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COMPARATIVE STUDY ON SENTIMENT ANALYSIS OF STOCK MARKET PRICE PREDICTION USING BERT, LSTM, NAIVE BAYES, AND SVM

Ms. Sameera Ibrahim Assistant Professor Department of Information Technology, SIES (Nerul) College of Arts, Science and Commerce (Autonomous)

ABSTRACT:

Predicting stock market movements is a complex task influenced by various factors, including publicsentiment. This study conducts a comparative analysis of four machine learning models—BERT, LSTM, Naive Bayes, and SVM—in the context of sentiment analysis for stock market price prediction. Utilizing a dataset off in ancial news headlines, we assess each model's performance based on accuracy, precision, recall, F1-score, and execution time. The results indicate that BERT achieves the highest accuracy, while Naive Bayes of ferst he fastest execution time. These findings provide insights into selecting appropriate models for sentiment-based stock market prediction.

INTRODUCTION:

The stock market is a dynamic entity influenced by myriad factors, including economic indicators, geopolitical events, and public sentiment. Accurately predicting stock prices has be enalong standing goal for investors and researchers a like. Traditional models primarilyrely on quantitative data; however, with the advent of digital media, qualitative data such as news articles and social media posts have become in valuable. Sentiment analysis, a branch of natural language processing (NLP), enables the extraction of subjective in formation from textual data, providing a means to gauge public sentiment. Recent advancements in machine learning have introduced sophisticated models capable of performing sentiment analysis with high accuracy. Notably, Bidirectional Encoder Representations from Transformers (BERT) and Long Short-Term Memory networks (LSTM) have demonstrated proficiency in understanding and interpreting human language. Conversely, traditional models like Naive Bayes and Support Vector Machines (SVM) have been foundational in text classification tasks. This study aims to evaluate and compare the effectiveness of these models in predicting stock market prices through sentiment analysis.

LITERATURE REVIEW:

Sentiment Analysis in Stock Market Prediction:

Theintegration of sentimentanalysis into stock market prediction has garnered significant attention. Hiewet al. (2019) constructed at extual-based sentiment index using BER Tand demonstrated its predictive power for individual stock returns. Similarly, Gu et al. (2024) developed a Fin BERT-LSTM model that integrates news sentimentanalysis for stock price prediction, highlighting the enhancement of predictive precision by incorporating weighted news categories.

Recent Advancements in Sentiment Analysis for Financial Applications

Recent years have witnessed the development of specialized models like FinBERT, a transformer-based model fine-tuned specifically for financial texts. Other innovations include domain-specific adaptations of GPT and RoBERTa, which leverage extensive financial datasets for pretraining. These models excel in capturing nuanced sentiments expressed in financial news, analyst reports, and earnings call transcripts.

Integration of Sentiment Analysis with Stock Market Prediction Models:

Hybrid approaches that integrate sentiment analysis with quantitative stock prediction models are gaining traction. For example, combining sentiment scores derived from NLP models with traditional

time-series models like ARIMA or LSTM has shown promise in enhancing predictive accuracy. These methods address the challenge of a ligning qualitative sentiment data with numerical market indicators.

Comparative Studies of Machine Learning Models:

Several studies have benchmarked the performance of machine learning models in sentiment analysis. Transformer-based models like BERT and FinBERT consistently outperform traditional approaches like Naive Bayes and SVM in accuracy but are computationally intensive. Recurrent neural networks, including LSTM, offer a balance between performance and computational efficiency, making them suitable for real-time applications. These comparative analyses provide insights into selecting the most appropriate model based on specific use cases.

OVERVIEW OF MODELS

- BERT (Bidirectional Encoder Representations from Transformers): A transformer-based model pre-trained on vast text corpora, BERT captures deep contextual relationships in language, making it adept at understanding sentiment in financial texts.
- LSTM(LongShort-TermMemory): Atypeofrecurrentneuralnetworkcapableoflearning long-term dependencies, LSTM is effective in modeling sequential data, such as time-series stock prices and sentiment sequences.
- Naive Bayes: A probabilistic classifier based on Bayes' theorem, Naive Bayes is simple yet effective for text classification tasks, including basic sentiment analysis.
- SVM (Support Vector Machine): A supervised learning model that constructs hyperplanes in high-dimensional space for classification, SVM has been applied to various text classification problems, including sentiment analysis.

METHODOLOGY:

Data Collection

The dataset comprises financial news headlines related to major technology companies, collected overaperiod of one year. Each head line is labeled with the corresponding stock price movement (up or down) on the following trading day. The data is sourced from reputable financial news outlets and stock market records.

Data Preprocessing:

- TextCleaning:Removalofpunctuation,numericalfigures,andspecial characters to retain meaningful words.
- Tokenization: Splitting of headlines into individual words or tokens.
- StopWordsRemoval:Eliminationofcommonwords(e.g., 'the', 'is')that do not contribute significantly to sentiment.
- Stemming/Lemmatization: Reduction of words to their base or root form.

Feature Extraction:

- TF-IDF (Term Frequency-Inverse Document Frequency): Applied to convert textual data into numerical vectors for Naive Bayes and SVM models.
- WordEmbeddings:UtilizedforLSTMandBERTmodelstocapturesemanticmeanings of words.

Model Implementation:

- BERT:Fine-tunedpre-trainedBERTmodelonthelabeleddatasetfor sentiment classification.
- LSTM: Constructed an LSTM network with embedding layers initialized with pre-

trained word vectors.

- NaiveBayes:ImplementedMultinomialNaiveBayesclassifierusingTF-IDFfeatures.
- SVM:Trainedalinear SVMclassifierontheTF-IDFfeatures.

Evaluation Metrics

- Accuracy:Proportionofcorrectlypredictedinstances.
- Precision:Ratio oftruepositivepredictionstothetotalpredictedpositives.
- Recall:Ratiooftruepositive predictionstothe totalactual positives.
- F1-Score:Harmonicmeanofprecisionandrecall.
- ExecutionTime: Timetakentotrainand testeachmodel.

RESULTS AND DISCUSSION:

Performance Metrics Theperformanceofeachmodelisevaluated based on the metrics mentioned above. The results are summarized in the following table:

Accuracy	Precision	Recall	F1-Score	ExecutionTime(s)
0.85	0.86	0.84	0.85	120
0.80	0.81	0.79	0.80	90
0.75	0.75	0.76	0.74	0
	0.85	0.85 0.86 0.80 0.81	0.85 0.86 0.84 0.80 0.81 0.79	0.85 0.86 0.84 0.85 0.80 0.81 0.79 0.80

CONCLUSION:

This study evaluated and compared the performance of four models—BERT, LSTM, Naive Bayes, and SVM—in the context of sentiment analysis for stock market price prediction. By analyzing financial newshead lines, each model was assessed on critical metrics such as accuracy, precision, recall, F1-score, and execution time. The results revealed notable insights into the strengths and limitations of these models

BERT emerged as the most accurate and robust model, achieving the highest accuracy (85%) and F1-score (85%). Its ability to capture deep contextual relationships and nuances in textual data makes it the most suitable choice for sentiment analysis in financial contexts. However, its high computational cost (execution time: 120 seconds) may limit its applicability in real-time systems.

LSTM demonstrated competitive performance, with an accuracyof80% and an F1-scoreof80%. Its strength lies in handling sequential data effectively, making it aviable option for time-series sentiment analysis. Additionally, its computational efficiency (execution time: 90 seconds) positions it as a balanced choice for tasks requiring both accuracy and speed.

NaiveBayes,despitebeingasimpler model,providedreasonableaccuracy(75%)andthe fastest executiontime (5 seconds). This makes it anexcellent choice for scenarios where computational resources are limited, or real-time predictions are required. However, it struggles with the complexity and subtlety of sentiment data compared to more advanced models.

SVMperformedmoderatelywell,achievinganaccuracyof78%andanF1-scoreof78%. Its execution time (10 seconds) is faster than BERT and LSTM but slower than Naive Bayes. Whileitisareliable model for linear separables entiment data, it may not capture complex relationships as effectively as BERT or LSTM.

SUGGESTIONS:

For high-accuracy requirements in complex sentiment analysis tasks, BERT is the most effective model, despite its computational demands.

Forabalancebetweenaccuracyandexecutiontime, LSTMisapracticalchoice.

For resource-constrained environments or tasks demanding rapid predictions, Naive Bayes offers an efficient alternative.

SVM serves as a middle ground, providing reasonable performance with moderate computational requirements.

Future Work:

Future research could explore the integration of hybrid models, combining the strengths of multiple approaches, such as using BERT for feature extraction and LSTM for sequence modeling. Additionally, incorporating more diverse datasets and expanding to other financial indicators may further enhance predictive capabilities

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