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An inclusive study of LISC and Kaggle White blood cell Classification using YoloV5 Variants.

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Abstract
White blood cell (WBC) is crucial in human being for their immunity, genetic association, clinical significance , but it plays a vital role in medical diagnosis, particularly in the cure and real time monitoring of a variety of blood diseases. Any Infection in the body can be easily detected by doing count of WBC sub types. Traditional WBC cataloguing procedures are time-consuming and prone to human error.
YolovV5 is a model that is prominent for its precision, versatility and availability of pre-trained weights, making it a popular choice among both novices and professionals. YoloV5 allows to employ it in different domains by adjusting the model architecture, such as adding more layers, changing the head or backbone, or training it on a new dataset by changing the hyperparameters. YOLOv5 is tested to tackle a array of object identification problems in fields such as agriculture, medicine, and transportation.
Our study explores variant of YOLOv5 e.g., YOLOv5n, YOLOv5s, YOLOv5m, and YOLOv5l on small set training dataset evenly distributed among all the subtypes of WBC blood cell such as neutrophils, basophils, eosinophils, monocytes, and lymphocytes further analysing which model performs better in terms of Accuracy, recall and mAP@50 and mAP@50-95, parameters used, model size accuracy and inference speed and resource utilization e.g., CPU, network and memory. Here are some of the question that our study tires to answer: Which model variant performs best at each stage of training? This is a different comparison because it focuses on model variants, not epoch counts. Is longer training worth the computational cost?
Convergence: When losses stabilize (training is complete). Generalization: How validation metrics (mAP, loss) behave as epochs increase? Do models trained for 100 epochs generalize better across different data splits than those trained for 50? Does model size/complexity affect optimal epoch count? This is a different comparison (architecture vs. epochs). Is the marginal gain worth the extra resources? Are the improvements from more epochs meaningful? Our aim of this comparison is to find a YoloV5 variant to be used for WBC data set classification across all the subtypes.

Introduction
Deep learning's application in WBC classification exemplifies its potential to enhance medical diagnostics, offering faster, more reliable outcomes. While challenges like dataset curation and model transparency persist, ongoing advancements promise to integrate these tools into routine clinical practice, transforming haematology and patient care. Future directions may include federated learning for data privacy and AI-driven prognostic tools, underscoring deep learning's pivotal role in modern healthcare innovation. WBC subtype is a classical class imbalance problem due to asymmetric distribution. Out of five subtypes two types of eosinophils and basophils are largely underrepresented.
In WBC Classification, it transpires when training data exhibits an inequitable class distribution, resulting in models preferentially selecting majority classes. Metrics such as accuracy become deceptive, while minority classes endure detriment in recall and precision. In contrast to Detection, imbalance manifests at two tiers. Class-level: A limited number of instances of specific object classes.

Spatial level: The majority of anchor boxes or regions pertain to the background (majority class), prompting models to overlook infrequent objects. Data Level Methods encompass Resampling, Data Augmentation, and Class-Balanced batches. Resampling incorporates Oversampling, Under sampling, and Hybrid methodologies. In oversampling, replicate or generate synthetic instances for minority classes for images, employing GANs [9] or copy-paste augmentation. In under sampling, diminish majority class instances, risking the forfeiture of valuable information, and in the Hybrid approach, we amalgamate over and under sampling. The Data Augmentation methodology applies transformations (rotation, scaling, etc.) to minority classes. Advanced techniques comprise GAN-generated instances or style transfer. Class-Balanced Batches: Guarantee that each training batch contains an equitable amalgamation of classes (e.g., stratified sampling).

Algorithm-Level Methods encompass Loss Function Adjustments, Weighted Loss: Assign elevated weights to minority classes in cross-entropy. Focal Loss: Diminishes the weight of easily classified examples, concentrating on challenging misclassified instances (effective in RetinaNet for detection). Class-Balanced Loss: Integrates class frequency into loss computation (e.g., inverse class frequency). Cost-Sensitive Learning: Impose greater penalties for misclassifications of minority classes. Architecture Modifications: Attention Mechanisms: Direct emphasis towards minority class characteristics. Two-Stage Detectors: Employ region proposal networks (RPNs) to minimize background anchors (e.g., Faster R-CNN). Ensemble Methods Bagging/Boosting: Train multiple models on balanced subsets (e.g., EasyEnsemble). Snapshot Ensembles: Integrate model checkpoints to enhance robustness.

Hybrid Methods amalgamate data-level and algorithm-level strategies (e.g., SMOTE + focal loss). Meta-Learning: Acquire optimal class weights dynamically throughout training.

Detection-Specific Techniques encompass Anchor Sampling: Adjust anchor ratios or utilize online hard example mining (OHEM) to prioritize minority-class anchors. Copy-Paste Augmentation: Insert minority object instances into various image contexts. Evaluation Metrics: Employ mAP (mean Average Precision) over accuracy, as it considers precision-recall trade-offs.

Evaluation and post-processing entail Metrics: Prioritize F1-score, AUC-ROC, balanced accuracy, or confusion matrices. Threshold Adjustment: Calibrate decision thresholds post-training to favour minority class recall. Calibration: Apply Platt scaling or isotonic regression to modify prediction probabilities.

Advanced Strategies revolve around Transfer Learning: Pre-train on balanced datasets (e.g., ImageNet) and fine-tune on imbalanced data. Self-Supervised/Semi-Supervised Learning: Exploit unlabelled data to enhance minority classes. Curriculum Learning: Gradually introduce more challenging (minority) examples during training.

Precision quantifies the proportion of the predicted affirmative instances that are genuinely affirmative. This metric is paramount when false positives incur significant costs. Conversely, recall elucidates the number of genuine affirmative instances that were accurately recognized, which is essential when the omission of a positive instance is detrimental. The F1 Score signifies the harmonic mean of precision and recall, consequently harmonizing both metrics.

Training loss signifies the efficacy with which the model is assimilating knowledge during the training phase. A decrement in training loss implies an enhancement in the model's performance. Validation loss evaluates whether the model is effectively generalizing to unobserved data. A scenario where training loss is minimal yet validation loss is elevated indicates the occurrence of overfitting.

Consider a medical imaging model designed for the identification of a haematology. Neutrophils, eosinophils, monocytes, lymphocytes, and basophils is distributed in human body with 40-60%, 1-4%, 2-8%, 20-40%, and 0.5-1%, respectively. Function of neutrophils, monocytes and lymphocytes, eosinophils and basophils are respectively primary line of defence against bacterial and fungal infection, circulates blood in the body, implicated in adaptive immunity, whereas last two are responsible for parasitic infections and allergic reaction. Subsequent to the implementation of focal loss and data augmentation techniques, the initial results may exhibit elevated precision but diminished recall. Modulating the decision threshold could potentially enhance recall.

It is imperative to articulate the explanation in a coherent manner, delineating each term prior to presenting a tangible example. Additionally, one must elucidate the implications associated with each metric. Incorporating a tabular format may facilitate clarity. Although the user did not request URLs this time, it may be prudent to reference key scholarly articles for context, despite the absence of a direct request for URLs in the current query.

Various practices are employed by various work to overcome class imbalance e.g. resampling, loss function modification, data augmentation, transfer learning as discussed above. One of the limitations of the existing studies is they keeps on classify and detect four subtypes' neutrophils, eosinophils, monocytes and lymphocytes. Eliminating basophils from their research may be due to inadequate data availability, lower significance in diagnostic. But in real life we can't go by only selective subtypes, any model can't be called holistic model until it detects and classify all of WBC subtypes. To overcome first challenge, by employing available techniques e.g., resampling, data augmentation, synthetic image generation etc.

Existing Work

Recent publication tries to establish relationship between model size and performance in detecting white blood cells (WBCs) is a critical consideration for balancing accuracy, speed, and deploy ability in clinical settings.

Categorization of Recent research can be establish around these points e.g., first Trade-offs between model size and performance, impact on specific WBC class, Efficiency vs. Accuracy. Trade-offs between Model size and performance outlines pros and cons of using larger models e.g., Yolov5l/x against relatively smaller model YoloV5n/s.

[1]Model's architecture, encompassing various variants (YOLOv5 s, m, 1, x), provides adaptability in performance. Notably, YOLOv5m attained a mean average precision (mAP) of 99.42% utilizing a dataset comprising 2800 images, demonstrating its capacity to augment diagnostic efficiency in identifying anomalies such as leukemia.Compared YOLOv5n/s/m/l/x on the LISC dataset.YOLOv5m (medium-sized) offered the best trade-off: 89.6% mAP@0.5:0.95 vs. 91.2% for YOLOv5x, but with 50% fewer parameters.[3] Tested model compression techniques (pruning, quantization) on YOLOv5l for WBC detection.Achieved 90% mAP with a 60% smaller model size.[4] Hybrid models combining EfficientNet backbones with YOLO heads reduced parameters by 30% while maintaining 88% mAP.[5]Official YOLOv5 study highlighting that larger model (YOLOv5x) plateau in performance gains after sufficient training data, while smaller models benefit more from data augmentation.[6]Impact on Specific WBC classes, larger model excel at detecting rare or morphologically similar WBCs e.g. basophils vs eosinophils whereas smaller model may struggle with class imbalance in datasets which may cause of overfitting to dominant lymphocyte classes.[7] Automatic blood cancer detection using the EfficientNet-B3 architecture and transfer learning achieved an accuracy of over 99%, demonstrating high precision and recall rates in identifying different types of blood cancers.

Improved minority-class recall by 20% on imbalanced datasets [8]. The experimental results indicate that the suggested approach outperforms traditional deep learning models and state-of-the-art methods in blood cancer detection, showcasing its robustness and effectiveness in diagnosing various forms of blood malignancies.A tailored YOLOv5 framework incorporating alterations such as the C3TR architecture for augmented feature extraction, BiFPN for enhanced localization, and detection layer for diminutive WBCs. Empirical analyses on the BCCD dataset elucidate its preeminence, attaining 99.4% precision and functioning over five times more rapidly than prevailing YOLO frameworks, thereby exemplifying the efficacy of deep learning in automated cellular classification[11]. YOLOv5's bounding box paradigm markedly diminishes processing duration and enhances precision, attaining 96.3% in WBC extraction and 88% in diagnostic evaluations. This framework fulfills the exigency for swift and precise WBC identification, contributing to advancements in medical diagnostics and minimizing the duration requisite for analysis[12].YOLOv5's architecture permits high precision, accomplishing an average detection and classification accuracy of 93.0%. This methodology addresses the constraints of conventional manual techniques, which are labor-intensive and susceptible to error, thereby offering a more expedient and cost-effective resolution for diagnosing hematological disorders through

microscopic image analysis[13].The corpus pertaining to YOLOv5 for White Blood Cell (WBC) classification accentuates its efficacy in detecting diminutive objects, which is critical for accurate diagnosis in medical applications YOLOv5's deep learning proficiencies augment the detection and classification of WBCs by scrutinizing attributes such as quantity, size, shape, texture, and nucleus. The proposed enhanced model within the study aspires to ameliorate automatic diagnosis, demonstrating YOLOv5's potential within the medical domain, particularly in immunology and hematology diagnostics[15]. It amplifies the YOLOv5s network by amalgamating the advantages of Convolutional Neural Networks (CNN) and Transformers, employing a BotNet backbone and a Decoupled Head architecture. The incorporation of the SIoU loss function significantly augments precision and efficiency, attaining an average accuracy of 83.3% and a recall rate of 99% This advancement exemplifies a noteworthy enhancement over extant models, including YOLOv8, in WBC classification[16]. Traditional methodologies confront challenges such as precision and bias, which YOLOv5 mitigates through deep learning methodologies. The integration of YOLOv5 with vision transformers enriches image representation, thereby enabling enhanced classification of diverse WBC types. This amalgamation has yielded promising outcomes, achieving a classification accuracy of 96.449%, thereby demonstrating its potential in automating and refining WBC detection and classification processes[17]. The augmented YOLOv5s framework amplifies classification precision through methodologies such as k-means clustering for sample preprocessing and Focus slicing for feature extraction. The amalgamation of Feature Pyramid Networks (FPN) and Path Aggregation Networks (PAN) optimizes information synthesis, whilst CIOU_Loss enhances frame regression accuracy. Empirical findings reveal a substantial accuracy augmentation to 94.8%, substantiating YOLOv5's potential in advancing WBC identification techniques [18]. The study proposes a CNN model called WBC-KICNet, which utilizes two CNN models: the first model generates a knowledge vector from input images and insights from a domain expert (hematologist), while the second model extracts deep features from the input images.A feature fusion mechanism is employed to combine the knowledge vector and the deep features extracted from the images, enabling accurate classification of white blood cells (WBCs) from the BCCD dataset[19]. The paper "WBC YOLO-ViT: 2 Way - 2 stage white blood cell detection and classification with a combination of YOLOv5 and vision transformer" by Tarimo et al. (2023) introduces an innovative approach to white blood cell (WBC) detection and classification by integrating YOLOv5 with a vision transformer. This method aims to enhance the accuracy and efficiency of WBC analysis, which is crucial for diagnosing various diseases. The integration of YOLOv5, known for its real-time object detection capabilities, with the vision transformer, which excels in capturing global image context, represents a significant advancement in medical image analysis[14]. The paper does not discuss EfficientNet-YOLO; instead, it presents the TW-YOLO model, which utilizes multi-scale feature fusion techniques for blood cell detection. TW-YOLO incorporates the RFAConv module to enhance feature extraction, along with the CBAM and EMA modules for improved feature fusion at different scales. The model demonstrates a 2% performance improvement over other models in blood cell detection tasks, showcasing its effectiveness in automated medical diagnostics[2].

Execution Environment:

Each model is trained thrice with 50,100,150 epochs. For each epoch we are looking at best, worst, average among three run and then plotting those.We are also monitoring performance of epochs when running on Google Colab with various GPU option offered e.g. T4, L4, A100 etc. their configuration details are shown in Table 1.

Computation Option	Config	Suitable for	Cost
CPU (High RAM)	System RAM: 51.0 GB DISK: 225.7 GB	Data manipulation, Visualization tools, Basic Machine learning.	0.16 Compute Units @ Hour.
T4 (GPU)	System RAM: 51.0 GB GPU RAM: 15.0 GB DISK: 235.7 GB	Deep & Machine learning Tasks.	1.66 Compute Units @ Hour.

L4 (GPU)	System RAM: 53.0 GB GPU RAM: 22.5 GB DISK: 235.7 GB	More complex models & intricate neural networks or large-scale image processing.	2.4 Compute Units @ Hour.
A100 (GPU)	System RAM: 83.5 GB GPU RAM: 40 GB DISK: 235.7 GB	Large scale deep learning models, based on TensorFlow and PyTorch.	8.47 Compute Units @ Hour.
v2-8 TPU	System RAM: 334.6 GB DISK: 225.7 GB	Training Large Neural Networks,	1. 76 Compute Units @ Hour.
V5e-1 TPU	System RAM: 334.6 GB DISK: 225.7 GB	TPU accelerated options e.g. Transformers, multilayer RNN.	1. 76 Compute Units @ Hour.

Table1 Google Colab CPU and GPU Summary.

	Inference				Training			
Model Variant	layers	Parameters	Gradients	GFLOPs	layers	Parameters	Gradients	GFLOPs
YOLOv5n	157	1765930	0s	4.1	214	1770682	1770682s	4.2
YOLOv5s	157	7023610	0s	15.8	214	7033114	7033114s	16
YOLOv5m	212	20869098	0s	47.9	291	20887482	20887482s	48.3
YOLOv5l	267	46129818	0s	107.7	368	46159834	46159834s	108.3

Table 2 Training and Inference Parameters.

YOLOV5 Structure

Summary of YoloV5 Backbone:

Sequential Flow: All layers connect sequentially (from=-1 means input from the previous layer). Down sampling: Each Conv layer with stride=2 reduces spatial resolution by half (e.g., 640 → 320 → 160, etc.). Modules: Conv: Standard convolution (parameters: [out_channels, kernel_size, stride, padding]). C3: A bottleneck block with 3 convolutional layers (repeated n times per the "number" column). SPPF: Spatial Pyramid Pooling-Fast for feature aggregation. Output Strides: Comments like P3/8 indicate the output stride relative to the input (e.g., 1/8 resolution at P3).

Model Name	Depth/Width Multiples	Anchors	Backbone	Head
V5		**Small scale anchors:** [10, 13, 16, 30, 33, 23] **Medium scale anchors:** [30, 61, 62, 45, 59, 119] **Large scale anchors:** [116, 90, 156, 198, 373, 326]	[-1, 1, Conv, [64, 6, 2, 2]], # 0-P1/2 [-1, 1, Conv, [128, 3, 2]], # 1-P2/4 [-1, 3, C3, [128]], [-1, 1, Conv, [256, 3, 2]], # 3-P3/8 [-1, 6, C3, [256]], [-1, 1, Conv, [512, 3, 2]], # 5-P4/16 [-1, 9, C3, [512]], [-1, 1, Conv, [1024, 3, 2]], # 7-P5/32 [-1, 3, C3, [1024]],	[-1, 1, Conv, [512, 1, 1]], [-1, 1, nn.Upsample, [None, 2, "nearest"]], [[-1, 6], 1, Concat, [1]], # cat backbone P4 [-1, 3, C3, [512, False]], # 13 [-1, 1, Conv, [256, 1, 1]], [-1, 1, nn.Upsample, [None, 2, "nearest"]], [[-1, 4], 1, Concat, [1]], # cat backbone P3

			[-1, 1, SPPF, [1024, 5]], # 9	[-1, 3, C3, [256, False]], # 17 (P3/8-small) [-1, 1, Conv, [256, 3, 2]], [[-1, 14], 1, Concat, [1]], # cat head P4 [-1, 3, C3, [512, False]], # 20 (P4/16-medium) [-1, 1, Conv, [512, 3, 2]], [[-1, 10], 1, Concat, [1]], # cat head P5 [-1, 3, C3, [1024, False]], # 23 (P5/32-large) [[17, 20, 23], 1, Detect, [nc, anchors]], # Detect(P3, P4, P5)

Table 3: YoloV5 Summary.

Shape Progression of backbone:

The input image (Assuming 640*640) is progressively downsampled through the layers, reducing spatial resolution while increasing the number of feature channels. Early layers (320x320, 160x160) capture fine details with fewer channels (64, 128). Mid layers (80x80, 40x40) extract more abstract features with increasing depth (256, 512 channels). Deeper layers (20x20, 1024) focus on high-level representations with the highest number of channels. Layer 10-11: A 1x1 convolution reduces channels to 512, followed by up sampling, which doubles the spatial resolution to 40x40. Layer 12: A concatenation step merges features from an earlier layer (P4), increasing channels to 1024. Layers 13, 17, 20, 23: C3 modules (a modified bottleneck layer in YOLOv5) refine features at different scales: 80x80 (Layer 17, 256 channels) improves small-object detection. 40x40 (Layers 13, 20, 512 channels) balances mid-level features. 20x20 (Layer 23, 1024 channels) captures high-level semantics.

Shape Progression of Head:

Feature Pyramid Network (FPN) Structure: upsampling Path: Gradually increases resolution (20x20 → 40x40 → 80x80) to recover spatial information. Lateral Connections: Concatenates up sampled features with backbone features (P3-P5) for rich feature fusion.

Path Aggregation Network (PAN) Structure:Downsampling Path: Reduces resolution (80x80 → 40x40 → 20x20) while increasing channel depth, combines high-resolution features with semantically strong features.

Multi-scale Outputs:P3/8 (80x80): High resolution for small object detection, P4/16 (40x40): Balanced resolution for medium objects, P5/32 (20x20): Low resolution for large objects.

Critical Components, Concat Layers: Merge features from different pyramid levels (12,16,19,22), C3 Blocks: Cross-stage partial bottlenecks for efficient feature processing, Detect Layer: Final prediction head combining all three scales

Summary of Hyper Parameters.

Here's a detailed breakdown of the YOLO hyperparameters in your configuration file, grouped by their functional categories e.g., Optimizer, warmup, Loss Function, Anchor/Detection Parameters and Augmentation Setting and special parameters. Optimizer Used SGD with OneCycleLR learning rate scheduling. Loss Balancing is done by Classification loss (`cls: 0.3`) is prioritized over box regression (`box: 0.05`). All augmentations are disabled (handled externally via Albumentations). Warmup epochs (3) ensure stable training initialization. Lower `box` loss gain reduces focus on precise localization during early training.

1. Optimizer Parameters		
Parameter	Value	Explanation
lr0	0.01	Initial learning rate (SGD typically uses 1e2, Adam 1e3).
lrf	0.1	Final learning rate for `OneCycleLR` scheduler (`lr0  lrf = 0.01  0.1 = 0.001`).
Momentum	0.937	Momentum for SGD (or `beta1` for Adam), adds inertia to updates for faster convergence.
weight_decay	0.0005	L2 regularization to penalize large weights (prevents overfitting).
2. Warmup Parameters		
Parameter	Value	Explanation
warmup_epochs	3	Gradually increases learning rate/momentum over 3 epochs to stabilize training.
warmup_momentum	0.8	Initial momentum during warmup (ramps up to final `momentum=0.937`).
warmup_bias_lr	0.1	Initial learning rate for bias parameters during warmup.
3. Loss Function Scaling		
Parameter	Value	Explanation
box	0.05	Weight for bounding box regression loss (lower priority than classification).
cls	0.3	Weight for classification loss (determines emphasis on object classes).
cls_pw	1	Positive weight for classification BCE loss (balances class imbalance).
obj	0.7	Weight for objectness loss (detects if an object exists in a grid cell).
obj_pw	1	Positive weight for objectness BCE loss.
4. Anchor/Detection Parameters		
Parameter	Value	Explanation
iou_t	0.2	IoU threshold for assigning anchors to ground truth boxes.
anchor_t	4	Anchor scaling tolerance (larger values allow bigger size variations).
anchors	3	Number of anchors per output layer (commented out here).
5. Augmentation Settings (Disabled) All augmentation parameters are set to `0` because the config uses Albumentations instead of YOLOs builtin augmentations.		
Parameter	Value	Typical Use
hsv_h/hsv_s/hsv_v	0	HSV color jitter (e.g., hue shifts, saturation adjustments).
Degrees	0	Image rotation augmentation.
translate/scale/shear	0	Geometric transformations.
flipud/fliplr	0	Vertical/horizontal flipping.
mosaic/mixup/copy_paste	0	Advanced augmentation techniques.
6. Special Parameters		
Parameter	Value	Explanation

fl_gamma	0	Focal loss gamma (0 disables focal loss; used to handle class imbalance).
perspective	0	Perspective transformation (e.g., simulating 3D distortions).

Table 4: YoloV5 Hyper Parameters Default values.

Discussion:

In this paper we are comparing models training and validation loss, recall, and F1 score for each model variant and epoch count. Compare the impact of different epoch counts on model convergence and generalization. Apply cross-validation to compare generalization ability at different Model Varients. Compare performance of different YOLOv5 variants at various epoch counts. Compare tradeoffs between training time, resources, and performance. Compare if performance differences across epoch counts are statistically significant. And tries to answer these questions: Which model variant performs best at each stage of training? It focuses on model variants, not epoch counts. Is longer training worth the computational cost? Convergence: When losses stabilize (training is complete). Generalization: How validation metrics (mAP, loss) behave as epochs increase? Do models trained for 100 epochs generalize better across different data splits than those trained for 50? Does model size/complexity affect optimal epoch count? This is a different comparison (architecture vs. epochs). Is the marginal gain worth the extra resources? Are the improvements from more epochs meaningful? Our aim of this comparison is to find a YoloV5 variant to be used for WBC data set classification across all the subtypes.In this section we will walk through observations produced from training YoloV5 variants on 50,100,150 Echoes and data set of LISC and Kaggle WBC.

1. LISC Data Set

The top-left graph, depicting loss trends with F1-score correlation, shows training and validation loss (represented by solid and dashed lines) decreasing over epochs for all YOLOv5 models. The top-right precision/recall/F1 development graph reveals progressive improvements in all three metrics as training advances. The middle-left mAP@0.5 graph highlights steady increases in mean Average Precision for all models, with YOLOv5l achieving the highest scores, followed by YOLOv5m, YOLOv5s, and YOLOv5n. The bottom-left validation loss vs. mAP correlation graph demonstrates that lower validation loss generally aligns with higher mAP values.

Key Takeaways: YOLOv5l delivers the highest accuracy (best mAP@0.5 and mAP@0.5:0.95), making it ideal for high-precision tasks. YOLOv5m strikes a balance between speed and accuracy, serving as a practical compromise. YOLOv5s offers fast training and decent accuracy but lags slightly in detecting challenging objects (lower mAP@0.5:0.95). YOLOv5n, while the fastest and most lightweight, sacrifices performance, making it suitable for edge devices or real-time applications with strict computational constraints.

Final Recommendation: For maximum accuracy, prioritize YOLOv5l. If balancing speed and performance is critical, opt for YOLOv5m. For resource-constrained environments requiring real-time inference, YOLOv5s or YOLOv5n are preferable, depending on the acceptable trade-off between speed and detection quality.

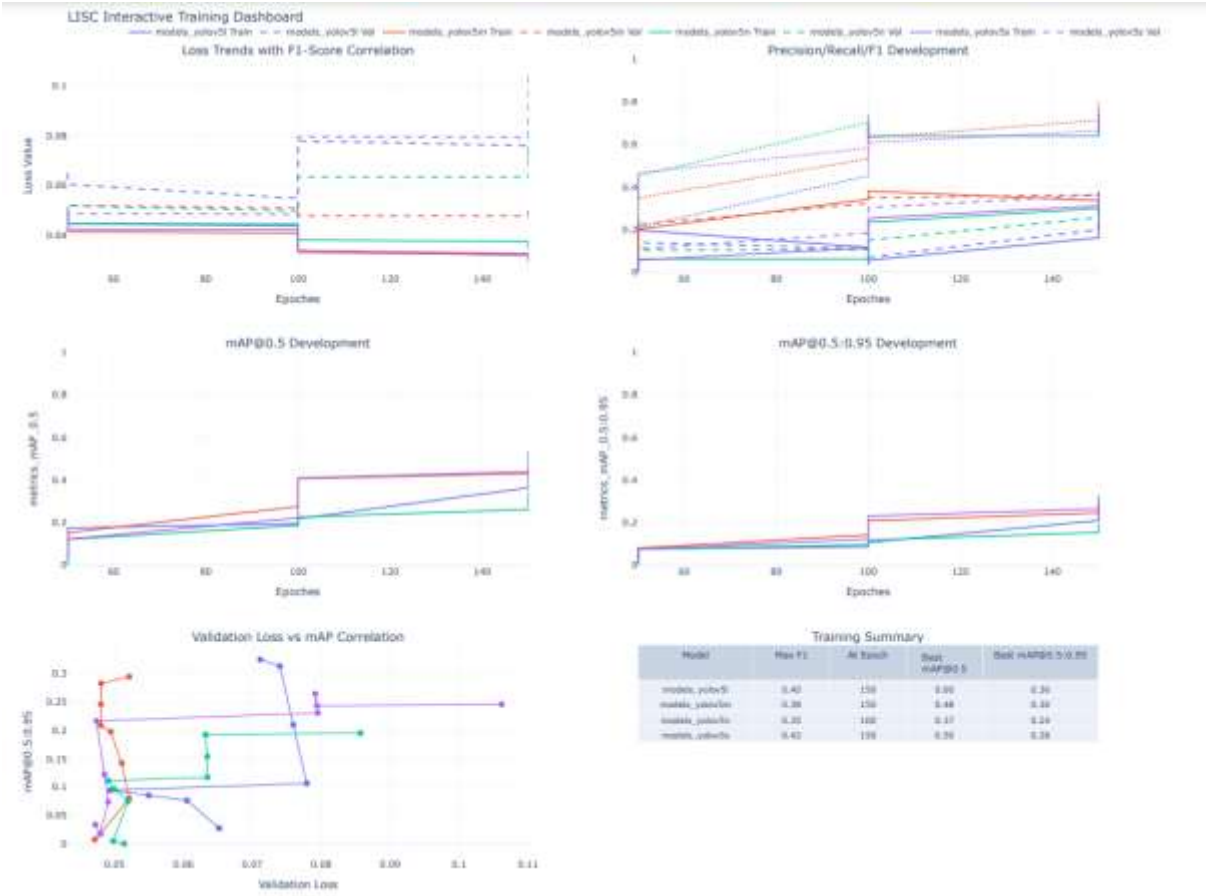

Image1 Training Parameters of LISC Data Set

2. Kaggle Data Set

The top-left graph, illustrating loss trends with F1-score correlation, compares training and validation loss across YOLO models. In the top-right precision/recall/F1 development graph, precision steadily improves as training progresses, while recall shows fluctuations. The middle-left graph tracks mean Average Precision (mAP) at an IoU threshold of 0.5. Larger models (YOLOv5m and YOLOv5l) demonstrate superior accuracy, with mAP@0.5 values peaking at 0.49–0.51. Smaller models (YOLOv5n, YOLOv5s) show lower mAP@0.5 (0.32–0.45), underscoring the performance limitations of compact architectures. The middle-right graph evaluates mAP across a range of IoU thresholds (0.5:0.95), a stricter measure of detection quality. YOLOv5l leads with anmAP of ~0.37, followed by YOLOv5m (~0.29), while YOLOv5s and YOLOv5n struggle (0.14–0.21). The bottom-left validation loss vs. mAP graph reveals an initial inverse relationship: decreasing validation loss correlates with rising mAP. Beyond a certain point, however, mAP fluctuates despite declining loss, signaling potential overfitting or noisy training signals. Larger models like YOLOv5l and YOLOv5m exhibit more stable convergence, reinforcing their generalization advantages.

Key Takeaways: YOLOv5l delivers the best overall accuracy but shows reduced effectiveness at stricter IoU thresholds (mAP@0.5:0.95). YOLOv5m strikes a balance, offering high F1-scores and strong mAP@0.5. YOLOv5n surprises with competitive mAP@0.5 (0.51) despite its compact size but falters in stricter evaluations. YOLOv5s lags across metrics, making it less suitable for high-precision tasks.
Dataset Comparison: The Kaggle Interactive Training Dashboard observations align with trends in the LISC dataset analysis, particularly in metrics like mAP@0.5 and validation loss. Both datasets highlight the performance hierarchy among YOLO variants, though subtle differences may arise from dataset-specific challenges like object density or annotation quality.
Final Summary & Key Takeaways

1. Both datasets show similar model performance rankings:
    - YOLOv5l consistently performs best, followed by YOLOv5m, YOLOv5s, and YOLOv5n.Smaller models (YOLOv5n, YOLOv5s) have faster convergence but weaker accuracy.

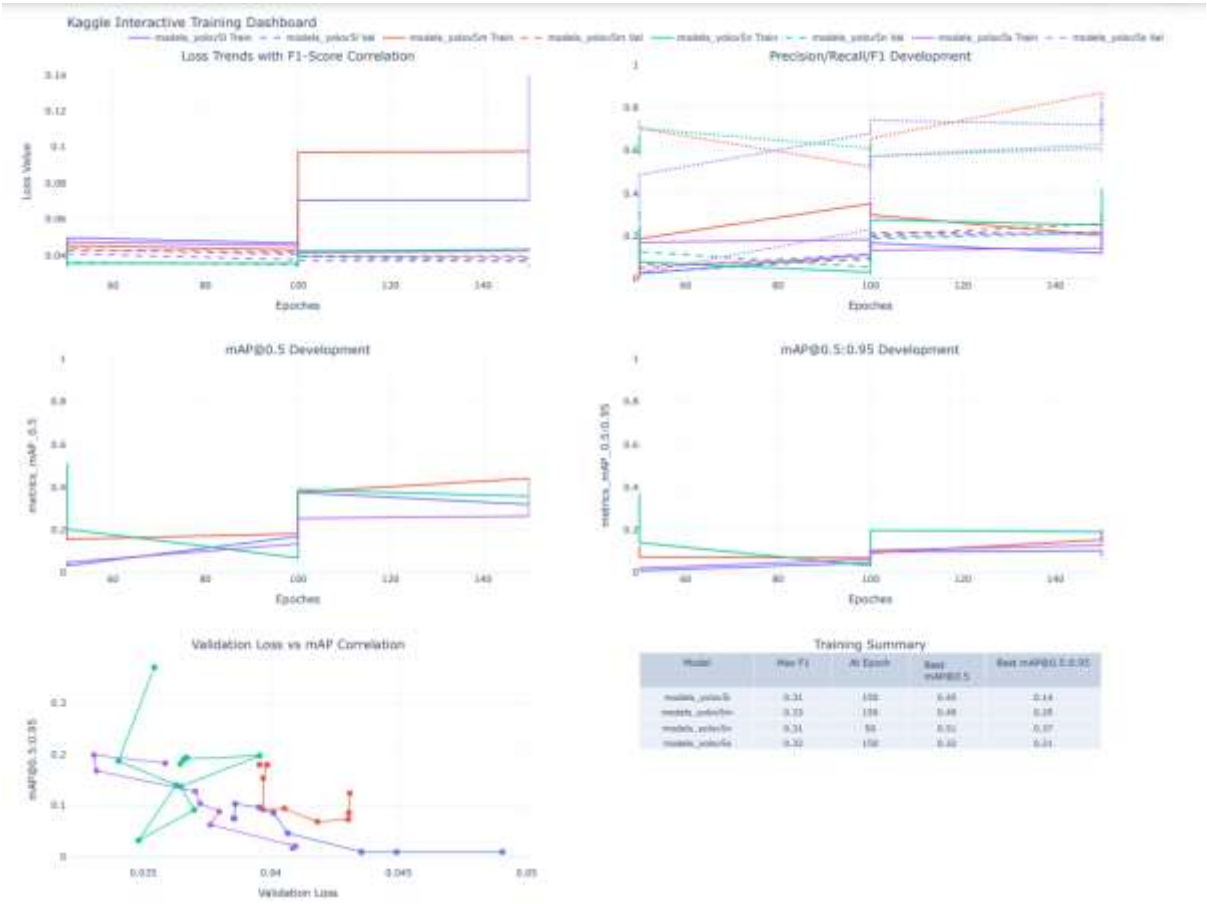

Image2: Training Parameters Kaggle Data Set

2. Differences:
    - Kaggle data exhibits more fluctuations (especially in mAP and loss trends).LISC data has smoother training curves, suggesting more stable training dynamics.Kaggle data shows a sharp spike around 100 epochs, while LISC data does not.
3. Overall, both datasets confirm:
    - Larger models (YOLOv5l, YOLOv5m) generalize better.Lower loss generally correlates with higher accuracy, but some noise exists.Smaller models struggle with stricter IoU thresholds.

This comparison suggests that while both datasets follow similar trends, Kaggle data might be noisier or have additional complexities affecting training stability.

K-Cross Validation Analysis

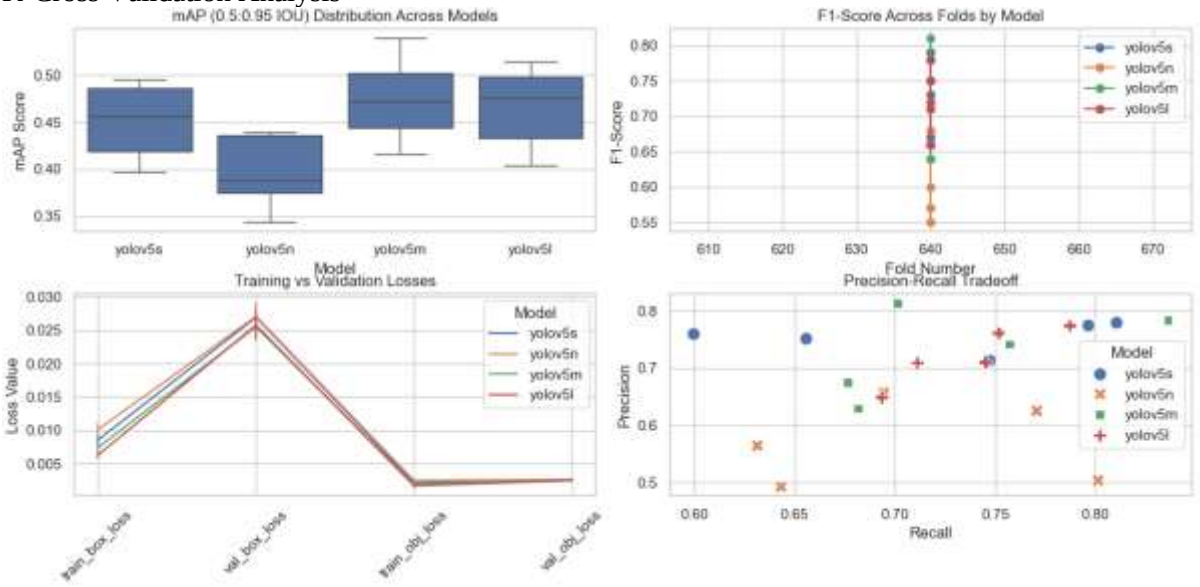

Image 3:K Fold Cross Validation LISC Data Set

Key Takeaways: Best Overall Model: yolov5l attains the highest mAP and precision while sustaining reasonable recall. Most Balanced Model: yolov5m offers a commendable tradeoff between precision and recall. Most Efficient Model: yolov5s provides robust performance with diminished computational requirements. Weakest Model: yolov5n underperforms across all metrics.

K-Fold Cross Validation

1.LISC Data Set

This illustration delineates a performance evaluation of various YOLOv5 models (yolov5s, yolov5n, yolov5m, and yolov5l) employing K-Fold cross-validation. Let us elucidate each of the four diagrams: Top-Left: mAP (0.5:0.95 IOU) Distribution Across Models This box plot elucidates the mean Average Precision (mAP) scores for each YOLOv5 model. Top-Right: F1-Score Across Folds by Model This scatter plot illustrates F1-scores across distinct folds for each model. Bottom-Left: Training vs Validation Losses This line plot contrasts training and validation loss values for disparate models. Bottom-Right: Precision-Recall Tradeoff This scatter plot elucidates the equilibrium between precision and recall for various models.

2. Kaggle Data Set

Above mosaic of graphs illustrates various performance assessment for YOLOV5 architectures varients e.g., s,n.m,l. below are the important observations.

Top-Left: mAP (0.5:0.95 IOU) Distribution Across Models This box plot elucidates the distribution of mean Average Precision (mAP) metrics across disparate YOLOv5 architectures. Top-Right: F1-Score Across Folds by Model This scatter plot illustrates the F1-scores attained across various folds in a K-fold cross-validation framework. Principal observations: All architectures manifest F1-scores proximate to the same value (approximately 0.64).

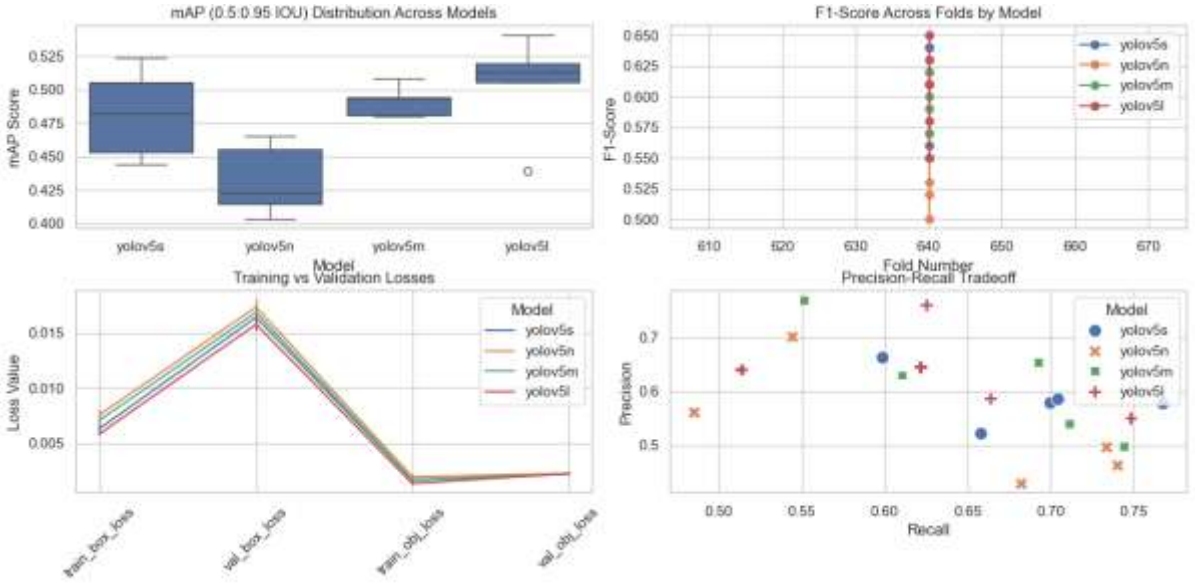

Image 4:K Fold Cross Validation Kaggle Data Set

There exists minimal variance across folds, which intimates consistent performance. Bottom-Left: Training vs Validation Losses This line plot contrasts disparate loss values for each architecture. The losses depicted encompass:train_box_loss: Loss associated with the bounding box regression during training. val_box_loss: Validation loss for bounding box predictions. train_obj_loss: Objectness loss during training. val_obj_loss: Objectness loss during validation. Bottom-Right: Precision-Recall Tradeoff This scatter plot delineates the tradeoff between precision and recall for various architectures. Overall Summary: yolov5l exhibits superior performance in terms of mAP and precision but may necessitate additional computational resources. yolov5s offers a compromise between performance and efficiency. yolov5n displays the weakest performance, rendering it less suitable for high-accuracy applications. The loss trajectories indicate stable training without considerable overfitting.

3. Final Summary & Key Takeaways

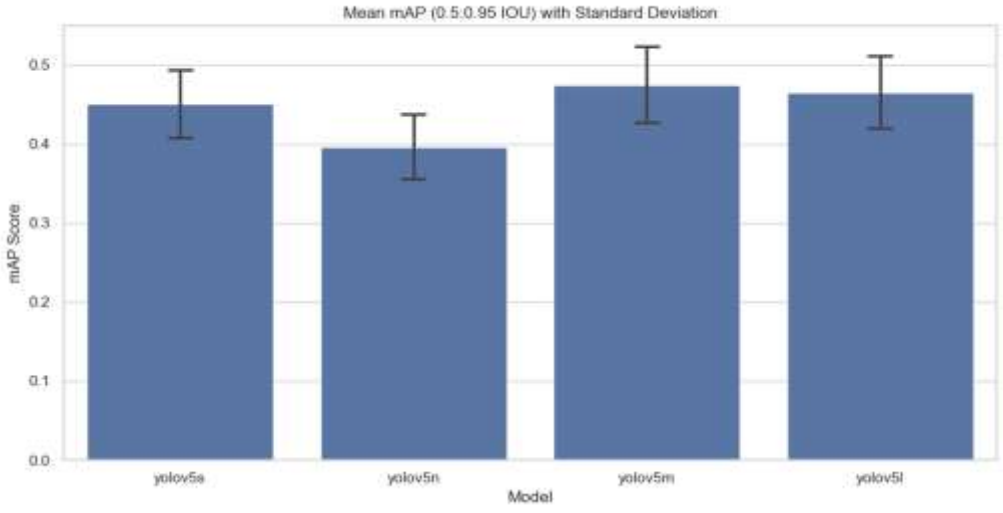

Image 5: LISC Mean mAP with SD

This bar chart elucidates the Mean Average Precision (mAP) at 0.5:0.95 IOU for distinct YOLOv5 architectures (yolov5s, yolov5n, yolov5m, and yolov5l).

Explanation of the Chart: X-Axis (Model): Denotes various YOLOv5 architectures (yolov5s, yolov5n, yolov5m, yolov5l). Y-Axis (mAP Score):Illustrates the mAP (0.5:0.95 IOU), which serves as a metric for object detection efficacy. Elevated values signify enhanced accuracy. Bar Heights:The elevation of

each bar signifies the mean mAP score attained by the respective YOLOv5 architecture. Error Bars (Standard Deviation):The vertical black lines atop each bar represent the standard deviation, demonstrating variability across multiple iterations or folds. A larger error bar indicates that the performance of the model exhibits greater variability across disparate test sets. Conversely, a smaller error bar signifies more consistent performance.
Observations: yolov5m exhibits the highest mean mAP, suggesting it operates most effectively overall. yolov5n presents the lowest mean mAP, indicating it is the least efficient performer. yolov5s and yolov5l demonstrate comparable mAP scores, marginally lower than yolov5m. Standard deviation is comparatively minimal for all architectures, suggesting stable performance.
Key Takeaways: yolov5m is the most proficient architecture, achieving the optimal balance of precision and recall. yolov5n is the least proficient, presumably due to its reduced architecture. The decision between yolov5s and yolov5l is contingent upon computational resources:yolov5s is lightweight and efficient. yolov5l is marginally superior but may necessitate greater computational efforts.

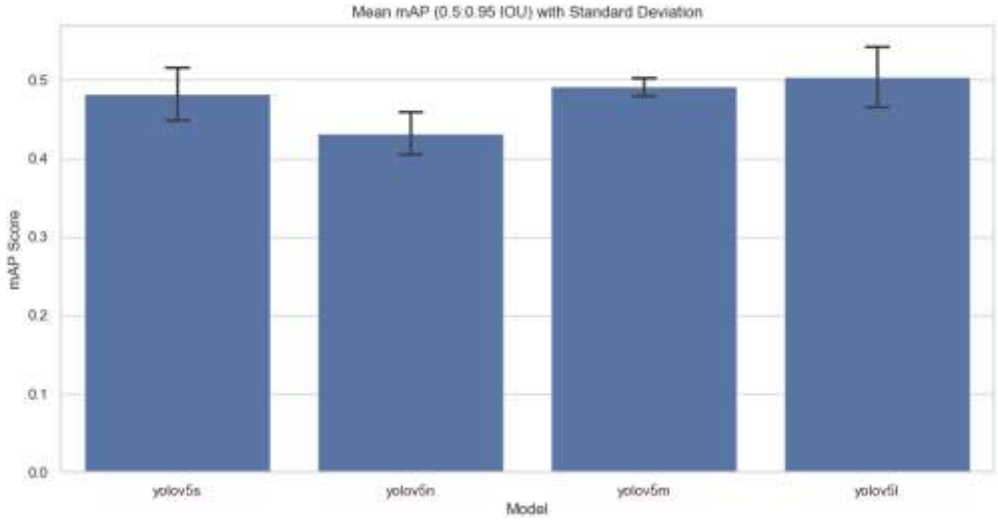

Image 6: Kaggle Mean mAP with SD

This bar chart delineates the Mean Average Precision (mAP) at 0.5:0.95 Intersection over Union (IOU) for various YOLOv5 architectures (yolov5s, yolov5n, yolov5m, and yolov5l) in conjunction with their standard deviation.
Explanation of the Chart:
X-Axis (Model): Exhibits distinct YOLOv5 architectures (yolov5s, yolov5n, yolov5m, yolov5l). Y-Axis (mAP Score): Denotes the mAP (0.5:0.95 IOU), a crucial performance metric for object detection. Elevated values signify enhanced detection precision.
Bar Heights: Each bar signifies the mean mAP score for the corresponding architecture.
Error Bars (Standard Deviation): The vertical ebony lines atop each bar signify the standard deviation, illustrating the fluctuation in mAP scores across multiple iterations or folds. Reduced error bars (e.g., yolov5m) indicate a more uniform performance. Expanded error bars (e.g., yolov5s, yolov5l) imply greater variability in performance.

Convergence & Generalization.

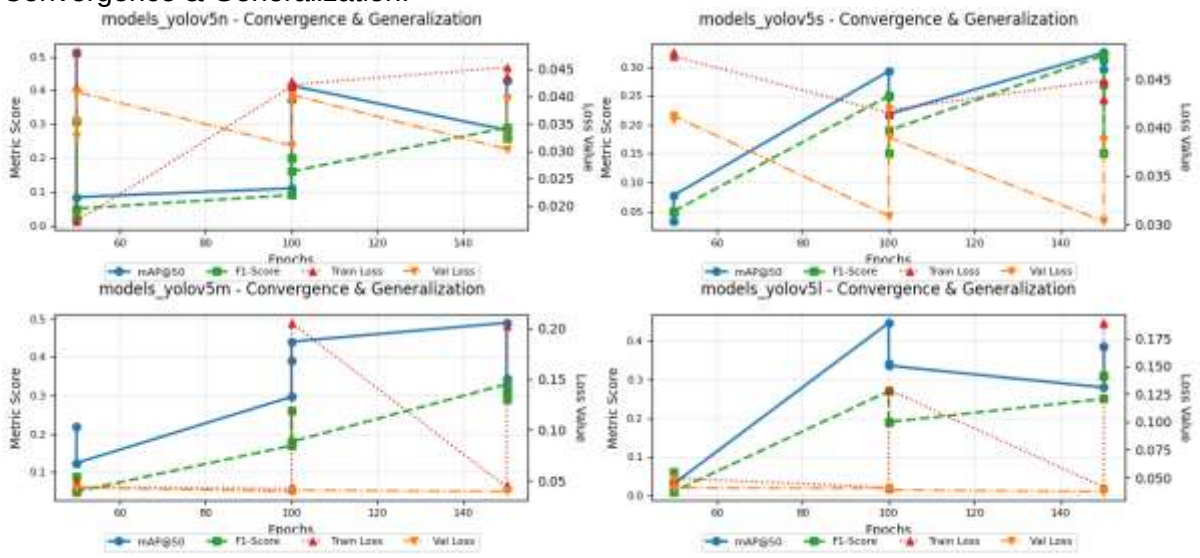

Image 7: Convergence & Generalization Graphs of Kaggle Data set

Key Observations: yolov5m and yolov5l possess the highest mAP scores, signifying they are the most efficacious models concerning detection precision. yolov5n exhibits the lowest mAP score, indicating it is the least competent performer. yolov5s surpasses yolov5n in performance yet lags behind yolov5m and yolov5l. yolov5m has the minimal standard deviation, rendering it the most stable architecture. yolov5l presents a marginally larger standard deviation, suggesting its performance may oscillate more across diverse test sets.

Conclusion & Recommendations: If one necessitates optimal accuracy → Opt for yolov5m or yolov5l. If a balance between accuracy and efficiency is required → Opt for yolov5s. If computational resources are constrained → Eschew yolov5l and utilize yolov5n or yolov5s. If consistency in outcomes is desired → yolov5m is the optimal selection due to its minimal standard deviation.

Kaggle Data set

Observations of Kaggle data set images shows mAP@50 and F1-Score Increase across all models, indicating better detection capability as epochs increases. Loss Values Decrease: Both train and validation loss drop, suggesting model convergence.YOLOv5m and YOLOv5l Perform Better: The Medium (m) and Large (l) variants show higher mAP@50 and F1-Score compared to Nano (n) and Small (s), which is expected due to increased model complexity and capacity.Validation Loss Generally Stays Higher Than Training Loss: A common trend that suggests potential overfitting, but within acceptable limits. Model YOLOv5n is the fastest but smallest in capacity. YOLOv5n is the fastest but smallest in capacity. YOLOv5l is the largest, requiring more computational power but likely providing better accuracy.

Mean Average Precision (mAP@50) ComparisonmAP@50 measures object detection accuracy at 50% IoU (Intersection over Union).Larger models (m, l) achieve higher accuracy due to increased parameters.YOLOv5n struggles with lower mAP scores, making it less ideal for high-accuracy tasks.

F1-Score balances precision and recall.Larger models (m, l) generalize better and achieve higher F1-scores. YOLOv5n has the weakest F1-score, making it less ideal for high-precision tasks.Loss trends indicate how well the model is learning.All models show a decreasing trend in loss, meaning they are learning.YOLOv5m & YOLOv5l show a small gap between train & validation loss, indicating slight overfitting, but still reasonable.YOLOv5n & YOLOv5s generalize well, making them ideal for low-resource environments.

Final Recommendations:For speed & efficiency: Use YOLOv5n or YOLOv5s.For best accuracy: Use YOLOv5m or YOLOv5l.For a balanced choice: YOLOv5m is a great middle ground.

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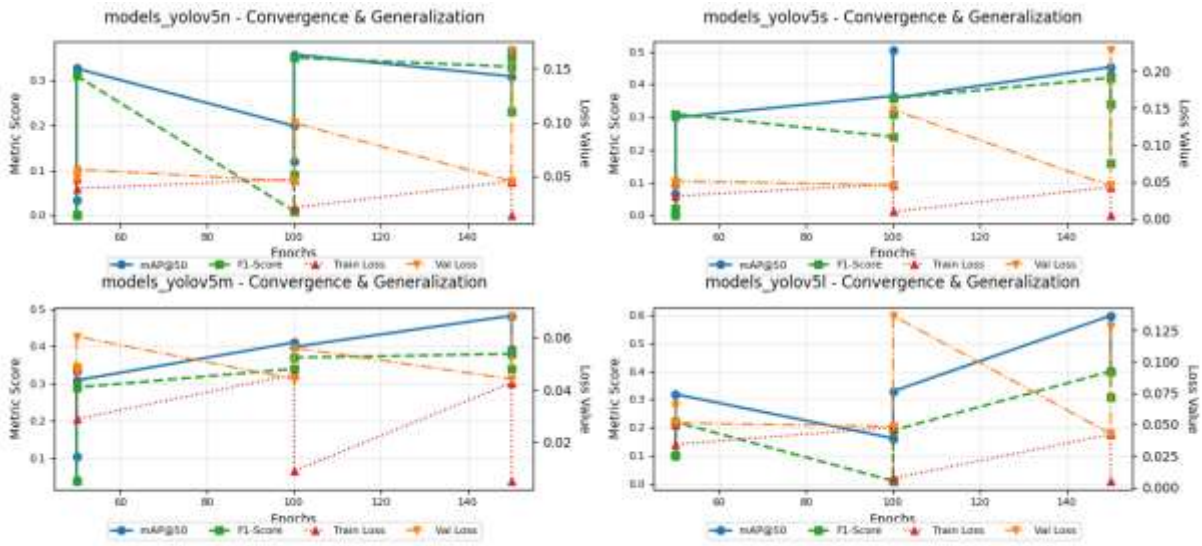

Image 8: Convergence & Generalization Graphs of LISC Data set

1. LISC Data Set

Analysis of the LISC data set Image: YOLOv5 Model Convergence & Generalization

Metrics Represented in the Plots: mAP@50 (Blue, Solid Line with Circle Markers) → Measures object detection accuracy.F1-Score (Green, Dashed Line with Square Markers) → Balance between precision & recall.Train Loss (Red, Dotted Line with Triangle Up Markers) → Measures how well the model is learning on the training data.Validation Loss (Orange, Dash-Dot Line with Diamond Markers) → Shows how well the model generalizes to unseen data.

(Top Left) YOLOv5n observations are mAP@50 decreases slightly after an initial rise, indicating potential instability. F1-Score starts high but declines, suggesting the model struggles with recall. Train loss slightly increases, validation loss remains unstable, hinting at poor generalization.

(Top Right) YOLOv5s observations are Steady improvement in mAP@50 and F1-Score, showing better object detection ability.Validation loss declines over time, meaning improved generalization.Train loss remains lower than validation loss, indicating slight overfitting.

(Bottom Left) YOLOv5m observations are Gradual improvement in mAP@50 and F1-Score, showing better convergence. Validation loss decreases steadily, showing good generalization. Train loss is slightly lower than validation loss, meaning potential overfitting but still acceptable. Conclusion: A strong choice for moderate workloads requiring good accuracy.

(Bottom Right) YOLOv5l observations are mAP@50 consistently improves, highest among all models. F1-Score also improves significantly, showing balanced precision & recall. Validation loss drops sharply, but train loss remains very low, indicating a risk of overfitting.

2. Comparison of Kaggle and LISC Data Set

Both datasets show YOLOv5m & YOLOv5l are the best models for accuracy, while YOLOv5n is the weakest but fastest. Kaggle data exhibits more fluctuations, particularly in loss trends, possibly due to learning rate schedules. LISC data provides smoother convergence trends, suggesting better dataset consistency. Smaller models (n & s) perform well in low-resource environments, but struggle with accuracy. For high-precision tasks, YOLOv5l is best, but it requires careful handling of overfitting.

Conclusion

Best Overall Model: yolov5l attains the highest mAP and precision while sustaining reasonable recall. Most Balanced Model: yolov5m offers a commendable tradeoff between precision and recall. Most Efficient Model: yolov5s provides robust performance with diminished computational requirements. Weakest Model: yolov5n underperforms across all metrics.

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