Automated Technical Analysis: Candlestick Pattern Detection using YOLOv8

Created by: Krunal Savaj, Axay Ghoghari

Section I: Introduction (Project Overview)

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Problem & Solution

Technical analysis relies on manual, subjective identification of visual patterns in price charts. Our solution is an automated Computer Vision system using **YOLOv8 Small (yolov8s)** to detect these candlestick patterns.

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Core Objective

To detect and classify 6 specific candlestick patterns using a Deep Learning pipeline, enhancing the efficiency and objectivity of financial market analysis.

System Architecture

Model: YOLOv8 Small (yolov8s.pt)

Framework: PyTorch 2.5.1 on CUDA

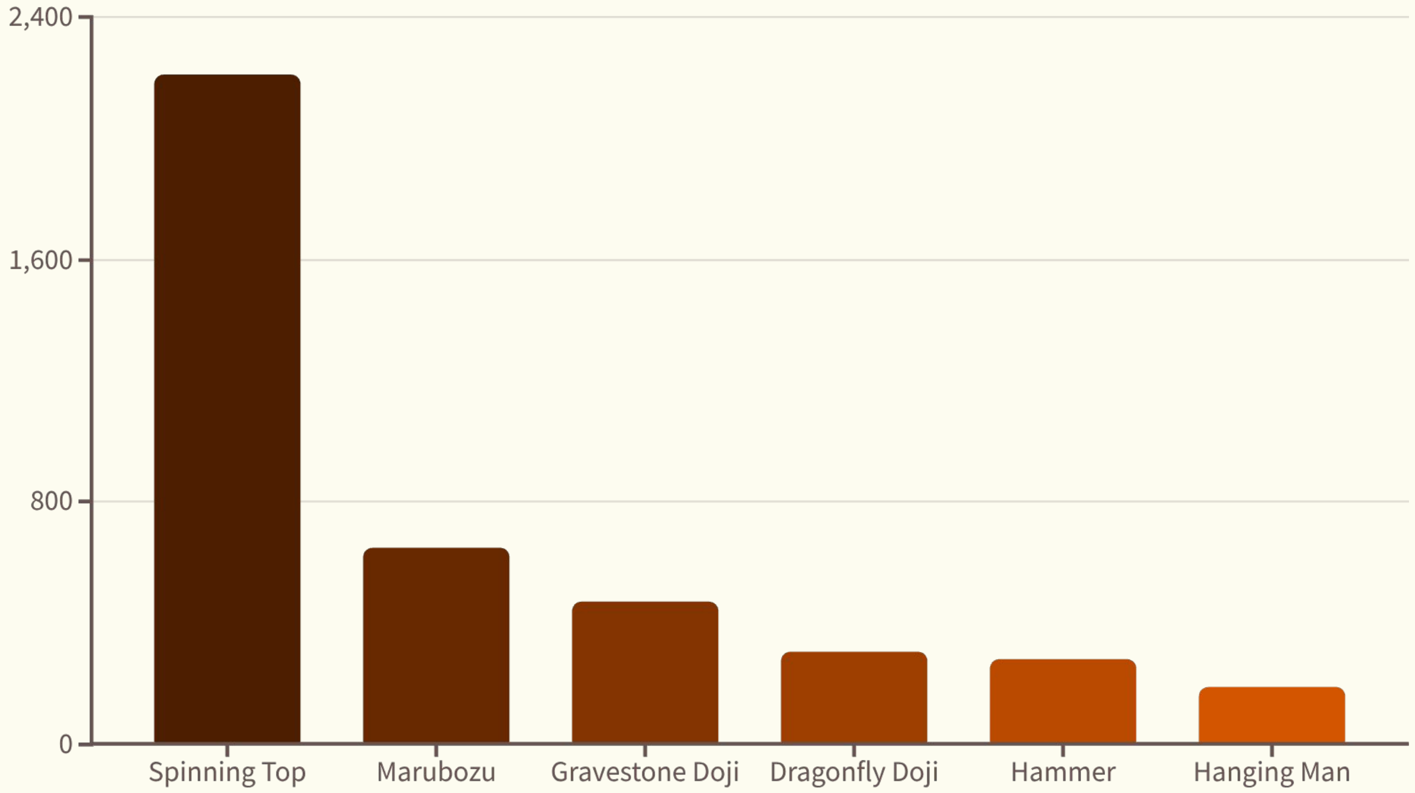
Infrastructure: Trained on a cluster with **4 Tesla P100-PCIE-12GB GPUs** for accelerated processing.

Section II: Basic Summary of Data

The Dataset Structure & Class Distribution

Dataset Overview

Total Images: 5,873
Training Set: 4,102 images
Validation Set: 1,175 images
Test Set: 596 images
Image Resolution: All data processed at 640x640 pixels



The dataset exhibits significant class imbalance, notably the "Spinning Top" pattern being dominant, and "Hanging Man" as the rarest, influencing model performance.

Section III: In-Depth Analysis (Training Methodology)

Efficient Training Configuration

Hardware & Speed

Training leveraged **4x Tesla P100 GPUs** with Distributed Data Parallel. This allowed 50 epochs to complete in approximately **0.416 hours (~25 minutes)**, demonstrating exceptional training efficiency.

Hyperparameters

Epochs: 50

Batch Size: 64 (effective across GPUs)

Optimizer: AdamW (lr0=0.01, momentum=0.937)

Patience: 15 epochs (for early stopping)

Loss Function Convergence

The model simultaneously minimised three loss functions over 50 epochs:

Box Loss

Converged to approximately **0.11**

Cls (Classification) Loss

Converged to approximately **0.70**

DFL (Distribution Focal) Loss

Converged to approximately 0.78

Section IV: Results

Overall Performance Metrics (Validation Set)

The model demonstrates a balanced performance with strong recall, indicating its ability to identify a high proportion of actual patterns.

0.6074

mAP@50

Mean Average Precision at 50% IoU (60.7%)

0.6062

mAP@50-95

Mean Average Precision across various IoU thresholds

0.7354

Recall

Identifies 73.5% of all patterns present

0.4681

Precision

Correct predictions approximately 47% of the time

Per-Class Performance Breakdown

Performance strongly correlates with the availability of training instances, highlighting the impact of class imbalance.

Best Performers

Marubozu: mAP@50 = 0.868

Spinning Top: mAP@50 = 0.867

Mid-Tier

Gravestone Doji: mAP@50 = 0.673

Hammer: mAP@50 = 0.546

Worst Performers (Rare Classes)

Hanging Man: mAP@50 = 0.211 (Lowest sample size: 189)

Dragonfly Doji: mAP@50 = 0.480

Section V: Issues Encountered

Key Challenges in Model Training

Class Imbalance

Issue: "Hanging Man" had only 189 training samples versus "Spinning Top" with 2,211.
Consequence: This led to significant performance disparities; 0.21 mAP for Hanging Man compared to 0.86 mAP for Spinning Top.

Precision vs. Recall Trade-off

Observation: The model prioritises Recall (0.735) over Precision (0.468).

Implication: This means the model is "eager" to detect patterns, potentially leading to false positives. Users must verify detections, balancing the benefit of not missing opportunities with the need for manual filtering.

Section VI: Future Work

Proposed Improvements for Enhanced Performance

Data Augmentation

Focus on minority classes (e.g., Hanging Man, Hammer) using synthetic augmentation to mitigate the 200 vs. 2,000 instance disparity and improve detection for under-represented patterns.

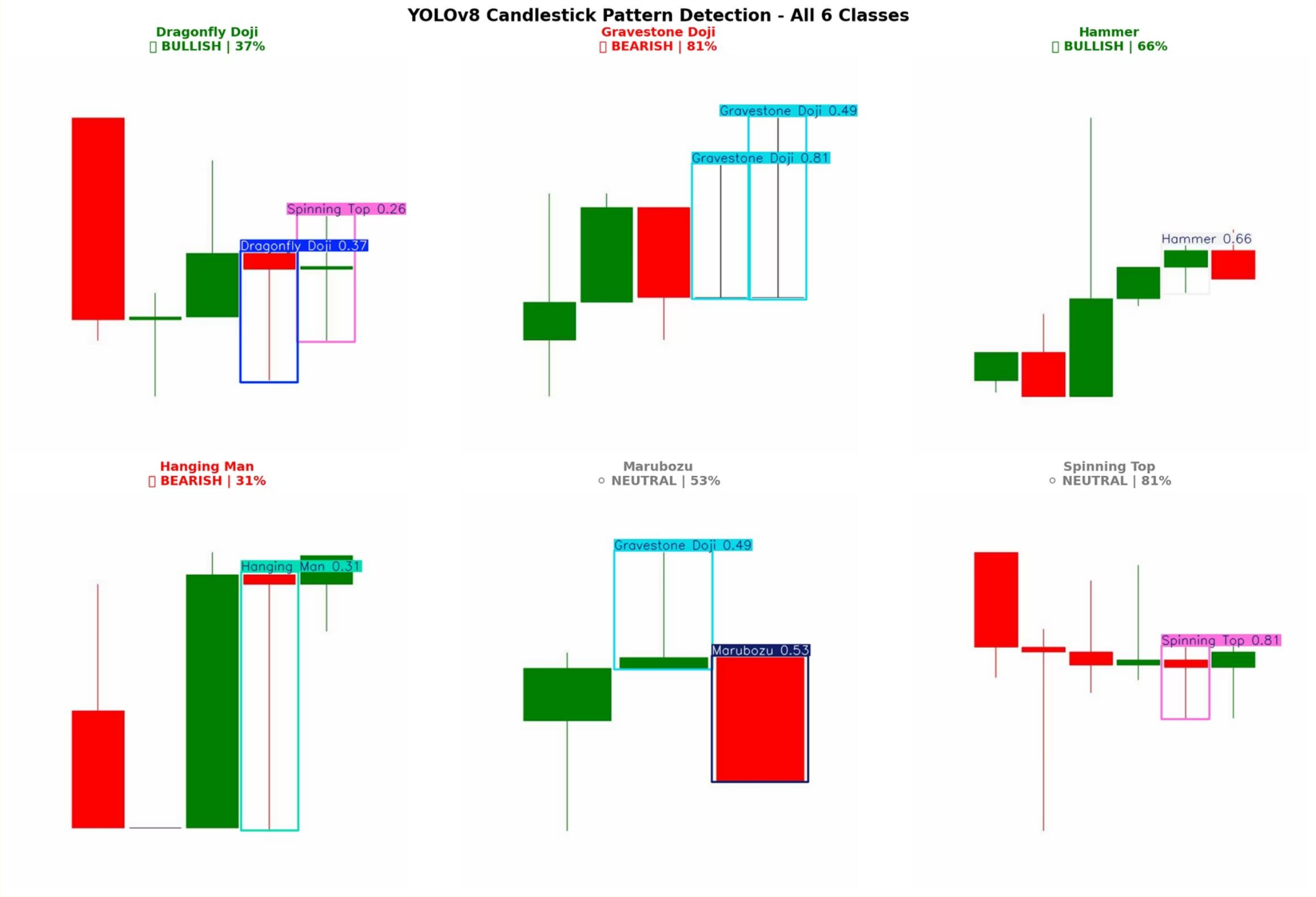
Hyperparameter Tuning

Optimise default gain values (e.g., box=7.5, cls=0.5). Targeted tuning can address the lower Precision score, making predictions more reliable.

Longer Training Regimes

Despite the rapid 25-minute training for 50 epochs, extending training to 100+ epochs could allow the model to converge further, particularly for challenging classes like Dragonfly Doji.

All Candlestick Patterns & Detection Output



Complete visualization of all 6 candlestick patterns detected by YOLOv8s with confidence scores and bounding boxes.

Section VII: Suggestions for the Client

Strategic Recommendations for Deployment & Usage

Deployment Readiness

The YOLOv8s model is lightweight (22.5 MB, `models/weights/best.pt`), making it suitable for deployment on edge devices or standard cloud instances.

Usage Strategy

Given the **0.46 Precision**, detections should be treated as "alerts" rather than definitive signals. The high **0.73 Recall** ensures few patterns are missed, but manual verification of results is crucial.

Focus on Strong Classes

Clients should place higher trust in signals from "Marubozu" and "Spinning Top" (86% accuracy) and exercise caution with "Hanging Man" signals (21% accuracy).