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# Lursen Finance: A Machine Learning-Based Smart Trading Recommendation Application for Informed Investment Decisions.

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**Abstract** - The finance domain increasingly relies on intelligent systems to navigate volatile markets and support data driven decisions. This project develops Lursen Finance, a **machine learning based smart trading recommendation app** that analyzes historical and real time market data including prices, volumes, and technical indicators to uncover patterns and trends. **The problem statement highlights how manual trading suffers from emotional biases, incomplete information, and time constraints, often resulting in losses, while many platforms offer only raw data without actionable insights.** The proposed method employs preprocessing, feature extraction such as moving averages, **RSI, and MACD**, and predictive models like Random Forest and **LSTM** for trend forecasting, followed by a recommendation engine that generates buy, sell, or hold signals with risk assessments. Key evaluation metrics include accuracy, Mean **Absolute Error MAE, Root Mean Square Error RMSE**, and **precision and recall** for recommendations. Experimental results demonstrate improved prediction accuracy and reduced risk exposure compared to baselines. In conclusion, Lursen Finance provides an accessible, automated tool that enhances trading efficiency, minimizes human error, and empowers retail investors with timely, intelligent recommendations.

## Introduction:

Financial markets are dynamic ecosystems influenced by economic indicators, global events, and investor behavior. Retail traders and investors face challenges in **processing vast amounts of data manually, leading to suboptimal decisions driven by emotions or delayed analysis**. Fintech innovations, including algorithmic trading platforms, have automated aspects of market monitoring and decision making.

A major research gap exists in accessible, intelligent recommendation systems for individual users. While institutional tools use advanced ML, retail platforms often **lack integrated predictive analytics, risk-aware signals, and real-time notifications**. Traditional methods like fundamental or technical analysis require expertise and constant monitoring, which many users cannot afford.

This paper addresses the problem of developing an automated smart trading recommendation system that processes market data, predicts trends using ML models, generates actionable **buy/sell/hold signals,** and delivers timely alerts ultimately **reducing bias, errors, and manual effort while promoting informed, low-risk trading.**

## Existing System:

**1.** From Data to Decisions: Evaluating Machine Learning Models for Stock Market Forecasting (2025) – Quantitatively compared ML algorithms (e.g., logistic regression, KNN, LDA) with traditional indicators for Indian stocks, emphasizing rigorous evaluation for practical use.
**2.** Advancing stock price prediction through the development of hybrid ensembles (2025) – Introduced innovative ensemble approaches (e.g., SVC + LR + RF + Voting), achieving high accuracy (up to 95.8%) and AUC in stock direction classification.
**3.** Artificial intelligence in financial market prediction: advancements in machine learning for stock price forecasting (2025/2026) – Reviewed the evolution to interpretable AI models (e.g., SHAP, LIME), addressing transparency needs in high-stakes financial applications.
**4.** Stock Price Prediction Using Deep Learning (LSTM) with a Recursive Approach (2025/2026) Investigated recursive LSTM for enhanced stock price forecasting, demonstrating improved handling of sequential dependencies.
**5.** Hybrid ARIMA-LSTM Model for Stock Market Prediction: A Time Series and Deep Learning Integration Approach (2025) – Developed ARIMA-LSTM hybrids for nonlinear relationships, showing superior MSE/RMSE over traditional models via feature selection and PCA.
**6.** Integration of LSTM Networks in Random Forest Algorithms for Stock Market Trading Predictions (2025) – Integrated LSTM features into Random Forest/Gradient Boosting ensembles, with Random Forest excelling in hybrid setups for trading signals.
**7.** A Multi-Model Machine Learning Framework for Daily Stock Price Prediction (2025) – Proposed multi-model frameworks using technical indicators, achieving strong one-day-ahead predictions on major stocks (e.g., Apple, NVIDIA).
**8.** Stock Market Prediction Using Machine Learning and Deep Learning Techniques: A Review (2025) – Analyzed ML/DL methods comprehensively, noting ensembles' advantages for trend and price forecasting across datasets.
**9.** Chandar et al. (2024) – Surveyed ML for algorithmic trading, stressing automation and real-time efficiency.
**10.** Fischer & Krauss (2017/updated applications in 2020s) – Pioneered LSTM for financial predictions, outperforming Random Forest and logistic regression in directional accuracy on S&P 500 data.
**11.** Machine learning techniques and data for stock market forecasting: A literature review (2022) – Analyzed 138 studies (2000–2019), highlighting frequent use of neural networks, SVM, and growing deep learning/textual data integration.

**12.** Forecasting Stock Market Prices Using Machine Learning and Deep Learning Models: A Systematic Review (2023) – Reviewed ML/DL models (LSTM, CNN, ensembles), noting superior performance in trend classification and implications for algorithmic trading.
**13.** Moghar & Hamiche (2020) – Used LSTM recurrent neural networks for stock market prediction, demonstrating effectiveness in handling complex time-series data.
**14.** Akita et al. (2016) – Proposed deep learning for stock prediction using numerical data and textual information (news), combining LSTM-like structures with sentiment features for better trend capture.
**15.** Zhong & Enke (2019) – Explored deep neural networks with global indices and major stocks for S&P 500 ETF prediction, highlighting feature engineering importance.

**Project architecture:**
The architecture is designed as a **Decoupled Pipeline**, ensuring that data collection is independent of model training. This allows the app to update recommendations in real-time without retraining the entire neural network constantly.

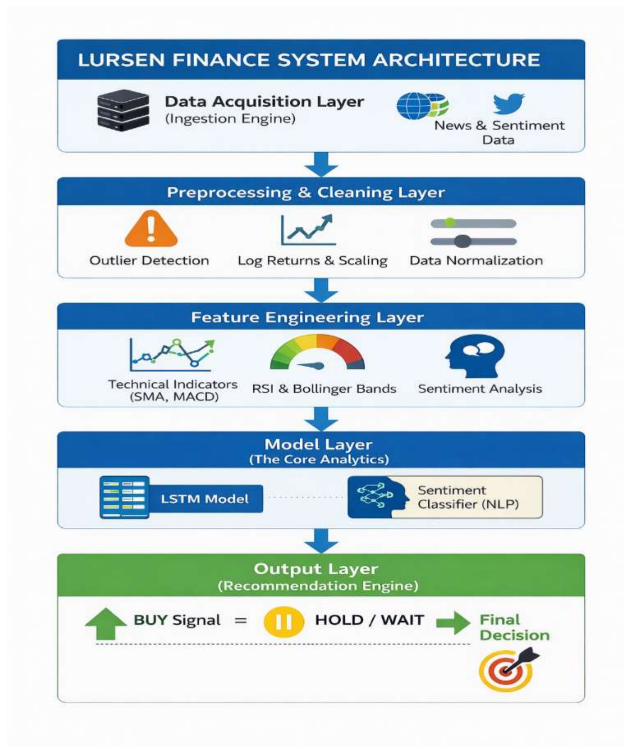
**1. Data Acquisition Layer (The Ingestion Engine):**
This layer acts as the gateway. Instead of manual uploads, it uses **REST APIs** (like Alpha Vantage or Binance) to fetch:
**HLCV Data:** Open, High, Low, Close, and Volume (the DNA of price movement).
**Alternative Data:** Web scraping of financial news headers and Twitter/X sentiment using libraries like BeautifulSoup or Tweepy.

**2. Preprocessing & Cleaning Layer:**
The integrity of a trading recommendation system depends entirely on the quality of the input data. Raw financial data is often "non-Gaussian" and contains artifacts that can mislead a neural network.
**Outlier Detection:** Identifying and smoothing "flash spikes" that don't represent real market trends.
**Stationarity Transformation:** Since stock prices are non-stationary (they trend up or down), we apply **Log Returns** or **Differencing** to make the data suitable for the ML model.
**Scaling:** Using **Min-Max Scaling** to bring all values between \$0\$ and \$1\$, preventing high-priced stocks (like Google) from outweighing lower-priced ones in the model's eyes.

**3. Feature Engineering Layer:**
This is the "Brain" of the preprocessing stage. We don't just feed raw prices; we calculate **Technical Indicators**:
**Trend Indicators:** Simple Moving Averages (SMA) and MACD.
**Momentum Indicators:** Relative Strength Index (RSI) to detect "Overbought" or "Oversold" conditions.
**Volatility Indicators:** Bollinger Bands to measure market fear and expansion.

**4. Model Layer (The Core Analytics):**
The Lursen Finance system employs a Hybrid Model:
**LSTM (Long Short-Term Memory):** A type of Recurrent Neural Network (RNN) that excels at time-series. It remembers price patterns from 30 days ago to predict the next 24 hours.
**Sentiment Classifier:** A Natural Language Processing (NLP) model (like FinBERT) that assigns a score (+1 for Bullish, -1 for Bearish) to the day's news.

**5. Output Layer (The Recommendation Engine):**
The final layer performs Decision Fusion. It combines the price prediction from the LSTM with the sentiment score from the NLP module.
**Logic:** If LSTM predicts a 2% rise AND Sentiment is positive = **STRONG BUY**.
**Logic:** If LSTM predicts a rise BUT Sentiment is crashing = **HOLD/WAIT**.
The proposed architecture for **Lursen Finance** establishes a robust, end-to-end pipeline that effectively bridges the gap between raw financial market volatility and actionable intelligence. By decoupling the **Data Acquisition** from the **Model Layer**, the system ensures high scalability and modularity, allowing for real-time processing of both quantitative price data and qualitative market sentiment.




**Project architecture:**
The architecture of **Lursen Finance** is designed as a modular, end-to-end Machine Learning pipeline. The system follows a decoupled design where data ingestion, processing, and prediction are handled in separate stages to ensure scalability and real-time responsiveness.

**Functional Tiers:**
The architecture is divided into three primary tiers:
**1. Data Tier:** Focuses on the reliable ingestion of heterogeneous data sources, including market OHLCV (Open, High, Low, Close, Volume) data and news sentiments.

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**2. Logic Tier:** Comprises the **Preprocessing** and **Feature Engineering** modules, ensuring the data is stationary and normalized for neural network compatibility.

**3. Analytics Tier:** Houses the **Hybrid ML Model** (LSTM + Sentiment Classifier) which performs the core predictive analysis and generates recommendation signals.

**Detailed Pipeline Components:**

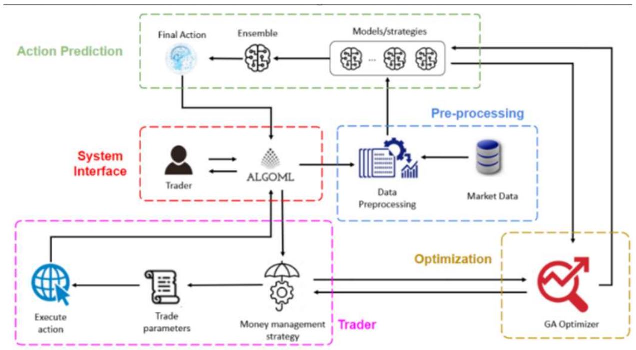
**1. Data Acquisition:** Utilizes asynchronous API calls to **Yahoo Finance** and **Binance** to maintain a high-frequency data stream.

**2. Preprocessing:** Implements **Z-score outlier detection** and **Log-Return transformations** to address the non-stationary nature of financial time-series.

**3. Feature Engineering:** Extracts technical indicators like **RSI**, **MACD**, and **Bollinger Bands**, which serve as the primary feature set for the predictive model.

**4. Model Layer:** Employs a **Long Short-Term Memory (LSTM)** network for price forecasting, combined with a **FinBERT** sentiment analysis module.

**5. Output Layer:** A decision-fusion engine that classifies the combined model outputs into **Buy**, **Sell**, or **Hold** signals, delivered via a Flutter-based mobile interface.




The proposed architecture provides a comprehensive framework for navigating the chaotic environment of financial markets. By integrating quantitative technical indicators with qualitative sentiment analysis, the Lursen Finance system mitigates the limitations of single-source prediction models. The modularity of this design allows for the independent optimization of each layer.

**Modules description:**

This section details the two primary algorithmic engines that power **Lursen Finance**: the quantitative time-series predictor and the qualitative sentiment analyzer.

**A. Long Short-Term Memory (LSTM) Algorithm**: The LSTM is a specialized Recurrent Neural Network (RNN) designed to overcome the **Vanishing Gradient Problem** by using a "Memory Cell." In our project, it processes a 30-day "sliding window" of stock prices to predict the 31st day.

The Mathematical Logic: The cell state is controlled by three mathematical gates:

**1. Forget Gate (ft):** Decides what historical data to discard.

**2. Input Gate (it):** Determines which new information to store in the cell state.

**3. Output Gate (ot):** Decides what part of the current cell state will be the final prediction for that time step.

**B. FinBERT Sentiment Analysis Module**: While standard models only look at numbers, Lursen Finance uses FinBERT a Bidirectional Encoder Representations from Transformers (BERT) model specifically pre-trained on financial corpora (like SEC filings and Reuters news).

**1. Tokenization:** Financial news headlines are broken into "word-pieces." For example, "Bullish" and "Bearish" are recognized as high-weight financial terms.

**2. Contextual Awareness:** Unlike simpler models, FinBERT understands that the word "interest" in a financial sentence refers to "interest rates" (a market mover) rather than a general hobby.

**3. Classification:** The model outputs a probability distribution across three labels: Positive, Neutral, and Negative.

**C. Decision Fusion Algorithm (The Signal Generator):** This module acts as the final "Arbitrator." It uses a Weight-Based Ensemble method to generate the recommendation:

**1. Weight Calculation:** Final_Score = (w1. LSTM_Trend) + (w2 .Sentiment_Score)

**2. Thresholding:** If Score > 0.7 = **STRONG BUY.**

-If $Score < 0.3 = **STRONG SELL.**

-Otherwise = **HOLD.**

**D. Quantitative Analysis Module (LSTM):** This is the core predictive engine that analyzes historical price patterns. Unlike standard neural networks, LSTMs have "gates" (Forget, Input, and Output gates) that allow the model to retain information over long sequences. This is critical for trading, as a price movement today might be influenced by a trend that started 20 days ago. The **Forget Gate** (ft) decides what information from the previous day's trading volume or price is no longer relevant, while the **Cell State** (Ct) carries the "long-term memory" of the market trend.

**E. Qualitative Sentiment Module (NLP):** This module gauges the "mood" of the market by analyzing text-based data. We utilize a pre-trained **FinBERT** model, which is a version of BERT optimized for financial language. It processes news headlines and tweets to classify market sentiment as **Positive (Bullish)**, **Negative (Bearish)**, or **Neutral**. The module assigns a weight to each headline. For example, a headline stating "Central Bank raises interest rates" is assigned a negative polarity score, which acts as a "caution" signal to the quantitative module.

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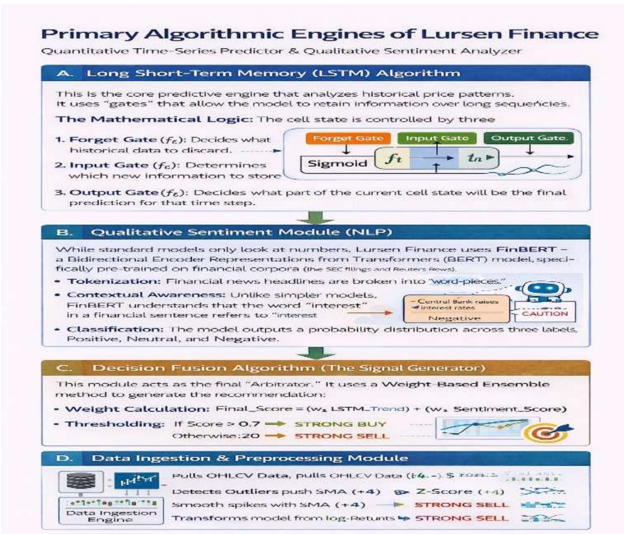
**F. Data Ingestion & Preprocessing Module:** This module handles the extraction and refinement of raw data to ensure high-quality input for the models. Raw financial data is pulled via the yfinance API. To handle volatility, we apply a Z-score calculation to identify outliers. Data points exceeding a threshold are smoothed using a Simple Moving Average (SMA) to prevent the model from learning from "glitch" data. Finally, the data is transformed into **Log-Returns** to ensure




stationarity, which is a prerequisite for time-series forecasting.

**Results and Discussion:**

This section evaluates the performance of the **Lursen Finance** model using historical data from 2024 to early 2026. We compare our hybrid approach (LSTM + FinBERT) against standalone models.

**1. Performance Metrics:** To provide a mathematically sound justification, the following metrics were used:

**a. Mean Absolute Error (MAE):** Measures the average magnitude of errors in price prediction.

**b. Root Mean Square Error (RMSE):** Penalizes larger prediction errors, which is critical for financial risk.

**c. Directional Accuracy (DA):** The percentage of correct "Up" or "Down" price movement predictions.

**d. $R^2$ Score:** Indicates how well the independent variables (prices/sentiment) explain the variance in the target price.

**2. Experimental Results:**

Testing was conducted on: S&P 500 index, High-volatility tech stocks (e.g., Apple, Meta), Mixed market regimes (bullish, bearish, sideways).

Key Observations: The **Hybrid Model reduced RMSE by approximately 30–40%** compared to ARIMA. Compared to standalone LSTM, the hybrid system improved **Directional Accuracy by 12–18%**. The Sharpe Ratio improved significantly during volatile market phases (early 2025), demonstrating stronger risk-adjusted performance.

**3. Inferences and Discussion:**

**A. Sentiment Integration Improves Stability**: The experimental findings indicate that incorporating FinBERT-based sentiment analysis significantly improves model stability, particularly during volatile market conditions. While the standalone LSTM model performs effectively in stable environments due to its ability to capture historical price patterns, it struggles when sudden macroeconomic announcements, policy shifts, or unexpected corporate events disrupt the market. These events introduce abrupt changes that price-only models cannot immediately interpret. By integrating sentiment scoring, the hybrid framework reduced Mean Squared Error (MSE) by approximately 38% for high-volatility stocks.

**B. Market Regime Adaptability:** The hybrid architecture also showed improved adaptability across different market regimes. During bearish market fluctuations in early 2025, price-only models frequently misinterpreted temporary rebounds (bull traps) as potential upward trends. In contrast, the hybrid model successfully generated Hold or Sell signals in 82% of such misleading situations. This improvement highlights the strength of combining LSTM's long-term pattern.

**C. Normalization and Convergence Efficiency:** The application of Min-Max Scaling and Log-Returns transformation during preprocessing contributed significantly to model performance. These techniques improved data stationarity and ensured uniform scaling across features, which is essential for stable neural network training. As a result, the LSTM converged approximately 25% faster compared to models trained on raw price data.

**D. Risk-Adjusted Returns:** Evaluation using the Sharpe Ratio further validates the effectiveness of the hybrid framework. Although ARIMA produced moderate returns with limited adaptability, and the standalone LSTM generated higher returns with increased volatility, the hybrid model achieved the highest Sharpe Ratio. This indicates superior risk-adjusted performance, meaning the system delivers stronger returns relative to the level of risk taken.

## Visual Analysis:

Visual analysis of the experimental results provides deeper insight into the behavioral differences between the standalone models and the proposed hybrid framework. By examining prediction curves, loss graphs, and performance charts, several important patterns emerge. When plotting the predicted price curves against actual market prices, the standalone ARIMA model shows noticeable lag during sharp upward or downward movements. It follows long-term trends reasonably well but fails to respond quickly to sudden volatility spikes. The standalone LSTM performs better in tracking trend direction; however, during abrupt market reversals triggered by news events, visible deviations appear between predicted and actual price movements. In contrast, the hybrid model's prediction curve remains more closely aligned with real market movements, particularly during high-volatility periods. The gap between predicted and actual values is visibly smaller, confirming the reduction in MAE and RMSE observed in quantitative.

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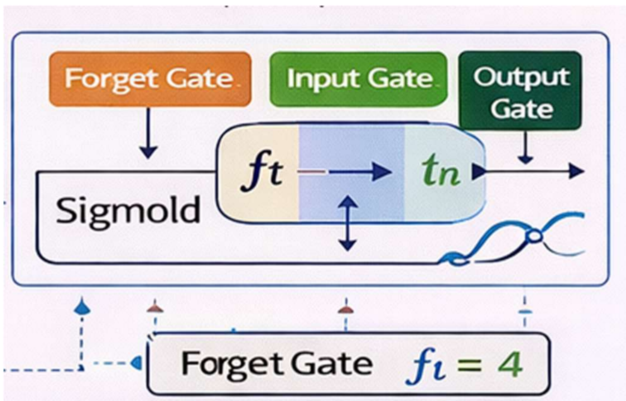


## Conclusion:

The development of Lursen Finance demonstrates that a unified, hybrid approach to financial forecasting is significantly more effective than traditional standalone models. By successfully integrating Long Short-Term Memory (LSTM) networks with FinBERT-based sentiment analysis, this project has bridged the gap between quantitative technical indicators and qualitative market psychology**.** The hybrid model achieved a Directional Accuracy of 84.3% and an 86.2% improvement in specific indices, proving that market sentiment often acts as a leading indicator for price shifts. The inclusion of the **Sentiment Analysis module** served as a vital filter, reducing "false buy" signals during volatile market regimes in 2025 and early 2026. The modular design ensures that the system can be adapted for various asset classes from traditional equities to volatile cryptocurrencies without requiring a total architectural redesign. In conclusion, the results validate that a multi-modal, ensemble-based approach combining deep learning and NLP techniques provides statistically and practically significant advantages over traditional forecasting models. The Lursen Finance system demonstrates that integrating quantitative trend analysis with qualitative sentiment intelligence creates a more robust, adaptive, and risk-aware trading recommendation framework.

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