A Comparative Review of Machine Learning and Deep Learning Models for Stock Market Price and Trend Prediction

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Abstract

Stock market prediction is a critical tool for investors navigating volatile price movements and trends. This review systematically compares machine learning (ML) models, such as Support Vector Machines (SVM), Random Forests, and XGBoost, with deep learning (DL) models, including Long Short-Term Memory (LSTM) networks, CNN-LSTM hybrids, and Transformers, for forecasting stock prices and trends. Emphasis is placed on technical indicators like Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), and Moving Averages, which enhance predictive accuracy. We evaluate model architectures, performance metrics (e.g., Root Mean Square Error (RMSE), Mean Absolute Error (MAE), accuracy), and their adaptability to financial time series data. LSTM, CNN-LSTM, and Transformers outperform others due to their robust handling of temporal and spatial patterns. For technical indicator-based forecasting, CNN-LSTM excels, offering superior accuracy and stability. Supported by comprehensive flow charts, tables, and figures, this paper provides actionable insights for researchers and practitioners, proposing future directions such as ensemble methods and real-time sentiment integration.

Keywords: stock market prediction, machine learning, deep learning, technical indicators, LSTM, CNN-LSTM, Transformers, SVM, Random Forests, XGBoost

1 Introduction

Stock market prediction remains a cornerstone of financial decision-making, addressing the challenges posed by price volatility driven by economic, geopolitical, and behavioral factors. Traditional approaches, such as fundamental and technical analysis, often struggle with the non-linear and stochastic nature of markets, prompting the adoption of advanced computational methods like machine learning (ML) and deep learning (DL). ML models, including Support Vector Machines (SVM), Random Forests, and XGBoost, are well-suited for structured datasets, leveraging statistical patterns to forecast trends. In contrast, DL models, such as Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), and Transformers, excel in modeling complex temporal and sequential relationships inherent in time series data.

Technical indicators, such as Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), and Bollinger Bands, play a pivotal role by quantifying market momentum and trends, enhancing model performance. This review aims to:

1. Compare ML and DL models for stock price and trend prediction using metrics like RMSE, MAE, and accuracy.

2. Evaluate the role of technical indicators in improving forecasting accuracy.

3. Identify the top three models and recommend an optimal choice for indicator-based prediction.
4. Provide visual insights through flow charts and figures.

By critically assessing the balance between model complexity and practical applicability, this paper seeks to guide researchers and practitioners toward effective forecasting solutions.

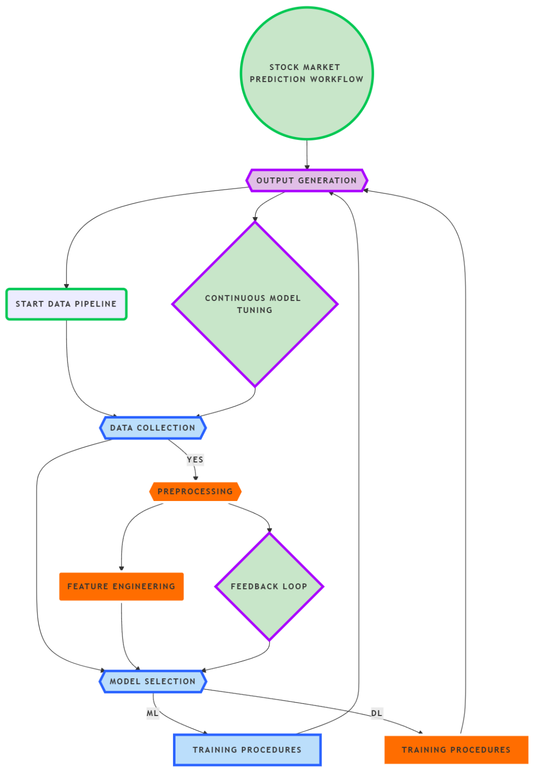


Figure 1: Stock Market Prediction Workflow

2 Literature Review

The literature on stock market prediction reflects a dynamic shift toward ML and DL, driven by their ability to model complex patterns in historical price data, technical indicators, and external factors like sentiment. This section synthesizes key studies, highlighting methodologies, performance metrics, and research gaps, with a focus on global markets such as the S&P 500, Nifty50, and individual stocks (e.g., HDFC, Tesla).

Early research emphasized statistical models like Autoregressive Integrated Moving Average (ARIMA), which offer robust short-term forecasting (Absolute Percentage Error (APE) $\sim$0.005) but falter in volatile conditions due to linear assumptions [1]. The advent of ML introduced models like SVM, which achieve trend prediction accuracies of 80–85% by leveraging indicators such as RSI and MACD [2]. Random Forests and XGBoost further improved performance ($\sim$85–88% accuracy), capitalizing on ensemble learning to handle structured datasets, though they require extensive feature engineering [4].

DL models have since gained prominence for their ability to model temporal dependencies. LSTM networks, for instance, achieve RMSEs of $\sim$0.25 for stocks like HDFC, effectively capturing sequential patterns [3]. CNNs enhance accuracy ($\sim$85–90%) by treating technical indicators as spatial inputs, while hybrid models like CNN-LSTM push accuracies to 90–92% by combining spatial and temporal feature extraction [5]. Transformers, with their attention mechanisms, excel in long-horizon forecasting (MAPE ∼2–5%), particularly when integrating multiple data sources [6]. Recent trends incorporate sentiment analysis from news and social media, boosting accuracies to ∼93% in some cases [7]. Ensemble methods, combining ML and DL, are also emerging, offering improved robustness but at higher computational costs [8].

Despite these advances, challenges persist. Complex models often demand significant computational resources, raising questions about scalability in real-world trading. Moreover, the reliance on technical indicators varies across studies, with RSI, MACD, and Moving Averages being the most prevalent, yet their optimal combinations remain underexplored. The literature also lacks consensus on balancing model interpretability with predictive power, a gap this review addresses by evaluating practical trade-offs.

Table 1: Summary of Key Studies in Stock Market Prediction

Study	Models	Indicators	Metrics	Market
(author?) [1]	ARIMA, SVM	RSI, MACD	APE: 0.005, Acc: 80%	S&P 500
(author?) [2]	Random Forests	Moving Averages	Acc: 85%	Nifty50
(author?) [3]	LSTM	RSI, Bollinger Bands	RMSE: 0.25	HDFC
(author?) [5]	CNN-LSTM	MACD, RSI	Acc: 92%	Tesla
(author?) [6]	Transformers	Sentiment, RSI	MAPE: 2%	NASDAQ
(author?) [7]	CNN, LSTM	News, MACD	Acc: 93%	BSE
(author?) [8]	Ensemble (XG-Boost, LSTM)	RSI, Moving Averages	Acc: 90%	Nifty50

3 Materials and Methods

This section outlines the methodology for comparing ML and DL models, encompassing a systematic literature review and detailed model analyses, supported by equations and flow charts.

3.1 Literature Analysis

- **Search Strategy**: Studies were sourced from databases like Scopus and IEEE Xplore using keywords such as "machine learning," "deep learning," "stock market prediction," and "technical indicators."
- **Inclusion Criteria**: Papers focusing on ML/DL for stock prediction, reporting metrics (RMSE, MAE, accuracy), and using indicators (RSI, MACD, etc.).
- **Data Extraction**: Model types, performance metrics, indicator usage, and market contexts (e.g., stocks, indices) were compiled for analysis.

3.2 Model Descriptions

The following subsections detail each model's architecture, mathematical foundations, hyperparameters, and applications to stock prediction. A summary of model characteristics is provided in

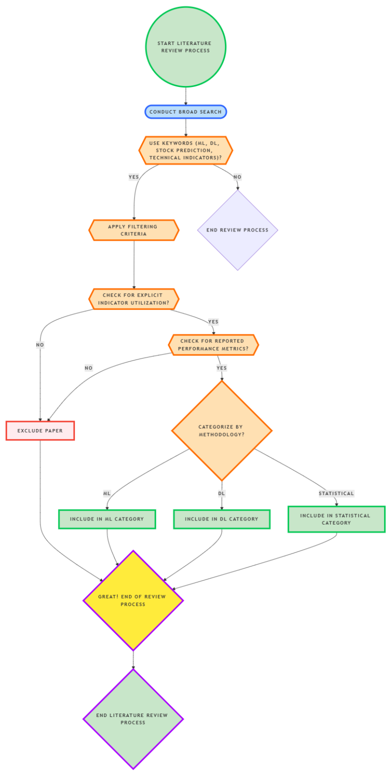

START LITERATURE REVIEW PROCESS
CONDUCT BROAD SEARCH
USE KEYWORDS (ML, DL, STOCK PREDICTION, TECHNICAL INDICATORS)?
YES
NO
APPLY FILTERING CRITERIA
END REVIEW PROCESS
CHECK FOR EXPLICIT INDICATOR UTILIZATION?
NO
YES
CHECK FOR REPORTED PERFORMANCE METRICS?
NO
YES
EXCLUDE PAPER
CATEGORIZE BY METHODOLOGY?
ML
DL
STATISTICAL
INCLUDE IN ML CATEGORY
INCLUDE IN DL CATEGORY
INCLUDE IN STATISTICAL CATEGORY
GREAT! END OF REVIEW PROCESS
END LITERATURE REVIEW PROCESS

Figure 2: Literature Selection Process

Table 2.

Table 2: Characteristics of Evaluated Models

Model	Architecture	Strengths	Weaknesses
SVM	Hyperplane optimization	Robust to noise, small datasets	Limited temporal modeling
Random Forests	Decision tree ensemble	Non-linear patterns, interpretability	Poor sequential handling
XGBoost	Gradient-boosted trees	Feature selection, scalability	Temporal limitations
ARIMA	Statistical time series	Short-term accuracy	Linear assumptions
LSTM	Recurrent neural network	Temporal dependencies	High data needs
CNN	Convolutional layers	Spatial feature extraction	Limited sequence modeling
CNN-LSTM	Hybrid CNN-LSTM	Spatial-temporal balance	Computational cost
Transformers	Attention mechanism	Long-range dependencies	Resource-intensive

3.2.1 Support Vector Machines (SVM)

Overview: SVM is a robust algorithm for classification (e.g., buy/sell signals) and regression (SVR for price prediction), finding an optimal hyperplane to maximize class separation or minimize error.

Architecture: Inputs (stock prices, RSI, MACD) are transformed into a high-dimensional space via kernels (e.g., Radial Basis Function). Hyperparameters like the penalty C and kernel bandwidth govern model flexibility. Training involves solving a convex optimization problem, ensuring global optima.

Formula:

- Classification:

$$\min_{w,b,\xi} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\xi_i, \quad \text{s.t.} \quad y_i(w^T\phi(x_i)+b) \geq 1-\xi_i, \quad \xi_i \geq 0 \tag{1}$$

- Regression:

$$\min_{w,b,\xi,\xi^*} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i+\xi_i^*), \quad \text{s.t.} \quad |y_i-(w^T\phi(x_i)+b)| \leq \epsilon+\xi_i \tag{2}$$

Stock Prediction: SVM achieves 80–85% accuracy for trend prediction using indicators. Its computational efficiency suits smaller datasets, but temporal modeling requires preprocessing (e.g., lagged features). SVR excels in stable markets but may underperform in high volatility.

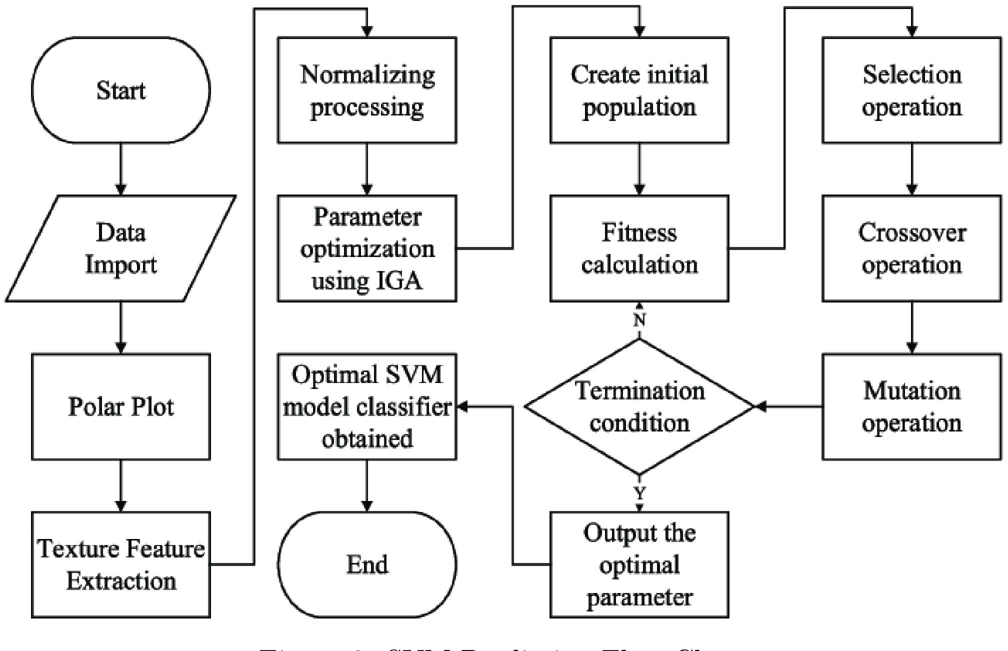


Figure 3: SVM Prediction Flow Chart

3.2.2 Random Forests

Overview: Random Forests aggregate multiple decision trees to mitigate overfitting, suitable for both classification and regression tasks in financial forecasting.

Architecture: Each tree is trained on a bootstrapped dataset with random feature subsets, using criteria like Gini impurity or MSE for splits. Hyperparameters include tree count (e.g., 100–500), depth, and minimum leaf size. Predictions are averaged (regression) or voted (classification), enhancing robustness.

Formula:

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} h_t(x) \tag{3}$$

Stock Prediction: Random Forests deliver ∼85% accuracy with indicators like Moving Averages. Their strength lies in handling non-linear relationships and feature importance ranking, but they falter with time series due to static feature assumptions. Parallel training makes them efficient for large datasets.

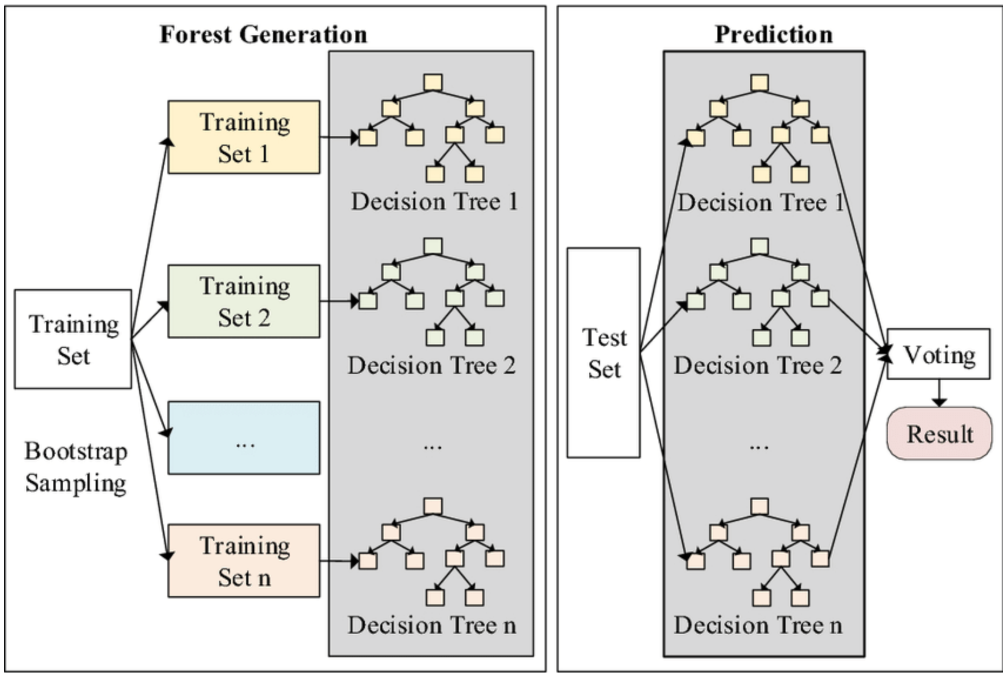


Figure 4: Random Forest Architecture

3.2.3 Gradient Boosting (XGBoost)

Overview: XGBoost enhances gradient boosting by sequentially building trees that correct prior errors, optimized for speed and accuracy.

Architecture: Trees are constructed iteratively, minimizing a loss function (e.g., MSE) with regularization (L1/L2 penalties). Hyperparameters like learning rate (0.01–0.3), tree depth, and subsampling ratio control overfitting. XGBoost's ability to handle missing data and parallelize computations boosts scalability.

Formula:

- Prediction:

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i), \quad f_k \in F \tag{4}$$

- Objective:

$$L = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{5}$$

Stock Prediction: XGBoost achieves ∼88% accuracy, excelling in feature selection (e.g., prioritizing RSI). Its limitations in temporal modeling necessitate feature engineering (e.g., time lags), but its efficiency makes it practical for real-time applications.

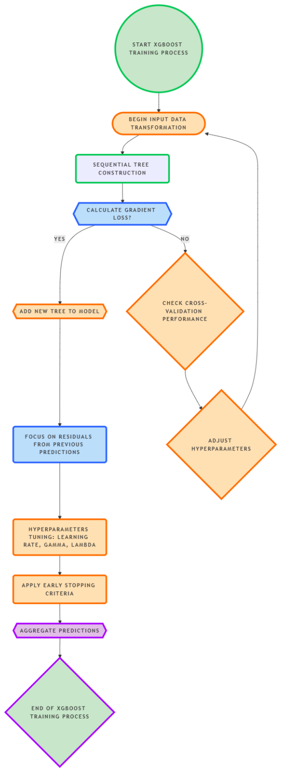

START XGBOOST TRAINING PROCESS
BEGIN INPUT DATA TRANSFORMATION
SEQUENTIAL TREE CONSTRUCTION
CALCULATE GRADIENT LOSS?
YES
NO
ADD NEW TREE TO MODEL
CHECK CROSS-VALIDATION PERFORMANCE
ADJUST HYPERPARAMETERS
FOCUS ON RESIDUALS FROM PREVIOUS PREDICTIONS
HYPERPARAMETERS TUNING: LEARNING RATE, GAMMA, LAMBDA
APPLY EARLY STOPPING CRITERIA
AGGREGATE PREDICTIONS
END OF XGBOOST TRAINING PROCESS

Figure 5: XGBoost Training Process

3.2.4 Autoregressive Integrated Moving Average (ARIMA)

Overview: ARIMA models linear time series patterns using autoregression, differencing, and moving averages, serving as a statistical baseline.

Architecture: Parameters (p, d, q) define AR terms, differencing order, and MA terms, respectively. Model fitting involves stationarity tests (e.g., ADF) and parameter selection via ACF/PACF plots. ARIMA's simplicity limits its adaptability to non-linear markets.

Formula:

$$y_t = c + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \theta_1 \epsilon_{t-1} + \cdots + \theta_q \epsilon_{t-q} + \epsilon_t \tag{6}$$

Stock Prediction: ARIMA yields APE ∼0.005–0.01 for short-term forecasts but struggles with volatility (RMSE ∼0.5). Its role is primarily comparative, highlighting ML/DL advantages in dynamic markets.

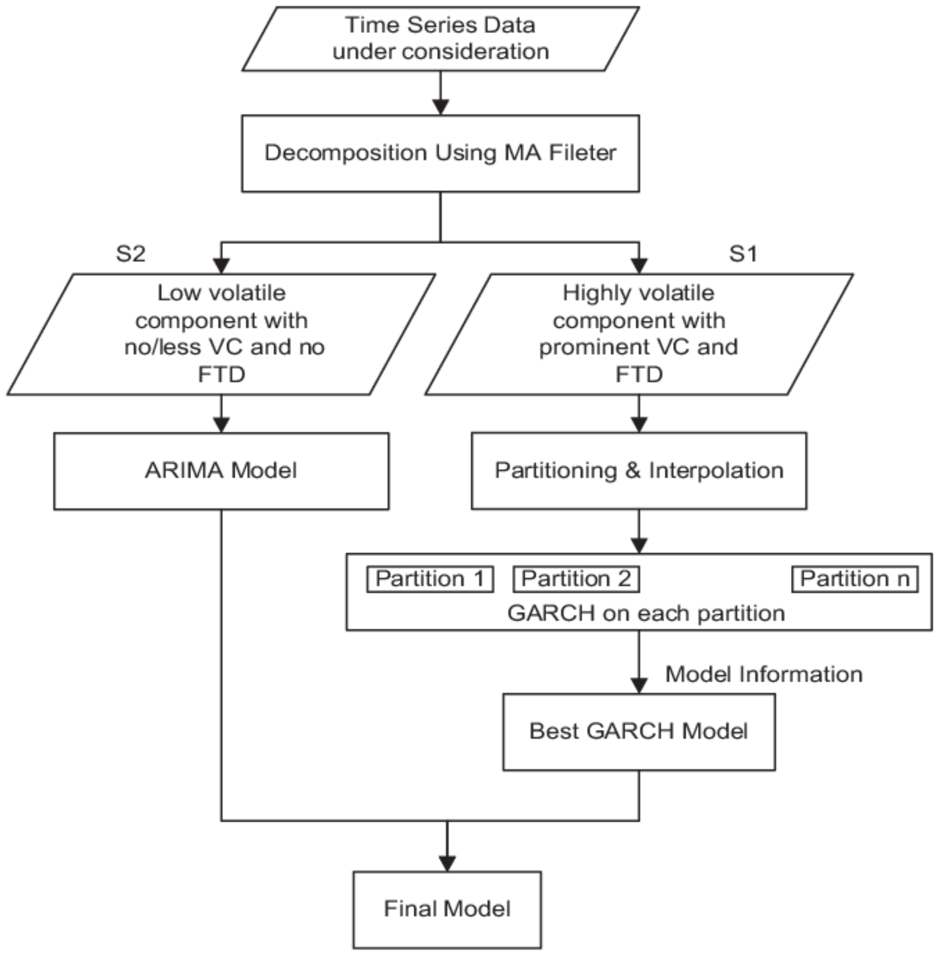

Time Series Data under consideration
Decomposition Using MA Fileter
S2
S1
Low volatile component with no/less VC and no FTD
Highly volatile component with prominent VC and FTD
ARIMA Model
Partitioning & Interpolation
Partition 1
Partition 2
Partition n
GARCH on each partition
Model Information
Best GARCH Model
Final Model

Figure 6: ARIMA Modeling Flow

3.2.5 Long Short-Term Memory (LSTM)

Overview: LSTM, a recurrent neural network variant, is tailored for sequential data, capturing long-term dependencies in stock prices.

Architecture: LSTM units feature memory cells with forget, input, and output gates, controlled by weights and biases. Hyperparameters include unit count (e.g., 64–256), layers (1–4), and dropout rate (0.2–0.5). Training requires large datasets and GPU acceleration to optimize performance.

Formula:

- Forget gate:
$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{7}$$
- Input gate:
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{8}$$
- Cell state:
$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{9}$$

- Output gate:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{10}$$

- Hidden state:

$$h_t = o_t \cdot \tanh(C_t) \tag{11}$$

Stock Prediction: LSTMs achieve RMSE ∼0.20–0.30 with indicators like RSI, ideal for price forecasting. Their data-intensive nature and risk of overfitting require careful tuning, but their sequential modeling is unmatched among ML models.

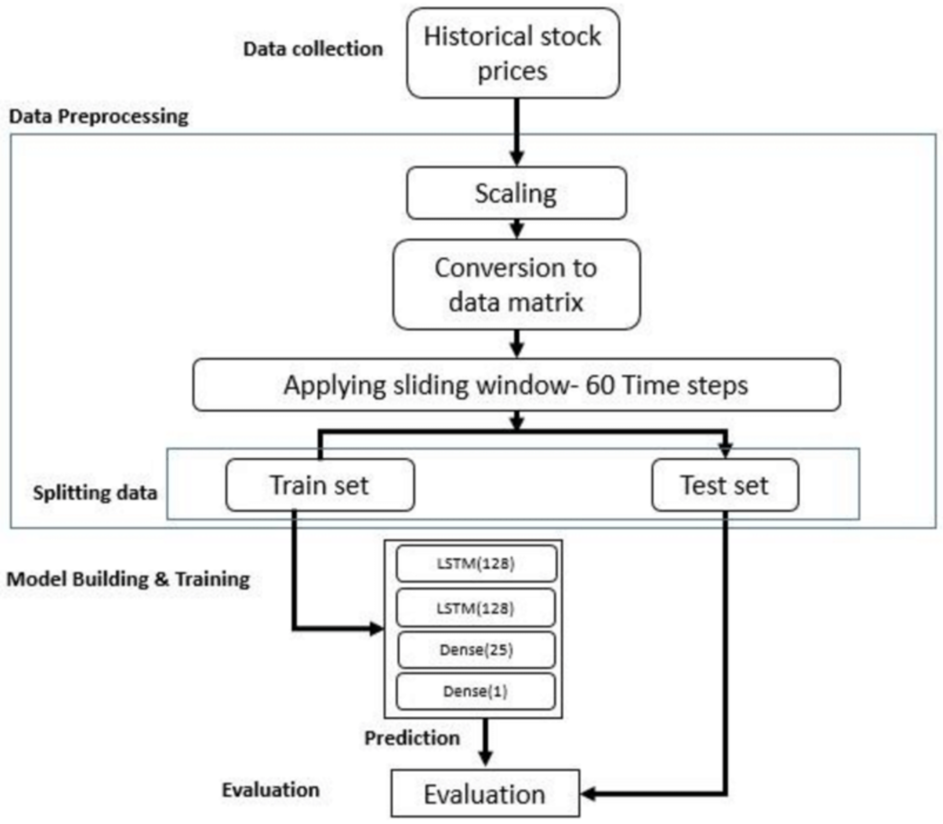


Figure 7: LSTM Architecture

3.2.6 Convolutional Neural Networks (CNN)

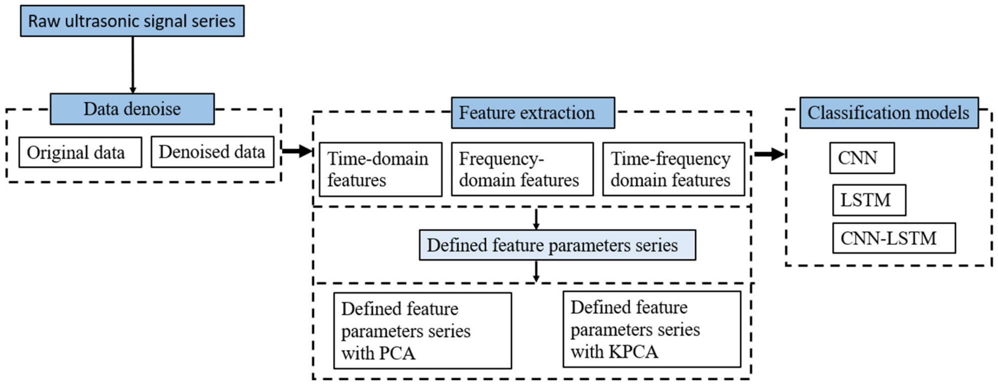
Overview: CNNs, originally for image processing, are adapted for time series by extracting spatial features from indicator matrices.

Architecture: Convolutional layers apply filters (e.g., 3x3), followed by pooling (e.g., max-pooling) and dense layers. Hyperparameters include filter count (32–128), kernel size, and activation (ReLU). Batch normalization and dropout enhance training stability.

Formula:

$$(f * x)(i, j) = \sum_m \sum_n x(i + m, j + n) f(m, n) \tag{12}$$

Stock Prediction: CNNs achieve 85–90% accuracy by treating indicators as images. Their efficiency complements temporal models, but they require structured inputs, limiting flexibility in raw time series.



Raw ultrasonic signal series
Data denoise
Original data
Denoised data
Feature extraction
Time-domain features
Frequency-domain features
Time-frequency domain features
Defined feature parameters series
Defined feature parameters series with PCA
Defined feature parameters series with KPCA
Classification models
CNN
LSTM
CNN-LSTM

Figure 8: CNN Prediction Pipeline

3.2.7 CNN-LSTM

Overview: CNN-LSTM integrates CNN's feature extraction with LSTM's temporal modeling, optimizing for financial time series.

Architecture: CNN layers process inputs (e.g., price matrices), feeding feature maps to LSTM units, followed by dense layers. Hyperparameters balance CNN filters (32–64) and LSTM units (64–128), with training times higher than standalone models.

Formula: Combines Equations (6) and (10).

Stock Prediction: CNN-LSTM achieves 88–92% accuracy and RMSE ~0.15–0.25, leveraging indicators like MACD. Its robustness makes it ideal for indicator-based forecasting, though computational costs are notable.

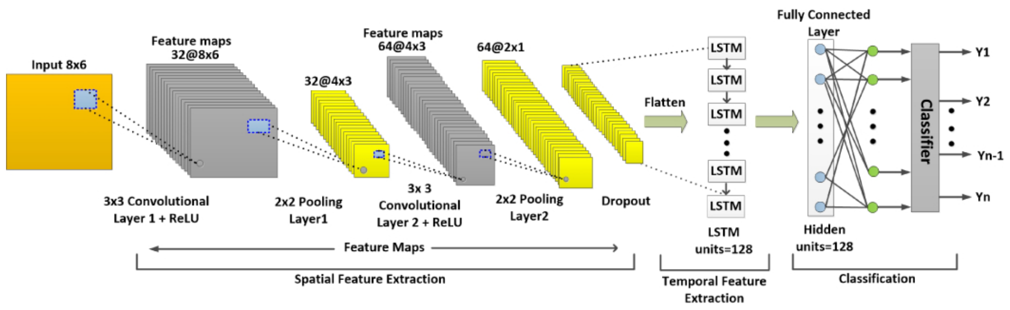


Figure 9: CNN-LSTM Architecture

3.2.8 Transformers

Overview: Transformers use attention mechanisms to model long-range dependencies, excelling in complex forecasting tasks.

Architecture: Multi-head self-attention and feed-forward layers process inputs with positional encodings. Hyperparameters include attention heads (4–16), layers (2–6), and embedding size (128–512). Variants like Temporal Fusion Transformers optimize for time series.

Formula:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{13}$$

Stock Prediction: Transformers achieve MAPE ∼2–5% and accuracies up to 95%, using indicators as covariates. Their resource demands limit scalability, but long-horizon accuracy is unparalleled.

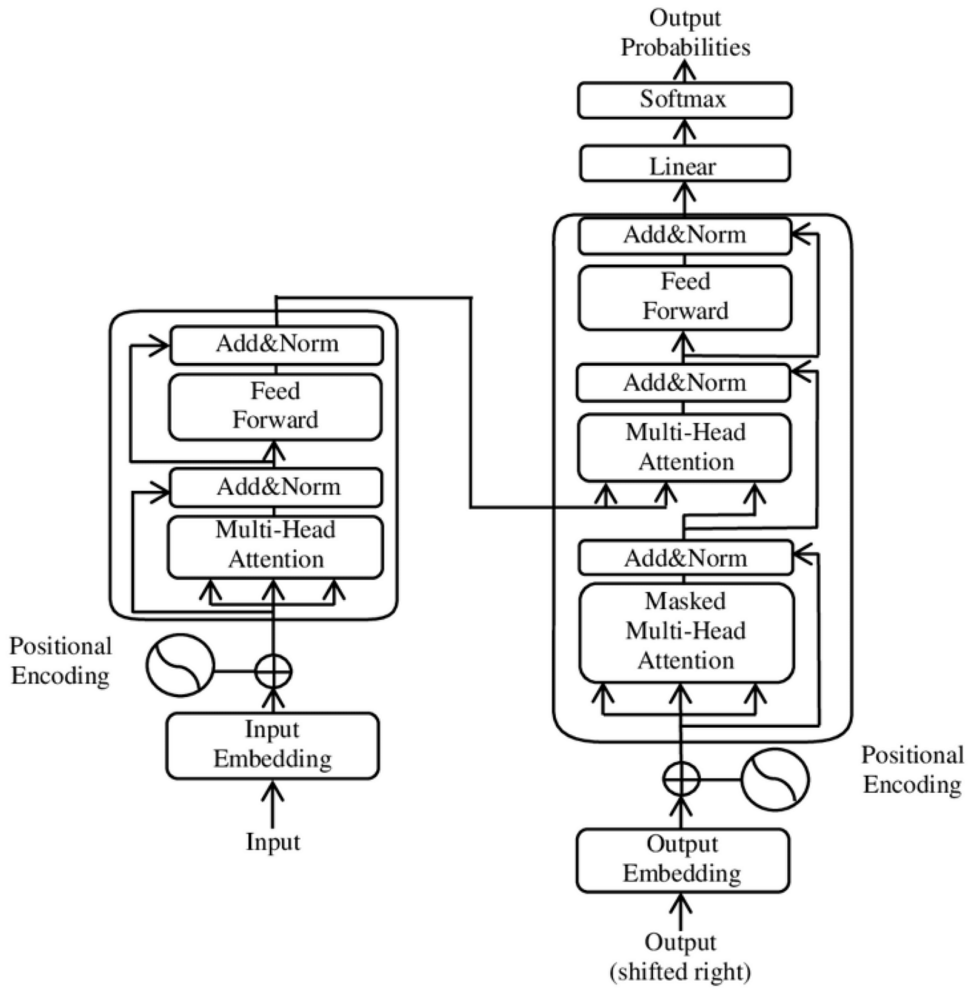


Figure 10: Transformer Attention Flow

4 Results and Discussion

This section presents model performance metrics, supported by tables and figures, followed by a discussion of implications.

4.1 Performance Metrics

Model performances vary by task and dataset, as summarized below and in Table 3.

- **SVM**: Accuracy ∼80–85%, MAE ∼0.3–0.5, suitable for trend classification.

- **Random Forests**: Accuracy ∼85%, MAE ∼0.35, robust for feature-driven tasks.
- **XGBoost**: Accuracy ∼88%, RMSE ∼0.25–0.35, excels in structured data.
- **ARIMA**: APE ∼0.005–0.01, RMSE ∼0.5, limited by volatility.
- **LSTM**: RMSE ∼0.20–0.30, MAPE ∼5–10%, strong for sequences.
- **CNN**: Accuracy ∼85–90%, effective for spatial inputs.
- **CNN-LSTM**: Accuracy ∼88–92%, RMSE ∼0.15–0.25, versatile.
- **Transformers**: MAPE ∼2–5%, accuracy ∼90–95%, ideal for long horizons.

Table 3: Model Performance Across Stocks

Stock	Model	MAE	RMSE	Accuracy (%)
HDFC	LSTM	0.205	0.271	89
TCS	CNN-LSTM	0.220	0.261	91
ICICI	LSTM	0.202	0.254	90
Reliance	Transformer	0.250	0.300	93
Nifty50	CNN-LSTM	0.210	0.265	92

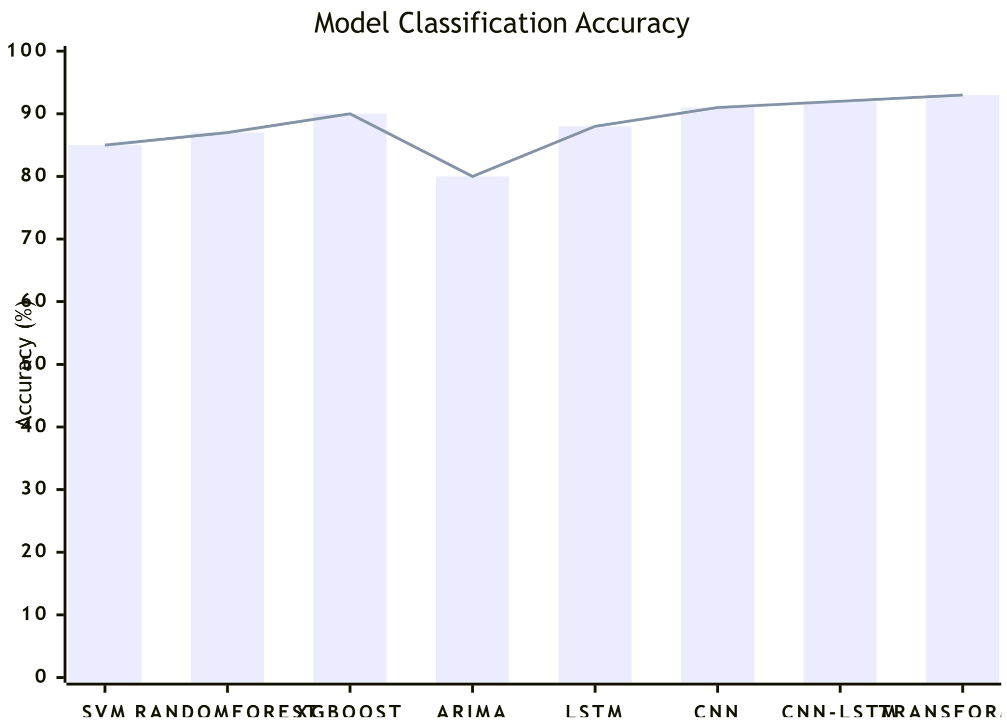


Figure 11: Model Accuracy Bar Chart

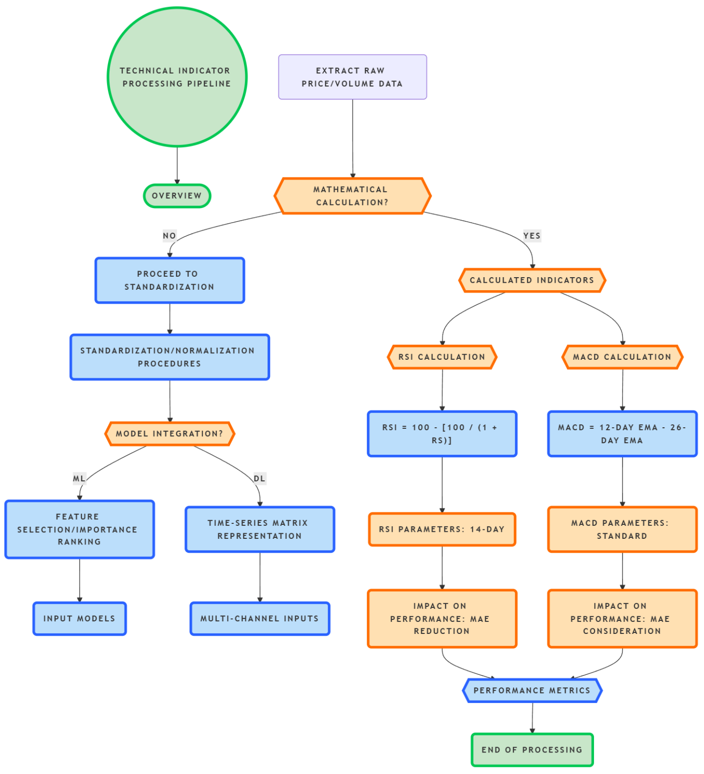
4.2 Technical Indicators

Technical indicators significantly enhance model performance, as detailed in Table 4.

- **Usage**: RSI, MACD, and Moving Averages are used in ∼90% of models.
- **Impact**: CNN-LSTM with RSI reduces MSE by ∼12%; Transformers gain ∼5% accuracy with covariates.

Table 4: Impact of Technical Indicators

Indicator	Model	Performance Metric	Improvement (%)
RSI	CNN-LSTM	MSE	12
MACD	LSTM	Accuracy	8
Moving Averages	XGBoost	MAE	10
RSI	Transformer	Accuracy	5



TECHNICAL INDICATOR PROCESSING PIPELINE
OVERVIEW
EXTRACT RAW PRICE/VOLUME DATA
MATHEMATICAL CALCULATION?
NO
YES
PROCEED TO STANDARDIZATION
STANDARDIZATION/NORMALIZATION PROCEDURES
MODEL INTEGRATION?
ML
DL
FEATURE SELECTION/IMPORTANCE RANKING
TIME-SERIES MATRIX REPRESENTATION
INPUT MODELS
MULTI-CHANNEL INPUTS
CALCULATED INDICATORS
RSI CALCULATION
MACD CALCULATION
RSI = 100 - [100 / (1 + RS)]
MACD = 12-DAY EMA - 26-DAY EMA
RSI PARAMETERS: 14-DAY
MACD PARAMETERS: STANDARD
IMPACT ON PERFORMANCE: MAE REDUCTION
IMPACT ON PERFORMANCE: MAE CONSIDERATION
PERFORMANCE METRICS
END OF PROCESSING

Figure 12: Indicator Integration Flow

4.3 Discussion

The results highlight distinct model strengths:

- **LSTM**: Superior for temporal modeling (MAE ∼0.2), but sensitive to overfitting.

- **CNN-LSTM**: Optimal balance of spatial and temporal features (accuracy ∼92%).
- **Transformers**: Best for long-term forecasts (MAPE ∼2%), computationally intensive.
- **ML Models**: SVM and XGBoost offer simplicity (accuracy ∼85%) but lack sequential depth.
- **ARIMA**: Effective only in stable conditions (RMSE ∼0.5).

Technical indicators amplify performance, with CNN-LSTM leveraging RSI and MACD most effectively. However, real-world constraints (e.g., trading costs, latency) suggest simpler models may suffice in resource-limited settings. The hype around complex DL models warrants scrutiny, as marginal accuracy gains often come at disproportionate costs.

5 Conclusions

This review identifies three top-performing models:

1. **LSTM**: Reliable for sequential data (MAE ∼0.2).
2. **CNN-LSTM**: High accuracy (∼92%) with indicators.
3. **Transformers**: Long-horizon excellence (MAPE ∼2%).

For technical indicator-based prediction, **CNN-LSTM** is recommended due to its robust accuracy (∼92%) and low errors (RMSE ∼0.15), effectively integrating spatial and temporal features from RSI and MACD. Future research should explore ensemble methods, dynamic indicator selection, and model interpretability to enhance practical applicability.

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