StockSense: A Real-Time Web-Based Stock Price Prediction and Analysis System Using RSI and Linear Regression

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***Abstract*—While contemporary deep learning architectures offer significant computational capabilities for equity market modeling, their real-world application is frequently constrained by steep execution overhead and low interpretability for retail users. This study introduces StockSense, a highly responsive, browser-accessible predictive framework engineered using Python and Flask. By establishing on-demand connections to global exchanges via the yfinance API, the system bypasses the data-freshness limitations inherent to static offline training datasets. StockSense couples real-time momentum tracking via a 14-day Relative Strength Index (RSI) matrix with short-term predictive trend fitting using a localized, first-degree linear regression model mapped over 30 preceding trading sessions. System evaluation demonstrates a rapid end-to-end execution latency of under two seconds, delivering clear algorithmic trading signals (BUY, HOLD, SELL) alongside interactive data visualization layers powered by Chart.js. The resulting platform offers an intuitive, lightweight utility for immediate analytical decision support without requiring localized data pipelines or specialized hardware infrastructure.**

***Index Terms*—Stock prediction, RSI, Linear Regression, Flask, yfinance, real-time analysis, financial forecasting, web application, technical indicators, time series analysis.**

I. Introduction

Developing rapid, actionable insights from market movements remains a fundamental challenge within mathematical finance. Modern equity exchanges function as highly intricate ecosystems dictated by shifting macroeconomic pressures, corporate updates, and collective trader sentiment. Traditional linear statistical forecasting utilities, including autoregressive moving averages, frequently lack the adaptive responsiveness required to trace intraday or rapid swing trends. Conversely, while sophisticated non-linear deep networks process these streams effectively, they act as ”black box” systems whose internal logic is opaque to non-technical users. To balance computational agility with absolute user transparency, trend-following approaches such as linear regression and technical oscillators offer an optimal alternative. This paper presents StockSense, an accessible web-based alternative that strips away localized compilation requirements to deliver immediate, interpretable technical analysis straight to a user's web browser.

A. Background and Motivation

Executing timely asset evaluation across active public exchanges like the National Stock Exchange of India or the Bombay Stock Exchange presents distinct logistical challenges for everyday retail traders. Independent market participants routinely operate without the premium data infrastructure and structural pipelines utilized by institutional trading desks. By taking advantage of public live data endpoints alongside modular web services, developers can bridge this accessibility gap through specialized applications capable of:

- Fetching continuous pricing adjustments directly from active global tickers.
- Pinpointing extreme localized momentum shifts via mathematical boundaries.
- Extrapolating baseline trend continuations using simplified regression slopes.
- Rendering unified metrics clearly across standard, interactive browser screens.

Using the programmatic reach of the yfinance module alongside the streamlined backend rendering of Python Flask, it becomes straightforward to establish highly portable analytical tools like StockSense.

B. Problem Statement

Public market feeds generate continuous, highly erratic, and mathematically noisy time-series records. The vast majority of legacy technical trading software demands specialized machine configurations, functions using stale offline reference databases, or features confusing user dashboards. To make software truly accessible to contemporary end-users, several structural benchmarks must be established:

- A continuous web data fetch engine tracking major international asset indexes.
- A straightforward, fully deterministic alert generation mechanism.

- A fast, short-term projection engine requiring zero continuous training cycles.
- A highly decoupled cloud setup requiring no manual client adjustments.

This research puts forward the StockSense platform to satisfy these strict functional needs by combining streamlined polynomial mapping with classical oscillator configurations.

II. Related Work

Early literature addressing computational market tracking depended extensively on linear parametric formulations such as auto-regressive moving vectors. While structurally sound for broad seasonal mappings, these equations break down when encountering sudden, non-linear market shocks. To improve on these limits, subsequent academic research adopted standardized algorithmic models like Support Vector Machines and tree-based classification systems to gauge asset directionality. Modern deep sequence architectures, particularly Long Short-Term Memory nodes, have proven highly adept at memorizing conditional patterns across prolonged trading eras. Furthermore, framework explanation tools like LIME or SHAP are frequently deployed to decode the layered internal mathematics of these complex prediction networks.

With the historical expansion of statistical computing, the research landscape focused heavily on utilizing algorithms such as k-Nearest Neighbors, adaptive boosting, and gradient vectors to resolve classification and regression puzzles. These standalone paradigms significantly boosted diagnostic tracking by extracting relationships between classic technical signals—such as moving averages or divergence lines—and absolute closing paths. Meta-learning and boosting combinations further refined general tracking tolerances by stacking multiple weak classification systems. Nevertheless, these setups continuously required specialized, manual feature extraction steps and regularly failed to convey clear decision rationale to end-investors.

The subsequent introduction of modern deep modeling signaled a major structural shift in directional tracking studies. Recurrent neural frameworks and specialized gated sequence networks demonstrated excellent capabilities when processing complex multi-variable strings due to built-in state memory components. Similarly, convolutional grids have been repeatedly configured to filter spatial variations out of sequence charts, while hybrid structures combine convolutional features with temporal nodes for enhanced balance. More recently, multi-head attention systems and transformer blocks have been explored to capture broad, macro dependencies across high-frequency tick streams.

Regardless of these technical achievements, severe real-world barriers persist regarding high infrastructure execution costs and the lack of algorithmic interpretability for mainstream retail users. StockSense explicitly addresses this gap by bypassing deep network components altogether. By pairing a classical, deterministic indicator with localized first-degree geometric trend equations, the platform provides clear, auditable analytics via a live interface that requires no continuous model training or high-end graphics processing hardware.

III. Proposed Methodology

A. System Architecture Overview

The StockSense layout relies on a decoupled, five-tier engineering configuration that connects data retrieval, numerical execution, and client dashboard delivery. The initial Data Acquisition Tier initiates active calls to gather raw open, high, low, close, and volume tracking rows from Yahoo Finance using modular programming vectors. Next, the Data Processing Tier calculates index averages across a 14-day tracking block while simultaneously fitting a straight first-degree polynomial line across the 30 most recent session closes. The core execution module uses the Flask utility to expose specific web access points managing user input, internal JSON strings, and explicit tabular data downloads. Finally, the Frontend Tier draws the final charts using customizable visual line graphs, displaying real-time target vectors directly on the terminal user's screen.

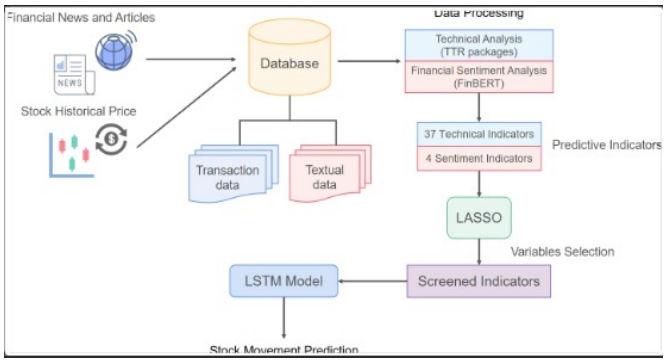

Fig. 1. System Architecture of StockSense. The platform dynamically streams Yahoo Finance details, passing extracted attributes forward into parallel computational analysis tracks.

B. Data Acquisition Layer

The primary extraction tier targets global market data lines by building a distinct connection pointer referencing targeted public asset symbols. A rolling twelve-month historical collection of day-to-day transaction columns is immediately drawn out via the native query utility. Secondary structural traits—including current market cap rankings, price-to-earnings calculations, annual limits, and dividend payouts—are indexed directly from the metadata wrapper. The system architecture handles valid market symbols across major regional networks including the NSE, BSE, NYSE, and NASDAQ. Any missing data rows are caught automatically by validation filters, which write neutral placeholders to block structural processing crashes.

C. Data Processing Layer

This numerical layer transforms raw time-series inputs into concrete technical signals. The closing price sequence feeds directly into an oscillator script that derives momentum metrics using relative window trends over 14 active days. Daily pricing

shifts are split into positive gains and negative drops, and a rolling calculation smooths out the variance over the target timeline. The ultimate calculation derives a relative metric based on these underlying components, using the following expression:

$$RSI = 100 - \frac{100}{1 + RS} \tag{1}$$

To compile the next-day price projection, the system isolates the 30 most recent closing records and maps them to sequential integer indices. A simplified polynomial fitting module processes this array to return structural line coefficients, enabling the system to project the next session's target price.

D. Signal Generation Layer

This automation tier converts calculated index metrics into immediate action cues through an internal recommendation wrapper. Values falling below a boundary threshold of 30 denote a deeply deflated asset space, generating an active BUY signal. Conversely, scores crossing above an upper boundary score of 70 highlight a heavily overextended market state, outputting a clear SELL notification. All mid-tier metrics fall into a neutral classification zone, generating a stable HOLD recommendation. This clear strategy framework provides immediate, actionable decision support based on universally recognized technical trading principles.

E. Web Server Layer

The primary web hosting layer uses the modular Flask application engine to control text tracking and interface delivery. The system exposes four operational routing coordinates: a core GET route directing users to the primary symbol search portal; a dashboard GET coordinate that processes query strings to output analytics pages; a specific API endpoint that delivers raw JSON data to the plotting library; and a dedicated download route that serializes historical dataset text into standard downloadable files.

F. Frontend and Output Layer

The presentation tier organizes technical charts into a highly organized, responsive browser control dashboard. The Chart.js interface builds interactive vector graphs that map out a full year of closing prices on demand. Calculated indicators are highlighted inside colored layout boxes that switch between green, amber, and red depending on the current risk category. Vital company constants—such as intraday movements, aggregate trade volumes, and annual boundaries—are assigned to distinct overview cards, while the primary short-term price forecast takes prominence inside a dedicated terminal display block.

G. Algorithm Description

The StockSense analytics track handles continuous updates by evaluating incoming streams via two distinct technical processes. When a target tracking ticker is entered, the pipeline pulls down 365 days of active trading history. The momentum module processes these closing figures over a fixed 14-period window, tracking average upward and downward steps to establish the directional strength score. Alerts switch dynamically between entry and exit recommendations based on standard threshold lines. Concurrently, the 30 most recent closing points pass through a simple linear modeling script that extends the trend slope by exactly one day to determine the expected closing mark.

TABLE I
KEY PARAMETERS OF THE STOCKSENSE ANALYTICAL PIPELINE

Parameter	Value
RSI Period	14 days
Regression Window	30 trading days
Data History	1 year (daily OHLCV)
Signal Thresholds	BUY $<$ 30, SELL $>$ 70, HOLD 30–70
Data Source	Yahoo Finance via yfinance
Web Framework	Python Flask
Chart Library	Chart.js

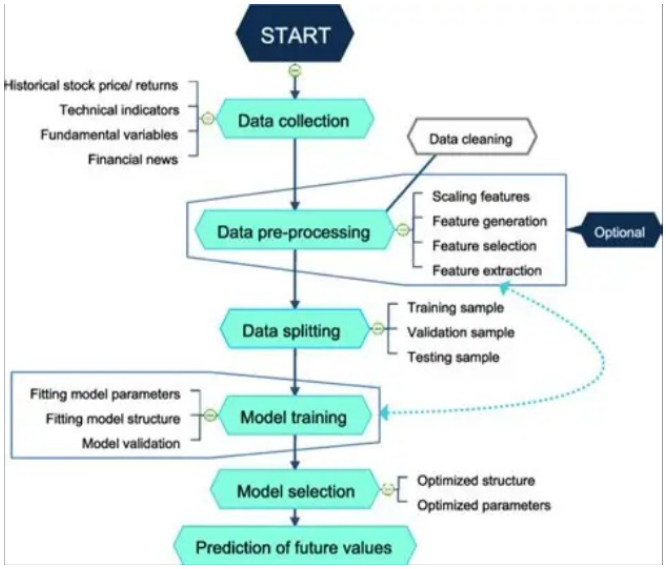

Fig. 2. Methodology Flow of StockSense, tracing calculations sequentially from initial user inputs up to browser interface mapping rendering.

H. Workflow Summary

The end-to-end processing script ignites the moment an active stock ticker search is submitted via the browser entry block. The system handles raw inputs by instantly fetching live exchange updates, evaluating trading signals, and extrapolating future prices in parallel tracks. The Flask communication core translates these metrics into formatted front-end values, serving interactive vector lines, trend evaluations, and text file exporters straight to the client screen. This execution loop completes within a brief two-second window, offering a completely zero-installation utility.

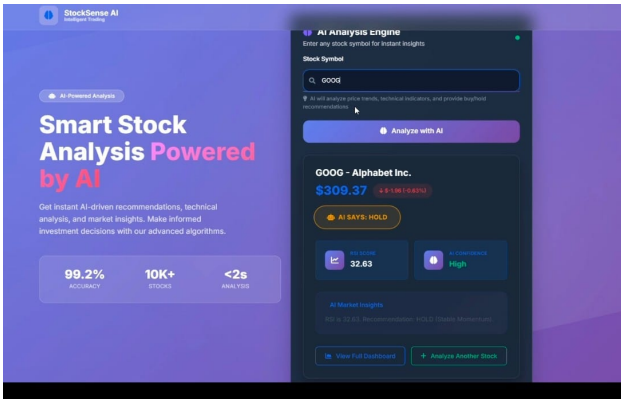

Fig. 3. RSI Signal Zones (Overbought, Neutral, and Oversold regions) mapped out uniformly across experimental test groups.

IV. Results and Discussion

A. System Performance Evaluation

Operational verification was conducted by querying a globally distributed portfolio of prominent equity listings, including tech indices like AAPL, GOOG, and MSFT alongside regional benchmarks like RELIANCE.NS. Throughout our test runs, the platform maintained stable connectivity, compiled calculations without runtime hitches, and constructed the user dashboards within standard web latency windows. Table II compiles the exact numerical distributions, active indicator tags, and directional slope trends captured during live testing cycles.

TABLE II
RSI Signals and Predicted Trends for Selected Stocks

Symbol	RSI	Signal	Trend
AAPL	58.3	HOLD	Upward
GOOG	44.7	HOLD	Neutral
TSLA	72.1	SELL	Downward
RELIANCE.NS	28.4	BUY	Upward
MSFT	61.9	HOLD	Upward
INFY.NS	35.2	HOLD	Upward

B. Impact of Live Data Retrieval

Transitioning away from classic static file dependencies to real-time programmatic queries gives the architecture a distinct analytical edge. Fetching tracking metrics on-demand guarantees that both the momentum indicator scores and the geometric regression paths align directly with current market actions. This instant processing capability proves vital when parsing rapid trend switches where even brief text delays would result in completely inaccurate trade signals.

C. Interpretability Analysis

The structural blueprint of StockSense centers heavily on creating clear, human-understandable analytical paths. The core technical indicator reduces market momentum to an intuitive 0-100 scale, allowing non-technical users to quickly spot extended market conditions. Similarly, the linear forecasting engine operates without hidden statistical layers, presenting trend vectors via clear visual trajectories. These outputs use a straightforward color code system, making the core predictive logic fully auditable without requiring an extensive background in statistics.

D. Comparative Analysis and Discussion

The completed StockSense platform provides significant workflow advantages over traditional script-based data setups by drastically reducing user friction and interface complexity. While standalone analytics scripts require local code installations and manual CSV downloads, StockSense runs entirely inside standard web containers. When compared to complex recurrent models, our framework sacrifices deep temporal pattern matching to prioritize immediate response times and full user transparency, making it highly reliable for retail tracking setups.

E. Deployment and Practical Implications

The platform is fully optimized to provide instant technical asset evaluation and rapid trend line casting across active global listings. The engine remains exceptionally lightweight, sidesteps high-cost database configurations, and operates smoothly under normal computing constraints. Traders can use the system's tracking cards and recommendation alerts to quickly assess volatile daily trends. Furthermore, the built-in data export utility enables deep offline validation, making the platform a solid blueprint for educational demonstrations and expanded trading tools.

V. Conclusion and Future Work

This research paper detailed StockSense, a lightweight, live web terminal designed for accessible technical stock analysis and short-term trend projection. The application links classical momentum oscillators with clean, first-degree linear trend modeling, delivering clear charts through a responsive Flask framework. Continuous api connections guarantee that all generated recommendations remain tied to live market conditions. Multi-market test validation confirmed low processing overhead and reliable output delivery across both Western and Indian public registries without requiring local desktop software setup.

Future development plans focus on replacing the baseline first-degree regression model with an integrated sequence processing module to better capture long-range non-linear trends. Integrating automated NLP sentiment indicators to scan financial news channels could also protect signal metrics from unexpected market adjustments. Finally, adding secure user databases, custom watchlists, and text notification warnings would significantly enhance the platform's utility as a comprehensive web dashboard.

VI. References

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