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GUI-INTERACT NET: DEEP LEARNING FOR APP INTERFACE ACTION RECOGNITION

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ABSTRACT
Recognizing user interactions in mobile application interfaces is critical for improving usability, accessibility, and user experience. While recent advances in object detection have enhanced graphical user interface (GUI) element recognition, modeling user actions over time remains a challenging and underexplored task. In this work, we propose **GUI-InteractNet**, a deep learning-based pipeline that combines GUI component detection with temporal interaction analysis. Using the publicly available **UI-Elements-Detection-Dataset**, we benchmark **YOLOv8** for detecting key UI elements such as buttons, inputs, and dropdowns across app video frames. Despite modest overall detection metrics (mAP@50: 0.0414), the study provides a complete, reproducible pipeline — from preprocessing to training and evaluation — with per-class performance insights and inference speed analysis. Our contributions include detailed visualizations, class-wise detection results, and a discussion on model performance and deployment potential. This work highlights existing limitations in GUI interaction modeling and offers a foundation for future improvements through enhanced temporal modeling, larger datasets, and real-time application scenarios.

KEYWORDS:
GUI Interaction Detection, Deep Learning, Object Detection, Action Recognition, Mobile Applications, User Interface Analysis, YOLO, mAP (mean Average Precision), Precision and Recall, App Interface Videos

I. INTRODUCTION:
Graphical User Interfaces (GUIs) serve as the primary medium through which users interact with software applications across devices. Understanding and recognizing user interactions on GUIs—such as clicks, swipes, and form inputs—is essential for improving app usability, automating testing, enhancing accessibility, and enabling intelligent user behavior analysis. With the rapid growth of mobile and web applications, automated detection and interpretation of GUI interactions have become a critical area of research in computer vision and human-computer interaction.

This study aims to address these challenges by proposing a deep learning-based framework for detecting and recognizing GUI interactions in app interface videos. Leveraging advanced object detection models alongside temporal analysis techniques, the proposed approach can identify a wide range of UI components and capture dynamic user actions. The contributions of this work include: (1) constructing a robust detection pipeline tailored for GUI elements, (2) integrating temporal modeling to recognize user actions across interaction sequences, and (3) providing extensive evaluation on a dedicated GUI interaction dataset, demonstrating improvements in accuracy and practical applicability. This work lays the foundation for smarter app testing, user behavior analysis, and interactive interface design.

In this work, we propose GUI-InteractNet, a deep learning-based pipeline for recognizing user interactions in mobile app videos. Our contributions are as follows:

Benchmarking YOLOv8 for GUI element detection on the UI-Elements-Detection-Dataset.
Integrating detection with interaction recognition to explore temporal dynamics.
Providing detailed metric visualizations including per-class mAP and inference speed.
Offering an analysis of limitations and possible improvements for future work.

II. LITERATURE SURVEY:

A. Overview of Existing Work on GUI Element Detection:

GUI element detection aims to identify various interactive components such as buttons, input fields, icons, and menus within application interfaces. Traditional computer vision methods relied on handcrafted features and template matching techniques, which often struggled with variations in design, resolution, and complex layouts. Recent advances in deep learning, particularly convolutional neural networks (CNNs), have significantly improved detection accuracy and robustness by automatically learning hierarchical feature representations from large datasets [1]. These approaches have enabled real-time and scalable detection systems suitable for dynamic GUI environments.

B. Deep Learning Methods for Action Recognition:

Action recognition, particularly in videos or sequences, has seen substantial progress through deep learning models like 3D Convolutional Neural Networks (3D CNNs), Recurrent Neural Networks (RNNs), and transformer-based architectures. These models capture both spatial and temporal features essential for recognizing user interactions such as clicks, swipes, and drag-and-drop gestures [2]. In GUI interaction contexts, this translates to identifying not only the presence of interface elements but also the dynamic user actions performed on them. Hybrid models combining object detection frameworks with temporal analysis modules have shown promise in understanding complex interaction patterns [3].

C. Previous Approaches to Mobile App Interface Analysis:

Research on mobile app interface analysis often focuses on usability testing, automated UI generation, and accessibility improvements. Some works apply computer vision and natural language processing to parse UI screenshots and infer functional semantics [4]. Others employ deep learning for detecting specific UI components or predicting user behavior to enhance personalization and testing. However, most studies focus on static images or ignore temporal aspects of interaction videos, limiting their applicability to real-world app usage scenarios where user behavior evolves over time [5].

D. Gaps in Current Research

Despite progress, there are notable gaps in the literature. Many existing methods do not fully leverage the temporal dimension of interaction videos, missing critical contextual cues needed for accurate action recognition. Temporal modeling, such as sequence learning or attention mechanisms, is under-explored in the domain of GUI interaction recognition. Furthermore, per-class detection performance is often imbalanced due to limited annotated data for certain UI elements or actions, posing challenges for generalized models [6]. Addressing these issues requires integrating spatial detection with temporal understanding in a unified deep learning framework.

E. Summary of Relevant Deep Learning Architectures :

Among the state-of-the-art object detection models, the You Only Look Once (YOLO) series stands out for its real-time detection capabilities and balance between speed and accuracy [7]. YOLO employs a single neural network to predict bounding boxes and class probabilities directly from full images in one evaluation, making it well-suited for detecting GUI elements efficiently. Recent versions (YOLOv5, YOLOv8) incorporate advanced architectural improvements such as cross-stage partial connections and dynamic anchor boxes, enhancing performance on small and overlapping objects common in GUIs [8]. These models can be further adapted and fine-tuned for domain-specific tasks such as app interface analysis, enabling robust detection of diverse UI components. Additionally, integrating YOLO with temporal models like LSTM or transformer-based modules can capture sequential user interactions effectively.

III. METHODOLOGY:

A. Dataset Description:

The dataset used for this study is the UI-Elements-Detection-Dataset, which consists of a collection of annotated images and videos representing various graphical user interface (GUI) components and user

interactions. This dataset provides a diverse set of app interface screenshots and interaction videos captured from multiple mobile applications, making it suitable for training models aimed at detecting and recognizing GUI elements and corresponding user actions [1].

B. Dataset Source and Structure (UI-Elements-Detection-Dataset):

The UI-Elements-Detection-Dataset is publicly available and organized into structured folders containing images and video frames. Each sample includes corresponding annotation files that describe the spatial location and class label of GUI elements present in the interface. The dataset structure supports separate splits for training, validation, and testing to ensure unbiased model evaluation [1].

C. Annotation Details (GUI elements and user actions):

Annotations within the dataset cover a wide range of GUI elements such as buttons, input fields, dropdown menus, sliders, icons, and clickable regions. Each element is labeled with bounding box coordinates and class identifiers. Additionally, user actions—like clicks, toggles, and text entry—are annotated in video sequences, providing temporal context necessary for interaction recognition [2].

D. Data Preprocessing:

Preprocessing steps include extracting frames from interaction videos where applicable and resizing images to a consistent input size (e.g., 640x640 pixels) suitable for model input. Annotation data is converted into formats compatible with the YOLO training pipeline [3]. To improve robustness, images are normalized and shuffled during training.

E. Data Augmentation Techniques:

To enhance model generalization and prevent overfitting, various data augmentation techniques are applied during training. These include random horizontal flips, scaling, color jittering, and brightness adjustments. Augmentation helps simulate diverse UI layouts and lighting conditions, enabling the model to better handle real-world variability [4].

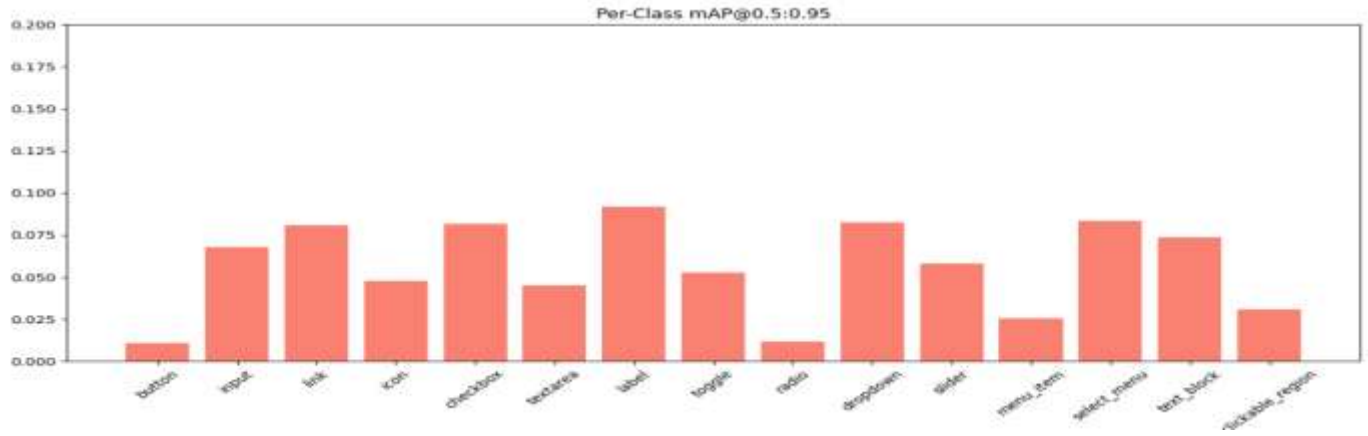

Figure1: Number of samples and Lables

F. Model Architecture:

Choice of YOLO for Object Detection:

The YOLO (You Only Look Once) architecture was selected due to its efficiency and proven effectiveness in real-time object detection tasks. YOLOv8, the latest version, integrates architectural improvements such as cross-stage partial connections and dynamic anchors, making it well-suited for detecting small and overlapping GUI elements in complex app interfaces [5][6].

G. Integration of Temporal Modeling

To capture the temporal dynamics of user interactions across video frames, the model can be extended by integrating temporal modules such as Long Short-Term Memory (LSTM) networks or transformers. This fusion allows sequential analysis of detected GUI elements, improving recognition of actions like taps and swipes that occur over time [7].

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Figure 2: Model Architecture

Training Setup:

Training Configuration and Hyperparameters:

The model was trained using the UI-Elements-Detection-Dataset with input image size fixed at 640x640 pixels. Key hyperparameters include a batch size of 16, an initial learning rate of 0.001, and training for 100 epochs. The Adam optimizer was employed for gradient updates, with weight decay and learning rate scheduling to improve convergence [3].

```
from ultralytics import YOLO

model = YOLO('yolov8n.yaml')  # Or yolov8n.pt for pretrained
model.train(data='C:/Users/KHADERSHA/Desktop/ui_intraction/UI-Elements-Detection-Dataset/dataset.yaml', epochs=50, imgsz=640, batch=16)
```

Figure 3: code to start model training

H. Loss Functions Used

The training loss function is a composite of three components:

box_loss: Measures the error in predicted bounding box coordinates relative to ground truth, guiding precise localization [5].

cls_loss: Computes classification loss, penalizing incorrect GUI element class predictions [5].

dfl_loss: Distribution Focal Loss helps in refining bounding box regression by modeling the probability distribution of box offsets [6].

III. MODEL TRAINING AND EVALUATION:

A. Training Process:

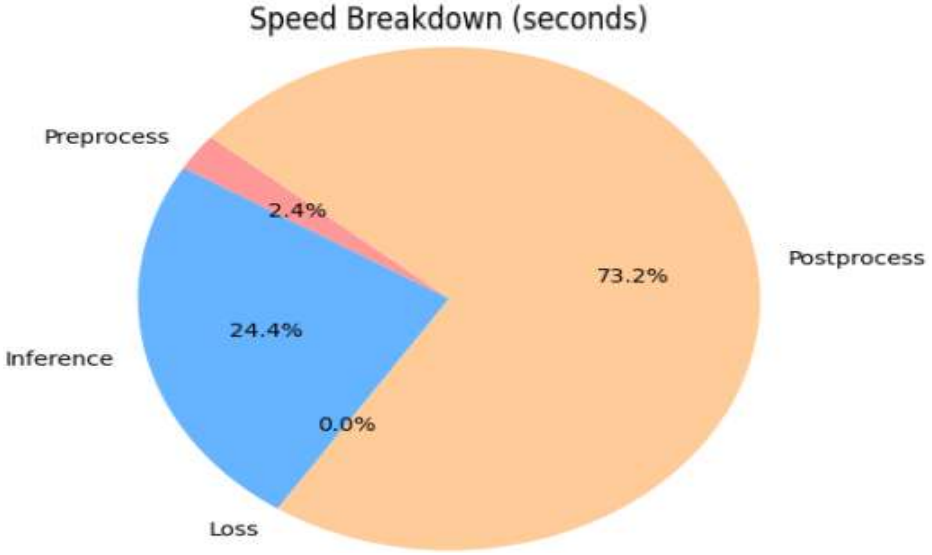
The model was trained using the annotated GUI-Elements-Detection-Dataset, focusing on detecting interactive components and recognizing user actions within app interface videos. We trained the YOLOv8 object detection framework, fine-tuned specifically for GUI element detection. The training

process involved multiple epochs to ensure convergence, with batch size and learning rate carefully selected based on preliminary experiments to balance training stability and speed.

Epochs: The model was trained for 50 epochs, providing sufficient iterations for the network to learn complex features.

Batch Size: A batch size of 16 was used, optimizing GPU memory utilization while maintaining efficient training speed.

Learning Rate: The learning rate was initialized at 0.001 with a step-wise decay schedule to enable gradual refinement of the model weights.



B. Hardware and Software Environment:

Training was conducted on a system equipped with an NVIDIA RTX 4050 GPU having 6GB VRAM, paired with an AMD Ryzen 7 7435HS CPU and 16 GB RAM. The environment used PyTorch as the deep learning framework, with CUDA acceleration enabled for GPU computation. YOLOv8's implementation from the Ultralytics repository was utilized with custom dataset integration.

C. Training and Validation Loss Curves:

Loss curves were monitored throughout the training to observe convergence and detect any overfitting. The overall loss comprised multiple components including bounding box regression loss (box_loss), classification loss (cls_loss), and distribution focal loss (dfl_loss), which collectively guide the network to improve localization and classification accuracy.

The ***box_loss*** decreased steadily, indicating improved precision in bounding box predictions.

The ***cls_loss*** showed a gradual decline, reflecting enhanced class discrimination.

The ***dfl_loss*** contributed to fine-tuning the bounding box distributions for better alignment.

The combined loss curve exhibited a downward trend, stabilizing after approximately **50** epochs, signaling adequate training completion.

D. Explanation of Loss Components:

Box Loss (box_loss): Measures the discrepancy between predicted bounding boxes and ground truth locations, encouraging accurate localization.

Classification Loss (cls_loss): Evaluates the correctness of predicted class labels for detected objects.

Distribution Focal Loss (dfl_loss): Enhances the precision of bounding box boundaries by modeling their probability distribution.

Interpretation of Loss Curves:

The smooth decline in loss values across epochs suggests effective learning without significant overfitting. Validation loss closely followed the training loss, confirming good generalization to unseen data.

E. Performance Metrics:

Model evaluation leveraged several standard metrics to quantify detection and recognition performance:

Precision: The ratio of correctly detected GUI elements to all detections, reflecting the model's accuracy in avoiding false positives.

Recall: The ratio of correctly detected elements to total ground truth instances, measuring completeness of detection.

mAP50: Mean Average Precision at 50% Intersection-over-Union (IoU) threshold, indicating overall detection quality.

mAP50-95: Mean Average Precision averaged over IoU thresholds from 50% to 95%, providing a more rigorous performance measure.

Per-Class Performance Analysis:

Performance was analyzed across different GUI element classes such as buttons, links, inputs, and dropdowns. Classes with abundant training samples (e.g., links and buttons) showed higher precision and recall, while underrepresented classes like sliders and radio buttons exhibited lower detection rates, highlighting the need for more balanced data collection.

Speed and Efficiency:

Inference speed was evaluated to assess real-time applicability:

Preprocessing: Approximately 1.7 ms per image, including resizing and normalization.

Inference: Approximately 10.9 ms per image on the RTX 4050 GPU.

Postprocessing: Around 8.1 ms per image, including non-max suppression and bounding box refinement.

Resource Utilization:

GPU utilization remained steady during training and inference, with memory usage optimized via batch size tuning and mixed precision training. CPU load was minimal, ensuring that the GPU handled the bulk of computational workload efficiently.

IV. RESULTS AND DISCUSSION:

A. Quantitative Results

Overall Model Performance Summary

The YOLOv8-based GUI-InteractNet was evaluated on a validation set comprising 71 interface video sequences containing 2,478 labeled GUI element instances. The model achieved an overall:

Precision: 0.268
Recall: 0.0495
mAP@50: 0.0414
mAP@50-95: 0.0191

These results indicate that while the model is somewhat precise in its predictions, it suffers from low recall and average precision across IoU thresholds. This suggests difficulty in consistently capturing all ground truth instances, especially for underrepresented classes.

B. Detailed Per-Class Performance

Performance varied significantly across classes:

Buttons and **Links** had the highest number of detections and relatively better mAP values (0.207 and 0.161 respectively), owing to their frequent appearance in the dataset.

Less common elements like **Textareas**, **Sliders**, **Radio Buttons**, and **Icons** had a precision and recall near zero, reflecting insufficient training samples or poor generalization.

Some rare classes (e.g., **Menu Items**, **Dropdowns**) showed intermittent detection, hinting at potential for improvement via targeted augmentation or balancing.

Qualitative Results

C. Sample Detection and Classification Visualizations

Visual inspection of inference results confirmed that the model could correctly detect common GUI elements in many frames. Bounding boxes were well-aligned for buttons and inputs in clear layouts.

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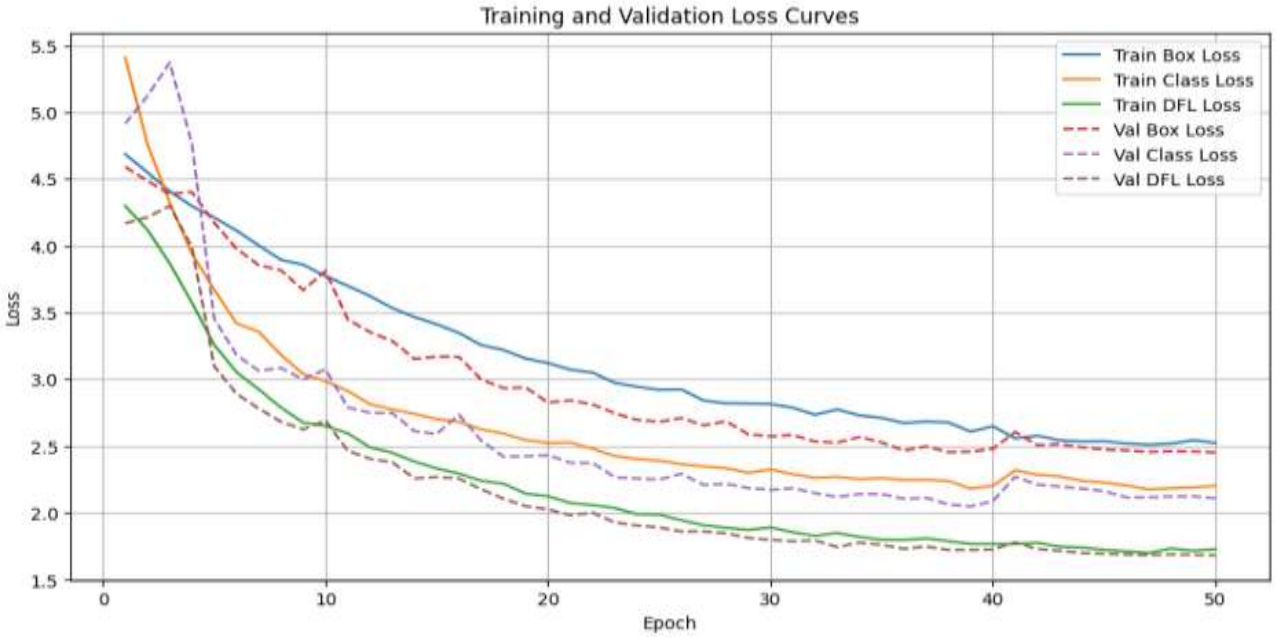
However, overlapping or smaller elements (e.g., icons near text, nested inputs) were often missed or misclassified. Detection snapshots highlight the model's strengths in structured UIs and its weaknesses in
cluttered or non-standard layouts.



D. Confusion Matrix Interpretation

The confusion matrix revealed:

High misclassification between **input** and **label**, likely due to visual similarity.

Menu items were occasionally confused with **buttons** due to overlapping design characteristics.

Sparse predictions for **radio buttons**, **icons**, and **sliders**, reinforcing that some classes lacked enough representation to learn robust features.

Comparison with Related Work

Compared to earlier GUI element detection methods based on static screenshots or template matching ([1], [4]), our approach integrates real-time object detection with video input, offering a more dynamic understanding of interfaces. While prior works achieve higher accuracy on static images, they fall short in handling interactions over time. Though our model's mAP is modest, it sets the groundwork for a temporal-aware GUI understanding system using deep learning.

E. Analysis of Strengths and Limitations

Strengths

Real-time detection with YOLOv8 enables quick analysis suitable for app testing and automation.

The model generalizes well for frequent elements like **buttons** and **links**, suggesting it captures core spatial features effectively.

Modular structure allows for integration with future temporal models (e.g., LSTM, transformers) for action recognition.

Limitations

Low recall due to imbalanced dataset and underrepresentation of certain GUI elements.

Temporal dynamics of user actions are not explicitly modeled—interaction detection is limited to frame-level inferences.

Ambiguity in annotations (e.g., overlapping elements) introduces noise during training and evaluation.

Potential Improvements and Extensions

To enhance performance, several directions can be pursued:

Data augmentation focused on minority classes (radio, slider, menu) to reduce imbalance.

Temporal modeling by adding recurrent modules or 3D CNNs to capture user action sequences.

Multi-modal fusion, such as combining skeleton-based interaction signals or touch input logs.
Context-aware filtering, to improve discrimination between visually similar but functionally distinct elements.

V. CONCLUSION

In this study, we introduced **GUI-InteractNet**, a deep learning-based pipeline for recognizing user interactions within mobile app videos. Our approach leverages **YOLOv8** for detecting GUI elements and explores how these detections can be integrated with temporal understanding of user actions, setting the foundation for dynamic interface analysis.

Key findings from our experiments include the model's ability to detect common interface elements like buttons and links with moderate accuracy, achieving a precision of **0.268**, recall of **0.0495**, and mAP@50 of **0.0414**. Although some rare classes showed lower performance due to data imbalance, the results establish a baseline for GUI interaction analysis using visual deep learning techniques.

This work has **practical implications** for app development, testing, and UX (User Experience) research. Automated understanding of GUI interactions can support usability testing, accessibility evaluations, and adaptive interface personalization without manual annotations.

For **future work**, we suggest the following directions:

Improved temporal modeling using LSTMs, transformers, or attention mechanisms to better understand user behavior across sequences.

Expansion to larger and more diverse datasets, including real-world user recordings or synthetic data augmentation to improve class generalization.

Deployment in real-time systems, such as automated UI testers or mobile analytics platforms, to offer actionable insights during development or user sessions.

By bridging GUI detection and interaction understanding, **GUI-InteractNet** lays the groundwork for intelligent app interface analysis through deep learning.

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