**Finance and stock market trend prediction related**

### **1) Lob‑based deep learning models for stock price trend prediction: a benchmark study : 🔹 Innovations (What makes this paper unique)**

1. Introduces **LOBCAST**, an open-source standardized benchmarking framework.
2. Implements **15 state-of-the-art deep learning models** for stock price trend prediction (SPTP).
3. Provides **LOB data preprocessing utilities** (normalization, splitting, labeling).
4. Integrates **hyperparameter tuning with WANDB** for efficient optimization.
5. Generates **detailed reports** on both model performance (F1, Accuracy, Recall) and complexity (training time, inference time, parameters).
6. Supports **backtesting with profit analysis** via Backtesting.py.
7. Reveals that many prior works **overstated model performance** by testing under inconsistent setups.
8. Identifies **BINCTABL** as the most robust and generalizable model, thanks to its adaptive bilinear normalization layer.

### **🔹 Limitations**

1. **High sensitivity to hyperparameters** – many models diverged during training.
2. Only **raw LOB features** were used (to ensure fairness), which limited models designed for richer features.
3. **Computationally expensive grid search** for hyperparameter tuning (needed GPUs and long training time).
4. **Ensemble models** did not outperform the best single models due to high agreement among systems.
5. Dataset imbalance (stationary class dominates) biased some predictions.

### **🔹 Lessons Learned**

1. **Standardized benchmarking is essential** to fairly evaluate financial DL models.
2. **Attention-based models** (like BINCTABL) perform best on LOB data.
3. **Short horizons (k=1–2)** are noisy and hard to predict.
4. **Medium to longer horizons (k=5–10)** yield more stable and accurate predictions.
5. Using **raw LOB features** can sometimes outperform handcrafted features (e.g., CNNLSTM case).

### **🔹 Future Directions**

1. Develop models that are **less sensitive to hyperparameters**.
2. Integrate **richer market features** (e.g., order flow imbalance, trader strategies, news sentiment).
3. Explore **online learning / adaptive models** for dynamic market changes.
4. Improve **explainability (XAI) for LOB models** to build trust in real-world trading.
5. Investigate **class imbalance handling** methods (e.g., better labeling or resampling).

**2) Predicting Stock Price Movements with Combined Deep Learning Models and Two-Tier Metaheuristic Optimization Algorithm**

### **🔹 Innovations (What makes this paper unique)**

1. **Two-tier optimization approach**

* Uses **Dingo Optimizer Algorithm (DOA)** for feature selection (filtering most relevant features).
* Uses **Equilibrium Optimizer (EO)** for hyperparameter tuning of the MHA-BiGRU model.

1. **Combined deep learning model**

* Proposes **MHA-BiGRU (Multi-Head Attention + Bi-directional GRU)**, which captures both temporal dependencies and attention-based feature importance.
* Better handling of noisy, high-dimensional financial time-series data.

1. **Pre-processing improvement**

* Applies **Z-score normalization** to ensure standardized input features, improving model consistency and convergence speed.

1. **Performance achievement**

* Achieved an extremely high correlation value (**CORR = 0.9999**), indicating near-perfect predictive accuracy on experimental datasets.

### **🔹 Limitations**

1. **Overfitting risk** – Very high CORR may indicate **possible overfitting** to experimental data rather than true generalization.
2. **Data constraints** – Only relies on **historical stock and technical indicators**, ignores macroeconomic, news, and sentiment factors.
3. **Computational complexity** – Combining DOA + EO + MHA-BiGRU increases training time and resource requirements.
4. **Interpretability issue** – Deep hybrid models lack transparency, which may reduce investor trust.
5. **Generalization uncertainty** – Model tested on limited datasets; unclear if it performs well in different markets (e.g., US, EU, or emerging markets).

### **🔹 Key Lessons Learned**

1. **Hybrid DL + metaheuristic optimization improves performance** compared to single techniques.
2. **Feature selection matters** — DOA effectively reduces noise and improves computational efficiency.
3. **Attention mechanisms enhance forecasting power** by identifying relevant temporal dependencies.
4. **Hyperparameter tuning is crucial** — EO improves stability and avoids poor manual selection.
5. **Pre-processing consistency is a foundation** — simple steps like Z-score normalization significantly improve model convergence.

### **🔹 Future Research Directions**

1. **Incorporate multi-source data**

* News, social media sentiment, macroeconomic indicators, and alternative data (Google Trends, ESG metrics).

1. **Model interpretability (XAI)**

* Apply SHAP, LIME, or attention visualization to improve transparency for investors.

1. **Robustness under extreme conditions**

* Test on Black Swan events (e.g., COVID crash, geopolitical crises).

1. **Scalability and real-time prediction**

* Adapt PSPMCDL-TTMO for high-frequency trading and real-time updates.

1. **Portfolio-level optimization**

* Extend from single-stock prediction to multi-stock **portfolio selection and risk management**.

1. **Comparative studies with transformers**

* Benchmark against newer architectures like Informer, Temporal Fusion Transformer (TFT), or FinanceBERT.

**3) Title: Stock Price Prediction in the Financial Market Using Machine Learning Models**

# **📘 Paper Overview** **Authors:** Diogo M. Teixeira and Ramiro S. Barbosa **Published in:** *Computation*, 2025, Volume 13, Issue 1, Article 3 **DOI:** [10.3390/computation13010003](https://doi.org/10.3390/computation13010003)

## **1. 🎯 Research Goal**

The paper investigates **how different ML/DL models perform in predicting stock prices**, focusing on:

* **Recurrent Neural Network (RNN)**
* **Long Short-Term Memory (LSTM)**
* **Gated Recurrent Unit (GRU)**
* **Convolutional Neural Network (CNN)**
* **XGBoost**
* **Hybrid models** (e.g., LSTM+GRU, CNN+LSTM, GRU+RNN).

The aim is to identify **which models and feature combinations are best suited for stock price forecasting**.

## **2. 📊 Dataset & Features**

* **Dataset:** Apple Inc. stock prices (1980–2024) from Yahoo Finance.
* **Features:**
* Raw prices (Open, High, Low, Close, Adj Close, Volume).
* **43 technical indicators & economic indices**: SMA, EMA, MACD, RSI, Treasury yields, Oil price, NASDAQ, S&P 500, Dow Jones, NYSE, etc.
* **Feature selection:** Used correlation analysis and SelectKBest → Top **20 most correlated features** were chosen.

## **3. ⚙️ Methodology**

* **Target variable:** Next-day Adjusted Close price.
* **Preprocessing:** Normalization (0–1 scaling), input window size = 100 days (optimized).
* **Validation:** **Time Series Cross Validation (10 folds)** (instead of random splits).
* **Optimization:** Bayesian optimization for hyperparameters.
* **Metrics:** MAE, MSE, RMSE, MAPE, R².

## **4. 🔬 Models Implemented**

* **LSTM** (2–5 layers tested; 2-layer best).
* **GRU** (2-layer best).
* **CNN** (alone + hybrid with LSTM/GRU).
* **RNN** (alone + hybrid with GRU/LSTM).
* **XGBoost** (optimized via GridSearchCV).
* **Total:** 44 model variations tested.

## **5. 📈 Key Results**

* **Best performers:**
* **GRU (2 layers)** → Lowest error on MSE & MAPE.
* **XGBoost** → Best on MAE, RMSE, R².
* **Moderate performer:** LSTM (good but weaker than GRU/XGBoost).
* **Poor performers:** RNN and LSTM+RNN (struggled with volatility).
* **Hybrid models:** Some improved accuracy (CNN+GRU, CNN+LSTM), others worsened performance.

## **6. 🏆 Innovations**

1. **Comprehensive comparison** of deep learning (LSTM, GRU, CNN, RNN) and boosting (XGBoost) models in one framework.
2. **Hybrid architectures tested extensively** (44 variations, unusual in scope).
3. **Feature engineering** combining stock prices, technical indicators, and macroeconomic indices.
4. **Time Series Cross Validation (10 folds)** → More realistic than random splits.
5. **Bayesian hyperparameter optimization** for fairness across models.

## **7. ⚠️ Limitations**

1. **Single dataset (Apple Inc.)** → results may not generalize to all stocks.
2. **Short-term forecast only (next-day prediction)** → no long-term horizon explored.
3. **Limited external signals** → no news, sentiment, or macroeconomic shocks considered.
4. **Hybrid models not always beneficial** (some combos degraded performance).
5. **High computational cost** (training 44 deep models + tuning).

## **8. 🔮 Future Work**

1. **Explore new algorithms** → Transformers, GANs, advanced hybrid deep learning.
2. **Apply to multiple companies/markets** for broader generalization.
3. **Include external features** (financial news, social media sentiment, economic indicators).
4. **Try classification models** (up/down movement) instead of only regression.
5. **Develop ensemble approaches** (mix boosting + DL).
6. **Optimize input window & architecture selection** with smarter validation.

**Extra**

**1.A Review of Stock Price Prediction Techniques using Machine Learning** International Journal for Research in Applied Science & Engineering Technology (IJRASET)

## **📌 Procedure (Step-by-Step)**

1. **Data Collection**

* Stock price data collected from Yahoo Finance (yfinance API).
* Structured dataset (historical stock price, technical indicators).

1. **Feature Engineering**

* Calculation of external indicators:
* Technical: SMA, EMA, RSI, MACD, Bollinger Bands.
* Macroeconomic: GDP, interest rates, unemployment.
* Market sentiment: VIX, trading volume, institutional buy/sell.
* News sentiment (financial news & social media).

1. **Model Design – Multi-Input LSTM**

* LSTM network designed with **gates (input, forget, output)** as shown in the diagram.
* Each input stream (prices + indicators) processed separately.
* Features merged before final prediction.

1. **Training & Evaluation**

* Models trained on historical data.
* Metrics: RMSE, MSE, MAE, MAPE, R², accuracy.
* Compared with other ML/DL models (RF, SVR, CEEMDAN-LSTM, CNN, etc.).

1. **Analysis & Visualization**

* Performance comparison graphs.
* Table summarizing advantages and challenges of past models.

1. **Conclusion**

* Multi-input LSTM provides better accuracy and robustness.

## **📌 Novelty**

* **Multi-Input LSTM**: Unlike normal LSTM models, this approach integrates multiple data streams (stock prices + technical + macroeconomic + sentiment indicators).
* **Structured Dataset Focus**: Prioritizes clean structured stock data over noisy unstructured data (like raw news).
* **Comparison with Literature**: Systematic review of hybrid models (CEEMDAN, EMD, ARIMAX) to identify gaps.
* **Enhanced Feature Context**: External indicators add context, reducing error in predictions.

## **📌 Innovations**

1. **Combination of Traditional & Advanced Models** – A blend of ML regressors, deep learning, and hybrid decomposition methods.
2. **Use of External Indicators in LSTM** – Expands the scope beyond historical prices.
3. **Improved Forecasting Accuracy** – Achieves lower RMSE and MSE compared to classical ML models.
4. **Framework for Multi-Feature Inputs** – Stock data, technical indicators, sentiment, and macroeconomic variables combined in one predictive model.

## **📌 Limitations**

* **High Computational Complexity** – Training LSTM with multiple inputs is resource-heavy.
* **Parameter Sensitivity** – Requires fine-tuning hyperparameters (hidden units, dropout, learning rate).
* **Market Unpredictability** – Sudden crashes, political or global events limit predictive power.
* **Data Constraints** – Mostly structured data used, missing real-time multimodal (text, images, social media).
* **Overfitting Risk** – LSTM may memorize noise if not carefully regularized.

## **📌 Future Integrations**

1. **Hyperparameter Tuning** – Use Bayesian optimization or Grid/Random Search.
2. **Feature Selection/Reduction** – PCA, Autoencoders, or RBM for dimensionality reduction.
3. **Hybrid Architectures** –

* CNN-LSTM (convolutions for feature extraction + LSTM for sequence learning).
* Transformer models (attention for long-term dependencies).

1. **Multimodal Learning** – Integrate structured stock data + financial news sentiment + social media data.
2. **Explainable AI (XAI)** – Use SHAP/LIME to make predictions interpretable for investors.
3. **Cross-Market Expansion** – Apply the model to commodities, forex, and cryptocurrencies.

✅ So, in short:

* **Procedure** → Collect data → Add external features → Build Multi-Input LSTM → Train & Evaluate → Compare.
* **Novelty** → Multi-input approach with structured + external indicators.
* **Innovations** → Combination of ML/DL, hybrid decomposition, and external indicators.
* **Limitations** → High complexity, parameter tuning, unpredictability of markets.
* **Future Integrations** → CNN-LSTM, transformers, XAI, multimodal sentiment analysis.

**2) An Interpretable Framework for Stock Market Forecasting Using Long Short-Term Memory (LSTM) Networks with SHAP-Explainable AI (XAI) Method**

|  |  |
| --- | --- |
| **Aspect** | **Details** |
| **Innovations** | - Integration of LSTM networks (for sequential/time-series prediction) with SHAP (Explainable AI) to enhance interpretability.- Provides feature-level explanations for stock price predictions, addressing the “black box” problem of deep learning.- Combines predictive power and transparency in a single framework. |
| **Limitations** | - Complexity of financial markets may still affect prediction accuracy despite interpretability.- Model trained only on HDFC Bank stock data from 2020–2025; limited generalizability to other stocks or markets.- Uses only historical closing prices; additional features like volume, news sentiment, or macroeconomic indicators not considered.- Computational overhead of SHAP analysis not quantified. |
| **Novelty** | - Directly combines LSTM forecasting with SHAP-based explainability in financial markets.- Provides actionable insights into which historical data points most influence predictions.- Enhances trust and understanding for analysts using AI-based forecasts. |
| **Gap Addressed** | - Lack of interpretability in traditional deep learning models for stock market forecasting.- Difficulty in understanding the contribution of individual historical data points to predictions. |
| **Future Work** | - Incorporate additional input features (volume, news sentiment, macroeconomic indicators, financial ratios).- Test framework across multiple stocks, markets, and longer time periods.- Improve visualization of SHAP explanations for analysts.- Explore real-time application and computational efficiency.- **Compare SHAP with other XAI methods for interpretability insights.** |
| **Dataset** | - Historical closing prices of **HDFC Bank** from **2020 to 2025**, sourced from **Yahoo Finance**.- Preprocessed (normalized) for LSTM training.- Exact size/frequency of dataset not specified. |

**Continue ...............**