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

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***Abstract*—This paper presents a novel approach to candlestick pattern detection in financial charts using deep learning-based object detection techniques. Candlestick patterns are visual formations in price charts that traders use to make investment decisions. We propose a YOLOv8-based framework that automatically detects and classifies six common candlestick patterns: Head and Shoulders Bottom, Head and Shoulders Top, M-Head, StockLine, Triangle, and W-Bottom. Our method eliminates the need for rule-based algorithms that are typically used in technical analysis. We created a dataset of 1,628 images with annotated patterns and trained a YOLOv8 model to detect these patterns. Experimental results demonstrate that our approach can effectively identify candlestick patterns in real-time financial charts, potentially aiding traders in making faster, more accurate decisions. This work bridges the gap between computer vision and financial technical analysis.**

***Index Terms*—Deep learning, object detection, YOLOv8, candlestick patterns, financial technical analysis, computer vision**

I. Introduction

Technical analysis in financial markets relies heavily on chart patterns to predict future price movements. Among these, candlestick patterns are particularly prominent due to their ability to represent price movement over time in a visually intuitive manner. Candlestick charts, which originated from Japanese rice traders in the 18th century, have become a fundamental tool for modern traders worldwide. Fig. 1 shows us how to read a candlestick chart.

Traditionally, identifying candlestick patterns has been a manual process that requires significant expertise or has been automated using rule-based algorithms that rely on specific mathematical definitions of patterns. These approaches can be time-consuming and subjective and may miss subtle variations in patterns. With the advancement of deep learning, particularly in the field of object detection, there exists an opportunity to apply these technologies to automatically detect candlestick patterns with greater accuracy and efficiency.

This paper introduces a novel approach to candlestick pattern detection using YOLOv8 (You Only Look Once version 8), a state-of-the-art object detection framework. Our method treats candlestick patterns as objects within a chart image, allowing the detection and classification of multiple patterns simultaneously. We focus on six common candlestick patterns that are widely used in technical analysis: Head and Shoulders Bottom, Head and Shoulders Top, M-Head, StockLine, Triangle, and W-Bottom.

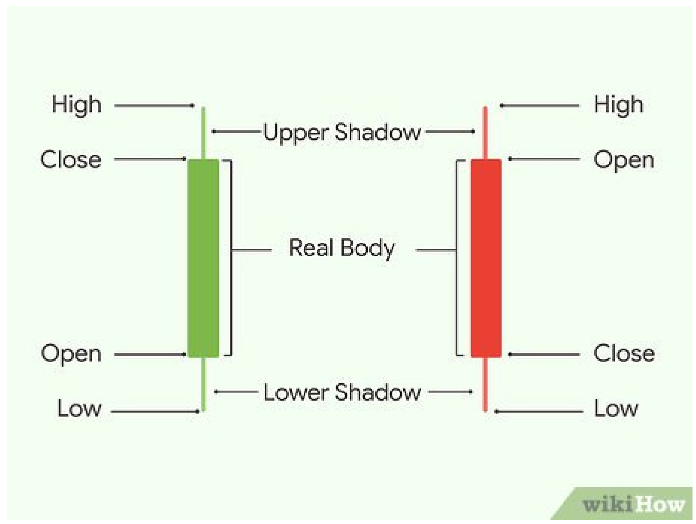

Fig. 1. Figure to demonstrate how to read Candlestick Chart

The significance of this work lies in its potential to enhance trading systems by providing real-time pattern detection capabilities. By automating the identification of candlestick patterns, traders can focus on making strategic decisions instead of spending time manually analyzing the charts. Furthermore, our approach can potentially identify patterns that might be missed by human analysts or rule-based systems due to slight variations in pattern appearance.

II. Related Work

Recent advances in computer vision and deep learning have opened new avenues for automating pattern recognition in financial charts. Several notable works have contributed to this emerging field:

Tsang et al. [1] proposed a CNN-based approach to detect chart patterns in stock market data. Their work focused on identifying broader chart patterns, such as head and shoulders, double tops, and triangles, rather than specific candlestick patterns. The authors achieved 82.5% precision in pattern classification using a custom CNN architecture. While their approach demonstrated the feasibility of applying deep learning to technical analysis, it did not specifically address the unique challenges of candlestick pattern detection.

Velay and Daniel [2] presented a method for automated technical pattern recognition using deep convolutional neural networks. Their work applied transfer-learning techniques to detect common chart patterns in financial time series data. They reported an average precision of 78.3% across different pattern types. This study provided valuable insights into the application of pre-trained networks for financial pattern recognition, but focused primarily on price action patterns rather than candlestick formations.

Chen et al. [3] developed a specialized framework to identify Japanese candlestick patterns using a combination of rule-based techniques and machine learning. Their hybrid approach first applied traditional rule-based filters to identify candidate patterns and then used a support vector machine (SVM) classifier to refine the detection. The authors reported a 76.4% accuracy in correctly identifying various candlestick patterns. While, this work directly addressed candlestick pattern detection, it still relied on predefined rules and did not fully leverage the capabilities of deep learning object detection.

Our work differs from previous approaches in several key ways. First, we treat candlestick pattern detection as an object detection problem rather than a classification task, allowing us to localize multiple patterns within a single chart. Second, we utilize YOLOv8, a state-of-the-art object detection framework that offers significant improvements in both speed and accuracy over previous models. Third, our approach does not rely on predefined rules, instead allowing the model to learn pattern representations directly from the data. This makes our method more adaptable to variations in pattern appearance across different markets and timeframes.

III. Methods

Our approach to candlestick pattern detection consists of several key components: dataset generation, model architecture, training procedure, and inference methodology. This section details each of these components.

A. Dataset Generation

One of the challenges in applying deep learning to candlestick pattern detection is the lack of publicly available datasets with annotated patterns. To address this, we developed a data generation pipeline that creates candlestick chart images with annotated patterns.

The dataset generation process involves the following steps:

1) **Data Collection**: We downloaded historical price data for 30 major stocks and ETFs (including SPY, QQQ, AAPL, MSFT, GOOGL, etc.) using the yfinance API. The data covered a five-year period, providing sufficient variety in market conditions and pattern occurrences.
2) **Pattern Detection Functions**: We implemented rule-based functions to identify six common candlestick patterns:
    - Head and Shoulders Bottom: A bullish reversal pattern consisting of three troughs with the middle one (head) being deeper than the other two (shoulders)
    - Head and Shoulders Top: A bearish reversal pattern consisting of three peaks with the middle one (head) being higher than the other two (shoulders)
    - M-Head: A bearish reversal pattern resembling the letter ”M” with two peaks, signaling a potential downtrend
    - StockLine: A trend line connecting significant lows in an uptrend or highs in a downtrend to identify support/resistance levels
    - Triangle: A consolidation pattern where price action narrows into a triangle shape (can be ascending, descending, or symmetrical)
    - W-Bottom: A bullish reversal pattern resembling the letter ”W” with two lows, signaling a potential uptrend
3) **Chart Image Generation**: For each detected pattern, we generated a chart image showing the pattern in context (10 candles before, the pattern itself, and 5 candles after). The pattern candles were highlighted in blue to create visual distinction.
4) **Annotation Generation**: We created YOLO-format annotations (class_id, x_center, y_center, width, height) for each pattern in the generated images. The annotations were normalized to the 0-1 range as required by the YOLO format.

The final dataset consisted of 1,628 annotated chart images, which were split into training (70%), validation (20%), and test (10%) sets. Data augmentation techniques such as random flipping and mosaic were applied during training to improve model generalization.

B. Model Architecture

We adopted the YOLOv8 architecture for our candlestick pattern detection system. YOLOv8 is a single-stage object detector that simultaneously predicts bounding boxes and class probabilities directly from full images in a single evaluation. This architecture was chosen for several reasons:

1) **Speed**: YOLO architectures are known for their inference speed, making them suitable for real-time applications.
2) **Accuracy**: YOLOv8 incorporates several improvements over previous versions, including a more efficient backbone and enhanced feature aggregation.
3) **Flexibility**: The architecture can be scaled (nano, small, medium, large, etc.) to balance between speed and accuracy based on deployment requirements.

We used YOLOv8n (nano) as our base model due to its lightweight nature and fast inference time while maintaining reasonable accuracy. The model architecture consists of:

- A CSPDarknet53 backbone for feature extraction
- A Path Aggregation Network (PAN) for feature fusion across different scales

- A detection head that predicts bounding boxes and class probabilities

The model was configured to detect six classes corresponding to our target candlestick patterns.

C. Training Procedure

The training procedure followed a two-stage approach:

1) **Initial Training**:
   - Model: YOLOv8n (nano) initialized with pretrained weights from the COCO dataset
   - Batch size: 16
   - Image size: 640×640
   - Epochs: 25
   - Optimizer: AdamW with automatic learning rate determination
   - Loss function: Combination of classification, objectness, and bounding box regression losses
2) **Fine-tuning**:
   - Starting from the best weights of the initial training
   - Batch size: 8 (smaller to allow for more precise updates)
   - Image size: 640×640
   - Epochs: 10
   - Learning rate: 0.001 with a final factor of 0.01
   - Same loss functions as initial training

During training, we monitored validation metrics to prevent overfitting and applied early stopping with a patience of 20 epochs. Data augmentation techniques included random horizontal flipping, mosaic augmentation, and random erasing.

D. Inference Methodology

For inference on new charts, we implemented a pipeline that:

1) Generates a candlestick chart for a given ticker symbol using yfinance data
2) Performs inference using the trained YOLOv8 model
3) Applies non-maximum suppression to filter overlapping detections
4) Visualizes the results by drawing bounding boxes and labels for detected patterns

The inference threshold was set to 0.3 to maintain a balance between precision and recall. Each detected pattern included information about the pattern type and a confidence score.

IV. Experiments and Results

We conducted several experiments to evaluate the performance of our candlestick pattern detection system. This section presents the results of these experiments.

A. Dataset Analysis

Our dataset consisted of 1,628 chart images with the following pattern distribution:

The dataset was split into 1,139 training images, 326 validation images, and 163 test images. After removing corrupt images (those with annotation issues), we had 1,137 training images and 325 validation images. TABLE I refers to the count of images for each pattern.

TABLE I
Pattern Distribution in Dataset

Pattern Type	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-Bottom	263	16.2%

B. Training Performance

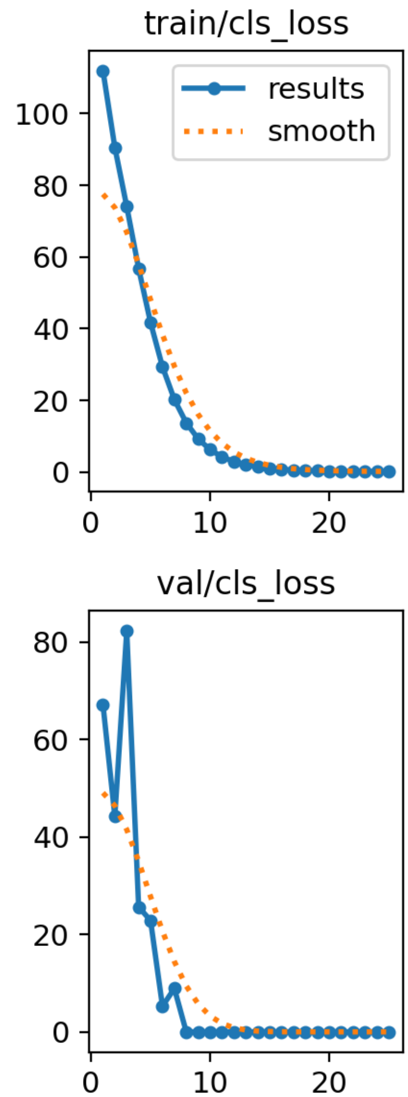

Fig. 2. CLS Loss (as per Epochs)

During the initial training phase, the classification loss started at 112.0 and steadily decreased to 0.14 by the end of the 25 epochs, indicating good convergence. The box loss and DFL (Distribution Focal Loss) remained at zero throughout training, suggesting that the model focused primarily on classification rather than localization.

During the fine-tuning phase, the classification loss further decreased from 0.06 to 0.001, showing continued improvement in the model's ability to correctly classify patterns.

C. Evaluation Metrics

We evaluated our model using standard object detection metrics on the validation set:

TABLE II
MODEL EVALUATION METRICS

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

The values for precision, recall, and mAP metrics are decent and suggest that the model needs more improvement to localize the patterns according to the strictness of the IoU (Intersection over Union) thresholds used in the evaluation. However, the decreasing loss values during training indicate that the model was learning to classify patterns correctly. This model is not the best but can serve as a good baseline to build from.

D. Inference Testing

We tested the trained model on real-world data by generating new charts for several major tech stocks (AAPL, MSFT, GOOGL, AMZN, TSLA) and performing inference on these charts. The inference speed was approximately 6.5ms per image on a NVIDIA A100-SXM4-80GB GPU, demonstrating the model's capability for real-time analysis.

In our test cases, the model did not detect all the patterns in the generated charts, which could be due to several factors:

1) The absence of clear patterns in the specific period analyzed
2) The conservative confidence threshold (0.3) used for detection
3) The model's training data was not proportionate, meaning we didn't have more images for certain patterns (eg, Triangle Pattern)

These results highlight areas for improvement in future iterations of the model.

V. DISCUSSION AND SUMMARY

This paper presented a deep learning approach to candlestick pattern detection using the YOLOv8 object detection framework. Our work demonstrates the feasibility of applying computer vision techniques to financial technical analysis, potentially offering a more flexible alternative to traditional rule-based pattern detection methods.

A. Key Findings

1) **Dataset Generation**: We successfully created a dataset of 1,628 annotated candlestick chart images covering six common patterns. This dataset can serve as a foundation for future research in this area.
2) **Training Dynamics**: The model showed good convergence in terms of classification loss, indicating that it was learning to distinguish between different pattern types. However, the values for localization metrics suggest that the model faced challenges in precisely localizing patterns according to the ground truth annotations.
3) **Real-time Capability**: With an inference time of approximately 6.5ms per image, the model demonstrates capability for real-time application in trading systems.

B. Limitations and Challenges

Several limitations and challenges were identified during this research:

1) **Annotation Precision**: The precise localization of candlestick patterns is inherently challenging due to their variable size and appearance. This may have contributed to the model's difficulty in achieving high localization metrics.
2) **Pattern Imbalance**: Some patterns, like Triangle (4.1% of the dataset), were significantly underrepresented compared to others like StockLine (24.6%). This imbalance could have affected the model's ability to learn these patterns effectively.
3) **Validation Metrics**: The values for precision, recall, and mAP metrics are concerning and warrant further investigation. They might indicate issues with the evaluation methodology or the annotation format.

C. Future Work

Based on our findings, several directions for future work emerge:

1) **Improved Annotation Methodology**: Developing a more robust approach to annotating candlestick patterns could improve the model's localization performance. This might involve using alternative representation formats beyond bounding boxes.
2) **Dataset Expansion**: Increasing the size and diversity of the dataset, particularly for underrepresented patterns, could enhance the model's generalization capability.
3) **Alternative Architectures**: Exploring different detection architectures or hybrid approaches that combine rule-based and learning-based methods could potentially yield better results.
4) **Pattern Trading Strategy**: Developing and backtesting a trading strategy based on the detected patterns would provide valuable insights into the practical utility of the system.

In conclusion, our work represents a novel approach to candlestick pattern detection that leverages recent advances in deep learning. Despite facing challenges in localization metrics, the model demonstrated the potential of object detection techniques for financial pattern recognition. With further refinements, such approaches could become valuable tools for traders and financial analysts, complementing traditional technical analysis methods.

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