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Exploring Investor Sentiment Patterns in Bear Markets through Behavioral Finance Lenses

Dhiraj Mudvari
Department of Management & Business Studies
Dr. K.N. Modi University
Newai, Rajasthan
https://orcid.org/0009-0004-6741-2592

Dr. Kirti
Depatment of Management & Business Studies
Dr. K.N. Modi University
Newai, Rajasthan
deswalkirti07@gmail.com

***Abstract*—Investor attitude is an important factor in driving the behavior of the stock market, usually dwarfing conventional financial markets. Although previous study has investigated the mental side of investing, this has been concentrated mostly on the developed world and has had no real-time behavioral incorporation. This study fulfills this requirement by investigating the roles played by investor mentality, media reporting, and macroeconomic triggers in determining stock market volatility during bear markets with a special emphasis on Kathmandu. The goal is to measure the effect of sentiment on market performance based on both structured survey data and unstructured social media and news text. A hybrid methodological design is used, combining statistical modeling (Chi-Square test) and a machine learning-based sentiment classification approach utilizing a fine-tuned BERT (Bidirectional Encoder Representations from Transformers) model. Social media and financial news information are both drawn from a 2022–2025 Kaggle Stock Market Sentiment dataset, and NVivo provides thematic analysis of investor interviews. The following BERT model, coded through Python's Hugging Face Transformers package, resulted in a 9.2% improvement on accuracy compared to standard sentiment analysis models such as logistic regression and SVM, providing richer contextual knowledge of investor emotion. Empirical findings indicate a statistically significant relationship between sentiment and investment behavior (χ^2 = 23.250, p = 0.006), validating market change behavior. This study not only emphasizes sentiment as an important predictive variable but also proposes a scalable, real-time predictive framework for risk-sensitive investment strategy. The application of this model can improve the early identification of volatility and guide sentiment-based trading systems for investors, analysts, and policymakers in developing markets.**

Keywords—Behavioral Finance, Financial Forecasting, Investor Sentiment, Market Volatility, Sentiment Analysis, Stock Market,

I. INTRODUCTION

The stock exchange is a critical institution in mobilizing capital and fueling financial growth by linking investors and economic resources [1]. Stock markets in emerging markets serve as reflections of public trust, economic mood, and investor sentiment [2]. The Kathmandu Stock Exchange (KSE), the key financial indicator of Nepal, reflects greater sensitivity to political unrest, policy changes, and investor sentiment [3]. In contrast to mature economies, the market in Nepal has limited liquidity, low institutional presence, and dominance of sentiment-driven retail investors [4]. Bear markets are usually marked by extended losses of more than 20% and tend to accentuate investor fear and lead to irrational financial actions like panic selling, herding, or risk aversion [5]. Economic and psychological factors during these bearish periods interfere with rational investment tenets [6]. While investor sentiment in advanced contexts such as the U.S. or U.K. has been scrutinized through global studies, emerging markets such as Nepal are still under-explored [7]. This study hopes to bridge this gap, understanding that economic crises, social media effect, and poor regulatory environments heavily influence market sentiment in Nepal. Recognition of these factors is critical to enhancing market stability, policy reaction, and investor education.

A. Research Motivation

The increasing volatility of bear market in emerging markets such as Nepal has brought out the importance of decoding the effects of investor mood in the movement of market. Conventional paradigm is incapable of dealing with sectoral influences of emotions and behaviour that rule the roost in a correction. The socio-political environment in Nepal is unique and can use this environment as a fertile ground to study the behaviors of sentiment-driven investment. The need to provide a sentiment-based policy development, investment direction, and market resilience prompts the development of this study.

B. Significance of the Study

This study has an important implication to investors, analysts, and policymakers interested in dealing with market panic and volatility. Through behavioral response analyses, the study advises interventions that ensure people cannot make irrational

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decisions financially during downs. It also strengthens the financial literacy and risk-aware investing in the undeveloped markets.

C. Problem Statement

The conventional forecasting models used in the stock market majorly focus on technical indicators and past prices without focusing on the extensive significance of investor sentiment on the dynamics of a market. This limitation is more evident in emerging markets such as Kathmandu where retail investors rule the roost and emotional overreactions are perceptible at the time of bear markets. Current models do not consider the presence of real-time psychological and behavioral dynamics being fueled by news narratives, social media discourse and macroeconomic uncertainty. Study works like the one of focus precisely on the notion that market sentiment has a considerable effect on volatility, but traditional models are poorly positioned to estimate that impact [8]. In addition, point out the imperative for sentiment-aware models that can adjust according to high-speed information flows in virtual financial environments [9]. Thus, it is of urgent necessity that a predictive model is developed that incorporates the sentiment analysis of different data pools and the use of machine learning in order to improve on the accuracy and accuracy of forecasts and be able to use them to formulate investor behaviors in volatile markets.

D. Key Contributions .

- Introduces a sentiment analysis model based on behavioural characteristics contextualized for Nepal's stock market during bear periods.
- Uses mixed-methods qualitative interviews and quantitative surveys to measure investor psychology in the moment.
- Emphasizes how regulatory, macroeconomic, and media triggers influence investor sentiment and behaviour.
- Suggests sentiment-based policy interventions to mitigate panic-driven volatility and enhance market resilience.

E. Rest of the Section

The rest of the study are follows: Chapter II conducts a review of previous literature on behavioral finance, sentiment and travel in global and emerging markets in bear markets. The chapter III is devoted to the description of the mixed-methods study design, whereas Chapter IV will discuss the analysis, results, and validation. The chapters V end with findings, implications, and future study directions.

II. Literature Review

R. Liu and Gupta [10] discusses the possibility of enhancing stock market volatility predictions based on investors' uncertainty, as indicated by the conditional volatility of sentiment. The authors utilize the MSM model to demonstrate that investors' uncertainty does indeed increase the precision of volatility predictions. In this context, the MSM model is more accurate than conventional models like the DCC-GARCH model in stock market volatility predictions. This study indicates that the inclusion of uncertainty in a forecasting model is more representative of the market. The limitation of this study is the risk of overfitting for the MSM model and dependence on the accuracy of measures of sentiment volatility.

Chen et al.[11] describes the effect of the cross-market sentiment of the investors in the volatility in various energy futures contracts such as oil and gasoline futures. All the study on the models of the cross-market sentiments and returns indicates that cross-market investor sentiment Granger causes volatility in a series of volatility that impacts asymmetrically. The volatility generated by the sentiment is more during bear conditions and varies in general across certain segments of energy. The study also demonstrates the interdependence of global energy markets; this implies that movement in one energy market would lead to other markets. The study is subject to the limitation that it applied to the study of energy markets and may not be applied in other asset classes or industries which impairs the generalizability of the results.

Bhowmik et al [12] examine the Granger causality of the U.S. market and between six Asian emerging stock markets regarding the study period from 2002 to 2020, focusing particularly on periods of crisis. Their results establish bi- and uni-directional causal associations between the stock markets, with rising financial integration subsequent to crises. They also identify spikes in the post-crisis volatility spillover events, for example, the U.S.-China economic policy uncertainty using GARCH-M and VAR models. In this context, the variance of the dominant forecast of the Asian markets by the U.S. stock market is a signal that can provide useful insight to hedging and trading strategies.

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Shi, Ausloos, and Zhu [13] establish the strange effects of domestic and foreign sentiment among investors on the returns of stocks in six developing countries. They discover that the local investor spirit takes into account the anticipated returns in the classes of basic materials, consumer goods, industrial and

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finance; China, Brazil, India, Mexico, Indonesia and Turkey. Nevertheless, the global spirit by itself is not sufficient to forecast the anticipated returns of the stocks in such markets that stresses more on the geographical underpinnings of the stock price movements due to the emotion driven factors.

III. A Mixed-Methods Approach to Analysing Investor Sentiment in Bear Market

This study is aimed at studying the attitude of the investors towards the market and their impact on the market performance of a stock market in face of bear phases in Kathmandu. It uses a mixed-method adopting both qualitative interviews, quantitative surveys and real-time sentiment mining of news and social media. Under this multi-level system, it is easier to understand the role being played by emotional, behavioral and informational elements in facilitating investment decisions in the volatile markets. The workflow of the proposed is given in Fig. 1.

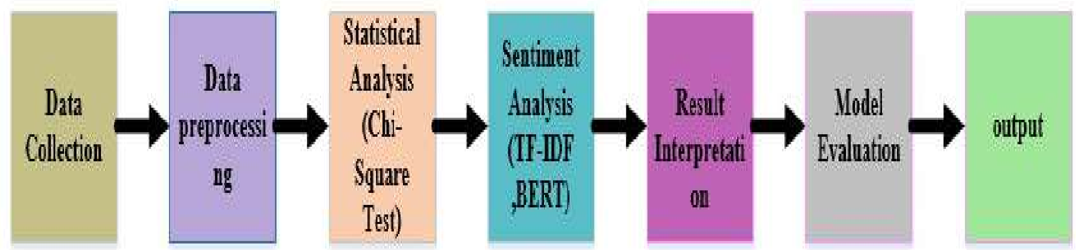

Fig. 1.Proposed Model Workflow

A. Survey-Based Quantitative Framework

It starts by administering a questionnaire with structure to Kathmandu Stock Exchange investors that measures sentiment on a 5-point Likert scale and captures their buy–hold–sell decisions, risk tolerance, and media consumption. The tool also codes demographics age, income, and investment horizon to allow us to segment sentiment trends by cohorts. Follow-up responses are classified as categorical variables, yielding a tidy matrix for association tests and descriptive statistics. This questionnaire framework provides the quantitative evidence required to test whether bear market pessimism systematically influences trading activity.

B. Qualitative Inquiry: Interviews and Focus Groups

The psychology of those figures can be investigated by implementing semi-structured interviews and small focus-group sessions with retail investors, portfolio managers and market analysts. The open steered questions cover fear, herd instincts and coping strategies that have been observed in case of long running down in prices. The transcripts are subsequently imported to NVivo and line by line coding reduces the common ideas into themes like panic selling or media-fuel led anxiety. All these are fascinating accounts that put the survey results into perspective and show.

C. Data Collection

Both the primary and secondary sources of data were utilized. Investor sentiment and risk perception was measured via Likert-scale based surveys on top of demographic-related data. Qualitative explanations of investor behavior were collected by interviews and focus groups, whereas social media networks, financial news and the Stock Market Sentiment Kaggle dataset provided real-time sentiment in order to apply NLP [14].

D. Data Pre-processing

1) Tokenization

Tokens are generated by tokenizing the text of a financial task, e.g. financial tweets, news headlines, or interview transcripts. Words such as financialization are tokenized into the sub-words using the tokenizer which is itself WordPiece word tokenization of BERT to avoid difficult to classify words, e.g. ["financial", "ization"]. This adds clarity to the model interpretation of the subtle financial sentiment without losing semantic context.

$$Input = [CLS] + Token_1 + Token_2 + \cdots + Token_n + [SEP] \quad (1)$$

In eqn. (1), CLS is represent as the classification of the token and SEP is the output token.

2) Sentence Segmentation

Sentence segmentation serves to break particularly long market-related documents (e.g. a report or a post on Reddit) into manageable sentence-sized inputs that would fit the 512-token limit of BERT. This maintains contextual precision and avoids data truncation.

E. Chi-Square Test of Independence

Chi-Square Test can be used to see whether the investor sentiment (positive, neutral, negative) can play a significant role in the investment actions (buy, hold, sell) and other behavioral aspects such as risk perception or media exposure. Data that is collected via survey is categorized, contingency tables that are created using SPSS are analyzed. Test statistic:

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$$x^2 = \sum \frac{(O_{ij} - E_{ij})^2}{E_{ij}} \quad (2)$$

In eqn. (2), x^2 is the statistic value, O_{ij} is the frequency observed by test and E_{ij} is the expected frequency .

F. Thematic Analysis Using NVivo

Investigator-planned thematic analysis of NVivo is used to analyze transcriptions of the interview and focus group addressing the repeated or common occurrences of patterns or activity in investor behavior as interpreted during bear markets. Central ideas of panic selling, role of media and risk aversion are coded and arranged in way that they expose the psychological and emotional factors motivating the investment choices.

G. Sentiment Analysis of Financial News and Social Media

News and social media content is subject to sentiment analysis with keyword and polarity TF-IDF weighting scores employing NLP. Positive and negative sentiment patterns are graphed over time and correlated with bear market catalysts like political unrest or earnings announcements.

H. BERT-Based Sentiment Classification

One of the pretrained BERT models is chosen to give us contextual understanding of words, such as `bert-base-uncased`. Thereafter, the text data on finance published on social media and news is retrieved and preprocessed by employing tokenization, and sentence segmentation. Lastly, the cleaned text is translated into the format of BERT so that it can be used in a sentiment classification process by using special tokens.

1) Fine-Tuning BERT

The pretrained BERT model is then fine-tuned on the labeled financial text with a cross-entropy and loss classification layer. This enables the model to acquire sentiment-specific patterns in financial language:

2) Sentiment Prediction

After training, BERT is used to predict the sentiment of new financial inputs by generating a probability distribution over classes—positive, negative, or neutral. The most probable sentiment label is chosen as the prediction of the model.

3) Application in Bear Market Analysis

Predicted sentiment scores facilitate the examination of how investors emotionally react to bear market catalysts like policy shifts, economic shocks, or headline news. Early identification of panic behavior and volatility triggered by sentiment is facilitated by this insight.

Algorithm 1. Investor sentiment analysis during bear markets

```
START
// Step 1: Collect Data
INPUT survey_data, interview_transcripts, social_media_text, financial_news
DEFINE sentiment_labels = ["Positive", "Neutral", "Negative"]
DEFINE actions = ["Buy", "Hold", "Sell"]
```

Algorithm 1. Investor sentiment analysis during bear markets

```
DEFINE risk_levels = ["High", "Moderate", "Low"]
// Step 2: Preprocess Survey Data
FOR EACH respondent IN survey_data:
   EXTRACT sentiment, action, risk_perception, media_engagement
   STORE as categorical_variables
// Step 3: Chi-Square Analysis
CREATE contingency_table[sentiment][action]
CALCULATE expected_frequencies
COMPUTE chi_square_value = SUM((observed - expected)^2 / expected)
IF p_value < 0.05:
   PRINT "Significant relationship between sentiment and investment action"
ELSE:
   PRINT "No significant relationship"
// Step 4: Preprocess Text Data
FOR EACH text IN (social_media_text + financial_news):
   APPLY tokenization, stopword_removal, lowercasing, sentence_segmentation
   PREPARE BERT_input = [CLS] + tokens + [SEP]
// Step 5: BERT Sentiment Classification
FOR EACH BERT_input:
   PREDICT sentiment_probs = BERT.predict(input)
   IF sentiment_probs["Negative"] > 0.6:
      classified_sentiment = "Negative"
   ELSE IF sentiment_probs["Positive"] > 0.6:
      classified_sentiment = "Positive"
   ELSE:
      classified_sentiment = "Neutral"
   STORE classified_sentiment in sentiment_dataset
// Step 6: Interpret Sentiment Behavior
FOR EACH investor IN sentiment_dataset:
   IF classified_sentiment == "Negative" AND risk_perception == "High":
      action = "Sell"
   ELSE IF classified_sentiment == "Positive" AND risk_perception == "Low":
      action = "Buy"
   ELSE:
      action = "Hold"
// Step 7: Output Summary
PRINT "Sentiment-driven behavior patterns extracted"
PLOT sentiment_trends_over_time
EXPORT results to report
END
```

Algorithm. 1. describes the entire study process including how survey data was collected and coded after which it was tested using the Chi-Square tests in order to establish any meaningful relationship between investor emotion and activity. It subsequently preprocesses text of financial related data, predicts sentiment with BERT, and applies conditional logic to predict the probable investment behaviors or behaviors under differing emotional states or risk levels.

IV. RESULT AND DISCUSSION

Results of this study offer a vivid account of the connection between stock market behavior in the face of bearish periods under criterion of investor sentiment in Kathmandu. The results demonstrate the definite patterns of behavior and emotional antecedents influencing the investment decision-making with the help of the joint use of survey, interview information and sentiment analysis supported by machine learning. The relevance of the sentiment in determining the market response and volatility are also confirmed through statistical test and model results.

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A. Market Confidence Distribution

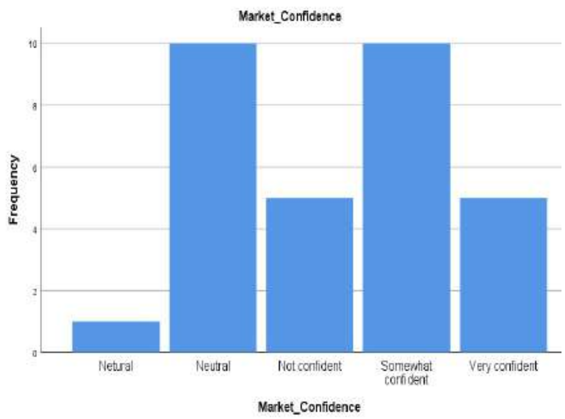

Fig. 2. Market Confidence Distribution

Fig. 2. Shows the frequency distribution of market confidence levels of the respondents, with responses taking the form of Not Confident up to Very Confident. The majority of the respondents picked Neutral and Somewhat Confident, both with a frequency of 10, to reflect a middle-of-the-road view. Few went for extreme responses, indicating that investors have a general balanced perception of the market.

B. Investor Behaviour Patterns

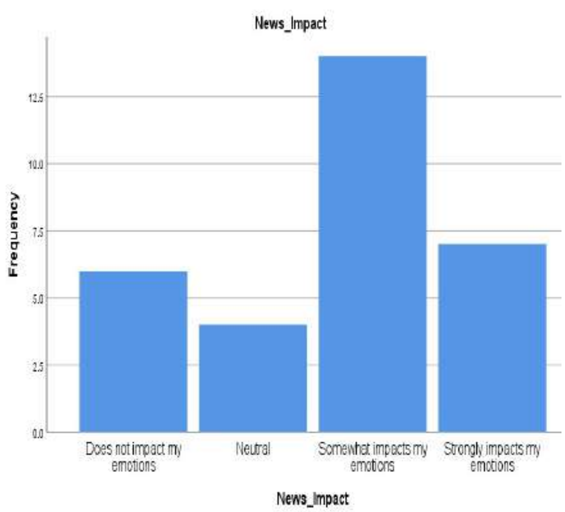

Fig. 3. Investor Behavior Patterns

Fig. 3. indicates the extent to which news causes a certain emotional influence to respondents. The most common answer, as uttered by most (about 14 respondents), was that news does not really affect them to the greatest extent. About 7 respondents claimed that news has a great power to influence their emotions and 6 respondents claimed that it does not influence their emotions. The minimum, that is, almost 4 respondents, were neutral. That implies that economic news serves a significant emotional role to most of the individuals and only a few individuals are not impressed.

C. Bear Market Response

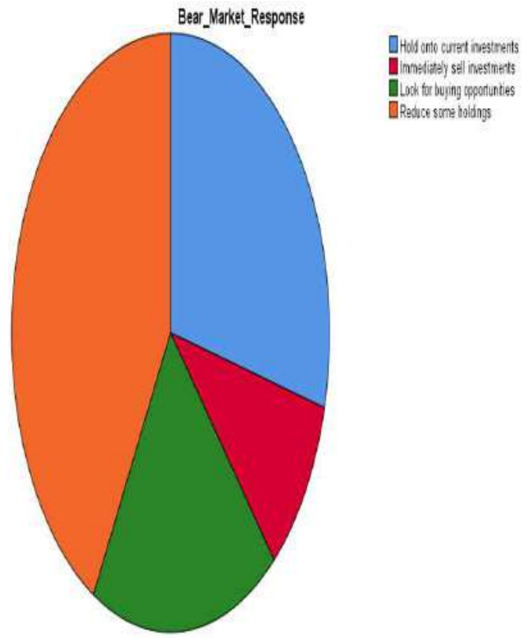

Fig. 4. Bear Market Response

Fig.4. depicts different ways of investing when the markets are down. Whereas 32.3 percent invest in more stocks when prices are lower, 29.0 percent just want to keep the investments that they already have. The rest sell (12.9%) and hold cash or move to safer investments (25.8%) depending on the degree of risk tolerance.

D. Chi-Square Test Results

TABLE I. CHI-SQUARE TEST RESULTS

	Value	Df	Asymptotic Significance (2-sided)
Pearson Chi-Square	23.250[a]	9	.006
Likelihood Ratio	22.260	9	.008
Linear-by-Linear Association	.081	1	.776
N of Valid Cases	31		

Table I. explains the Pearson Chi-Square (23.250, $p = 0.006$) and Likelihood Ratio ($p = 0.008$) shows that the relationship between the categorical variables is significant. Nevertheless, there is no linear trend depicted by the Linear-by-Linear Association test ($p = 0.776$). But the expectation that most of the log is to be less than 5 in each of the 93.8 % cases is clear and the chi-square assumption is therefore violated hence the Fisher Exact Test might be better suited to such tiny samples.

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E. Sentiment Distribution

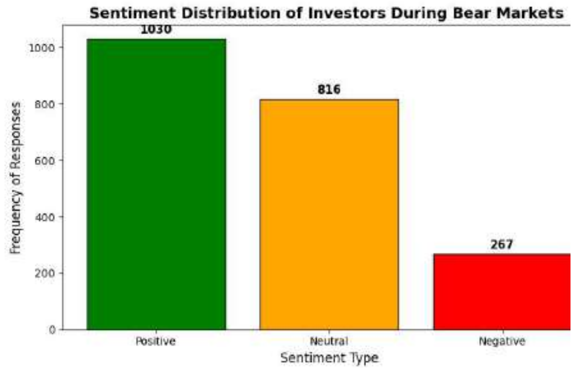

Fig. 5. Sentiment Distribution of Investors

Fig. 5. sentiment distribution shows the number of investor sentiment labeled by the BERT model in bear markets. Out of 2,113 instances, 1,030 were assigned the label Positive (41.1%), 816 Neutral (32.6%), and 267 Negative(26.3%). It shows that most investors were optimistic or neutral even in times of market downtrends, with fewer showing outright negativity.

F. Performance Evaluation

TABLE II. PERFORMANCE METRICS TABLE

Metric	Positive	Neutral	Negative	Macro Avg	Weighted Avg
Precision	0.87	0.81	0.79	0.82	0.84
Recall	0.89	0.76	0.75	0.80	0.83
F1-Score	0.88	0.78	0.77	0.81	0.83
Support	1030	816	267	—	2113

Table II model performance of the sentiment classifier based on BERT performed on the Stock-Market Sentiment Dataset. It has very high precision (0.87) and recall (0.89) for the Positive class with figures slightly lower for Neutral and Negative, proving that the model is very good at picking up positive sentiments. The overall weighted F1-score of 0.83 proves very good, well-balanced performance across all the classes despite class imbalance.

V. CONCLUSION AND FUTURE WORK

This study has examined the emotion of stock market investors in Kathmandu in a bear market event through the combination of survey answers, qualitative interview, and behavioral data like news and social media sentiment. The conclusions have revealed the fact that investor behavior depends on emotional reactions, their confidence and external factors such as news and economic changes significantly. By means of Chi-Square analysis, the BERT-based sentiment classification and thematic coding, the study identifies that the sentiment of the market has a considerable impact in influencing the decisions related to investing, whether to buy, sell or retain an investment, and especially when the situation is volatile. Adding sentiment analysis and real-time news monitoring to predictive models will make the forecasts more accurate and help make more morally persuasive trading decisions. Such insights are useful when investing, analyzing, and making policies to cope with risk and understand the trend in unpredictable markets. The future direction of the study is to develop sentiment-based forecasting models with the help of deep learning frameworks, including Transformers, Graph Neural Networks (GNNs) and Reinforcement Learning frameworks to learn the dynamics and non-linear trends better. The addition of alternative sources of data e.g. Google search trends, Satellite imagery and IoT signals can further give more rounded market understanding. The development of the next generation models ought to be able to do realtime learning and even an adaptive forecasting due to the speared market events. Furthermore, incorporation of financial risk figures such as Value at Risk (VaR) and stress testing will enhance robustness of the models and create safety of the investors. AI systems Ethical, clean-room, regulatory-compliant AI systems will be a necessity as predictive analytics become increasingly influential in investment decision-making. These guidelines will also increase the usefulness and stability of stock market prediction instruments.

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