PROJECT PROPOSAL

Explainable AI for Daily Short-Term Risk Prediction in Coinage Metal Markets

University of West London – School of Computing and Engineering

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Final Year Project

Level 6

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Introduction

Artificial Intelligence integration has transformed how financial analysts evaluate market risk, providing advanced forecasting tools. Coinage metals such as gold, silver, and copper play a vital role in global markets, serving both as industrial commodities and economic indicators. Although gold and silver are traditionally viewed as long-term hedging assets, their short-term price movements are influenced by a combination of market sentiment, macroeconomic indicators, and geopolitical events. Traditional statistical models often struggle to capture these complex and dynamic relationships, highlighting the need for more advanced and adaptive predictive approaches.

Machine Learning algorithms demonstrate substantial promise in finance through their capacity to process extensive market data while detecting complex non-linear behavioral patterns. However, many ML models operate as black boxes which don't provide much understanding into how predictions are generated. This lack of transparency is a significant challenge in finance, where interpretability and trust are critical. As a result, Explainable AI has emerged as an important research area as it aims to make model predictions more transparent and accountable.

Natural Language Processing can extract sentiment from unstructured textual data such as financial news. By integrating machine learning, NLP-driven sentiment analysis, and explainable AI techniques, this project aims to develop an interpretable framework for near real-time downside risk prediction in coinage metal markets, supporting transparent and informed financial risk analysis.

Literature Review

AI and Machine Learning in Financial Risk Prediction

ML adoption within finance has grown substantially, allowing algorithms to process extensive market information while detecting intricate valuation patterns and risk indicators. Traditional econometric models such as ARIMA and GARCH rely on strong statistical assumptions and thus reduce accuracy when modelling the volatility and non-linear trends in financial data. ML algorithms like: Random Forests, Gradient Boosting, and Long Short-Term Memory (LSTM), networks are better when capturing complex relationships within financial markets (Fischer & Krauss, 2018).

Despite their predictive capabilities, a drawback of many ML models is their lack of interpretability. Even when high predictive accuracy is achieved, models are known as "black boxes," . Inputs and outputs are observable, but the decision-making processes are not understandable (Molnar, 2022). This lack of transparency has increased research into Explainable AI (XAI) frameworks to improve trust within AI-driven financial systems (Monica, 2023).

Explainable AI (XAI) and Model Interpretability

Explainable AI is a collection of methods which make the outputs of ML models understandable to humans like, SHAP (SHapley Additive ExPlanations), based on game theory, and attention mechanisms in neural networks are increasingly applied in financial prediction tasks (Lundberg & Lee, 2017; Ribeiro et al., 2016). XAI helps in visualizing the contribution of input features to model predictions. This enhances transparency and trust in AI-driven financial analysis (Doshi-Velez & Kim, 2018).

SHAP is selected as the primary explainability framework due to its ability to assign fair and consistent importance values to all features. By modelling input features as participants in a cooperative game, SHAP calculates how much each input contributes to the final prediction. In financial modeling contexts, SHAP can be used to highlight the most influential risk factors while maintaining the overall predictive performance of the model.

My current research leads me to understand that most XAI applications focus on equity markets or credit risk assessment, with relatively limited research dedicated to commodity or metal markets. This highlights a gap in explainable risk modelling for coinage metals, where understanding drivers like supply-demand and geopolitical events is particularly important.

Natural Language Processing and Sentiment Analysis in Market Prediction

Natural Language Processing is a tool for analyzing unstructured textual data such as financial news, social media and investor reports. Sentiment analysis techniques include lexicon-based approaches and deep learning models that extract market sentiment signals that can influence price movements and volatility (Bollen et al., 2011). A Lexicon-based approach relies on predefined dictionaries in which words are assigned sentiment labels such as positive, negative or neutral, while deep learning models learn contextual meaning directly from data. Previous research has shown that combining sentiment-derived features with numerical financial indicators can improve predictive performance in financial forecasting tasks (Li et al., 2020).

Despite their effectiveness, many sentiment-based prediction models provide limited interpretability, making it difficult to clearly understand how sentimental features influence model outputs. This lack of transparency presents challenges when sentiment information is integrated into financial risk prediction systems, particularly in contexts where model explanations and justification of predictions are required.

Research Gap and Summary

First, most explainable AI applications are concentrated on equity markets, with limited focus on commodity-specific risk prediction (Giudici et al., 2024). Secondly, although sentiment analysis has improved predictive performance in financial markets, few studies combine NLP with explainable models in the context of metal markets. Thirdly, existing approaches often prioritize predictive accuracy over interpretability, limiting analysts' ability to validate model outputs against economic fundamentals.

These gaps are particularly significant for coinage metals, where understanding the drivers of downside risks such as supply disruptions, currency movements, and geopolitical tensions are essential for effective risk analysis. This project aims to address these limitations by integrating explainable AI techniques with NLP-driven sentiment analysis to develop an interpretable framework for short-term downside risk prediction in gold, silver, and copper markets.

Rationale

The increased integration of AI in financial analytics has significantly improved the ability to predict market movements, but it has also introduced a significant challenge: the lack of trust supported by evidence when models make decisions. In markets where prices are highly sensitive to geopolitical factors and macroeconomic events, such as gold, silver, and copper, understanding the model's prediction is as important as the accuracy of the prediction itself. This need for interpretability is especially important in financial risk analysis, where analysts must be able to evaluate and justify model outputs.

Research Question

This leads to the main research question of the project:

Can a Random Forest classifier integrating FinBERT sentiment analysis accurately predict daily downside risk events (>2% price decline) in gold, silver, and copper markets while providing interpretable probability-based risk scores and SHAP explanations that align with established financial risk drivers?

This research question reflects the growing demand for predictive systems that combine strong performance with transparency in financial risk analysis. Although machine learning models have demonstrated effectiveness in forecasting market behavior, their adoption in financial contexts is often limited by a lack of interpretability. This limitation is particularly relevant in commodity markets, where understanding the underlying drivers of risk is as important as identifying periods of elevated risk. Existing research has largely focused on equity and cryptocurrency markets, with comparatively limited attention given to explainable risk prediction in metal markets, despite their economic significance.

By focusing on coinage metals, my dissertation aims to address this gap by integrating numerical market data with sentimental information derived from financial news, while applying explainable AI techniques to improve transparency. A downside risk threshold of a 2% daily price decline is selected to represent economically meaningful adverse movements that warrant risk management attention. This threshold is expected to capture a sufficient proportion of downside events, based on observed historical volatility patterns, to support effective model training while filtering out minor price fluctuations.

Project Aim and Objectives

Aim

The aim is to develop an explainable machine learning model for predicting short-term downside risks in coinage metal markets (gold, silver, and copper) by integrating technical price indicators with NLP-derived market sentiment. The system will generate probability-based risk scores supported by SHAP explanations to enhance transparency and support informed financial risk analysis.

Objectives

1. Conduct systematic literature review examining ML, XAI, and NLP applications in commodity market prediction.
2. Evaluate whether integrating FinBERT-derived sentiment features improves downside risk prediction performance compared to using technical indicators alone.
3. Develop and validate a Random Forest classifier to predict daily downside risk events defined as price declines exceeding 2% in gold, silver, and copper markets.
4. Assess the impact of SHAP-based explanations on the interpretability of financial prediction models while maintaining predictive performance.
5. Determine which feature categories (technical, macroeconomic, sentiment, temporal) contribute most significantly to prediction performance.
6. Assess model calibration quality using probabilistic metrics to ensure trustworthy risk probabilities

7. Validate SHAP explanations through case study analysis of historical market events to confirm alignment with economic fundamentals
8. Document findings, limitations, and implications for the use of transparent and explainable AI in financial risk analysis.

Research Methodology

Research Design

The project adopts a comparative experimental design for the predictive performance and interpretability of the risk prediction system. The project will be conducted in three stages. First, a baseline model will be trained using technical indicators and macroeconomic features derived from numerical data only (excluding sentiment). Second, the model will be enhanced by incorporating FinBERT-derived sentiment features extracted from financial news to assess whether sentiment information improves predictive performance beyond technical and macro indicators alone. Third, XAI will be used to interpret the models' outputs using SHAP explanations. This structured comparison enables a clear assessment of the added value of sentiment analysis and the effectiveness of explainability methods.

Data Collection

Two primary data sources will be used in this project. Numerical market data will consist of historical OHLCV (Open, High, Low, Close, Volume) price data for gold, silver, and copper covering the period from 2020 to 2025, using the yFinance API. Textual data will include financial news headlines related to commodity markets sourced via NewsAPI or financial news aggregators, which will be processed using the FinBERT model to generate sentiment scores. In addition, macroeconomic indicators including the US Dollar Index (DXY), VIX volatility index, 10-year Treasury yields and the S&P 500 returns will be collected via yFinance to capture broader market conditions that influence metal prices. To ensure consistency between numerical and textual inputs, both datasets will be aggregated and aligned at daily intervals, allowing sentimental information to be matched with corresponding market movements.

Model Development Strategy

The model development process starts with feature engineering, where technical indicators like Bollinger Bands, moving averages, Relative Strength Index, volatility measures will be derived from the price data, supplemented by macroeconomic features (USD Index, VIX, Treasury yields, S&P 500 returns) and sentiment scores from financial news. The dataset will then be split using the 60-20-20 method into training, validation and testing to reduce the risk of overfitting and ensure robustness in model evaluation. Random Forest classifier was selected for its high performance on non-linear financial data and its suitability for explainable AI techniques. Hyperparameter optimization will be performed using GridSearchCV to identify the most effective model configuration. As extreme downside events occur less frequently, class imbalance will be addressed using appropriate class-weighting techniques.

Evaluation Framework

Model performance will be evaluated using a combination of probabilistic and classification-based metrics. Probabilistic evaluation will include the Brier Score and Log Loss to assess the accuracy and calibration of predicted risk probabilities. Classification performance indicators like ROC-AUC, recall, precision and F1-score to be used to evaluate high-risk market conditions. To assess real-world applicability, back testing will be conducted using unseen data from the 2024–2025 period. In addition, qualitative evaluation will be performed by analyzing SHAP explanations to determine whether identified risk drivers align with known market events and established economic principles.

Limitations

While the proposed approach aims to provide robust and interpretable risk predictions, it is subject to certain limitations. Financial markets are dynamic by nature and models trained in previous data may struggle to generalize about unprecedented events or extreme market conditions. Consequently, model outputs should be interpreted as analytical risk indicators rather than definitive forecasts.

Project Plan

The project will run from October 2025 to May 2026. Work will be organized into seven key phases, aligned with the Agile framework to allow iterative development.

Project Phases

Phase 1: Research Foundation (October - November 2025)

- Finalize project topic and confirm supervisor
- Complete the literature review
- Identify research gaps and decide on main research question
- Prepare and review the project proposal with the supervisor

Phase 2: Data Infrastructure (December 2025 - January 2026)

- Design and implement PostgreSQL database schema
- Develop data collection scripts (yFinance API integration)
- Collect macroeconomic indicators (USD Index, VIX, Treasury yields, S&P 500)
- Implement FinBERT pipeline for sentiment extraction
- Build feature engineering functions

Phase 3: Model Development (January - February 2026)

- Train Random Forest classifier (technical indicators only)
- Train enhanced model (technical + sentiment features)
- Implement hyperparameter tuning via GridSearchCV
- Integrate SHAP XAI framework

Phase 4: System Integration (February - March 2026)

- Develop Stream Lit Dashboard interface
- Implement real-time prediction display
- Add SHAP visualization components
- Add optional Excel export functionality for results, subject to time constraints

Phase 5: Evaluation and Validation (March - April 2026)

- Calculate performance metrics (Brier Score, ROC-AUC, F1-score, calibration plots)
- Conduct back testing on 2025/26 unseen data
- Validate SHAP explanations against historical market events
- Refine model based on validation results

Phase 6: Documentation (April - May 2026)

- Complete the 10,000-word dissertation report
- Document system architecture, methodology, and results
- Prepare full code and documentation
- Create project poster

Phase 7: Presentation (May 2026)

- Prepare oral presentation and demonstration
- Present the project poster and do the oral discussion

Indicative Gantt Chart

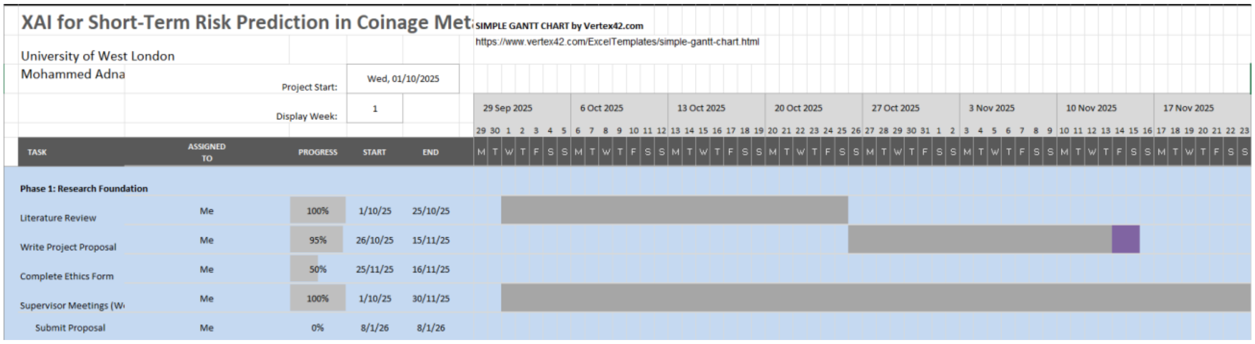

Figure 1: Project Gantt Chart - Phase 1: Research Foundation (Oct-Nov 2025)

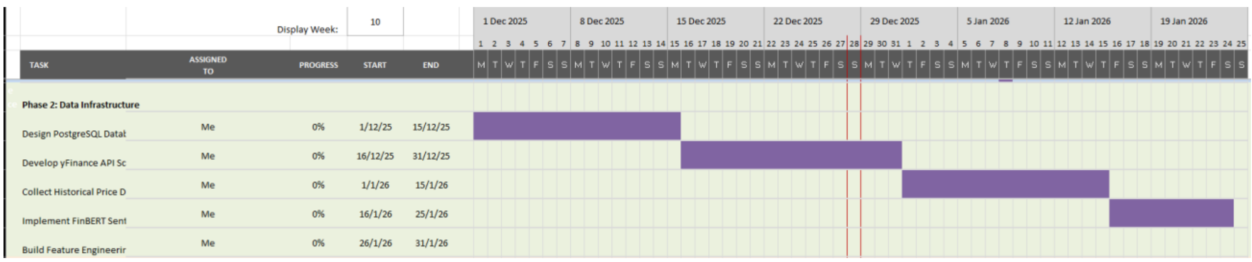

Figure 2: Project Gantt Chart - Phase 2: Data Infrastructure (Dec 2025-Jan 2026)

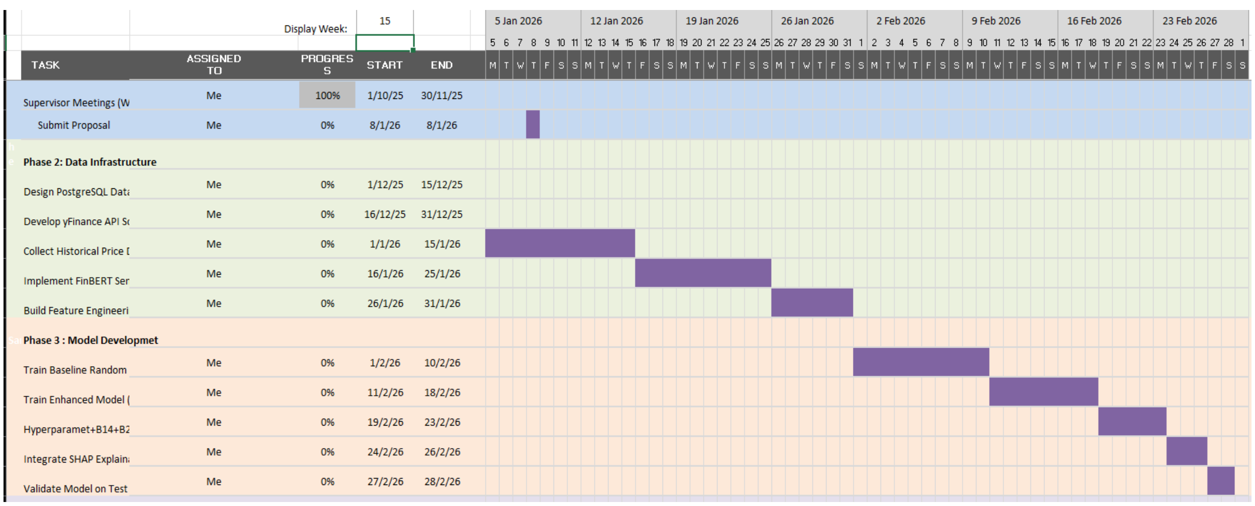

Figure 3: Project Gantt Chart - Phase 3: Model Development (Jan-Feb 2026)

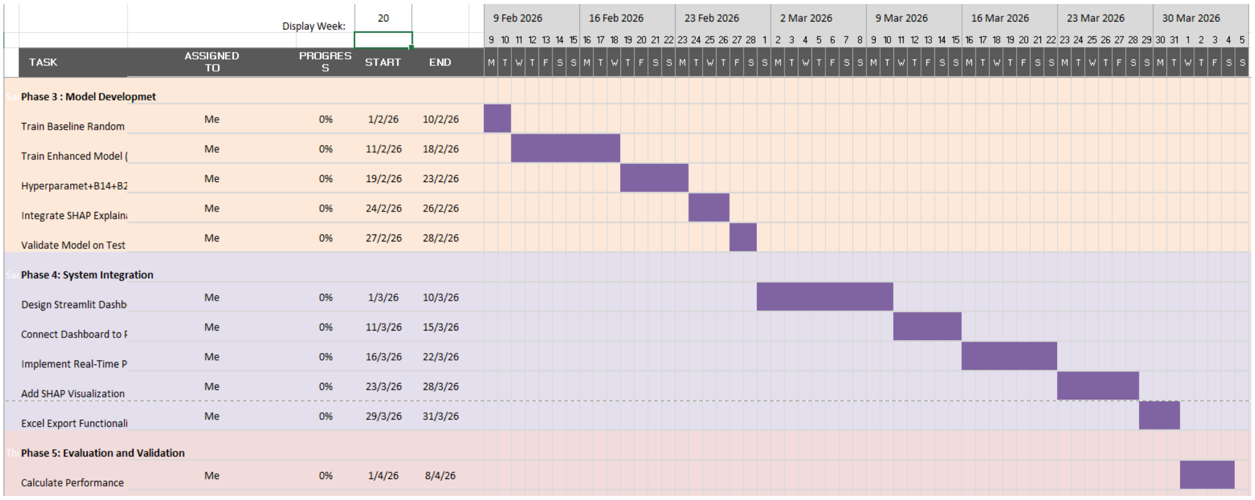

Figure 4: Phase 4-5: Integration & Evaluation (Feb-Apr 2026)

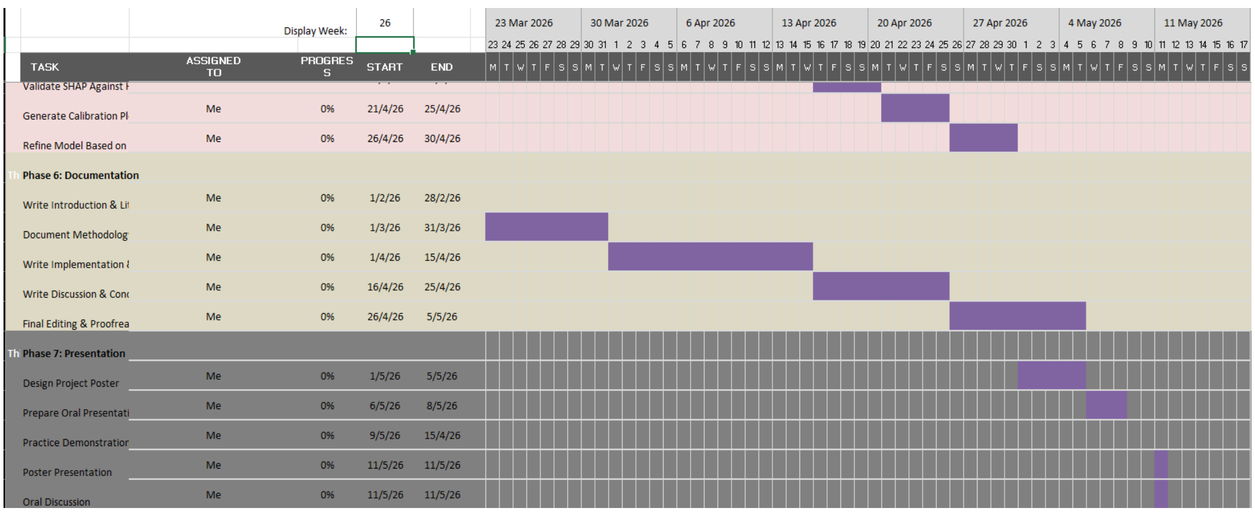

Figure 5: Phase 6-7: Documentation & Presentation (Apr-May 2026)

Weekly Progress Logbook

Weekly Progress Logbook - Semester 1 (Sept 2025 to Jan 2026)

Student ID:	**33114153**
Student Name:	**Mohammed Adnan Osman**
Course:	**Computer Science**
Project Title:	**Explainable AI for Short-Term Risk Prediction in Coinage Metal Markets.**
Supervisor Name:	**Dr Nasim Dadashi**

w/c (Mon)	Week	Weekly log of progress	Supervisor Initials
29/09/2025	1	Reviewed module guide - reviewing range of potential topics for project	M.R
06/10/2025	2	Selected project topic on explainable AI for metal-market risk prediction and reviewed module guide.	M.R
13/10/2025	3	Finalised project title and drafted aims and objectives. - changed from all precious metals to only coinage.	
20/10/2025	4	Started reading papers (5) on Machine Learning & Explainable AI (XAI) in finance.	
27/10/2025	5	Wrote introduction for proposal.	
03/11/2025	6	Began outlining literature review sections. - Read more papers (4) on my Topic.	
10/11/2025	7	Completed literature review and refined research question - Wrote all refernces in Harvard Style.	N.D
17/11/2025	8	Wrote methodology section: planned data sources - Yahoo Finance (API) , tools (Python (ML), SQL, SHAP - XAI).	N.D
24/11/2025	9	Outlined project plan	N.D
01/12/2025	10	Made the Gantt Chart	N.D
08/12/2025	11	Completed full Project Proposal. - slight edit to predict a more than 2% downside risk rather than just decline.	N.D
15/12/2025	12	Completed Ethics Form - Sent Ethics form to supervisor in PDF Format.	N.D
Winter break			
05/01/2026	13	Contacted Dr. Nasim through email for final approval	
12/01/2026	14	Submitting the full Project Proposal with this weekly logbook and the Ethics Form	
19/01/2026	15		
26/01/2026	16		

Bibliography

Bollen, J., Mao, H., and Zeng, X. (2011) ‘Twitter mood predicts the stock market’, Journal of Computational Science, 2(1). URL: https://arxiv.org/pdf/1010.3003 (Last Accessed: [29/9/2025])

Doshi-Velez, F., and Kim, B. (2018) Towards a rigorous science of interpretable machine learning’, arXiv preprint arXiv. URL: https://arxiv.org/pdf/1702.08608 (Last Accessed: [2/10/2025])

Fischer, T., and Krauss, C. (2018) ‘Deep learning with long short-term memory networks for financial market predictions’, European Journal of Operational Research, 270(2). URL: https://iranarze.ir/wp-content/uploads/2019/01/E10789-IranArze.pdf (Last Accessed: [17/10/2025])

Li, Q., Wang, T., and Wu, J. (2020) ‘Financial sentiment analysis for risk prediction using hybrid deep learning’, Expert Systems with Applications, . URL :

https://www.researchgate.net/publication/258821644_Financial_Sentiment_Analysis_for_Risk_Prediction (Last Accessed: [28/10/2025])

Lundberg, S.M. and Lee, S.I. (2017) ‘A unified approach to interpreting model predictions’, Advances in Neural Information Processing Systems (NeurIPS), URL: https://arxiv.org/pdf/1705.07874 (Last Accessed: [02/11/2025])

Molnar, C. (2022) Interpretable Machine Learning: A Guide for Making Black Box Models Explainable. 2nd edn. Independently published. URL: https://originalstatic.aminer.cn/misc/pdf/Molnar-interpretable-machine-learning_compressed.pdf (Last Accessed: [09/11/2025])

Ribeiro, M.T., Singh, S. and Guestrin, C. (2016) Why should I trust you?: Explaining the predictions of any classifier’, Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, URL: https://www.kdd.org/kdd2016/papers/files/rfp0573-ribeiroA.pdf (Last Accessed: [09/11/2025])

Monica Hovsepian, (2023) The Benefits and risks of AI in Financial Services, Forbes Finance Council. URL : https://www.forbes.com/councils/forbesfinancecouncil/2023/12/26/the-benefits-and-risks-of-ai-in-financial-services/ (Last Accessed: [12/11/2025])

P. Giudici, A. Piergallini, M.C. Recchioni and E. Raffinetti (2024) Explainable Artificial Intelligence methods for financial time series, Department of Economics and Management, University of Pavia, Pavia, Italy. URL : https://www.sciencedirect.com/science/article/pii/S037843712400685X?via%3Dihub#sec3 (Last Accessed: [12/11/2025])

Dhole, Y. (2024) 'Unveiling Market Sentiments: FinBERT-Powered Analysis of Stock News Headlines', International Journal of Scientific Research in Engineering and Management, 8(4), URL: https://www.researchgate.net/publication/392123072_Unveiling_Market_Sentiments_Finbert-Powered_Analysis_of_Stock_News_Headlines (Last Accessed: [15/11/2025])