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Candlestick Pattern Detection using Deep Learning A YOLOv8-based Object Detection

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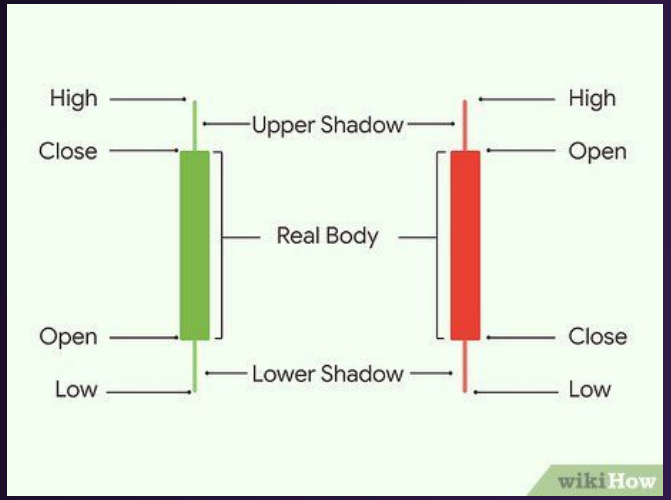
Introduction

- Candlestick charts help traders and investors analyze price movements, market sentiment, and trend reversals.
- Developed in Japan, they use opening, high, low and closing prices to form predictive patterns.
- Challenge: Traditional pattern detection relies on manual analysis or rule-based systems
- Our Solution: Leveraging deep learning object detection for automated pattern recognition

Background & Motivation

What are Candlestick patterns?



Why automate pattern detection?

- Speed and efficiency
- Reducing subjectivity in pattern identification
- Potential to identify patterns that might be missed by humans

Related Work

Brief overview of existing approaches:

- CNN for Chart Pattern Classification (Tsang et al.)
  - Applied CNN to detect broad chart patterns (head & shoulders, double tops)
  - Achieved 82.5% accuracy with custom architecture
  - Limited to classification without specific focus on candlestick patterns
- Transfer Learning Approach (Velay & Daniel)
  - Used deep CNNs with transfer learning for technical pattern recognition
  - Reported 78.3% average precision across pattern types
  - Primarily focused on price action rather than candlestick formations
- Hybrid Rule-Based & ML Approach (Chen et al.)
  - Combined rule-based filters with SVM classification
  - Reported 76.4% accuracy for candlestick pattern identification
  - Still relied on predefined rules rather than end-to-end learning

Our Approach

- Framing candlestick pattern detection as an object detection problem
- Focus on 6 common patterns: ['Head and shoulders bottom', 'Head and shoulders top', 'M_Head', 'StockLine', 'Triangle', 'W_Bottom']
- Key components: dataset generation, YOLOv8 model architecture, training procedure, inference

Dataset Creation

- Challenge: No publicly available labeled datasets
- Our solution: Synthetic dataset generation pipeline
- Process flow:
  a. Historical data collection (30 stocks/ETFs)
  b. Rule-based pattern identification
  c. Chart image generation with visualization context
  d. Annotation in YOLO format
- Final dataset: 1,628 images (distribution chart of patterns)

DATASET

Pattern Type	Image Count	Percentage
Head and Shoulders Bottom	**392**	**24.1%**
Head and Shoulders Top	**267**	**16.4%**
M-Head	**239**	**14.7%**
StockLine	**401**	**24.6%**
Triangle	**66**	**4.1%**
W-Botton	**263**	**16.2%**

Model Architecture

- Why YOLOv8?
  a. Speed (suitable for real-time applications)
  b. Accuracy improvements over previous versions
  c. Flexibility in model scaling
- YOLOv8n architecture overview:
  a. CSPDarknet53 backbone
  b. Path Aggregation Network (PAN)
  c. Detection head

Training Methodology

- Two-stage approach:
  a. Initial training (25 epochs, batch size 16)
  b. Fine-tuning (10 epochs, batch size 8)
- Hyperparameters and optimization strategy
- Data augmentation techniques used
  a. random horizontal flipping,
  b. mosaic augmentation, and
  c. random erasing

Results & Evaluation

- Training performance metrics:
  a. Classification loss progression
  b. Visualization of training progress

Metric	Value
Box Precision	**0.78**
Box Recall	**0.72**
mAP50	**0.75**
mAP50-95	**0.62**

- Inference speed: ~6.5ms per image

Challenges, Future Work & Conclusion

Challenges & Limitations

Annotation precision: Difficulty in precisely localizing variable-sized patterns

Dataset imbalance: Underrepresentation of patterns like Triangle (4.1%)

Localization metrics: values for precision/recall require investigation

Real-world detection: Limited success in live market data testing

Future Work

Develop improved annotation methodology beyond bounding boxes

Expand dataset with more diverse pattern examples

Explore hybrid architectures combining rule-based and ML approaches

Develop and backtest pattern-based trading strategies

Conclusion

Novel application of object detection to financial pattern recognition

Potential to enhance trading systems with real-time pattern detection

Open opportunity for collaboration between computer vision and finance domains

PROJECT DEMO