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Research Proposal

Module Name: Research Methods and Professional Development

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Comparative analysis of Deep Learning Model for Forecasting Volatility with sentiment analysis and explainability.

1.Introduction

1.1 Context and background:

Financial markets are the place where trades take place, and the markets are highly volatile. The volatility depends on different economic conditions like global news, politics, wars, interest rates, budget allocations and investments. S&P 500 is the index which has more liquidity because it has top 500 publicly traded companies of United States. S&P 500 is widely used to know the market conditions and investor sentiment [1]. Market volatility is an important measure that indicates how fast the market move in either direction. If the volatility is high then the market movement is high which form higher highs or lower lows, if the market volatility is low then the market movement is low and stays clam which is known as sideways market. Volatility is not only useful for direct participant in the market like traders or investors but also helpful for brokers, banks, financial institutions, risk managers, firm operators and Insurance companies. Retail or institutional traders highly depend on volatility for short and mid-term trades they manage their portfolios accordingly. Brookers and brokerage firms use volatility to set the margins and calculate the client risks and make sure clients positions are in the limited risk. Banks and financial institutions use volatility to prevent losses and maintain financial stability[2]. Using AI techniques to forecast the volatility of the market can capture complex patterns and can learn patterns like nonlinearity without mentioning the structure in advance. As financial markets produce a lot of data because of high frequency trading and including different types of data to forecast volatility like news sentiment, economic indicators, return and prices can be handled

easily and achieve better results by using AI. Financial markets are highly unpredictable and highly responsive to crises, booms and new policies, AI models can adapt to new pattern easily[3]. Analysing sentiment of the market through financial news can capture public emotion by which can guess the moment of the market is more volatile or less volatile. In financial market, majority of the retailer's emotions like FOMO creates hype in buying, fear creates panic selling which leads to high volatility[4].

1.2 Research Problem:

As the financial markets are noisy, non-linear and highly reactive to various events, predicting volatility is quite difficult. S&P 500 is more liquid and high volatile market because it contains publicly traded companies from different sectors, so market will be volatile most of the time. Traditional econometric approaches like ARCH family models are good at forecasting short-term and assumes linear but the real markets contain structural breaks and non-linear. Traditional models struggle to capture complex patterns and structural breaks and fail to forecast volatility at the time crises. Deep learning models have shown improved forecasting capabilities in learning long term financial data. Deep learning models are lack interpretability and offer limited transparency; this black box nature creates major problem in financial markets[5]. Considering sentiments like news while predicting volatility can improve the forecasting capabilities by incorporating financial information[6]. Contribution of the sentiment with interpretability within deep learning architecture is rarely addressed.

 **Research question:** There is a need for an S&P 500 volatility forecasting approach that leverages deep learning and sentiment information while improving interpretability, so that prediction gains can be achieved without sacrificing transparency and trust.

1.3 Research Aim and Objectives:

Aim: Comparative analysis of deep learning models for forecasting volatility of S&P 500 with sentiment information from financial news and enhance modal transparency.

Objectives:

1. Collect price data of S&P 500 and collect sentiment data like financial news.
2. Pre-process the collected financial price data and compute the sentiment score from financial using language processing techniques.
3. Train and evaluate deep learning models for forecasting volatility.
4. Apply explainability techniques to interpret model predictions and compare the models

The main aim of the project is to conduct a comparative analysis of deep learning models for forecasting volatility by combining sentiment analysis and explainability techniques. The novelty of the research is deep learning models can predict better volatility when combined with sentiment and explainability. And to achieve the aim, first

objective is to collect the price data of S&P 500 index and sentiment data of financial market. Second, preprocess the collected data and calculate sentiment score using language processing techniques. Third, build and evaluate deep learning models for forecasting volatility of S&P 500 index. Then, apply explainability techniques to interpret the model predictions and assess the contribution of sentiment and financial variables. Finally compare the performance of the deep learning models in forecasting volatility.

1.4 Significance of Research

This research contributes to get more accuracy and reliability in forecasting volatility on which investors, trader, brokers and banks are relied. Forecasting better volatility helps investors to manage portfolios, planning trading strategies. Including sentiment analysis from financial news, can capture the market mood, which traditional models often fail to capture, as a result improved forecasting performance. And deep learning models identify the complex patterns in the time series data which results to better forecasting. Additionally, explainability techniques improve the transparency by explaining how different variables influence model predictions which brings more trust on models to use in financial markets[2].

2. literature Review

2.1 Introduction

This is a thematic literature review as this study concentrates on three themes which are related to forecasting volatility: deep learning approaches, sentiment analysis and explainability. this review is organised around these three themes to compare different deep learning approaches by including sentiment and model interpretability. In this review there no individual authors or chronological theme. This is a review of existing literature related to volatility forecasting by using deep learning models, with a particular attention on combining of sentiment analysis and explainability techniques to improve the forecasting performance. The main intention of this review is to examine current approaches, methodologies, and research gaps in financial volatility forecasting. It specifically examines how models such as deep learning models have been applied to financial time-series forecasting and how sentiment data from financial news improves forecasting performance. Additionally, the review examines the importance of explainability in enhancing transparency and interpretability in forecasting volatility of financial market by deep learning models.

2.2 Traditional Volatility Models

Traditional volatility forecasting models are Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) can capture the time varying volatility by using the variance of returns in financial data. ARCH model can predict the volatility by focusing on the past errors. GARCH model can use both past variances and past errors, so it is more flexible and commonly used in financial econometrics. Although traditional models are

effective failed to capture nonlinear patterns, treats financial markets as linear structure and struggles to learn complex. These traditional models heavily depend on past historical price data and do not include additional variables like market sentiment, news or macroeconomic indicators[7]. Their assumption about financial markets is normally distributed but in real financial markets are noisy and contains complex pattern. The model performance goes down when the market is influenced by additional variables like sentiment and creates complex patterns which requires advanced deep learning approaches.

2.3 Deep Learning Models.

Deep learning models play an important role in forecasting volatility because of their capability to learn complex, nonlinear structures in financial time series price data. In the recurrent architectures, Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are commonly used for time series data especially for financial data. LSTM performs well in learning long-term relations in between past and future values though its cell and gating mechanisms which makes it suitable for learning financial patterns for forecasting volatility and it has higher computational cost and longer training time[7]. Although, LSTM good at learning time series patterns and handling sequential data it has many parameters which leads to slow training. In handling nonlinear patterns LSTM is better than GARCH but training takes more time than GRU. Gated Recurrent Unit will reduce the gates and reduce number of parameters to simplify the structure and more efficient. The computational cost to build GRU is less as it requires less computational resources like memory, processing power but GRU is less effective in learning very long-term dependencies in highly volatile financial time series[8]. As GRU has fewer gates, faster training it may lose memory and performs is like LSTM. Some studies show GRU is better than LSTM and some show LSTM is better than GRU[9].

Hybrid models additionally increase predicting performance by combining capabilities of different approaches. CNN-LSTM combine convolutional layers with LSTM to learn both patterns at same point and patterns from past to futures and this feature is effective particularly effective for high frequency financial data and it has some architectural complexities[10]. CNN-LSTM performs well in handling complex relations and high frequency data. As it has more parameters and performs more calculations it needs more memory and takes longer to train. LSTM-GARCH is another hybrid model, it can include classical econometric model to deep learning. Financial volatility clustering and conditional variance can be captured by GARCH and non-linear relations in time series data. This hybrid approach enhances interpretability when compared standalone deep learning models[11].

Recently transformer models become powerful alternative by using attention mechanisms rather than sequential processing, transformer process the data in parallel and take multiple inputs such as financial market indicators and sentiment data[12].

Although transformers have high forecasting accuracy, they need larger datasets and larger resources like GPU, memory, training time and electricity and it often lack transparency.

No single model is perfectly suitable for forecasting, but transformers achieve higher accuracy but demands high computational cost and lower interpretability. LSTM delivers balance between performance and sequence learning, at the same time GRU delivers efficiency with somewhat reduced modelling capacity. Hybrid models like CNN-LSTM and LSTM-GARCH improve predicting performance but brings some complexities like architectural complexity, hyperparameter tuning, training complexity, overfitting risk and interpretability.

Model	Strength	Weakness	Better to use for-
GARCH	Simple and interpretable.	Fails at nonlinear relations, long-term dependencies and struggles with high-frequency data.	Basic Volatility predictions.
LSTM	Captures long term dependencies.	Training is slow	Sequential data forecasting.
GRU	Faster training.	simpler memory structure.	Small datasets.
CNN-LSTM	Learns complex temporal patterns.	Computational cost is high.	High-frequency data.
LSTM-GARCH	Combines linear and nonlinear volatility modelling.	Complex architecture	Financial volatility forecasting.
Transformer	Strong long range dependency learning	Requires more data and computationally expensive.	Large-scale forecasting.

2.4 Sentiment Analysis in Finance

Sentiment analysis has a major importance in predicting financial market, as market movements are not only depending on numerical data but also depends on public emotions and investor sentiment. Sentiment is taken from textual scores like news deadlines, social media and different financial data and then computed to sentiment scores to train the models. Market behaviour is highly relied on news sentiment which includes financial news articles, social media effect, and macroeconomic announcements can change the investor opinions. Positive hearings can create increased buying activity and demand while negative news leads to panic selling and higher volatility. News sources provide structured and high-quality sentiment signals[4]. For extracting sentiment from financial news, FinBERT performs better as it build on

bidirectional encoder representations from transformers and especially for finance. It can learn all the financial terminology as it was built exclusively for financial usage[13] .

2.5 Explainable AI

Deep learning models contains the nature of Black Box because the decision the process of decision making are not easily interpretable. The models like LSTM, GRU, LSTM-GARCH, CNN-LSTM and transformers can achieve high accuracy but won't provide which features are plays crucial role to predict output and these lack of interpretability is a major concern in finance. Because relying on the forecasting requires some interpretable explanation about the predictions. To overcome this issue widely use methods are Shapley Addictive explanations (SHAP) and Lime Interpretable Model-agnostic Explanations. SHAP assigns importance values to each variable and shows how much each variable influences the prediction. It provides interpretability at both global and local level. Although SHAP provides theoretical explanation consistently, it is expensive in cost. LIME looks at specific predictions and explains the decision of the model, it won't take complete complex model it just takes local prediction to explain, and it takes simple models instead of complex deep learning models. It provides less consistent explanations but faster and flexible. These techniques can bring more transparency and trust towards deep learning models in forecasting volatility[14].

2.6 Research Gap

In financial forecasting volatility, only few studies combine deep learning models with sentiment and explainability. Many studies concentrated on using deep learning techniques and its forecasting accuracy or including sentiment analysis to forecasting volatility but hardly ever included interpretability techniques like SHAP and LIME. And lack of comparative analysis of deep learning models for forecasting volatility with sentiment analysis and explainability.

2.7 Summary

This literature reviewed traditional models and deep learning models for forecasting volatility, discussing their strengths and limitations. And the importance of sentiment analysis and explainable AI in improving forecasting accuracy and transparency is also discussed. Finally found that there is need of comparative analysis of deep learning model for forecasting volatility with sentiment and explainability.

3 Research Design and Methodology

3.1 Research Design

This is a quantitative experimental study with comparative research design, as this study evaluate and compare the predictive capabilities of different deep learning

models for forecasting volatility. This research systematically compares deep learning models like LSTM, GRU, CNN-LSTM, LSTM-GARCH and transformer under equal conditions and using same datasets and evaluation metrics. This establishes the consistency and uniformity in comparing models. In this study historical prices data and sentiment financial news data of S&P 500 is used which brings real-world scenario. This will give the ability to the research that the models are evaluated and tested in real market scenario.

3.2 Research Methodology

In this study, a quantitative methodology to develop, compare and evaluate deep learning models for financial volatility forecasting, data collection, data processing, data integration, building development and evaluating the models are different stages of methodology. This study uses quantitative methodology as it uses numerical financial price data and financial news sentiment data and evaluates deep learning models performance in forecasting volatility. For this study, experimental strategy is correct as this involves developing different models and testing them in same experimental conditions.

3.2.1 Data Collection:

In this study, numerical financial price data and textual sentiment data is collected to understand the market conditions.

Financial Data: The price data of S&P 500 is collected from yahoo finance, and it contains variable like open, high, low, volume and close values of time frame. By this, returns and volatility can be calculated[1].

Sentiment Data: From Kaggle, financial news datasets can provide sentiment data, and these datasets contains headings of the financial news, and some sentiment signals can be included from social media platforms like twitter and reddit to read the different market sentiment[4]. In this study market prices are observed, and sentiment scores are taken from financial news which indicates positivism of philosophy, and the time horizon is longitudinal as the historical financial price data is collected over a period.

3.2.2 Data Processing:

Multiple steps are taken place before preparing the data for models.

Data Processing: Returns and log returns are calculated by using the closing values and volatility is a calculated using rolling window mechanism.

Text Pre-processing: Raw financial news text is processed by techniques like tokenisation, lowercasing and removing of stop words, punctuations and irrelevant characters are used to clean the text data.

Sentiment Scoring: By Using FinBERT, the processed text is converted into sentiment scores which brings more accurate sentiment scores. It converts financial news into sentiment score, and the sentiment score is used to train models. FinBERT is language model specially made for financial text. It is based on bidirectional encoder representations from transformers but build for financial usage like news, company reports, statements so it can understand words like profit, loss, market crash, bullish, bearish, inflation better than normal language models[13].

3.2.3 Data Integration:

Once pre-processed, financial dataset and sentiment dataset are combined using the date variable. As the sentiment reflects in market with some delay, lagged sentiment variables are introduced. So, models can learn delayed impact of news and investor sentiment on volatility[15].

3.2.4 Model Development:

In this study, multiple deep learning models are developed and compared. The models are LSTM (Long Short-Term Memory)- Memory cells and gating mechanisms can capture the long-term future values depend on the past financial prices in time series data. So, LSTM is effective for capturing long term structures in financial time series. GRU (Gated Recurrent Unit)- GRU is simpler and faster version of LSTM with few parameters but performs better than LSTM and faster training. CNN-LSTM- In this hybrid approach, short term fluctuations will be learned by convolutional neural network and long-term dependencies will be captured by long short-term memory, it shows effectiveness in handling high frequency trading data with complex patterns. LSTM-GARCH- Combining traditional econometrics with deep learning techniques can helps in learning volatility and variance by GARCH and long term non-linear temporal dependencies can be captured by LSTM. Transformers- uses attention mechanisms to learn relations and process in parallel and it includes different data inputs like financial price data and sentiment news data for effective prediction performance. For training all these models, same dataset is used which contains historical financial price data and sentiment scores for comparing and splitting the dataset into training, validation and testing will be done by using time series like training on old data, validating on middle data and testing on most recent data. To optimise performance, hyperparameters like learning rate, number of epochs, batch sizes, number of layers are tuned. Early stopping and regularisation techniques are used Ensure the models do not overfit[16]. In this study existing theories and models are tested to evaluate their predictive performance in forecasting volatility which is deductive approach.

3.2.5 Evaluation Metrics:

Mean squared error (MSE), Root mean squared error (RMSE), mean absolute error (MAE) and Quasi-likelihood loss function (Qlike) are used tell how the models are performed individually. MSE gives the average squared difference for predicted and actual values.

RMSE gives how wrong the predictions are in the same unit as your data; it makes easy to understand the size of your errors. MAE simply calculate the average mistake size of your predictions and giving a fair and balanced measure of model accuracy. Qlike is most common metric in volatility forecasting that evaluates the accuracy of predicted variance[17].

3.2.6 Model comparison

Diebold Mariano (DM) Test is used to compare two models to know which model is better. DM Test tells which model is statistically superior and whether the results are meaningful or random. We can know that difference in forecasting performance between two models is real or just a random by chance[12]. Calculate the errors by comparing predicted values with actual values after the models make predictions. Then apply the loss function like squared errors to measure the prediction. After that, finding the loss difference of two models, that is difference between the errors of the two models. The DM test check whether the average of the difference is close to zero or some value. If the difference is close to zero, then the performance of the two models is same otherwise, one model is better than other. By using p-value we can say the result is meaningful or just by chance. If the p-value is less than 0.05, the result is meaningful otherwise the difference is just by chance. This study uses an experimental strategy by comparing deep learning models to find the best model and explainable method for forecasting volatility.

3.3 Explainability

Explainability is the key component in this research, discussing the black-box nature of deep learning models. To bring the interpretability to the model predictions, this study applies SHAP (SHaply Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) techniques on best performing models. First SHAP values are calculated using test dataset with inputs like lagged volatility, trading volume, returns and aggregated sentiment scores. SHAP is mainly used to know the importance of globally by identifying which variable in the dataset plays major role in forecasting volatility. Second LIME is used for predictions from the test set. For each complex model LIME creates a simple model which approximate the behaviour of the complex model. This gives the contribution of sentiment and price-based variables influences a single prediction. The results of SHAP and LIME are compared to know the effect of sentiment variables and price variables in achieving consistency and interpretability of the models. Explainability tells which features affect forecasting volatility and role of sentiment data and financial price data[14].

3.4 Materials

DATA:

For developing models and analysis, this study uses publicly available financial data and financial news data for sentiment, so there are no ethical risks, and these datasets are used for educational purpose in this study. The main dataset is historical financial price data of S&P 500 which contains daily values like opening price, high, low, trading volume and closing price. This is publicly available and obtained from yahoo finance. And for sentiment analysis, financial news dataset is collected from publicly available platform like Kaggle. This financial news dataset contains top headlines of finance and from the dataset sentiment scores are calculated and combined with financial price dataset.

Software:

The execution will be done by using python, deep learning models built by using TensorFlow and PyTorch. Libraries like Pandas and NumPy are used for data preprocessing and analysis. For sentiment extraction and evaluation Scikit-learn and language processing techniques are used. All the coding is done in Google Colab with GPU to train deep learning models efficiently.

Hardware:

Over standard CPU, GPU is recommended because of its parallel computation capability which helps in training deep learning models. If possible TPUs can be consider for training transformers as they match the computational power. Using Google Colab may be helpful for high computational resources.

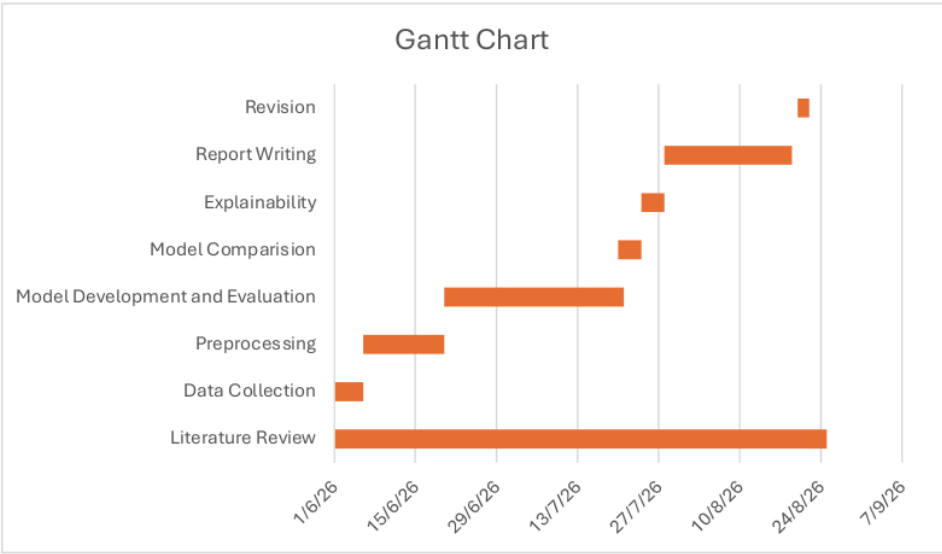


Research Onion.

4. Expected Outputs

In this study, most effective deep learning model for forecasting volatility will be identified, models like LSTM and transformers may perform better in learning long-term relations and complex patterns in historical time series data. Hybrid models like CNN-LSTM and LSTM-GARCH may improve performance in forecasting. It also expected that including sentiment data derived from financial news may improve forecasting accuracy when compared to models using only historical price-based features. Sentiment signals are likely to be particularly valuable during periods of markets uncertainty, where investor behaviour and news events influence volatility. Considering interpretability, SHAP is expected to provide the importance of features. The analysis should tell the contribution of sentiment scores and traditional financial indicators like returns and historical volatility. This helps to know that the sentiment analysis plays an important role in boosting model predictions. This study provides an improved risk management for investors, traders, banks and policymakers and explainable AI can bring more trust and transparency towards the deep learning models in forecasting volatility. And the limitations are this study is conducted on S&P 500; the results may not work on other markets and other environments.

5. Timeline



References

- [1] L. Li and C. R. Chen, "Volatility Risk and Volatility-of-Volatility Risk: State-Dependent Correlations Between VIX and the S&P 500 Stock Index and Hedging Effectiveness," *The Journal of Futures Markets*, vol. 45, (11), pp. 2166–2185, 2025. . DOI: 10.1002/fut.70035.
- [2] H. Zeng *et al*, "Forecasting Volatility of Australian Stock Market Applying WTC-DCA-Informer Framework," *J. Forecast.*, vol. 44, (6), pp. 1851–1866, 2025. . DOI: 10.1002/for.3264.
- [3] P. K *et al*, "Machine learning based indian stock market forecasting," in 2024, . DOI: 10.1109/ICDCC62744.2024.10961860.
- [4] D. Hirshleifer, L. Peng and Q. Wang, "News Diffusion in Social Networks and Stock Market Reactions," *The Review of Financial Studies*, vol. 38, (3), pp. 883–937, 2025. . DOI: 10.1093/rfs/hhae025.
- [5] K. Sharma *et al*, "Explainable AI for temporal feature interpretation in volatility forecasting," in 2025, . DOI: 10.1109/CICN67655.2025.11368102.
- [6] M. R. Kabir *et al*, "LSTM–Transformer-Based Robust Hybrid Deep Learning Model for Financial Time Series Forecasting," *Sci*, vol. 7, (1), 2025. . DOI: 10.3390/sci7010007.
- [7] P. D. Quang, N. K. Huyen and H. N. Quyen, "Analysis and Forecasting of Bitcoin Price Volatility: A Deep Learning Approach Using DNN, LSTM, Transformers, and the ARMA-GARCH Model," *Journal of Applied Mathematics*, vol. 2025, (1), 2025. . DOI: 10.1155/jama/9089827.
- [8] Y. Li, "An Improved GRU Financial Time Series Prediction Model," *Fractal and Fractional*, vol. 10, (4), pp. 227, 2026. . DOI: 10.3390/fractalfract10040227.
- [9] X. Yan, "A comparative study of LSTM, ARIMA-LSTM, and CNN-LSTM models for S&P 500 closing price prediction," in 2025, . DOI: 10.1109/ICEACE67491.2025.11439234.
- [10] N. Siddiraju and R. Hasan, "A hybrid LSTM-GARCH network for stock market volatility prediction," in 2025, . DOI: 10.1109/CCWC62904.2025.10903807.
- [11] G. Taneva-Angelova and D. Granchev, "Deep Learning and Transformer Architectures for Volatility Forecasting: Evidence from U.S. Equity Indices," *JRFM*, vol. 18, (12), 2025. . DOI: 10.3390/jrfm18120685.

[12] Y. Ibrahim, M. S. Sharif and N. D. Moussa, "From wall street to heartbeat: AI forecasting for financial volatility and investor well-being," in 2025, . DOI: 10.1109/3ict68299.2025.11442213.

[13] J. Kim, H. Kim and S. Choi, "Forecasting the S&P 500 Index Using Mathematical-Based Sentiment Analysis and Deep Learning Models: A FinBERT Transformer Model and LSTM," *Axioms*, vol. 12, (9), pp. 835, 2023. . DOI: 10.3390/axioms12090835.

[14] T. E. Pratas, F. R. Ramos and L. Rubio, "Forecasting bitcoin volatility: exploring the potential of deep learning," *Eurasian Econ Rev*, vol. 13, (2), pp. 285–305, 2023. . DOI: 10.1007/s40822-023-00232-0.

[15] R. Urniezius *et al*, "Enhancing Prediction by Incorporating Entropy Loss in Volatility Forecasting," *Entropy (Basel, Switzerland)*, vol. 27, (8), pp. 806, 2025. . DOI: 10.3390/e27080806.

FINAL GRADE

GENERAL COMMENTS

62/100

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Comment 1

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Comment 2

This is not a research question

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TEJA VAMSI DEVALLA**62****ENGAGEMENT WITH LIT.SKILL [30]**

Structure and Organization of the literature review [8 Marks] Critical Engagement with Literature [10 Marks] Relevance and Positioning of Your Study [7 Marks] Recent and Relevant in-text citations and reference list [5 Marks]



The review is organised into clear thematic sections.

The literature is largely descriptive, focusing on listing models (LSTM, GRU, etc.) rather than critically comparing their performance, limitations, and suitability for volatility forecasting.

The research gap is identified, but it is weakly justified, as the proposal does not clearly demonstrate how existing studies fail to integrate sentiment and explainability effectively.

The references include some recent studies, but the literature review does not consistently engage with them critically, and some claims are made without proper citation support.

20**KNOWLEDGE & UNDERSTANDING [20]**

Brief overview and current developments in the proposed research area [10 Marks] Research problem statement [7 Marks] Significance of the study [3 Marks]



The proposal demonstrates a basic understanding of volatility, deep learning and sentiment analysis. The problem is relevant but weakly articulated and lacks a clear, concise statement; it mixes multiple issues (nonlinearity, interpretability, sentiment) without clearly defining the core problem supported by the literature. The significance is stated, but it is generic

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COGNITIVE & INTELLECTUAL [10]

Clearly state the aim of the research based on the identified research problem [5] Break down the research aim into smaller, measurable, and achievable steps [5]



The aim is relevant but not clearly written and lacks precision; it should be more focused and expressed in a clearer academic form. The objectives are relevant but poorly written, lack clarity, and are not clearly measurable; they are more task-based rather than well-defined research outcomes.

6

PRACTICAL APPLICATION [25]

*Research Design (Explanation of the overall research approach) [7]
Research methods [10] - a detailed explanation about the research methods to achieve the research objectives Research materials [8] - in terms of Software and hardware*

13



The design is described as comparative and experimental, which is appropriate; however, the justification is weak.

The methodology outlines a clear workflow, but lacks strong academic justification for key choices, particularly model selection and evaluation methods.

The section also contains inconsistent tense usage and informal explanations, which reduce academic quality; for example, phrases such as “data is collected” and “data is analysed” should be written in the future tense

The Research Onion is briefly mentioned, but it is not properly explained or applied.

TRANSFERABLE SKILLS [15]

Project planning and resource management [5 Marks] Description of the project's potential impact and limitations [5 Marks] - Expected outcome Presentation style [5 Marks]



Timeline is provided
Limitations are briefly mentioned.

The writing quality is poor, with frequent grammatical errors, repetition, and inconsistent tense usage (mix of present and past tense), which affects academic quality.

9