Prediction in the Stock Market using Deep Learning

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Agenda

- Introduction
- Technical Indicators
- Data Preparation
- Multi-sized Filter Maps and Convolutional Neural Network for Prediction
- Experiments & Results

Introduction

- Types of Analysis in Stock Market

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  - Fundamental Analysis
  - Technical Analysis

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    - This approach involves studying a company's financial statements, earnings reports, management team, industry trends, and economic indicators to predict a stock's future performance.

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  - Fundamental Analysis
    - This approach involves studying a company's financial statements, earnings reports, management team, industry trends, and economic indicators to predict a stock's future performance.
    - It uses metrics like price-to-earnings ratios (P/E), earnings per share (EPS), and dividend yields (DY) to assess the intrinsic value of a stock.

Introduction

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  - Technical Analysis
    - Technical analysts study past price and trading volume data to identify patterns, trends, and support/resistance levels.

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- Types of Analysis in Stock Market
  - Technical Analysis
    - Technical analysts study past price and trading volume data to identify patterns, trends, and support/resistance levels.
    - They use charts and various technical indicators (e.g., moving averages, relative strength index) to predict future price movements.

Introduction

- Prediction in Stock Market

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- Prediction in Stock Market
  - Predicting the movement
  - Predicting the closing price
  - Portfolio optimization

Technical Indicators

- Smoothing Indicators
- Momentum Indicators
- Overbought/Oversold Signal
- Volume Indicators
- Volatility Indicators
- Trend Indicators

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  - Examples include moving averages and exponential moving averages (EMAs).

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  - Common momentum indicators include the Relative Strength Index (RSI) and the Moving Average Convergence Divergence (MACD).

Technical Indicators

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  - These indicators suggest when a stock may be overbought (potentially due for a price decline) or oversold (potentially due for a price increase).

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Technical Indicators

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  - The On-Balance Volume (OBV) and Volume Weighted Average Price (VWAP) are examples.

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  - They gauge the extent of price fluctuations.
  - Bollinger Bands and the Average True Range (ATR) are popular indicators for measuring volatility.

Technical Indicators

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  - Examples include trendlines, Moving Averages, and Average Directional Index (ADX).

Data Preparation

Table 1 All technical indicators used in the experiments

Indicator type	*Indicator*	*Equation*
Smoothing	SMA	$\frac{\sum_{i=1}^{n} C_{t-i}}{n}$
	WMA	$\frac{\sum_{i=1}^{n} i*C_{t-i}}{\sum_{i=1}^{n} i}$
	EMA	$EMA_{t-1} + \frac{2}{1+n} * (C_t - EMA_{t-1})$
	HMA	$WMA(2 * WMA(data, n/2) - WMA(data, n)), \sqrt{n})$
Momentum	ROC	$C_t - C_{t-n}$
	MACD	$MACD_{t-1} + \frac{2}{1+n} * ((EMA(12)_t - EMA(26)_t) - MACD_{t-1})$
	RSI	$100 - \frac{100}{1+\frac{\sum_{i=0}^{n-1} Up_{t-i}}{\sum_{i=0}^{n-1} Dw_{t-i}}}$
	Williams %R	$\frac{HH_n - C_t}{HH_n - LL_n} * 100$
	MFI	$100 - \frac{100}{1+\frac{TP*PV_t}{TP*NV_t}}$
	Stochastic %K	$\frac{C_t - LL_{t-n}}{HH_{t-n} - LL_{t-n}} * 100$
	Stochastic %D	$\frac{\sum_{i=0}^{n-1} \%K_{t-i}}{n}$
Overbought/oversold signals	CCI	$\frac{TP_t - SMA_{TP_t}}{0.015*MD_t}$
Volume	ADL	$ADL_{t-1} + MF_t * V_t$
	CMF	$\frac{\sum_{i=0}^{n-1} MF_t*V_{t-i}}{\sum_{i=0}^{n-1} V_{t-i}}$
	OBV	$OBV_{t-1} + X$ $X = (+V_t)$ if $C_t > C_{t-1}$ else $(-V_t)$
	EMV	$SMA(n)\left\{\frac{(H_t+L_t)/2-(H_{t-1}+L_{t-1})/2}{(V_t/100{,}000{,}000)/(H_t-L_t)}\right\}$
Volatility	ATR	$\frac{ATR_{t-1}*(n-1)+TR_t}{n}$
	Mass index	$\frac{EMA(n)\{H_t-L_t\}}{EMA(n)\{EMA(n)\{H_t-L_t\}\}}$
Trends	Ichimoku	*Span A:* $((H_9 + L_9)/2 + (H_{26} + L_{26})/2)/2$ *Span B:* $(H_{52} + L_{52})/2$
	Aroon Index	ArUp: $\frac{25-(days\ since\ H_{25})}{25} * 100$ ArDown: $\frac{25-(days\ since\ L_{25})}{25} * 100$ *Aroon Oscillator* = ArUp − ArDown
	ADX	$PDI_t = \frac{\max(H_t-H_{t-1},0)}{ATR_t}, MDI_t = \frac{\max(L_t-L_{t-1},0)}{ATR_t}$ $DX_t = \frac{100 * (PDI_t - MDI_t)}{PDI_t + MDI_t}$ $ADX_t = \frac{(ADX_{t-1} * (n-1) + DX_t)}{n}$

Data Preparation

- Computing Technical Indicators

Notes: The indicators used by specific models are mentioned explicitly. C_t is the closing price, H_t and L_t are the high and low for the day t. V_t is the traded volume, PV_t is volume when price rises, NV_t is volume when price falls. $WMA(data, n)$ returns WMA on the dataset for window n. Up_t and Dw_t are the upward and downward price changes. HH_n and LL_n are the highest high and the lowest low for n time periods. $TP_t = \frac{H_t+L_t+C_t}{3}$, $MD_t = \frac{\sum_{i=1}^{n} \|TP_{t-i+1} - SM_t\|}{n}$. $MF_t = \frac{(C_t-L_t)-(H_t-C_t)}{H_t-L_t}$, $TR_t = \max((H_t - L_t), (H_t - C_t), (C_t - L_t))$.

Data Preparation

- Data
  - 2 July 2008 to 31 March 2020 (80%, 20%)
- Data Distribution in Different Stocks

Stocks	*Train set UP*	*Train set DOWN*	*Train set total*	*Test set UP*	*Test set DOWN*	*Test set total*
BPCL	1,023	1,028	2,051	262	251	513
HDFCBANK	1,042	1,010	2,052	282	231	513
HINDUNILVR	1,032	1,019	2,051	271	242	513
RELIANCE	1,009	1,042	2,051	269	244	513
SUNPHARMA	1,065	986	2,051	240	273	513

Data Preparation

- Target Variable Labelling

Algorithm 1 Target variable labelling

for $curr\_date \in dates$ **do**
  if $price[curr\_date + 1] > price[curr\_date]$ **then**
    $label[curr\_date + 1] \leftarrow 1$
  else
    $label[curr\_date + 1] \leftarrow 0$
  end if
end for

Data Preparation

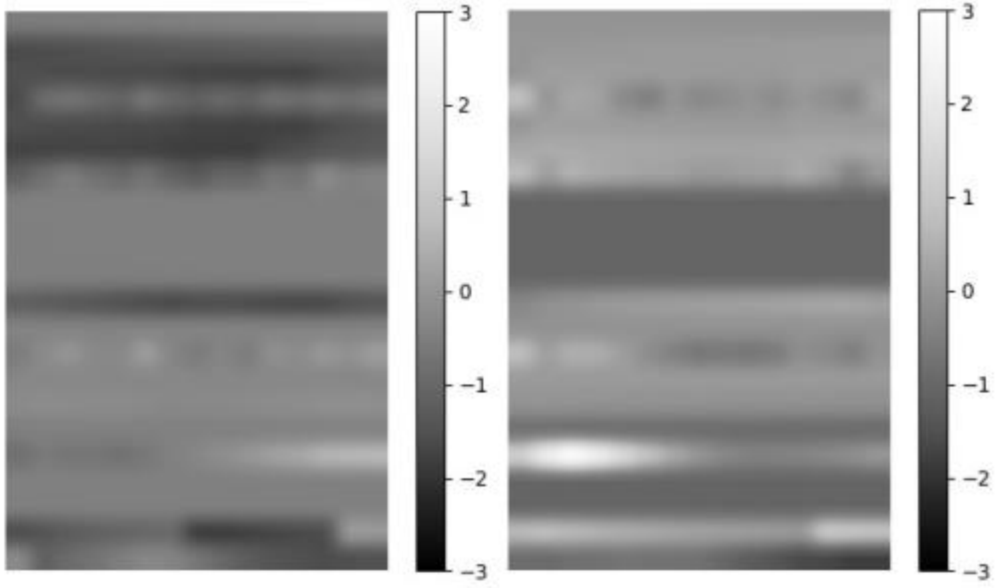
- Can we spatially map technical indicators?

Sezer, Omer Berat, and Ahmet Murat Ozbayoglu. "Algorithmic financial trading with deep convolutional neural networks: Time series to image conversion approach." Applied Soft Computing 70 (2018): 525-538.

Data Preparation

- Spatial Mapping

Figure 1 22 × 15 spatial mapping of stock market data given as input, (a) UP (b) DOWN



(a) (b)

The x-axis represents the 15 different window sizes from 6–20 for each indicator, while the y-axis holds the 22 different indicators in this sequence: ‘adj_open’, ‘adj_high’, ‘adj_low’, ‘adj_close’, ‘volume’, ‘macd_w’, ‘rsi_w’, ‘wr_w’, ‘mfi_w’, ‘stochk_w’, ‘stochd_w’, ‘roc_w’, ‘sma_w’, ‘wma_w’, ‘ema_w’, ‘hma_w’, ‘cci_w’, ‘adl’, ‘cmf_w’, ‘obv’, ‘emv_w’, ‘atr_w’, ‘mass_ind_w’, ‘ichimoku_a’,‘ichimoku_b’, ‘aroon_ind_w’ and ‘adx_w’.

Premise

- Salient parts in the image can have extremely large variations in size.
- For instance, an image with a dog can be either of the following, as shown below.
- The area occupied by the dog is different in each image.

From left: A dog occupying most of the image, a dog occupying a part of it, and a dog occupying very little space (Images obtained from Unsplash.com).

https://towardsdatascience.com/a-simple-guide-to-the-versions-of-the-inception-network-7fc52b863202
Szegedy, Christian, et al. "Going deeper with convolutions." Proceedings of the IEEE conference on computer vision and pattern recognition. 2015.

Premise

- Because of this huge variation in the location/size of the information, choosing the right kernel size for the convolution operation becomes tough.

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- A larger kernel is preferred for information that is distributed more globally, and a smaller kernel is preferred for information that is distributed more locally.

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Premise

- Because of this huge variation in the location of the information, choosing the right kernel size for the convolution operation becomes tough.

- A larger kernel is preferred for information that is distributed more globally, and a smaller kernel is preferred for information that is distributed more locally.

- Naively stacking large convolution operations is computationally expensive.

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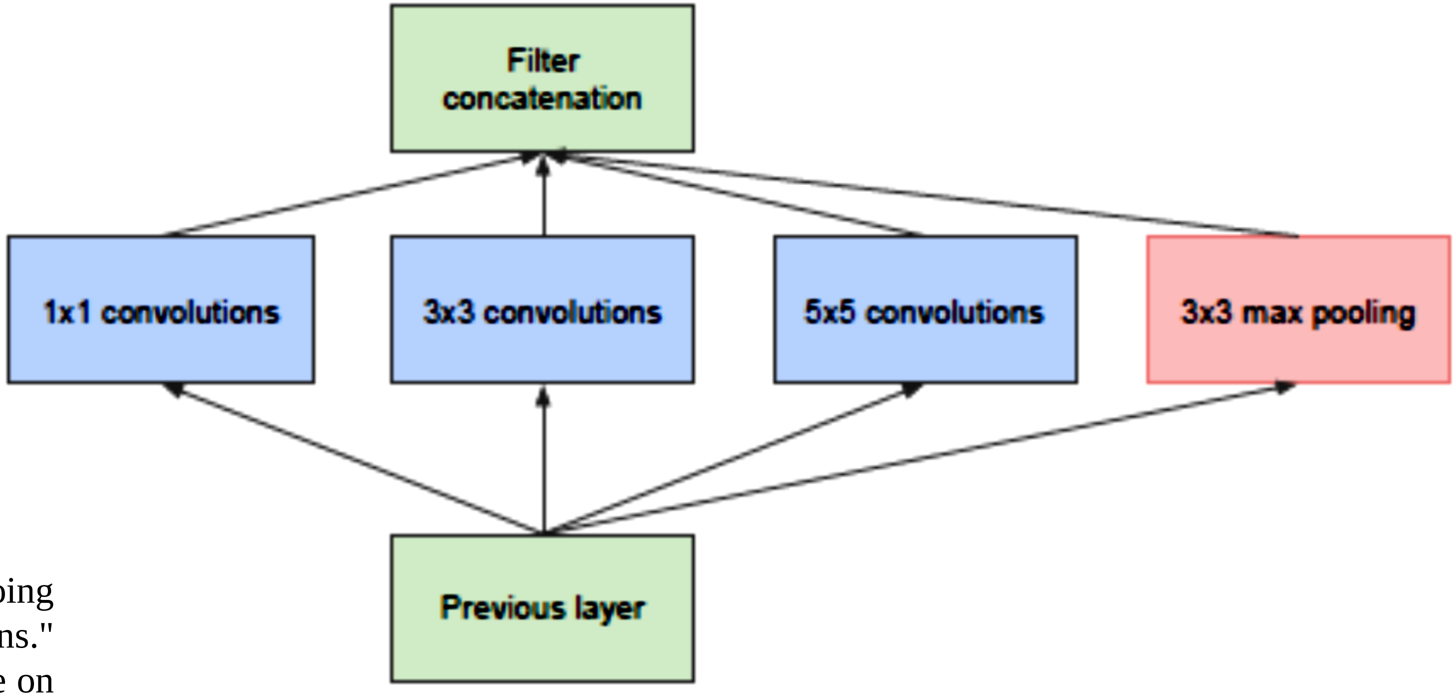
Premise

- What is the solution?
  - Why not have filters with multiple sizes operate on the same level?
  - The network essentially would get a bit “wider” rather than “deeper”. The authors designed the inception module to reflect the same.

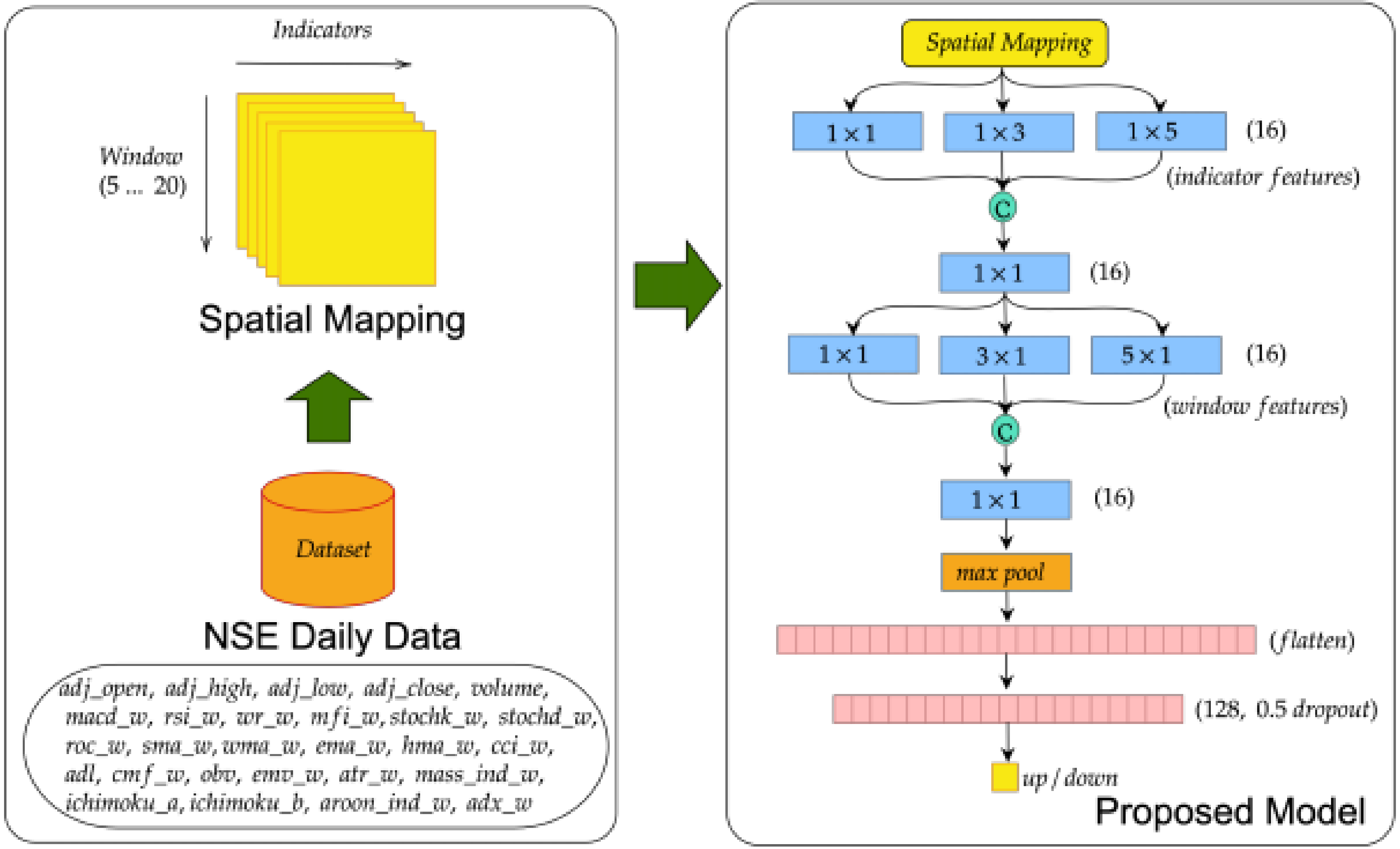


(a) Inception module, naïve version

Szegedy, Christian, et al. "Going deeper with convolutions." Proceedings of the IEEE conference on computer vision and pattern recognition. 2015.

Proposed Approach

- Multi-sized Filter Maps and Convolutional Neural Network



Experiments & Results

- Data
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Experimental Evaluation

- Results - Predicting next-day stock price movement

Results CNN-TA

Stocks	*Precision UP*	*Precision DOWN*	*Precision*	*Recall UP*	*Recall DOWN*	*Recall*	*F1-score UP*	*F1-score DOWN*	*F1-score*
BPCL	0.68	0.77	0.73	0.83	0.59	0.71	0.75	0.67	0.71
HDFCBANK	0.74	0.77	0.76	0.84	0.63	0.74	0.79	0.69	0.74
HINDUNILVR	0.76	0.75	0.76	0.79	0.73	0.76	0.77	0.74	0.76
RELIANCE	0.79	0.69	0.74	0.68	0.80	0.74	0.73	0.74	0.74
SUNPHARMA	0.83	0.81	0.82	0.76	0.87	0.82	0.79	0.84	0.82
Avg.	0.76	0.76	0.76	0.78	0.72	0.75	0.77	0.74	0.75

Results – Proposed Approach

Stocks	*Precision UP*	*Precision DOWN*	*Precision*	*Recall UP*	*Recall DOWN*	*Recall*	*F1-score UP*	*F1-score DOWN*	*F1-score*
BPCL	0.77	0.79	0.78	0.81	0.75	0.78	0.79	0.77	0.78
HDFCBANK	0.79	0.77	0.78	0.82	0.73	0.78	0.81	0.75	0.78
HINDUNILVR	0.84	0.80	0.82	0.81	0.83	0.82	0.83	0.81	0.82
RELIANCE	0.83	0.75	0.79	0.77	0.82	0.80	0.79	0.78	0.79
SUNPHARMA	0.78	0.87	0.83	0.86	0.79	0.83	0.82	0.83	0.83
Avg.	0.80	0.80	0.80	0.81	0.78	0.80	0.81	0.79	0.80

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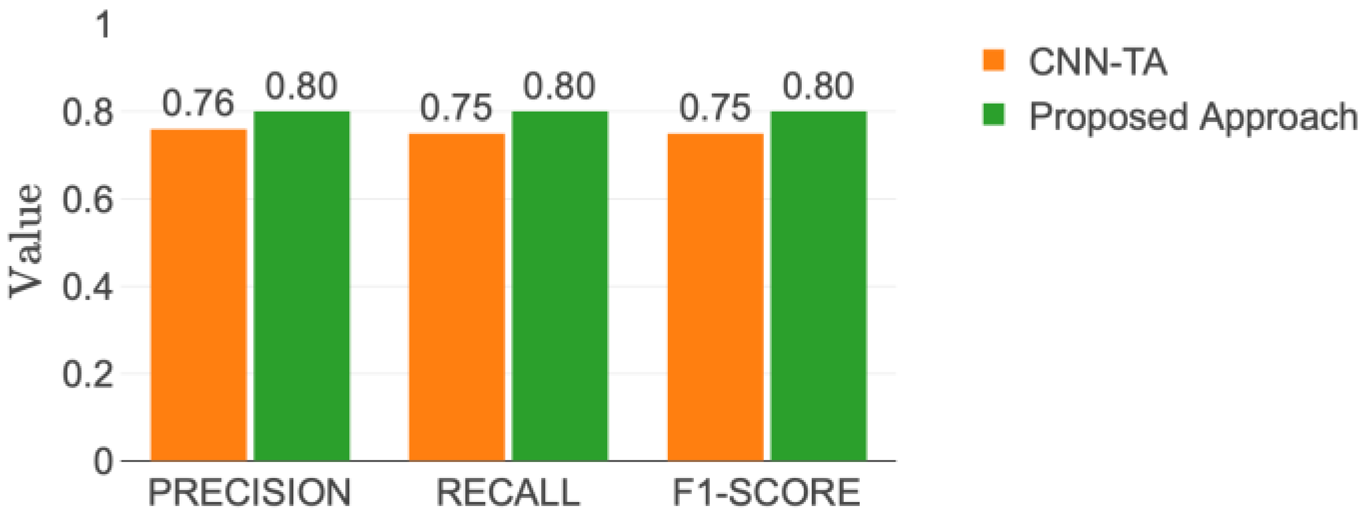
Experimental Evaluation

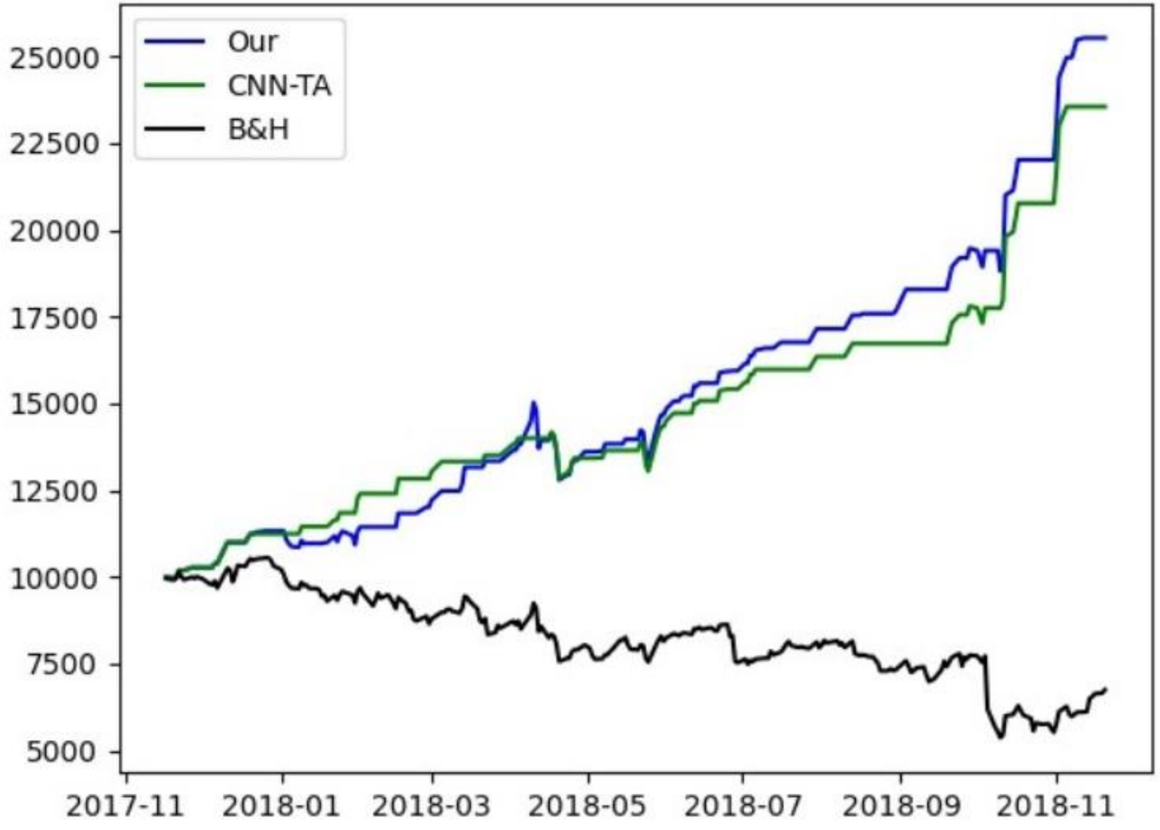
- Results - Predicting next-day stock price movement

Figure 3 Comparison of our approach with CNN-TA for precision, recall and F1-score (see online version for colours)

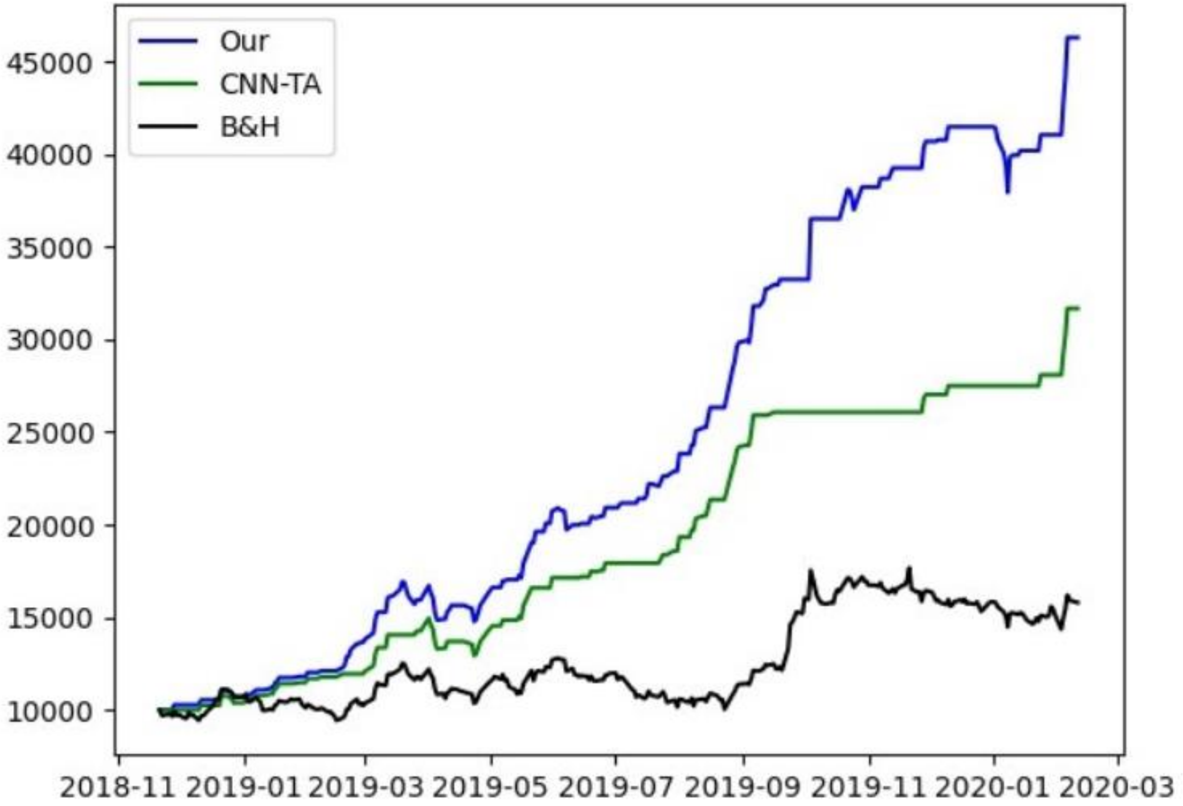


Experimental Evaluation

- Results – Returns from the Trading Strategy (BPCL)



(a)

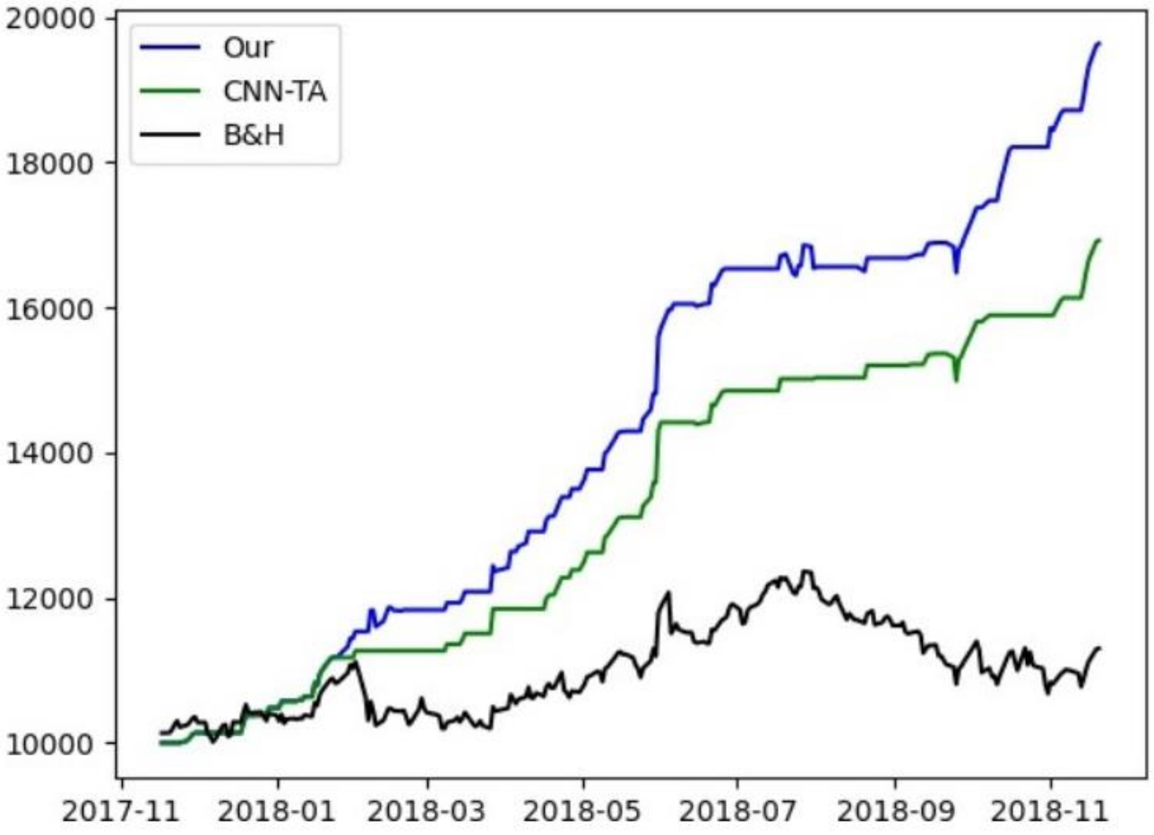


(b)

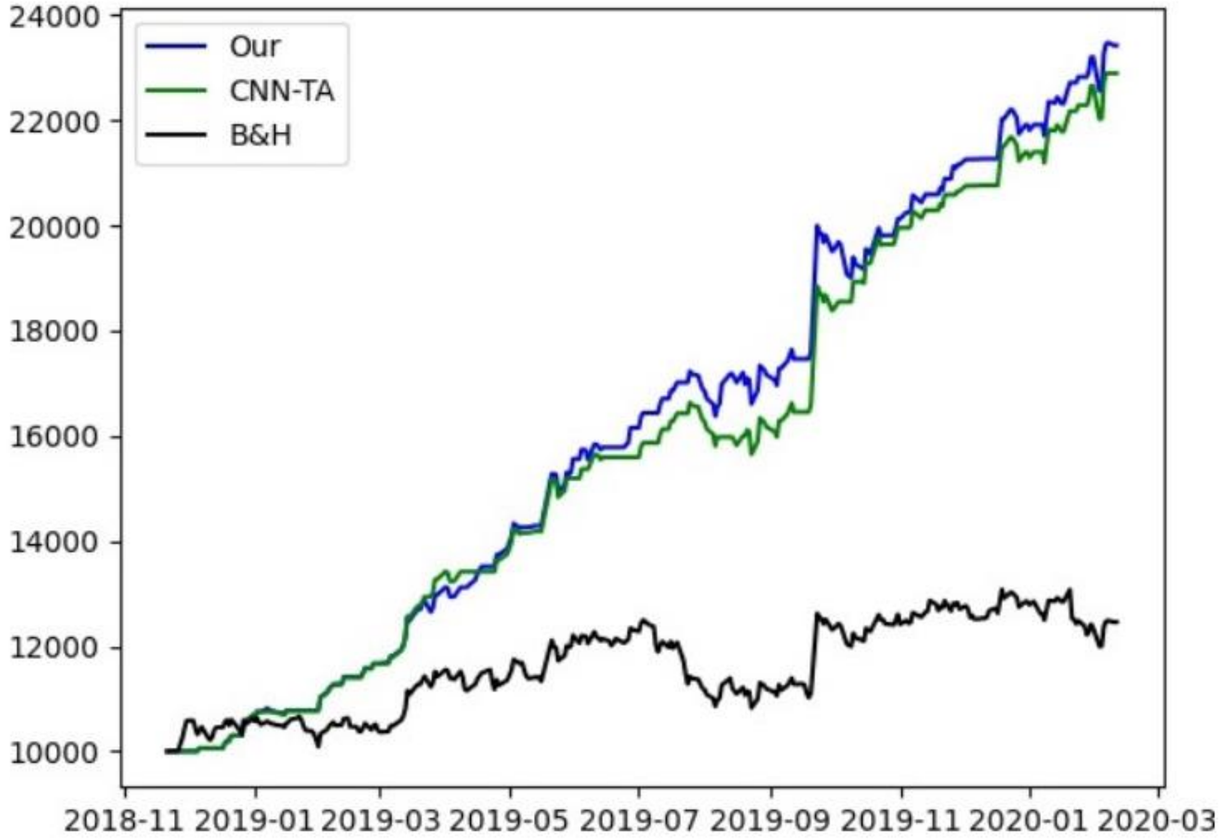
Comparison of BPCL returns for two testing years, (a) comparison of BPCL returns (2017–2018), (b) comparison of BPCL returns (2018–2020)

Experimental Evaluation

- Results – Returns from the Trading Strategy (HDFC BANK)



(a)

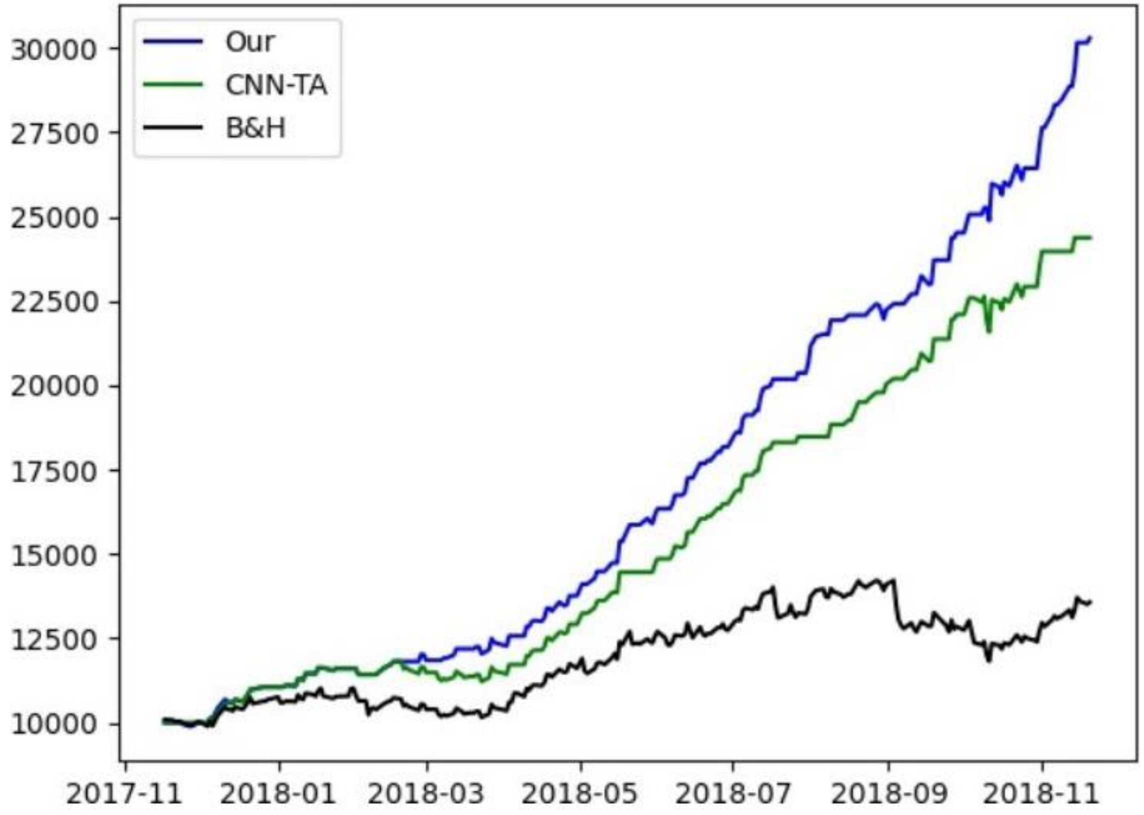


(b)

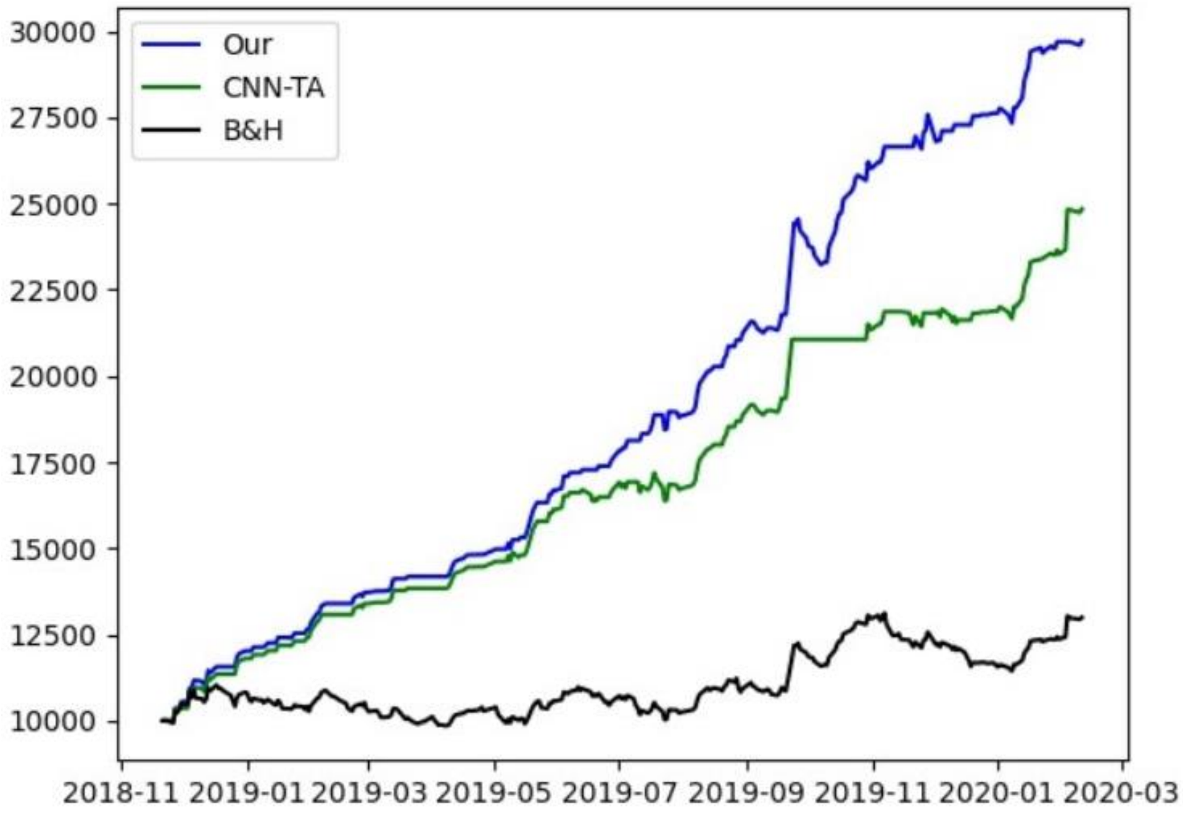
Comparison of HDFCBANK returns for two testing years, (a) comparison of HDFCBANK returns (2017–2018) (b) comparison of HDFCBANK returns (2018-2020)

Experimental Evaluation

- Results – Returns from the Trading Strategy (HINDUNILVR)



(a)

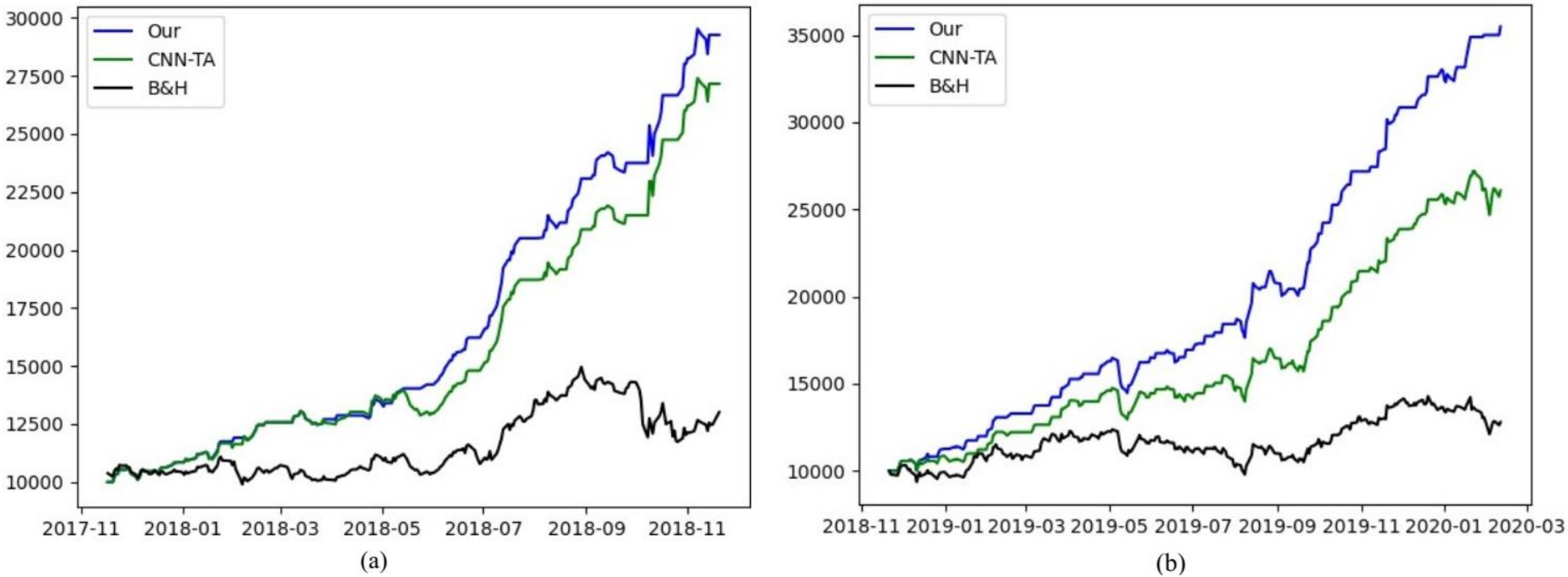


(b)

Comparison of HINDUNILVR returns for two testing years, (a) comparison of HINDUNILVR returns (2017–2018) (b) comparison of HINDUNILVR returns (2018–2020)

Experimental Evaluation

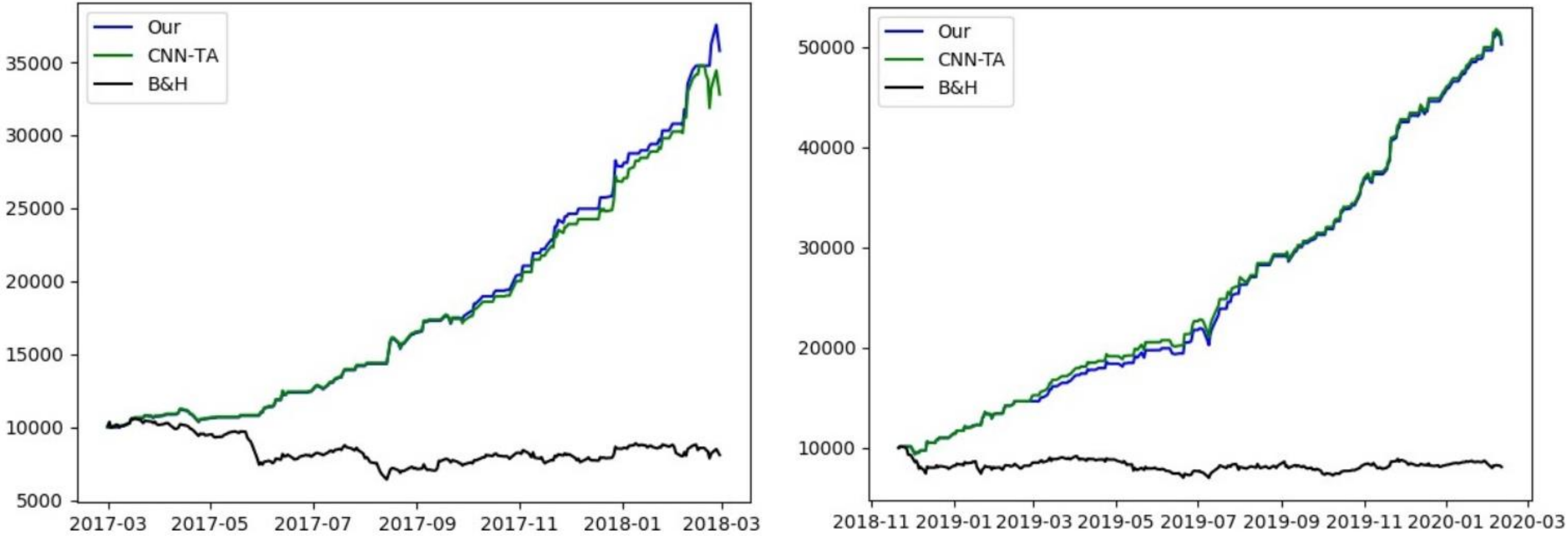
- Results – Returns from the Trading Strategy (RELIANCE)



Comparison of RELIANCE returns for two testing years, (a) comparison of RELIANCE returns (2017–2018) (b) comparison of RELIANCE returns (2018–2020)

Experimental Evaluation

❑ Results – Returns from the Trading Strategy (SUNPHARMA)

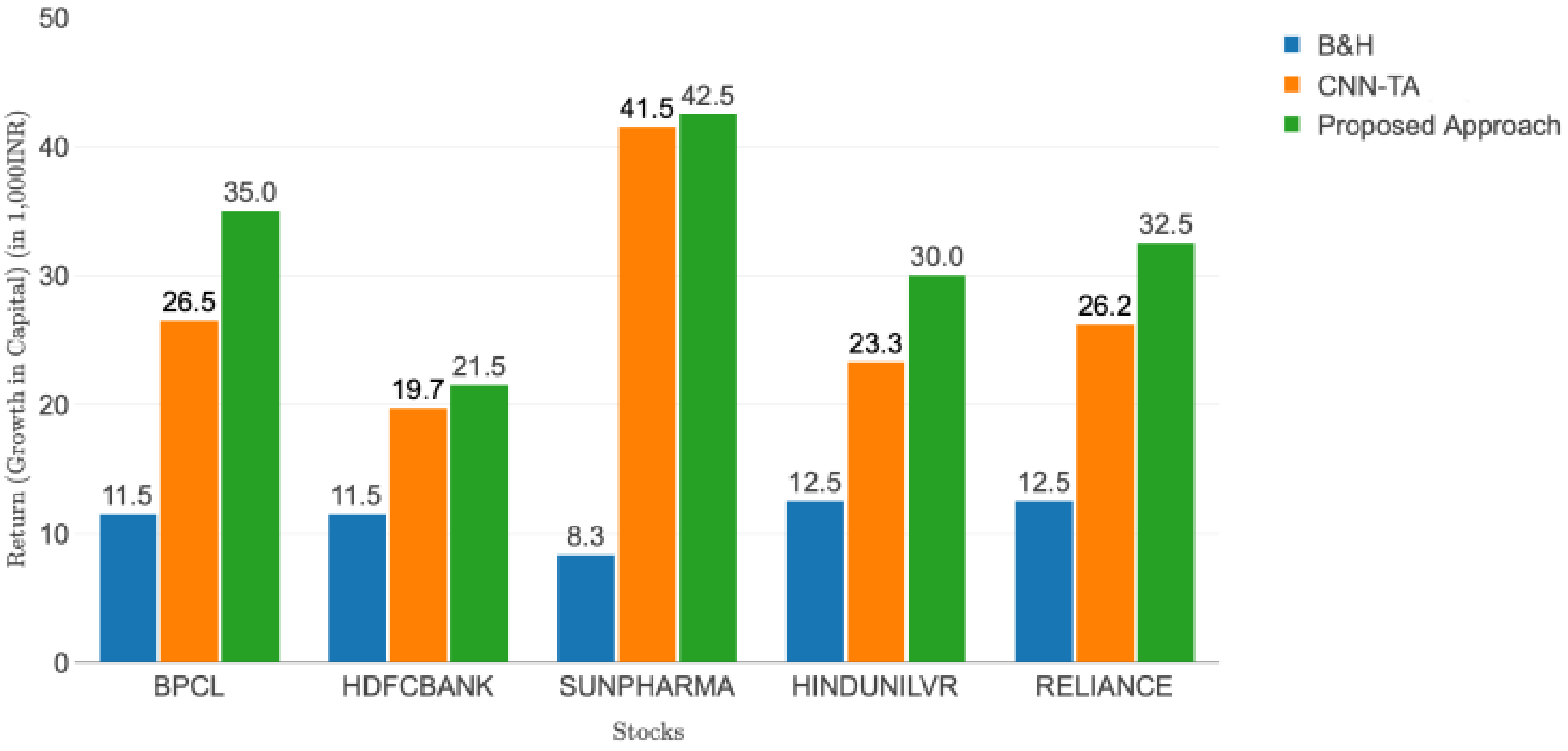


(a) (b)

Comparison of SUNPHARMA returns for two testing years, (a) comparison of SUNPHARMA returns (2017–2018) (b) comparison of SUNPHARMA returns (2018–2020)

Experimental Evaluation

- Results – On an Average



Comparison of return – Proposed Approach vs. B&H vs. CNN-TA

Thank You

Disclaimer

- Slides are not original and are prepared from various sources for teaching/discussion purpose.