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STOCK TREND ANALYZER

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ABSTRACT

In today's fast-evolving technological landscape, accuratelypredictingmarkettrendsplaysacriticalrolein minimizing financial risks and maximizing potential returns. This work introduces a novel approach, the MS- SSA-LSTMmodel,designedtoharnessmulti-sourcedata in the prediction of stock prices. By incorporating sentiment analysis, swarm intelligence techniques, and deep learning, this method analyses data such as posts from theEast Moneyforum tocreate a custom sentiment lexiconandcalculatesentimentindices.Theseindicesare then integrated with traditional market data, with the Sparrow Search Algorithm (SSA) optimizing the parameters of a Long Short-Term Memory (LSTM) network.TheresultsshowthattheMS-SSA-LSTMmodel significantlyimprovesforecastingaccuracy,achievingan average R^2 increase of 10.74% compared to standard LSTM methods. Furthermore, the combination of sentiment indices and hyperparameter optimization enhances the model's performance, offering a robust solution forshort-termstockpriceforecasting,especially in volatile markets like that of China.

INTRODUCTION

Stock price prediction has long been a critical area of research in financial markets, traditionally relying on historical price data, technical indicators, and fundamental analysis. However, with therise of big data and advanced computing, machine learning (ML) has emerged as a powerful tool for forecasting stock prices with greater accuracy.

One promising approach to enhancing stock price prediction is incorporating investor sentiment, which reflects the collective emotions and opinions of market participants. Investor sentiment, derived from news articles, social media, financial reports, and other online sources, has been shown toinfluencemarketmovements significantly. By integrating sentiment analysis with ML models, researchers and traders can capture market psychology, providing deeper insights into price trends and volatility.

This study explores how investor sentiment, when combined with advanced ML techniques, can improve stock price prediction accuracy. By leveraging natural language processing (NLP) for sentiment analysis and ML algorithms such as deep learning, ensemble models, and reinforcement learning, this approach aims to refine financial forecasting and inform better investment.

Stock price prediction has been a focal point of financial research and investment strategies, aiming to anticipate market movements and optimize trading decisions. Traditional forecasting methods rely on historical price trends, technical indicators, and fundamental financial metrics. However, these approaches often fall short in capturingthecomplex,dynamic,andsometimesirrational nature of financial markets. With the rise of artificial intelligence(AI)andmachinelearning(ML),data-driven models have revolutionized predictive analytics, providingmoresophisticatedandadaptivetechniquesfor stock price forecasting. A critical factor that influences stock prices beyond historicaldataisinvestorsentiment—thecollectivemood andemotionsofmarketparticipants. Marketsentimentis often shaped by news reports, earnings announcements, social media discussions, expert analyses,

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and macroeconomicevents.Psychologicalbiasesandinvestor emotions, such as fear and greed, frequently drive price fluctuations that are not always reflected in traditional quantitative models.

EXISTINGSYSTEM

Yan et al. developed a high-precision prediction model using the LSTM deep neural network for short-term financial markets, showing superior prediction accuracy over BP neural networks and standard RNNs, successfullyforecastingstockprices.Similarly,Nabipour etal.usedtentechnicalindicatorsasinputsandfoundthat LSTM outperformed other models like decision trees, random forests, Adaboost, XGBoost, ANN, and RNN in termsofmodel-fittingability.AksehirandKilicproposed a CNN-basedmodel topredictnext-daytradingbehavior for Dow Jones Index equities, incorporating technical indicators, gold, and oil price data, with results 3-22% more accurate than other CNN-based models. However, the manual setting of hyperparameters in LSTM networks, which directly impacts model performance, is subjective and resource-intensive. To address this, scholars have turned to Swarm Intelligence (SI) algorithms to optimize these hyperparameters. SI can globallysearch for optimalsolutionsandreducetheneed for extensivemanualeffort.Jietal.demonstratedthatan LSTM optimized using the Improved Particle Swarm Optimization (IPSO) model outperforms the standard LSTM, while Zeng et al. used an Adaptive Genetic Algorithm (AGA) to enhance prediction accuracy. The Sparrow Search Algorithm (SSA), inspired by the foragingandanti-predation behaviorsofsparrows,offers robust optimization abilities in price prediction, surpassing traditional particle swarm and gray wolf algorithms. SSA's global search capabilities and adaptabilitytodifferentproblemsetsmakeiteffectivefor optimization. Moreover, real-time stock forum content provides valuable insights into investor sentiment, impacting investment decisions and stock price fluctuations. Analyzing thistext dataisessential, though sentiment classification methods such as machine learning and semantic analysis have their challenges. Machine learning offers high classification accuracy but requiresmanualtrainingsetclassification,whilesemantic analysis is easier but struggles with applying standard dictionaries to the economic context, necessitating the development of specialized financial dictionaries.

DISADVANTAGESOFEXISTINGSYSTEM

- Cannot Handle Complex Patterns – Linear and Logistic Regression assume simple relationships, making them ineffective for capturing complex air qualitytrends.
- Sensitive to Outliers and Imbalanced Data – These models can be easilyaffected byextreme valuesand strugglewhenoneclassismuchlargerthantheother.
- LowerAccuracy–Duetotheirlimitations,theyoften perform worse than advanced models like Decision Trees, which can handle more complex data.

PROPOSEDSYSTEM

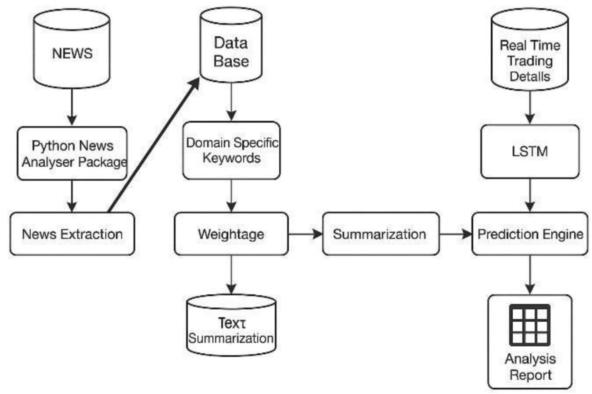
TheMS-SSA-LSTMmodelisintroducedforpredicting stockprices,integratingLSTMneuralnetworkswiththe Sparrow Search Algorithm (SSA) to efficiently handle multi-source data. The model assists investors and tradersbyforecastingstock pricesandgeneratingstock price trend charts, enabling more informed investment decisions. It takes various inputs, including historical transaction data and comments from stock market shareholders,topredictthestockpriceforthefollowing day.Akeyimprovementinthemodelistheinclusionof sentiment indicators, which enhance prediction accuracy. However, using a general dictionary for sentimentanalysisinthefinancialsectorisnoteffective, highlighting the need for a specialized sentiment dictionary tailored specifically for individual stocks. Additionally, stock priceseriesarecomplex,exhibiting characteristics such as nonlinearity, high noise, and strong time-variability, making the LSTM network particularly suitable for processing such time-series data. Hyperparameter tuning in LSTM networks significantlyimpactsprediction accuracy, butmanually selecting the optimal hyperparameters is resource- intensive. To overcome this challenge, the Sparrow Search Algorithm, introduced in 2020, is used to optimize the LSTM model, improving its predictive capabilities while reducing the computational cost associated with manual hyperparameter selection.

ADVANTAGESPROPOSEDSYSTEM

- More Accurate Predictions – Combines multi-source data and sentiment indicators for better stock price forecasting.
- HandlesComplex Data – LSTMeffectivelyprocesses nonlinear and time-variable stock price trends.

- Automated Optimization – The Sparrow Search Algorithm fine-tunes the model, reducing manual effort and improving performance.

SYSTEM ARCHITECTURE



Thediagramrepresentsastockmarketpredictionsystem thatintegratesnewsanalysiswithreal-timetradingdata.

TheprocessbeginswithaPython NewsAnalyzer

Package,whichextractsrelevantinformationfromnews articles.

This extracted data is then stored in a database, where domain-specific keywords are identified and assigned weightagebasedonrelevance.Tostreamlineprocessing, text summarization condenses the extracted news. Simultaneously, real-time trading details are incorporatedintothesystem.Thesummarizednewsand marketdataundergofurthersummarizationbeforebeing processed by an LSTM (Long Short-Term Memory) neural network, which serves as the prediction engine. The final predictions are compiled into an analysis report,aidinginvestorsandfinancialanalystsin making informed decisions. By combining news sentiment analysiswithreal-timetradingdata,thismodelenhances stock market forecasting accuracy while reducing information overload.

Additionally, theintegration of news sentiment analysis with real-time trading data ensures that the system remains responsive to market dynamics and investor sentiment, which are key drivers of stock prices. By leveraging advanced machine learning techniques and naturallanguageprocessing(NLP),thismodelenhances stock market forecasting accuracy while reducing information overload. It eliminates the need for manual news analysis, making the prediction process more efficientandautomated.Furthermore,thesystemcan be expanded byincorporatingalternativedata sourcessuch as social media sentiment, economic indicators, and macroeconomicfactors, furtherimprovingitspredictive capabilities.Theadaptabilityofthisframeworkallowsit to be fine-tuned for different financial market.

Simultaneously, real-timetrading details are fed into an LSTM model, which learns from past stock trends to improvepredictionaccuracy.Thesummarizednewsand LSTM outputs are combined in the prediction engine, which generates a final analysis report. This integration of news sentiment analysis and real-time trading data helps enhance stock market forecasting. By leveraging text summarization, keyword-based weighting, and LSTM's ability to detect patterns, the model provides a moreefficientandaccurateapproachtostockmarket predictions.

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