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# Abstract

This report covers the entire production cycle for two reasonably complex AI models representative of some of the major areas of past, current and even potential future research in this domain; random forest and “xLSTM-TS” (a unique variant of “Long Short Term Memory”), by following two case studies (with an emphasis on the later) as blueprints for developing and applying a practical understanding of the general practices commonly used, the theory and mathematics that underpin how these models function and future recommendations for both further study and areas of weakness in the report to more effectively evaluate its aim and outcomes.

The case studies were focused on exploring the effectiveness of different techniques on creating effective time series forecasting in financial markets. While this report narrows that focus more specifically to the potential time series models have in trend prediction/forecasting for high volatility markets. Bitcoin-US dollar price paring (BTC-USD) was selected due to domain familiarity, with a variety of loosely correlated feature sets and selection methods. The evaluations of these approaches attempted to cast a wide net, detailing practical considerations and key areas essential for the models performance.

As AI models mature in sophistication, increasing in the utility and the potential they provide to financial forecasting. The importance something conclusion.

# Introduction

In this report we will be detailing the design and development process of two fairly complex AI models commonly used in time series forecasting, for the express purpose of understanding recent and past developments in the research in this area. Two case studies will be used and referenced throughout (Gil et al., 2024) (Tyralis & Papacharalampous, 2017), replicating (where applicable) their designs and implementations of specific aspects of AI model design. This will ideally provide a practical understanding of the theories and best practices of developing, training and evaluating machine learning algorithms.

While the case studies themselves are invaluable resources deviations from their methods where deemed appropriate will be taken. Since the other main goal is to evaluate how practical a machine learning model at this scale, would be for financial time series forecasting for trend analysis in volatile markets such as Bitcoin.

# Problem statement

“Retail” trading (non-professional trading) is generally seen as a risk, especially when considering unregulated and highly volatile markets such as crypto-currencies. Conversely, if it is indeed possible to ascertain some kind of “edge” (Farley, 2024) in such a market, that volatility would be more of an advantage than a risk (Assuming the risk/reward ratio is positive and accurate).

There are a number of different strategies traders may use to attempt to game the markets or develop an edge all of which is out of scope. For the purposes of this report the real world use to consider would be “trend trading” (Gishen, 2024), knowing the odds on changes especially in highly volatile market prices structures is highly valuable.

Using the daily historical price data for Bitcoin (BTC) (acquired from yahoo finance) for the last ten years, in isolation might not likely be enough to provide sufficient useable data for analysis. So additional features will need to be acquired, the decision was made to stick to real world data.

While the case studies and other similar research tended to lean towards using more technical analysis approaches to additional features. These “indicators” are fundamentally derived from the same source (that being, the historical price action, such as moving averages). It was deemed more interesting and prudent to attempt to examine other less directly related features for inclusion, the specifics of which were ascertained through domain familiarity or “expertise”.

# Aims and objectives

Aims:

Use two case studies as a blueprint to build, test, adapt and evaluate their methods and approaches in using complex ML models in time series forecasting for BTC price trends.

Objectives:

* Produce two working and trained models, adapted where appropriate from existing examples of successful research.
* Collect, clean, process and examine a variety of relevant features and compile a suitable dataset.
* Use a number of methods for feature selection, for evaluation and comparison. As well as a single feature dataset as a control.
* Demonstrate a clear work flow and process for the development pipeline, identifying the general best practices and common techniques.
* Data visualizations for most if not all of the data collected over the entire process, and use it to inform production.
* Comprehensive evaluation, comparison and assessment of the value these approaches have to the problem statement.
* Recommendations on future improvements, and reflections on the reports outcomes.

# AI approach

We will do

Model selection:

1. Extended Long Short-Term Memory for Time Series (xLSTM-TS), case study: (Gil et al., 2024)
2. Random forest, case study: (Tyralis & Papacharalampous, 2017)

Dataset = yahoo finance, block.api, :

17 feature sets

Normalized & de-noised.

3 feature selection methods:

Random forest – case study

xLSTM-TS – case study

justification:

(PlanB, 2029)

# Libraries, dependencies and dataset

adfhadh

# Exploratory data analysis

adfhadfh

# Data cleaning

agadfgadg

# Data visualization

adfhgadg

# Data pre-processing

agasg

# Feature selection

asdgasg

# Model select

Asdgasg

Learning models

Asdgasg

List of different models

Asdgasg

Advanced models we're looking at

asdgasg

# Model evaluations

Asdgasg

Feature selection comparison

Asdg

Hyper Parameter tuning comparison

sadfgasfg

# Summery

asasfd

# Conclusion

asdfasf

# Recommendations

asfasf

# Future considerations

This section presents the results for directional movement prediction metrics, focusing on Train Accuracy, Validation Accuracy, Test Accuracy, Precision (Rise), Precision (Fall), and F1 Score." (Gil et al., 2024)

# References

asdfasf

# Appendix

The directional loss function is instead designed with the aim of, naturally adding directionality to the loss function while also reducing the importance of numerical accuracy as the trends in forecasting financial data are much more relevant and important than the specific prediction values of price. (Gil et al., 2024)

(Anthropic, 2024)

(PlanB, 2029)

(Gil et al., 2024)

(Tyralis & Papacharalampous, 2017)

(Kursa & Rudnicki, 2010)

(Pabuccu & Barbu, 2023)

(Peng et al., 2021)

(Chen et al., 2024)