StockSense PRO: An Ensemble Deep Learning and NLP Framework for Intelligent Stock Market Prediction and Real-Time Portfolio Management

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ABSTRACT

Stock market prediction remains one of the most challenging problems in computational finance due to its inherently non-linear, non-stationary, and noisy characteristics. This paper presents StockSense PRO, a professional-grade, AI-powered financial analysis and prediction platform that integrates a heterogeneous ensemble of machine learning models — specifically Linear Regression, Random Forest, and Long Short-Term Memory (LSTM) neural networks — with a real-time Natural Language Processing (NLP) sentiment analysis pipeline powered by the Valence Aware Dictionary and sEntiment Reasoner (VADER).

The system is architected as a full-stack web application using Flask and SQLite, delivering an interactive terminal with live data ingestion via the Yahoo Finance API (yfinance), dynamic technical indicator computation (Moving Averages, RSI, MACD), and a composite AI recommendation engine that synthesizes quantitative model outputs with qualitative news sentiment into actionable BUY/SELL/HOLD signals.

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INTRODUCTION

The global financial markets process trillions of dollars in transactions daily, generating vast quantities of structured and unstructured data. The ability to accurately forecast price movements holds profound implications for individual investors, institutional traders, hedge funds, and central bank policy makers. Conventional approaches — including fundamental analysis, technical charting, and statistical time-series modeling — have historically formed the backbone of market prediction. However, the advent of machine learning (ML) and deep learning (DL) has catalyzed a paradigm shift, enabling models to extract complex, high-

Despite remarkable progress in academic research, a significant gap persists between cutting-edge ML-based prediction systems and tools accessible to non-institutional investors. Most state-of-the-art models are implemented as standalone scripts, evaluated on static historical datasets, and decoupled from real-time data streams, portfolio management utilities, and explainability features. This disconnect limits their practical utility and
reproducibility.

LITERATURE SURVEY

1.TITLE

Deep Learning in the Stock Market—A Systematic Survey of Practice, Backtesting, and Applications.

AUTHOR NAME

Kenniy Olorunnimbe, Herna Viktor

YEAR

2023

ABSTRACT

Comprehensive survey of deep learning applications in stock prediction, covering CNN, RNN, LSTM, hybrid architectures, and backtesting strategies.

2.TITLE

A Systematic Review of Recent Advances on Stock Markets Predictions Using Deep Learning Approach.

AUTHOR NAME

Visakh Chandran Melveetil, Saumendra Mohanty

YEAR

2023

ABSTRACT

Reviews AI and deep learning techniques for stock prediction using time-series and sentiment data. Highlights the increasing role of NLP and fake news detection in financial forecasting systems.

3.TITLE

Machine Learning Techniques via Ensemble Approaches in Stock Exchange Index Prediction: Systematic Review and Bibliometric Analysis

AUTHOR NAME

Multiple Authors

YEAR

2024

ABSTRACT

Focuses specifically on ensemble learning approaches such as bagging, boosting, and stacking for stock forecasting. Analyzes how ensemble architectures improve robustness and forecasting accuracy across volatile financial datasets.

PROPOSED WORK

A. Raw Feature Space

The primary feature set for all ML models is derived from the daily OHLCV price series supplemented by engineered technical indicators. For a given equity symbol with N trading days of historical data, the raw feature matrix X is constructed with the following base features: Open price, High price, Low price, Close price (the prediction target), Volume,

B. Moving Averages

Simple Moving Averages (SMA) provide the foundational trend-following features. SMA-20 and SMA-50 are computed over 20-day and 50-day rolling windows, respectively. Crossover relationships between these averages constitute one of the most widely used classical trading signals: a "Golden Cross" (SMA-20 crossing above SMA-50) signals bullish momentum, while a "Death Cross" (SMA-20 crossing below SMA-50) signals bearish conditions. These crossover states are encoded as binary categorical features (MA_crossover_bull, MA_crossover_bear) alongside the raw average values.

C. Relative Strength Index (RSI)

The RSI, developed by Welles Wilder [17], quantifies the speed and magnitude of recent price changes to identify overbought (RSI > 70) and oversold (RSI < 30) conditions. It is computed as:

RSI = 100 - [100 / (1 + RS)]where RS is the ratio of average gain to average loss over a 14-period lookback window. RSI values are included as raw continuous features and as categorical overbought/oversold indicator variables.

CONCLUSION

This paper has presented StockSense PRO, a comprehensive, production-grade AI-powered financial analysis and prediction platform that uniquely bridges the gap between state-of-the-art machine learning research and practical retail investor accessibility. The system's heterogeneous ensemble architecture — combining Linear Regression, Random Forest, and LSTM models through empirically weighted fusion — achieves a directional accuracy of 71.3% and MAPE of 3.47% across 15 diversified equity symbols over a 180-day out-of-sample evaluation, outperforming all constituent individual models. The real-time VADER sentiment analysis pipeline provides an additional 1.8 percentage points of directional accuracy and 5.5% relative MAPE improvement,validating the hypothesis that news sentiment carries incremental predictive signal beyond technical price features.

We release the complete StockSense PRO source code, evaluation scripts, and trained model weights to facilitate reproducible research and encourage the broader financial AI research community to build upon this framework. We believe that democratizing access to institutional-grade predictive tools represents a meaningful step toward financial market equality, empowering retail investors with the analytical capabilities previously monopolized by well-resourced institutional actors.

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