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The University of Westminster, Coat of Arms

A Novel Approach to Time Series Forecasting using Liquid Time-constant Networks

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Acronyms

AI	Artificial Intelligence.
API	Application Programming Interface.
ARIMA	Autoregressive Integrated Moving Average.
BPTT	Back-Propagation Through Time.
BTC	Bitcoin.
CT-GRU	Continuous-time Gated Recurrent Unit.
CT-RNN	Continuous-time Recurrent Neural Network.
DL	Deep Learning.
GPU	Graphics Processing Unit.
LSTM	Long Short-Term Memory.
LTC	Liquid Time-constant.
ML	Machine Learning.
(s)MAPE	Symmetric Mean Absolute Product Error.
MASE	Mean Absolute Scaled Error.
MSE	Mean Squared Error.
N-BEATS	Neural Basis Expansion Analysis for interpretable Time Series.
NER	Named Entity Recognition.
NLP	Natural Language Processing.
ODE	Ordinary Differential Equations.
POC	Proof-Of-Concept.
REST	Representational State Transfer.
RMSE	Root Mean Squared Error.
RNN	Recurrent Neural Network.
TS	Time Series.
XAI	Explainable Artificial Intelligence.

1. CHAPTER OVERVIEW

In this chapter, the author focuses on identifying the requirements and the steps followed to gather these requirements. In detail, possible stakeholders, alongside their interaction points and roles, are documented using a rich picture diagram and a stakeholder onion model. Furthermore, the requirement-gathering techniques followed and the insights obtained to analyze and produce functional and non-functional requirements, use case diagrams, and prototype descriptions are defined.

2. RICH PICTURE

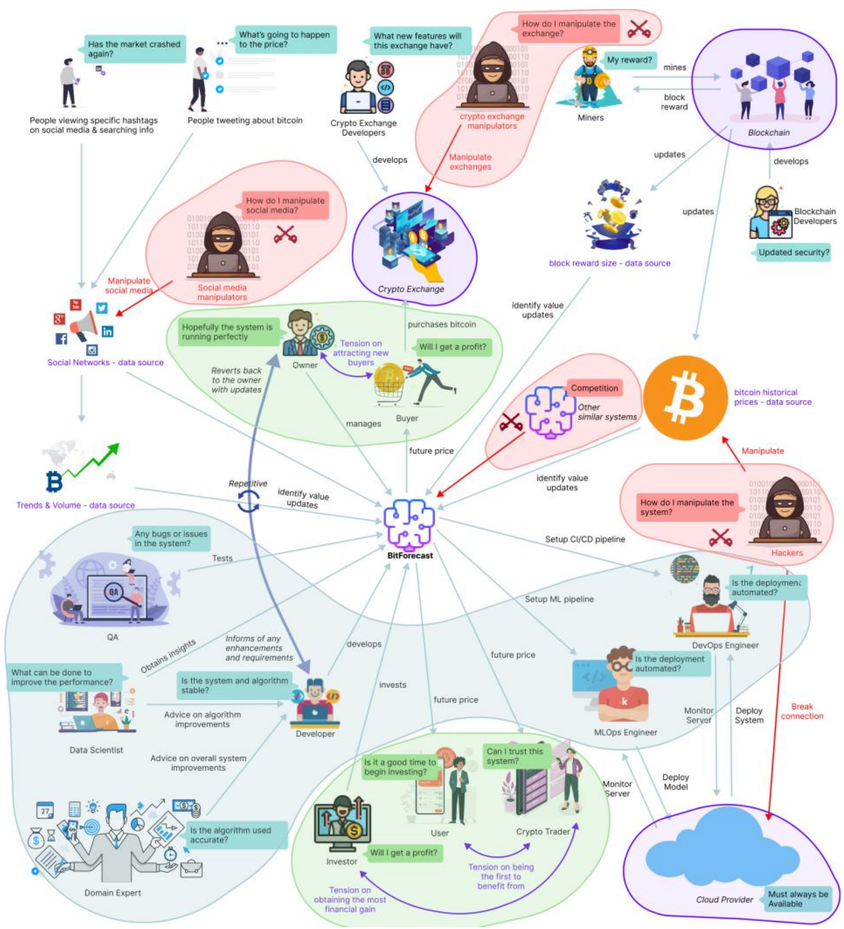


Figure 1: Rich picture diagram (*Self-Composed*)

The above diagram illustrates a helicopter view of the wider environment, how specific stakeholders would interact with the system, and how they would benefit. Furthermore, the possibilities of negative impact on the design and possible critical analysis are identified, alongside the knowledge the researcher could receive to improve the system.

3. STAKEHOLDER ANALYSIS

The following section recognizes key stakeholders associated with the system, their relationships, and their respective roles. The stakeholder onion model depicts this information, and the stakeholder viewpoints further detail it.

3.1 Stakeholder onion model

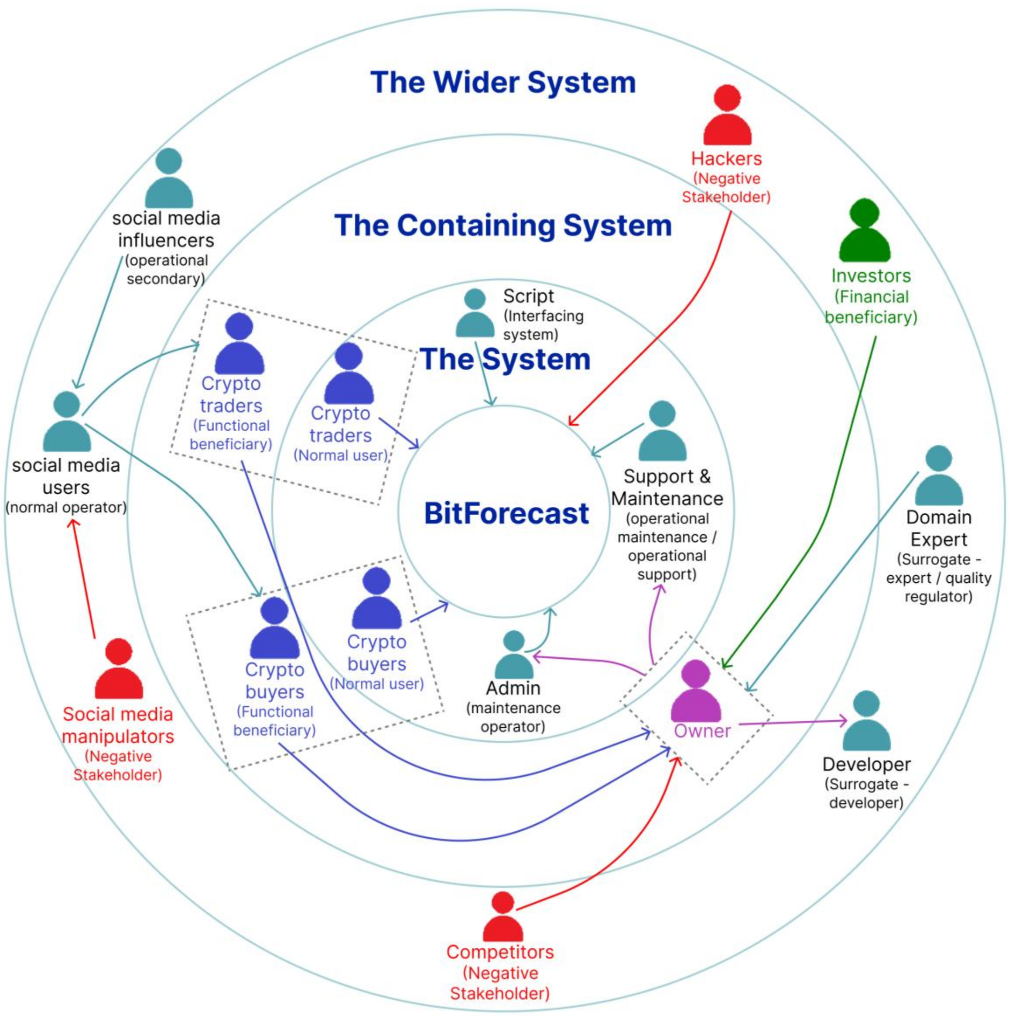


Figure 2: Stakeholder onion model (*self-Composed*)

3.2 Stakeholder viewpoints

Table 1: Stakeholder viewpoints (*self-Composed*)

Stakeholder	Role	Benefits/Description
Support & Maintenance	Operational – support & Operational - maintenance	Maintains the health of the system and attends to user inquiries.
Admin	Maintenance operator	Monitors and updates the system when necessary.
Script	Interfacing system	Fetches data and makes sure system is updated.
Owner	Owner & Operational - administration	Manages other operators, listens to feedback, and communicates with other stakeholders.
Crypto trader	Functional beneficiary	More convenient for deciding whether to purchase or sell currently held assets.
Crypto buyer		
Investor	Financial beneficiary	Makes profit, by investing in the system, upon marketing or user subscriptions.
Domain expert	Surrogate – expert & Quality regulator	Provides advice on overall system improvements.
Developer	Surrogate – developer	Develops the system.
Social media influencers	Operational - secondary	Influence users, drive trends, and provide thoughts.
Social media users	Normal operator	Get influenced to invest or sell currently held assets.
Competitors	Negative stakeholder	Build competing products that outperform or have better value.
Social media manipulators		Manipulate set trends and influencer thoughts.
Hackers		Disrupt the system and corrupt data.

4. REQUIREMENT ELICITATION METHODOLOGIES

Researchers can carry out requirement elicitation methodologies to gather requirements. The following table discusses the selected ones and their purpose.

Table 2: Requirement elicitation methodologies (*Self-Composed*)

Method 01: Literature review
An exhaustive literature review has been conducted to identify a respectable research gap in a cutting-edge research field and a domain of interest. The author studied existing systems to determine limitations and future research. A brief understanding of the implementation methods was also identified, alongside necessary best practices.
Method 02: Observations
Upon conducting the literature review, analysis of similar systems is an added advantage. Validating and evaluating its viability is paramount as the chosen research domain is relatively new. Existing algorithmic POCs must be studied and thoroughly assessed, as this will provide the author with the necessary insights and techniques to implement.
Method 03: Survey
Obtaining insights and expectations from end users can be gathered by conducting a survey, specifically, the questionnaire. Upon receiving this prominent information, the author can decide whether the proposed system is helpful for the target audience and understand how the target audience intends to benefit from it. As they are large in sample size, the survey is a powerful choice for data collection.
Method 04: Interview
Interviews can help gather knowledge and insights into more theoretical concepts that will be helpful behind the scenes for implementing the research component and associating with and answering the proposed research questions. The author can interview specific niche experts with knowledge of neural ODEs and SDEs to obtain said intuition, which they cannot acquire by conducting a survey.
Method 05: Prototyping
Prototyping will allow the developer to iterate between implementations and improvements. As the architecture is more novel, this procedure will be used abundantly as a straightforward approach to obtaining the optimal performance is unlikely and will take time.

5. ANALYSIS OF ELICITATION METHODOLOGIES

The essential stakeholders were separated into groups, and each group was analyzed in the most suited methodology. The table breakdown of these stakeholders is available in **APPENDIX I**.

5.1 Literature review

Research domain

Hasani et al. (2021) mentioned that existing solutions in TS forecasting use traditional neural nets or statistics. Additionally, existing neural ODEs were underwhelming in performance compared to existing neural nets. Additionally, the proposed architecture by Hasani et al. (2020) uses the obsolete ODE, which lacks rapid adaptability (Duvenaud, 2021) - using an SDE instead can improve flexibility further. Therefore, combining both would produce the optimal architecture.

Problem domain

Based on the reviewed literature, work that included multiple exogenous features had not utilized a non-linear model (ex: Abraham et al., 2018; Valencia et al., 2019), and work that used a non-linear model had not included the additional features that the author aims to include (ex: Fleischer et al., 2022; Serafini et al., 2020). Moreover, the available literature did not include all the features; using a non-linear model with multiple features would produce the optimal solution.

5.2 Observations

Table 3: Observations findings (*Self-Composed*)

Criteria
The author did observations for two different scenarios. • To find approaches to creating a neural SDE to implement the core research component. • To find approaches taken to implement the additional component of BTC forecasting.
Discussion of findings
The author noticed that POCs of neural SDEs are available sparingly and had yet to be utilized in an ML system like the proposed solution. Although POCs of BTC forecasting systems that use LSTMs and statistical algorithms are available in abundance, what was noticed is that they all naively utilize only the closing price as a feature or the closing price with the Twitter

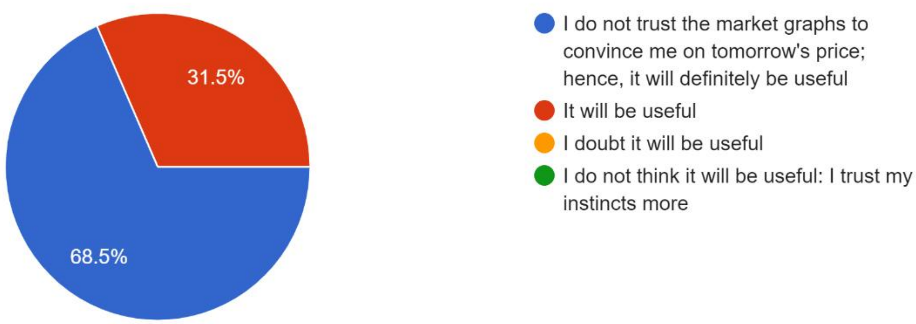
sentiment. Considering this, they decided to build the primary research component first so that the algorithm could be used to build ML systems and create the supplementary BTC forecasting system utilizing as many exogenous features as possible that can be of effect. It is also safe to assume that building the research component could be later used as a baseline for future neural SDE implementations. Therefore, insights into implementing the supplementary system and effective evaluation techniques were acquired.

5.3 Survey

A survey was conducted to gather requirements from the target audience to infer functionalities to implement for the supplementary product developed.

Table 4: Survey analysis (*Self-Composed*)

<table>
<tr><td>Question</td><td>How much would a system capable of assuming tomorrow's price benefit you?</td></tr>
<tr><td>Aim of question</td><td>To identify whether the system is beneficial in the first place</td></tr>
<tr><td colspan="2">Findings & conclusions



All the participants believed that the proposed system would be beneficial – where the majority had a greater belief than others. Having obtained this information, it is evident that the supplementary proposed system will be helpful. As identified, not a single participant thought that the system would not be beneficial. Notably, this validates the problem domain and gives the author the ‘green light’ to go ahead.</td></tr>
<tr><td>Question</td><td>Who do you think would benefit from this system?</td></tr>
<tr><td>Aim of question</td><td>To identify beneficiaries and target audience</td></tr>
<tr><td colspan="2">Findings & conclusions</td></tr>
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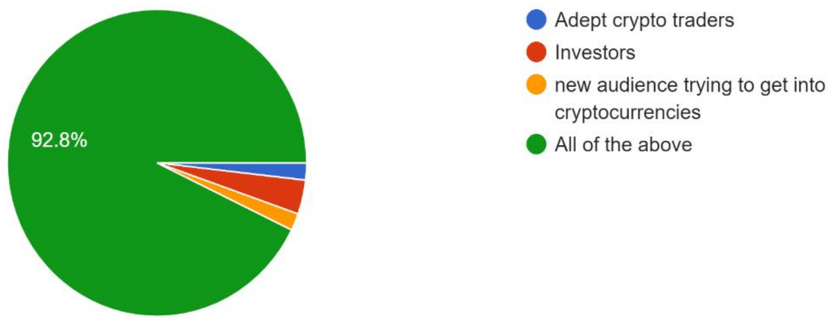
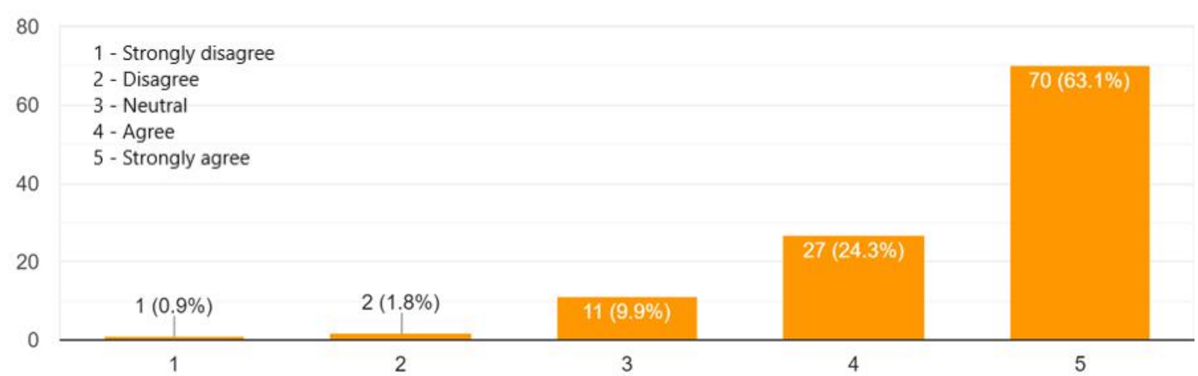
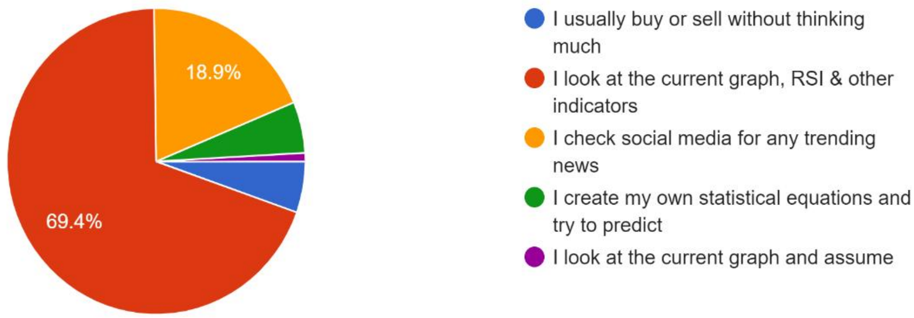
<tr><td colspan="2">

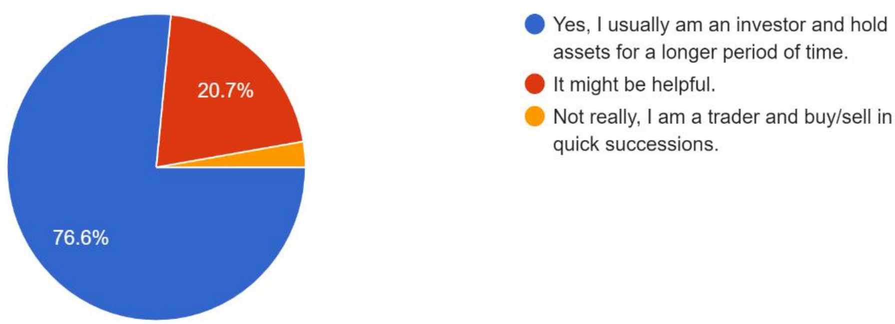
The majority of the participants believed that the system would be beneficial for expert traders, investors as well as a new audience. However, what can be identified, is that a minute portion of participants assumed that the system would be helpful primarily for people who are already involved in the market – this is some evidence that the system must be made as simple as possible to attract a newer audience. It is also identified to help only a new audience – this is evidence that the system must not be immature.</td></tr>
<tr><td>Question</td><td>This system will also benefit people who are not experts in cryptocurrencies</td></tr>
<tr><td>Aim of question</td><td>To identify whether non-technical crypto traders would benefit</td></tr>
<tr><td colspan="2">Findings & conclusions


The responses to the above question show that the system will also apply to audiences who are not cryptocurrency experts. This question goes hand in hand with the previous question to confirm whether the system can target a newer audience of people to get into cryptocurrencies rather than just focusing on a niche audience who are experts or current investors/traders.</td></tr>
<tr><td>Question</td><td>How do you decide whether to buy or sell assets?</td></tr>
</table>

<table>
<tr><td>Aim of question</td><td>To understand how a buyer/seller proceeds with their decision</td></tr>
<tr><td colspan="2">Findings & conclusions



The responses to the above question are more of a ‘Know Your Customer’ question with no specific project-related purpose. Nevertheless, what can be identified is that most of the respondents have some knowledge of cryptocurrencies, where almost 70% are experienced in trading/investing cryptocurrencies – a great insight as nearly all the respondents have specific knowledge. Therefore, the author could use this to reach out to the respondents (whom they gathered requirements from) during the evaluation phase.</td></tr>
<tr><td>Question</td><td>Do you think predicting a more future date (ex: a week from now) is as important as tomorrow's price?</td></tr>
<tr><td>Aim of question</td><td>To identify whether a greater future date prediction is also necessary</td></tr>
<tr><td colspan="2">Findings & conclusions



The author initially considered only having a single horizon forecast, considering the limited time. However, based on the above responses, it is evident that the audience would also expect forecasts for multi horizons. Therefore, the author will additionally aim to implement the ability of multi-horizon forecasting.</td></tr>
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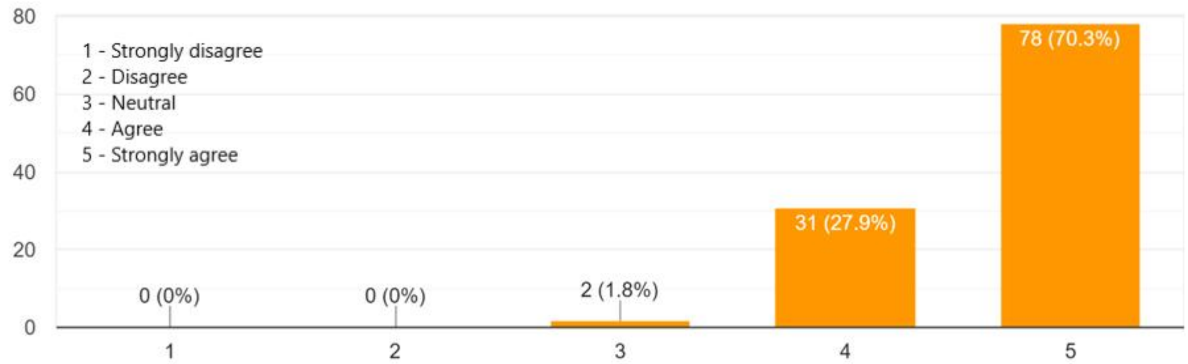
Question	Social media trends can impact the price
Aim of question	To identify whether the community believes that social media trends impact the price

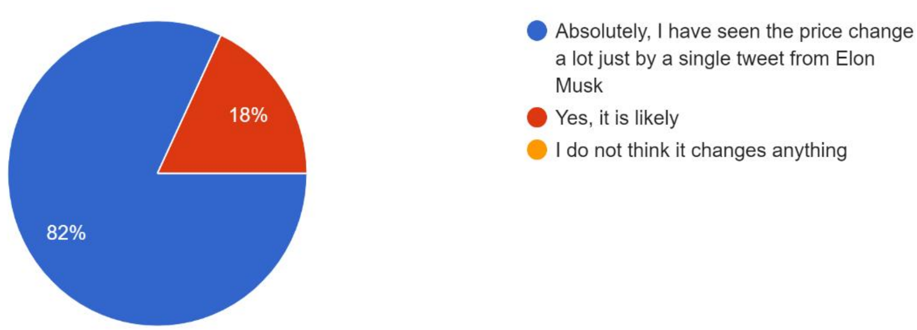
Findings & conclusions



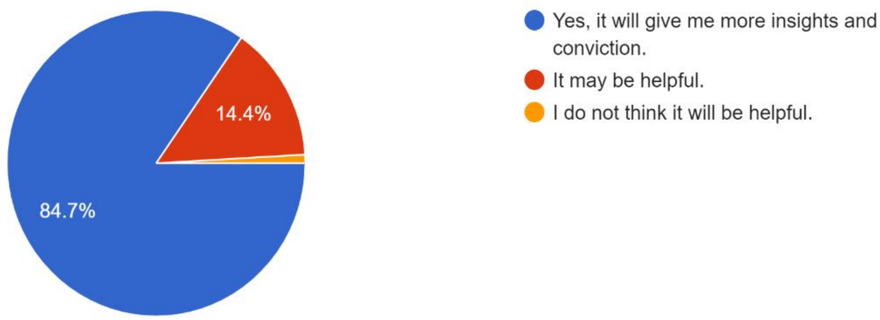
The majority of the respondents believe that social trends impact the price. Therefore, it is necessary to consider as many trends as possible. Considering the project's limited time and scope, the author has decided to use Twitter volume and Google Trends; however, Reddit, Facebook, and others would also provide insights and could be considered future work.

Question	If a highly influential person tweets about Bitcoin, do you expect the price to tip to the side in favor of their tweets meaning?
Aim of question	To identify whether including Twitter sentiment is beneficial and to confirm the problem domain contribution.

Findings & conclusions



All participants believe that the current thoughts on social media affect the price in one way or another. Most participants further believed that the tweeter's influence adds additional significance. Considering this and the previous question, it is apparent that the mentioned

<table>
<tr><td colspan="2">social factors contribute to price changes, which validates the problem domain contribution. Additionally, based on the responses, the requirement for NER and weighted search is more apparent to give more weightage to specific tweeter's sentiments.</td></tr>
<tr><td>Question</td><td>Would it be helpful to obtain a range of prices rather than a point price? (Ex: 10,000 - 15,000 instead of 12,500)</td></tr>
<tr><td>Aim of question</td><td>To identify whether including uncertainty estimates is beneficial</td></tr>
<tr><td colspan="2">Findings & conclusions


The author initially decided on only providing a point forecast for the system, as this research aims to develop a novel architecture for TS forecasting. However, based on the responses and while conducting prototyping, it became evident that a single-point prediction is likely to be less valuable than a range of prices. A point prediction is implausible to be accurate, which makes the requirement of uncertainty estimates more vital.</td></tr>
<tr><td>Question</td><td>What functionalities would you expect to have in a bitcoin forecasting system?</td></tr>
<tr><td>Aim of question</td><td>To identify any additional requirements</td></tr>
<tr><td colspan="2">Findings & conclusions
To analyze opened ended questions, the author can perform thematic analysis. The analysis, including the theme and related codes, is available in APPENDIX II.
Based on the analysis conducted, it is evident that the participants would appreciate some Explainability. Including XAI is an addition that the author could look into if time permits. The participants also mentioned that the system would be better performant and robust if it utilized as many exogenous factors while making it as simple as possible. Based on these findings, the author will aim to include as much Explainability as possible and make it</td></tr>
</table>

mandatory to use the mentioned exogenous features.	
Question	Any extra feedback you would like to provide?
Aim of question	No specific reason – is mainly used to obtain any additional feedback
Findings & conclusions The respondents submitted a few motivational sentences to inspire and motivate the author to perform their best.	

5.4 Interviews

Interviews were conducted to obtain domain expertise and any information that the author may have missed and could be significant. The author interviewed only a few candidates as the research domain is new and unknown; fortunately, they were the most knowledgeable. The author also interviewed a candidate experienced in the problem domain area. The findings were analyzed using thematic analysis and presented below. The participants affiliations and their respective expertise area are presented in **APPENDIX III**.

Table 5: Interview thematic analysis codes, themes & conclusions (*Self-Composed*)

Code	Theme
Research component	
Algorithm architecture	Research Problem & Gap
Resource intensive	Requirements
Obsolete, Inflexible	Advice
Visualizations, Explainability	Other suggestions
Problem domain	
External features and trends	Robustness

Theme	Conclusion	Evidence
Research component		
Research Problem & Gap	The interviewees validated the research gap and the defined problem. They were also happy that the author	"Yes, there are many TS forecasting algorithms; however, many are obsolete."

	had been conducting this research, as few papers were published in this domain.	“Yes, the chosen field of architectures can be considered an advancement.” “As per my knowledge, I have not seen a system using the basic LTC architecture itself, so this new architecture will be novel.”
Requirements	The interviewees were concerned that ODEs and SDEs could be expensive to compute and hence could take some time, which can be an issue given that the forecasts must be produced quickly. Therefore, the author must optimize the model as much as possible to avoid user-unfriendliness.	“They are expensive to compute.” “It can be resource-intensive.”
Advice	The author had initially planned on only creating an implementation of the LTC architecture proposed by Hasani et al. (2020). However, the author could further improve the architecture by using SDEs instead (the base LTC uses ODEs), which could manifest into a novel algorithm, which is the author’s current aim as it carries more significance and a potentially more outstanding contribution.	“I think latent ODEs are obsolete.” “You should look into latent SDEs instead.” “Latent SDEs are more flexible, you could try applying LTC architectures to those more flexible models instead.”
Other suggestions	What was concluded here was that XAI is primarily present for image classification, and there needs to be more literature on the TS domain. However, XAI integration into TS	“Yea, in the domain of TS I have not seen many explainable AI research conducted.” “Explainable AI is flourishing in image classification but I have not

	modelling could be confusing and complicated due to the temporal component. Additionally, XAI for SDEs needs to be researched, which the author could look into if time permits.	seen it in TS." "Integrating explainable AI might not be straightforward as other domains."
Problem domain		
Robustness	The interview was an additional validation for the data collected in the survey. Most suggestions were to use as many extra features as possible to make the model robust. Therefore, the author will ensure that they utilize the mentioned exogenous features.	"It is best if you try to include as many features as possible." "It is not practical to forecast with only historical prices."

5.5 Prototyping

Table 6: Prototyping findings (*Self-Composed*)

Criteria
To explore the feasibility of creating the primary research component.
Discussion of findings
U Upon iterative prototyping, challenges that the developer did not expect to arise emerged. Challenges ranged from finding a suitable dataset to implementing the algorithm itself. Building the algorithm is intimidating, as no proper reference exists. They realized that, alongside traditional DL theories, implementing the algorithm required more profound knowledge and understanding of SDEs and differential solvers. Furthermore, they had depended on the Twitter API to get tweet sentiment of specific days; however, this was impossible as Twitter had updated the API only to provide tweets of the past seven days. Fortunately, there were public datasets available up to a certain point in time; therefore, they had to use a third-party library to scrape tweets of dates ahead of that point in time. Moreover, upon experimentation, they gained an

epiphany that solely the point price prediction would be useless; instead, a range of uncertainty estimations that provide a range of values would be more helpful. Furthermore, any explainable insights from the networks can be valuable to provide intuition into the forecast generation.

7. SUMMARY OF FINDINGS

ID	Finding	Literature Review	Observations	Survey	Interview	Prototyping
Research component						
1	Validate research domain and gap.	✓	✓		✓	
2	The novelty of the research hypothesis (an architecture inspired by the LTC).	✓	✓		✓	
3	Neural ODEs are an advancement for TS forecasting.	✓			✓	
4	Try to integrate latent SDEs into an LTC architecture for a novel algorithm implementation instead of using the same obsolete latent ODE.				✓	✓
Problem domain						
5	The system will be of use to experts and new audiences.			✓		
6	Social trends can be a source of impact.	✓		✓		
7	Well-known influencers' opinions cause a more drastic impact.	✓		✓		
8	A system combining all exogenous features in a non-linear model has yet to be explored.	✓				
9	Including a range of prices than a point price is an added advantage and can produce more credibility.			✓		✓
10	Implementing an Explainability component will			✓		✓

	drastically make the system more credible.					
11	A system capable of changing its hyperparameters would make it worthwhile for experts.			✓		

7. CONTEXT DIAGRAM

The following diagram depicts the system's boundaries and interactions. Determining them before development will provide the author insight into how the information should flow.

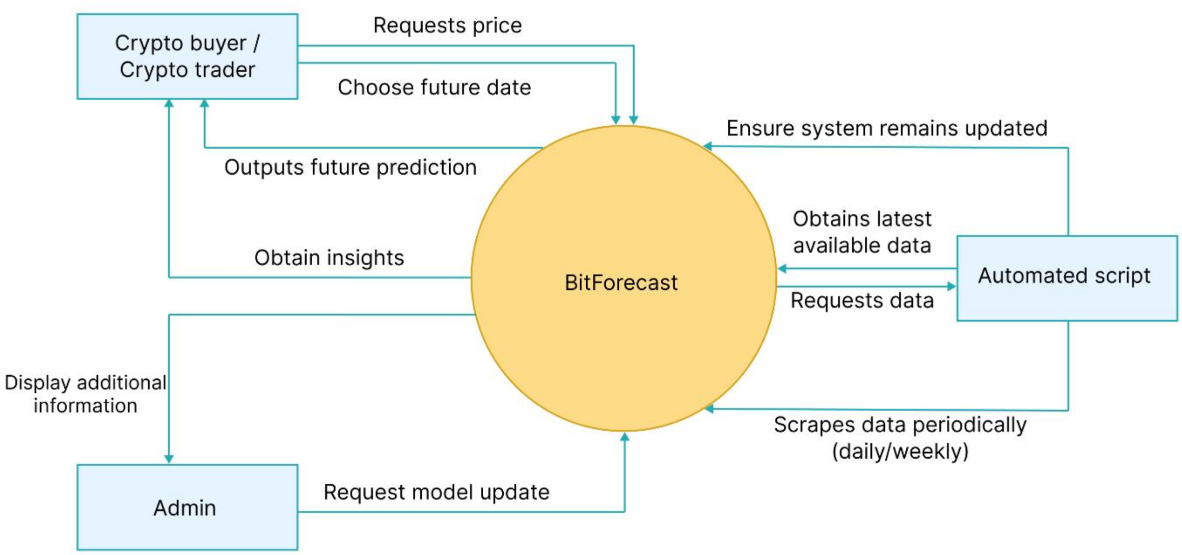


Figure 3: Context diagram (*Self-Composed*)

8. USE CASE DIAGRAM

The below diagram demonstrates the "sea level" use cases of the proposed system, describing the functionalities at a high level the system will provide end users with.

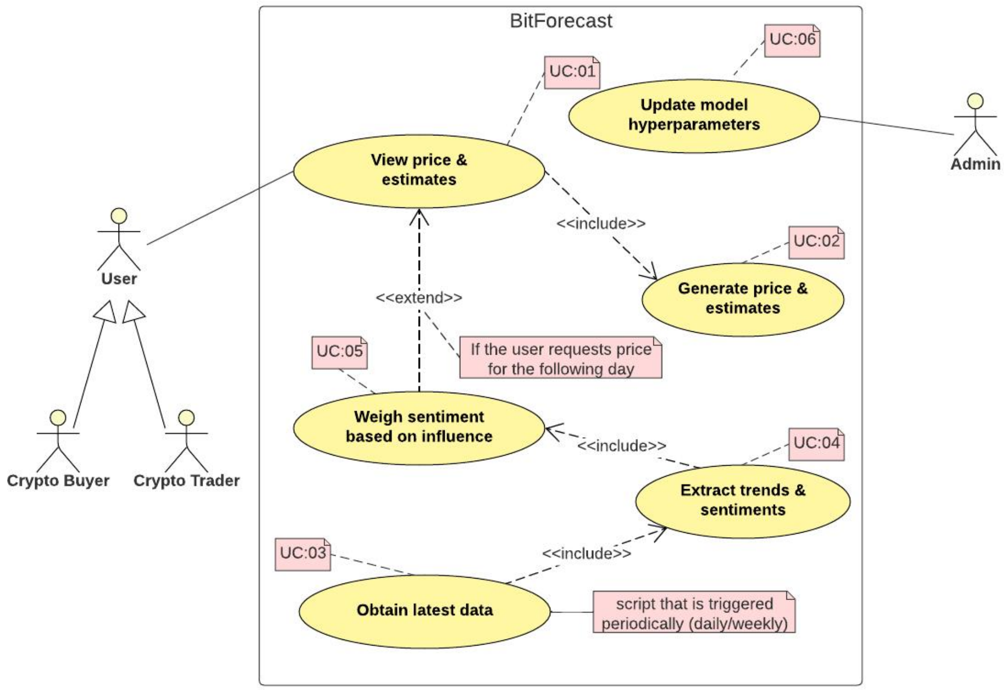


Figure 4: Use case diagram (*Self-Composed*)

9. USE CASE DESCRIPTIONS

The core use case descriptions are presented below, any sub-descriptions are available in **APPENDIX IV**.

Table 7: Use case description UC:03; UC:04 (*Self-Composed*)

Use case	Display price & estimates
Id	UC:01; UC:02
Description	Display future prices and their respective uncertainty estimations based on the user's choice of date, alongside any Explainability insights.
Actor	User
Supporting actor (if any)	None
Stakeholders (if any)	Crypto buyer, crypto trader
Pre-conditions	All the data must be scraped and preprocessed, and the forecast should have

	been generated.
Main flow	MF1. User requests tomorrow's price. MF2. The system recognizes the need to utilize available exogenous features. MF3. The system ensures data available is up-to-date (must be in this case, as the script will run periodically automatically). If not: 1. Obtains the latest available data. 2. Performs sentiment analysis and self-retrains. MF4. The system generates price and upper and lower estimations. MF5. Display output to the user along with any insights.
Alternative flows	AF1. The user requests the price for a date ahead of tomorrow. AF2. The system recognizes the inability to utilize other features. AF3. The system generates price and upper and lower estimations. AF4. Display output to the user along with any insights.
Exceptional flows	EF1. The system could not generate a prediction – display a user-friendly error message.
Post-conditions	The user is displayed with a forecast and necessary insights.

Table 8: Use case description UC:05; UC:06 (*Self-Composed*)

Use case	Manage exogenous features
Id	UC:03; UC:04; UC:05
Description	Manage and process new data without the need for manual interaction.
Actor	Script
Supporting actor (if any)	None
Stakeholders (if any)	None
Pre-conditions	The latest available data must be scraped and available.
Main flow	MF1. A Cron job triggered fetches the latest historical prices, tweets, Twitter volume, trends, and block reward size data.

	MF2. Twitter volume, Google trends, and block reward size are scaled and cleaned. MF3. Tweets undergo sentiment analysis to determine current speculation. MF4. The sentiment is further weighted based on the Tweeter's importance (ex: Elon Musk) MF5. Features are combined with historical closing prices to create an enriched dataset and retrain the model.
Alternative flows	None
Exceptional flows	EF1. The script could not fetch recent data – retry a few days later or alert Admin for manual overhaul.
Post-conditions	A new enriched dataset with the features is generated.

10. REQUIREMENTS

10.1 Functional requirements

The functional requirements were determined based on priority using the 'MoSCoW' technique, which is detailed below.

Table 9: 'MoSCoW' technique of requirement prioritization (*Self-Composed*)

Priority level	**Description**
M (Must have)	The author must implement requirements with this priority for the project to succeed.
S (Should have)	Requirements that would be of value but are not necessary.
C (could have)	Features that are optional and have no significant impact. It is desirable to implement them if time permits.
W (Will not have)	Requirements that will not be a part of the implementation at this point.

Table 10: Functional requirements

ID	Description	Priority	Use Case
Research level			
FR1	A robust and scalable implementation of the novel algorithm must follow recommended standards.	M	-
FR2	The developed algorithm must be able to be used as existing layers and algorithms (ex: LSTM, CNN).	M	-
System level			
FR3	Users must be able to choose a future date.	M	UC:01
FR4	Users must be able to view the point prediction price.	M	UC:03
FR5	The system must generate the point prediction price based on the user's choice of date.	M	UC:02
FR6	The script must obtain the latest data available periodically.	M	UC:04
FR7	The script must extract trends and sentiments from obtained data.	M	UC:05
FR8	The script should weigh sentiment based on any influential personnel's tweet.	S	UC:06
FR9	Users should be able to view a range of prices along with the single-point price.	S	UC:03
FR10	The system should generate higher and lower bound uncertainty estimations.	S	UC:02
FR11	The GUI should plot the forecast with the current prices in a single graph to show the growth/decline.	S	UC:03
FR12	The system could display some insights to the user, such as a highly influential tweet that made it predict the price.	C	UC:03
FR13	Admins could authenticate and update the model with different parameters.	C	N/A
FR14	Admins could get additional information about a prediction, such as the evaluation metric and accuracy.	C	N/A

FR15	The system will not produce forecasts for other cryptocurrencies.	W	N/A
FR16	The system will not produce real-time forecasts (ex: hourly).	W	N/A

10.2 Non-functional requirements

The author prioritized the non-functional requirements based on the following two levels:

- Important – best to have them.
- Desirable – better to have them.

Table 11: Non-functional requirements

ID	Requirement	Description	Priority
NFR1	Performance	The system must take little time to generate a forecast, given that a couple of extra features are in use.	Important
NFR2	Performance	The system must not unnecessarily keep updating its data.	Important
NFR3	Usability	The user interface must be simple and effective and provide user-friendly errors if any occur.	Important
NFR4	Maintainability	The author must document the codebase well in case of future reference, mainly the algorithm development repository.	Important
NFR5	Quality	The output must be of good quality so that it provides vital insights.	Desirable
NFR6	Scalability	The system must be deployed to a cloud with no scaling issues and good resources for efficient and optimal performance, especially as there could be multiple concurrent active user requests.	Desirable
NFR7	Security	The system must be resilient to attackers, specifically to prevent data manipulation.	Desirable
NFR8	Compatibility	To ensure compatibility, the developer must test the system on most browsers and mobile phones.	Desirable
NFR9	Availability	In critical failures, the primary operator must be available and solve issues as soon as possible.	Desirable

11. CHAPTER SUMMARY

In this chapter, the author defined necessary stakeholders interacting with the system and described how the interaction would occur, visualizing this using a rich picture diagram and Saunder’s Onion model. Additionally, requirement elicitation techniques, their reasoning, and their respective findings were discussed and presented. Finally, they specified the use cases, associated descriptions, and system requirements.

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APPENDIX I – Requirement Elicitation Methodologies

Table 12: Stakeholder groups (*Self-Composed*)

Group	Stakeholders	Reason	Instrument
G1	Domain experts (neural ODE/SDE and blockchain/crypto)	Gather any insights and knowledge specifically in the research domain to answer research questions and anything the author may have missed.	Interview
G2	End users (trader & buyer)	Gather requirements for supplementary application implementation.	Survey
G3	Competitors	Analyze any existing systems and literature in the research and problem domain.	LR/Observations
G4	Developers	Ensure completion and feasibility of the project.	Prototyping

APPENDIX II – Survey Thematic Analysis

Table 13: Survey thematic analysis codes, themes & conclusions (*Self-Composed*)

Code	**Theme**
Exogenous factors	Robustness
Explainability, Insights	Reliability
Simplicity, Convenience	User-friendly
Tuning	Editability
On-demand	Future consideration

Theme	**Conclusion**	**Evidence**
Robustness	Participants believed that prediction needed more than just including historical prices and that social media Trends and other factors (ex: sentiment) are required to make the system as robust and performant as possible.	"Use previous trends in the past." "Consider all possible external factors."
Reliability	Almost all respondents requested that the system provide an Explainability component so that the insights obtained can be reliable as the inference becomes as transparent as possible.	"Insights about the forecast will be beneficial." "Provide as much Explainability to make the prediction as credible as possible." "The rate of success of the prediction would be useful."
User-friendly	A couple of participants requested that the system provide some cryptocurrency news to make it convenient and make the inference procedure as straightforward as possible so there is no hindrance.	"Show some news about the current cryptocurrency world in the platform, so it's convenient for the users." "Make the steps from choosing a date to forecasting as simple as

		possible."
Editability	An ML-knowledgeable participant mentioned that it would be an ideal scenario if the system could tune the hyperparameters of the model in use, which could be an excellent enhancement to the system as the model anyways retrains periodically.	"Coming from machine learning point of view, I think it'll be a good idea if there's a functionality to change the hyperparameters used."
Future considerations	A couple of participants mentioned some additional features the author believes they will not be able to cover, given the time allotted.	"Predict the market for any given time duration." "Ability to identify a pump and dump scenario compared to an actual increase in the price of stock/crypto."

APPENDIX III – Interview Thematic Analysis

Table 14: Interview participant details (*Self-Composed*)

Participant ID	**Affiliation**	**Expertise related to the research**
P1	Google Brain visiting researcher and Associate Professor at University of Toronto.	Neural ODEs and SDEs.
P2	Research scientist at Deepmind.	Neural ODEs and SDEs.
P3	Research scientist at Meta AI.	Probabilistic DL and differential equations.
P4	PhD candidate at University of Nottingham.	XAI
P5	Chief Product Officer at Niftron.	Blockchain and cryptocurrencies.

APPENDIX IV – Use Case Descriptions

Table 15: Use case description UC:07 (*Self-Composed*)

Use case	Update model hyperparameters
Id	UC:07
Description	Manually change the hyperparameters used by the model.
Actor	Admin
Supporting actor (if any)	None
Stakeholders (if any)	None
Pre-conditions	All the data must be scraped and preprocessed (as the model would ideally need to be retrained upon hyperparameter tuning).
Main flow	MF1. Admin authorizes themselves. MF2. Admin can change the hyperparameters in use to a set of predefined values. MF3. The system ensures data available is up-to-date (must be in this case, as the script will run periodically automatically). If not: 1. Obtains the latest available data. 2. Performs sentiment analysis and self-retrains. MF4. The system retrains itself with the data and new hyperparameters.
Alternative flows	None
Exceptional flows	None
Post-conditions	The model is updated with the chosen hyperparameters.