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NSE Stock Forecasting & Prediction System Using Machine Learning and Deep Learning

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Abstract - Stock markets are complex, dynamic, and highly volatile systems influenced by macroeconomic indicators, corporate performance, geopolitical events, and investor psychology. Conventional stock forecasting approaches rely heavily on single predictive models, static technical indicators, or human intuition, which are inadequate in capturing non-linear dependencies, regime shifts, and predictive uncertainty inherent in financial time-series data. These limitations increase investment risk and reduce the reliability of automated trading systems, particularly for retail investors in emerging markets such as the National Stock Exchange (NSE) of India. This paper proposes an AI-driven NSE Stock Forecasting and Risk-Aware Trading Decision Support System that integrates classical machine learning, deep learning, market regime detection, and probabilistic uncertainty estimation within a unified multi-model framework. The system employs Linear Regression, Long Short-Term Memory (LSTM), Bidirectional Gated Recurrent Units (GRU), and Temporal Fusion Transformer (TFT) models for multi-horizon forecasting over one to fourteen days. A market regime detection module classifies market conditions into Bull, Bear, or Sideways states and dynamically adjusts model weights in a regime-aware ensemble mechanism, while Monte Carlo Dropout is utilized to generate ninety-five percent confidence intervals to support risk-aware decision-making. A prototype implementation is developed using Python, TensorFlow/Keras, Scikit-learn, Pandas, and Streamlit, operating on historical NSE OHLCV data enriched with thirty-two technical indicators. Experimental results demonstrate that the proposed ensemble framework outperforms single-model baselines in terms of prediction accuracy, variance reduction, and trading signal reliability. The system delivers interpretable forecasts, confidence bands, and automated BUY, SELL, or HOLD recommendations through an interactive dashboard, making it suitable for investors, traders, analysts, and researchers.

Keywords - Stock Market Forecasting; National Stock Exchange of India (NSE); Machine Learning; Deep Learning; Long Short-Term Memory (LSTM); Gated Recurrent Unit (GRU); Temporal Fusion Transformer (TFT); Ensemble Learning; Market Regime Detection; Monte Carlo Dropout; Probabilistic Forecasting; Risk-Aware Trading; Time-Series Prediction; Algorithmic Trading; Decision Support Systems.

INTRODUCTION

The financial market plays a crucial role in economic development by enabling capital allocation, investment, and wealth generation. However, predicting stock prices remains one of the most challenging problems in computational finance due to market non-linearity, noise, and stochastic behavior. Traditional forecasting methods, including moving averages, trend analysis, and chart patterns, rely on deterministic rules that fail to generalize across different market conditions.

With the availability of large-scale financial datasets and advancements in artificial intelligence, machine learning and deep learning techniques have become central to modern stock forecasting. These models can learn complex temporal relationships, extract hidden patterns from historical data, and adapt to changing market dynamics. Nevertheless, most existing systems provide only point predictions without confidence estimates, ignore different market regimes such as Bull, Bear, or Sideways phases, and depend on a single predictive model, which increases bias and variance.

To overcome these challenges, this research introduces an AI-driven multi-model forecasting system that combines regime-aware ensemble learning with uncertainty quantification to provide reliable, interpretable, and risk-aware predictions for NSE stocks.

II. MOTIVATION AND RESEARCH GAPS

Existing stock prediction systems suffer from several critical limitations, including excessive reliance on single models such as LSTM or Linear Regression, lack of uncertainty estimation, static feature selection that does not adapt to evolving market behavior, absence of automated trading logic, and inadequate mechanisms for assessing prediction reliability. These shortcomings make traditional approaches unsuitable for real-world financial decision-making.

To address these issues, there is a need for an intelligent forecasting framework that integrates multiple predictive models, detects market regime changes, quantifies prediction uncertainty, provides interpretable trading recommendations, and supports multi-horizon forecasting. The architecture of the proposed system follows a structured pipeline consisting of data ingestion, feature engineering, predictive modeling, ensemble fusion, and visualization.

III. CONTRIBUTIONS OF THIS PAPER

This work proposes a complete end-to-end AI-driven stock forecasting framework that integrates classical machine learning, deep learning, and transformer-based architectures within a unified pipeline. The framework seamlessly connects data ingestion, feature engineering, predictive modeling, uncertainty estimation, decision generation, and visualization, ensuring consistency and efficiency. Classical models provide interpretability and stable baselines, while sequential deep learning models capture temporal dependencies and attention-based models effectively handle long-range relationships in multi-horizon forecasting.

A novel market regime detection mechanism classifies market conditions into Bull, Bear, or Sideways states based on technical indicators such as RSI, price momentum, volatility, and moving averages. This dynamic adaptation improves prediction performance during high volatility and enhances model robustness. The system incorporates uncertainty quantification using Monte Carlo Dropout to generate ninety-five percent confidence intervals around predicted prices, enabling investors to assess risk before making decisions.

A regime-aware weighted ensemble strategy dynamically adjusts model importance based on detected market conditions, reducing bias and variance while improving forecasting stability. An automated trading decision module generates BUY, SELL, or HOLD signals along with confidence scores and reasoning by considering predicted price trends, market regime alignment, technical indicators, and uncertainty levels.

An interactive Streamlit dashboard presents results through candlestick charts, forecast trends, confidence bands, and comparative performance visualizations, making the system accessible to both technical and non-technical users. The framework is rigorously evaluated using real-world NSE data and benchmarked against traditional single-model approaches using metrics such as MAE, RMSE, prediction variance, trading reliability, and false-positive reduction.

IV. RELATED WORK

Stock market prediction has been widely studied using statistical models, machine learning, and deep learning techniques, yet many approaches remain limited in handling uncertainty, regime shifts, and real-world trading requirements. Early research relied on classical models such as Linear Regression, Decision Trees, Support Vector Machines, and Random Forests, which provided reasonable performance under stable conditions but struggled with non-linear dependencies, temporal relationships, and noise sensitivity.

The emergence of deep learning led to the widespread use of LSTM and GRU networks, which demonstrated superior performance in modeling sequential data. However, these models are prone to overfitting, require significant computational resources, and lack uncertainty estimation, limiting their practical applicability.

Recent studies have emphasized probabilistic forecasting using Monte Carlo Dropout to generate confidence intervals, improving transparency and risk awareness. However, most uncertainty-aware models do not incorporate market regime detection or ensemble learning.

Ensemble methods combining multiple models have shown improved robustness and generalization, yet existing approaches typically rely on fixed weights and lack dynamic adaptation to market conditions or uncertainty modeling.

These gaps motivate the proposed system, which integrates deep learning, classical models, market regime detection, ensemble learning, uncertainty quantification, and automated trading decision support within a single unified framework for NSE forecasting.

V. SYSTEM MODEL AND PROBLEM DEFINITION

The proposed system operates as a modular, data-driven, and AI-enabled forecasting framework that processes historical stock data and generates risk-aware trading decisions through a structured analytical pipeline. The Data Ingestion Module retrieves OHLCV data from reliable sources, handles missing values, removes anomalies, and stores cleaned time-series data.

The Feature Engineering Module generates thirty-two technical indicators, including trend, momentum, volatility, and lag features, and applies MinMax scaling to ensure numerical stability. The Market Regime Detection Module classifies market conditions into Bull, Bear, or Sideways states based on technical indicators, guiding the ensemble forecasting strategy.

The Prediction Layer consists of Linear Regression, LSTM, Bidirectional GRU, and Temporal Fusion Transformer models operating in parallel to generate multi-horizon forecasts. The Ensemble Fusion Layer dynamically weights model outputs based on market regime, while the Uncertainty Estimation Layer applies Monte Carlo Dropout to compute confidence intervals.

The Trading Decision Module converts predictions into actionable BUY, SELL, or HOLD signals with confidence scores and reasoning. The Visualization Layer presents results through an interactive Streamlit dashboard featuring candlestick charts, forecast trends, and model comparisons.

The primary objective is to design a system that accurately predicts stock prices for one to fourteen days, detects market regimes, quantifies uncertainty, generates actionable trading signals, and outperforms traditional single-model approaches.

Proposed Ai-Driven Architecture

The proposed architecture is modular, scalable, and event-driven, integrating data collection, feature engineering, prediction, regime detection, ensemble fusion, uncertainty estimation, decision generation, and visualization. The Data Collection Layer retrieves historical OHLCV data, cleans inconsistencies, and normalizes features using MinMax scaling.

The Feature Engineering Layer extracts thirty-two technical indicators covering trend, momentum, volatility, and lagged price movements. The Prediction Layer employs Linear Regression as a baseline, LSTM for long-term dependency learning, Bidirectional GRU for improved sequence modeling, and TFT for multi-horizon forecasting.

The Market Regime Detection module classifies conditions into Bull, Bear, or Sideways states, guiding the Ensemble Fusion Layer, which dynamically adjusts model weights to improve stability and accuracy. The Uncertainty Estimation Layer applies Monte Carlo Dropout to generate ninety-five percent confidence intervals.

The Trading Signal Generator produces BUY, SELL, or HOLD recommendations based on predicted trends, regime alignment, RSI, MACD, and uncertainty levels. The Visualization Dashboard presents results through interactive charts, confidence bands, and model comparison plots.

Ai Models and Multi-Agent Framework

The system follows a multi-agent predictive architecture where each model functions as an independent forecasting agent contributing to a unified prediction outcome. Linear Regression serves as a stability agent, providing interpretable baseline forecasts in low-volatility markets. It assumes a linear relationship between time and stock price, where the predicted price depends on time or derived technical features. Although it cannot capture complex non-linear patterns, it provides stable reference predictions in sideways markets.

$$Y = \beta_0 + \beta_1 X$$

LSTM acts as a long-term trend agent, capturing sequential dependencies through memory cells regulated by input, forget, and output gates. Bidirectional GRU enhances learning by processing data in both forward and backward directions, making it effective in volatile markets, while TFT functions as a strategic multi-horizon agent using attention mechanisms to model complex relationships across multiple time steps.

Instead of relying on a single model, the system applies a regime-aware weighted ensemble strategy. Each model produces an independent forecast, the market regime is detected, and model weights are adjusted accordingly to improve robustness across different market conditions.

$$\hat{Y}_{ensemble} = \sum_{i=1}^{n} w_i \hat{Y}_i$$

This reduces bias and variance while improving robustness across different market conditions.

For uncertainty modeling, Monte Carlo Dropout remains active during inference, allowing multiple forward passes through the network. The system computes a mean prediction and standard deviation from these samples and constructs a ninety-five percent confidence interval.

$$[\mu - 1.96\sigma, \mu + 1.96\sigma]$$

This probabilistic approach supports risk-aware decision-making by explicitly quantifying prediction uncertainty.

Experimental Setup

The experimental study uses real-world historical NSE stock data from Yahoo Finance and Kaggle, covering multiple years and diverse market conditions. The dataset includes OHLCV attributes and thirty-two engineered technical indicators, all normalized using MinMax scaling. The data is split into seventy percent training, fifteen percent validation, and fifteen percent testing sets.

Baseline comparisons are conducted using a single Linear Regression model and a standalone LSTM model trained under identical conditions. Performance is evaluated using several quantitative metrics. Mean Absolute Error measures the average prediction deviation without considering direction.

$$\mathrm{MAE} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}} |\mathrm{y_i} - \hat{\mathrm{y}}_\mathrm{i}|$$

Root Mean Square Error penalizes larger errors more heavily and is critical in financial forecasting.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

Prediction variance measures stability across market regimes, while trading accuracy evaluates whether BUY, SELL, or HOLD signals correctly anticipated actual price movements.

The evaluation process involves training all models, tuning hyperparameters, generating forecasts, applying ensemble fusion, estimating uncertainty, and analyzing performance across Bull, Bear, and Sideways regimes.

Results and Discussion

The proposed regime-aware ensemble model consistently outperformed baseline models in terms of MAE and RMSE across multiple NSE stocks and market conditions. In highly volatile periods, the combination of Bidirectional GRU and TFT delivered the best performance by effectively capturing short-term fluctuations and long-term dependencies.

Uncertainty modeling significantly reduced false-positive trading signals, particularly in sideways markets, by preventing overreaction to minor price movements. Compared to baseline models, the proposed system demonstrated greater decision reliability and risk awareness.

Trading signals aligned closely with actual market trends, with BUY recommendations preceding upward movements, SELL signals anticipating declines, and HOLD signals issued during uncertain conditions. Each signal included a confidence score and technical justification based on RSI, MACD, and regime classification.

Despite increased computational complexity, parallel model execution and asynchronous processing ensured minimal pipeline overhead, maintaining real-time feasibility.

VI. CONCLUSION AND FUTURE WORK

This paper presented a comprehensive AI-driven NSE Stock Forecasting and Risk-Aware Trading Decision Support System that integrates multi-model ensemble learning, market regime detection, and probabilistic uncertainty estimation. The proposed architecture combines classical and deep learning models within a dynamic regime-aware framework and employs Monte Carlo Dropout to generate confidence intervals, enabling risk-aware investment decisions.

Experimental results demonstrated superior accuracy, stability, and trading reliability compared to single-model baselines, while maintaining acceptable computational efficiency through parallel processing. The interactive Streamlit dashboard enhances usability and interpretability for both technical and non-technical users.

Future work will focus on real-time market integration using financial APIs, incorporation of sentiment analysis from news and social media, extension to cryptocurrency and forex markets, and development of an automated algorithmic trading bot with risk management strategies. Additional enhancements include federated learning across multiple stocks, reinforcement learning for adaptive trading, graph neural networks for inter-stock relationships, and continual learning to adapt to evolving market conditions.

Overall, this research establishes a strong foundation for next-generation intelligent trading platforms that support data-driven, transparent, and responsible investment strategies.

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