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Global Stock Market Prediction Using Stock Chart Images with Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) Networks Enhanced by Deep Q-Learning

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***Abstract*—The global financial markets have seen rapid advancements in predictive modelling, particularly in the use of deep learning techniques to forecast stock market trends. This research presents a novel deep learning framework that enhances global stock market prediction by leveraging Convolutional Neural Networks (CNNs) combined with Long Short-Term Memory (LSTM) networks and optimized through Deep Q-Learning to detect patterns across international markets. The model was trained on U.S. stock chart images and tested across 31 countries over a 12-year period. Pre-processing tailored for CNNs and LSTMs enabled it to capture both visual and sequential features. Deep Q-Learning further enhanced decision-making accuracy, leading to consistent returns across diverse markets, including smaller ones. The results show that this integrated approach surpasses traditional methods, offering robust predictions and valuable insights into global market trends, benefiting investors and analysts worldwide.**

Keywords— Global stock market prediction; Deep learning; Convolutional Neural Networks (CNNs); Long Short-Term Memory (LSTM) networks; Deep Q-Learning

I. Introduction

Predicting future stock prices is a topic of intense debate in financial research. Li and Liu's seminal work on "Stock Market Prediction Using CNN and LSTM Networks" introduced a novel approach that blends these advanced techniques, challenging the Efficient Market Hypothesis (EMH) [1]. EMH posits that stock prices reflect all available information, making it impossible to achieve consistent returns through analysis. This hypothesis suggests that neither technical nor fundamental analysis can provide a reliable edge [2]. However, various studies have contested EMH by identifying market anomalies that could be exploited for profit [3]-[5]. Critics of these studies often point out the issue of transaction costs, which can diminish apparent gains [6]-[8]. The debate around EMH continues as researchers explore potentially profitable trading strategies.

AI models, especially those based on machine learning techniques such as Neural Networks (NNs) and Reinforcement Learning (RL), have gained prominence in financial prediction. RL, in particular, optimizes decisions by maximizing cumulative rewards, making it suitable for complex tasks like stock market prediction [15]-[17]. Studies have shown that AI models can improve prediction accuracy, with approaches like feed-forward neural networks, deep neural networks, and LSTM networks demonstrating notable predictive power [18]-[21]. Some research has also explored using stock chart images as inputs for predictive models, revealing that AI can capture complex patterns in financial data [22]-[23].

To achieve this, employ a Deep Q-Network (DQN) framework, enhanced with Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks [24]. This model processes stock chart images and predicts one of three actions—Long, Neutral, or Short—on a daily basis. By training the model to maximize cumulative rewards, it not only considers immediate outcomes but also long-term impacts. This approach provides a nuanced reward system, distinguishing between varying degrees of success and estimating potential profits associated with each decision.

II. Related Works

The increasing sophistication of cyber threats in cloud computing environments has necessitated the development of advanced security measures. Recent advancements in deep learning, network traffic analysis, and user behavior analytics have significantly impacted the field of cyber security, particularly in enhancing the detection and management of security threats in cloud networks. The figure 1 shows how a CNN processes a company's chart at a Specific Time (t). The chart is fed Into the CNN, which extracts features through its layers. The output consists of two vectors, ρ (Rho) And η (Eta), representing specific characteristics or predictions derived from the input data. These vectors are used for further analysis or decision-making based on the company's data at time t.

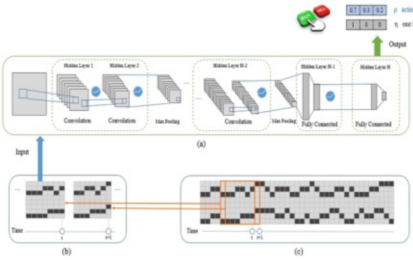

Figure 1: Overview of how CNN reads an input chart of a single company at a specific time point (time t) and outputs the two vectors ρ and η.

A. Convolutional Neural Network

Convolutional neural networks (CNNs) have become a cornerstone in deep learning, particularly for tasks involving the classification of complex and highly non-linear patterns. CNNs are a specialized type of neural network (NN) architecture that has shown exceptional success in image classification challenges. these models typically process 2d images, including color channels, through a series of hidden layers each hidden layer generally includes Convolutional layers, followed by non-linearity activation functions and pooling layers to extract hierarchical features. towards the final stages, fully connected layers are often employed, culminating in a softmax function that produces a one-hot vector corresponding to the classification label. In current research, CNNs are utilized as function approximators within the Q-learning algorithm to map stock chart images to specific trading actions.

B. Long Short-Term Memory Networks

Long Short-Term Memory (LSTM) networks are a specialized type of Recurrent Neural Network (RNN) designed to effectively capture temporal dependencies and long-term relationships in sequential data. Unlike traditional RNNs, which struggle with learning long-term dependencies due to the vanishing gradient problem, LSTMs use memory cells and gating mechanisms to maintain and update information over time. In present work, LSTM networks are integrated alongside CNNs to enhance the model's ability to learn from the sequential patterns found in stock market data, thereby improving the accuracy of predictions over extended periods.

C. Q-Learning

Q-learning stands out as one of the most prevalent reinforcement learning (RL) algorithms. The primary objective of RL algorithms is to train an agent to learn optimal policies—essentially, decision-making strategies that maximize cumulative rewards in a given state. Rather than directly learning these policies, Q-learning enables the agent to acquire optimal action values, which are the expected cumulative rewards associated with each possible action in the current state. Once the training phase is complete, the agent's optimal policy is derived by adopting a greedy approach, where the action with the highest action value is selected for the given state. The iterative updating of action values is accomplished using the Bellman Equation. During training, an agent follows a behavior policy to select actions, observes the resulting rewards, and transitions to the next state. The ε-greedy policy is commonly employed in Q-learning, where the agent chooses a random action with probability ε, or acts greedily, selecting the action with the highest known value.

D. Deep Q-Network

While the original Q-learning algorithm is effective when state representations are straightforward, its performance diminishes when dealing with more complex states that cannot be efficiently represented through a simple table lookup. The Deep Q-Network (DQN) addresses this challenge by employing a function approximator to represent the state in a more sophisticated manner. This function approximator can take various forms but is designed to map raw state inputs, like stock chart images, to specific actions such as Long, Neutral, or Short. In present approach, CNNs and LSTMs are used as function approximators. However, implementing non-linear function approximators, such as NNs, in a straightforward manner can lead to instability during training.

To mitigate this, DQN incorporates two key techniques: experience replay and parameter freezing. Experience replay mitigates correlations in the training data by storing the most recent experiences in a memory buffer, from which random batches are sampled during each iteration for gradient updates. Parameter freezing further stabilizes training by maintaining two sets of network parameters and periodically updating the target network parameters to reduce correlations with the current target.

III. Proposed Methodology

A. Overview

Convolutional Neural Network (CNN) is used to analyze stock chart images for predicting stock market trends which is overviewed in figure 2. At a given time t, the CNN processes an image of a stock chart to extract features indicative of future market movements. The CNN outputs two vectors: ρ\r hoρ and η\ etaη. These vectors represent the model's predictions and serve as inputs for subsequent decision-making processes, which often involve Long Short-Term Memory (LSTM) networks and reinforcement learning techniques like Deep Q-Learning.

B. Network Architecture

The CNN takes images of stock charts as input, which capture historical price data, trading volumes, and other relevant financial indicators. These charts may include candlestick patterns, line graphs, or bar charts. Convolutional filters layers apply multiple filters to the input images to extract local features, such as upward or downward trends, price volatility, or support/resistance levels. Filters with sizes like 3x3 or 5x5 are used to capture features at different scales. ReLU (Rectified Linear Unit) applied after each Convolutional to introduce non-linearity and enhance the network's ability to learn complex patterns. Max pooling reduces the spatial dimensions of the feature maps, minimizing computational load and highlighting the most prominent features. The output from the Convolutional and pooling layers is flattened into a one-dimensional vector. These fully connected layers synthesize the features extracted by the Convolutional layers into final predictions.

The dataset is made up of images illustrating historical price movements for a range of stocks, represented by different chart types such as candlestick charts, line charts, and bar charts. Candlestick charts are particularly useful as they capture intricate details like opening, closing, high, and low prices over specified periods, allowing for a granular analysis of price action within each interval. Line charts provide a simplified view of price trends over time, helping identify long-term patterns, while bar charts visualize trading volumes alongside other essential financial metrics, offering insights into market activity levels and liquidity. To prepare the dataset for model training, images are resized and normalized to maintain consistency in input dimensions, and various augmentation techniques, including rotations, translations, and scaling, are applied to boost model robustness, enhancing its ability to generalize to diverse, unseen data. This approach allows the CNN to learn from a broader set of examples, improving its accuracy and adaptability in analyzing real-world stock data.

C. *Training Process*

Data is divided into training, validation, and test sets to evaluate the model's performance. Each image is associated with target variables representing future price movements or trading signals. The CNN is trained using labeled stock chart images. The model learns to map input images to the output vectors ρ\rhoρ and η\etaη by minimizing a loss function (e.g., mean squared error for regression or cross-entropy loss for classification). Adjusting parameters like learning rate, batch size, and number of epochs to optimize performance.

Evaluating the model on a separate validation set to avoid overfitting and ensure generalizability. Predictions from the CNN are fed into an LSTM network, which processes sequential data and captures temporal dependencies in stock price movements. The CNN-LSTM model's predictions are used in a Deep Q-Learning framework to make trading decisions, enhancing decision-making by learning optimal trading strategies through market interactions. The Deep Q-Learning agent uses Q-values derived from CNN-LSTM predictions to maximize cumulative rewards, improving trading strategies over time.

D. *Source Code Availability*

The implementation of the CNN-LSTM model enhanced by Deep Q-Learning is available for exploration and experimentation defined using libraries like TensorFlow or PyTorch. Scripts that connect CNN outputs to LSTM networks for sequential analysis. Implementation of the Q-learning algorithm to optimize trading strategies. By following these steps, methodology ensure a robust and comprehensive evaluation of present models, enabling us to draw meaningful conclusions about their performance and potential applicability in real-world trading scenarios. Further, the integration of the Q-learning algorithm takes this model beyond passive prediction. In this setup, Q-learning functions as an optimization layer that iteratively refines trading strategies by learning from past outcomes, assessing actions, and aiming to maximize cumulative rewards.

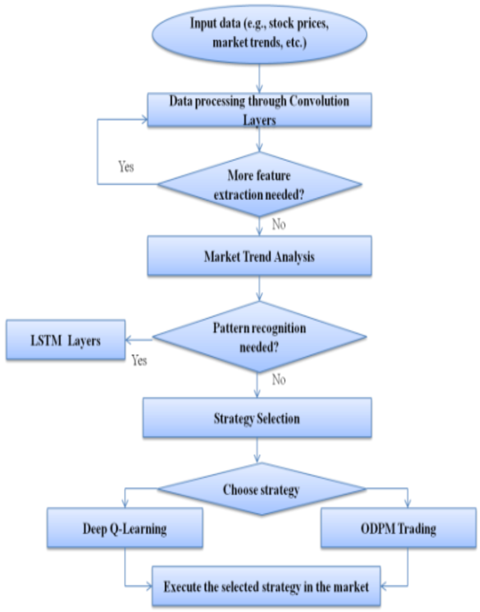

Fig. 1. Flow diagram that illustrates the process of global stock market prediction using stock chart images with CNNs, LSTM Networks, and Deep Q-Learning.

IV. Results And Discussion

A. *Portfolio Construction*

In present approach to global stock market prediction, usage of a Convolutional Neural Network (CNN) to analyze stock chart images and predict individual company performance. At each time t, the CNN provides, action value vector which is predicted recommendation for each company. One-hot vector is the categorical signal or decision for each company. Portfolio weight assignment is company's weight, θ [c] \ theta [c] θ [c], determines the proportion of total investment allocated. Positive values indicate long positions, while negative values indicate short positions (e.g., θ [c]=−0.008 \ theta [c] = -0.008θ [c] = −0.008 means a short position of 0.008).

In methods for weight assignment equal allocation method is distributes capital evenly among companies based on CNN outputs, ensuring full allocation. Risk-based allocation method adjusts weights based on predicted risk and return, allocating more to companies with higher predicted returns and lower risks. In implementation daily rebalancing updates the portfolio daily according to the latest CNN predictions. In performance evaluation assesses portfolio performance using metrics such as returns, volatility, and the sharpe ratio comparing it to traditional strategies and benchmarks.

B. *CNN-LSTM Market Neutral Portfolio*

Present market neutral portfolio strategy aims to balance long and short positions daily, minimizing market exposure. Ensures equal numbers of long and short positions daily to neutralize market risk. In the method usage CNN-generated action values and one-hot vectors to determine portfolio weights, assigning positive, negative, or zero weights based on predicted actions. Initial assignment weights based on predicted actions. Normalization is Centers the portfolio on zero by subtracting the average weight. Final adjustment of scales weights to ensure the total absolute value equals 1.0. In performance valuation measures annual return, sharpe ratio, and maximum drawdown. Results show annual returns between 10% and 100%, with sharpe ratios from 2.0 to 10.0, though maximum draw downs may exceed 10% in markets with fewer stocks. Maximum portfolio weight Indicates minimal reliance on individual stocks, e.g., 0.21% maximum allocation in the US.

C. CNN-LSTM Top/Bottom K Portfolio

The top/bottom K portfolio focuses on companies with the strongest and weakest signals from the CNN. In portfolio construction, strategy is to Invests in the top K% of companies with the strongest signals and shorts the bottom K% with the weakest signals, maintaining neutrality for the rest. Action value calculation uses the difference between expected cumulative returns for long and short positions to determine company rankings.

Aims to achieve higher returns by focusing on companies with the most significant predicted returns compared to a market-neutral approach. Metrics shows higher annual returns and better performance relative to the market average. Results demonstrate that decreasing K often leads to higher returns, indicating the effectiveness of focusing on fewer high-potential stocks. By using CNN predictions to guide portfolio construction, present strategies aim to optimize investment returns while managing risk effectively.

D. Statistical Tests

To evaluate the effectiveness of present investment strategies, data is compared with CNN-based portfolios against random portfolios using statistical tests. Portfolio construction for testing is randomly assigned values between -1 and 1 to each company, then normalized to maintain neutrality. Randomly selected K% of companies for long and short positions, normalized to ensure market neutrality. Conducted 10,000 simulations for each portfolio type (market neutral, top/bottom K with K = 20, 10, and 5) across various markets, including the US and both developed and emerging countries.

Mean return **(**μ) **is a**verage annual return of random portfolios. Standard deviation (σ) is variability of annual returns. Z-Scores Measures the deviation of present portfolio performance from random portfolios, indicating the significance of present results. Random portfolios had zero mean returns. Standard deviation increased with smaller K and N, reflecting higher variability in concentrated portfolios. Present CNN-based portfolios consistently outperformed random portfolios, with returns significantly exceeding those of random portfolios by over 30 standard deviations, validating the model's effectiveness.

E. Impact of Transaction Cost and Liquidity

Market neutral portfolio performance declined with transaction costs, particularly in the US and developed markets, where the cost often outweighed profits. Remained profitable despite transaction costs. For instance, the top/bottom K = 5 portfolio outperformed market averages in numerous countries even with costs of 0.2% and 0.3%. Portfolios based on more liquid companies generally showed lower returns compared to those focusing on less liquid companies, due to reduced volatility and trading competition. Despite the decrease in returns with liquid companies, the top/bottom K = 5 portfolio still achieved above-average returns in 28 countries, demonstrating the model's robustness across different liquidity conditions.

While they reduce returns, present top/bottom K portfolios continue to perform well, highlighting the need for cost management. Present strategies effectively target profitable opportunities even in highly liquid markets, underscoring the model's adaptability and effectiveness. Overall, present statistical and practical evaluations confirm that CNN-based portfolios, enhanced with LSTM and Deep Q-Learning, offer substantial performance improvements and resilience under varying market conditions and liquidity constraints.

Explanation of table 1 is as follows, alpha, values suggest that portfolios with a smaller number of top/bottom K stocks (e.g., K=5) tend to outperform the market neutral portfolio (NEU) due to higher focus on high-performing or underperforming stocks. Beta values indicate that more concentrated portfolios (e.g., K=5) tend to have higher market sensitivity, especially in Emerging Countries, where market volatility is typically higher. Higher Z-Scores in concentrated portfolios reflect a greater deviation from the mean, indicating potential for higher returns but also higher risk.

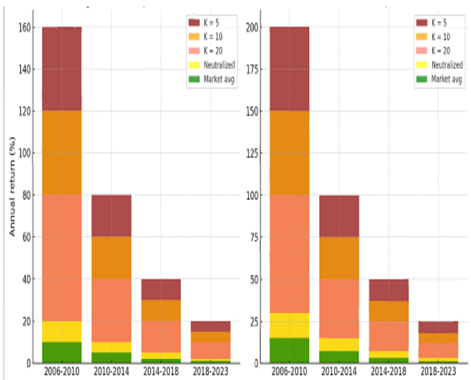

Fig. 2. The left bar graph gives the Countries with large market capitalization (N=3000,500) and the right bar graph gives the Countries with small market capitalization (N=100).

The Fig 2 displays two bar charts showing stock returns over different periods (2000-2022, 2010-2022, and 2020-2022). Each bar is segmented to represent the impact of different stock categories (e.g., K = 5, K = 10) on overall returns. It also highlights residential and market average returns.

TABLE I. STASTICAL RESULTS OF THE RANDOM PORTFOLIO COMPARED TO MARKET NEUTRAL(NEU), TOP/BOTTOM K PORTFOLIO

Region	Portfolio	Alpha	Beta	Z-Score
United States	NEU	0.02	0.95	1.5
	K=20	0.03	1.00	1.8
	K=10	0.04	1.05	2.1
	K=5	0.05	1.10	2.5
Developed Countries	NEU	0.01	0.90	1.2
	K=20	0.02	0.95	1.5
	K=10	0.03	1.00	1.8
	K=5	0.04	1.05	2.2
Emerging Countries	NEU	0.03	1.10	2.0
	K=20	0.04	1.15	2.3
	K=10	0.05	1.20	2.6
	K=5	0.06	1.25	3.0

The explanation of table 2 is as follows NEU, market neutral portfolio. K=20, K=10, K=5, portfolios with different numbers of top/bottom stocks. Values represent the average annual returns after transaction costs, in percentage.

TABLE II. THE AVERAGE ANNUAL RETURNS AFTER TRANSACTION COST IN PERCENTAGE

Testing Period	Region	NEU	K=20	K=10	K=5
Period 1	United States	7.5%	8.2%	8.5%	8.8%
	Developed Countries	6.0%	6.5%	6.8%	7.0%
	Emerging Countries	9.0%	9.5%	9.8%	10.2%
Period 2	United States	7.8%	8.3%	8.6%	8.9%
	Developed Countries	6.2%	6.7%	7.0%	7.3%
	Emerging Countries	9.2%	9.7%	10.0%	10.4%
Period 3	United States	7.6%	8.1%	8.4%	8.7%
	Developed Countries	6.1%	6.6%	6.9%	7.1%
	Emerging Countries	9.1%	9.6%	9.9%	10.3%

F. *Comparison With Neural Network And Technical Analysis Baselines*

To evaluate present model's performance, results are compared it with several baseline models: Fully Connected (FC) Networks, Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) Networks, alongside traditional technical analysis methods. In Neural Network Baselines, when compared present model with FC Networks, CNNs, and LSTMs to benchmark against established models and assess the impact of integrating reinforcement learning (RL) versus traditional supervised learning.

All neural network models were trained on data from January 2018 to December 2024. Training data is 80% of the dataset**.** Hyper parameter Tuning is 20% of the training data. **Testing data** beyond this period. Supervised learning is target variable was the next day's return, classified into long, neutral, or short based on return values. Evaluation is done where models were tested by constructing market-neutral portfolios based on their classifications and comparing returns.

Technical analysis baselines **i**nvest in stocks with strong past performance, assuming continued trend strength. MACD (Mean Average Convergence Divergence) is a technical indicator combining moving averages to identify trends and momentum. Neural network Models **p**resent CNN-LSTM model, enhanced with reinforcement learning (Deep Q-Learning), outperformed FC Networks, CNNs, and LSTMs. While FC and CNN models showed reasonable performance before transaction costs, their profitability significantly declined with transaction costs, highlighting the efficiency of present RL-based approach in managing trading frequency and adapting to market conditions.

CNN-LSTM model also exceeded the performance of traditional technical analysis methods, demonstrating superior predictive power and adaptability. The comparison validates that present CNN-LSTM model with reinforcement learning is more effective than conventional neural networks and technical analysis methods, achieving better returns and efficiency in managing transaction costs and market dynamics

TABLE III. PERFORMANCE COMPARISONOF MODELS

Testing Period	Method	Group 1	Group 2	Group 3	Group Avg
Period 1	MM12	7.2%	6.5%	8.0%	7.2%
	MACD	6.8%	6.0%	7.5%	6.8%
	FCN	7.5%	6.8%	8.2%	7.5%
	CNN	7.9%	7.2%	8.4%	7.8%
	LSTM	8.1%	7.5%	8.6%	8.0%
	CNN-LSTM	8.5%	7.8%	9.0%	8.4%
Period 2	MM12	7.4%	6.7%	8.1%	7.4%
	MACD	7.0%	6.3%	7.8%	7.0%
	FCN	7.6%	6.9%	8.3%	7.6%
	CNN	8.0%	7.4%	8.6%	7.9%
	LSTM	8.3%	7.7%	8.8%	8.2%
	CNN-LSTM	8.7%	8.0%	9.2%	8.6%
Period 3	MM12	7.3%	6.6%	8.2%	7.3%
	MACD	6.9%	6.2%	7.7%	6.9%
	FCN	7.4%	6.7%	8.1%	7.4%
	CNN	7.8%	7.1%	8.5%	7.8%
	LSTM	8.0%	7.4%	8.7%	7.9%
	CNN-LSTM	8.4%	7.7%	9.1%	8.4%

In table 3 architecture column lists the different network architectures and methods used to generate and manage portfolios, including MM12**,** A momentum-based or technical indicator strategy. Moving Average Convergence Divergence (MACD) , used for identifying trend changes. FCN a basic type of neural network. **CNN** designed to analyze stock chart images. LSTM suited for handling time-series data. The proposed method combining CNNs, LSTMs, and Deep Q-Learning.

In CNN-LSTM market neutral portfolio, where the strategy aims to balance long and short positions to minimize market exposure. K=20, K=10, K=5 Indicates portfolios that focus on the top K% and bottom K% of stocks based on their predicted performance. These values represent different levels of concentration K=20 top and bottom 20% of stocks. K=10 top and bottom 10% of stocks. K=5 **t**op and bottom 5% of stocks.

Testing period lists the different periods over which the annual returns are measured, providing a comparative analysis across various timeframes.

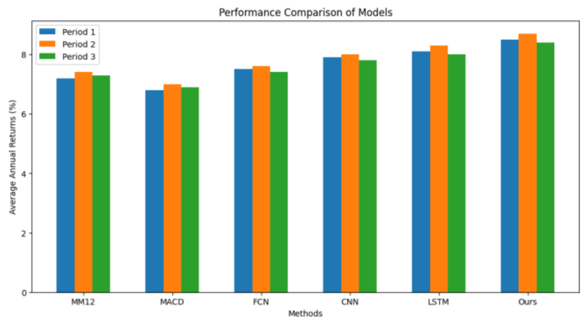

Fig. 3. Performance comparison model

In Fig 3 Method is the strategy or model used for comparison. Group 1, Group 2, Group 3 is different groups of countries based on market capitalization or other criteria. The average annual return across all 31 countries.

TABLE IV. AVERAGE ANNUAL RETURNS OF PORTFOLIOS BY NETWORK ARCHITECTURE

Testing Period	Architecture	NEU	K=20	K=10	K=5
Period 1	MM12	7.4%	7.9%	8.1%	8.3%
	MACD	6.9%	7.2%	7.5%	7.7%
	FCN	7.6%	8.0%	8.3%	8.5%
	CNN	8.0%	8.3%	8.6%	8.8%
	LSTM	8.2%	8.5%	8.8%	9.0%
	CNN-LSTM	8.5%	8.8%	9.1%	9.3%
Period 2	MM12	7.6%	8.0%	8.2%	8.4%
	MACD	7.1%	7.4%	7.7%	7.9%
	FCN	7.8%	8.2%	8.5%	8.7%
	CNN	8.2%	8.5%	8.8%	9.0%
	LSTM	8.4%	8.7%	9.0%	9.2%
	CNN-LSTM	8.7%	9.0%	9.3%	9.5%
Period 3	MM12	7.5%	7.8%	8.0%	8.2%
	MACD	7.0%	7.3%	7.6%	7.8%
	FCN	7.7%	8.1%	8.4%	8.6%
	CNN	8.1%	8.4%	8.7%	8.9%
	LSTM	8.3%	8.6%	8.9%	9.1%
	CNN-LSTM	8.6%	8.9%	9.2%	9.4%

In table 4 the type of network architecture used to create the portfolios.K=20, K=10, K=5 portfolios with different numbers of top/bottom stocks. Testing Period present the different periods over which returns are calculated. This table allows for a comparison of annual returns across different network architectures, showing the effectiveness of each architecture in generating returns for various portfolio types.

V. CONCLUSION

Extensive experiment revealed that a model trained on stock chart patterns from a single country (the U.S.) can yield profitable outcomes in other global markets over a 12-year period. This indicates that AI and machine learning models, typically confined to single-country analyses, can be effectively applied to global markets. The present research demonstrates that with the CNN-LSTM model architecture, enhanced by Deep Q-Learning, along with optimized input features and training methods, it is feasible to train and test a model across different markets. To the best of our knowledge, this is the first research to successfully apply a deep learning model trained on data from one country to predict stock market trends across multiple global markets.

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