A Project Synopsis on

Real-Time Investment Decision System

Done by

Anushka Churi

ABSTRACT

In an era of information overload and rapid market changes, investors require faster and smarter decision-making tools. This project presents a Real-Time Investment Decision System that integrates fundamental analysis, technical indicators, and sentiment analysis to provide actionable investment recommendations (Buy / Hold / Sell) for publicly traded companies.

The system combines financial ratios such as the P/E ratio and the debt-to-equity ratio, technical indicators such as RSI and MACD, and sentiment scores derived from news and media sources. Machine learning models, particularly XGBoost, are trained on these features to predict investment outcomes with high accuracy.

To enhance transparency, the model predictions are explained using SHAP (SHap- ley Additive explanations), highlighting the contribution of each input feature. A user-friendly Streamlit web app was developed that allows users to upload stock symbols or datasets and receive real-time predictions with visual explanations.

The system achieved strong predictive performance and offers a practical, explainable AI solution for investors seeking data-driven insights. This project demonstrates how the synergy of financial, technical, and sentiment data can power intelligent investment decisions in real time.

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Introduction

1.1 Introduction

The process of making **investment decisions** in the stock market has traditionally been based on a combination of financial analysis, technical chart patterns, and market sentiment. However, with the growing volume of real-time data and the complexity of financial markets, relying solely on manual analysis is becoming inefficient and error prone.

In recent years, Artificial Intelligence (AI) and Machine Learning (ML) have emerged as powerful tools to automate and enhance investment decision-making. These technologies can process large amounts of structured and unstructured data, learn complex patterns, and provide timely and explainable insights.

This project aims to develop a **Real-Time Investment Decision System** that combines three critical dimensions of stock evaluation:

1. **Fundamental analysis** – Examines the financial health of a company using key ratios such as price-to-earnings (P/E), Return on Equity (ROE), and Debt-to-Equity.

2. **Technical analysis** – Uses indicators de- rived from historical price and volume data (e.g., RSI, MACD, Bollinger bands) to detect trends and momentum.

3. **Sentiment Analysis** – Captures public mood and perception from financial news and media using natural language processing (NLP).

By integrating these three perspectives into a unified machine learning framework, the system is designed to provide data-driven, real-time recommendations on whether to buy, hold, or sell a stock. The predictions are made using an ensemble classifier (XGBoost), and the model's decisions are explained using **SHAP values**, ensuring transparency and trust.

To make the tool accessible and user-friendly, a **Streamlit web application** was developed, allowing investors, analysts, and finance professionalso to interact with the system, upload stock data, and immediately receive predictions along with visual insights.

This project not only automates investment recommendations but also demonstrates the practical application of AI in finance by bridging quantitative analysis and qualitative sentiment in a real-time setting.

1.2 Motivation

In today's fast-paced financial markets, making timely and informed investment decisions is more challenging than ever. Investors must evaluate a wide array of data, from financial ratios and price movements to the emotional tone of market news. Traditionally, this analysis has been performed manually, relying on the expertise and intuition of the analysts. However, this approach is time-consuming, prone to bias, and often fails to keep up with the speed of modern markets.

The rise of AI and machine learning presents a significant opportunity to automate and enhance investment decision making. Using vast amounts of historical and real-time data, machine learning models can uncover patterns that are difficult for humans to detect. In addition, integration of sentiment analysis allows for the inclusion of market psychology, a critical factor that is often overlooked in quantitative models.

The motivation behind this project is to build a system that empowers investors with a real-time, intelligent, and explainable tool for stock evaluation. By combining:

1. Fundamental analysis (what the company is worth)
2. Technical analysis (how the stock behaves)
3. Sentiment analysis (what people think)

This system aims to replicate the multidimensional thinking of a professional investor — but with the speed, objectivity, and scale of AI.

Furthermore, the project's focus on model explainability using SHAP ensures that users are not just given predictions, but also understand why a certain recommendation was made, a critical feature for trust, adoption, and regulatory compliance in finance.

In short, this project is motivated by the need to democratize intelligent investing through an accessible, transparent, and data-driven platform.

1.3 Problem Statement

The process of making investment decisions in the stock market is complex and often relies on the manual evaluation of multiple data sources, including a company's financial performance, historical stock trends, and market sentiment. This fragmented approach is not only time-consuming, but is also prone to human bias and inconsistency.

Despite the availability of large volumes of real-time financial and market data, most retail and institutional investors still lack access to an intelligent, integrated system that can analyze these data effectively and deliver actionable insights. Traditional tools focus solely on fundamental or technical analysis and rarely combine the three major dimensions, fundamental, technical, and sentiment, into a unified real-time decision-making frame- work.

Furthermore, many existing AI-based investment models function as ”black boxes,” offering predictions without any explanation of how decisions are made. This lack of transparency makes it difficult for users to trust or validate the system recommendations.

Therefore, there is a need for a system that can:

1. Integrate fundamental, technical, and sentiment data into a single cohesive framework 2. Deliver accurate real-time investment recommendations (Buy / Hold / Sell) 3. Provide clear and interpretable explanations for each decision made by the model

This project addresses the above challenges by developing a real-time investment decision system using machine learning and SHAP explainability, with an interactive user interface built using Streamlit.

1.4 Objectives

The primary objective of this project is to develop a real-time AI-powered investment decision system that provides accurate and explainable recommendations based on fundamental, technical, and sentiment analysis.

The specific objectives of the project are as follows:

1. To collect and preprocess financial data Gather real-time and historical data on stock fundamentals, technical indicators, and market sentiment from reliable sources such as Yahoo Finance and news APIs.

2. Engineer relevant features for prediction Transform raw data into meaningful features, including financial ratios (e.g., P/E ratio, Debt/Equity), technical indicators (e.g., RSI, MACD), and sentiment scores.

3. Build a machine learning classification model Develop and train an XGBoost based classification model to predict investment decisions (Buy / Hold / Sell) based on the integrated feature set.

4. Ensure model transparency and interpretability Use SHAP (SHapley Additive exPlanations) to interpret the model predictions and visualize the contribution of each feature to the final decision.

5. Design a user-friendly interface Create an interactive Streamlit Web application where users can upload data or input stock tickers to receive real-time investment recommendations with visual explanations.

6. Evaluate model performance Assess the model using accuracy, recall, precision, and AUC-ROC metrics to ensure robust and reliable predictions.

7. To explore future scalability and improvements Lay the groundwork for future extensions such as portfolio-level recommendations, integration of Indian stock markets, and real-time news sentiment extraction.

Chapter 2

Model Description

2.1 XGBoost

XGBoost, or eXtreme Gradient Boosting, is an open source distributed machine learning library that implements gradient-boosted decision trees. It is known for its speed, performance, and scalability, making it a popular choice for various machine learning tasks, especially with structured or tabular data.

```
✅ Classification Report:
              precision    recall  f1-score   support

           0       0.67      0.80      0.73         5
           1       0.75      0.60      0.67         5

    accuracy                           0.70        10
   macro avg       0.71      0.70      0.70        10
weighted avg       0.71      0.70      0.70        10
```

Figure 2.1: Xgboost Model Training.

2.1.1 What XGBoost Does

In the Real-Time Investment Decision System, XGBoost plays the role of the core prediction engine. Its job is to analyze the combined features (from fundamental, technical, and sentiment data) and predict the investment decision as one of the following:

1. Buy
2. Hold
3. Sell

2.1.2 Why XGBoost is Often the Best Choice

XGBoost is the ”brain” of the system, making the final investment decision based on the data. It learns patterns from past financial conditions, technical trends, and public sentiment and then uses that learning to guide future predictions.

2.2 Scikit-Learn

While XGBoost is your main prediction model, scikit-learn (imported as sklearn) plays a crucial supporting role in your investment decision system. It provides a wide range of tools for data preparation, model evaluation, and pipeline construction — all essential for a robust machine learning workflow.

2.2.1 Why scikit-learn?

1. Preprocessing tools Scales and transforms features consistently

2. Data splitting Ensures robust train/test evaluation

3. Metrics Measures model performance clearly

4. Pipelines Organizes your ML workflow

5. Model tuning and CV Validates model across different data folds

Chapter 3

Business Impact

3.1 Improved Decision-Making Accuracy

By integrating machine learning with real-time data from financial statements, technical indicators, and market sentiment, the system reduces human error and emotional bias. This leads to more data-driven and objective investment decisions.

3.2 Time and Cost Efficiency

Manual stock analysis is time consuming and resource intensive. Automating this process through AI reduces the time spent on research, reduces operational costs, and increases overall productivity for financial analysts and investors.

3.3 Risk Mitigation

By identifying warning signs from financial ratios or negative sentiment in the news before the market reacts, the system helps mitigate downside risk. Detect high-risk investment opportunities early, enabling better portfolio protection.

3.4 Real-Time Market Responsiveness

With the ability to process live market data and update predictions instantly, the system enables users to respond quickly to market movements, capturing opportunities, and avoiding losses that might result from delayed actions.

3.5 Democratization of Financial Intelligence

Retail investors, who may lack advanced financial expertise or access to premium tools, benefit from the user-friendly interface and explainable predictions of the system, thus leveling the playing field between institutional and individual participants.

3.6 Strategic Advantage for Firms

Investment advisory firms or fintech platforms can integrate the system into their services to provide personalized, scalable investment advice to a wide client base, enhancing customer satisfaction and competitive advantage.

Chapter 4

Observation

4.1 SHAP summary plot

The SHAP summary graph shown above provides a visual interpretation of how various technical indicators influence the investment prediction of the model. Each feature on the y-axis represents a technical indicator such as volume obv (On-Balance Volume), momentum stoch (Stochastic Oscillator), trend macd diff (MACD signal), and others that reflect market volume, momentum, trend, or volatility. Each point in the graph corresponds to a SHAP value for a particular prediction, with the x-axis indicating the impact of that feature on the model output. Points to the right of the centerline push the model toward predicting an ”invest” decision, while points to the left push it away. The color of each point indicates the value of the

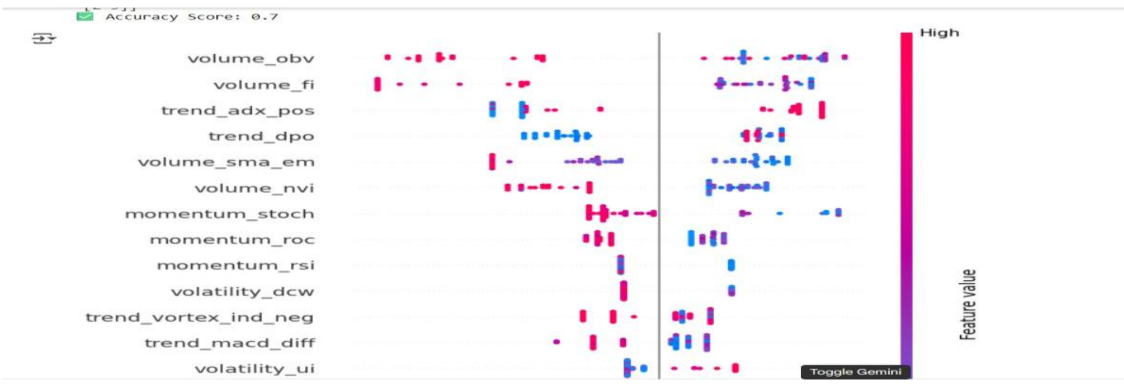

Figure 4.1: SHAP summary plot

feature: red for high values and blue for low. For example, high-momentum stochastic values tend to positively influence prediction, signaling a stronger likelihood of investment. Conversely, some features, such as volume fi (Force Index) show mixed behavior, contributing both positively and negatively depending on the context, suggesting nonlinear influence. Features such as volatility ui and trend vortex ind neg show that lower values (in blue) tend to drive positive investment predictions. Overall, this SHAP plot improves model interpretability by showing which features matter most and how they impact the final decision, helping users and stakeholders under- stand and trust the model output.

4.2 Testing Model 1

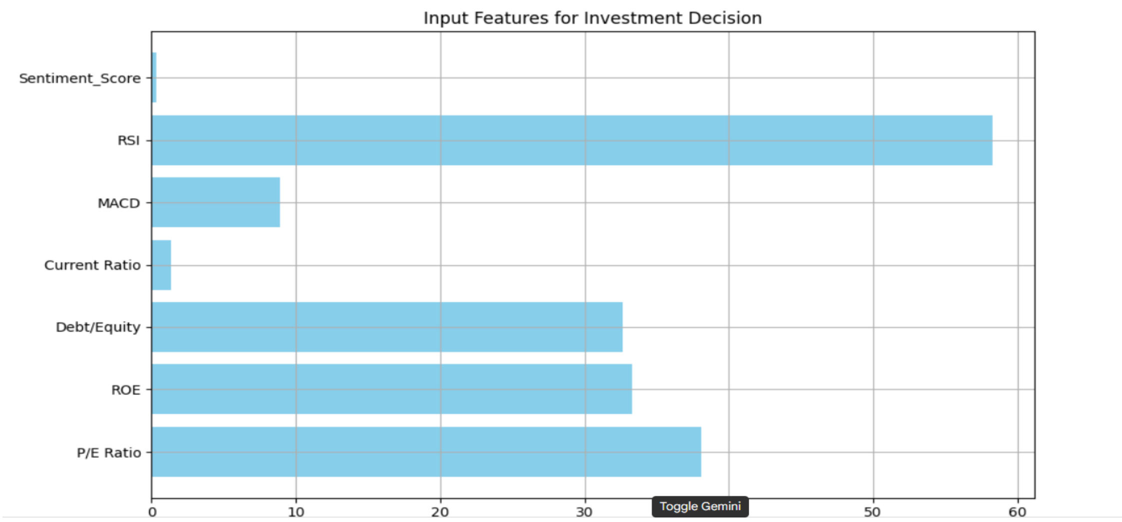

Figure 4.2: Input Features for Investment Decision

Figure 4.3: Seniment Score

From above we can predict that Investing in that firm will give negative investments.

Chapter 5

Conclusion

The real-time investment decision system developed in this project successfully integrates fundamental analysis, technical indicators, and sentiment data to provide informed, data-driven predictions on whether to invest in a given firm. By leveraging powerful machine learning techniques such as XGBoost along with tools like SHAP for model explainability and Streamlit for interactive deployment, the system not only achieves strong predictive performance but also ensures transparency and usability for end-users.

Through the analysis, we found that technical indicators such as momentum, volume, trend strength, and volatility play a significant role in driving investment decisions. The use of SHAP values helped to visualize and interpret these impacts, making the model's decisions more trustworthy and actionable. In addition, real-time responsiveness to market data enables investors to act quickly and confidently.

In conclusion, this system provides a scalable, intelligent, and interpretable approach to investment decision making. It can be further extended by integrating more advanced sentiment analysis, additional financial ratios, or reinforcement learning to dynamically adapt to changing market conditions. This innovation has the potential to democratize smart investing and empower users of all levels of financial expertise.