A novel trading system for the stock market using Deep Q-Network action and instance selection

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Introduction

Consequently, trading systems designed to generate high stock market returns are developed via several supervised learning methods

✓ However, methods based on them make it difficult to adapt to the real-time nature of the stock market (can be noisy and fail to consider the nonlinear and complex nature of stock prices)

Contribution

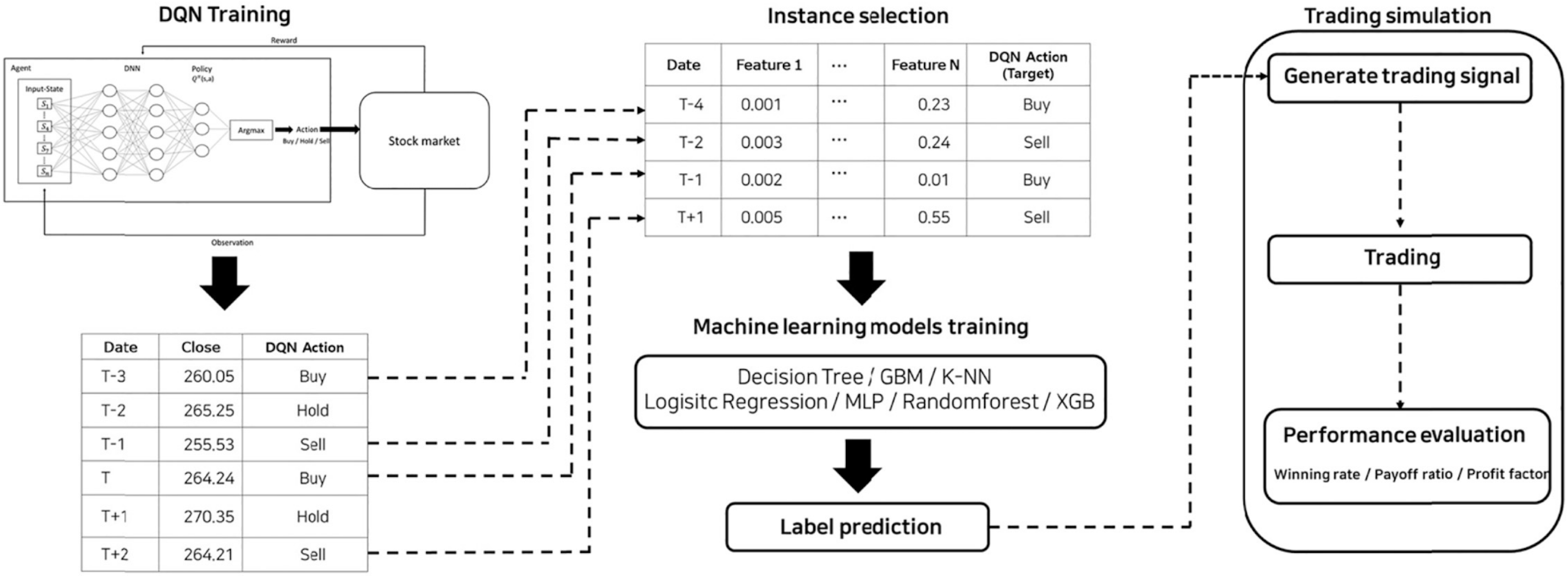
1. By applying reinforcement learning to stock trading, flexible strategies can be developed to adapt to changing market conditions

2. Existing literatures use price up/down labeling as labels, while this paper uses buy/sell signals trained by DQN

This study proposes a Deep Q-Network (DQN) Action Instance Selection Trading System (DAIS) to improve the limitations of both supervised learning and reinforcement learning trading systems

Methodology

2) The learning data (buy/sell signal + all technical indicators) and machine learning algorithm were constructed using instance selection



1) Gather information about the stock market and extract actions

3) Use a machine learning algorithm to predict and generate trading signals

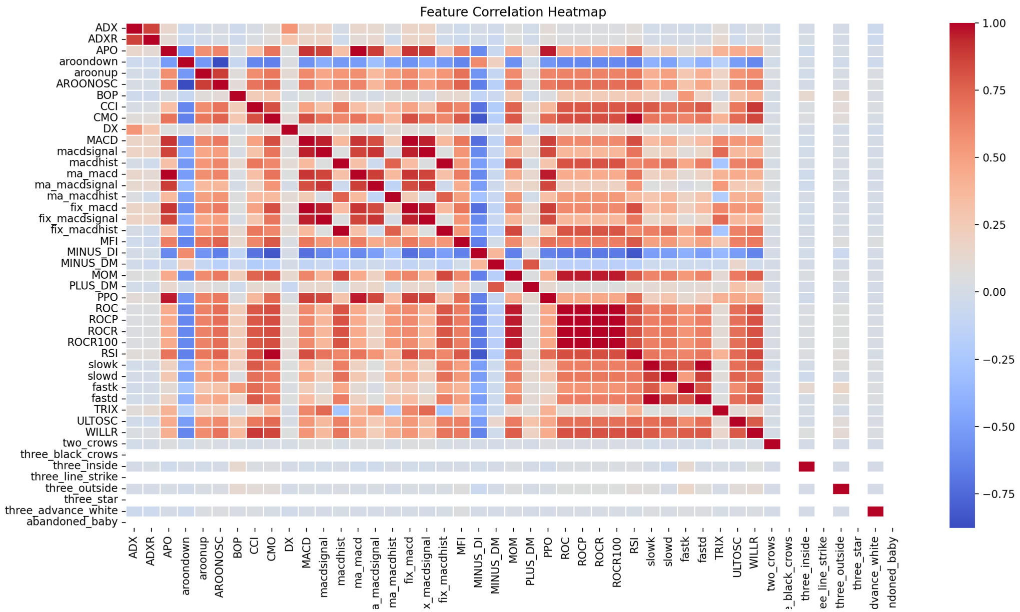
4) Conduct a simulation using the generated trading signal and evaluate its performance

Contribution

✓ Limitation of Paper:

> This study had some limitations. First, we arbitrarily selected the technical indicators to construct the reinforcement learning environment. The results may have been different if we had used more technical indicators or significant technical indicators. Second, we used the DQN

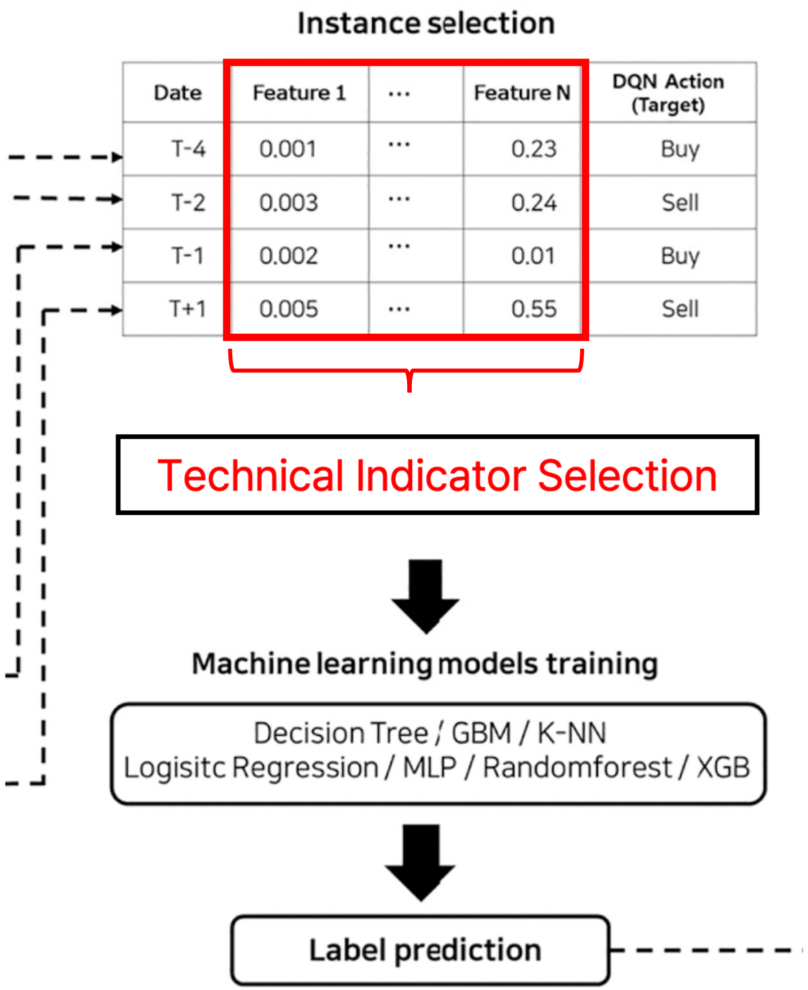
✓ Correlations among technical indicators



∴ Technical Indicator Selection is needed.

→ Feature selection is done using 1) Randomforest
2) mRMR

N → Select Top 20 features



Improvement

Feature Selection code

```
import pandas as pd
import numpy as np
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_selection import SelectKBest, f_classif
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from mrmr import mrmr_classif

feature_cols = [
    'ADX','ADXR','APO','aroondown','aroonup','AROONOSC','BOP','CCI','CMO','DX',
    'MACD','macdsignal','macdhist','ma_macd','ma_macdsignal','ma_macdhist',
    'fix_macd','fix_macdsignal','fix_macdhist','MFI','MINUS_DI','MINUS_DM',
    'MOM','PLUS_DM','PPO','ROC','ROCP','ROCR','ROCR100','RSI','slowk','slowd',
    'fastk','fastd','TRIX','ULTOSC','WILLR','two_crows','three_black_crows',
    'three_inside','three_line_strike','three_outside','three_star',
    'three_advance_white','abandoned_baby'
]

train_combined = []
for i in train_data:
    if 'label' in i.columns:
        tmp = i[feature_cols + ['label']].dropna()
        if not tmp.empty:
            train_combined.append(tmp)

data_all = pd.concat(train_combined, ignore_index=True)

X = data_all[feature_cols]
y = data_all['label']
y_bin = (y == 1).astype(int)  # Buy = 1, Sell = 0

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_df = pd.DataFrame(X_scaled, columns=X.columns)
```

```
rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X_scaled, y_bin)
importances = rf.feature_importances_
selected_rf = X.columns[np.argsort(importances)[-20:]]

selected_mrmr = mrmr_classif(X=X_df, y=y_bin, K=20)

print("RandomForest Top 20 Features:", selected_rf.tolist())
print("MRMR Top 20 Features:", selected_mrmr)

import seaborn as sns
import matplotlib.pyplot as plt

corr_matrix = X_df.corr()
plt.figure(figsize=(15, 12))
sns.heatmap(corr_matrix, cmap='coolwarm', annot=False, fmt='.2f', linewidths=0.5)
plt.title("Feature Correlation Heatmap")
plt.tight_layout()
plt.show()
```

Improvement

Selected Top 20 Features

RandomForest Top 20 Features: ['MOM', 'CCI', 'PPO', 'MINUS_DI', 'MACD', 'TRIX', 'fix_macd', 'ma_macdsignal', 'DX', 'MFI', 'ULTOSC', 'macdhist', 'ADXR', 'fix_macdhist', 'ma_macdhist', 'ADX', 'macdsignal', 'fix_macdsignal', 'MINUS_DM', 'PLUS_DM']

MRMR Top 20 Features: ['PLUS_DM', 'two_crows', 'ADX', 'MINUS_DI', 'MINUS_DM', 'ma_macdsignal', 'DX', 'ADXR', 'fix_macdsignal', 'ma_macdhist', 'macdsignal', 'BOP', 'fix_macd', 'MACD', 'APO', 'ma_macd', 'TRIX', 'macdhist', 'fix_macdhist', 'PPO']

→ We adopted top 20 features from **random forest** according to the results of performance improvement

Results

Table 5
Trading performance by DQN and DAIS trading system.

Model	No. trades	Winning ratio	Payoff ratio	Profit factor	Sharpe ratio
Decision tree	90.30	0.48	1.10 (0.30)	1.11 (0.53)	1.03
GBM	88.27	0.47	1.10 (0.28)	1.10 (0.57)	0.66
knn	78.62	0.49	1.10 (0.40)	1.13 (0.67)	0.92
Logisitic Regression	52.70	0.49	1.12 (0.59)	1.21 (1.93)	0.58
MLP	61.35	0.49	1.12 (0.53)	1.21 (0.89)	0.67
Random forest	76.98	0.49	1.15 (0.34)	1.20 (0.58)	1.09
XGB	89.04	0.49	1.04 (0.28)	1.09 (0.52)	0.93
DQN	84.01	0.46	0.97 (0.45)	0.94 (0.59)	0.38

Note: Values for trading performance are given as average (standard deviation).

Trading Performance of Original Paper

methodology	year	stock_name	No.trades	Win%
pred_logistic	2019~2020	005930_삼성전자	33	0.666667
pred_decision	2019~2020	005930_삼성전자	98	0.581633
pred_naive (DQN)	2019~2020	005930_삼성전자	29	0.758621
pred_randomforest	2019~2020	005930_삼성전자	65	0.461538
pred_knn	2019~2020	005930_삼성전자	51	0.509804
pred_neural	2019~2020	005930_삼성전자	42	0.52381
pred_voting	2019~2020	005930_삼성전자	45	0.488889
pred_gbm	2019~2020	005930_삼성전자	107	0.336449

Trading Performance of Proposed Methodology (using RF)

- ✓ Overall, the winning ratio has generally improved compared to the pre-improvement range (0.48~0.49).
- ✓ Several models achieved a winning ratio above 50%, suggesting a higher likelihood of making profitable trades.
- ✓ However, the number of trades has slightly decreased, averaging around 50–60 trades over two years (indicating relatively low trading frequency)
- ✓ Although the improved winning ratio implies better algorithmic performance, the small number of trades (n) limits the application of the law of large numbers, potentially introducing statistical noise.

Thank You

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[Reference] Park, M., Kim, J., & Enke, D. (2024). A novel trading system for the stock market using Deep Q-Network action and instance selection. Expert Systems with Applications, 257, 125043.