Using **MATLAB** to Generate **Cryptocurrency Trading Insights** Based on the **Fear and Greed Index**

Student Name: Lorcan Gourley

Registration No.: B00808863

Module Code: EEE516

Course Title: BEng Hons Mechatronic Engineering

Supervisor: Dr Mark Ng

School of Engineering

Faculty of Computing and Engineering

Student Support
ulster.ac.uk/studentsupport

FOR THE ATTENTION OF THE MARKER

This coursework/examination script has been written by a student with a **Specific Learning Difficulty**. Please mark with sympathetic consideration for errors of spelling and grammar.

Acknowledgements

I would like to thank Dr Mark Ng for taking on my project and for providing me with his continued support and guidance throughout the duration of this project.

I would like to thank the following people for support, assistance and feedback which helped me complete this project, Mr Jamie Thompson, Mr Edward Gourley, Mr Martin Gourley and my girlfriend Mabel Thompson. I am extremely grateful for your continued enthusiasm in my work and interests which gave me the energy to push the boundaries of what I thought I could accomplish.

Abstract

Machine Learning is one of the biggest advancements of the 21st century, having had a huge impact especially within the financial market. It has led to significant capabilities in not only accurately predicting market movements but also at discovering underlying trends, which traditional techniques with technical analysis would overlook.

With the ever-growing realm of Cryptocurrency and its use for investing, along with the infamous nature of losses incurred by those who have mistepped when trying to navigate the complex market. It is crucial that the tools available are utilised to engineer an advanced algorithm that can navigate the industry's market and mitigate these huge losses.

This thesis uses MATLAB's predictive capabilities to simulate trading using the Fear and Greed Index (FGI) as an indicator for triggering decision-making signals. The FGI is a sentiment indicator which displays the overall 'mood' of a market and when utilised properly can serve as a significant factor in predicting market trends. The aim is to further understand the correlation between the FGI and Cryptocurrency Markets to create reliable ML models which can be acted upon.

To ensure this project produces reliable results which can further the understanding we have between the FGI and Cryptocurrency prices, relevant data will be collected and useful features will be generated. These features and the FGI will then be divided into specific ranges which represent the different overall 'moods' of the Cryptocurrency markets. Using these concentrated models, predictions will be made to generate buy or sell signals which can be acted upon by participants within the market.

The result of this research accurately displays a unique correlation between price changes in BTC and DOGE and the specific FGI ranges and challenges an already established viewpoint that the FGI and Cryptocurrency prices follow a 'U' shaped correlation with the least accurate results found at a neutral mood level.

Contents

List of Figures

Nomenclature

AI	Artificial Intelligence
BTC	Bitcoin
DOGE	Dogecoin
FGI	Fear and Greed Index
FOMO	Fear of Missing Out
GPR	Gaussian Process Regression
LR	Logistic Regression
MA	Moving Average
ML	Machine Learning
MLP	Multilayer Perceptron
NN	Neural Network
STD DEV	Standard Deviation
SVM	Support Vector Machines
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network

1.0 Introduction

1.1 Motivation

The dynamic landscape of the ever-growing Cryptocurrency market has caused vast fortunes to be made but also a magnitude of losses to accumulate[1]. This has created a demand for advanced and unique Machine Learning algorithms which investors can add to their arsenal of Data Analysis tools to further their understanding of a dynamic market.

Traditional technical Analysis techniques applied to specific Cryptocurrencies is one of the main tools which traders use in order to create an insight into whether to buy and sell. However, by quantifying Market sentiment investors are able to pick up on unique trends which haven't previously been acted upon. The FGI is a widely recognised sentiment indicator and incorporating it's data into a predictive model gives traders a market advantage.

Furthermore, MATLAB has toolboxes equipped with the necessary equipment for data analysis and Machine Learning development and combining these computational abilities with sentiment analysis techniques, this research seeks to further the understanding between the FGI and Cryptocurrency price changes (need to add some more oomph).

Ultimately, the results found within this project have the ability to inform trading decisions and contribute to the understanding of sentiment indicators in understanding financial market wide price changes among Cryptocurrencies.

1.2 Problem Statement

The FGI has is known for having a correlation which represents a 'U' shape curve which shows higher levels of correlation between extreme levels of Fear and Greed. Therefore, to create a robust trading model to create accurate insights the increments within the FGI need to be studied further. This can be completed by dividing the FGI into appropriate ranges and studying these increments individually by training a Machine Learning model with the specific data which correlates to these specific market 'moods'.

1,3 Aims and Objectives

It is essential to outline the overall goals of this project in order to create a reliable and robust model which will provide accurate forecasts which can be acted upon with confidence.

1. Data Acquisition and Feature Generation
   The objective of creating any trading indicator is ensuring that it is reliable and to ensure this the model must be built off accurate and necessary data in order to ensure the ML model is able to accurately adapt to any changes within the environment it is acting within, such as sudden media influence or economic changes.
2. Creating accurate ML models
   Testing a variety of ML models with various feature selection and selecting the models with the lowest RMSE on average across all tested Cryptocurrencies will ensure that the model is able to perform well within the market.
3. Finding Unique Incremental FGI Trends
   Finding unique trends which represent a more accurate representation of a market when in an environment of extreme fear, fear, neutral, greed, extreme greed will ensure that the model can make accurate predictions based on every situation.
4. Generating Buy and Sell Signals
   The aim of this research is to use the incremental relationships built on the data acquired to trigger buy and sell signals which can be acted upon which are accurate and can be applied across a wide range of Cryptocurrencies.

These objectives will ensure the signals generated are accurate and the models built are versatile and can be applied to any situation within the Cryptocurrency market environment.

2.0 Literature Review

2.1 Importance

Literature reviews are important to include when completing a project as research that has already been carried out within the topic is the foundational base for which to base one's own project from. By reviewing existing academic papers, it highlights differing approaches taken, any known problems encountered and contrasting viewpoints otherwise missed. In the modern day, with how important digital assets have become such as cryptocurrency, there is plenty of research and articles done which explore in great depth this area of the industry. This research however lacks in specifics when it comes to my particular interest as the Fear and Greed Index is a recent development as a sentiment indicator. The gap in knowledge presented allows me the opportunity to probe further into this specialisation. My project will explore the underutilised relationship between this tool and traders, expanding the usage of a sentiment indicator to assist traders by finding another market and trends to add to the indicators.

To ensure that I have grasped a basis in which I can base my own project on is crucial, so understanding and analysing the methodology which others have employed is the first task to undertake. By doing so, this allows me to not only identify approaches used but the errors and miscalculations made by other academics so that I can ensure that my research does not share the same or similar pitfalls. This creates a strong backbone for the base of my project to rest on, creating a unique and stable model that can be used on a larger scale.

2.2 Predictive Capabilities

It was important to ensure that it was indeed possible to quantify human behaviour for the use of predicting future price changes, therefore an aspect of the literature I focussed on was the use of trend analysis when making market predictions within Cryptocurrencies and stocks.

This question seems to be under a lot of scrutiny and hosts an abundance of controversial opinions, however, this factor accentuates its importance and warrants the need for closer examination, especially as this limitation is one which I face within my own project. Henceforth, I need to know if this gap in research is one which I am able to fill and how I can carry this out. Some sources, such as research carried out by Andrew W Lo, exhibit an extreme disregard and outright dismiss the possibility, stating that changes within a market will be made at random due to participants having their own unique perceptions and expectations and making it near impossible to quantify. Andrew W Lo stated the idea that everyone within a market is driven by profitable opportunities and that a large quantity of investors will act on any informational advantage and in doing so eliminate all profitable opportunities which first motivated their actions[2]. This key piece of information is one which I considered before beginning my project, as I believe there is truth in the opinions held, and if my predictive model doesn't have a unique enough prospective and data influence and can't act on trends with more accuracy than previously created models or find trends which other models can't, then there will be no opportunities for profit to be made before these opportunities are eliminated.

However, this is challenged by Karsten Schierholtz and Cihan H. Dagli, whose study considers separating actions to try classify trends among these categories; buying, selling, and holding[3]. This paper is important to my research as it shows trends in classifying these actions in favour of future price prediction among a portfolio. A second research paper carried out by [4]Vignesh CK demonstrates the ability to also classify actions and apply these to the closing values of Cryptocurrencies to find correlations. A limitation this research paper faces however, due to the nature of the data available, is the inability to act on trends which occur during the day which can lead to incorrect results or missing out on pivotal price changes.

2.3 Fear and Greed Index

Another aspect of the literature review was to determine which indicator(s) I wanted to use as a feature to train my Machine Learning models to further the knowledge available in the field of AI and Cryptocurrency prediction. The research papers previously mentioned[3,4] focussed on combining multiple indicators to generate a trading signal, in contrast to my project, which I aim to solely focus on the Fear and Greed Index, a measure of market sentiment, as my sole parameter[12]. I chose this indicator as I wanted to focus on furthering the understanding of sentiment indicators rather than traditional analysis techniques as non-sentiment technical analysis techniques are generated through pattern recognition and if this same approach is followed, there will be no unique benefit created[2].

A proven correlation between the FGI and profits has been researched and my project aims to further the understanding there is of this relationship. The FGI takes human behaviour into consideration, which factor is usually overlooked even though this feature is important to take into account as a mass number of investors in a good or bad mood has been proven to alter prices within stocks. An example of this significance is a research paper carried out by Raúl Gómez Martínez, María Luisa Medrano García and Camilo Prado Román states that stock returns are significantly lower in market season around full moon and higher returns are expected around new moon. This study however did find some limitations within the FGI as it proved that markets were more predictable at extreme levels of fear and greed and only had a year of data to work with[5]. The Fear and Greed Index is an indicator which is more commonly used alongside other indicators and as the previous research notes that the future of this indicator is reliant on further research. My project aims to bridge this gap by providing a unique perspective when comparing the FGI to price changes and study trends between these variables to provide useful insights.

2.4 General Framework

The use of Artificial Intelligence for the application of price prediction is a heavily researched area and there are a multitude of various approaches which have been taken to create the most accurate and robust models. A general framework used for predictive modelling using Artificial Intelligence and applied to financial forecasting is shown in figure 2.1[6]. This general framework outlines the steps which have to be followed to create an accurate predictive model.

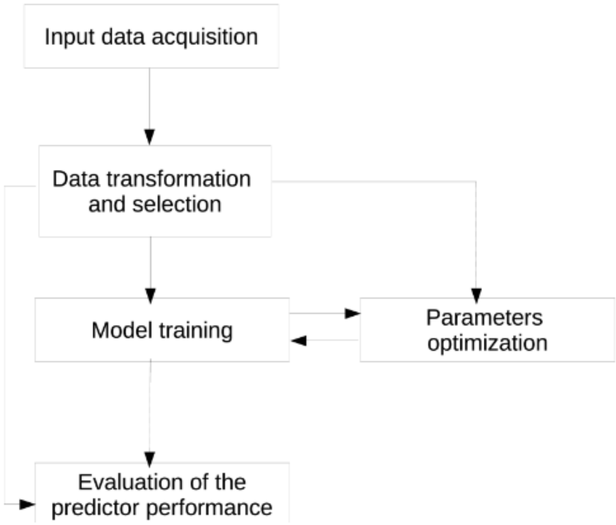


Figure 2. 1 - Flowchart for financial forecasting with AI model prediction.

2.5 Data: Input, Transformation, Selection

This section of my literature review focuses on reviewing data in terms of acquisition, transformation and selection. The first step is to acquire the necessary input data, as previously mentioned my project aims to find a correlation between Cryptocurrency price changes and the FGI. One approach which has been taken to study this correlation is to directly study how Cryptocurrency prices respond to the FGI directly, this was researched by Qichuan Huang[7]. The relationship between these two quantities was found to be 0.24, which doesn't represent a strong correlation, however, a cluster point was found around three value lines, which is speculated to have been caused by the extreme changes of BTC prices. This study therefore found a strong relationship between BTC price changes and the FGI when excluding months which involved huge fluctuations of BTC price changes.

A paper completed by Mehar Vijha, Deeksha Chandolab, Vinay Anand Tikkiwalb and Arun Kumarc, used 7 selected features to train their ML model[10]. Using the variables accumulated online; high, low, close, open, adjusted close, volume the following calculations were computed:

1. Stock High minus Low price (High price - Low price)
2. Stock Close minus Open price (Open price - Closing price)
3. Stock price's seven days' moving average (7 DAYS MA)
4. Stock price's fourteen days' moving average (14 DAYS MA)
5. Stock price's twenty-one days' moving average (21 DAYS MA)
6. Stock price's standard deviation for the past seven days (7 DAYS STD DEV)

These 6 features and the stock volume where then used to train their model. The research paper returned accurate results and although focuses on stock prices and differs from my research on Cryptocurrencies, still provides a useful insight due to shining light on how they have dealt with using the variables they are able to extract and create useful data which will be used to train their ML models. Although the research found a way to deal with the limited variables available, this should also be noted as a limitation to the model, as access to a complete data set will increase the accuracy of the predicted output due to having more training points and access to find more correlation and trends.

2.6 Machine Learning Models

This section of my Methodology focuses on all the Machine Learning Methods which can be applied to the Cryptocurrency market, such as methods of price prediction or reviewing models which have been applied to the Fear and Greed Index. Reviewing this literature will give me an insight into different methods applied and how I can avoid similar issues I may encounter regarding ML model training and testing.

Research carried out by Helder Sebastião and Pedro Godinho, trained a range of ML models to generate buy and sell signals by predicting future Cryptocurrency prices. The models included within this study included, Linear, Random Forests, and Support Vector Machines[11]. This research paper is beneficial for my project as it was able to successfully implement different ML models to analyse data sets and generate trading signals. This research studied the data as a complete set ranging a timespan of the mid-2017 and the bear market situation afterwards. My project also aims to follow this structure and study all available data including periods of uncertainty within the Cryptocurrency market as I aim to try quantify the human behaviour during all time periods to try find underlying trends within the Cryptocurrency market, which some research excludes to try improve the performance of the models which they are training[3]. However, a limitation was found within the completed project as no ML model was deemed to be more superior over the rest and therefore a trading strategy was implemented of generating a buy or sell signal when 4 or more indicators agreed on whether there was to be a rise or fall in price, this is due to not having a singular model which is consistent enough in predicting future values accurately. This limiting factor shows a discrepancy between all of the ML models and reduces the accuracy of each stand-alone model.

Another method which has been utilised for predictive modelling is Neural Network Classification, a 2020 research paper by Rahmat Albariqi and Edi Winarko[9] uses Neural Networks to predict Bitcoin price movements in the short and long term. This paper compares two different Neural Network methods, which were, Multilayer Perceptron and Recurrent Neural Networks. This paper not only portrayed the differences between two different NN models but also the difference between long term and short-term Bitcoin price predictions. The study concluded that MLP performed better than RNN in both terms and the long-term predictions for both models performed better than the short-term predictions. This conclusion provides a very useful insight into Bitcoin price changes and shows that short term price predictions may be unreliable compared to long term gains. This research does have some limitations to consider, such as not providing comparisons against other ML algorithms and will need to be reviewed against other research papers and personal trial and error to find the model which will provide the most accurate results. This study, although including a sentiment indicator, fails to acknowledge the significance of the FGI and doesn't provide a relationship which I can review and study further.

Research carried out by Patrick Jaquart, Sven Kopke, and Christof Weinhardt tested and compared different types of predictive models, including recurrent neural networks, convolutional neural networks, tree-based ensemble methods, and the logistic regression (LR). This research concluded that as portfolio size decreased the accuracy across all models increased in the short-term, and that investor behaviour may be easier to predict during market downturn due to increased herding behaviour[13]. A limitation to this research however is the lack of input data to train the models, as the data used was only based on Cryptocurrency closing prices and fails to acknowledge other important variables such as highs and lows within Cryptocurrency price fluctuations or the volume or using any sentiment indicators to train the model on external forces which could affect the market. This lack of variables can lead to less accurate ML models due to a lack of training data.

2.7 FGI 'U' Shape Correlation – Bridge the Gap

Research completed by Jying-Nan Wang, Hung-Chun Liu, Yuan-Teng Hsu found a correlation between the FGI and price synchronicity which demonstrated a 'U' shaped relationship[8]. This paper concluded that at more extreme levels of Fear and Greed there was a higher synchronicity of price movements and at more neutral levels the correlation was reduced. A limitation of the approach taken in this paper was the failed acknowledgement of taking a different approach to find a correlation at more neutral levels and would be more useful if this approach had been considered. My project aims to build upon this research by dividing the FGI into individual increments correlating to levels of extreme fear, fear, neutral, greed and extreme greed and aims to find a unique correlation relating to the synchronicity of Cryptocurrency price changes and the specific increments.

A research paper carried out by Brahim Gaies, Mohamed Sahbi Nakhli, Jean-Michel Sahut, and Denis Schweizer aims to research the interactions between the Fear and Greed Index and Bitcoin prices. This research paper found a negative correlation between the FGI and BTC prices as even when BTC prices were lowering and you could expect the sentiment to be displaying 'fear' like behaviour, due to optimistic investors anticipating an inflection point as prices fall the sentiment indicator could still present a ‘greed’ value. A noteworthy point stated is that during the Covid-19 pandemic a positive bi-directional link between FGI and BTC existed, which is speculated due to the lowering of value of standard currencies and assets during this time period pushing investors into BTC investing. However, this study lacks the inclusion of comparing how other Cryptocurrencies reacted during this time period, as although BTC is a highly volatile and unpredictable Cryptocurrency, it is still highly established and not as volatile and as easily influenced by external forces as Cryptocurrencies of lower value.

3.0 Methodology

3.1 Importance

To adequately approach my project research, comparative qualitative research is quintessential to gaining an in-depth understanding of external factors can influence and impact the quality of my model. A second important aspect is the gathering and analysing of non-numerical data to ensure that no factors are missed, as this project is data heavy, it is important to widen the scope to ensure the data's reliability. The other form of research that is vital to my project is quantitative research, which consists of all the numerical data from my own model but also the data from the methods I explore to gain a basis of knowledge.

To create reliable models which can be used to accurately and consistently predict Cryptocurrency price changes through analysing increments of the Fear and Greed Index a process had to be followed. The steps which I took to complete this project are listed:

i. Cryptocurrency and FGI Selection
ii. Data Acquisition and Preparation
iii. Feature Creation
iv. Model Generation
v. Model Optimisation for Results
vi. Future Input Data Generation
vii. Signal Generation
viii. Limitations

3.2 Cryptocurrency and FGI Selection

My project aims to find correlations between the Fear and Greed Index and the Cryptocurrency market. In order to achieve this goal, I had to test my models on the Cryptocurrencies which I deemed the most suitable Cryptocurrencies for this project. There is a wide range of Currencies which would be appropriate to carry out this project, however the few I considered testing on were Ethereum, Dogecoin and Bitcoin. Out of these options I selected to test my ML models on both Bitcoin (BTC) and Dogecoin (DOGE). I selected these particular Cryptocurrencies as BTC is a highly established cryptocurrency, which has more price stability and isn't as reactive as other Cryptocurrencies. The media's involvement with Dogecoin meant that the coin was heavily reactive to media changes and public opinion. This can be seen through media output, such as articles and social media, comparing it to the trends in the data. Giving an often-overlooked view point of people's behaviour, perceptions and very real FOMO that the public has. It also highlights the limitations of my model as even though I may have a grasp on the influences, the AI model is trained on the numerical data imputed, so therefore, if Dogecoin's prices are being affected by an external factor which cannot be quantified, so my model cannot predict the correct output.

The second decision I had to make was selecting which FGI indicator would be the best fit for this project. The two indicators which I looked into was the CNN and Alternative.me FGI. After looking into both indicators, I decided to use the Alternative.me Fear and Greed Index as it uses the following features to calculate the daily Index; volatility, market momentum/volume, social media, surveys, dominance and trends. Although these values are calculated from BTC the outputted Index still provides a noteworthy outlook on the Cryptocurrency market and the overall 'mood' of the environment. I decided to use this indicator as Alternative.me allows for their indicator to be downloaded straight from their website and therefore I had easy access to this data which I could update in real time.

3.3 Data Acquisition and Preparation

Data acquisition and preparation is the most vital step when completing this project as it is the backbone to which my models will be based on and having incorrect, incomplete or irrelevant data will lead to models which are inaccurate and provide results which are lacklustre in meaning. Due to the nature of the data I require, which is high frequency real-time data, very limited data is available and there are price walls needed if you want to acquire more advanced data sets, which I figured out due to trying to get data from websites such as CoinGeko, I was eventually able to collect the following variables for both BTC and DOGE using the reliable and accurate source of Yahoo Finance, which releases data on a daily frequency. Using this source, I was able to download the historic data for both the BTC-USD and DOGE-USD conversion for the following data points:

a. Open Price
b. Highest Value
c. Lowest Value
d. Close Price
e. Adjusted Close Price
f. Volume

Bitcoin Data:

Date	Open	High	Low	Close	AdjClose	Volume
01-Jan-2019	3746.7	3850.9	3707.2	3843.5	3843.5	4.3242e+09
02-Jan-2019	3849.2	3948	3817.4	3943.4	3943.4	5.2449e+09

Figure 3. 1 – Bitcoin data which has been taken from Yahoo Finance

Dogecoin Data:

Date	Open	High	Low	Close	AdjClose	Volume
01-Jan-2019	0.002346	0.002392	0.002322	0.002392	0.002392	1.7365e+07
02-Jan-2019	0.002388	0.002458	0.002372	0.002407	0.002407	1.8015e+07

Figure 3. 2 – Dogecoin data which has been taken from Yahoo Finance

Figure 3.1 and figure 3.2 displays a couple of the rows of data that has been imported for BTC and DOGE. As shown the data is accurate and precise. After importing this data into a csv file, which allows the data to be saved in a table format, I prepared the data by ensuring that any missing values were filled with a 0 so that all the data available would be able to get processed without any errors. As I wanted to test all the data points available to me, I didn't exclude any values during time periods of market uncertainty or during economic crisis periods, such as the pandemic, and therefore I used all data points from 2019 to present.

Using the Alternative.me website I was able to download the data available for the Fear and Greed Index in order to train the Machine Learning Models. Please see figure 3 which shows the layout of how this data is imported. This data was imported in a format from newest to oldest as shown in figure 3.3. This varies from the BTC and DOGE data as shown by 3.1 and 3.2, which was imported from oldest to newest. This meant that before combining this data into one spreadsheet, I had to rearrange the FGI values to also display from oldest to newest in order to ensure all variables were correctly aligned in order to have this data processed properly by the ML models.

date	fng_classification	fng_value
01/05/2024	54	Neutral
30/04/2024	67	Greed
29/04/2024	67	Greed
28/04/2024	65	Greed
27/04/2024	67	Greed

Figure 3. 3 – Data displaying how the Fear and Greed Index is saved into a csv file

3.4 Feature Selection

After the necessary data has been successfully acquired and prepared for implementation, relevant features must be generated in order to feed Machine Learning models with useful insights in order to make the most accurate predictions as incorrect or useless data can inhibit a ML models' ability to make predictions, which are reliable to act on. There are many features and tradition technical analysis techniques, which can be used to create insights; however, my project heavily focuses on finding trends comparing the FGI with Cryptocurrency price changes and therefore I only require a few relevant features that are created by manipulating the data I have acquired to assist with price prediction whilst mainly focussing on the relationship between the Fear and Greed Index has with both BTC and DOGE. Using the variables imported shown in figures 3.1 and 3.2, I created the following features:

a. High minus Low price (High price - Low price)
b. Close - Open (Close price - Open price)
c. seven days' moving average (7 DAYS MA)

$$MA_i = \frac{1}{7} \sum_{j=i-6}^{i} x_j$$

d. fourteen days' moving average (14 DAYS MA)

$$MA_i = \frac{1}{14} \sum_{j=i-13}^{i} x_j$$

e. twenty-one days' moving average (21 DAYS MA)

$$MA_i = \frac{1}{21} \sum_{j=i-20}^{i} x_j$$

After these features had been created for each daily point of BTC and DOGE, I added them to a file with the FGI and volume data relevant to the specific date. I then proceeded to divide this data into the ranges of the FGI which I initially wanted to test. This was divided into the subsets

0-20, 21-40, 41-60, 61-80, 81-100 and the overall range 0-100. This data was then saved into their own separate csv file, which I could open into any MATLAB app I wanted to use. Using these features within their specified increments will ensure that the ML models which I am training have enough information to accurately and consistently make predictions and give insights into how the market reacts to different levels of mood within Cryptocurrency markets.

3.5 Model Generation

After these features have been created the next step is choosing how I want to create the ML models on MATLAB. MATLAB has a lot to offer in the realm of ML training options, the options which I considered when completing this project consisted of either manually coding the ML models myself or using apps available such as the classification learner or regression learner to assist with the model training and validating.
Due to the complexity of my project and the large quantity of models I would have to create and test I decided to use the regression learner, which is used frequently for data analysis projects and would allow me to select which features I wanted to test, split my data into training and test data and provide me the root mean squared error (RMSE) to determine the performance of each individual model for both the training and test sets. Another reason I decided to use this app was the ability to export my models to my workspace and generate a code I could use to make predictions on new data sets.

After opening my selected data in the Regression Learner App, in order to generate my models, I selected all the features which I wanted to train my models on and chose a 5 fold cross validation method and split my data into 80% validation and 20% test data, I chose this split as I wanted to incorporate as much training data as possible whilst also having enough testing data to validate my models, which is why I chose the 80/20 split rather than the 70/30. After selecting the best options to optimise my models I needed to see which ML models create the most accurate results, the different models I trained consisted of, Neural Networks, Support Vector Machines, Gaussian Process Regression, Linear Regression Models, Regression Trees, Ensemble Trees and Kernal Approximation Regression.

After training my models for both BTC and DOGE I proceeded to take note of the best performing models as the next step was to compare the best performing models and select the model which outputted the best performance based on the RMSE on average. I chose this method as I was attempting to find a correlation between the FGI and the Cryptocurrency market as a whole rather than between individual currencies and therefore finding which model performs the best across BTC and DOGE will ensure that I have the best results across the Crypto market as a whole.

3.6 Model Optimisation for Results

As my main project goal is to find a unique correlation between the Fear and Greed Index increments and Cryptocurrency prices, the next part of this project was to adjust my input FGI data according to my previous findings on the FGI ranges 0-20, 21-40, 41-60, 61-80, 81-100. This is because the initial increments were only used as a general guideline based on Extreme Fear, Fear, Neutral, Greed, Extreme Greed to train my Models and now I'll be able to finetune which increments I should divide my features into based on determining where the outliers in my data set are and be able to obtain more accurate results to hold a more robust opinion between the correlation between the FGI and Cryptocurrency price changes.

3.7 Future Input Data Generation

The MATLAB regression learner is a very useful tool which relies on input data in order to make predictions, therefore to generate a forecast of Cryptocurrency price changes I have to acquire reliable future data to input into the ML model to make these predictions. To complete this I used a general predictive method of generating 7-, 14- and 21-day average of the most recent results available and calculating an average of these results for all the necessary features.

3.8 Buy or Sell Singal Generation Results

The secondary results I obtain from this project is the generation of a trading signals (buy/sell signals) which will indicate when is the optimal time to buy or sell a specific Cryptocurrency. This process was completed by exporting all the best performing ML models to the MATLAB workspace and using the forecasted features as input values. These forecasted features were entered into both the BTC and DOGE ML model for the overall FGI range 0-100 to obtain an overall trend based on all values. This outputted prediction for the overall trend was then compared with a more niche value, which was obtained by using the ML model which coincided by the predicted FGI value in order to calculate an underlying trend which may be overlooked. This overall value and underlying trend value were then used to trigger buy or sell signals, as if both signals indicated positive a buy signal would be triggered and if both signals indicated negative a sell signal would be produced.

4.0 Limitations

This project unfortunately, due to its nature, will always suffer from some type of limitation. This section will discuss all the limitations I have encounter throughout the duration of completing this work, noting down these limitations is an important part of the methodology as it can provide an overview for what can be worked on to improve the reliability if future work is to be completed. Limitations can also provide information to others who are trying to complete related works what issues they may encounter and how to avoid these problems.

Firstly, in terms of data collection there will be some limitations due to the data which is available online to download in order to train my ML models. This is due to not having access to real time data and due to the volatility of Cryptocurrency prices a price crash or rise due to unexpected real-world events can cause my model not to interpret this event. A noteworthy point, which isn't a limitation but should be noted, is the use of Alternative.me Fear and Greed Index as although it is a trusted and reliable source, the values almost always differ from the CNN Fear and Greed Index and CNN did create the original Fear and Greed Index and therefore a ML model which has been trained on the CNN FGI might provide differing results to the results which I have found.

Another limitation in the design is the limited amount of plot points towards the extreme values of Fear and Greed as by dividing up the data into sets I am reducing the sample size each time and therefore, although I am aiming to increase accuracy by creating more direct correlation between the sample groups, I am directly leading to less data the models are trained on, which can lead to less accurate results within the ranges of Extreme Fear and Extreme Greed.

The final limitation which I have encountered is the inability to forecast future results directly through using the MATLAB Regression Learner. The inability for this app to forecast future results without needing to input data means that in order to predict future price changes I need to first generate data which can then be used to make the price prediction. This requirement means that if the information getting fed into the model to make the prediction is incorrect it can lead to discrepancies and an unreliability among the results outputted price predictions.

5.0 Problems Encountered

Over the course of this project, I encountered several problems due to having limited relevant literature completed which I could review as this project covers a niche topic area within a huge area trying to combine the MATLAB capabilities with the incremental behaviour of a sentiment indicator.

The first issue I encountered was trying to have my code update my data in real time in order make the future progress of the project easier instead of having to download and save the data every time I wanted to make new predictions. To try do this I attempted many different options such as web scraping, which didn't work due to website restriction and the inability to gather the correct information and attempting to use other websites than Yahoo Finance. Unfortunately, due to high costs and limitations I was unable to get updated real time data for BTC and DOGE and still have to download the files manually from yahoo finance in order to make future predictions using the most recent data points. I was however able to automatically download the Fear and Greed Index through Alternative.me which allows for automatic updating and download through code.

Another issue I encountered was trying to generate future forecasts for data which hasn't already been released in order to generate buy or sell signals. This was hard to do as the Regression Learner which I was using didn't allow for creating future predictions without any input data, to overcome this issue I had to find a way to accurately represent future features which I could use as data points in order for future predictions. Therefore, I calculated a 7-, 14- and 21-day average of the most recent point in order to generate an average velocity of the individual features movement to create a general algorithm to assist in future forecasting.

The last issue I encountered was the inability to have date points in my future predictions. This was an issue as due to my project understanding the relationship between the incremental ranges of the FGI my data sets wouldn't include all the data from the start to end date, therefore leading to not knowing which model is to be used on a certain day in order for future prices to be predicted accurately. In order to overcome this, I devised a 2-step authentication type system where the overall range 0-100 would act as an overarching trend and as it is a complete data set the next predicted value would be the future prediction, I would then use the future FGI predicted to choose which model range I would use as an underlying trend prediction and if both these values are positive or negative a signal would get generated.

6.0 Results

This section of my project will discuss the results which I have obtained for both sections of my project therefore it will consist of two different sets of results correlating to the two main aims of my project, these will be my primary and secondary results. The Primary set of results will showcase the correlation found between the Fear and Greed Index and both the studied Cryptocurrencies, Bitcoin and Dogecoin, this is the main part of my project as my goal is to find a unique correlation between the increments of the FGI and Cryptocurrency prices. My secondary set of results are generated through using these models to generate a buy or sell signal based on whether the future predicted price is increasing or decreasing using the predicted future features as input data.

6.1 Primary Results

My primary results will consist of all the Machine Learning Models results with their calculated test RMSE provided followed by a comparison of the RMSE across all cryptocurrency ranges to showcase whether the results found agree or disagree with the statement “the Fear and Greed Index has a ‘U’ shaped correlation”. To assist with this, I have selected to present the Regression Line of Best Fit and the residuals error graph for both BTC and DOGE for each tested increment of the FGI. These two graphs will assist with visual inspection to see where outlier points congregate and how accurate these models are.

6.2 Primary Model Results and RMSE Performance

BTC Overall (FGI Range 0-100)

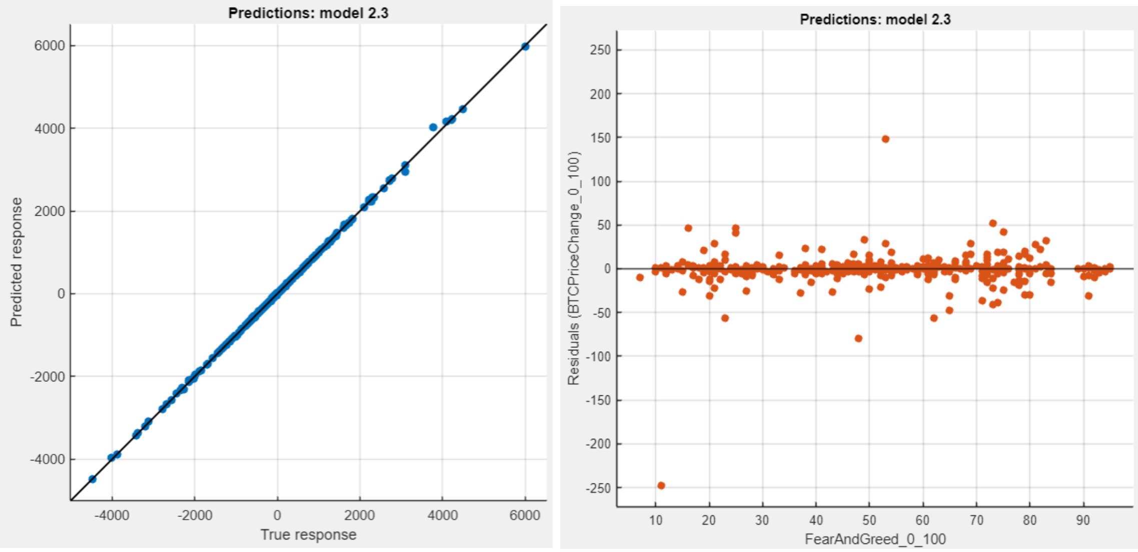


Figure 6. 1 – BTC Results Line of Best Fit and Residual error displacement for FGI Range 0-100

DOGE Overall (FGI Range 0-100)

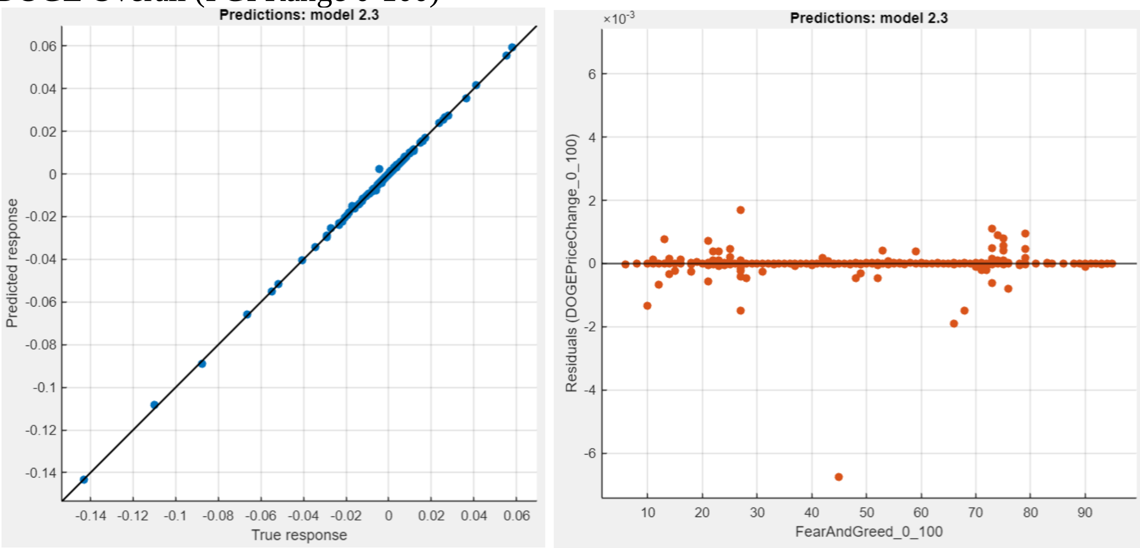


Figure 6. 2 – DOGE Results Line of Best Fit and Residual error displacement for FGI Range 0-100

Figure 6.1 and 6.2 displays the overall trend for both BTC and DOGE (using the test data) within the entirety of the Fear and Greed Index. These results were found using a Robust Linear Machine Learning technique. The RMSE (Test) for BTC was 19.124, DOGE was 0.000419.

BTC (FGI Range 0-15)

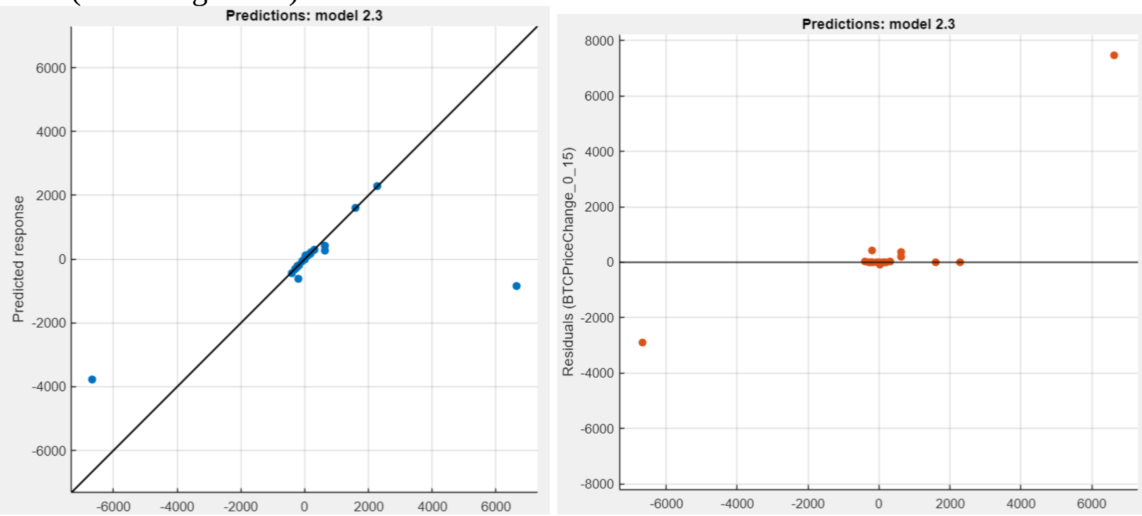


Figure 6. 3 – BTC Results Line of Best Fit and Residual error displacement for FGI Range 0-15

DOGE (FGI Range 0-15)

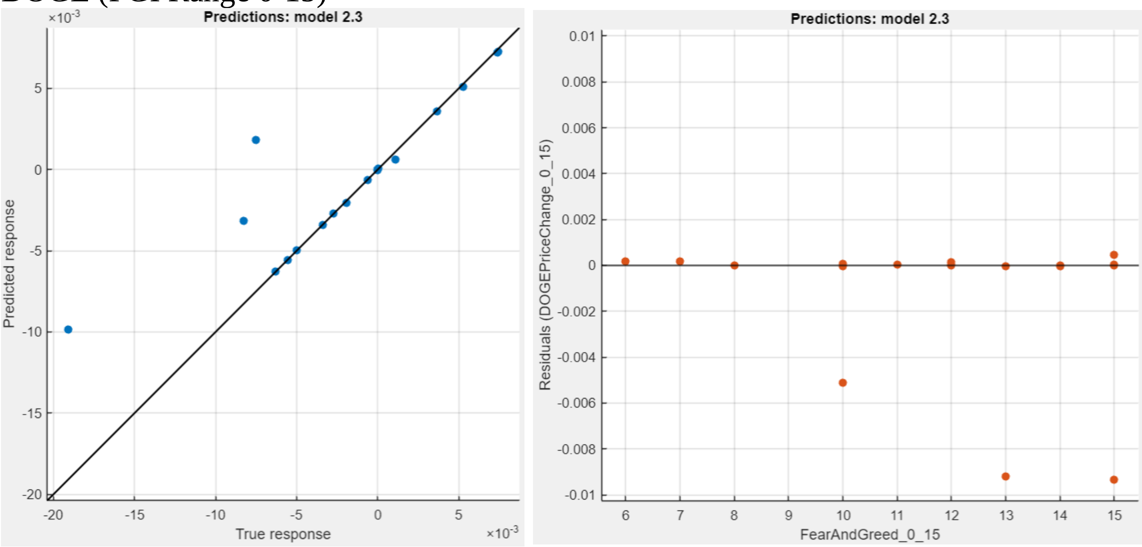


Figure 6. 4 – DOGE Results Line of Best Fit and Residual error displacement for FGI Range 0-15

Figures 6.3 and 6.4 display the trend for both BTC and DOGE at extreme levels of Fear (using the test data). These results were found using a Robust Linear Machine Learning technique. The RMSE (Test) for BTC was 1675.3, DOGE was 0.0030032.

BTC (FGI Range 16-30)

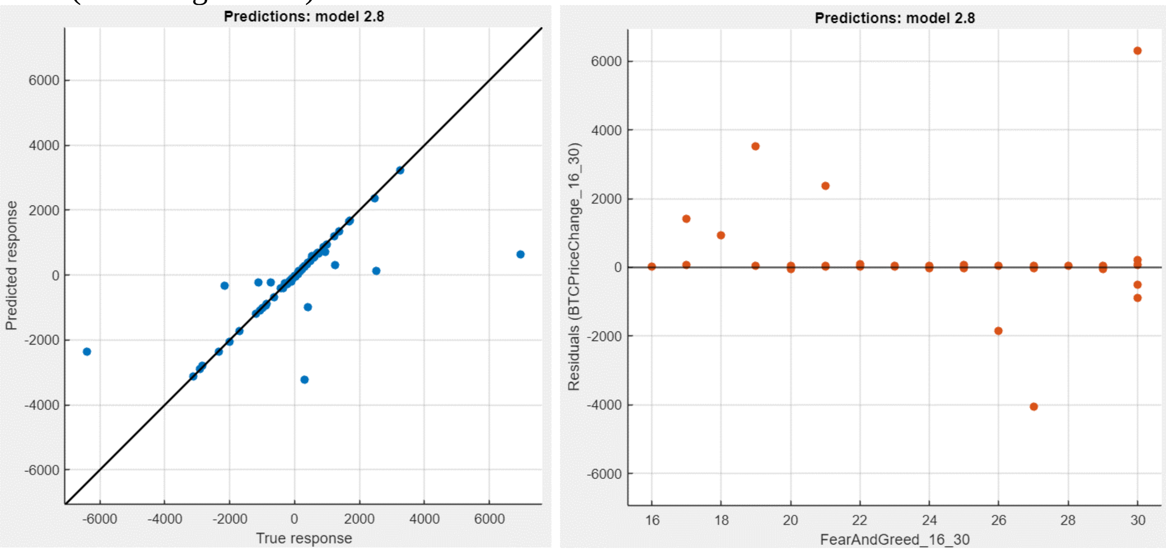


Figure 6. 5 – BTC Results Line of Best Fit and Residual error displacement for FGI Range 16-30

DOGE (FGI Range 16-30)

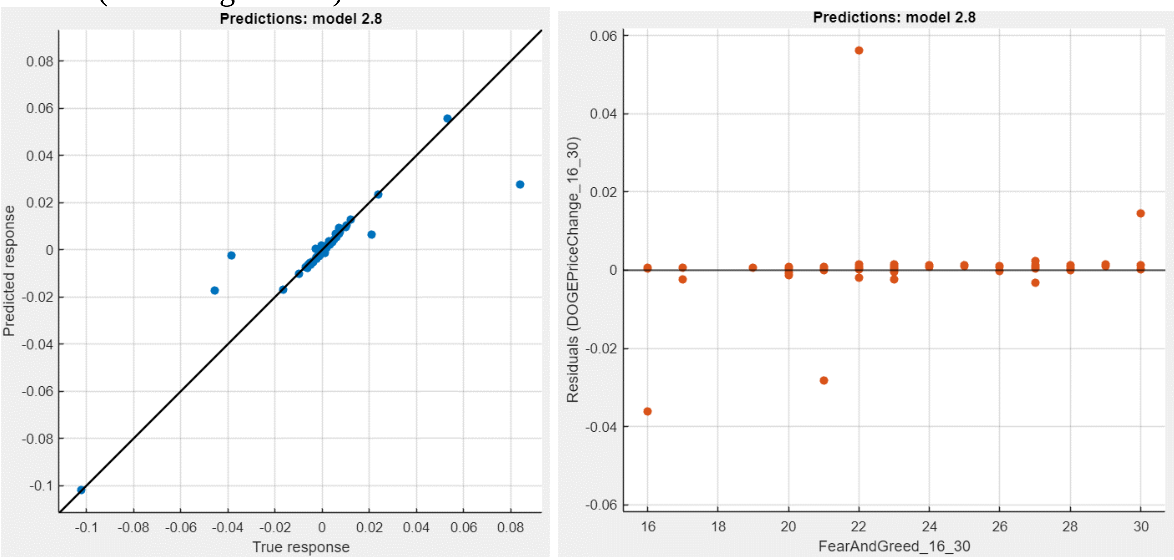


Figure 6. 6 – DOGE Results Line of Best Fit and Residual error displacement for FGI Range 16-30

Figures 6.5 and 6.6 display the trend for both BTC and DOGE at a level of Fear that's transferring from extreme Fear to Fear (using the test data). These results were found using a Linear SVM Machine Learning technique. The RMSE (Test) for BTC was 981.35, DOGE was 0.0080948.

BTC (FGI Range 31-44)

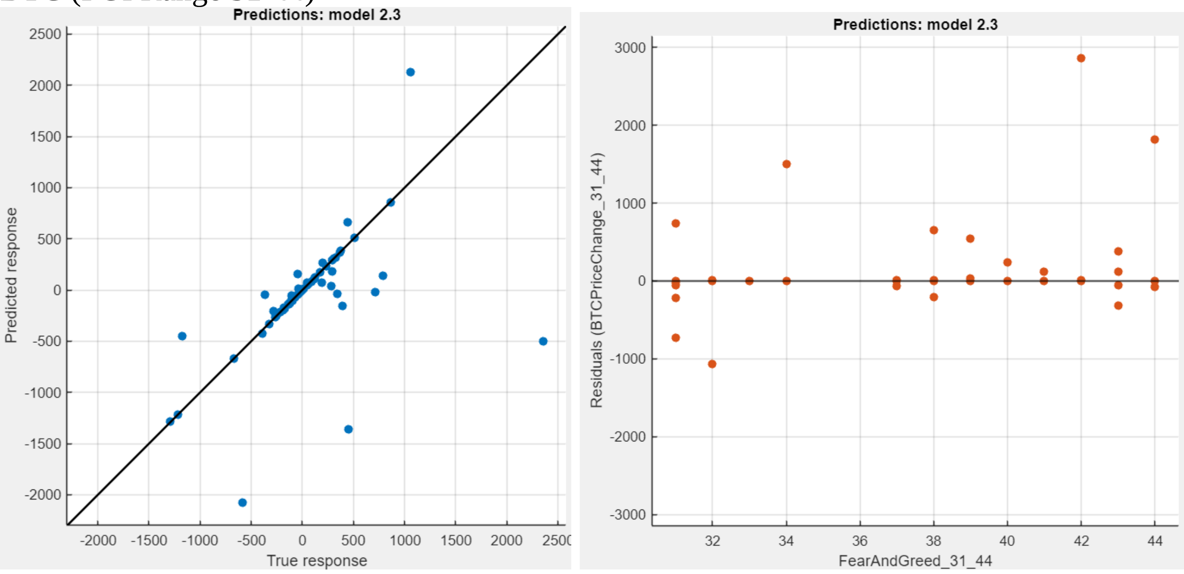


Figure 6. 7 BTC Results Line of Best Fit and Residual error displacement for FGI Range 31-44

DOGE (FGI Range 31-44)

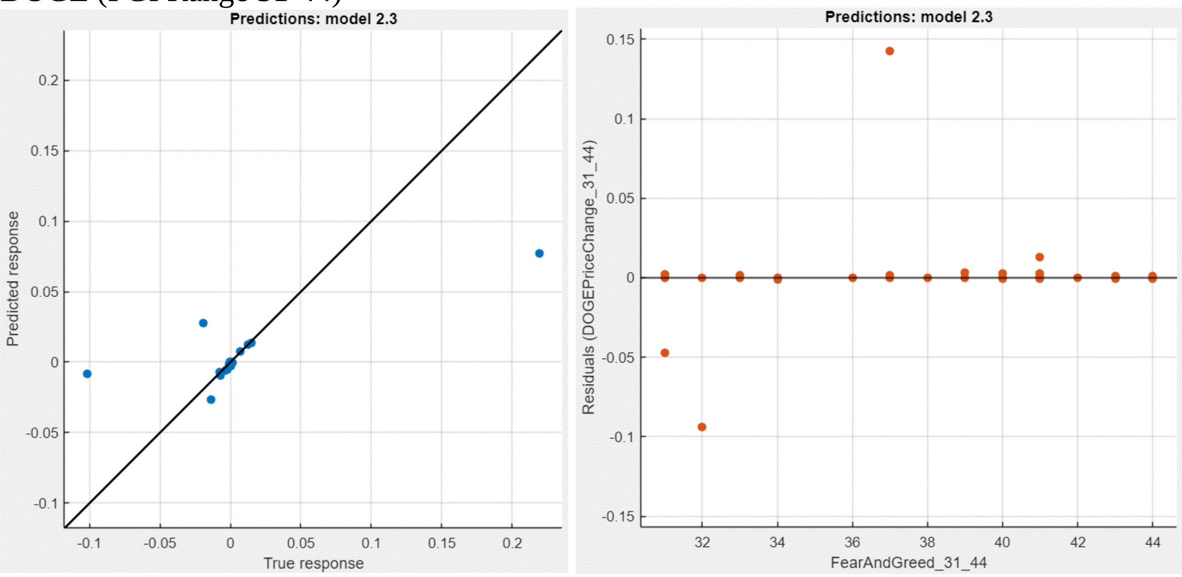


Figure 6. 8 – DOGE Results Line of Best Fit and Residual error displacement for FGI Range 31-44

Figures 6.7 and 6.8 display the trend for both BTC and DOGE at lower levels of Fear (using the test data). These results were found using a Robust Linear Machine Learning technique. The RMSE (Test) for BTC was 497.42, DOGE was 0.021551.

BTC (FGI Range 45-55)

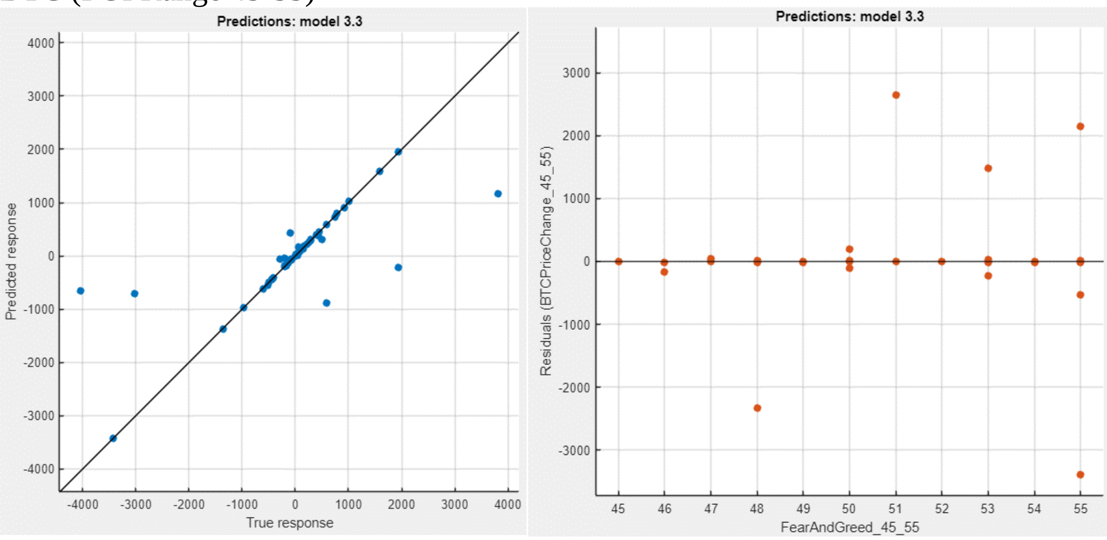


Figure 6. 9 – BTC Results Line of Best Fit and Residual error displacement for FGI Range 45-55

DOGE (FGI Range 45-55)

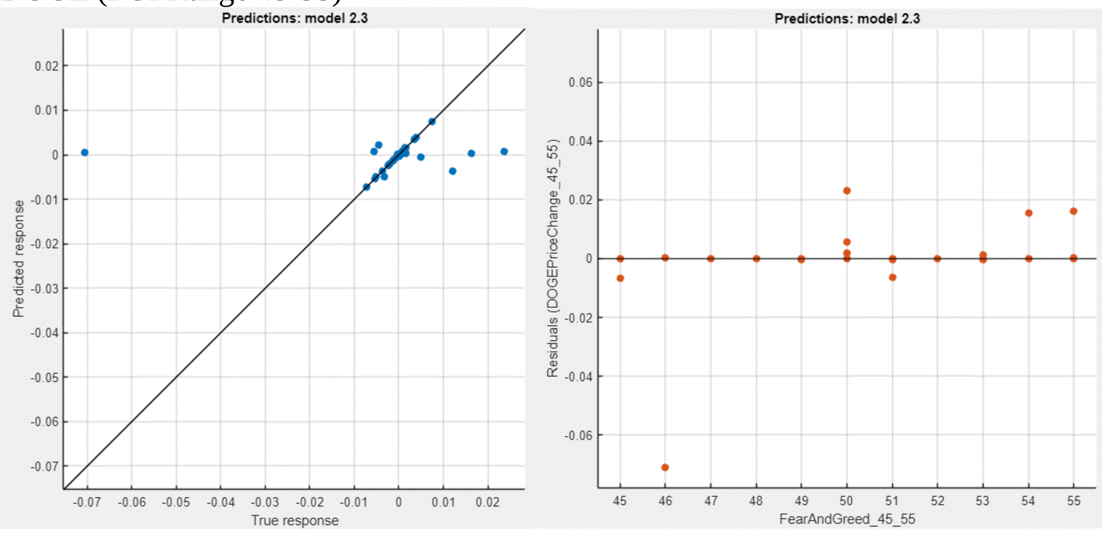


Figure 6. 10 – DOGE Results Line of Best Fit and Residual error displacement for FGI Range 45-55

Figures 6.9 and 6.10 display the trend for both BTC and DOGE at neutral levels (using the test data). These results were found using a Robust Linear Machine Learning technique. The RMSE (Test) for BTC was 677.43, DOGE was 0.009554.

BTC (FGI Range 56-70)

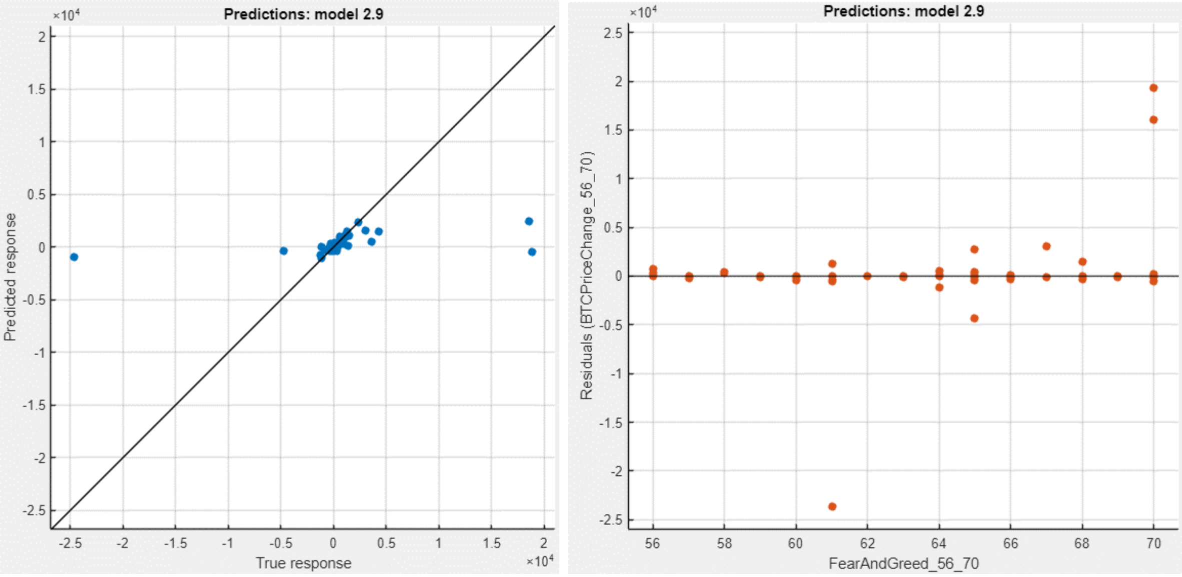


Figure 6. 11 – BTC Results Line of Best Fit and Residual error displacement for FGI Range 56-70

DOGE (FGI Range 56-70)

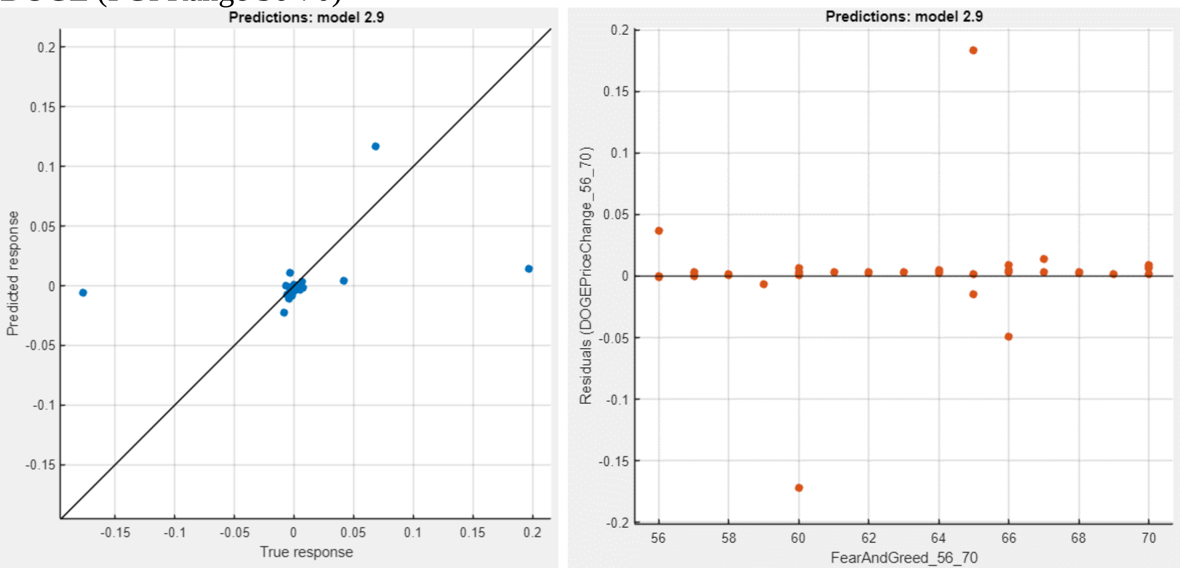


Figure 6. 12 – DOGE Results Line of Best Fit and Residual error displacement for FGI Range 56-70

Figures 6.11 and 6.12 display the trend for both BTC and DOGE at lower levels of Greed (using the test data). These results were found using a Quadratic SVM Machine Learning technique. The RMSE (Test) for BTC was 4502, DOGE was 0.033629.

BTC (FGI Range 71-85)

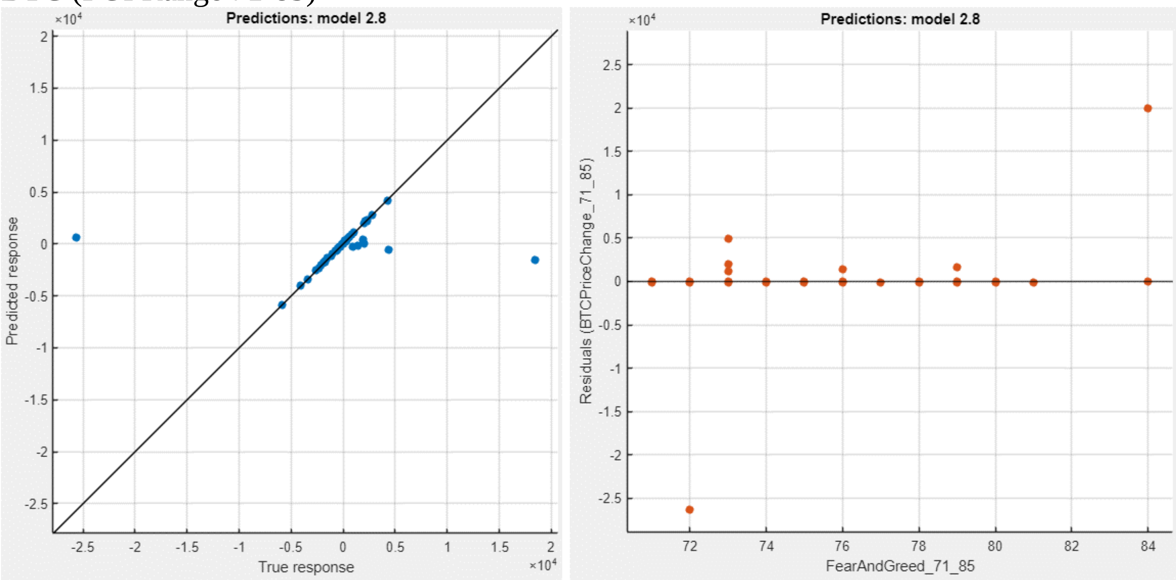


Figure 6. 13 – BTC Results Line of Best Fit and Residual error displacement for FGI Range 71-85

DOGE (FGI Range 71-85)

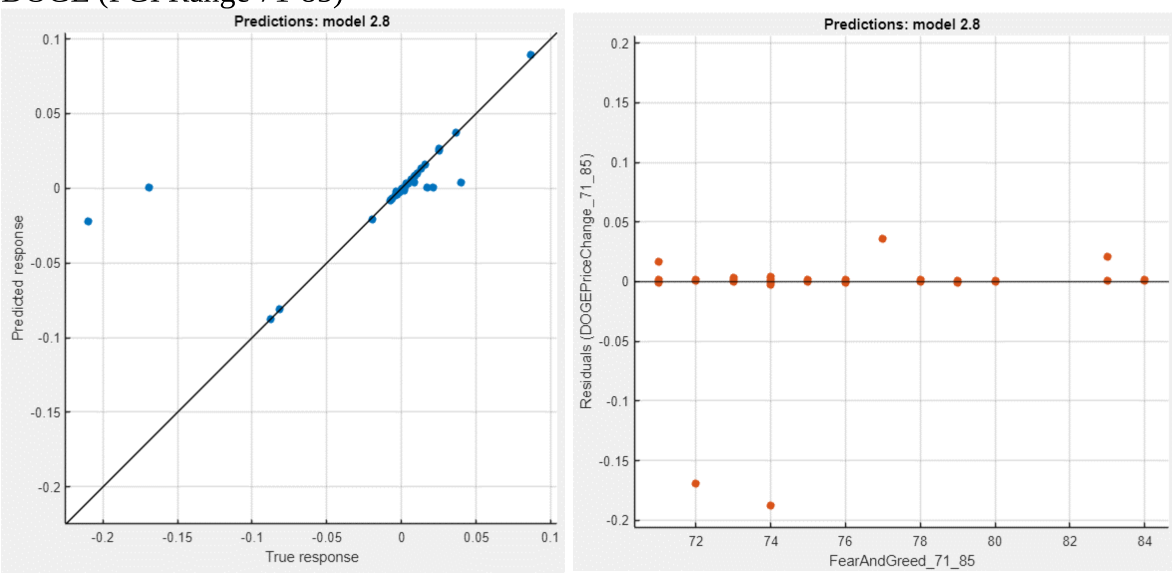


Figure 6. 14 – DOGE Results Line of Best Fit and Residual error displacement for FGI Range 71-85

Figures 6.13 and 6.14 display the trend for both BTC and DOGE at a level of Greed that's transferring from extreme Greed to Greed (using the test data). These results were found using a Linear SVM Machine Learning technique. The RMSE (Test) for BTC was 4199.5, DOGE was 0.032122.

BTC (FGI Range 86-100)

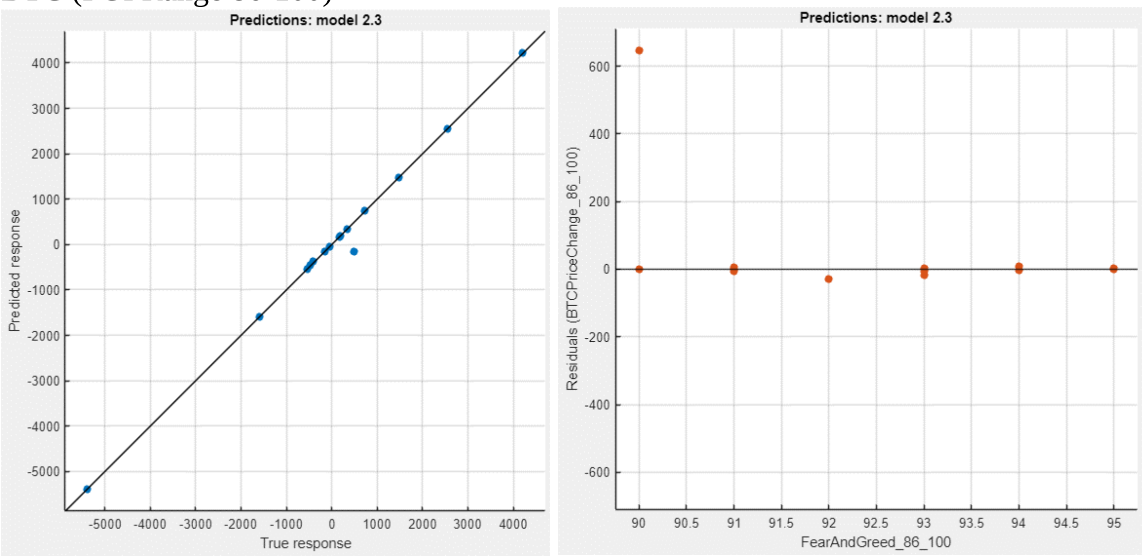


Figure 6. 15 – BTC Results Line of Best Fit and Residual error displacement for FGI Range 86-100

DOGE (FGI Range 86-100)

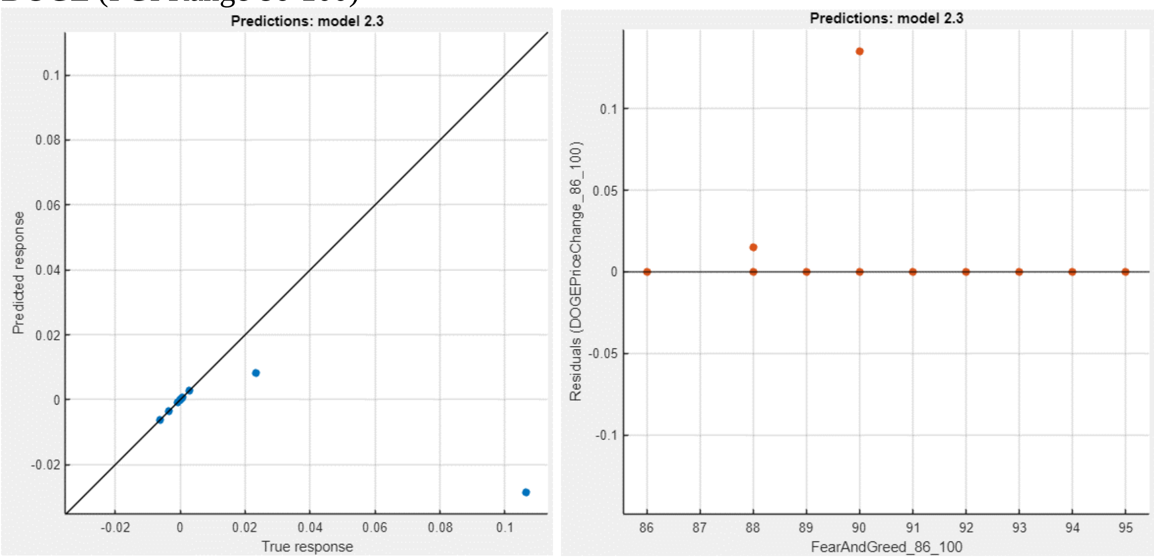


Figure 6. 16 – DOGE Results Line of Best Fit and Residual error displacement for FGI Range 86-100

Figures 6.15 and 6.16 display the trend for both BTC and DOGE at a level of extreme Greed (using the test data). These results were found using a Robust Linear Learning technique. The RMSE (Test) for BTC was 157.15, DOGE was 0.032963.

Combined Overall Graphical Correlation

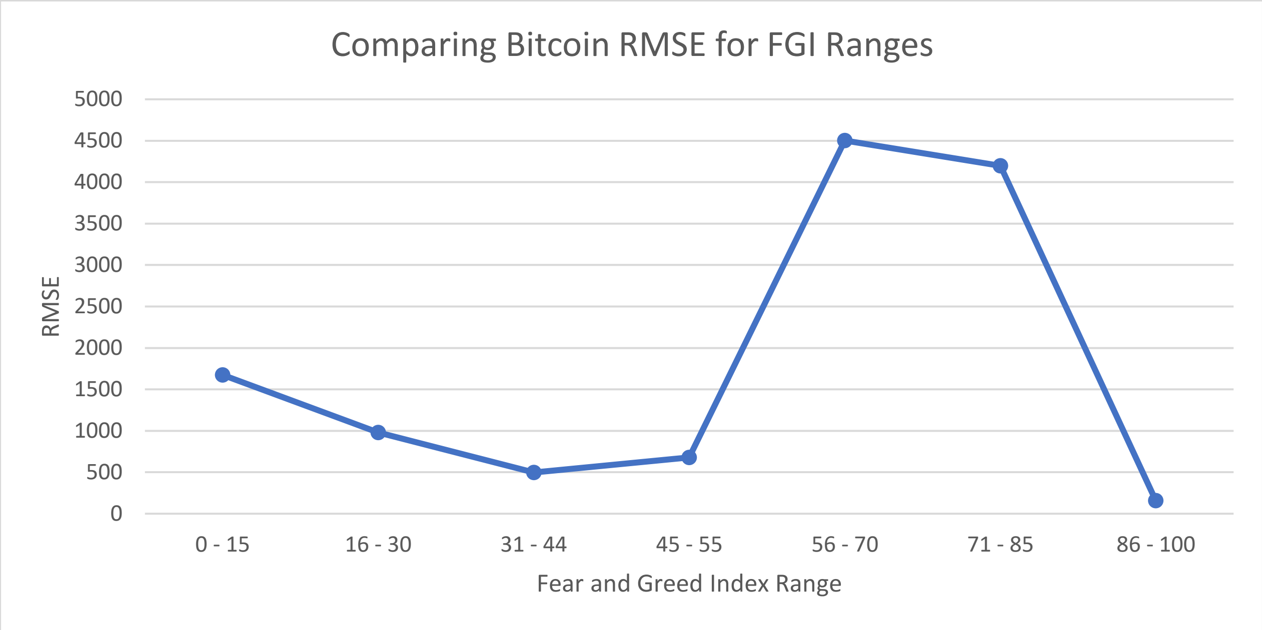


Figure 6. 17 – Displays the RMSE calculated for all ranges of the Fear and Greed Index for Bitcoin

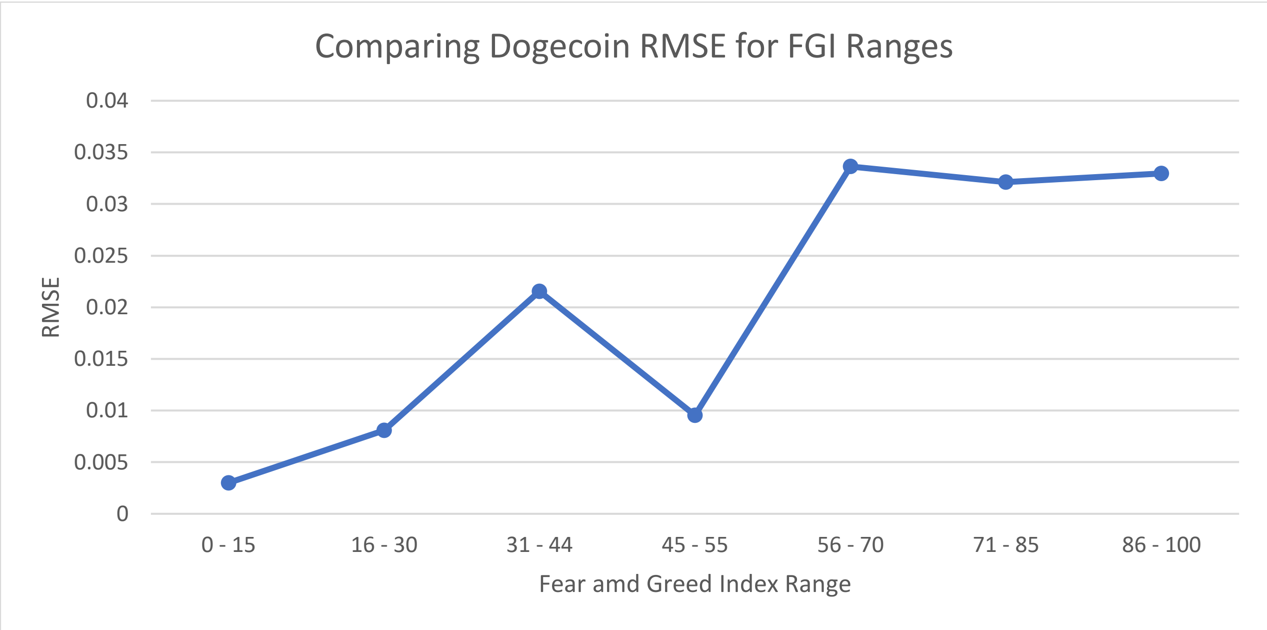


Figure 6. 18 – Displays the RMSE calculated for all ranges of the Fear and Greed Index for Dogecoin

Figures 6.17 and 6.18 display the overall RMSE for the specified FGI ranges to aid with visual inspection to understand the correlation which the FGI increments has with Cryptocurrency price changes, with a lower RMSE correlating to more correlation.

6.3 Secondary Results

The secondary results are calculated using the primary findings, these primary are then used to generate buy or sell signals. A buy signal is generated whenever the overall trend (0-100) is showing a positive number and the corresponding FGI range, for example if the predicted FGI is 20 the 16-30 model is used, if this range agrees with the overall trend, then a buy signal is generated and if the price change is predicted to be negative a sell signal will be generated.

6.4 Secondary Results Compared to Real Price Changes

	Predicted Price Change for 14th April
BTC 0-100	**31.34897093**
BTC 56-70	**77.30849502**
DOGE 0-100	**-8.09E-06**
DOGE 56-70	**-0.003546541**
	Real Price Change 14th April
BTC	**1902.5**
DOGE	**0.009117**

Figure 6. 19 – The predicted price change for FGI ranges 0-100 and 56-70 and actual price change of BTC and DOGE for the 14th April

```
BUY NOW for BTC
SELL NOW for DOGE
```

Figure 6. 20 – The display of my MATLAB code when a buy or sell signal is generated for BTC or DOGE

As shown by figures 6.19 and 6.20 my MATLAB code the secondary results generated for the 14th April show that BTC should be bought and DOGE should be sold as the price is expected to rise for BTC for both the 0-100 and 56-70 range and fall for DOGE, whereas the actual price change was a rise for both BTC and DOGE.

7.0 Discussion

This section of my project will discuss my findings and if these results agree or disagree with previous research carried out and reasons why this is and how my research has furthered the knowledge within this field by making advances within this gap in research to increase the understanding known within this field.

The main goal of my project was to further understand the correlation which the Fear and Greed Index had with Cryptocurrency price changes. In order to further the understanding available regarding the Fear and Greed Index I wanted to find if there was a way to increase the reliability when the market was experiencing a more 'neutral' mood as this is when this sentiment indicator is least accurate based on the 'U' shaped correlation.

Based on the overall RMSE trend shown, whenever applying a separate Machine Learning algorithm on ranges of the Fear and Greed Index there isn't a distinct 'U' correlation relating to a lower synchronicity the FGI has with Cryptocurrencies at neutral levels, or in the case of my results an 'n' shape as a higher error means there's less correlation. My results dictate that the overall range with the least correlation is the 56-85 range and the best correlation recorded was in the 0-55 range, with the 86-100 range displaying opposing behaviours between BTC and DOGE.

Reviewing the overall trend of both BTC and DOGE whilst in the Fear and neutral range from 0-55 there's a negative correlation between the BTC and DOGE, as whilst the RMSE for Bitcoin decreases the RMSE for Dogecoin increases showing that up until this point BTC doesn't follow the previously discovered trend whilst DOGE does. A reason for this could be due to a herding mentality[13], as Dogecoin not being a well-established Cryptocurrency could have better predictions for all levels of fear as whilst the price falls for DOGE the faith in the value of the coin due to its volatile behaviour can drop rapidly and therefore predictions will be more accurate as people are behaving as expected consistently creating a common trend, whereas for BTC even though there's a 'Fear' behaviour we can almost expect the opposite of this 'normal' behaviour as investors have faith in BTC being able to recover any price drop and therefore will buy into this Cryptocurrency whilst prices are dropping and the FGI is low in order to create profits and due to this inconsistency the error margin within this range can increase. And although we can consider this behaviour expected the ML model can only be trained on its inputted data and inconsistent human behaviour reactions within these ranges can lead to less accurate predictions.

An interesting point is at neutral levels of FGI, 45-55 range, the accuracy of BTC reduces by an almost insignificant amount and the accuracy for DOGE increases substantially. A neutral level of FGI being the third most accurate point level contradicts fully the statement 'the Fear and Greed Index has a 'U' shaped correlation' and shows that the FGI must be studied incrementally in order to make further progress in understanding this sentiment indicator. This lower RMSE dictates that the market is behaving as expected at this neutral level which could be due to lower levels of activity or less drastic decisions from investors, to understand why this occurs residuals for this FGI range 45-55 will have to be reviewed, which will be discussed when the individual ranges are being critically analysed.

At lower levels of Greed, 56-85 range, both the BTC and DOGE markets have the highest RMSE recorded. This shows that at levels of Greed the market becomes the most unpredictable, this dictates that a herd mentality, as discussed for a mood range of fear in DOGE, doesn't exist here. This could be caused by both BTC and DOGE investors trying to maximise profits by trying to predict when prices are going to drop in a market and therefore selling or holding their assets in an inconsistent pattern and because of this an increased RMSE between levels of Greed and Cryptocurrency price changes can be expected due to this behaviour, however this makes price prediction less accurate for levels of Greed. The only difference between BTC and DOGE, when comparing FGI over 55, is that at extreme levels of Greed the RMSE for BTC recovers whereas the DOGE RMSE stays at a high level. It can therefore be speculated that at extreme levels of greed the herd mentality for BTC is reinstated as the confidence in the Cryptocurrency is exceptionally high and people behave as expected, whereas the overall high RMSE for DOGE whenever the market is said to be experiencing any levels of ‘Greed’ can be due to Dogecoin having a reputation of crashing and only increasing in price due to media influence and until this happens the market cannot behave as expected due to a consistently low confidence in the value of DOGE increasing.

Comparing the overall RMSE for both Cryptocurrencies to this overall trend which was found to be 19.124 for BTC and 000.419 for DOGE and this performance was calculated using the Robust Linear Technique, and as a whole is highly reliable as most plot points are close to the line of best fit. This overall trend is the lowest RMSE recorded and could be due to containing a larger sample size and therefore increased number of training points, however, besides this based on the residuals BTC shows to have a consistent inaccuracy throughout all ranges of FGI excluding a few outliers, these results can show that BTC is a very predictable Cryptocurrency as it has long been established and therefore the market responds consistently to the environment it is within. In contrast to this DOGE actually displays almost what is expected when one ML technique is applied to the data set as a whole with the inaccuracies increasing as the values at 0 and 100 verge towards 50, the only difference this data set shows to displaying a ‘U’ shaped correlation is at neutral levels the number of residuals have decreased.

Comparing the overall residuals (0-100) with the residuals for the specific FGI ranges, the results behave as expected, with the highest inaccuracies recorded at extreme levels of fear and lower levels of Greed between the 0-30 and 60-80 increments, which is the ranges which found more accurate results using other machine learning techniques. These findings for DOGE display how using other ML methods on these increments can improve the accuracy and disproves the hypothesis that the Fear and Greed Index has a ‘U’ shaped correlation. The inconsistent quantity of residuals for DOGE can be due to containing the opposite qualities of BTC and due to it being a volatile Cryptocurrency doesn't respond consistently to different moods of a market.

Focussing on the residual graphs for the ranges of the FGI it is also clear to see how the ‘U’ shaped correlation isn’t clearly displayed as if this was the case you would expect to see an increased number of errors tending towards the neutral level of FGI 50. This would be shown by an increased number of residuals to the right of the graphs in the 0-45 range and left of the graph in the 55-100 range. As this isn’t the case for either BTC or DOGE it can be said that humans don’t behave as expected but as there is a clear correlation displayed by most values falling on the Line of Best Fit this unexpected behaviour can still be quantified by a ML Linear Regression calculation for the different ‘moods’ of Cryptocurrency markets.

These results are important as they contradict a belief that sentiment indicators have a correlation which is non-accurate at a neutral level, these results show that the FGI is a complex sentiment indicator that although doesn’t dictate a traditional correlation of herd mentality at levels of fear and greed amongst all Cryptocurrencies there is a consistent behaviour and underlying herd mentality that does exist consistently and can be used to make price predictions accurately.

My secondary results display the capabilities of my models for future predictions and although the results available show a small amount of data due to limitations and setbacks I had to overcome, the ML models are still able to accurately predict the price of BTC increasing. My results however did predict DOGE decreasing, which could represent an inability to predict the future prices of Cryptocurrencies due to the predicted feature selection algorithm I had implemented. However, in order to confidently say my signal generation is accurate in reference to future price prediction future testing of different algorithms on my future feature selection or use a MATLAB ML future forecasting app which doesn't require input data in order to make future predictions. Nevertheless, this result still showcases the ability to generate buy or sell signals using the varying ML models and indicates that not just one model needs to be applied towards future price prediction using sentiment indicators such as the FGI and generate signals based on an inaccurate ‘U’ shaped correlation and applying an increased accuracy algorithm to my feature selection should increase the reliability of my forecasting results.

Reviewing both my primary and secondary results it is clear to see that the FGI is an accurate and reliable sentiment indicator, which needs to be studied further and has an underlying relationship even when considering two Cryptocurrencies with very different qualities.

8.0 Future Work

This project, although complete, does have some areas in which future developments can assist to make it a more reliable trading system. The three main areas which need to be improved to increase either reliability or ease of use is to increase the accuracy of my generated signals, further breakdown of the FGI ranges and incorporate more automatically updating data.

In order to improve the reliability of the generated trading signals future work on the future feature selection can be carried out to improve the reliability of the predictions or a forecasting method can be implemented in order to not require any future input data but instead implement a model which can predict future price data without needing to forecast future features. In order to increase the reliability of the inputted features more algorithms can be tested to accurately predict future features and test this historical prediction against real price changes to generate a prediction which is the most accurate.

The second future development which can be implemented is to further break down the FGI ranges and especially to test the data in an unorthodox method instead of the traditional breakups which I have tested. This could consider testing neutral and greed ranges together such as a range of 50-70 or test smaller ranges such as 10 increment ranges. Testing the FGI against Cryptocurrency price changes for these ranges could eliminate any doubt about herd mentalities within different FGI ranges or discover underlying trends which can be studied further.

The last future development which can be implemented is creating a model which is more user friendly, such as, finding a way to automatically update the models and to have the price predictions be produced automatically, as at the moment the code which I have used contains multiple scripts and is very complex to use in order to generate the results. Finding a way to automatically gather data and predict future price changes would make this system highly useable amongst traders either alongside other traditional technical indicators or as a standalone indicator.

9.0 Conclusion

This section of my project will review the overall contents of my findings and how the limitations I have mentioned may hinder the practical and theoretical contributions this research can be applied to.

My results have highlighted a key issue which is commonly overlooked when using the FGI, which is to look at this sentiment indicator as a whole and not incrementally, as it was previously found that herd mentality behaviour is found at levels of fear and greed and at neutral levels there is less correlation and my primary findings have clearly shown that this is not the case and applying separate ML models incrementally, we can understand this indicator to a higher degree. These results were found using a complete set of data and a very relevant feature selection, which I believe furthers the reliability of my primary findings. However, further testing in this area could be carried out to try improve reliability such as testing on more features such as STD DEV or moving averages which range over 21 days as well as combining this analysis technique with other technical analysis tools could further the reliability of this project.

My secondary results, which were found using a two authentication factor before generating a trading signal in order to increase the reliability were predicated based on an algorithm which isn't as complex or robust as my primary results, due to limitations I have encountered, this therefore makes my secondary results unreliable and therefore in order to make these findings more than just a trading indicator that has to be paired alongside other technical analysis techniques and to be a standalone model, future work has to be completed in order to increase the reliability of my secondary results.

The results found do have very practical and theoretical contributions, this is due to my research project challenging a long-standing point of view that the FGI is inaccurate at neutral ranges and therefore theoretically there is a huge contribution as it has led to an expansion of understanding in this area and practically there are many practical applications which these new findings can be applied.

Practically my primary results found can be used to accurately predict a herd mentality are specific FGI ranges which can give traders a unique insight into a Cryptocurrency market to make trades before the profit margins have been eradicated by fast acting traders within this fast-paced dynamic market. The results found also have very useful theoretical implications as the results show clear signs that the Fear and Greed Index doesn't follow the once thought of 'U' correlation. This research therefore concludes that another line of research can be studied and taken further in order to increase the understanding of the sentiment indicator further so that future predictions can be made with higher accuracy and reliability within this volatile market.

To conclude, using the MATLAB computational and predictive capabilities to create relevant and accurate feature selections and the versatility which MATLAB offers to create several useful ML model which disproved a long standing opinion regarding the price change synchronicity between the Fear and Greed Index and Cryptocurrency price ranges, this new found relationship can be used to generate buy and sell signals and with some future work to enhance the reliability of the future features to generate accurate predictions or using a forecasting method can generate accurate signals which can be used in several different application within the finance industry and also showcases MATLAB's ability in the realm of Machine Learning, Data Analysis and Price Prediction.

10.0 References

[1] Hooson, M. (2024) *Cryptocurrency statistics 2024, Forbes*. Available at: https://www.forbes.com/uk/advisor/investing/cryptocurrency/cryptocurrency-statistics/#:~:text=According%20to%20a%20survey%20from%20lendingtree.com%2C%20conducted%20in,made%20a%20profit%2C%20and%20only%2013%25%20broke%20even. (Accessed: 07 May 2024).

[2] Lo, A.W. (2007) *Efficient Markets hypothesis, SSRN*. Available at: https://deliverypdf.ssrn.com/delivery.php?ID=451118121020029081127001076097076094058033002011036016126081005122000029010120081027056058010054013097015080016086006120080109085044061032068121065086095029032001086106096069084084101083089092100121115067086067120030079026125127066026030085115&EXT=pdf&INDEX=TRUE (Accessed: 05 February 2024).

[3] K. Schierholt and C. H. Dagli, "Stock market prediction using different neural network classification architectures," IEEE/IAFE 1996 Conference on Computational Intelligence for Financial Engineering (CIFEr), New York, NY, USA, 1996, pp. 72-78, doi: 10.1109/CIFER.1996.501826. keywords: {Stock markets;Neural networks;Portfolios;Multilayer perceptrons;Economic forecasting;Research and development management;Multi-layer neural network;Chaos;Predictive models;Exchange rates},

[4] *Applying machine learning models in stock market prediction - EPRA journals*. Available at: https://eprajournals.com/jpanel/upload/138am_82.EPRA%20Journals-4361.pdf (Accessed: 12 February 2024).

[5] Gómez-Martínez, R., Medrano-García, M.L. and Prado Román, C. (2023) *CNN fear and Greed Index as trend signal in global financial markets, SSRN*. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4384869 (Accessed: 12 February 2024).

[6] *Artificial Intelligence applied to stock market trading ... - IEEE xplore*. Available at: https://ieeexplore.ieee.org/document/9350582/ (Accessed: 12 February 2024)

[7] *(PDF) bitcoin price prediction based on Fear & Greed index - researchgate*. Available at: https://www.researchgate.net/publication/377467293_Bitcoin_price_prediction_based_on_fear_greed_index (Accessed: 12 February 2024).

[8] Author links open overlay panel Jying-Nan Wang a *et al.* (2023) *A U-shaped relationship between the crypto fear-greed index and the price synchronicity of cryptocurrencies*, *Finance Research Letters*. Available at: https://www.sciencedirect.com/science/article/pii/S1544612323011352 (Accessed: 12 February 2024).

[9] *Prediction of bitcoin price change using neural networks | IEEE ...* Available at: https://ieeexplore.ieee.org/document/9079257/ (Accessed: 12 February 2024).

[10] Author links open overlay panel Mehar Vijh a *et al.* (2020) *Stock closing price prediction using Machine Learning Techniques*, *Procedia Computer Science*. Available at: https://www.sciencedirect.com/science/article/pii/S1877050920307924 (Accessed: 12 February 2024).

[11] Sebastiatilde;o, H. and Godinho, P. (2021) *Forecasting and trading cryptocurrencies with machine learning under changing market conditions - financial innovation*, *Springer Open*. Available at: https://jfin-swufe.springeropen.com/articles/10.1186/s40854-020-00217-x (Accessed: 12 February 2024).

[12] *Crypto Fear & Greed index - bitcoin sentiment* (no date) *Bitcoin Sentiment - Alternative.me*. Available at: https://alternative.me/crypto/fear-and-greed-index/ (Accessed: 07 May 2024).

[13] Author links open overlay panel Patrick Jaquart and Abstract We employ and analyze various machine learning models for daily cryptocurrency market prediction and trading. We train the models to predict binary relative daily market movements of the 100 largest cryptocurrencies. Our results show that all empl (2022) *Machine learning for cryptocurrency market prediction and trading*, *The Journal of Finance and Data Science*. Available at: https://www.sciencedirect.com/science/article/pii/S2405918822000174?ref=pdf_download&fr=RR-2&rr=8809bde978077799 (Accessed: 08 May 2024).

11.0 Appendix

Code to acquire and manipulate data and create useful graphs

```
% Build the complete API URL with optional parameters
fng_api_url = [fng_api_url '?limit=' num2str(limit) '&format=' format '&date_format=' date_format];

% Define the file path for your Fear and Greed Index CSV data file
fngFilePath = 'C:\Users\Lorcan\OneDrive\Documenten\Final year project\CODE\fear and greed 2\';
fngFileName = 'MyFearAndGreedData.csv';

% Combine the file path and filename
fngFileName = [fngFilePath fngFileName];

% Check if the CSV file exists and delete it if it does
combinedFileName = 'combinedData2.csv';
if isfile(combinedFileName)
    delete(combinedFileName);
    disp(['Deleted existing CSV file: ' combinedFileName]);
end

try
    % Download the Fear and Greed Index CSV data and save it to the specified file
    websave(fngFileName, fng_api_url);

    disp(['Fear and Greed Index CSV data saved to ' fngFileName]);

    % Read the Fear and Greed Index CSV data into a table with specified variable names
    variableNamesFNG = {'Date', 'FearAndGreedIndex', 'GNF'}; % Specify the variable names
    optsFNG = detectImportOptions(fngFileName);
    optsFNG.VariableNames = variableNamesFNG;

    % Set 'VariableNamingRule' to 'preserve' to use the original column headers
    optsFNG.VariableNamingRule = 'preserve';

    % Convert the Date column from string to datetime
    optsFNG.VariableTypes{1} = 'datetime';
    optsFNG = setvaropts(optsFNG, 'Date', 'InputFormat', 'dd-MM-yyyy'); % Specify the InputFormat

    fngData = readtable(fngFileName, optsFNG);

    % Filter Fear and Greed Index data for dates starting from 2019
    fngData = fngData(fngData.Date >= datetime('2019-01-01'), :);
```

```
% Define the file path for your Bitcoin CSV data file
bitcoinFilePath = 'C:\Users\Lorcan\OneDrive\Documenten\Final year project\CODE\code trials\BTC-USD.csv';

% Read the Bitcoin CSV file into a table
bitcoinData = readtable(bitcoinFilePath);

% Filter Bitcoin data for dates starting from 2019
bitcoinData = bitcoinData(bitcoinData.Date >= datetime('2019-01-01'), :);

% Display the first few rows of the Bitcoin data
disp('Bitcoin Data:');
disp('----------------------------');
disp(bitcoinData);

% Specifying the numeric columns to handle missing data
numericColumnsBitcoin = {'Open', 'High', 'Low', 'Close', 'AdjClose', 'Volume'};

% Looping each numeric column and filling missing values with zeros
for i = 1:numel(numericColumnsBitcoin)
    columnName = numericColumnsBitcoin{i};
    bitcoinData.(columnName) = fillmissing(bitcoinData.(columnName), 'constant', 0);
end

% Removing duplicate rows based on all columns
bitcoinData = unique(bitcoinData);

% Calculate daily returns using the AdjClose column
bitcoinData.DailyReturns = [NaN; diff(bitcoinData.AdjClose) ./ bitcoinData.AdjClose(1:end-1)];

% Convert the 'Date' column from string to DateTime format
bitcoinData.Date = datetime(bitcoinData.Date, 'Format', 'yyyy-MM-dd');

% Set the API URL for Fear and Greed Index
fng_api_url = 'https://api.alternative.me/fng/';

% Set optional parameters
limit = 0;  % Fetch all available historical data
format = 'csv';  % Data format (csv)
date_format = 'world';  % Date format
```

Appendix

```
% Flip Fear and Greed Index data to display oldest to newest
fngData = flipud(fngData);

% Display the Fear and Greed Index CSV data
disp('Fear and Greed Index CSV Data:');
disp('-----------------------------');
disp(fngData);

% Define the file path for your Dogecoin CSV data file
dogeFilePath = 'C:\Users\Lorcan\OneDrive\Documenten\Final year project\CODE\code trials\DOGE-USD.csv';

% Read the Dogecoin CSV file into a table
dogeData = readtable(dogeFilePath);

% Filter Dogecoin data for dates starting from 2019
dogeData = dogeData(dogeData.Date >= datetime('2019-01-01'), :);

% Display the first few rows of the Dogecoin data
disp('Dogecoin Data:');
disp('-----------------------------');
disp(dogeData);

% Specifying the numeric columns to handle missing data
numericColumnsDoge = {'Open', 'High', 'Low', 'Close', 'AdjClose', 'Volume'};

% Looping each numeric column and filling missing values with zeros
for i = 1:numel(numericColumnsDoge)
    columnName = numericColumnsDoge{i};
    dogeData.(columnName) = fillmissing(dogeData.(columnName), 'constant', 0);
end

% Removing duplicate rows based on all columns
dogeData = unique(dogeData);

% Calculate daily returns using the 'AdjClose' column
dogeData.DailyReturns = [NaN; diff(dogeData.AdjClose) ./ dogeData.AdjClose(1:end-1)];

% Convert the 'Date' column from string to DateTime format
dogeData.Date = datetime(dogeData.Date, 'Format', 'yyyy-MM-dd');
```

```
% Calculate 7-day moving average for Bitcoin Close - Open difference
bitcoinData.MovingAverage_7 = movmean(bitcoinData.Close - bitcoinData.Open, [6 0]); % 7-day moving average

% Calculate 14-day moving average for Bitcoin Close - Open difference
bitcoinData.MovingAverage_14 = movmean(bitcoinData.Close - bitcoinData.Open, [13 0]); % 14-day moving average

% Calculate 21-day moving average for Bitcoin Close - Open difference
bitcoinData.MovingAverage_21 = movmean(bitcoinData.Close - bitcoinData.Open, [20 0]); % 21-day moving average

% Calculate 7-day moving average for Dogecoin Close - Open difference
dogeData.MovingAverage_7 = movmean(dogeData.Close - dogeData.Open, [6 0]); % 7-day moving average

% Calculate 14-day moving average for Dogecoin Close - Open difference
dogeData.MovingAverage_14 = movmean(dogeData.Close - dogeData.Open, [13 0]); % 14-day moving average

% Calculate 21-day moving average for Dogecoin Close - Open difference
dogeData.MovingAverage_21 = movmean(dogeData.Close - dogeData.Open, [20 0]); % 21-day moving average

% Combine Bitcoin, Dogecoin, and Fear and Greed Index data
combinedData = table();
combinedData.Date = fngData.Date;
combinedData.FearAndGreedIndex = fngData.FearAndGreedIndex;
combinedData.Bitcoin_AdjClose = bitcoinData.AdjClose(ismember(bitcoinData.Date, fngData.Date));
combinedData.Bitcoin_HighLowDifference = bitcoinData.High - bitcoinData.Low;
combinedData.Bitcoin_CloseOpenDifference = bitcoinData.Close - bitcoinData.Open;
combinedData.Bitcoin_MovingAverage_7 = bitcoinData.MovingAverage_7(ismember(bitcoinData.Date, fngData.Date));
combinedData.Bitcoin_MovingAverage_14 = bitcoinData.MovingAverage_14(ismember(bitcoinData.Date, fngData.Date));
combinedData.Bitcoin_MovingAverage_21 = bitcoinData.MovingAverage_21(ismember(bitcoinData.Date, fngData.Date));
combinedData.Bitcoin_Volume = bitcoinData.Volume(ismember(bitcoinData.Date, fngData.Date));
combinedData.Dogecoin_AdjClose = dogeData.AdjClose(ismember(dogeData.Date, fngData.Date));
combinedData.Dogecoin_HighLowDifference = dogeData.High - dogeData.Low;
combinedData.Dogecoin_CloseOpenDifference = dogeData.Close - dogeData.Open;
combinedData.Dogecoin_MovingAverage_7 = dogeData.MovingAverage_7(ismember(dogeData.Date, fngData.Date));
combinedData.Dogecoin_MovingAverage_14 = dogeData.MovingAverage_14(ismember(dogeData.Date, fngData.Date));
combinedData.Dogecoin_MovingAverage_21 = dogeData.MovingAverage_21(ismember(dogeData.Date, fngData.Date));
combinedData.Dogecoin_Volume = dogeData.Volume(ismember(dogeData.Date, fngData.Date));
```

Appendix

```
    % Save the combined data to CSV
    combinedFileName = 'combinedData2.csv';
    writetable(combinedData, combinedFileName);
    disp(['Combined data with moving averages saved to ' combinedFileName]);

    % Display the first few lines of combinedData2.csv
    disp('First few lines of combinedData2.csv:');
    disp('-----------------------------------');
    disp(head(readtable(combinedFileName)));

   % Define fear and greed index ranges
fngRanges = [0, 15; 16, 30; 31, 44; 45, 55; 56, 70; 71, 85; 86, 100; 0, 20; 21, 40; 41, 60; 61, 80; 81, 100; 0, 100]; % Updated ranges


    % Create a cell array to store the data tables
    dataTables = cell(size(fngRanges, 1), 1);

    % Loop through each fear and greed index range
    for i = 1:size(fngRanges, 1)
        range = fngRanges(i, :);

        % Filter combined data based on fear and greed index range
        filteredData = combinedData(combinedData.FearAndGreedIndex >= range(1) & combinedData.FearAndGreedIndex <= range(2), :);

        % Calculate price changes for Bitcoin and Dogecoin
        priceChangeBitcoin = [NaN; diff(filteredData.Bitcoin_AdjClose)];
        priceChangeDogecoin = [NaN; diff(filteredData.Dogecoin_AdjClose)];

        % Create a table with the required columns
        dataTable = table(filteredData.Date, filteredData.FearAndGreedIndex, ...
            priceChangeBitcoin, priceChangeDogecoin, ...
            filteredData.Bitcoin_HighLowDifference, filteredData.Bitcoin_CloseOpenDifference, ...
            filteredData.Bitcoin_MovingAverage_7, filteredData.Bitcoin_MovingAverage_14, filteredData.Bitcoin_MovingAverage_21, filteredData.Bitcoin_Volume, ...
            filteredData.Dogecoin_HighLowDifference, filteredData.Dogecoin_CloseOpenDifference, ...
            filteredData.Dogecoin_MovingAverage_7, filteredData.Dogecoin_MovingAverage_14, filteredData.Dogecoin_MovingAverage_21, filteredData.Dogecoin_Volume,
            'VariableNames', {'Date', ['FearAndGreed_' num2str(range(1)) '_' num2str(range(2))], ...
            ['BTCPriceChange_' num2str(range(1)) '_' num2str(range(2))], ['DOGEPriceChange_' num2str(range(1)) '_' num2str(range(2))], ...
            'Bitcoin_HighLowDifference', 'Bitcoin_CloseOpenDifference', ...
            'Bitcoin_MovingAverage_7', 'Bitcoin_MovingAverage_14', 'Bitcoin_MovingAverage_21', 'Bitcoin_Volume', ...
            'Dogecoin_HighLowDifference', 'Dogecoin_CloseOpenDifference', ...
            'Dogecoin_MovingAverage_7', 'Dogecoin_MovingAverage_14', 'Dogecoin_MovingAverage_21', 'Dogecoin_Volume'});

        % Save the table to a CSV file
        csvFileName = ['combinedData_' num2str(range(1)) '_' num2str(range(2)) '.csv'];
        writetable(dataTable, csvFileName);
        disp(['Data saved to ' csvFileName]);

        % Store the table in the cell array
        dataTables{i} = dataTable;
    end

    % Create figures for Bitcoin
    for i = 1:size(fngRanges, 1)
        range = fngRanges(i, :);

        % Filter combined data based on fear and greed index range
        filteredData = combinedData(combinedData.FearAndGreedIndex >= range(1) & combinedData.FearAndGreedIndex <= range(2), :);

        % Calculate price change for Bitcoin
        priceChangeBitcoin = [NaN; diff(filteredData.Bitcoin_AdjClose)];

        % Create figure for Bitcoin
        figure;
        plot(filteredData.Date, priceChangeBitcoin, '-o');
        ylabel('Bitcoin Price Change');
        xlabel('Date');
        title(sprintf('Bitcoin Price Change with Respect to Fear and Greed Index (%d-%d)', range(1), range(2)));
        grid on;
    end

    % Create figures for Dogecoin
    for i = 1:size(fngRanges, 1)
        range = fngRanges(i, :);

        % Filter combined data based on fear and greed index range
        filteredData = combinedData(combinedData.FearAndGreedIndex >= range(1) & combinedData.FearAndGreedIndex <= range(2), :);

        % Calculate price change for Dogecoin
        priceChangeDogecoin = [NaN; diff(filteredData.Dogecoin_AdjClose)];

        % Create figure for Dogecoin
        figure;
        plot(filteredData.Date, priceChangeDogecoin, '-o');
        ylabel('Dogecoin Price Change');
        xlabel('Date');
        title(sprintf('Dogecoin Price Change with Respect to Fear and Greed Index (%d-%d)', range(1), range(2)));
        grid on;
    end

catch exception
    % Display a more specific error message and details
    fprintf('Error reading, processing, or saving data:\n%s\n', exception.message);
end
```

combinedData_0_10
combinedData_0_15
combinedData_0_20
combinedData_0_100
combinedData_11_30
combinedData_16_30
combinedData_21_40
combinedData_31_44
combinedData_41_60
combinedData_45_55
combinedData_56_70
combinedData_61_80
combinedData_71_85
combinedData_71_90
combinedData_81_100
combinedData_86_100
combinedData_91_100
combinedData2

CSV Files for Testing Models and Making Predictions

PredictedforTraining

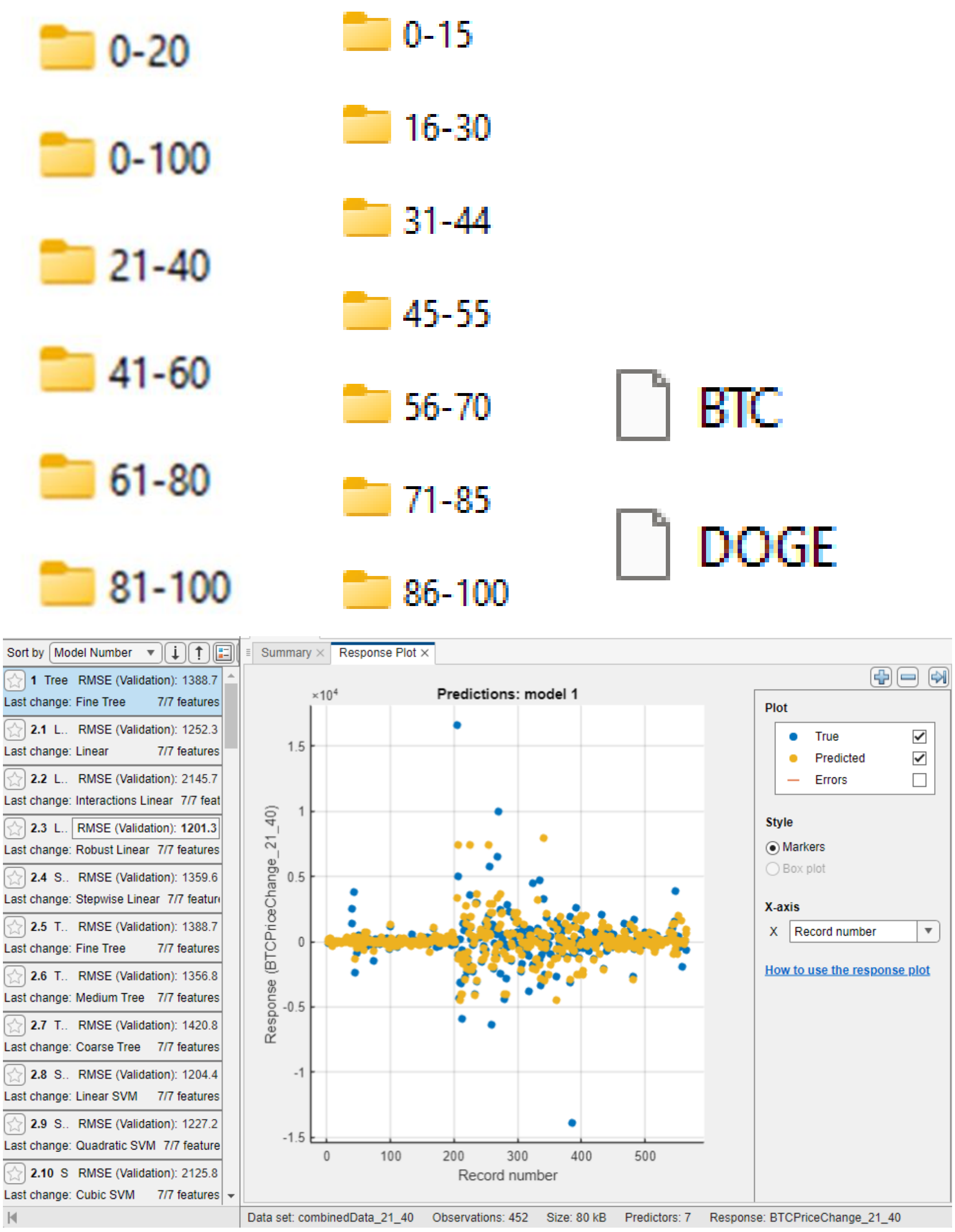
PredictedforTraining61_80

```
% Rename the column in the first table
PredictedforTraining.Properties.VariableNames{'FearAndGreed_56_70'} = 'FearAndGreed_0_100';

% Assign the modified first table to a new variable
PredictedforTraining56_70 = PredictedforTraining;
```

```
% Check if BTC0_100 and BTC56_70 are both positive
if all(BTC0_100 > 0) && all(BTC56_70 > 0)
    disp('BUY NOW for BTC');
elseif all(BTC0_100 < 0) && all(BTC56_70 < 0)
    disp('SELL NOW for BTC');
else
    disp('Hold for BTC');
end

% Check if DOGE0_100 and DOGE56_70 are both positive
if all(DOGE0_100 > 0) && all(DOGE56_70 > 0)
    disp('BUY NOW for DOGE');
elseif all(DOGE0_100 < 0) && all(DOGE56_70 < 0)
    disp('SELL NOW for DOGE');
else
    disp('Hold for DOGE');
end
```

Code for Generating Secondary Results

Appendix



Machine Learning Models for BTC and DOGE for each studied FGI Increment