AI-Driven Multimodal Stock Market Forecasting: Integrating LLM-Based Real-Time Sentiment Analysis with Structured Financial Data

human centred artificial intelligence masters

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Abstract: Financial market forecasting has traditionally relied on structured historical data such as stock prices and economic indicators. However, market trends are increasingly influenced by real-time unstructured data, including financial news, social media sentiment, and corporate announcements. Existing models often fail to integrate these diverse data sources effectively, limiting their predictive accuracy and trustworthiness. This research proposes a human-centered multimodal AI model that combines Large Language Model (LLM)-based real-time sentiment analysis with structured financial data to improve stock market forecasting.

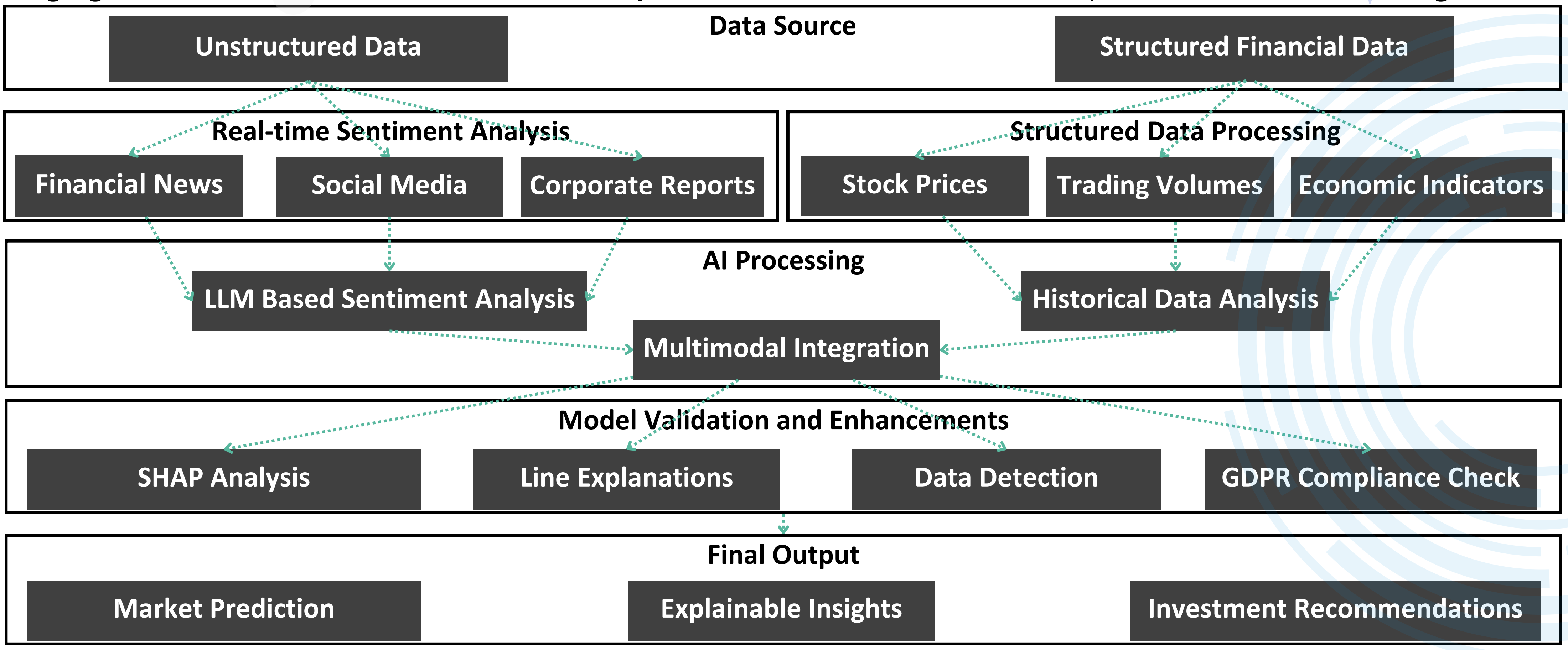

Fig. 1. Multimodal Stock Market Forecasting System Flow

INTRODUCTION

Stock market forecasting is a crucial challenge in financial analytics, with investors relying on predictive models to anticipate market trends. Traditional approaches primarily use structured historical data such as stock prices and trading volumes. However, market movements are increasingly influenced by real-time unstructured data, including news, social media sentiment, and corporate reports. Existing models fail to fully integrate these diverse data sources, limiting their accuracy and reliability. This research introduces a human-centered multimodal AI framework that combines LLM-based sentiment analysis with structured financial data, improving forecasting precision, transparency, and trust for investors, traders, and analysts.

LITERATURE REVIEW

Stock market forecasting has traditionally relied on historical structured data, such as stock prices and trading volumes. However, financial markets are highly volatile and influenced by real-time sentiment from news and social media. Recent advancements in Large Language Models (LLMs), such as GPT-based models and FinBERT, have enabled sentiment-driven stock predictions, outperforming traditional models in short-term forecasting [1], [2].

However, LLMs alone lack explainability and robustness, making their integration with structured financial data crucial for accuracy [3]. Multimodal AI frameworks combining numerical and textual data have shown 23% improvement in predictive performance [4]. Studies emphasize the need for explain ability tools like SHAP and LIME to enhance investor trust [5]. Ethical concerns, such as bias in AI models, raise regulatory challenges under GDPR compliance [6].

RESEARCH METHODOLOGY

- Multimodal AI Framework: Combines LLM-based real-time sentiment analysis with structured stock market data for better forecasting.
- Structured data: Stock prices, trading volumes (via financial APIs).
- Unstructured data: Sentiment extraction using LLMs.
- Cleaning, tokenization, and synchronization for seamless integration.
- Uses transformers and deep learning models.
- Applies early and intermediate fusion for combining textual and numerical insights.
- Implements bias mitigation strategies.
- Ensures GDPR compliance for responsible AI use.

EXPECTED OUTCOMES

- Improved stock market forecasting by integrating LLM-based sentiment analysis with structured financial data.
- Real-time sentiment analysis enables faster responses to market fluctuations.
- SHAP and LIME tools provide clear, interpretable model outputs, ensuring trust in AI-driven predictions.
- Ethical AI implementation to prevent algorithmic bias and ensure GDPR compliance.
- A scalable AI framework that can be adapted for financial institutions, hedge funds, and retail investors.

CONCLUSIONS

This research introduces a human-centered multimodal AI framework that integrates LLM-based real-time sentiment analysis with structured financial data to improve stock market forecasting. Unlike traditional models, our approach captures market sentiment, ensures transparency, and enhances prediction accuracy using deep learning and explain ability tools like SHAP and LIME. By prioritizing bias mitigation and GDPR compliance, this model fosters trust and fairness in financial AI applications. The findings will contribute to more reliable, ethical, and data-driven decision-making for investors, traders, and financial institutions, bridging the gap between AI-driven finance and human interpretability.

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