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# **Indian Stock Market Analysis Using AI**

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#### Abstract

This paper presents an AI-driven system that predicts stock market trends using a combination of machine learning (ML), deep learning (DL), and technical analysis. Leveraging models such as LSTM, ARIMA, and XGBoost, the system forecasts stock price movements and integrates key technical indicators like MACD, RSI, and Bollinger Bands for enhanced interpretability. The research addresses the limitations of human intuition in stock trading and offers a user-friendly tool for data-driven decision-making. Backed by real-time data and Python implementation, this project aims to provide retail investors with a reliable method for anticipating market trends.

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#### I. Introduction

Stock trading requires the ability to make fast and informed decisions in an environment characterized by volatility, high stakes, and cognitive bias. Retail traders often rely on personal judgment or social media opinions, which can lead to inconsistent results. In contrast, AI-based systems can analyze large volumes of data, identify patterns, and generate objective predictions.

This research introduces a stock prediction system that uses ML and DL models along with technical analysis to guide buy/sell decisions. Unlike traditional models that only forecast prices, our approach provides clear market insights such as trend direction, price range, and market conditions (e.g., overbought or oversold).

#### II. Literature Review

Stock prediction has been extensively explored across multiple disciplines:

- Statistical Approaches: ARIMA and GARCH models are commonly used for time-series analysis but lack adaptability to non-linear data.
- Machine Learning: SVM, Random Forests, and XGBoost have been applied to predict trends with varying success. Their strength lies in classification tasks based on structured data.
- Deep Learning: LSTM and GRU models capture long-term dependencies in sequential data and have shown improved results in predicting stock trends.

However, many of these models suffer from interpretability issues. Traders need not just predictions, but actionable insights. Our work combines predictive accuracy with intuitive signals through integration of technical indicators.

#### III. Methodology

## 3.1 Data Collection

The system uses live data fetched from Yahoo Finance via the yfinance library in Python. Data includes:

- Closing price
- High/low price
- Trading volume
- Timestamps

#### 3.2 Technical Indicator Engineering

To enhance signal quality and interpretability, we compute:

- RSI (Relative Strength Index): Identifies overbought (>70) or oversold (<30) conditions
- MACD (Moving Average Convergence Divergence): Highlights trend direction and momentum
- Bollinger Bands: Detect volatility and potential reversal zones
- EMA (Exponential Moving Average): Smooths price data for trend analysis

These indicators act as both input features and validation checkpoints.

#### 3.3 Model Building

Three predictive models were developed:

## a. LSTM (Long Short-Term Memory)

- Best suited for time-series prediction.
- Learns long-term dependencies.
- Used to forecast future closing prices.

## b. ARIMA (AutoRegressive Integrated Moving Average)

- Classical time series model.
- Best for short-term price predictions.
- Used as a benchmark against LSTM.

## c. XGBoost (Extreme Gradient Boosting)

- Tree-based ensemble model.
- Used to classify whether the market is trending up or down.
- Fast and interpretable.

#### 3.4 User Interface

A Streamlit-based GUI allows users to:

- Enter stock name and prediction window
- View predicted vs actual prices
- See buy/sell signals with indicator values
- Analyze visualizations such as candlestick charts

#### IV. Results and Evaluation

### 4.1 Accuracy Metrics

Models were evaluated using:

- RMSE (Root Mean Square Error)
- MAPE (Mean Absolute Percentage Error)
- Trend Accuracy (% of correct up/down movements)

Example for Infosys (INFY) Stock:

for infosys (INT 1) Stock.			
Model	RMSE	MAPE	Trend Accuracy
			·
LSTM	9.84	2.1%	87%
ARIMA	13.20	3.4%	75%
XGBoost	_	_	84% (Up/Down classification)
11020000			o 170 (Op/20 viii classification)

## 4.2 User-Level Output

For each stock, the system provides:

- Prediction range: e.g., □1480 to □1510
- Trend signal: Bullish or Bearish
- Status: Overbought / Oversold
- Strategy suggestion: Buy, Hold, or Sell

These indicators help users make fast and informed decisions.

#### V. Industry Applications

This model can be deployed for:

- Retail Investors: Provides daily actionable predictions
- Robo-Advisors: Enhances automated portfolio suggestions
- Financial Analysts: Supports human insight with quantitative models
- Traders: Aids in entry and exit decision-making

AI models are already used by hedge funds, HFT firms, and robo-advisory platforms like Zerodha's Rainmatter, Upstox, and Groww. This system provides a simplified version tailored for educational and retail trading use.

## VI. Case Study: INFY Prediction

A mini case study was conducted on Infosys Ltd (INFY):

- RSI  $> 70 \rightarrow \text{Overbought}$
- MACD crossover → Bearish signal

- LSTM model forecasted a 2% drop
- Actual price dropped within 3 days

This confirmed that combining technical analysis with ML models increases prediction reliability.

## VII. Limitations

- Market Volatility: Models cannot predict black swan events like COVID-19.
- Data Dependency: Heavily reliant on historical price data.
- Lack of Fundamental Data: Earnings, news, and macro indicators are not included.
- Short-Term Forecast: Best suited for swing or positional trades, not long-term investing.

#### VIII. Future Work

- Sentiment Analysis: Integrating Twitter/news data to capture investor mood.
- Reinforcement Learning: Models that learn and adapt with each trade.
- Portfolio-Level Prediction: Instead of individual stocks, optimize entire portfolios.
- Explainable AI (XAI): Use SHAP or LIME to explain predictions.
- Backtesting Engine: To simulate past trades and test strategies.
- Mobile App Deployment: Deliver real-time alerts on smartphones.

#### IX. Conclusion

This AI-based trading assistant combines the power of machine learning and technical indicators to provide a reliable and interpretable system for predicting stock trends. With LSTM for forecasting, XGBoost for classification, and indicators for strategy, the system offers a balanced and user-friendly solution for modern traders. While not a replacement for professional advice, it empowers retail users with a structured approach to market analysis.