**Summary of research**

**1. A Profitable Trading Algorithm for Cryptocurrencies Using a Neural Network Model**

**Authors: Mimmo Parente, Luca Rizzuti, Mario Trerotola  
Source: *Expert Systems With Applications* (2024)**

This paper explores the development of a machine learning-based trading algorithm for cryptocurrencies, utilizing a Multi-Layer Perceptron (MLP) neural network. The authors formulate the trading decision-making process as a classification problem with three possible outcomes: Buy, Hold, and Sell. They introduce a novel labeling approach based on market movements and temporal windows to optimize predictions. The algorithm is validated across different market conditions (bull, bear, and flat markets) using an extensive backtesting strategy, demonstrating profitability across multiple cryptocurrency assets. The study emphasizes the importance of feature selection in improving model performance and employs explainable AI techniques like Shapley values to assess feature contributions. The findings highlight that neural network-based strategies can outperform traditional heuristic approaches in high-volatility environments such as the crypto market​.

**2. Deep Reinforcement Learning Approach for Trading Automation in The Stock Market**

**Authors: Taylan Kabbani, Ekrem Duman  
Source: *IEEE Access* (2022)**

This paper presents a deep reinforcement learning (DRL) framework for automated stock market trading. The authors model the trading environment as a Partially Observed Markov Decision Process (POMDP) and employ the Twin Delayed Deep Deterministic Policy Gradient (TD3) algorithm to optimize portfolio allocation dynamically. Unlike traditional supervised learning models, which separately handle price prediction and allocation, this approach unifies both tasks, allowing an autonomous agent to learn optimal trading strategies through trial and error. The system integrates technical indicators and sentiment analysis of financial news to enhance state representation. Backtesting results on real-world data yield a Sharpe ratio of 2.68, indicating strong risk-adjusted performance. The paper concludes that DRL-based trading systems offer superior adaptability to market dynamics compared to rule-based or supervised learning approaches​.

**3. Using LSTM for Stock Prediction and Quantitative Trading**

**Authors: Zhichao Zou, Zihao Qu  
Source: *Stanford University (CS230: Deep Learning, Winter 2020)***

This study applies Long Short-Term Memory (LSTM) models to stock price prediction, comparing single-layer LSTM, Stacked-LSTM, and Attention-Based LSTM architectures against a baseline ARIMA model. The dataset consists of historical stock prices, trading volumes, and corporate accounting statistics for S&P 500 companies from 2004 to 2013. The results indicate that the Attention-LSTM model outperforms the other models in predictive accuracy and trading strategy returns. The authors implement two trading strategies—Long-Only and Long-Short—based on the model’s predictions, demonstrating significant outperformance compared to the S&P 500 benchmark. Interestingly, they find that adding more complexity via a Stacked-LSTM does not necessarily improve performance, suggesting diminishing returns in model depth. Future research is suggested on volatility-adjusted strategies to improve stability​.