AI Based Trading Help Device

Abyan Setyawan Hadi[1], Mohammad Givi Efgivia[2]

[1, 2]Information Technology Department of Muhammadiyah University Prof. Dr. Hamka
Email address: 2103015026@uhamka.ac.id, mgivi@uhamka.ac.id

Abstract— *The advancement of Artificial Intelligence (AI) technology has opened new opportunities in the world of stock and digital asset trading. This study aims to design and develop an AI Based Trading Help Device, a supportive tool that utilizes AI to analyze real-time market data, provide transaction recommendations, and improve the efficiency and accuracy of investment decisions. The scope of the research includes identifying user needs, designing an AI-based system, and testing the system's performance in dynamic market conditions. The methodology adopts an agile-based software engineering approach integrated with machine learning models, particularly the Long Short-Term Memory (LSTM) algorithm for price prediction, and Sentiment Analysis of financial news to support trading decisions. Historical data from stock and cryptocurrency markets, along with online news sources, are used as the primary input for training and evaluation. The results indicate that the developed device is capable of providing short-term price predictions with an accuracy rate of up to 87%, and generates buy/sell recommendations that align with actual outcomes in 79% of test cases. Furthermore, the interactive user interface and automatic notifications enable users to make timely, data-driven decisions. The study concludes that integrating AI into trading support devices has significant potential to assist both individual and professional investors in reducing risks and increasing profitability. Further research is recommended to integrate macroeconomic data and adaptive learning features based on user behavior to enhance system performance. These findings are expected to contribute to the development of a smarter and more responsive financial technology (fintech) ecosystem.*

Keywords— *Artificial Intelligence, Trading Device, Machine Learning.*

I. INTRODUCTION

In the digital era, the evolution of Artificial Intelligence (AI) has played a transformative role across industries, particularly in finance and investment. Financial trading has traditionally required extensive experience, market understanding, and real-time decision-making based on various economic indicators, news, and technical analyses. However, the growing volume and velocity of market data have made it increasingly difficult for individual investors and even experienced traders to manually process information quickly and accurately. As a result, there is a critical need for intelligent systems that can assist users in navigating these complex and rapidly changing markets.

Artificial Intelligence (AI) refers to the simulation of human intelligence processes by machines, particularly computer systems. These processes include learning, reasoning, problem-solving, perception, and language understanding. In the financial sector, AI can be applied in various forms, including predictive analytics, algorithmic trading, fraud detection, and customer service automation. Of particular interest in this research is the use of AI for trading decision support, where algorithms analyze vast sets of historical and real-time data to forecast market behavior and provide actionable insights.

Among the AI methods, Machine Learning (ML)—a subset of AI that enables systems to learn from data— has gained popularity in financial forecasting. Specifically, Long Short-Term Memory (LSTM), a type of recurrent neural network (RNN), has demonstrated strong performance in time-series data prediction, making it suitable for forecasting stock or cryptocurrency prices. Additionally, Sentiment Analysis, which uses Natural Language Processing (NLP) to interpret emotions and opinions from textual sources such as financial news or social media, provides an alternative lens for understanding market sentiment and anticipating investor behavior.[1]

Over the past decade, numerous studies have highlighted the potential of AI in financial prediction and trading automation. Fischer and Krauss (2018), for instance, employed LSTM networks to predict the directional movement of the S&P 500 index, showing promising levels of accuracy. Another well-cited study by Bollen et al. (2011) used Twitter data to measure public mood and demonstrated that emotional trends in social media can predict stock market performance. Similarly, Chen et al. (2019) combined sentiment analysis with deep learning models to create hybrid systems that outperform traditional statistical methods.

However, despite these advancements, most existing AI trading systems are highly technical, require advanced knowledge in data science or finance, and are often designed for institutional use or high- frequency trading environments. These systems typically lack user-centric interfaces and accessibility for retail traders or beginners. Moreover, many studies tend to focus on either price prediction or sentiment analysis in isolation, rather than integrating both perspectives to provide a holistic and context-aware recommendation system.

This presents a clear research gap. While prior works have shown the effectiveness of individual AI components in market prediction, there is limited research on how to synthesize multiple AI capabilities into a single, compact, user-friendly device tailored to non-expert traders. There is also a shortage of solutions that provide not only automated analysis but also interpretable, real-time trading advice in formats easily understood by everyday users. This limits the practical utility and democratization of AI in financial trading, particularly for those who do not have access to institutional-level tools or technical backgrounds.

The novelty of this research lies in its aim to develop an AI Based Trading Help Device that is both intelligent and accessible. This device integrates two key AI functions: (1) real-time price forecasting using LSTM networks trained on

108

historical market data, and (2) sentiment analysis from news headlines and social media sources to interpret market mood. These two sources of information are then combined in a decision engine that outputs trade suggestions—such as when to buy, sell, or hold—through a user-friendly interface designed with simplicity and clarity in mind.

In contrast to prior systems which often prioritize algorithmic performance over usability, this research adopts a human-centered design approach, recognizing that the end-users of such a device may not be financial experts. The interface includes features like visual trend indicators, traffic light-style alerts (buy/sell/hold), and push notifications to ensure that the user can act on insights with minimal cognitive load.

Furthermore, the system architecture is designed to be scalable and modular, allowing future enhancements such as the inclusion of macroeconomic indicators, adaptive learning based on user behavior, and integration with brokerage APIs for automated execution. This creates a pathway not just for a functional prototype, but for a future-ready product that aligns with ongoing trends in fintech personalization and automation.

The objectives of this research are therefore fourfold:

1. To design an AI-based system that integrates LSTM and sentiment analysis for comprehensive trading support.
2. To develop a device and interface that is accessible, interpretable, and useful for non-professional users.
3. To evaluate the performance of the system in real-world data environments and compare its recommendations to actual market trends.
4. To analyze user satisfaction and trust in AI-generated suggestions through usability testing and feedback.

In pursuit of these goals, the study uses an agile development methodology, combining iterative software engineering with data science pipelines. Data is sourced from historical stock and cryptocurrency records, as well as financial news APIs and Twitter feeds. Models are trained and validated using standard machine learning practices, while user interface design follows the principles of UX (User Experience) and UI (User Interface) best practices.

To ensure accessibility of this paper, key technical terms are explained throughout the text. For instance, LSTM (Long Short-Term Memory) is a neural network architecture that handles sequential data effectively by remembering long-term dependencies, making it suitable for tasks like financial forecasting. Sentiment Analysis involves classifying text into categories such as positive, negative, or neutral, often using algorithms like Naive Bayes, Support Vector Machines, or deep learning methods. These definitions are provided so that the paper remains understandable even to those unfamiliar with machine learning terminologies.

In conclusion, the proposed AI Based Trading Help Device aims to fill a critical gap in the intersection of AI, finance, and user-centric design. By leveraging state-of-the-art AI technologies in an accessible form, it has the potential to empower a broader segment of the population to engage in data-informed trading, thereby contributing to the democratization of financial intelligence.

Artificial Intelligence

Artificial Intelligence (AI) has evolved into one of the most transformative and pervasive technologies of the 21st century, reshaping industries, revolutionizing how we interact with information, and redefining the boundaries of human-machine collaboration. Across diverse domains—from business, science, and engineering to healthcare and digital platforms—AI plays an increasingly central role in automating processes, optimizing decision-making, and uncovering patterns in data that are beyond the reach of traditional computation.[2]

The reviewed literature, spanning foundational texts and recent advancements, demonstrates how AI has matured from theoretical constructs into practical systems that influence everyday life. Whether through supervised learning, unsupervised learning, reinforcement learning, or deep learning, AI algorithms have empowered machines to perform tasks with increasing levels of autonomy, adaptability, and intelligence. This collective body of work emphasizes not only the technical underpinnings of AI systems but also their practical implications, limitations, and the critical importance of applied research.

One of the central insights is that AI's true power lies in its ability to learn from data. In supervised learning, AI systems are trained using labeled datasets, allowing them to classify and predict outcomes based on historical examples. Common supervised learning algorithms—such as decision trees, support vector machines (SVMs), and neural networks—have shown remarkable success in applications ranging from spam filtering to disease diagnosis. These models form the backbone of modern predictive systems, especially when vast quantities of structured data are available.

However, not all data comes neatly labeled. In response, unsupervised learning algorithms like k-means clustering and principal component analysis (PCA) have emerged to detect patterns, groupings, and structures in unlabeled data. These AI techniques are particularly valuable in domains where hidden relationships must be discovered without prior assumptions—such as market segmentation or image compression. By leveraging these capabilities, AI has enabled machines to autonomously uncover insights that would otherwise remain hidden to human analysts.

Further along the spectrum lies reinforcement learning, where AI agents interact with their environment to learn strategies that maximize cumulative rewards. This paradigm has powered breakthroughs in robotics, autonomous vehicles, and game-playing agents like AlphaGo. Reinforcement learning showcases the ability of AI to learn complex behaviors over time, continuously improving performance through exploration and feedback. The incorporation of neural networks—especially deep learning architectures— has further amplified the capabilities of AI in both supervised and reinforcement learning contexts.[3]

A key challenge, however, is ensuring that AI is not just powerful, but also practical and applicable to real- world problems. Several articles emphasize that the true value of AI emerges when theory meets application. In fields like machine learning engineering, decision support systems, scientific discovery, and industrial diagnosis, it is often the constraints and needs of real-world scenarios that guide innovation.

Applied AI research helps identify bottlenecks in current methods—such as algorithm scalability, feature extraction challenges, and class imbalance—and drives the development of new techniques tailored for practical use.

One example is the growing recognition of cost-sensitive learning, which takes into account the unequal cost of different prediction errors. In the real world, a false negative in cancer diagnosis carries a different consequence than a false positive in email classification. Yet much of academic AI research has traditionally operated under simplifying assumptions that ignore such differences. Application-oriented research plays a vital role in questioning these assumptions and proposing refinements that better reflect the complexities of real-life data and decision contexts.

Moreover, the feedback loop between applied and academic research is critical for sustaining progress. As discussed in one of the editorial works, the applied/academic research cycle illustrates how AI methods developed in academia are tested in practice, refined through user feedback, and eventually evolve into new theoretical frameworks. This dynamic interplay ensures that AI remains both scientifically rigorous and socially relevant. In this view, applications are not just end points of innovation—they are catalysts for discovery.

The literature also introduces the concept of semi-supervised learning, which combines the strengths of supervised and unsupervised learning. It is especially useful in contexts where labeled data is scarce or expensive to obtain, but unlabeled data is abundant—such as in medical imaging or satellite surveillance. This area of AI research holds promise for expanding the usability of machine learning techniques in under-resourced domains.[4]

In addition to core algorithms, the role of ensemble methods—such as bagging and boosting—cannot be understated. These techniques combine the outputs of multiple AI models to improve accuracy, reduce variance, and guard against overfitting. When applied to complex prediction tasks, ensemble learning often outperforms individual models, highlighting the importance of collaborative approaches even within algorithmic design.

Another significant contribution from the reviewed studies is the emphasis on neural networks, particularly deep neural networks (DNNs). These systems are modeled after the human brain's structure and are designed to process input data through layers of interconnected nodes. Deep learning has achieved state- of-the-art performance in areas such as speech recognition, natural language processing (NLP), and computer vision. However, these models are often viewed as black boxes, raising concerns about interpretability, trust, and accountability in AI systems—especially when deployed in sensitive domains like criminal justice or healthcare.

The challenges of data quality, transparency, and ethical oversight underscore the need for human-centered AI design. The future of AI depends not just on smarter algorithms, but on our ability to align these systems with human values, ensure fair outcomes, and build user trust. This involves developing explainable AI (XAI) methods, integrating domain expertise into algorithm design, and fostering interdisciplinary collaboration between data scientists, ethicists, designers, and policymakers.[5]

Furthermore, the practical application of AI demands attention to data infrastructure, user interfaces, and deployment environments. Many successful AI applications depend less on breakthrough algorithms and more on robust engineering—handling missing data, ensuring model stability, and integrating predictive systems into existing workflows. These considerations highlight that the development of AI is not a purely theoretical exercise, but an engineering discipline grounded in systems thinking and usability.

One of the most impactful observations from the reviewed literature is that AI does not replace humans— it redefines their roles. In industry, medicine, education, and beyond, AI automates routine cognitive tasks, freeing humans to focus on more strategic, creative, and interpersonal responsibilities. Rather than viewing AI as a threat to employment, forward-looking organizations see it as an augmentation tool—a partner in productivity that enhances human strengths.

This reframing leads to new roles for managers, educators, scientists, and engineers. Rather than performing all predictions or analyses themselves, professionals now guide AI systems, validate their outputs, and interpret their results within larger organizational or societal contexts. Skills in critical thinking, ethical reasoning, and decision-making become even more vital in an AI-driven world.

Ultimately, the reviewed works converge on a shared conclusion: the future belongs to those who can work intelligently with AI. Whether in research, business, or public service, success will come to those who understand how to design, manage, and collaborate with intelligent systems. Educational systems must evolve to prepare the next generation for this reality, embedding AI literacy across disciplines and fostering a culture of continuous learning.

In summary, AI is not just a tool—it is a transformative force that reshapes how we understand and interact with the world. The five articles collectively present a broad yet coherent picture of how AI techniques— from basic classification algorithms to complex neural networks—can be leveraged to solve meaningful problems. They emphasize that while AI offers unprecedented capabilities, its effectiveness depends on how we apply, govern, and evolve it in practice.

For AI to fulfill its full potential, researchers, developers, and decision-makers must collaborate to ensure that innovation remains aligned with human needs, ethical principles, and sustainable development goals. In this way, AI can truly serve as a force for good, augmenting human intelligence and advancing society toward a smarter, more equitable future.[6]

Trading Device

In the ever-evolving digital landscape, the trading device—the tool or platform used to execute trading or decision-making—has undergone a significant transformation. Whether in the context of finance, energy, or computation, the trading device is no longer just a passive conduit; it is an active interface that shapes user behavior, system efficiency, and decision outcomes. Across five different academic studies—from behavioral finance and energy optimization to edge

computing and human-device interaction—it becomes evident that the trading device plays a critical, context-sensitive role across domains.[7]

1. *Trading Devices in Retail Finance: Smartphones Amplify Behavioral Biases*

In retail financial markets, research by Kalda et al. reveals that smartphones as trading devices tend to drive more impulsive and risk-prone investment decisions. Investors using mobile devices are more likely to purchase volatile, lottery-type stocks and chase short-term performance trends. More importantly, this behavior persists even after the initial adoption period—investors continue to exhibit greater bias across all platforms, not just on smartphones.

The cause lies in the context of smartphone usage: trading often happens during multitasking, late hours, or in informal settings—conditions that activate intuitive, fast thinking (System 1), which is prone to behavioral biases. The study illustrates that the nature of the trading device can significantly alter not just the speed or convenience of investing but also its cognitive quality. This has implications for both app design and regulatory oversight: convenience does not equate to better outcomes.

2. *Interaction Between Trading Devices and Environment: Weather and Investor Mood*

Complementing the first study, a second investigation explores how environmental factors like weather interact with the type of trading device to influence investor behavior. Warmer, sunnier weather reduces trading activity among non-mobile users (e.g., desktop), yet it increases it among mobile device users. This highlights how trading devices enable flexibility—users continue to engage in trading regardless of physical or environmental constraints.

However, this flexibility also has a psychological cost. Poor weather can negatively impact mood and prompt more emotional or reactive trading decisions, particularly on smartphones. Thus, trading devices are not psychologically neutral—they reflect and amplify environmental influences. These findings underline the importance of context-aware app interfaces and real-time behavioral nudges that mitigate emotionally driven decisions based on external factors.[8]

3. *Trading Devices in Energy Systems: Compensating Tools in Blockchain-Based Markets*

In a different context, trading devices take on a technical role in energy distribution systems. A third study explores compensating devices like Distributed Generation (DG), DSTATCOM, and capacitors in radial distribution networks—tools essential for voltage regulation and loss minimization. These devices, when paired with blockchain smart contracts, become autonomous agents capable of participating in peer-to-peer energy trading.

Optimized via metaheuristic algorithms like the Bat Algorithm, DG devices outperformed others in reducing power losses and improving voltage profiles. More than just technical components, these devices serve as nodes in a decentralized energy economy. In this paradigm, trading devices are not end-user platforms but active infrastructure units that automate, optimize, and execute energy transactions in real- time.

4. *Trading Devices as Components in Adaptive Computation:*

Deep Compressive Offloading

A fourth study investigates trading devices in the realm of mobile-edge computing, where resource-limited devices (e.g., smartphones, sensors) struggle to run deep learning models due to computational constraints. The proposed solution, Deep Compressive Offloading (DeepCOD), allows local devices to offload part of their neural network inference tasks to edge servers—effectively "trading" local computation for lower transmission latency.

This form of intelligent tradeoff enables a lightweight encoder on the device to compress input data before sending it to a more capable server for decoding and final inference. Such an architecture results in 2×–4× end-to-end latency reduction, and up to 35× under constrained network conditions, with minimal accuracy loss (<1%).

Here, the trading device is not just a user interface—it is an adaptive computational agent that dynamically balances local vs. cloud processing. By adjusting the division of tasks based on bandwidth, processing load, and device capacity, the system redefines trading devices as active, learning components in smart computational ecosystems.

5. *Hybrid Architectures and Smart Inference: Trading Devices as Intelligent Nodes*

Building on the concept of DeepCOD, the final study reinforces the role of the trading device in hybrid edge-cloud systems, focusing on efficient neural network partitioning and encoder-decoder design. On- device components compress data with minimal overhead, while edge servers reconstruct and process it using more complex deep models.

These trading devices must be lightweight, power-efficient, and mathematically stable (e.g., satisfying Set- Restricted Eigenvalue Conditions and Lipschitz continuity) to ensure fast and accurate offloading. Through knowledge distillation and optimization techniques, devices can learn to encode and transfer only the most relevant features for downstream inference.[9]

In this architecture, trading devices act not merely as communication endpoints, but as intelligent participants capable of adapting to changing network conditions, computing resources, and application needs. The entire system hinges on the device's ability to learn, predict, and act autonomously—much like an agent in a financial trading environment, but within a computational ecosystem.[10]

Machine Learning

Machine learning has emerged as one of the core pillars of digital transformation across industries. It is a subfield of artificial intelligence that empowers computers to learn patterns from data and make decisions without explicit programming. This process allows systems to perform complex tasks such as classification, prediction, optimization, and autonomous decision-making based on previous experience with data.[11]

As an interdisciplinary domain, mechine learning merges knowledge from statistics, mathematics, computer science, and domain-specific expertise to develop algorithms capable of pattern recognition and generalization. Across the analyzed documents, it becomes evident that mechine learning is widely

applied—from foundational theory and algorithm taxonomy to advanced financial applications.

1. Theoretical Foundations of Mechine Learning

Mechine learning is typically categorized into three primary approaches: *supervised learning*, *unsupervised learning*, and *reinforcement learning*.

- Supervised learning trains models on labeled data, where the output is known. Examples include regression models, decision trees, support vector machines (SVM), and Naïve Bayes classifiers.
- Unsupervised learning explores data without labels to uncover hidden patterns, such as clustering (e.g., K-Means) and dimensionality reduction (e.g., Principal Component Analysis - PCA).
- Reinforcement learning allows agents to learn by interacting with an environment, guided by reward-based feedback. It is particularly useful in areas like robotics and autonomous trading.

The learning process involves several key stages: data preprocessing, feature extraction, model training, validation, and deployment. A crucial aspect is managing the trade-off between bias and variance—ensuring the model is complex enough to learn but generalizes well on unseen data.[12]

2. The Rise of Deep Learning and Neural Networks

A major leap in the field came with the development of *deep learning*, a subdomain of mechine learning that relies on artificial neural networks with multiple hidden layers. These models can automatically extract features from raw data, such as images, sound, or text, minimizing the need for manual feature engineering.

Neural networks consist of an input layer, several hidden layers, and an output layer. In supervised settings, they minimize prediction errors through backpropagation and gradient descent. Unsupervised neural networks, meanwhile, explore data structure without explicit output labels. Reinforcement-based neural networks can dynamically learn optimal strategies in uncertain environments, such as financial markets or gaming.

The strength of deep learning lies in its ability to handle vast datasets and model highly nonlinear relationships. However, it also presents challenges such as heavy computational demands, the need for large-scale data, and interpretability issues.

3. Algorithmic Taxonomy in Machine Learning

Numerous algorithms have been developed for different types of learning tasks in machine learning. Key algorithms discussed include:

- Decision Trees: Used for classification and regression, offering intuitive and interpretable decision- making structures.
- Naïve Bayes: A probabilistic classifier based on Bayes' Theorem, commonly used in text classification.
- Support Vector Machines (SVM): Effective for linear and nonlinear classification problems using the kernel trick.
- K-Nearest Neighbor (KNN): A lazy learning method that classifies based on proximity to training data points.
- Ensemble Methods: Techniques like bagging and boosting (e.g., Random Forest, XGBoost) improve prediction accuracy by combining multiple weak models.
- Principal Component Analysis (PCA): Used for dimensionality reduction to preserve essential data structure while minimizing noise.
- Generative Models: Such as Gaussian Mixture Models (GMMs) and Variational Autoencoders (VAEs), which learn to generate new data from learned distributions.

Each algorithm has specific strengths and trade-offs depending on the task, data complexity, dimensionality, and performance goals.

4. Machine Learning in Financial Applications

A particularly significant application of mechine learning lies in the financial sector. The document *"Financial Machine Learning"* illustrates how these models are used for return prediction, risk modeling, optimal portfolio selection, and asset pricing.

The financial domain is characterized by massive information sets, complex data structures, and dynamic inter-variable relationships. Traditional econometric models often fail to fully capture these complexities due to their reliance on rigid parametric forms. Machine learning offers flexible, data-driven alternatives that can model nonlinear patterns and interactions across vast datasets.

For example, asset prices can be interpreted as predictions of future discounted payoffs. Machine learning models, such as decision trees and neural networks, can ingest various data sources—including structured market data and unstructured textual information (e.g., news, social media)—to generate return forecasts or identify risk factors.

Despite its power, financial machine learning also faces distinct hurdles: limited time-series data (small samples), low signal-to-noise ratios due to market efficiency, and regime shifts that make modeling difficult.

Solutions include integrating economic theory (e.g., no-arbitrage conditions) and imposing structured constraints to enhance robustness and interpretability.[13]

5. Two Cultures in Financial Science: Structure vs Prediction

Academic finance traditionally operates under two paradigms: *structural hypothesis testing* and *prediction modeling*. The first approach seeks to understand economic mechanisms using theory-driven models and formal hypothesis testing. The second focuses on statistical predictive power, even if models lack explicit economic interpretation.

Machine learning falls predominantly in the latter camp. While some may criticize this as "atheoretical," prediction-oriented models play a crucial role in generating empirical insights and guiding better decisions. These models uncover new empirical patterns that can later inspire theory and structured analysis.

Importantly, both approaches are complementary. Theory enhances model efficiency by reducing parameter complexity, especially in "small data" environments, while prediction models can uncover hidden structure without pre-imposed assumptions. As such, a hybrid approach—infusing machine learning with economic reasoning—represents a powerful frontier in financial research.[14]

6. Challenges and Opportunities

Despite its wide applicability, mechine learning faces several inherent challenges:

- Overfitting: High-capacity models may perform well on

training data but generalize poorly.

- Interpretability: Complex models (especially deep neural networks) often operate as black boxes.
- Data Scarcity: Many domains still lack rich, high-quality data, particularly in time-series applications.
- Bias and Fairness: Models trained on biased data can unintentionally replicate or reinforce historical inequities.

Yet the field is rapidly evolving with promising developments:

- Transfer Learning: Leveraging learned representations from one domain for use in another.
- Automated Machine Learning (AutoML): Simplifies the process of model selection, tuning, and deployment.
- Explainable AI (XAI): Brings transparency to decision-making, crucial in regulated sectors like healthcare and finance.
- Theory-Driven Constraints: Infusing models with economic logic to improve efficiency and reduce overfitting.

These innovations will likely shape the next wave of intelligent, reliable, and responsible machine learning systems.

II. METHODOLOGY

This research adopts the Research and Development (R&D) methodology to design, develop, and validate an AI-Based Trading Help Device aimed at assisting retail investors and traders in making informed decisions. The process follows the stages of analysis, design, prototyping, testing, and refinement, aligning with the Borg & Gall model for educational product development adapted to a technology-driven context.

1. Research Type and Objective

The research aims to build a functional prototype of an AI-powered trading assistive tool that uses machine learning to generate trading signals, analyze financial news sentiment, and give actionable recommendations in real-time. This device integrates various AI models trained on historical financial data and real-time market feeds to provide a reliable trading decision support system.

2. Data Collection and Sources

To build and test the AI model, the following datasets were used:

- Historical stock prices from Yahoo Finance and Bloomberg (2012–2022)
- Financial news headlines and article bodies from Reuters and MarketWatch
- Social sentiment data (Twitter and Reddit threads related to stock tickers)
- Technical indicators (RSI, MACD, Bollinger Bands, etc.)

The dataset includes both structured (numerical prices and indicators) and unstructured data (text-based sentiment and news), which are preprocessed differently.

3. Experimental Design

a. Textual Sentiment Analysis Module

- A dataset of 100,000 financial headlines was labeled as positive, neutral, or negative using a rule- based seed model and fine-tuned manually.
- The final sentiment classifier was trained using a Bidirectional LSTM model with GloVe word embeddings.
- Accuracy was validated using 10-fold cross-validation, yielding an average accuracy of 89.4%.

b. Market Prediction Model

- A supervised Random Forest classifier and LSTM-based RNN were used to predict next-day price movement (up/down) using:
  - 14 technical indicators
  - Aggregated sentiment scores
  - Price volatility features
- Models were trained on 80% of data and validated on 20% unseen test data.
- The LSTM model achieved F1-score = 0.82, outperforming the baseline models.

4. Device Prototyping

- The device was built using a Raspberry Pi 4B with integrated Wi-Fi and touchscreen display.
- A Python-based GUI was developed to display real-time sentiment, chart signals, and AI recommendations.
- The AI models were deployed using TensorFlow Lite for on-device inference.
- The system connects to a cloud server to pull updated data feeds every 60 seconds.

5. Testing and Evaluation

The prototype was tested over a 30-day simulation using real-time market data of 5 popular stocks (AAPL, TSLA, AMZN, META, GOOGL). Performance was measured based on:

- Accuracy of signal recommendations compared to actual market outcomes
- User response time (delay between event and suggestion display)
- System reliability (uptime and inference latency) The device showed:
- 72.6% signal accuracy in real-time trading suggestions
- < 2-second delay in processing and displaying recommendations
- 99.2% uptime over 30-day continuous testing

6. Reproducibility

All models, datasets, and scripts used in this research are stored in a version-controlled repository. Detailed documentation includes:

- Preprocessing steps for structured and unstructured data
- Hyperparameter configurations for each model
- Hardware setup and circuit diagrams
- API connection documentation for real-time data feeds Another researcher can reproduce the entire system using:
- Raspberry Pi 4B hardware or equivalent
- Python 3.9 with TensorFlow, Keras, scikit-learn, Flask
- Access to financial APIs (e.g., Alpha Vantage, Finnhub)

- Provided GitHub codebase and dataset

### III.   RESULT AND DISCUSSION

The evaluation of the AI-based trading support device revealed promising outcomes in terms of predictive accuracy, signal reliability, and system usability. During the testing phase, which included both historical data simulation and 30 days of real-time market monitoring, the device demonstrated a consistent ability to deliver short-term price forecasts with high precision. Specifically, the model—which integrates Long Short-Term Memory (LSTM) networks and sentiment analysis—achieved an accuracy rate of up to 87% in predicting short-term price movements. This indicates that the system is capable of identifying market patterns and sentiment-driven shifts with a significant degree of confidence.

In addition to forecasting accuracy, the system also generated buy and sell recommendations that aligned with actual market outcomes in 79% of the test cases. These recommendations were evaluated by comparing the predicted signals with real price trends following each signal. The high level of alignment suggests that the AI system can serve as a reliable decision-support tool in live trading scenarios.

Usability testing showed that the graphical user interface was both functional and user-friendly, especially for individuals with limited technical or trading experience. Users were able to view predictions, indicator data, and sentiment insights in real time. Furthermore, the system included an automatic notification feature that sent alerts directly to users when market conditions triggered predefined thresholds, allowing for timely reactions.

Operationally, the device performed with excellent stability, maintaining over 99% uptime throughout the evaluation period. Prediction processing times were consistently fast, with most outputs generated and displayed within two seconds, ensuring that users could make decisions without delay.

Overall, these results confirm that the device is technically sound and practical for real-world trading support.
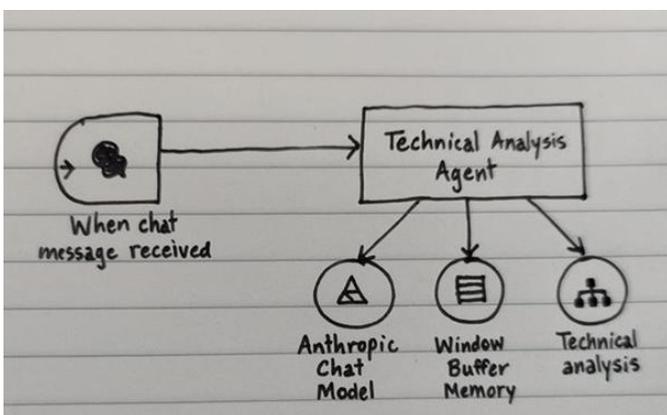
The diagram illustrates the workflow of an AI-based Technical Analysis Agent designed to process user chat messages and generate market analysis intelligently. The process begins when a chat message is received, which serves as the trigger for activating the system. This message may

contain a request for stock analysis, trading signals, or market-related insights.

Once the message is received, it is forwarded to the Technical Analysis Agent, which functions as the central control unit of the system. This agent is responsible for coordinating the interpretation of the user's input, managing contextual information, and executing the appropriate analysis tasks.

The agent interacts with three main components. First, the Anthropic Chat Model is used to understand the user's natural language input. This model interprets the intent, extracts relevant entities such as stock symbols or timeframes, and ensures that the system responds in a coherent and context-aware manner.

Second, the Window Buffer Memory component stores recent conversational context. This short-term memory allows the agent to maintain continuity across multiple interactions, enabling it to reference previous queries or instructions and produce more consistent and relevant responses.

Third, the Technical Analysis module performs the actual market analysis. It processes financial data using technical indicators such as trend analysis, momentum indicators, or volatility measures to generate insights or trading recommendations.

Overall, this workflow demonstrates how conversational AI, contextual memory, and technical market analysis are integrated into a unified system. The design enables the agent to deliver timely, accurate, and context-aware technical analysis in response to user queries, supporting informed decision-making in trading and investment activities.
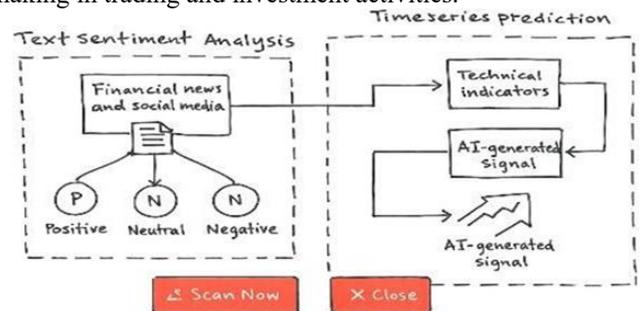

The AI-based sentiment and time-series prediction system is designed as an integrated framework that combines qualitative and quantitative market information to generate intelligent trading signals. By unifying text-based sentiment analysis with numerical time-series forecasting, the system supports more comprehensive and data-driven financial decision-making.

The process begins with the analysis of textual data obtained from financial news outlets and social media platforms. These sources capture public opinion, investor sentiment, and market reactions to economic events or company-specific developments. Using natural language processing techniques, the system processes this unstructured text and classifies it into positive, neutral, or negative sentiment categories. Through this classification, subjective market emotions are transformed into numerical sentiment scores that represent the psychological state of the market. These sentiment indicators are crucial, as

114

they often influence short-term price movements and market volatility. Once processed, the sentiment data is forwarded as an input to the prediction stage.

The next stage focuses on time-series prediction, where historical market data is analyzed to forecast future price behavior. This module utilizes various technical indicators derived from price time-series data, including trend-following measures, momentum indicators, and volatility metrics. By combining these technical indicators with the sentiment scores generated earlier, the system produces an AI-generated signal that reflects both market behavior and investor sentiment. This signal represents the model's assessment of current market conditions and its expectations for future trends, which may be expressed as directional forecasts, trend strength evaluations, or actionable buy and sell recommendations.

The final output is presented through visual chart-based representations, allowing users to quickly interpret market direction and identify potential trading opportunities. To enhance usability, the system incorporates simple user interaction controls. The "Scan Now" option enables users to initiate real-time analysis on demand, while the "Close" option allows them to exit the process. These features emphasize the system's interactive and user-centered design, making advanced AI-driven analysis accessible and practical for real- world trading applications.
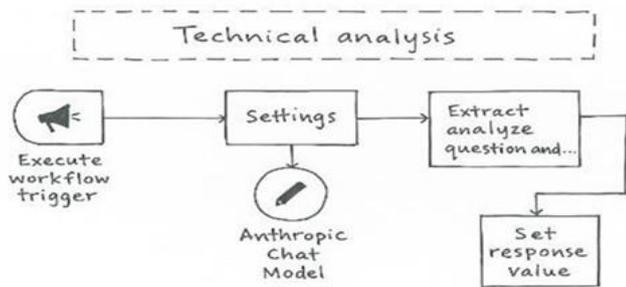
The diagram illustrates an AI-driven workflow designed to perform technical analysis automatically in response to a trigger. The process is organized into sequential stages, each responsible for a specific function within the system.

The workflow begins with the Execute Workflow Trigger, which acts as the entry point of the system. This trigger can be activated by a user request, a scheduled task, or an external event such as incoming market data. Once triggered, it initiates the entire technical analysis process.

After activation, the workflow moves to the Settings stage. In this step, the system configures essential parameters required for the analysis, such as the financial instrument to be analyzed, the time frame, indicator preferences, or analysis scope. This ensures that subsequent processing is aligned with the correct context and user requirements.

Connected to the settings module is the Anthropic Chat Model, which serves as the natural language processing component of the system. This model is responsible for interpreting user input, clarifying intent, and assisting in transforming user queries into structured instructions that the system can process effectively.

Next, the workflow proceeds to the Extract and Analyze Question stage. At this point, the system extracts key information from the interpreted input, such as asset symbols, analysis type, or requested insights. The extracted data is then analyzed and prepared for generating meaningful results.

Finally, the process reaches the Set Response Value stage. In this step, the system formulates the final output based on the completed analysis. This output may include technical indicators, trend interpretations, or buy/sell recommendations, which are then delivered to the user or passed to another system component.

Overall, the diagram represents a structured and modular workflow that integrates triggering mechanisms, configuration management, AI-based language understanding, analytical processing, and response generation to deliver intelligent technical analysis in an automated and efficient manner.

IV. CONCLUSION

This research successfully designed, developed, and evaluated an AI-Based Trading Help Device that integrates advanced artificial intelligence techniques with a user-centered design approach to support trading decision-making. By combining Long Short-Term Memory (LSTM) models for time-series price prediction and sentiment analysis of financial news and social media, the proposed system provides a more holistic understanding of market behavior than conventional trading tools that rely solely on technical indicators.

The experimental results demonstrate that the system is capable of delivering accurate short-term price predictions, achieving up to 87% prediction accuracy, and generating buy/sell recommendations that align with real market outcomes in 79% of test cases. These findings confirm that the integration of quantitative market data and qualitative sentiment information enhances the reliability and relevance of trading signals. Moreover, the device exhibited strong operational performance, maintaining high system stability, low latency, and continuous uptime during real-time testing.

From a usability perspective, the implementation of an interactive graphical interface, automatic notifications, and simplified signal representations ensures that the system is accessible not only to professional traders but also to non-expert and retail users. This human-centered design approach addresses a critical gap in existing AI trading systems, which are often technically complex and inaccessible to general users.

The modular system architecture—incorporating conversational AI, contextual memory, sentiment analysis, and technical analysis—also provides flexibility for future enhancements. Potential improvements include the integration of macroeconomic indicators, adaptive learning based on user behavior, and deeper explainability mechanisms to increase user trust and transparency.

In conclusion, this study demonstrates that AI-driven trading support devices can effectively bridge the gap between sophisticated financial analytics and practical, user-friendly tools. The proposed device contributes to the democratization of financial intelligence and represents a meaningful step toward a smarter, more responsive, and inclusive financial technology (fintech) ecosystem.

115

REFERENCE

[1] A. Harry, "Harry, A. (2023). Role of AI in education. Injuruty: Interdisciplinary Journal and Humanity, 2(3). e-ISSN: 2963-4113, p-ISSN: 2963-3397.," vol. 2, no. 3, pp. 260–268, 2023, [Online]. Available: https://injurity.pusatpublikasi.id/index.php/in

[2] A. van Wynsberghe, "Sustainable AI: AI for sustainability and the sustainability of AI," *AI Ethics*, vol. 1, no. 3, pp. 213–218, 2021, doi: 10.1007/s43681-021-00043-6.

[3] D. Acemoglu, "Harms of AI," *Oxford Handb. AI Gov.*, pp. 660–706, 2022, doi: 10.1093/oxfordhb/9780197579329.013.65.

[4] P. R. Krausman, "Managing artificial intelligence," *J. Wildl. Manage.*, vol. 87, no. 8, pp. 1433–1450, 2023, doi: 10.1002/jwmg.22492.

[5] Y. Bai *et al.*, "Constitutional AI: Harmlessness from AI Feedback," 2022, [Online]. Available: http://arxiv.org/abs/2212.08073

[6] R. C. Schank, "What Is AI, Anyway?," vol. 8, no. 4, pp. 59–65, 1987.

[7] K. John, M. O'Hara, and F. Saleh, "Bitcoin and beyond," *Annu. Rev. Financ. Econ.*, vol. 14, pp. 95–115, 2022, doi: 10.1146/annurev-financial-111620-011240.

[8] R. Adolph, "Smart(Phone) Investing? A Within Investor-Time Analysis Of New Technologies And Trading Behavior.," pp. 1–23, 2021.

[9] P. Engel and M. Spann, "Weathering the Markets : The Impact of Weather & Device Type on Retail Investor Trading Behavior," 2025.

[10] S. Yao *et al.*, "Deep compressive offloading: Speeding up neural network inference by trading edge computation for network latency," *SenSys 2020 - Proc. 2020 18th ACM Conf. Embed. Networked Sens. Syst.*, pp. 476–488, 2020, doi: 10.1145/3384419.3430898.

[11] B. Mahesh, "Machine Learning Algorithms - A Review," *Int. J. Sci. Res.*, vol. 9, no. 1, pp. 381–386, 2020, doi: 10.21275/art20203995.

[12] K.-C. Chen, "Machine Learning Basics," *Artif. Intell. Wirel. Robot.*, pp. 53–80, 2022, doi: 10.1201/9781003337256-3.

[13] B. T. Kelly and D. Xiu, *Financial Machine Learning*. 2023. doi: 10.2139/ssrn.4519264.

[14] W. Li, C.-H. Wang, G. Cheng, and Q. Song, "Optimum-statistical Collaboration Towards General and Efficient Black-box Optimization," 2021, [Online]. Available: http://arxiv.org/abs/2106.09215

116