Deep Learning Course Project

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Deep Learning Model for Cryptographic Algorithmic Trading

The problem statement requires a deep learning model to analyze massive cryptocurrency market data, find patterns and trends, and make informed decisions on when to buy, sell, or hold cryptocurrencies. The ultimate goal is to *maximize expected return from crypto markets' volatility, empirical risk minimization and dynamics.*
Thus, we mainly focused on stock price prediction and their technical indicators, and then we used our predicted data to decide trading strategies

Solution Strategy

Capturing Long-term Dependencies
Long-term Memory: Traditional RNNs struggle with capturing long-term dependencies due to the vanishing and exploding gradient problems. LSTM and BiLSTM architectures are designed to overcome this issue by maintaining a cell state, allowing them to remember long-term dependencies in the data.
Handling Sequential Data

Sequential Data Processing:
Cryptocurrency data, like other time series data, has a sequential nature. LSTM and BiLSTM are specifically designed to process sequences and can effectively capture patterns and trends in sequential data.

Complex Temporal Patterns Crypto markets exhibit complex temporal patterns, which can be nonlinear and non-stationary. The ability of LSTM and BiLSTM to model complex temporal relationships makes them suitable for capturing these intricate patterns.
Feature Learning

Automatic Feature Learning: LSTM and BiLSTM can automatically learn and extract relevant features from the input data, reducing the need for manual feature engineering, which can be time-consuming and may not always capture the most relevant features.
Handling Missing Data and Noise

Robustness to Missing Data and Noise: Cryptocurrency data can often be noisy and may contain missing values. LSTM and BiLSTM can handle missing data and are robust to noise, making them suitable for dealing with such imperfect data.

BiLSTM Advantage
Bidirectional Information Flow: BiLSTM processes the input sequence in both forward and backward directions, capturing past and future context. This bidirectional information flow can help in better understanding the underlying patterns and making more accurate predictions.

Motivation
In summary, LSTM and BiLSTM networks are well-suited for crypto price prediction models due to their ability to capture long-term dependencies, handle sequential data, model complex temporal patterns, automatically learn relevant features, and robustness to noise and missing data. The bidirectional nature of BiLSTM further enhances its capability by capturing both past and future context.

Dataset

Raw Data

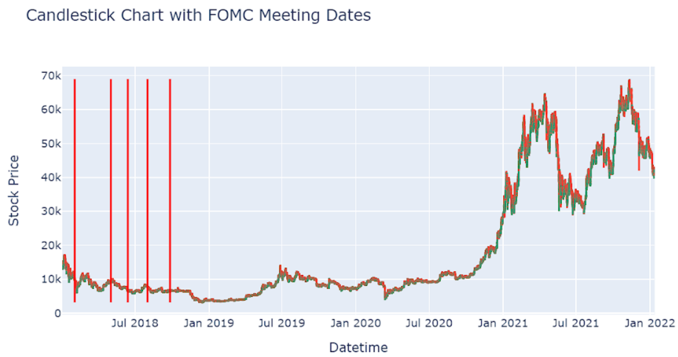
The dataset contains Bitcoin opening, closing, low and high prices over a period of 4 years at equal timestamps 1hr. The target in this case remains volume (volitality) of the asset. There are no missing entries or categorical features, a few tuples of which are shown in *table 1*.

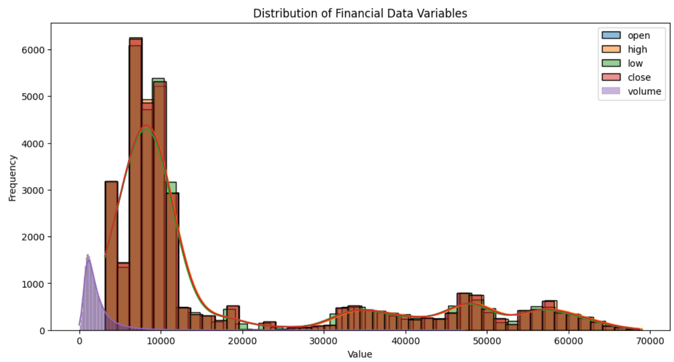
Table 1

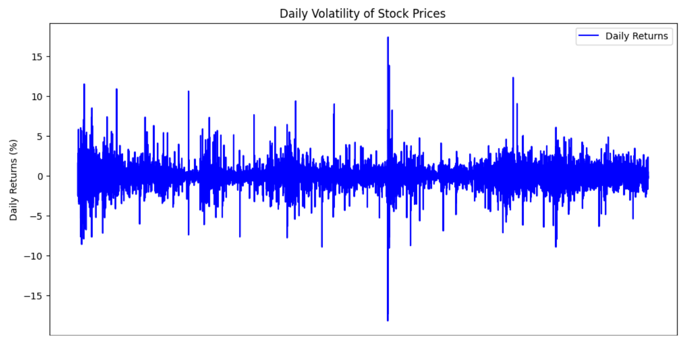
	datetime	open	high	low	close	volume
0	2018-01-01 05:30:00	13715.65	13715.65	13400.01	13529.01	443.356199
1	2018-01-01 06:30:00	13528.99	13595.89	13155.38	13203.06	383.697006
2	2018-01-01 07:30:00	13203.00	13418.43	13200.00	13330.18	429.064572
3	2018-01-01 08:30:00	13330.26	13611.27	13290.00	13410.03	420.087030
4	2018-01-01 09:30:00	13434.98	13623.29	13322.15	13601.01	340.807329
...	...	...	...	...	...	...
35203	2022-01-12 01:30:00	42972.04	43095.26	42692.19	42800.38	1219.601780
35204	2022-01-12 02:30:00	42797.62	42823.69	42643.74	42659.20	702.103800
35205	2022-01-12 03:30:00	42664.71	42776.14	42597.41	42713.13	561.859930
35206	2022-01-12 04:30:00	42713.12	42886.28	42633.97	42729.29	681.142010
35207	2022-01-12 05:30:00	42729.29	42965.00	42578.02	42675.00	1004.906890

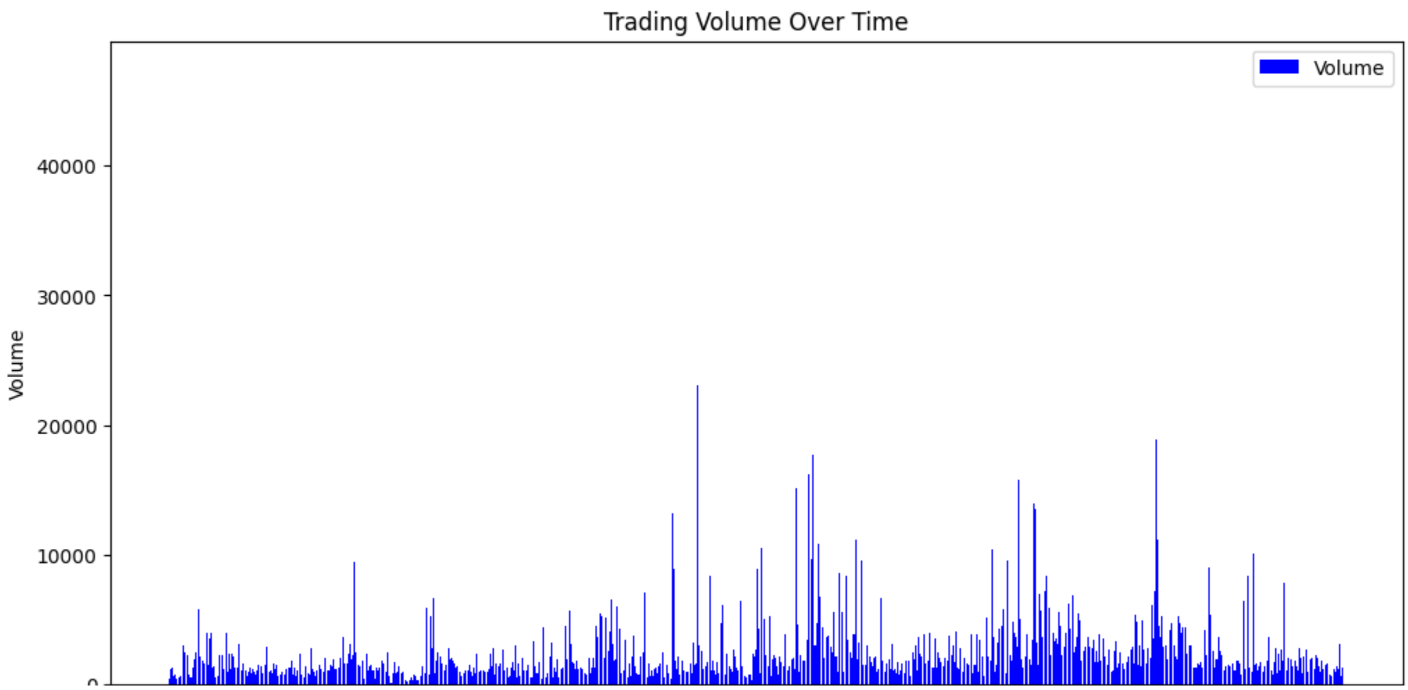
Data Visualisation


Closing Prices with Moving Average
Closing Price
30-day Moving Average
Closing Price
70000
60000
50000
40000
30000
20000
10000
0


Candlestick Chart with FOMC Meeting Dates
Stock Price
70k
60k
50k
40k
30k
20k
10k
0
Jul 2018
Jan 2019
Jul 2019
Jan 2020
Jul 2020
Jan 2021
Jul 2021
Jan 2022
Datetime


Distribution of Financial Data Variables
open
high
low
close
volume
Frequency
6000
5000
4000
3000
2000
1000
0
0
10000
20000
30000
40000
50000
60000
70000
Value


Daily Volatility of Stock Prices
Daily Returns
Daily Returns (%)
15
10
5
0
−5
−10
−15


Trading Volume Over Time
Volume
Volume
40000
30000
20000
10000
0

Major Innovations (Architecture)

Feature Engineering

We introduced more relevant features by computing various techincal indicators such as:

- **RSI (Relative Strength Index)**: Measures the speed and change of price movements, indicating overbought or oversold conditions in a market. Values above 70 suggest overbought, below 30 suggest oversold.
- **EMA (Exponential Moving Average)**: A type of moving average that gives more weight to recent prices, reacting faster to price changes compared to a simple moving average (SMA).
- **EMWA (Exponential Moving Weighted Average)**: Similar to EMA, but gives more weight to recent data points, making it even more responsive to price changes.
- **EMAF (Exponential Moving Average Ribbon)**: Uses multiple EMAs of different periods to show trend strength and potential reversal points, displayed as a ribbon on the price chart.
- **Bollinger Bands**: Consists of a middle band (SMA) with upper and lower bands that are standard deviations away from the middle band. They show volatility and potential reversal points when prices move outside the bands.

Few tuples of engineered dataset are shown in table 2

Table 2

open	high	low	close	volume	RSI	EMAF	EMAM	EMAS	Target
16564.00	16683.44	16400.00	16417.05	721.569884	44.224762	16674.0106	15686.961719	14963.62540	328.99
16418.00	16749.98	16409.71	16746.99	577.845180	53.801147	16680.9610	15707.952378	14987.24612	−27.98
16747.00	16886.75	16695.66	16719.02	640.796589	52.975010	16684.5857	15727.973519	15010.18352	−28.95
16719.01	16800.00	16579.33	16690.06	443.503664	52.087721	16685.1070	15747.024736	15032.43354	48.94
16690.06	16814.72	16633.16	16739.00	215.643791	53.497966	16690.2397	15766.667811	15055.03707	−131.99

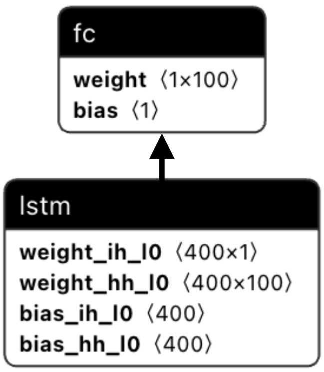


Fig 1

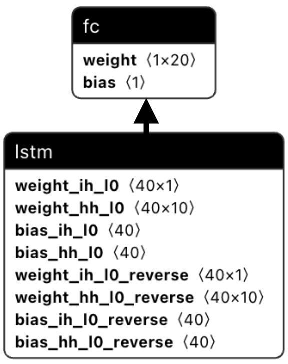


Fig 2

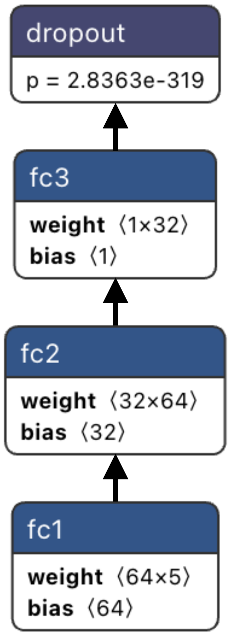


Fig 3

Model Architectures

Simple LSTM

The model archiecture is shown in Fig1. It uses MSE loss for training, optimizer beign ADAM, learning rate being 0.001, trained for 500 epochs. Hidden size for LSTM layer is 100, input size being 10, number of layers being 2.

Bidirectional LSTM

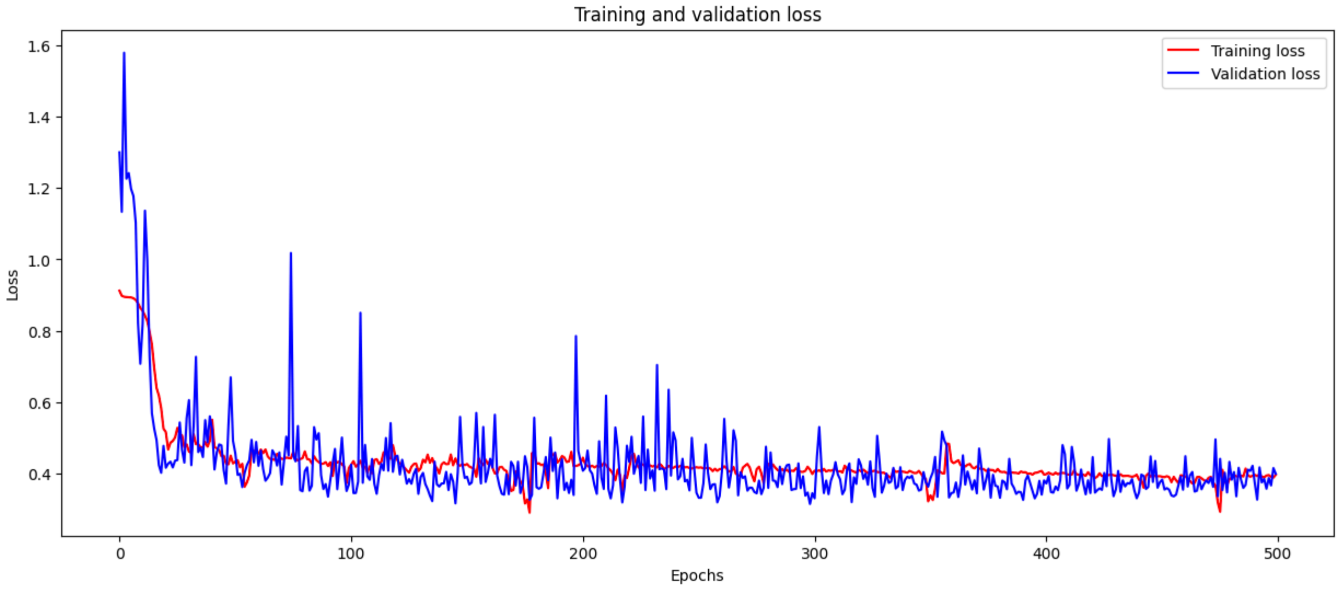
The model archiecture is shown in Fig2. It uses MSE loss for training, optimizer beign ADAM, learning rate being 0.001, trained for 500 epochs. Hidden size being 100, input size = 10, num_layers = 2

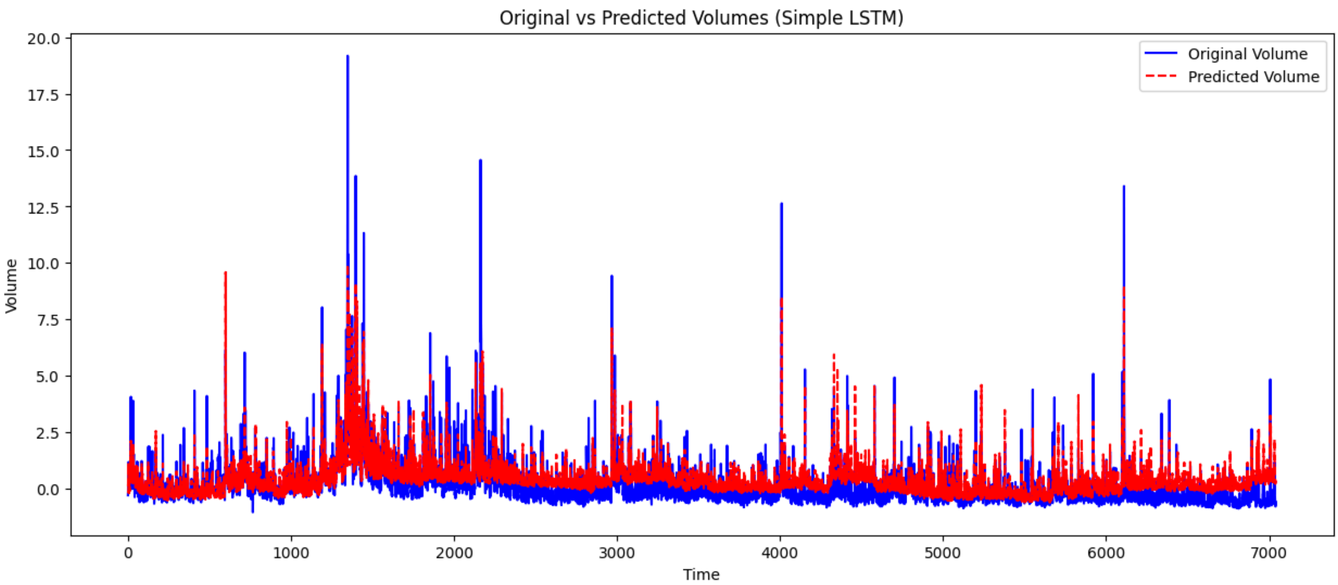
Custom Made volume predictor architecutre

The model archiecture is shown in Fig3. It uses MSE loss for training, optimizer beign ADAM, learning rate being 0.001, trained for 1000 epochs. It consists two hidden layers, hidden size 1 being 64, hidden size 2 being 32, input size 100. Last fully connected has a dropout applied to it.

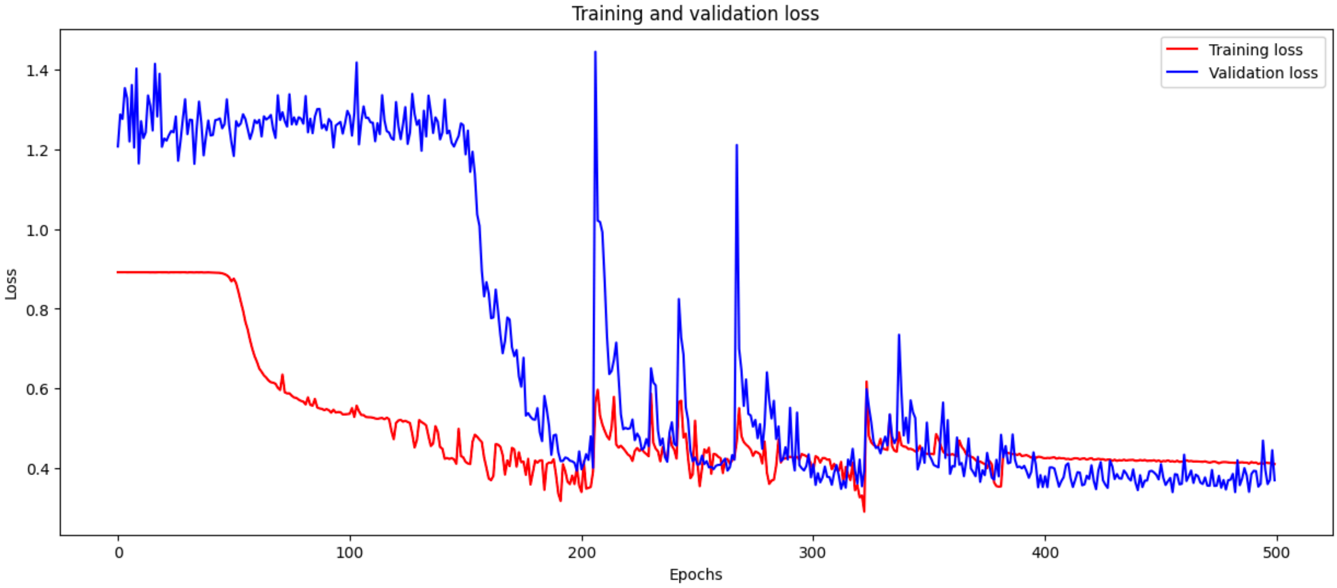
Results

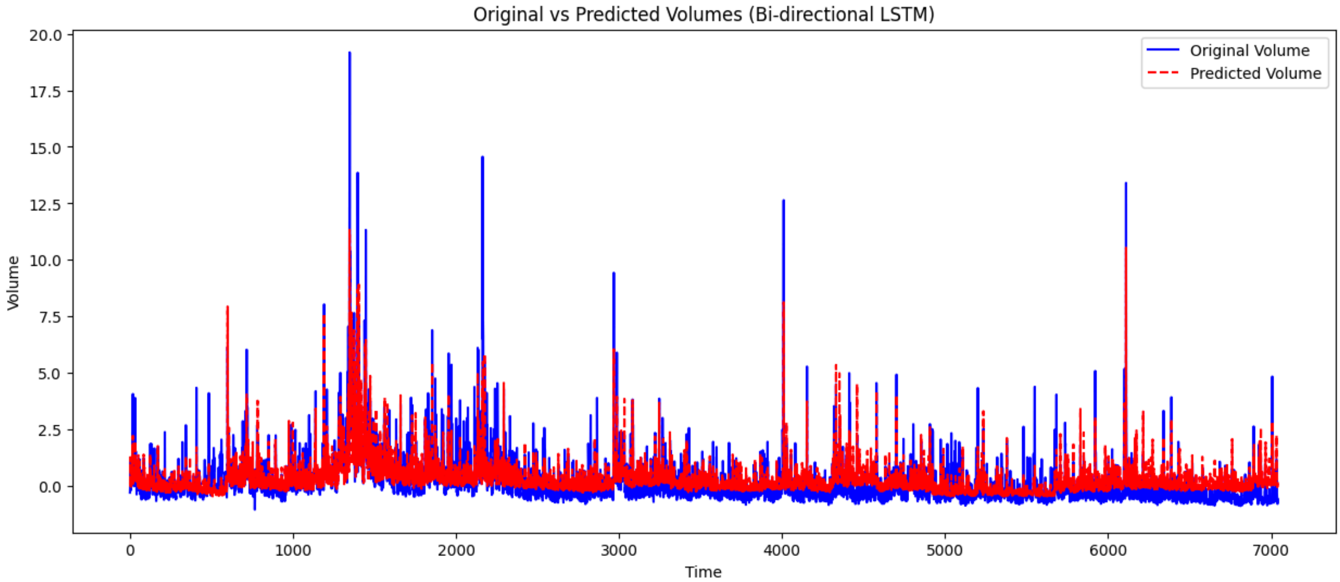
Simple LSTM



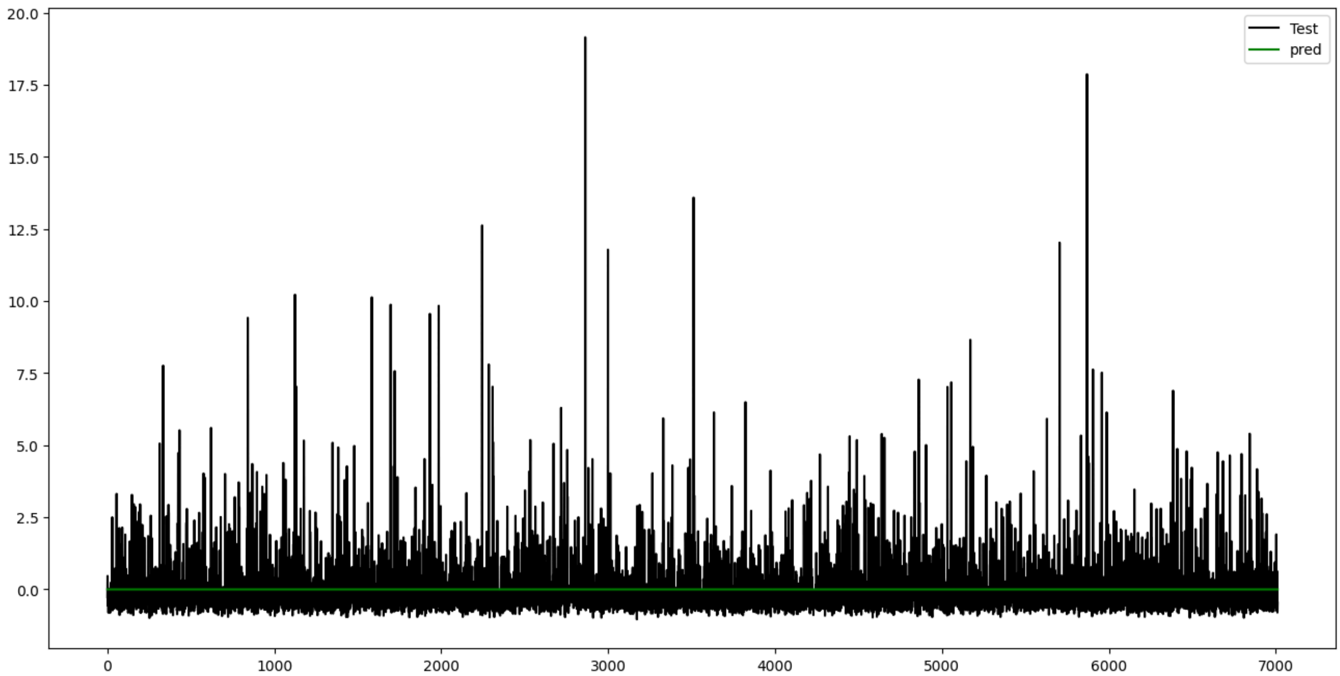


Bidirectional LSTM





Custom Volume Predictor



Analysis & Scope of Improvement

We obtained the following training and validation losses for our models:

Model	Training Loss	Validation Loss
Simple LSTM	0.3973	0.4001
BiLSTM	0.4106	0.3698
Custom Volume Predictor	0.967	1.1453

The model fails to predict the volume volitality when the closing prices highly undershoot or overshoot, since this makes a case of anomaly. This occurs in exceptional circumstances such as arbitrages opportunities, or global market events or value disruption of underlying assets.

Scope of Improvement* -** However a solution proposed to the above problem is ***sentiment analysis which takes news headlines and works as a natural language processing utility to help detect these anomalies and predict the volume / volatility accordingly.
We tried adding this feature using the dataset shown in table 3, but to utter disappointment couldn't produce satisfactory results. These could be further improved with enhanced hyperparameters, language tokenization and model architecutre experimentation.

Table 3

Label	Top1	Top2	Top3	Top4	Top5	Top6	Top7
2000-01-03	0	A 'hindrance to operations': extracts from the...	Scorecard	Hughes' instant hit buoys Blues	Jack gets his skates on at ice-cold Alex	Chaos as Maracana builds up for United	Depleted Leicester prevail as Elliott spoils E...
2000-01-04	0	Scorecard	The best lake scene	Leader: German sleaze inquiry	Cheerio, boyo	The main recommendations	Has Cubie killed fees?
2000-01-05	0	Coventry caught on counter by Flo	United's rivals on the road to Rio	Thatcher issues defence before trial by video	Police help Smith lay down the law at Everton	Tale of Trautmann bears two more retellings	England on the rack
2000-01-06	1	Pilgrim knows how to progress	Thatcher facing ban	McIlroy calls for Irish fighting spirit	Leicester bin stadium blueprint	United braced for Mexican wave	Auntie back in fashion, even if the dress look...
2000-01-07	1	Hitches and Horlocks	Beckham off but United survive	Breast cancer screening	Alan Parker	Guardian readers: are you all whingers?	Hollywood Beyond

Conclusion

Given the results of our sequence models like LSTM and its variations, further enhanced with more experimentation and fine-tuning, coupled with improvement features like sentiment analysis for anomaly detection give satisfactory performance in predicting the underlying assets price alongwith buy-sell actions and hence help in financial markets in maximizing expected returns while minimizing the empirical risks.

Anomaly detection is crucial in financial markets, where unexpected events can lead to significant price fluctuations. LSTM models, when augmented with sentiment analysis, become adept at identifying these anomalies. Whether it's a sudden surge in positive sentiment followed by a price jump or a negative sentiment trend signaling a potential downturn, these models can flag such events, alerting investors to take appropriate actions. The combined power of LSTM models, fine-tuning, and sentiment analysis offers a comprehensive approach to financial market analysis. Investors and traders can leverage these tools to make informed decisions on when to buy, sell, or hold assets.

By maximizing expected returns, they aim to achieve greater profitability while minimizing empirical risks. Moreover, the application of these models is not limited to individual asset prediction. Portfolio optimization, risk management, and even algorithmic trading strategies benefit from these advanced techniques. A portfolio manager, for instance, can use LSTM-based models to optimize asset allocations based on predicted returns and risks, thereby improving the overall performance of the portfolio.

Contributions

- ***Vansh*** **- Algorithmic trading domain knowledge & Model Architecture**
- **Ashudeep - Algorithmic trading domain knowledge & Model Architecture**
- **Saman - Semantic Analysis & Dataset preparation**
- **Vishal - Semantic Analysis & Dataset preparation**

References

- Class slides
- https://arxiv.org/pdf/1707.03746.pdf
- https://arxiv.org/pdf/1506.01513.pdf
- https://arxiv.org/ftp/arxiv/papers/2105/2105.06827.pdf

Google Colab Links

- Custom Volume Predictor
- LSTM & BiLSTM
- Sentiment Analysis
- GitHub link