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# Ai-Powered Natural Language Stock Screener and Advisory System

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**Abstract-:** ***Investors often need to examine large amounts of financial information before making investment decisions. Traditional stock screening systems generally require users to understand financial terms, screening parameters, and technical interfaces. An AI-powered natural language stock screener and advisory system can reduce this difficulty by allowing users to describe their requirements in ordinary language. Natural Language Processing (NLP) can interpret user queries, while financial data analysis and machine learning techniques can identify stocks that match specified criteria. The system can analyse factors such as price, market capitalization, financial ratios, historical performance, and other available market indicators. An advisory component can present the analysed information in an understandable form and support users in comparing investment alternatives. This paper reviews the major technologies, methodologies, limitations, and future possibilities associated with AI-powered natural language stock screening and advisory systems***.

**Keywords: Artificial Intelligence, Natural Language Processing, Stock Screener, Machine Learning, Financial Data Analysis, Investment Advisory**.

## I. INTRODUCTION

The stock market contains a large amount of financial information that must be analysed before selecting suitable investment opportunities. Investors may need to compare companies using price, market capitalization, earnings, financial ratios, historical performance, and other indicators. Conventional stock screeners provide filtering facilities, but users generally need to know the exact parameters and terminology required by the system.

Artificial Intelligence can make stock screening more accessible by providing a natural language interface. Instead of entering multiple technical filters, a user can describe an investment requirement in a sentence. The system can process the query using Natural Language Processing and convert it into structured screening conditions. The resulting conditions can then be applied to available financial data to identify matching stocks.

An AI-powered advisory system can further explain the screening results by presenting relevant financial indicators, comparisons, risks, and other available information. Such a system is intended to support analysis and decision-making rather than replace professional financial advice. This paper provides an overview of natural language stock screening and AI-based advisory approaches, including their methodologies, limitations, and possible future developments.

## II. METHODOLOGIES FOR AI-POWERED STOCK SCREENING AND ADVISORY

### 1. Natural Language Processing

Natural Language Processing is used to understand the user's investment query. The system identifies important entities, conditions, numerical values, comparison operators, and financial concepts from natural language. For example, a query asking for companies

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with a specified market capitalization and a particular price-to-earnings ratio can be transformed into structured screening parameters. Query interpretation is therefore an important step because incorrect understanding can produce irrelevant results.

**2. Financial Data Collection and Pre-processing**

The screening process requires financial and market information from reliable data sources. The collected data may include company information, stock prices, market capitalization, financial ratios, historical values, and other relevant indicators. Before analysis, the data should be cleaned, organized, normalized where required, and checked for missing or inconsistent values. Proper preprocessing is important because the quality of the output depends on the quality and availability of the underlying financial data.

**3. Stock Screening**

After the natural language query has been converted into structured conditions, the screening module applies these conditions to the available stock data. Multiple conditions can be combined to narrow the results. The system can rank or organize matching stocks according to the user's selected criteria. This approach can reduce the time required to manually examine a large number of companies.

**4. Machine Learning Approaches**

Machine learning can be used to identify patterns in financial data and improve the ranking or classification of stocks. Supervised learning methods can classify or predict outcomes using historical data, while clustering techniques can group companies with similar characteristics. Ensemble approaches can combine multiple models to improve robustness. However, financial markets are affected by many changing factors, so model performance must be evaluated carefully using suitable validation methods.

**5. AI-Based Advisory**

The advisory component converts analytical results into an understandable response. It can summarize the reasons a stock matches the user's screening criteria, compare selected companies, and highlight relevant indicators and possible risks. A natural language generation component can make the output easier to understand for users who may not have advanced financial knowledge. The system should clearly distinguish analytical information from guaranteed returns and should communicate uncertainty when appropriate.

**6. Query-to-Decision Workflow**

A general workflow consists of user query input, natural language processing, extraction of screening conditions, retrieval and preprocessing of financial data, application of screening rules or models, ranking of results, and generation of an explanatory response. Feedback from users can also be considered for improving query interpretation and system usability. Security, privacy, reliability, and responsible use are important throughout this workflow.

## III. LIMITATIONS IN AI-POWERED STOCK SCREENING AND ADVISORY

1. Data Quality and Availability: The accuracy of screening results depends on the availability, correctness, timeliness, and consistency of financial data. Missing, delayed, or incorrect information can affect the output.

2. Natural Language Ambiguity: Users may express the same investment requirement in different ways. Ambiguous financial terms or incomplete queries may lead to incorrect interpretation and unsuitable screening conditions.

3. Market Uncertainty: Stock prices are influenced by economic conditions, company events, investor behaviour, news, and other factors. Historical patterns cannot guarantee future performance.

4. Model Accuracy and Validation: Machine learning models require appropriate training, testing, and validation. Overfitting, biased data, and changing market conditions may reduce model effectiveness.

5. Explainability and Trust: Users need understandable reasons for the results produced by an AI system. Complex models may be difficult to interpret, making transparency an important requirement.

6. Privacy and Security: Financial preferences and user queries may contain sensitive information. Appropriate privacy and security measures are necessary when collecting and processing such information.

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## IV. FUTURE PERSPECTIVE

As Artificial Intelligence and financial data technologies continue to develop, natural language stock screening and advisory systems can become more interactive and useful. Several technical developments can be considered:

1. Real-Time Natural Language Screening: Future systems can process updated market information and allow users to modify screening conditions through conversational queries.

2. Multilingual Financial Interaction: Supporting multiple languages can make AI-based stock screening accessible to a wider range of users.

3. Explainable AI: Explainable models and transparent reasoning can help users understand why particular stocks were identified and what factors influenced the result.

4. Integration of Multiple Data Sources: Financial statements, market data, news, economic indicators, and other relevant information can be combined to provide a broader analytical view.

5. Personalized Advisory: Systems can consider user-defined objectives, risk preferences, and investment constraints to produce more relevant analytical responses, while maintaining appropriate safeguards.

6. Advanced Generative AI: Generative AI can improve conversational interaction by summarizing financial information and answering follow-up questions, provided that the underlying data and generated information are carefully validated.

## CONCLUSION

AI-powered natural language stock screening and advisory systems can simplify the process of searching and analysing stocks by combining Natural Language Processing, financial data analysis, machine learning, and conversational AI. Users can express investment requirements in ordinary language instead of manually configuring complex screening parameters. The system can then identify matching stocks and present analytical information in an understandable form. However, data quality, natural language ambiguity, market uncertainty, model accuracy, explainability, privacy, and responsible use remain important challenges. Future research can focus on real-time data integration, multilingual interaction, explainable AI, personalized analysis, and reliable generative AI techniques to improve the effectiveness and usability of such systems.

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