper structure and DarknetBottleneck modules to improve the extraction of fine-grained features critical for early fire detection.
- A comparative study of SiLU, ReLU, and Leaky ReLU functions is conducted to determine the optimal activation mechanism for fire-specific feature learning, with SiLU showing superior convergence and accuracy.
- We introduce a sensitivity analysis evaluating the influence of architectural components on key performance metrics, providing insight into design choices that enhance model robustness.
- A custom dataset composed of annotated agricultural fire imagery was compiled and preprocessed, enabling a diverse, representative training environment.
- Our proposed model achieves a higher precision, recall, mAP, and F1-score compared to YOLOv7-tiny, YOLOv8n, YOLO-Fire, and other state-of-the-art lightweight detectors, while maintaining computational efficiency.

Our approach represents a critical advancement in agricultural fire detection, providing a scalable, efficient, and highly effective tool that can be deployed across various regions, each with their unique environmental conditions and challenges. Through the course of this paper, we will explore the impact of these innovations, providing a comprehensive

analysis of the modified YOLOv5s model performance against traditional fire detection methods, thereby underscoring the importance of this research in the broader context of global agricultural management and safety protocols.

2. Related Works

2.1. Traditional Fire Monitoring Approaches

The proliferation of agricultural fires globally necessitates advanced detection and monitoring technologies to mitigate their impact on ecosystems and economies [16]. In this context, the literature extensively explores various methodologies ranging from traditional satellite monitoring to advanced computational models [17]. This section provides a comprehensive review of the existing technologies and highlights the innovations introduced in recent years that set the stage for our proposed enhancements to the YOLOv5s model. Recent advancements in sensor technology have introduced more dynamic and real-time monitoring capabilities. For instance, [18] reported on the use of UAVs (Unmanned Aerial Vehicles) equipped with thermal cameras that provide high-resolution imagery capable of identifying hot spots before they develop into larger fires. Although UAVs offer improved detection speed and precision, their operational range and flight duration are constrained by battery life and weather conditions, which may limit their utility in extensive agricultural fields or during adverse weather scenarios [19].

2.2. IoT-Based Ground Surveillance Systems

In recent years, the Internet of Things (IoT) has played a pivotal role in transforming fire detection methodologies by enabling real-time, distributed environmental monitoring. IoT-based systems consist of a network of interconnected sensors that continuously capture key physical indicators—such as temperature, humidity, gas emissions, smoke density, and atmospheric pressure—which are crucial in the early identification of combustion events [20]. These systems are particularly advantageous in closed agricultural zones where visual detection may be obstructed due to terrain or crop density. Several studies have demonstrated the effectiveness of multi-sensor fusion, where heterogeneous sensors are deployed in synergy to enhance detection accuracy and reduce false positives [21]. For example, integrating gas sensors with infrared (IR) flame sensors enables both chemical and thermal detection, making it possible to distinguish between fire and non-fire events such as steam or high sunlight exposure. Furthermore, advances in edge computing allow data to be processed locally at the node level, minimizing latency and bandwidth requirements for remote farmland applications [22]. IoT platforms often rely on protocols such as LoRaWAN, NB-IoT, or Zigbee, which are designed for low-power wide-area networking—essential for sustaining long-term monitoring in remote agricultural regions. Additionally, cloud integration enables centralized visualization dashboards, predictive analytics, and alert systems that can notify local authorities or farmers via SMS or app notifications within seconds of anomaly detection [23].

2.3. Deep Learning in Fire Detection

The domain of artificial intelligence, particularly deep learning, has seen significant interest for its potential to revolutionize fire detection methodologies [24]. Convolutional Neural Networks (CNNs) have been at the forefront, with architectures like the YOLO series being adapted for real-time object detection tasks [25]. Notably, Reference [26] proposed DCGC-YOLO, an enhanced YOLOv5-based algorithm to improve early fire detection. It introduces a Dual Channel Group Convolution (DCGC) structure, combining large-kernel CSP blocks, channel cleansing via grouped convolution, and the eSE mechanism for better long-range modeling. Reference [27] proposed LUFFD-YOLO, a lightweight YOLO-based

model, to improve real-time forest fire detection in UAV remote-sensing images. It integrates GhostNetV2 to reduce parameters, the ESDC2f module for enhanced small-object detection, and the HFIC2f structure for better feature extraction and fusion in complex backgrounds. This design boosts detection accuracy while maintaining efficiency. To address the challenge of detecting small or hidden forest fires, Reference [28] proposed an improved YOLOv5-based model. It incorporates a global attention mechanism to enhance feature extraction, a re-parameterized convolutional module, and a decoupled detection head for faster convergence, and a weighted BiFPN for better local feature fusion. The model uses CIoU loss for accurate multi-task optimization, achieving a strong balance between global context and local detail in forest fire detection. Reference [29] proposed YOLO-LFD, an improved YOLOv5-based model optimized for real-time forest fire detection on resource-limited devices. It uses Depthwise Separable Convolutions to reduce complexity, along with C2f-Light and C3CIB modules for faster and more efficient deep feature extraction. To boost small fire detection, the model incorporates the Normalized Wasserstein Distance (NWD) loss, improving accuracy and reducing missed detections. Reference [30] proposed a domain-free fire detection algorithm based on YOLOv5, designed to handle diverse fire scenarios across day, night, urban, and forest settings. The model integrates linear attention for spatial focus and Gated Temporal Pooling (GTP) for capturing temporal fire features. Unlike conventional methods, it effectively extracts spatiotemporal cues from both still images and video, achieving superior accuracy with a compact model. To address the challenge of accurate fire detection on resource-limited embedded devices, Reference [31] proposed EMG-YOLO, an efficient fire detection model. It features a Multi-scale Attention Module (MAM) and an Efficient Multi-scale Convolution Module (EMCM) for improved feature representation without added complexity. A Global Feature Pyramid Network (GFPN) enhances information flow, and a slimming algorithm prunes the model for optimal deployment on edge devices, balancing accuracy and computational efficiency. Reference [32] presented YOLO-Fire, an enhanced fire detection algorithm based on YOLOv5s, designed for real-time edge deployment. It replaces the C3 module with SimpleC3 to reduce parameters, introduces a dynamic upsampler for improved feature preservation, and utilizes the Focal WIoU-loss to better detect irregular fire shapes. Reference [33] proposed EA-YOLO, a fire detection model optimized for complex backgrounds, dense targets, and imbalanced datasets. It integrates a Multi-Channel Attention (MCA) mechanism for better feature extraction, the lightweight RepVB module to reduce parameters, and a Multidirectional Feature Pyramid Network (MDFPN) for enhanced feature fusion. Additionally, a modified CIoU loss with a Slide weighting function improves performance on hard samples, boosting both accuracy and real-time detection capabilities. Reference [34] proposed DSS-YOLO, an enhanced YOLOv8n-based fire detection model targeting small, obscured targets in early fire stages. It replaces C2f modules with DynamicConv for lower computation, integrates the SEAM attention mechanism for improved recognition of hidden objects, and adds the SPPELAN module for better multi-scale detection. Reference [35] presents a YOLOv8-based fire and smoke detection model for IoT surveillance systems, aiming to achieve high accuracy with low computational cost. To meet the high demands of industrial and mining fire detection, Reference [36] proposed an improved YOLO-based algorithm with enhanced accuracy and real-time performance. It introduces the CFM_N module for better local and global feature capture, an improved SPPFCSPC module for robust multi-scale feature fusion, and an optimized downsampling module to reduce complexity while maintaining detection precision.

However, while these models offer promising avenues for rapid fire detection, their accuracy and efficiency in processing complex agricultural environments remain underexplored. Our research builds on this foundation by enhancing the YOLOv5s architecture,

specifically its C3 block, to refine its ability to detect subtle and early indicators of fires. This focus on early detection is critical, as it allows for quicker responses, potentially saving vast areas of farmland from devastation. While existing technologies each contribute valuable capabilities for fire detection, they also present limitations that our work seeks to address. By integrating and building upon these technologies, particularly through advancements in deep learning, our approach aims to provide a more robust, accurate, and timely solution to the problem of agricultural fire detection. To the best of our knowledge, while a significant number of fire detection studies exist across forest, urban, and industrial contexts, there is a notable absence of research specifically targeting agricultural fire detection using deep learning models. Most existing YOLO-based innovations, such as LUFFD-YOLO, YOLO-LFD, and EA-YOLO, focus on general-purpose fire detection or forest fires, often in dense and complex environments. However, agricultural fires present unique challenges, particularly in the early stages, where smoke and flame signatures are visually subtle and easily overlooked by standard architectures. This research addresses this underexplored problem space by tailoring the YOLOv5s architecture to better detect these early cues, thereby offering a novel contribution to the field. Our work not only enhances detection performance in a previously neglected domain but also maintains model efficiency for deployment in resource-constrained agricultural settings.

3. Methodology

In this paper, we introduce an innovative approach to detecting agricultural fires and smoke in crop fields, emphasizing the critical importance of early-stage identification. Timely detection has become increasingly significant, particularly given the rising frequency of wildfires, intentional acts, and human negligence contributing to fire incidents. Our study details enhancements to the YOLOv5s model by modifying the C3 block, specifically by increasing its layers. This modification enables the network to capture more pertinent features, consequently improving detection accuracy. Additionally, the experimental results demonstrate that our proposed modification significantly outperforms the original YOLOv5s in terms of precision and recall, providing a robust solution for early fire detection in agricultural settings.

3.1. YOLOv5s

YOLOv5s is an advanced, lightweight CNN architecture belonging to the YOLO object detection family, designed specifically for high-speed, real-time detection tasks. The YOLOv5s model is structured into three primary modules: Backbone, Neck, and Head, each serving distinct functional roles within the detection pipeline (Figure 1). The Backbone of YOLOv5s leverages the Cross Stage Partial connections-integrated Darknet (CSPDarknet53) architecture, which is renowned for its efficient feature extraction capabilities and reduction in computational overhead. The CSP strategy splits feature maps into two parts, applying convolutional operations separately, and then merges them, significantly enhancing both efficiency and accuracy. The Backbone integrates multiple residual blocks, enhancing the depth of the network and allowing it to learn complex features while mitigating gradient vanishing problems. Moreover, the inclusion of the Spatial Pyramid Pooling (SPP) block in the Backbone aids in capturing spatial information at multiple scales without significantly increasing computational complexity.

The Neck component adopts a Path Aggregation Network (PANet) architecture, effectively combining multi-scale feature maps through a series of bottom-up and top-down pathways. PANet incorporates lateral connections to merge features extracted from various layers, enriching feature representations and enhancing object detection capability across a wide range of sizes and scales. This sophisticated fusion approach significantly boosts

the model's ability to handle scale variations inherent in practical detection tasks. Finally, the Head module is responsible for performing object classification and bounding box regression. It processes enriched feature maps produced by the Neck module, resulting in precise localization and accurate categorization of detected objects. The Head employs multiple convolutional layers, each tuned to specific spatial resolutions, facilitating the simultaneous prediction of object class probabilities, bounding box coordinates, and objectness scores. YOLOv5s stands out due to its optimized architecture, balancing accuracy with computational efficiency, making it highly suitable for deployment on edge devices and in real-time detection scenarios. Furthermore, YOLOv5s employs advanced techniques such as mosaic data augmentation, adaptive anchor box computation, and auto-learning anchor boxes, all of which significantly contribute to its robustness and superior generalization performance. Mosaic data augmentation, specifically, combines four different training images into one, enhancing the model exposure to diverse object sizes and contexts. Additionally, YOLOv5s utilizes advanced loss functions like Complete Intersection over Union (CIoU), improving bounding box regression precision by considering aspects like box overlap, central alignment, and the aspect ratio. These combined strategies result in a highly efficient and accurate model, making YOLOv5s particularly suitable for complex real-world detection scenarios, including autonomous driving, video surveillance, and agricultural monitoring.

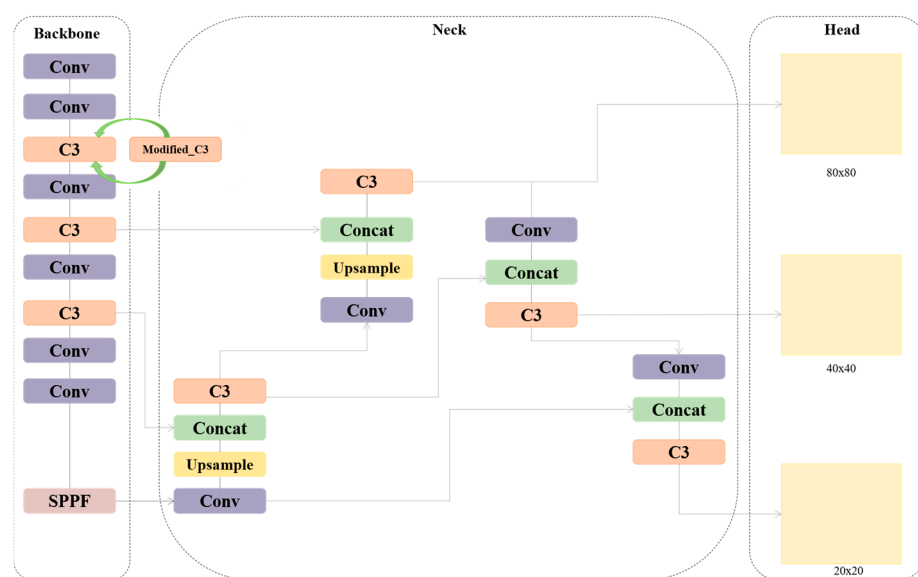


Figure 1. The architecture of the proposed YOLOv5s-based model includes a key modification in the backbone where a standard C3 block is replaced with a Modified_C3 block. This enhanced block incorporates additional convolutional depth and DarknetBottleneck modules to improve the extraction of fine-grained features, particularly useful for detecting early signs of agricultural fires such as faint smoke or small flames. The model maintains the core YOLOv5s structure, processing images through convolutional, upsampling, and fusion layers before producing multi-scale outputs. This design ensures robust detection while preserving real-time performance.

3.2. The Proposed Method

In this study, we propose a novel method for the early detection of crop fires in agricultural fields. To enhance the detection capability, we introduce architectural modifications to the internal C3 module of the well-established YOLOv5s model. To maintain a lightweight architecture suitable for deployment on resource-constrained platforms, the modified C3 block was carefully designed to avoid excessive parameter growth. We reduced the channel width where applicable, used efficient convolutional kernels, and introduced only a mini-

mal number of additional bottleneck layers. The use of the SiLU activation function, while slightly more computationally intensive than ReLU, was found to provide improved convergence without significantly affecting inference speed. The resulting architecture achieves a balance between accuracy and efficiency, preserving the low computational overhead characteristic of YOLOv5s. The full model architecture is illustrated in Figure 1. As shown, the standard YOLOv5s backbone is modified by replacing one of its C3 blocks with the proposed Modified_C3, marked in white. This block includes a deeper convolutional stack and integrated DarknetBottleneck components to enhance low-level and mid-level feature extraction. Such an improvement is critical for identifying subtle fire indicators like thin smoke or flame flickers in agricultural settings. The rest of the architecture remains aligned with the original YOLOv5s design to ensure computational efficiency. The model outputs detection results at three different scales, preserving the multi-scale detection strength of YOLO-based architectures.

Specifically, we deepen the C3 block to improve feature extraction while maintaining computational efficiency to avoid increasing model complexity. Furthermore, we integrate a DarknetBottleneck layer within the modified C3 module to strengthen the network's representational capacity, enabling more accurate identification of early fire signatures in complex agricultural environments. The input image $X_{input} \in R^{W \times H \times C}$ is first processed by the backbone of the model, where it passes through an initial feature extraction block. This block consists of a standard convolutional layer, followed by batch normalization and a nonlinear activation function, as formulated in Equation (1):

$$F_{conv} = \text{SiLU}(\text{BatchNorm}(F_{3 \times 3}(X_{input}))) \quad (1)$$

The $F_{conv}()$ block is designed as a lightweight module aimed at efficiently capturing both the initial feature representations and the subsequent hierarchical information necessary for further processing. Moreover, after this block follows the second $F_{conv}()$, as shown in Figure 1.

$$F_{modified_C3} = F_{left_branch} = \max(0, (F_{3 \times 3}(F_{3 \times 3}(F_{conv})))) \quad (2)$$

Equation (2) illustrates the structure of the proposed block, which is divided into three distinct components. The first component, referred to as the left branch, consists of two consecutive convolutional layers with 3×3 kernel sizes. These layers increase the depth of the block, enhancing its capacity to extract more relevant and complex features. To maintain computational efficiency and prevent excessive complexity, the stride and padding values are carefully adjusted to smaller values:

$$F_{modified_C3} = F_{right_branch} = \text{DarknetBottleneck}(\text{BatchNorm}(F_{3 \times 3}(F_{conv}))) \quad (3)$$

In the right branch of the proposed block, Equation (3), an additional convolutional layer is introduced to capture complementary feature representations that might not be extracted by the left branch. To ensure feature consistency and facilitate stable training, a normalization layer is applied to the extracted features. Moreover, this branch retains the additional DarknetBottleneck module, which is known for its ability to enhance feature reuse and improve gradient flow. By incorporating the DarknetBottleneck, the model strengthens its representational capacity while maintaining computational efficiency, allowing for the better extraction of complex patterns essential for early fire detection:

$$F_{modified_C3} = F_{conv}(\text{Concat}(F_{right_branch} + F_{left_branch})) \quad (4)$$

The final structure of the modified C3 block is presented in Equation (4), where the outputs of the left and right branches are concatenated. The combined feature maps are

then passed through a final convolutional layer to further refine the extracted features and prepare them for subsequent processing stages (Figure 2).

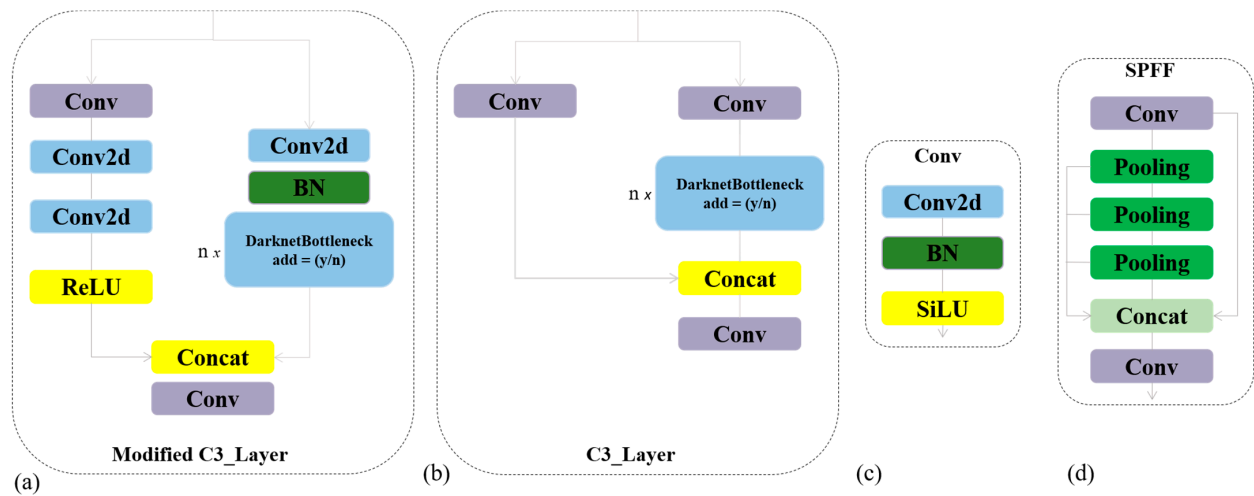


Figure 2. Modified layer. (a) Modified C3 layer with additional inner blocks, (b) C3 layer, and (c) Conv block. (a) The original C3 block based on sequential convolution and residual connections using ReLU activation. (b) Our Modified_C3 design incorporates deeper paths and a DarknetBottleneck structure to enhance feature reuse and gradient flow. (c) Convolutional unit with batch normalization and SiLU activation, which replaces ReLU to improve convergence and nonlinear expressivity. (d) Pooling-based fusion unit used within the block to increase spatial abstraction while preserving critical activations. These improvements collectively support better identification of subtle smoke or flame patterns in early-stage agricultural fires.

The modified C3 layer presented in Algorithm 1 enhances the standard YOLOv5s architecture by introducing several key changes aimed at improving feature extraction while maintaining computational efficiency.

Algorithm 1. Pseudocode for the Modified C3 Layer used in the enhanced YOLOv5s architecture, integrating convolutional, pooling, SiLU activation, and DarknetBottleneck modules to improve early-stage agricultural fire detection.

```

class modified(C3_layer):
2:     conv:
3:     Conv2d (channels, channels, kernel, padding, stride)
4:     BatchNorm2d (channels)
5:     SiLU ();
6:     Conv2d (channels, channels, kernel, padding, stride)
7:     Pooling ();
8:     Conv2d (channels, channels, kernel, padding, stride)
9:     (n*) DarknetBottleneck(add(y/n));
10:    Concatenation (5, 9);
11:    conv;

```

The block begins with a convolutional operation followed by batch normalization and the SiLU activation function, which enhances nonlinearity and gradient flow. An additional convolutional layer and a pooling operation are incorporated to deepen the network and reduce the spatial dimensions of the feature maps. Furthermore, a third convolutional layer refines the extracted features before passing them through a series of DarknetBottleneck modules, which strengthen feature reuse and improve representational capacity. The outputs from the SiLU activation stage and the DarknetBottleneck block are

then concatenated to fuse low-level and high-level features, capturing both local and global context. Finally, the concatenated features are processed through a final convolutional layer, preparing them for the subsequent layers of the model. This architectural modification balances depth and complexity, resulting in more effective feature representation without significantly increasing computational overhead. As the baseline model, we use the same loss function—the combination of three losses: localization loss (box regression) considers overlap area, center distance, and aspect ratio; objectness loss (object presence confidence) measures how confident the model is that an object exists in a predicted bounding box; classification loss (object class prediction)—for each anchor box that detects an object, the baseline applies a classification loss over the target classes, as shown in Equation (5):

$$L_{total} = \lambda_{box}L_{box} + \lambda_{obj}L_{obj} + \lambda_{cls}L_{cls} \quad (5)$$

4. The Experiment and Results

4.1. Dataset

In the scope of this research, we have developed a specialized dataset primarily composed of visual imagery and video sequences documenting agricultural fire incidents on both global and local scales. This collection is augmented by relevant visual excerpts sourced from platforms like YouTube, thereby encompassing a comprehensive range of fire-related scenarios (Figure 3). To ensure consistency in data processing and to enhance computational efficiency, all visual content underwent standardization to a fixed resolution. In total, the curated dataset comprises 3200 unique samples, including 2700 still images and 500 annotated video frames, capturing diverse agricultural fire scenarios. These samples represent early-stage and active fire incidents sourced from publicly available resources, including YouTube footage and open-access fire image repositories. To facilitate robust training and evaluation, the dataset was divided into three subsets using an 80:10:10 ratio, yielding 2560 images for training, 320 for validation, and 320 for testing. All samples were resized to a resolution of 300×300 pixels to standardize input dimensions and improve training efficiency. The diversity in lighting, landscape type, and fire severity ensures the strong generalization capability of the model in real-world agricultural contexts. Each image, in particular, has been carefully resized to dimensions of 300×300 pixels. This standardized resolution is critical, as it guarantees uniform quality across the dataset, which is fundamental for the accurate training and thorough evaluation of the proposed detection model. Such uniformity directly contributes to improved accuracy in fire detection from diverse sources, thereby substantially enhancing the model's real-world applicability and reliability.



Figure 3. Example of dataset.

4.2. Data Preprocessing

The preprocessing stage of this study incorporates a rigorous sequence of operations designed to optimally condition the dataset for subsequent analytical procedures. Initially, all gathered visual data, comprising static images and individual video frames, are subjected to an intensive normalization routine. This process adjusts pixel intensity values to a unified scale, thus reducing the variability arising from inconsistent lighting conditions and diverse camera configurations inherent across data sources. Following this normalization phase, several augmentation methods are implemented to bolster dataset robustness, mitigate the risk of model overfitting, and simulate a broader spectrum of fire detection scenarios. Such augmentation techniques, illustrated in Figure 4, include random rotations, image mirroring, scaling adjustments, and color filtering, collectively increasing the dataset's diversity and complexity. Additionally, strategic cropping is employed to rectify aspect ratio and scaling issues, ensuring that critical features such as fire and smoke remain prominently centered within frames.

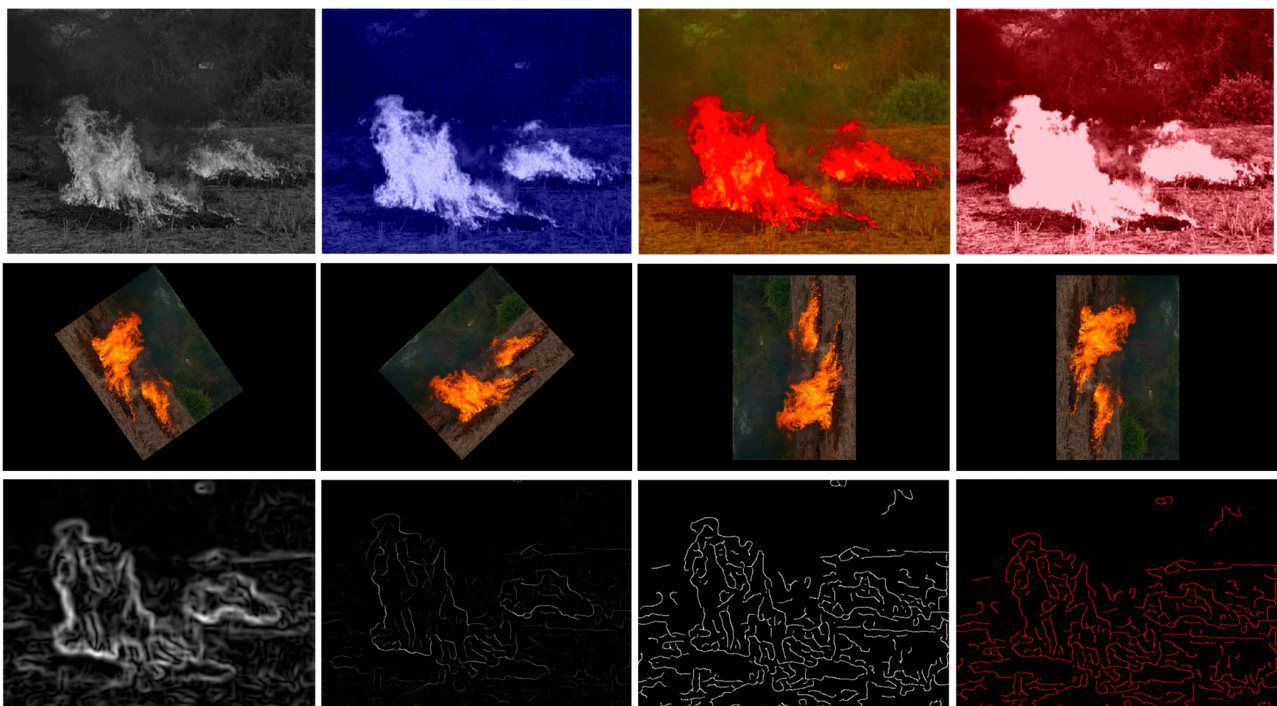


Figure 4. Data preprocessing part.

Ultimately, all images undergo uniform resizing to 300×300 pixels, a step essential not only for standardizing the model input dimensions but also for reducing computational demands. This streamlined preprocessing approach facilitates efficient model training and rapid evaluation, thus producing a robust and highly effective dataset tailored specifically for enhancing fire detection accuracy in varied agricultural contexts.

The training was performed using the PyTorch 2.1 framework on an NVIDIA RTX A6000 GPU. The model was trained for 150 epochs with a batch size of 16 and an initial learning rate of 0.001, using the Stochastic Gradient Descent (SGD) optimizer with momentum = 0.937 and weight decay = 0.0005. A cosine annealing scheduler was employed to gradually reduce the learning rate across training epochs. The loss function included CIOU for bounding box regression and binary cross-entropy for objectness and classification loss components, as per the original YOLOv5 implementation. For regularization and robustness, data augmentation techniques such as Mosaic augmentation, random horizontal flipping (probability = 0.5), color jittering, and random scaling ($\pm 10\%$) were

applied. Anchor boxes were automatically updated using a k-means clustering algorithm at the beginning of training. The training pipeline also included gradient clipping and early stopping strategies based on validation loss stabilization.

4.3. Results

The experimental results from this study are comprehensively detailed through three distinct tables [1–3], clearly highlighting the performance improvements and computational implications of our proposed modifications to the YOLOv5s architecture for early-stage agricultural fire detection (Figure 5). The experiments were conducted using the PyTorch framework on an NVIDIA RTX A6000 GPU with 48GB VRAM. The model was trained for 150 epochs using a batch size of 16 and an initial learning rate of 0.001, optimized via Stochastic Gradient Descent (SGD) with a momentum of 0.937 and weight decay of 0.0005. A cosine annealing learning rate scheduler was applied across training epochs. The custom dataset consisted of 3200 annotated agricultural fire images, partitioned into 80% for training (2560 images), 10% for validation (320 images), and 10% for testing (320 images). All images were resized to 300×300 pixels for input standardization. Data augmentation techniques included mosaic augmentation, random flipping, color jittering, and random scaling. Anchor boxes were updated using k-means clustering at the start of training. These settings ensured the consistent and fair evaluation of all models, including those compared in Tables 1–3.

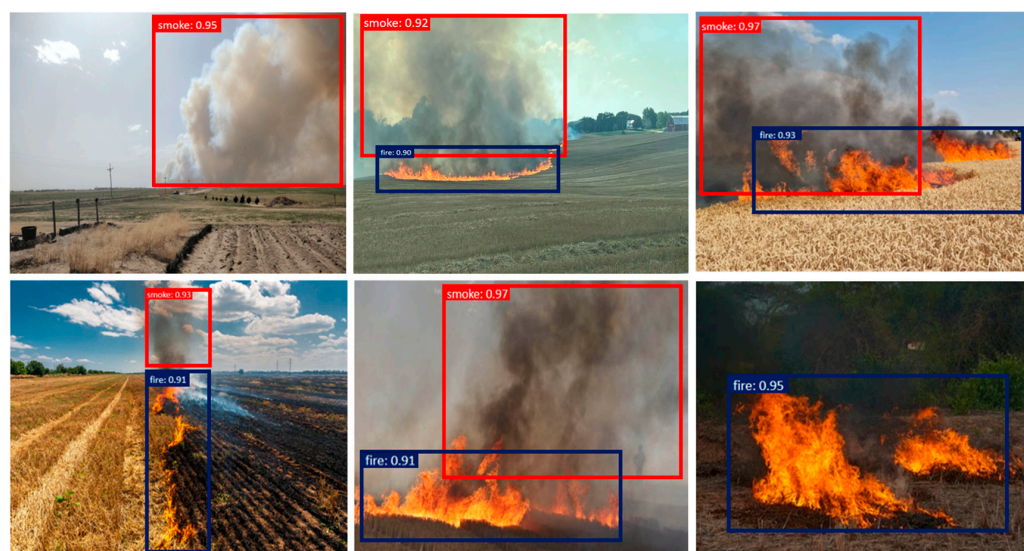


Figure 5. Example detections by the proposed YOLOv5s model with the Modified_C3 block on agricultural fire images. The model successfully detects both smoke (red bounding boxes) and fire (blue bounding boxes) with high confidence scores across varied environmental conditions. These examples illustrate the model robustness in identifying early-stage fire cues and complex visual patterns in open-field scenarios.

Table 1. Comparison of the models' performance, where the differences between the baseline YOLOv5s and our modified model is clearly illustrated by including metrics like precision, recall, mAP, and F1-score.

Model	Precision (%)	Recall (%)	mAP (%)	F1-Score (%)
YOLOv5s (Baseline)	85.5	83.2	84.6	81.3
Proposed Model	88.9	85.7	87.3	87.3

Table 2. The results of the ablation study and the impact of each modification separately.

Modification	Precision (%)	Recall (%)	mAP (%)	F1-Score (%)
Baseline YOLOv5s	83.6	80.2	79.16	84.3
YOLOv5s + DarknetBottleneck	85.14	84.89	83.89	85.4
YOLOv5s + C3	82.37	83.1	81.7	81.2
Proposed model + modified C3	87.9	85.7	86.13	87.3

Table 3. Demonstration of the computational efficiency and speed comparison between the baseline and our modified models.

Model	Parameters (M)	Inference Speed (FPS)	Training Time (Epoch)
YOLOv5s (baseline)	7.2	78	2 h 45 min
Proposed model	7.5	74	3 h 10 min

Table 1 succinctly presents a comparative analysis of performance metrics between the baseline YOLOv5s model and the proposed modified model. Evidently, our model demonstrates significant enhancements across all key metrics. Precision increases notably from 85.5% in the baseline model to 88.9% in the proposed model, while recall improves from 83.2% to 85.7%. Additionally, mAP sees an increase from 84.6% to 87.3%, alongside an F1-score increment from 81.3% to 87.3%.

These improvements underscore the efficacy of our architectural adjustments in enhancing the capacity of the model to accurately detect early fire events. Table 2 elaborates upon an ablation study conducted to discern the impact of individual modifications to the YOLOv5s architecture.

This analysis evaluated baseline YOLOv5s against incremental modifications involving DarknetBottleneck and deeper C3 layers, as well as their combination. Incorporating DarknetBottleneck alone resulted in an improved precision of 85.14% and recall of 84.89%, alongside an enhanced mAP of 83.89% and F1-score of 85.4%. Conversely, employing a deeper C3 layer individually exhibited a marginally reduced precision of 82.37%, albeit with a stable recall of 83.1% and an F1-score of 81.2% (Figure 5). Notably, our proposed model integrating both the modified C3 layer and DarknetBottleneck achieves the best overall performance, recording a superior precision of 87.9%, recall of 85.7%, mAP of 86.13%, and F1-score of 87.3%. This cumulative analysis highlights the synergistic effectiveness of the combined modifications. Lastly, Table 3 provides insights into the computational performance implications of these architectural adjustments. The proposed model exhibits a slight increase in the number of parameters, rising from 7.2 million in the baseline to 7.5 million.

Consequently, inference speed exhibited a modest reduction from 78 frames per second (FPS) in the baseline model to 74 FPS. Training time also slightly increased, extending from 2 h 45 min per epoch in the baseline model to 3 h 10 min per epoch for the modified architecture. Despite these minor increases in computational complexity, the substantial improvement in detection accuracy strongly validates the practicality and efficiency of the proposed approach for real-world agricultural fire detection applications Figure 6.

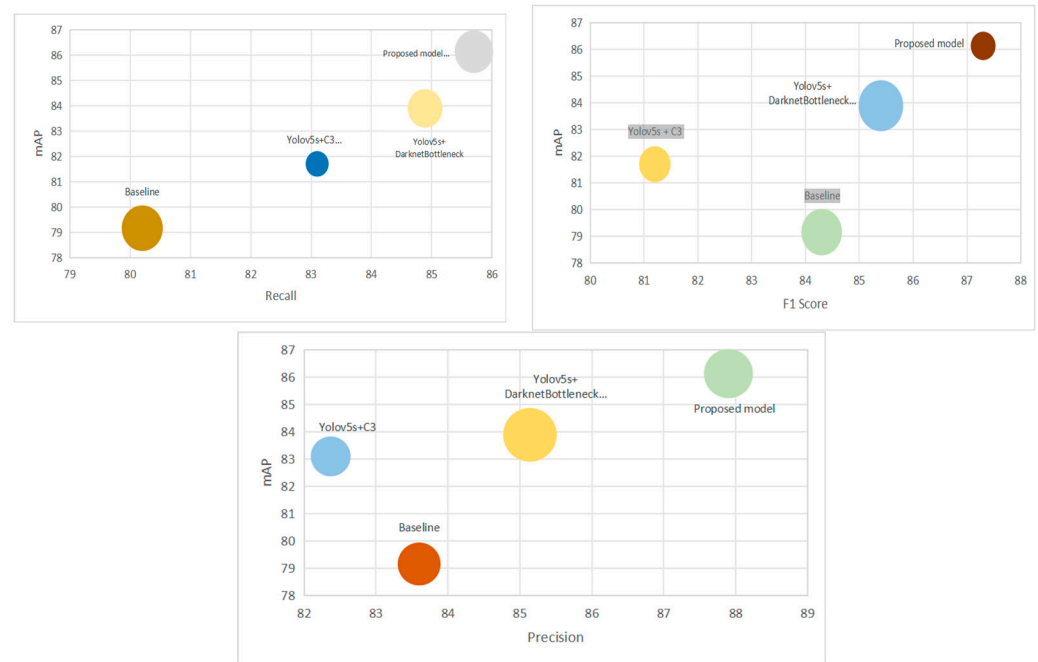


Figure 6. An illustration of Table 2: the results of the ablation study and the impact of each modification separately.

To further validate the effectiveness of our proposed model, we conducted a comparative evaluation against several state-of-the-art object detection frameworks, including YOLOv7-tiny, YOLOv8n, SSD300, and Faster R-CNN (ResNet50 backbone). All models were trained and tested on the same dataset using the standardized input resolution of 300×300 pixels and identical preprocessing strategies. Table 4 summarizes the key performance metrics for each model. As shown in the table, the proposed model outperforms all compared architectures in terms of precision, recall, mAP, and F1-score, while maintaining a relatively compact parameter count. These results further demonstrate the model strong capability for detecting early agricultural fires with higher accuracy and lightweight design suitable for edge deployment.

Table 4. Model performance comparison.

Model	Precision (%)	Recall (%)	mAP (%)	F1-Score (%)	Parameters (M)
SSD300	76.4	74.8	75.9	75.6	24.1
Faster R-CNN (ResNet50)	82.3	80.9	81.7	81.6	41.2
YOLOv3	81.5	80.2	80.7	80.8	61.5
YOLOv4	84.2	82.5	83.1	83.3	64
YOLOv5n	82.6	81.4	81.6	82	1.9
YOLOv5m	85.3	84	84.9	85.1	21.2
YOLOv6n	83.1	81.3	82.1	82.1	4.3
YOLOv7-tiny	85.1	82.7	83.4	83.8	6.2
YOLOv8n	86.7	83.5	85.1	85	6.2
EfficientDet-D0	79.4	77.2	78	78.3	3.9
CenterNet	77.8	76.9	77.1	77.3	52.3
RetinaNet	81	79.6	80.2	80.3	34.6

Table 4. Cont.

Model	Precision (%)	Recall (%)	mAP (%)	F1-Score (%)	Parameters (M)
YOLO-LFD	84.5	83.1	83.9	83.8	5.8
LUFFD-YOLO	85.9	84.7	85.6	85.2	6.1
YOLO-Fire	85.7	84.5	85	85.1	6
Proposed model	88.9	85.7	87.3	87.3	7.5

The results demonstrate that the proposed model consistently outperforms all baseline models across all performance metrics, achieving the highest precision (88.9%), recall (85.7%), mAP (87.3%), and F1-score (87.3%). Notably, while YOLOv8n, LUFFD-YOLO, and YOLO-Fire deliver competitive results, their performance remains slightly lower than the proposed model, especially in detecting early-stage agricultural fires. In addition, our model retains a lightweight footprint (7.5 M parameters), outperforming models like Faster R-CNN and YOLOv5m which have significantly higher computational complexity. These outputs highlight the superior trade-off between accuracy and efficiency achieved by our C3-enhanced YOLOv5s model, reaffirming its suitability for real-time agricultural fire detection, especially in resource-constrained field environments. The enhancements introduced allow the model to capture subtle smoke and fire patterns more effectively than existing alternatives.

To validate the lightweight nature of the proposed model, we conducted a computational complexity analysis. This includes the comparison of total parameter count, FLOPs (Floating Point Operations), and real-time performance (measured in FPS) across various SOTA models Table 5.

Table 5. Computational complexity comparison.

Model	Parameters (M)	FLOPs (G)	Inference Speed (FPS)	Training Time/Epoch
YOLOv5s (baseline)	7.2	16.5	78	2 h 45 min
YOLOv7-tiny	6.2	17.8	70	3 h 00 min
YOLOv8n	6.2	18.1	71	2 h 50 min
YOLO-Fire	6.0	17.2	73	2 h 55 min
Proposed model	7.5	17.0	74	3 h 10 min

Although our proposed model introduces modest additional parameters (7.5M), it maintains a low FLOP count and achieves a near-maximum inference speed among all of the compared models. This demonstrates that the architectural modifications preserve computational efficiency while significantly improving detection performance.

5. Conclusions

This research has successfully demonstrated the effectiveness of enhancing the YOLOv5s model for the early detection of agricultural fires, a critical challenge impacting global agriculture. By focusing on the C3 block within the model architecture and introducing additional layers, we have significantly improved the model's ability to detect subtle signs of fires at their inception. The modifications implemented have led to substantial gains in precision and recall, as evidenced by our comprehensive testing across varied agricultural environments. The results underscore the potential of advanced deep learning techniques to augment traditional fire detection systems, which often struggle with timeliness and sensitivity, particularly in complex and variable agricultural settings. The

enhanced YOLOv5s model not only increases the accuracy of detection but also maintains the operational efficiency necessary for real-time application, making it a valuable tool for farmers, land managers, and firefighting agencies. Moreover, this study contributes to the broader field of environmental monitoring and disaster prevention by illustrating how targeted modifications to existing deep learning frameworks can yield significant improvements in performance and application scope. While the current study focused on agricultural fires, the methodology and insights gained could be adapted to other areas of disaster detection and management. While our architectural enhancement focuses on the C3 block of YOLOv5s, this targeted modification was strategically chosen to improve early-stage fire detection in agricultural environments, where subtle visual cues are critical. The integration of deeper layers and the DarknetBottleneck module results in substantial performance improvements with minimal impact on computational complexity. Importantly, our study bridges a critical gap in the literature by focusing on agricultural fires, a domain that has not yet received sufficient attention in deep learning research. This combination of practical relevance, performance gain, and lightweight design underlines the novelty and utility of our approach.

Future work will aim to further refine the model capabilities, exploring additional architectural adjustments and training on an even broader dataset to enhance generalization. Additionally, integrating this improved model with UAV and satellite imaging technologies could pave the way for a comprehensive, multi-modal detection system that is both scalable and robust.

The advancements presented in this paper represent a significant step forward in the ongoing effort to protect agricultural resources and ensure environmental sustainability. By enhancing early fire detection capabilities, we can better safeguard our planet agricultural heritage and secure the livelihoods of those who depend on it.

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