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ArthaYukti: An Integrated Deep Learning Framework for Financial Sentiment Analysis and Stock Price Forecasting

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Abstract: This paper presents ArthaYukti, a unified deep learning framework that integrates financial sentiment analysis with stock price forecasting to generate actionable market intelligence. The system employs FinBERT for domain-specific sentiment classificationandLongShort-Term Memory(LSTM) networks for time-series forecasting. A dynamic weighting mechanism adaptively fuses sentiment- driven signals with technical indicators, thereby improving predictive accuracy over standalone models. Experimental results demonstrate notable reductions in forecasting error, improved sentiment detection, and efficient real-time processing. The proposed platform facilitates enhanced decision making for investors and financial institutions.
Keywords: Sentiment Analysis, Stock Price Prediction, Fin BERT, LSTM Networks, Deep Learning, Financial Analytics, Time-Series Forecasting, Hybrid Prediction Models.

I. INTRODUCTION

Financial markets are highly dynamic, influenced by economicindicators,corporateannouncements,geopolitical conditions, and public sentiment. Traditional analysis techniques—such as technical and fundamental analysis— often fail to capture the complex, nonlinear interactions between these diverse factors. With the advancements in deep learning and natural language processing (NLP), machine-driven analysis has demonstrated substantial improvements in extracting hidden patterns from both structured and unstructured market data.LSTMnetworkshaveshownstrongcapabilitiesinmodeling long-term dependencies in financial time series [1], while transformer-based architectures such as BERT have revolutionized contextual understanding in textual data [2]. FinBERT—an adaptation of BERT for financial corpora— has achieved state-of-the-art performance in financial sentiment classification [3]. However, existing approaches typically treat sentiment analysis and price forecasting as independent tasks, resulting in fragmented predictions that overlook cross-modal interactions.

ArthaYuktibridgesthisgap through ahybriddeep learning system that jointly incorporates sentiment signals and historicalstockdata.Thekeychallengesaddressedinclude:

- High-frequencydataprocessingforreal-time forecasting.
- Accuratesentimentextractionfromfinancialnews using domain-specific language models.
- Dynamicintegrationofsentimentandtechnical indicators through adaptive weighting.

Themajorcontributionsofthisworkare:

- Areal-timeETLpipelineforfinancialmarketdata and news streams.
- AFinBERT-basedsentimentanalysismodule optimized for financial text.
- AnLSTM-drivenstockforecastingmechanism.
- Adynamicweightingalgorithmthatfuses multimodal insights.
- Ascalablefrontend-backendarchitecture supporting real-time analytics.

II. SYSTEM ARCHITECTURE

The ArthaYukti platform is designed as a modular, multi-layered architecture comprising three major components: (a) data acquisition pipeline, (b) analysis and prediction engine, and (c) user interface.

A. Data Acquisition and Processing

Historical and real-time stock data are acquired using the *yfinance* API. The dataset comprises over 129,000 rows of NIFTY50 stock information spanning 2014– 2025. A PostgreSQL database stores structured data, while Redishand lescachingto reduce response latency. News articles are aggregated from financial feeds and preprocessed for NLP.

B. Sentiment Analysis Module

FinBERTisemployedforsentimentclassification.The model categorizes financial news into bullish, bearish, orneutralsentiments. Tokenization,embedding,contextualencoding,andsoftmaxclassification generate probability-weighted outputs, which serveas sentiment indicators.

C. Price Forecasting Module

TheforecastingsubsystemleveragesLSTMnetworksto model sequential dependencies. Multiple stacked LSTM layers are used to predict closing prices using normalized features such as open, high, low, close, volume, moving averages, and RSI.

D. Dynamic Weighting Mechanism

Unlike fixed-weight models, ArthaYukti dynamically adjusts weights between sentiment analysis and technicalforecasting.Asigmoid-basedfunctionassigns adaptive blending factors based on confidence scores, capturing real-time market fluctuations.

III. METHODOLOGY

A. Market Data Pipeline

Market data undergoes transformation involving cleaning, missing-value handling, normalization, and technical feature extraction.Indicators such asMAand RSI supplement core price data to enhance predictive performance.
Letthehistoricalmarketdatasetberepresented as:

$$D_{\text{raw}}=\{(o_t,h_t,l_t,c_t,v_t)\}^T_{t=1}$$

Where

o_t= Openpriceattimet

h_t=High priceattimet

l_t=Lowprice at timet

c_t=Closepriceattimet

v_t=Volume attimet

B. News Data Processing Pipeline

Preprocessing includes tokenization, stop-word removal, financial term normalization, metadata tagging, timestamp alignment, and NER-based entity extraction. Articles are stored with source credibility factors.

1) DataCleaning&Transformation

Missingvaluesareimputedusinglinearinterpolation:

$$x_t = x_{t-1} + \frac{x_{t+1} - x_{t-1}}{}, \qquad x \in \{o,h,l,c,v\}\ 2$$

Logreturnsarecomputedas:

$$r_t = \ln\left(\frac{c_t}{c_{t-1}}\right)$$

2) *Feature Engineering*

MovingAverage(MA):

$$MA_n(t)=\frac{1}{n}\sum_{i=0}^{n-1}c_{t-i}$$

ExponentialMovingAverage(EMA):

$$EMA_n(t)=\alpha c_t+(1-\alpha)EMA_n(t-1)$$

Where, $\alpha=\frac{n+1}{2}$

RelativeStrengthIndex(RSI):

$$RSI(t)=100-\frac{100}{1+\frac{G(t)}{L(t)}}$$

where

$$G(t)=\frac{1}{n}\sum_{i=1}^{n}\max(r_{t-i},0),$$

$$L(t)=\frac{1}{n}\sum_{i=1}^{n}\max(-r_{t-i},0)$$

Thefinalnormalizedfeaturematrixbecomes:

$$X_{norm}=\text{MinMaxScaler}(X)$$

C. *FinBERTSentiment Analysis*

FinBERT processes tokenized news through transformer layers, resulting in contextual embeddings. A classification head outputs categorical probabilities. Thresholding ensures noise reduction and removes unrelated text.

Letafinancialnewsarticlebetokenizedinto:

$$X=\{w_1,w_2,\ldots,w_n\}$$

EachtokenisembeddedusingBERT'scontextual embedding:

$$E=\text{BERT}(X)\in\mathbb{R}^{n\times d}$$

CLStokenembedding:

$$h_{cls}=E_1\in\mathbb{R}^d$$

Classificationhead:

$$z=Wh_{cls}+b$$

Softmaxprobabilitydistribution:

$$P(y=k\mid X)=\frac{e^{z_k}}{\sum_{i=1}^{3}e^{z_i}},\ k\in\{\text{bullish},\text{bearish},\text{neutral}\}$$

Sentimentconfidencescore:

$$S=\max_k P(y=k\mid X)$$

Polarityindex(usedlaterinweighting):

$$\pi=P(\text{bullish})-P(\text{bearish})$$

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D. LSTM Price Forecasting

TheLSTMmodeluseshiddenandcellstatestocapture sequential patterns. The system predicts *t+1* closing prices using optimized learning rates, dropout regularization, and batch normalization to avoid overfitting.

Giventhenormalizedsequence:

$X=\{x_1,x_2,...,x_T\},x_t\in\mathbb{R}^m$

TheLSTMcellcomputes:

$$
\begin{aligned}
f_t &= \sigma(W_f[x_t,h_{t-1}]+b_f)\\
i_t &= \sigma(W_i[x_t,h_{t-1}]+b_i)\\
\tilde{c}_t &= \tanh(W_c[x_t,h_{t-1}]+b_c)\\
c_t &= f_t\odot c_{t-1}+i_t\odot\tilde{c}_t\\
o_t &= \sigma(W_o[x_t,h_{t-1}]+b_o)\\
h_t &= o_t\odot\tanh(c_t)
\end{aligned}
$$

Prediction:

$$\hat{y}_{t+1}=W_y h_t+b_y$$

Forecastingerrormetrics:

$$MAE=\frac{1}{N}\sum_{t=1}^{N}|y_t-y_t|$$

$$RMSE=\sqrt{\frac{1}{N}\sum_{t=1}^{N}(y_t-\hat{y}_t)^2}$$

E. HybridDynamicWeightAssignment

The adaptive mechanism computes:

$$Wfinal=\alpha(t)Wsentiment+(1-\alpha(t))Wtechnical$$

where$\alpha(t)$is determined using:

$$\alpha(t)=1+e-k(t-t0)1$$

Thisenableshybriddecision-making,particularly during volatility spikes.

Sentimentandtechnicalpredictionsarecombined using:

$$P_{sent}=f(\pi,S),P_{tech}=\hat{y}_{t+1}$$

Theadaptivefusion weight:

$$\alpha(t)=\frac{1}{1+e^{-k(\pi(t)-\tau)}}$$

where:

- $\pi(t)$= sentimentpolarity
- τ=sentimentstabilitythreshold

- k=steepnesscontrolparameter

The final hybrid prediction:

$$P_{final}=\alpha(t)\cdot P_{sent}+(1-\alpha(t))\cdot P_{tech}$$

Weightedconfidence:

$$C_{final}=\alpha(t)\cdot S+(1-\alpha(t))\cdot C_{tech}$$

This ensures:
- Ifsentimentisstrongthenthemodelshifts toward FinBERT.
- IfmarketisstablethenLSTMdominates.
- Duringvolatilitytheweightsadapt rapidly.

F. Implementation Architecture
The system employs:
- Backend:FlaskAPI,Celeryworkers, PostgreSQL, Redis.
- Monitoring:Prometheus+Grafana.
- Frontend:ReactJS,WebSockets,Highcharts- based visualization.
- Deployment: Docker-based microservices, Kubernetesorchestration,CI/CDpipelines.

IV. RESULTS
Experimentswereconductedusingfiveyearsof NIFTY50 stock and news data. The FinBERT sentiment module achieved:
- Accuracy:89.7%
- F1-Score:89.3%

TheLSTMforecastingmodel obtained:
- MAE:1.34
- RMSE:1.62

The hybrid model improved prediction accuracy by 6.4% over LSTM-only models through adaptive weighting,especiallyduringsuddenmarketsentiment shifts.
Systemperformancetestsshowed:
- AverageAPIlatency:320 ms
- LatencyreductionwithRedis:37%
- Concurrentuserssupported:Upto500 User surveys reported:
- 83%positivefeedbackoninterface
- 77%appreciationforsentiment-driveninsights

V. FUTURE SCOPE
The integration of sentiment and technical forecasting demonstrates that market predictions benefit significantly from multimodal fusion. FinBERT captures subtle financial cues often missed by generic models, while LSTM models long-term dependencies. Thedynamicweightingmechanismprovidesresilience to sudden market shocks by adjusting reliance on sentiment or technical indicators depending on confidence scores.

However,challengespersist:

- Real-timenewsstreamsmaycontainnoiseor misinformation.
- Marketanomaliessuchasblackswanevents remain difficult to model.
- Hybridmodelsrequirefrequentretrainingto avoid drift.

Nonetheless,resultsindicatethatArthaYuktioffersa practical improvement over traditional single-source models.

VI. CONCLUSION

ArthaYukti introduces a novel hybrid approach integrating financial sentiment analysis with LSTM- based stock forecasting. The system's adaptive weighting algorithm, real-time ETL pipeline, and scalable architecture position it as a valuable tool for modern financial analytics. The results confirm that combiningsentimentandtechnicalfactorsyieldsmore accurate and reliable market predictions.

VII. FUTURE SCOPE

Futureextensionsinclude:

1) Reinforcementlearningagentsforautonomous trading decisions.
2) Multilingualsentimentanalysisforglobal financial markets.
3) Transformer-basedforecastingmodels(e.g., Informer, Temporal Fusion Transformers).
4) Graphneuralnetworkstomodelinter-stock relationships.
5) Marketanomalydetectionusingunsupervised deep learning.
6) ExplainableAI(XAI)tointerprethybrid model predictions.
7) IntegrationwithlivebrokerageAPIsfor automated execution.

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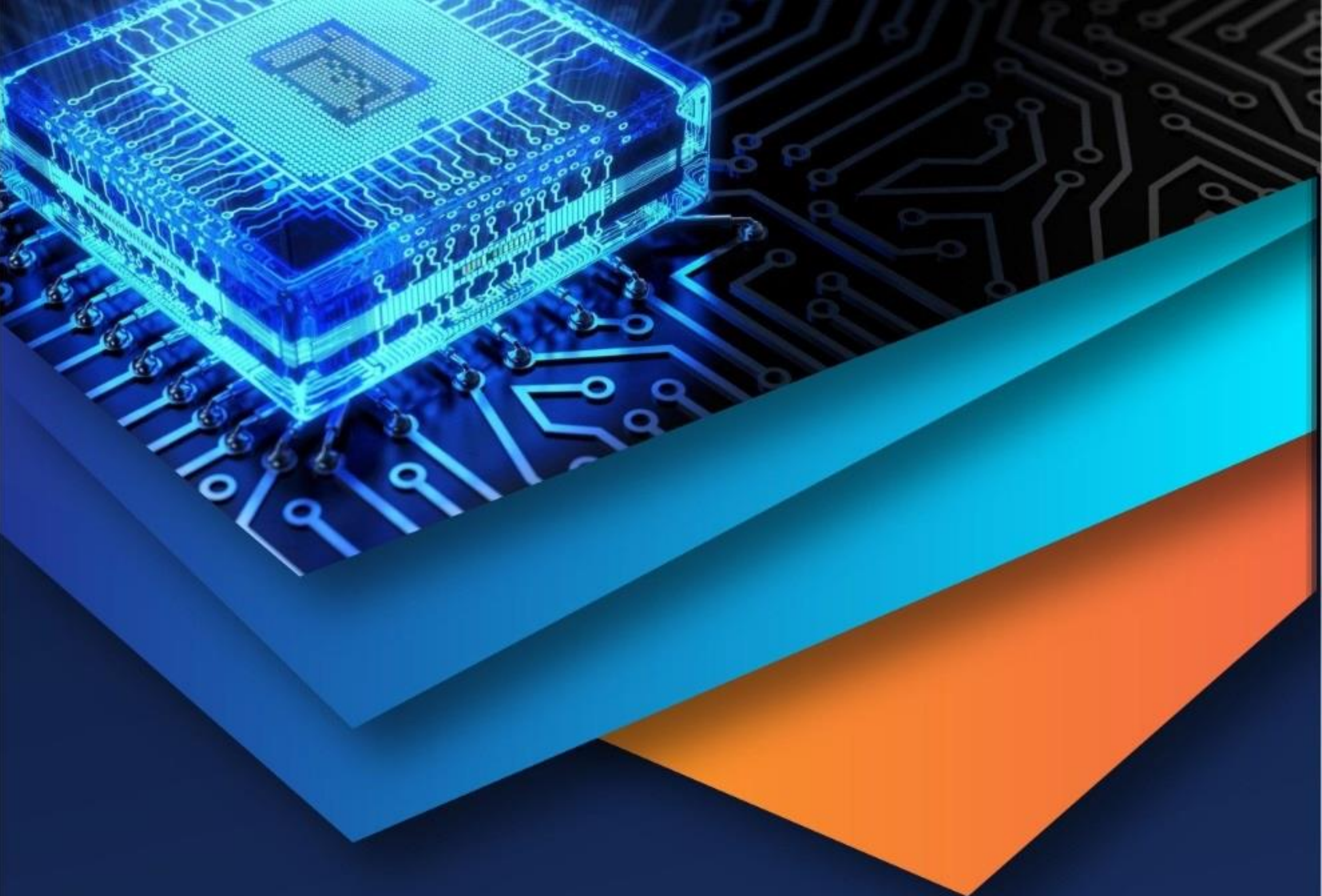

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