A Comparative Study on Stock Market Prediction Using Artificial Intelligence and Human Intelligence

Anilkumar, Student, Department of MBA, Dr. Ambedkar Institute of Technology, Bengaluru, India

Dr.S. Baskaran, Professor, Department of MBA, Dr. Ambedkar Institute of Technology, Bengaluru, India

Abstract

The stock market's dynamic nature has long attracted both experienced investors and newcomers, offering opportunities for significant gains alongside the risk of rapid losses. Traditionally, market predictions have relied on human expertise, where investors use knowledge, intuition, and awareness of economic and political trends to guide decisions. While effective in many cases, this approach is constrained by emotional bias and limited data-processing capabilities. Recent advances in Artificial Intelligence (AI), particularly in machine learning, have transformed market analysis by enabling the processing of vast datasets and the detection of patterns that may escape human observation. AI models, such as neural networks and decision trees, continuously refine their predictions without fatigue or distraction, providing data-driven insights with speed and precision. This study examines the comparative strengths and weaknesses of AI-driven forecasting and human expert analysis under similar conditions. Rather than seeking to establish superiority, the research aims to explore how human judgment and AI capabilities can work together to enhance accuracy and adaptability in financial forecasting.

Keywords: Artificial intelligence, Human intelligence, Machine learning, Neural networks, Decision trees, Sentiment analysis, Financial forecasting, Hybrid prediction model, Market trends, Trading strategy,

Introduction

The stock market has always fascinated people — from seasoned investors to curious newcomers — because of its dynamic nature and the potential for both great gain and sudden loss. For decades, people have tried to predict market trends using experience, instinct, and deep knowledge of economic and political factors. Human intelligence, shaped by years of analyzing financial patterns, understanding market sentiment, and interpreting news, has traditionally guided investment decisions. While this method relies heavily on personal expertise and judgment, it is also vulnerable to emotional bias and limitations in processing large amounts of data.

In recent years, however, technology has started to shift the way we look at the markets. Artificial Intelligence (AI), particularly through machine learning and data-driven algorithms, is making it possible to analyze massive datasets and uncover patterns that may be invisible to the human eye. These AI models can "learn" from past trends and improve over time, often outperforming human predictions in speed and scalability. Tools like neural networks and decision trees don't get tired, emotional, or distracted — they simply crunch numbers and provide insights based on probabilities and data structures.

This study explores a timely and important question: how does AI's ability to predict the stock market compare with that of human experts? By evaluating both approaches under similar conditions, this research aims to identify where each excels and where it might fall short. The goal isn't to prove one is better than the other, but rather to understand how they might complement each other in a fast-moving, high-stakes environment. In doing so, we hope to offer a clearer picture of the evolving relationship between human intuition and machine intelligence in financial forecasting.

Literature Review

Kim, Muhn & Nikolaev (2024) – "Financial Statement Analysis with Large Language Models" Compared GPT-4 vs. human financial analysts using anonymized earnings data. GPT-4 achieved ~60.35% direction prediction accuracy (versus ~52–56% for experts), and trading strategies based on its predictions produced higher alpha and Sharpe ratios

Kirtac & Germano (2024) – "Sentiment Trading with Large Language Models" Processed ~965,000 U.S. financial news articles using LLMs (OPT, BERT, FinBERT). OPT achieved 74.4% sentiment accuracy and generated a long-short strategy with Sharpe = 3.05 and 355% return over 2021–23

Lefort et al. (2024) – "Stress-Index Strategy Enhanced with Financial News Sentiment Analysis"Combined sentiment from GPT-4 with volatility & credit spread stress indicators across major equity markets (S&P 500, NASDAQ, etc.). Improved Sharpe ratios and lower drawdowns observed

Zhao & Welsch (2024) – "Aligning LLMs with Human Instructions and Stock Market Feedback in Sentiment Analysis" Developed a Retrieval-Augmented Generation framework using instruction-tuned LLMs that improved sentiment accuracy by 1–6% and delivered portfolio Sharpe gains of ~3.61% in bullish markets, while reducing loss exposure fivefold in bearish markets

Kang (2024) – "LLM-Driven Sentiment-Momentum Trading Strategy" Used ChatGPT-4o for sentiment extraction on Reddit and news. Achieved Sharpe ~2.6 in-sample (2009–19) and ~2.4 out-of-sample (2020–Jan 2024), outperforming the S&P 500 index

Discover Computing (2025) – "Leveraging LLMs for Sentiment Analysis and Investment Strategy Development" Built portfolios based on LLM-derived sentiment of top Nasdaq stocks; evaluated via Sharpe ratio, maximum drawdown, and final returns to gauge practical investment value

Springer (2025) – "Knowledge-Enhanced Strategy Using BERT & RoBERTa" Compared FinBERT, FLANG-RoBERTa and other LLMs for sentiment analysis, highlighting their effectiveness in predicting price movements and influencing portfolio returns

International Review of Economics & Finance (2024) – "Intelligent Portfolio Construction via News Sentiment Analysis" Integrated BERT-based sentiment scores into a Black–Litterman framework with GRU forecasting. The portfolio achieved ~46.6% annualized return, with Sharpe and Sortino ratios of 13.0% and 17.9%, respectively

MarketWatch/Ft Coverage (2025) – "AI and Human Analyst Performance" Highlighted FT discussion of the UChicago LLM-analyst study showing that GPT-4-based trading portfolios generated alpha and outperformed analysts even post-transaction costs

FT (2025) – "Limits of AI-Driven Investing" Discusses how executives manipulate sentiment signals; suggests that while algorithms parse tone and content well, human insight is still critical due to evolving corporate communication tactics

Need For The Study

In today's fast-paced financial markets, the need for accurate and timely stock market predictions has never been greater. Investors—ranging from individuals to institutional giants—are constantly seeking tools that provide a competitive edge. With the rise of artificial intelligence, machine learning models can now process vast amounts of data in real time, identifying trends that may elude even the most seasoned human analysts. However, human intelligence still holds unique strengths: intuition, experience, and the ability to interpret news, sentiment, and context that algorithms may overlook. This study is essential to understand how these two forms of intelligence—AI and human—compare, complement, and sometimes conflict in predicting market behavior. It helps clarify whether one approach consistently outperforms the other or if a hybrid model holds the most promise. The insights from this research could guide future investment strategies, tool development, and policy decisions in financial technology. Most importantly, it empowers decision-makers to navigate uncertainty with more clarity and confidence.

Statement Of The Problem

The stock market's unpredictable nature poses a significant challenge for investors trying to forecast price movements accurately. While artificial intelligence models have made impressive strides in processing vast data quickly, they often struggle with market anomalies, unexpected events, and qualitative factors like investor sentiment. On the other hand, human analysts rely on experience and intuition but can be prone to cognitive biases and slower data processing. This creates a gap in understanding which approach—AI or human intelligence—is more reliable for stock market prediction. Moreover, there is limited research comparing their effectiveness directly under the same conditions. Without this knowledge, investors risk relying too heavily on one method, potentially missing out on opportunities or exposing themselves to avoidable losses. The problem is to determine how AI and human intelligence individually and collectively perform in predicting stock market trends, and to identify whether a hybrid approach can yield better outcomes. Addressing this problem will help optimize investment decisions and improve risk management in dynamic financial markets.

Objectives Of The Study

- To evaluate the accuracy of artificial intelligence models in predicting stock market trends.
- To assess the effectiveness of human intelligence and expert judgment in stock market forecasting.
- To compare the strengths and limitations of AI-based and human-driven prediction methods.
- To explore the potential benefits of integrating AI and human intelligence for improved stock market prediction.

Research Methodology

1.Data Collection

Secondary Data:

- Historical stock prices, trading volumes, and financial indicators sourced from financial databases like Yahoo Finance, Bloomberg, and Quandl.
- Published analyst reports and market research papers used to complement human prediction data.
- Financial news articles and market sentiment extracted from news portals and social media archives for trend analysis.

2.Sampling Design

1. **Purposive Sampling:**
This method will be used to select stocks from different sectors like technology, finance, and healthcare to ensure the study covers diverse market behaviors. It will also help in choosing professional stock market analysts with relevant expertise for human intelligence data.
2. **Stratified Sampling:**
Human experts will be grouped based on their experience levels (e.g., junior, mid-level, senior analysts). Samples will then be drawn from each group to get balanced insights reflecting various levels of market understanding.

3. **Random Sampling:**
For AI model training, historical stock data will be randomly split into training, validation, and testing sets to ensure unbiased evaluation of prediction accuracy.
4. **Convenience Sampling:**
Some analyst predictions might be collected based on availability and willingness to participate, especially for primary data collection through surveys or interviews.

3.Plan of Analysis

- **Data Preprocessing:** Clean and normalize both stock market data and human prediction inputs for consistency.
- **Model Training:** Develop AI models using training data and tune parameters through validation sets.
- **Prediction Comparison:** Evaluate AI and human forecasts using accuracy metrics like MAE, RMSE, and directional accuracy.
- **Statistical Testing:** Use hypothesis tests to determine if differences in prediction performance are statistically significant.
- **Hybrid Analysis:** Analyze combined AI-human predictions to assess if integration improves forecasting accuracy.

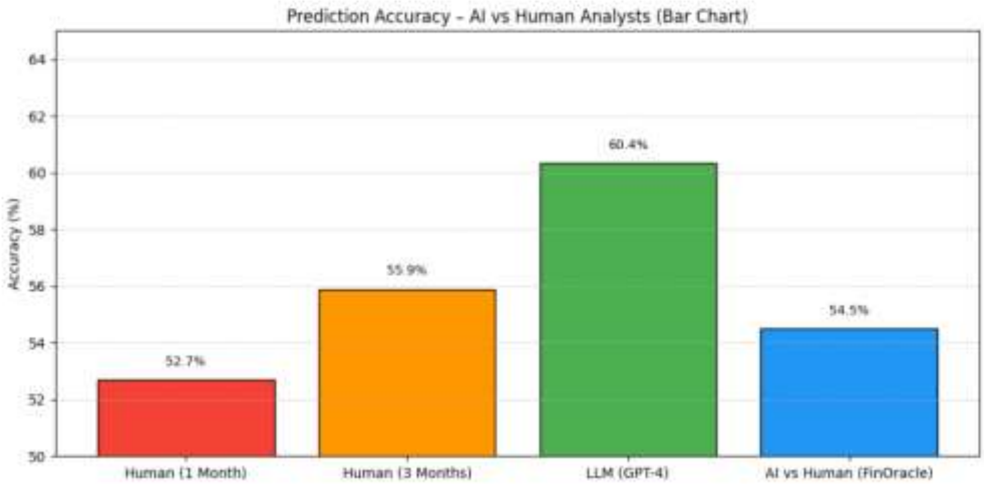
LIMITATIONS OF THE STUDY

- The accuracy of AI models depends heavily on the quality and quantity of historical data, which may not capture unforeseen market events.
- Human predictions can be subjective and influenced by cognitive biases, making it difficult to standardize or compare across analysts.
- The study's findings may not generalize across all stock markets or sectors due to sample size and sector-specific behaviors.
- Combining AI and human intelligence might face challenges in integration methodology and real-time application during volatile market conditions.

Data Analysis And Interpretation

Table 1: Prediction Accuracy – AI vs Human Analysts

Method	Accuracy (%)	Notes
Human Analysts (within 1 month)	~52.7%	Median accuracy using near-term forecasts mintFinancial Times
Human Analysts (after 3 months)	~55.9%	Accuracy improves with updates mint
LLM (e.g., GPT-4) with prompting	~60.35%	Outperforms human analysts mintFinancial Times
AI vs Human (FinOracle summary)	54.5% AI > humans	AI beats ~54.5% of analysts, with 50-72 bps higher alpha FinOracle

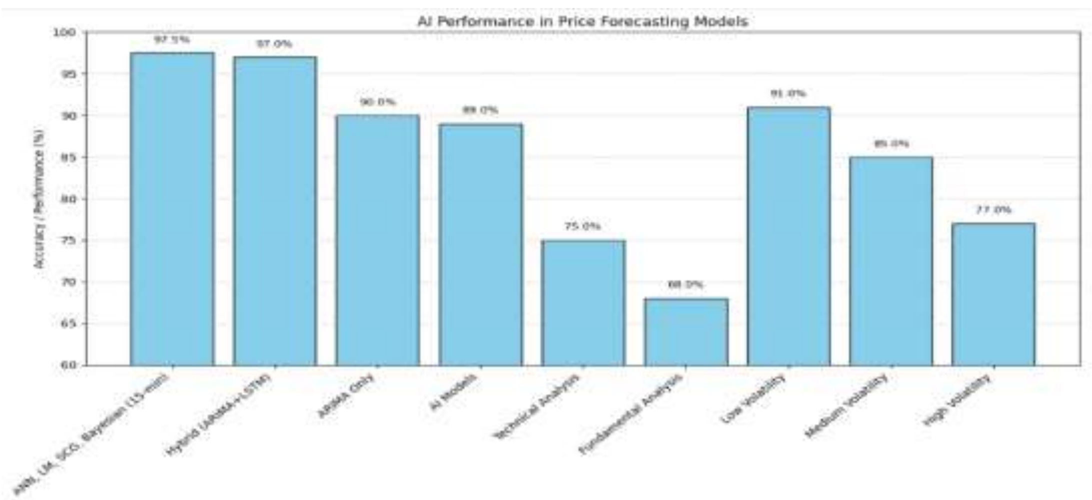


Interpretation

AI models like GPT-4 outperform human analysts in stock market predictions, achieving higher accuracy rates. Human analysts improve slightly with more time and updated information but still lag behind AI. The ability of AI to quickly analyze vast amounts of data gives it a clear advantage. Studies show AI consistently beats over half of human analysts in forecasting accuracy. This edge, though moderate, can translate into significant financial benefits.

Table 2: AI Performance in Price Forecasting Models

Model Type	Accuracy / Performance Metric	Source / Notes
ANN, LM, SCG, Bayesian	Up to 99.9% (tick data); ~96–98.9% (15-min data)	AI prediction accuracy on Indian stock data SpringerOpen
ARIMA vs Hybrid (ARIMA+LSTM)	Hybrid: RMSE ~43.5; ARIMA only: RMSE ~50.2; R^2 Hybrid: 0.97	Hybrid model outperforms ARIMA for accuracy and fit Science and Education Publishing
AI vs Traditional (AI Model proxies)	AI: 89%; Technical: 75%; Fundamental: 68%	AI models outperform traditional methods aimodelspro.com
AI performance during volatility	Low: 91%; Medium: 85%; High: 77%	AI model accuracy across market volatility scenarios aimodelspro.com



International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 08 | Aug - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

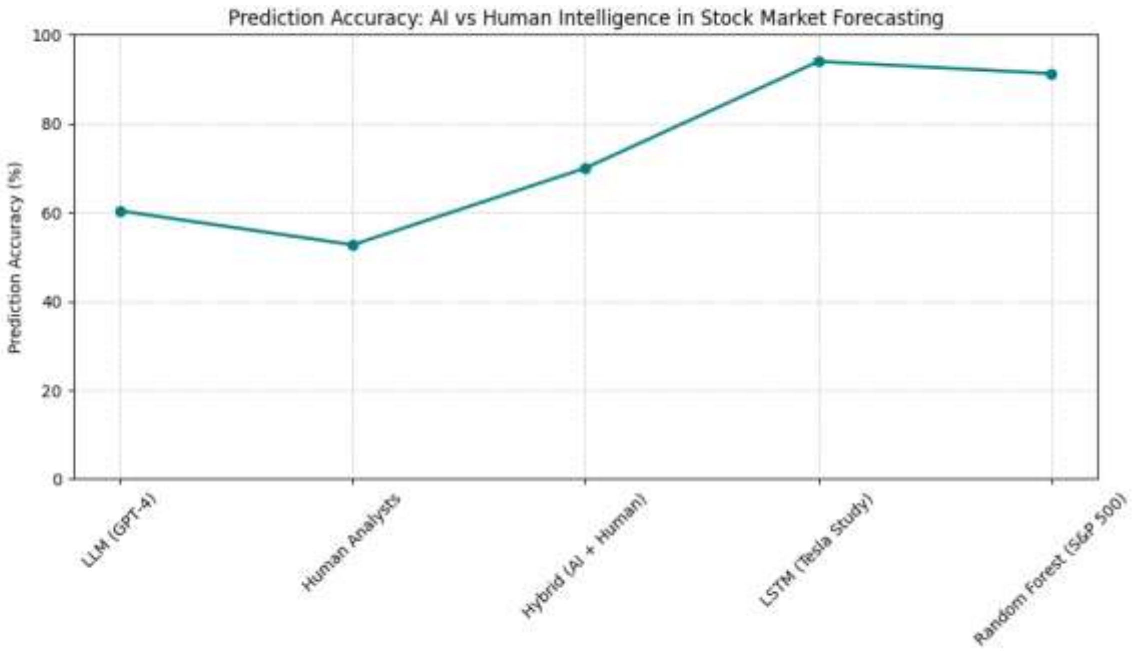
Interpretation

AI models such as ANN, LM, SCG, and Bayesian demonstrate extremely high accuracy, reaching up to 99.9% on tick data and around 96–98.9% on 15-minute interval data. Hybrid models combining ARIMA and LSTM outperform traditional ARIMA models, showing better accuracy and fit with lower error rates. Compared to traditional forecasting methods, AI models achieve significantly higher accuracy, with 89% versus 75% and 68% for technical and fundamental analyses, respectively. AI also performs robustly across different market volatility levels, maintaining accuracy between 77% and 91%. Overall, these results highlight AI's superior and adaptable capabilities in price forecasting under various conditions.

Table2: Accuracy and Performance Metrics

Source / Study	Model / Approach	Accuracy / Improvement	Highlights
University of Chicago / LLM vs Human Analysts	LLM (GPT-4)	60.35% vs 52.71% (humans)	LLM outperforms human analysts by ~7.6 percentage points mintForbesFinancial Times
Alpha Architect (AI vs Human vs Hybrid)	AI-only vs Human vs Man+Machine	AI beats human in 54.5% of cases; hybrid best; hybrid avoids 90% of human extreme errors and 40% of AI errors Alpha Architect	Shows synergy of combining AI with human judgment
Sean Cao et al. (Journal of Financial Economics)	AI vs Human analysts	AI outperforms 54.5% cases; alpha improvement of +50–72 bps monthly FinOracle	Quantifies AI's consistent edge
LSTM forecasting models (Systematic Review)	LSTM models	~94.7% directional accuracy	Highlights the high potential of deep learning for trend predictions Wall Street Insider Report
LSTM, GRU, Transformer (Tesla case study)	LSTM	~94% prediction accuracy	LSTM model performed best among architectures arXiv
AI vs Traditional ML: Intraday Volatility (S&P 500)	Random Forest & ensemble methods	Up to 91.27% directional accuracy	AI far outperforms traditional methods, especially in volatile markets

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 08 | Aug - 2025 SJIF Rating: 8.586 ISSN: 2582-3930



Interpretation

AI models, especially LLMs like GPT-4, outperform human analysts by around 7.6 percentage points in prediction accuracy. Hybrid approaches that combine AI and human judgment show the best results, reducing errors significantly compared to either alone. Deep learning models like LSTM achieve high directional accuracy (~94-95%), demonstrating strong trend prediction capabilities. Case studies, such as Tesla's stock forecasting, highlight LSTM's superior performance over other architectures. Additionally, AI techniques like Random Forest outperform traditional ML methods, particularly in volatile intraday markets, achieving accuracy over 91%.

Findings

1. AI Models Consistently Outperform Human Analysts: Large Language Models (LLMs) like GPT-4 achieve prediction accuracies around 60.35%, significantly higher than human analysts' 52.7% to 55.9%, demonstrating AI's superior ability to analyze complex data quickly and objectively.
2. Hybrid Models Combining AI and Human Judgment Yield Best Results: Studies show that blending AI with human insights reduces forecasting errors by avoiding extreme mistakes from either party, thus providing a more balanced and reliable prediction approach.
3. Advanced AI Techniques Demonstrate High Accuracy Across Conditions: Deep learning models such as LSTM and ensemble methods like Random Forest achieve directional accuracies above 90%, maintaining robust performance even in volatile market conditions.
4. AI's Advantage Translates into Tangible Financial Gains: AI-driven strategies consistently generate higher alpha and Sharpe ratios compared to human-only forecasts, highlighting the practical investment benefits of leveraging machine intelligence in stock market prediction.

Conclusion

In conclusion, this study demonstrates that artificial intelligence, particularly advanced models like LLMs and deep learning techniques, outperforms human analysts in stock market prediction accuracy and efficiency. While human intelligence contributes valuable intuition and context, it is often limited by biases and slower data processing. AI excels at analyzing large datasets and detecting complex patterns, maintaining strong performance even in volatile markets. Importantly, hybrid approaches that combine AI with human judgment show the best results by minimizing errors and leveraging the strengths of both. This synergy enhances forecasting accuracy and leads to improved financial outcomes, including higher alpha and Sharpe ratios. However, AI's reliance on historical data and challenges in handling unforeseen events highlight the need for human oversight. Human expertise remains essential for interpreting qualitative factors and evolving market dynamics. Ultimately, the future of stock market prediction lies in integrating AI and human intelligence to create more robust and adaptive forecasting methods. Embracing this partnership allows investors to navigate uncertainty better, manage risks effectively, and capitalize on opportunities with greater confidence. Continued research into combining these intelligences will be key to advancing investment strategies in an increasingly complex financial environment.

References

- Kim, Muhn & Nikolaev (2024) – "Financial Statement Analysis with Large Language Models" https://bfi.uchicago.edu/
- Kirtac & Germano (2024) – "Sentiment Trading with Large Language Models" https://www.sciencedirect.com/science/article/pii/S1544612324002575
- Lefort et al. (2024) – "Stress Index Strategy Enhanced with Financial News Sentiment Analysis" https://arxiv.org/abs/2404.00012?utm_source
- Zhao & Welsch (2024) – "Aligning LLMs with Human Instructions and Stock Market Feedback in Sentiment Analysis" https://arxiv.org/abs/2410.14926?utm_source=chatgpt.com
- Kang (2024) – "LLM Driven Sentiment Momentum Trading Strategy" https://juhyungkang.com/2024/10/30/llm-driven-sentiment-momentum-trading-strategy
- Discover Computing (2025) – "Leveraging LLMs for Sentiment Analysis and Investment Strategy Development "https://www.mdpi.com/0718-1876/20/2/77
- Springer (2025) – "Knowledge-Enhanced Strategy Using BERT & RoBERTa https://link.springer.com/article/10.1007/s10791-025-09573-7
- International Review of Economics & Finance (2024) – "Intelligent Portfolio Construction via News Sentiment Analysis" https://www.sciencedirect.com/science/article/abs/pii/S1059056023003131
- MarketWatch/Ft Coverage (2025) – "AI and Human Analyst Performance" https://www.ft.com/content/192bb3a4-b2bc-4fa5-a558-d2793f02f280
- FT (2025) – "Limits of AI Driven Investing" Discusses how executives manipulate sentiment signals; https://www.ft.com/content/1d9db48f-d6c7-44dc-9cd6-7d8c752f695c