Interpretable image-based deep learning for price trend prediction in ETF markets

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一、 Introduction

探討將金融時間序列轉換為圖像的可行性，建立CNN+通道注意力機制的CS-ACNN模型，利用圖像化的深度學習模型來提高ETF價格趨勢的預測準確性。

資料集:

S&P 500 ETF (SPY)	January 29, 1993 - February 10, 2022
the Hang Seng Index ETF (2833.HK)	September 21, 2004 - February 10, 2022
SSE 50 ETF (510050.SS)	February 23, 2005 - February 10, 2022

training set (64%), a validation set (16%), and a test set (20%)

模型目標是對價格走勢進行預測(上漲or下跌)，而非預測確切的股票價格。

二、金融時間序列轉換為圖像-Augmented candlestick charts

1.增加訓練數據量

2.增加學習特徵

3.提高模型泛化

(a) Original candlestick chart.

(b) Enhanced candlestick center. >強調o、c 、漲跌幅

(c) Weakened candlestick center. >強調上下隱線

(d) Enhanced candlestick edges. >強調h、c、價格波動

(e) Weakened candlestick edges.

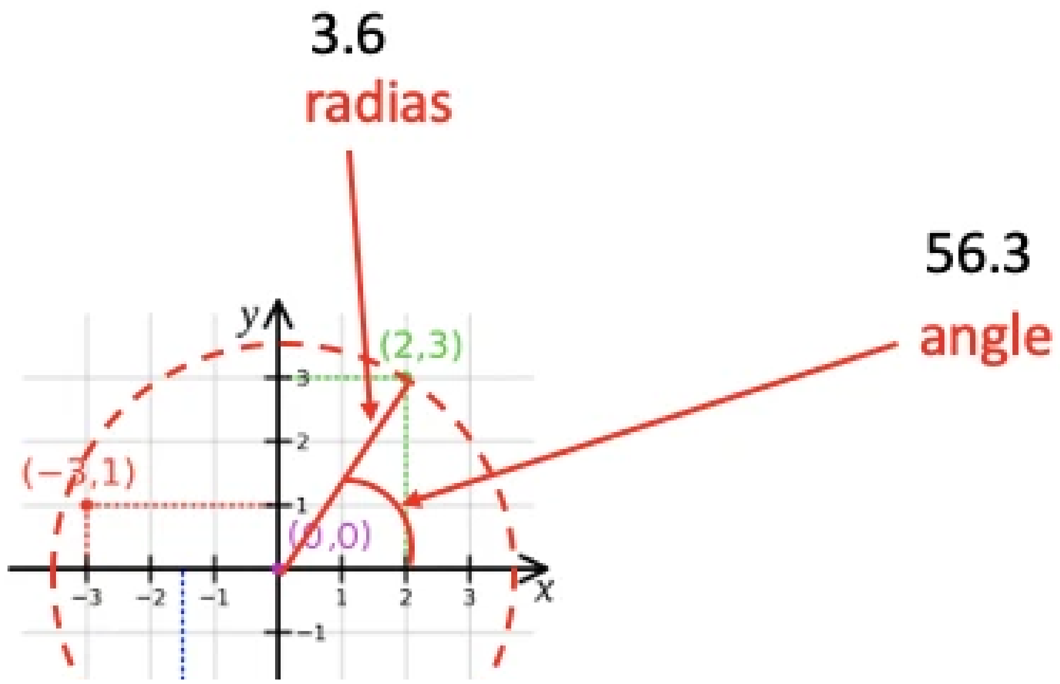
(a) (b) (c) (d) (e)

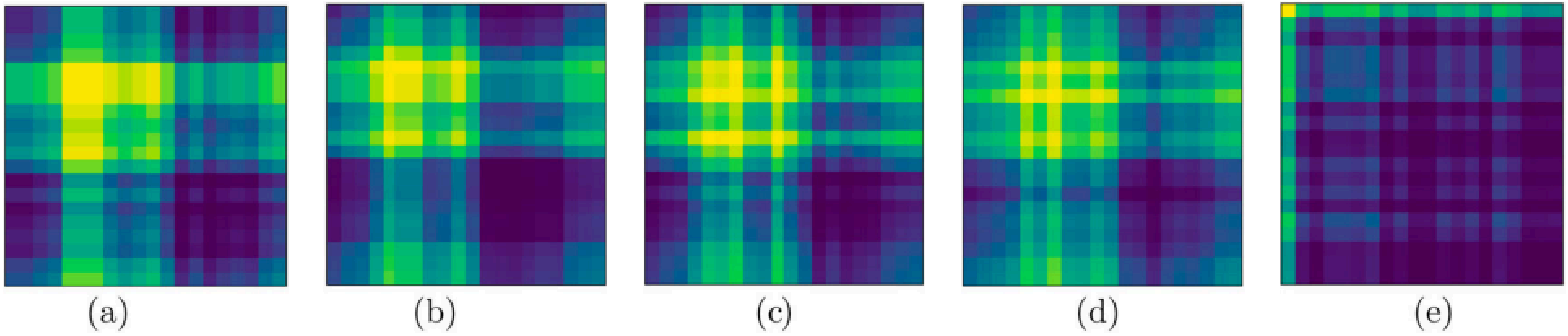
二、金融時間序列轉換為圖像-Gramian angular field (GAF)

1.將x(OHLCV)正規化，使其落在[0,1]

2.將時間序列資料表示為極座標，值為角度、時間為半徑

3.透過每一點之間的cos值，製作矩陣





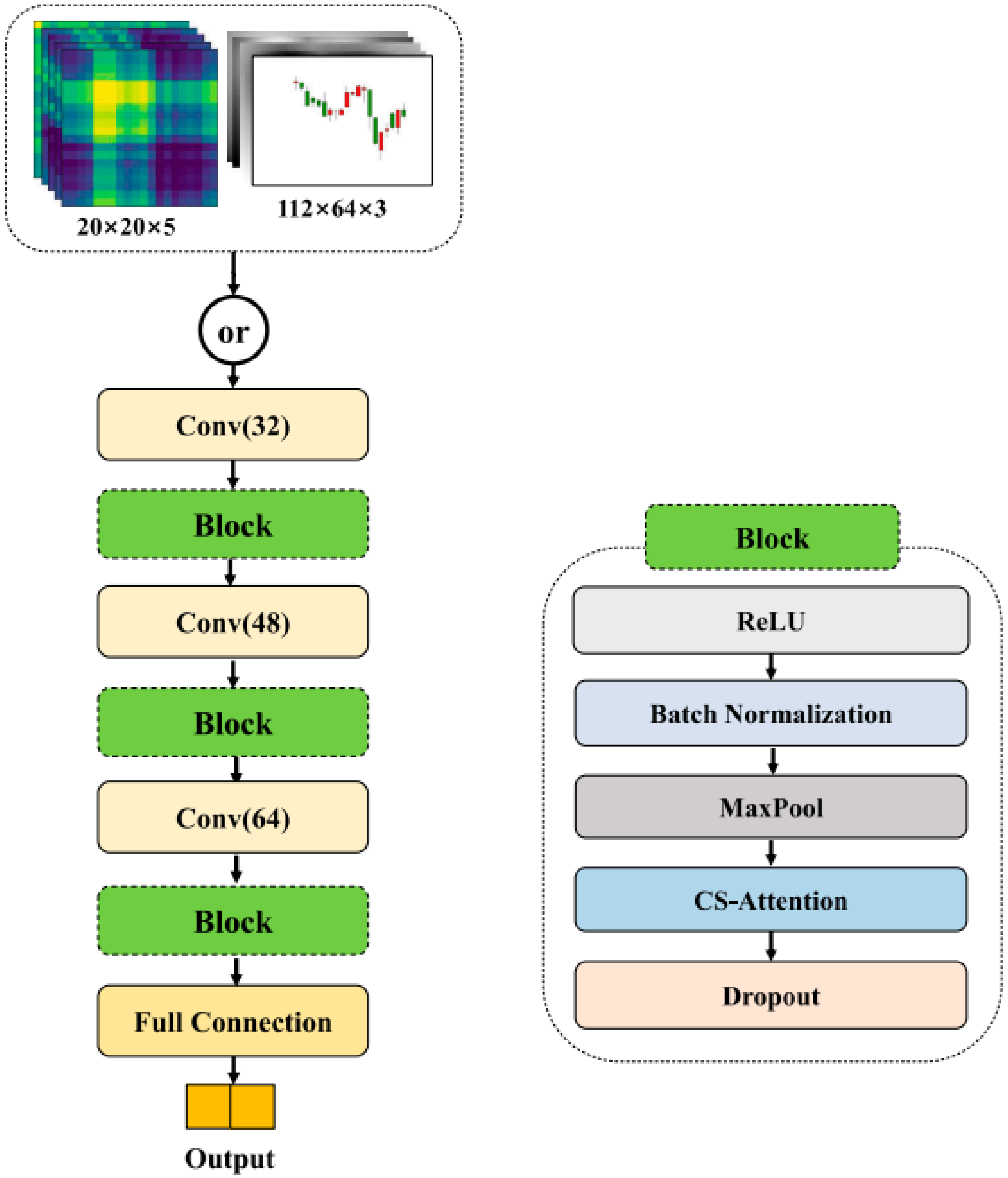
三、模型流程-CS-ACNN

1.Batch Normalization

減少不同批次數據之間的變異性，並降低過擬合的風險。

2.CS-Attetion

判斷不同通道(特徵)的重要性，並根據其重要性分配不同的權重。使模型能夠聚焦於關鍵特徵的通道，提升預測準確性。



四、Model-Performance

Model	Image	Accuracy	Precision	Recall	Specificity	AUC
Panel A: SPY						
CS-ACNN	GAF	0.567	0.591	0.764	0.312	0.547
	Candlestick	**0.573**	**0.597**	0.753	0.339	**0.568**
SVM	GAF	0.517	0.553	0.764	0.196	0.491
	Candlestick	0.565	0.565	**1.000**	0.000	0.500
CNN-TA	GAF	0.542	0.567	0.803	0.202	0.522
	Candlestick	0.540	0.580	0.660	**0.384**	0.532
Panel B: 2833.HK						
CS-ACNN	GAF	0.565	0.609	0.602	0.519	**0.555**
	Candlestick	**0.571**	**0.638**	0.523	**0.631**	0.551
SVM	GAF	0.504	0.567	0.445	0.578	0.491
	Candlestick	0.554	0.554	**1.000**	0.000	0.500
CNN-TA	GAF	0.524	0.591	0.460	0.604	0.522
	Candlestick	0.541	0.534	0.561	0.521	0.527
Panel C: 510050.SS						
CS-ACNN	GAF	0.551	0.563	0.637	0.457	0.545
	Candlestick	**0.566**	**0.593**	0.545	**0.590**	**0.549**
SVM	GAF	0.511	0.532	0.531	0.488	0.518
	Candlestick	0.523	0.523	**1.000**	0.000	0.500
CNN-TA	GAF	0.530	0.546	0.604	0.449	0.522
	Candlestick	0.523	0.528	0.514	0.533	0.526

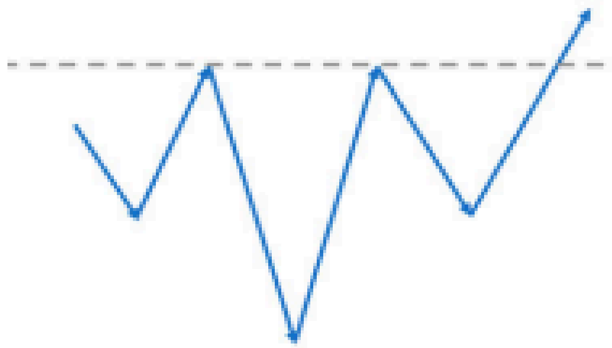
五、Profitability

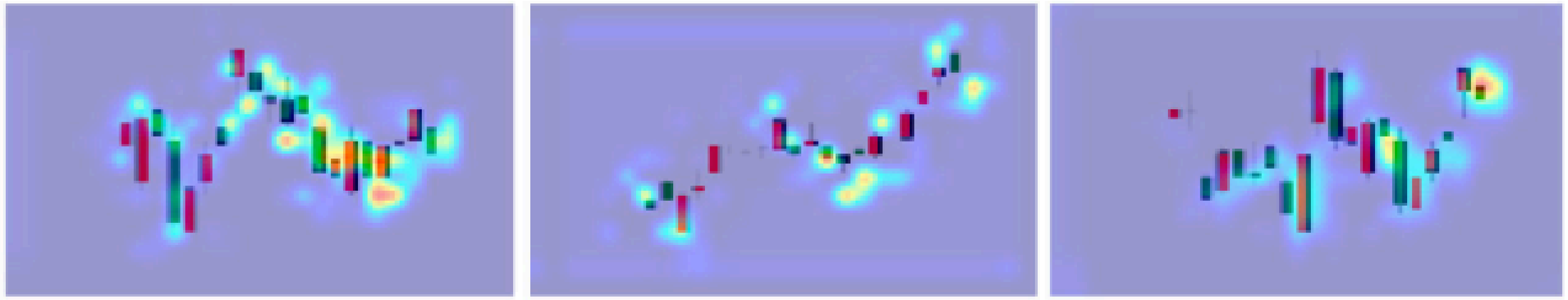
Model	Input	AnnualR		SR		MDD	
		long-only	long-short	long-only	long-short	long-only	long-short
Panel A: SPY							
CS-ACNN	Time Series	18.24%	19.94%	1.48	0.99	9.70%	28.60%
	GAF	24.14%	31.72%	1.44	1.65	20.13%	19.43%
	Candlestick	**25.25%**	**33.95%**	1.57	**1.78**	17.22%	**17.22%**
SVM	Time Series	15.38%	14.23%	0.74	0.67	34.10%	34.10%
	GAF	12.15%	7.77%	0.59	0.32	33.08%	43.21%
	Candlestick	16.53%	16.53%	0.80	0.80	34.10%	34.10%
CNN-TA	GAF	15.49%	14.45%	0.78	0.69	28.74%	28.74%
	Candlestick	15.38%	14.47%	0.77	0.73	27.13%	29.33%
LSTM	Time Series	12.00%	7.45%	**1.97**	0.30	8.47%	38.48%
1D-CNN	Time Series	10.72%	4.90%	1.96	0.16	**3.97**%	56.48%
Buy-and-hold		17.81%		0.87		34.10%	
Panel B: 2833.HK							
CS-ACNN	Time Series	10.53%	18.88%	0.58	0.83	14.65%	14.64%
	GAF	22.12%	42.05%	1.32	2.00	10.82%	11.01%
	Candlestick	**26.71%**	**51.24%**	**1.75**	**2.46**	**7.13**%	**7.93%**
SVM	Time Series	2.14%	2.14%	0.01	0.01	25.43%	25.43%
	GAF	8.50%	14.84%	0.45	0.63	16.92%	15.96%
	Candlestick	2.15%	2.15%	0.01	0.01	25.67%	25.67%
CNN-TA	GAF	12.84%	23.51%	0.76	1.06	12.63%	13.99%
	Candlestick	13.34%	17.48%	0.88	1.21	13.31%	15.59%
LSTM	Time Series	12.30%	22.42%	0.25	1.01	14.18%	14.42%
1D-CNN	Time Series	14.64%	27.12%	1.28	1.24	10.82%	23.17%
Buy-and-hold		0.27%		−0.08		25.67%	

六、BlackBox解釋性-Grad-CAM

論文中使用Grad-CAM技術顯示模型在預測上漲or下跌時的關鍵區域。
將模型熱圖與傳統技術分析型態做比較，模型能有效捕捉股價關鍵轉折點。

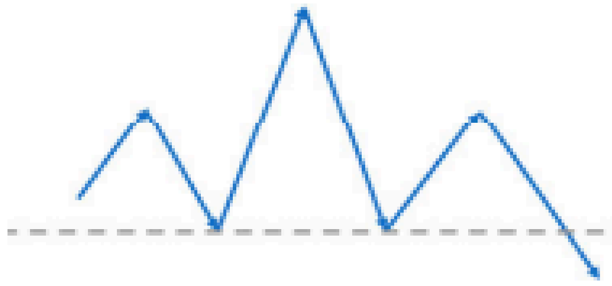
Up: inverted head and shoulders

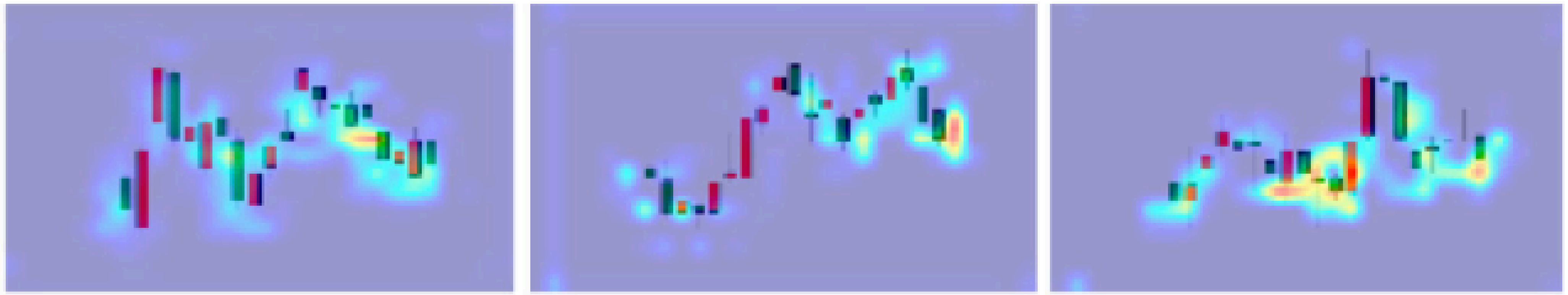




(a)

Down: head and shoulders





(b)

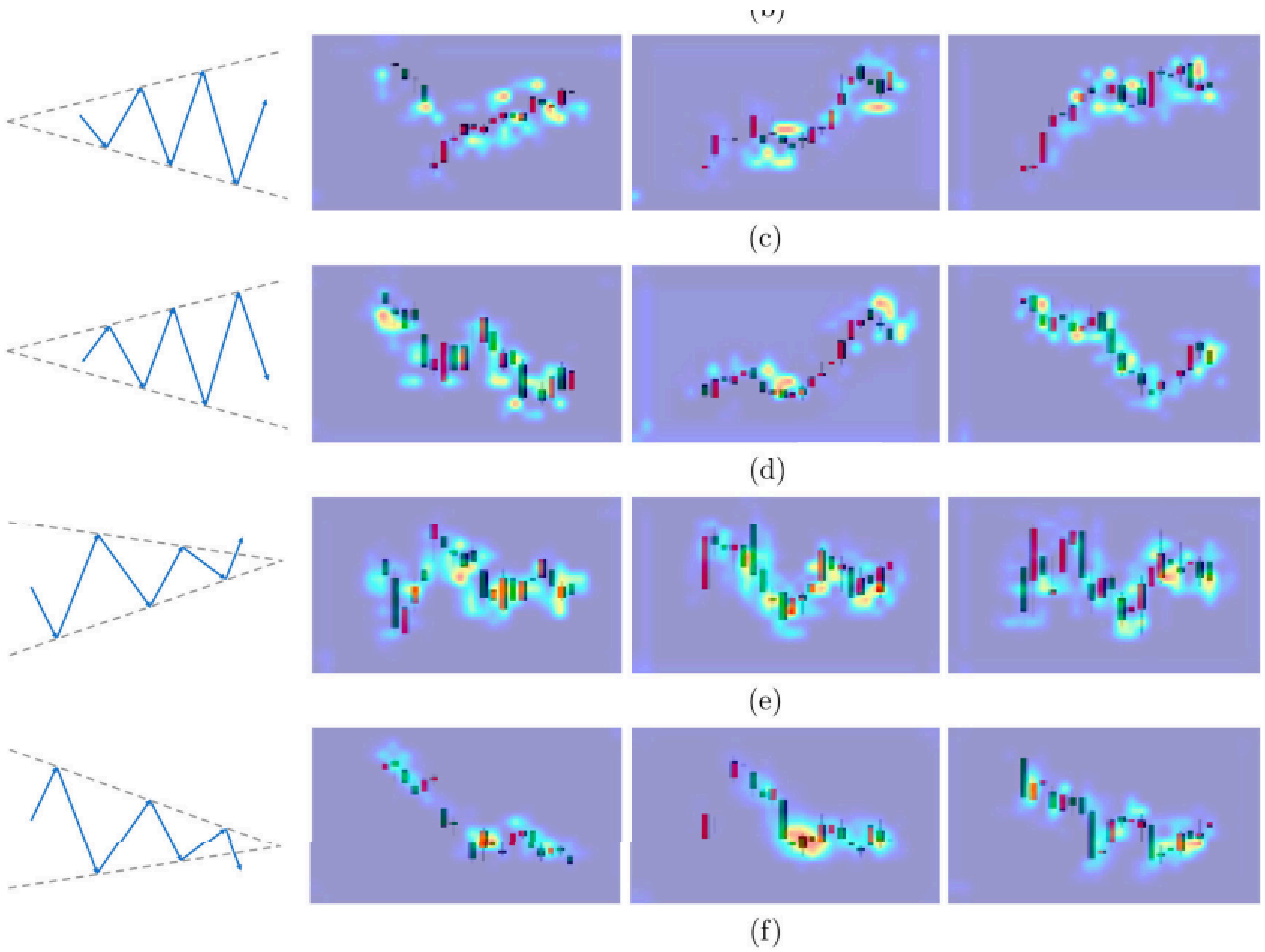
六、BlackBox解釋性-Grad-CAM

Up: broadening bottom

Down: broadening top

Up: triangle bottom

Down: triangle top.



七、Stock Pattern

Table 7. Number of candlestick charts identified with different technical patterns and the accuracy of the CS-ACNN model when using candlestick charts with these technical patterns.

Metric	All	HS	IHS	BTOP	BBOT	TTOP	TBOT
Panel A: SPY							
Number	1,463	718	707	198	84	123	178
Accuracy	0.573	0.570	0.576	0.551	0.560	0.561	0.573
Panel B: 2833.HK							
Number	858	288	312	52	49	76	44
Accuracy	0.571	0.573	0.571	0.558	0.571	0.566	0.568
Panel C: 510050.SS							
Number	826	374	402	54	72	51	50
Accuracy	0.566	0.564	0.567	0.574	0.583	0.569	0.580

八、Conclusion

- 作者認為將金融時間序列轉換為圖像能夠提升模型能力，因為這類似於視覺認知，使模型透過圖表去解釋數據之間的關聯性。利用從金融圖像中提取特徵，增強技術分析的預測效能。

- 未來可以在圖像中加入更多信息，例如技術指標、公司基本面和投資者情緒。

資料:https://www.tandfonline.com/doi/full/10.1080/1351847X.2023.2275567