Research Project Prototype
Version 1

January 26, 2025

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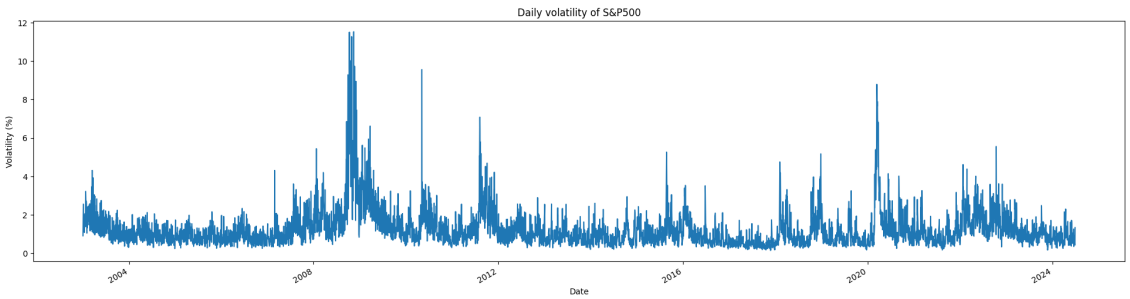
1 Introduction

One of the first and most important approaches to the Research Project is to build an initial prototype to confirm the feasibility of the project and identify potential flaws. In this report, the goal is to synthetically discuss the methodology, the results, and conclude about the first prototype to move forward with the overall project and ensure to start with strong foundations.



2 Methodology

2.1 Data

Data is a key aspect of ANN results. To ensure data quality, I went through a data preprocessing script, "dataPreprocessing.ipynb." Alongside having clean data, it is crucial to have proper features to train the models. Their importance is defined by their correlation with the target. For volatility, the price of the last traded options or market data may be very relevant. All the classified features impacting volatility can be found in the document "volatility.html." The data is downloaded within the code using yfinance, and some, like economic indicators, are downloaded manually from the FRED website.
For this prototype and to gain simplicity and time, I have used Python for data treatment and analysis. I might use R in the future, depending on the pros and cons. Below is a data dictionary of the df after data gathering and preprocessing, before being split by the ANN:

Table 1: Data Dictionary

Type	**Column**	**Data Type**	**Description**
Feature	Date	datetime64[ns]	The date of the record.
Feature	Inflation	float64	The inflation rate at the given date.
Feature	CPI	float64	Consumer Price Index (CPI) value.
Feature	Treasury_Yield	float64	Yield on 10-year Treasury bonds.
Feature	Open	float64	Opening value of the S&P500 index.
Feature	High	float64	Max S&P500 price during the day.
Feature	Low	float64	Min S&P500 price during the day.
Feature	Close	float64	Closing value of S&P500.
Feature	SP500_Adj_Close	float64	Adjusted closing value of S&P500.
Feature	Volume	int64	Volume of trades in the S&P 500 index.
Feature	GDP	float64	Gross Domestic Product value.
Feature	mortage	float64	Average mortgage rate.
Feature	unemployement	float64	Unemployment rate.
Feature	fed_fund_rate	float64	Federal funds rate.
Feature	volatility	float64	Historical volatility of the S&P500 index.
Target	volatility_forcast	float64	Forecasted volatility of the S&P 500.
Feature	returns	float64	Logarithmic returns of the S&P 500 index.
Feature	EWMA_VM	float64	Exponentially weighted moving average.
Feature	GARCH_VM	float64	GARCH volatility measure.
Feature	EGARCH_VM	float64	EGARCH volatility measure.
Feature	RogersSatchell_VM	float64	Rogers-Satchell volatility measure.
Feature	garman_klass	float64	Garman-Klass volatility measure.
Feature	parkinson	float64	Parkinson volatility measure.
Feature	yang_zhang	float64	Yang-Zhang volatility measure.

2.2 Artificial Neural Network

For this implementation, I decided to work with TensorFlow as it offers both time gain and ease of use with good performance for well-known algorithms. Starting from the same data, I tested two different algorithms. A dense-layer ANN, MLP with 4096 input parameters, and multiple layers

with batch normalization and regular dropout. And a second type of RNN, an LSTM MLP, with 1024 as the input layer and most layers as LSTM except for the last few ones, also with batch normalization and dropout.

To train both of these models, I applied an early stopping method as well as a reduced learning rate to make sure training was properly completed as the models gave their best.

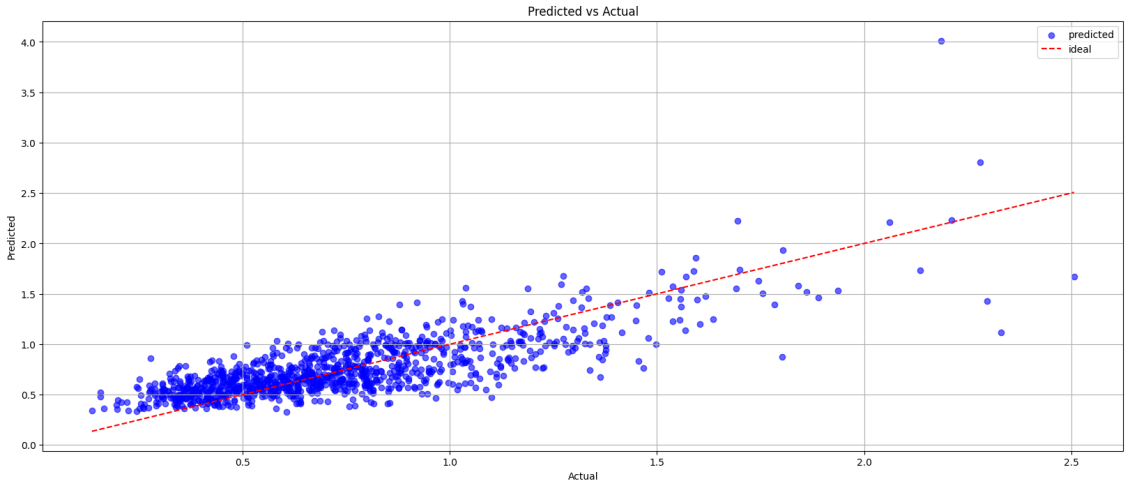
In addition, I also experimented with a Classifier ANN by labeling the days that were above 30% of the volatility average. Even though the results suggest some convergence, I do not think it's the best way to go, and I will certainly keep progressing with ANN regressor.

3 Results

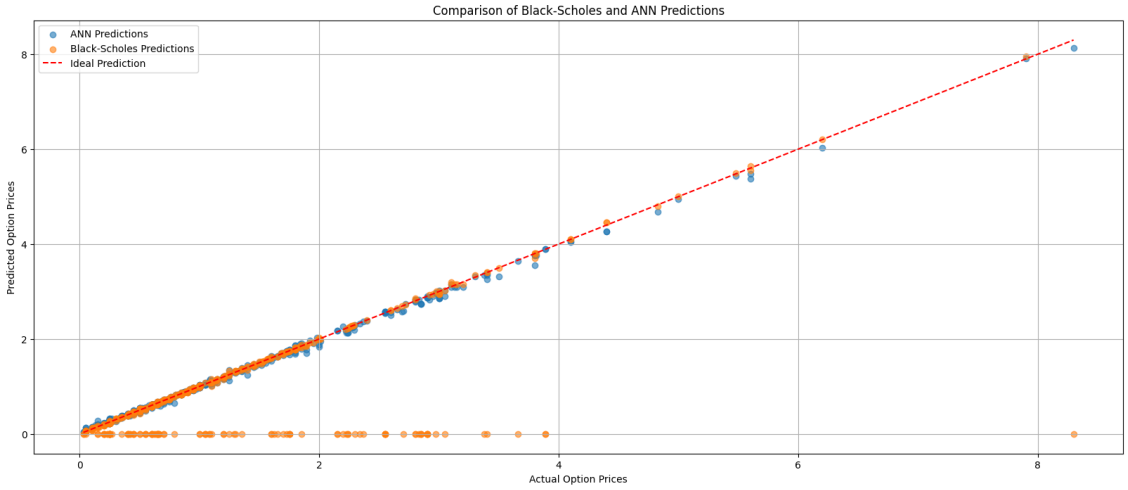
After training the models and predicting the target, results show no major differences between the MLP-only and LSTM MLP models. However, it is important to note that the MLP-only model has 4096 input parameters, while the LSTM MLP has 1024 input parameters. This is due to computational power constraints. LSTM models are heavier to train and predict, so 4096 would take hours, while both models took a little less than 2 minutes.

For both models, performances showed evidence of good regression but with challenging data and target complexity, highlighting the challenge of volatility forecasting.

Below an exemple of volatility prediction :



And the second neural network for option pricing compare to black scholes output :



4 Next Steps

As stated in the results section, regression has been challenging for the models, with room for improvement despite decent regression evidence. This project will focus on improving volatility forecasting by ANN. The next step is to tune LSTM hyperparameters to improve its performance and gain the most from its memory advantage. Data work, like outlier suppression, will also be a fundamental aspect to build models and new methods on solid ground.