

Assignment-1

- Assignment Title: Project title proposal
- Course Title: Research methods and professional management
- Course Code: ACFA7004
- Student Name: Devalla Teja Vamsi
- Student Id: 2505091

Project Title

- Forecasting Volatility Using Hybrid Deep Learning Model(GARCH-LSTM) with market sentiment.

Financial Volatility Context

- What is volatility
 - Volatility measures how much value of a stock fluctuates up and down at particular period.
 - It is important for:
 - Risk management
 - Derivatives pricing
 - Portfolio review
 - Fundamental analysis[1]

Why Volatility Forecasting Matters

- Used in Value-at-Risk (VaR)
 - High volatility indicates high risk.
 - Low volatility indicates low risk.
- Volatility is one of the option Greek
- Important during financial crises (2008, COVID-19, 2020 crash)
- Volatility is very important indicator during the financial crises like 2008 market crash, COVID-19 and 2020 market crash.[2]

Traditional Models For forecasting volatility

- ARCH
- GARCH
- EGARCH, TGARCH

These traditional models captures volatility clustering but struggles with structural breaks and assumes linear structure.[3]

Deep Learning Models For Forecasting Volatility

- LSTM
- CNN-LSTM
- GRU
- Transformers
- These deep learning models predicts non-linear time patterns, but these are considered as black box because it won't give financial interpretability.[4]
 - If it predicted tomorrow will be high volatility, we won't know why it predicted as high volatility and what are the reasoning factors for high volatility.

Hybrid Models

- GARCH-LSTM
- LSTM-GARCH
- CNN-GARCH

These hybrid models perform well when compared to standalone models but limited testing under stress periods like covid-19 and also lack of systematic evolution.[5]

Research Problem Statment

- Even though traditional econometric models like GARCH accurately captures volatility clustering and LSTM model capture non-linear temporal patterns, there is inconsistence when these models are used independently. [5]
- Not included the market sentiment such as news, social media and investor sentiment which is most important to predict the volatility of the stock market.[5]

Identified Literature Gap

- Lack of market sentiment while forecasting volatility
- During high volatility period like covid-19, crash only limited evolution
- Many studies test hybrid models only on single dataset
- Few studies compare interpretability vs performance trade off
- Lack of standardised evolution metrics across papers

Research Problem

There is limited systematic evaluation of hybrid GARCH-LSTM models which includes market sentiment across multiple market conditions to determine whether they consistently outperform traditional and standalone deep learning models in volatility forecasting.[5]

Research Aim

To develop and evaluate a hybrid GARCH-LSTM model that combines market sentiment to improve financial volatility forecasting over different market regimes.

Research Objectives

- Critical analysis of context.
- Implementation of models.
 - To implement baseline econometric models (GARCH family).
 - To implement standalone LSTM-based volatility models.
 - To implement Hybrid volatility model.
- Integrate a market sentiment indicator that gives social media and news to hybrid model
- To evaluate forecasting performance using RMSE, MAE, QLIKE to analyse model interpretability and robustness and compare model performance during:
 - Normal market periods
 - High volatility periods (e.g., COVID-19)

Literature Review

- Current studies reported that hybrid models integrating econometric models such as Generalized Autoregressive Conditional Heteroskedasticity (GARCH) with deep learning models such as Long Short-Term Memory (LSTM) have shown positive findings in financial volatility forecasting. These hybrid models identify both statistical volatility patterns and nonlinear temporal dependencies in financial time series.[6]
- That said, current research provides that hybrid models GARCH-LSTM can improve volatility forecasting accuracy when compared to individual models and their efficiency has no consistency in different market conditions and sentiment-based information sources. In addition, many existing studies focus primarily on historical price data while neglecting external information sources such as market news and investor sentiment.[5][6]

Literature summary:

Therefore, a structured comparative study integrating market sentiment from financial news and social media is required to evaluate whether hybrid GARCH–LSTM models can improve volatility forecasting performance under varying market conditions.

Research Methodology

- Data Collection
 - Data source options
 - Yahoo Finance(market data)
 - Kaggle dataset(news)
 - FRED database
 - Redit(social media)
 - Data
 - Daily closing price of stock market
 - News sentiment
 - Social sentiment
 - Time span: 10 years
 - Including Covid-19(2020)

Research Methodology

- Data Preprocessing
 - Calculating log returns
 - Compute realised volatility
 - Calculate news and social sentiment score
 - Train-test split
 - Rolling window forecasting
- Models To Implement
 - GARCH(1,1)
 - LSTM
 - Hybrid GRACH-LSTM

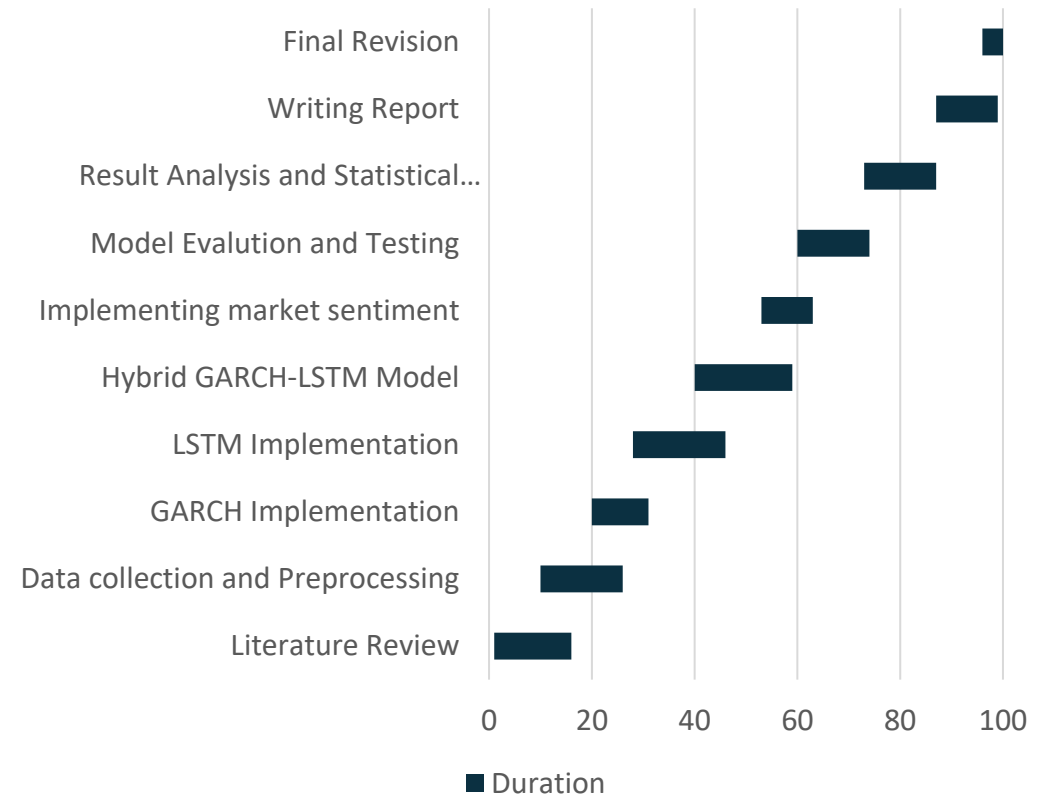
Research Methodology

- Hybrid model design
 - GARCH estimates conditional variance
 - Residuals fed into LSTM
 - LSTM captures non-linear components
- Evaluation metrics
 - RMSE
 - MAE
 - QLIKE

Project Planning And Resources

Project Planning:

Gantt Chart



Project Planning And Resources

- Resources Required
 - Software
 - Python
 - Jupyter notebook
 - Python libraries:

Task	Libraries
Data collection	yfinance, requests, praw
Data preprocessing	pandas, numpy
Volatility Model	arch, statsmodels
Deep Learning	tensorflow, keras
Sentiment Analysis	vaderSentiment / transformers
Visualization	matplotlib, seaborn
Evaluation	scikit-learn

Project Impact And Limitations

- Potential Impact
 - Improved volatility forecasting accuracy
 - Better portfolio risk management
 - Useful for hedge funds and banks
 - Academia contribution to hybrid modelling research
- Limitations
 - Model overfitting Risk
 - Limited to historical data
 - Market regime dependency
 - Computational complexity

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