University of London

DSM500 Final Project

Daily Stock Price Prediction With Multivariant TCN Model On The Singapore Market

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Daily Stock Price Prediction With Multivariant TCN Model On The Singapore Market

1 Abstract

Singapore, though small in geographical stature, holds significant importance as a global investment hub (The Economic Development Board Singapore, 2023). This study aims to bridge a critical research gap by employing a multivariate Temporal Convolutional Network (TCN) model to forecast the daily Close price of Singapore's Straits Times Index (STI), providing a novel and context-specific approach.

Our research methodology adopts a quantitative and experimental approach, utilizing a comprehensive dataset spanning a decade, encompassing granular daily data across diverse variables. This extensive dataset serves as the foundation for training and assessing multiple predictive models, including the Temporal Convolutional Network (TCN), Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), and 1D-Convolutional Neural Networks (1D-CNN). We conduct a systematic evaluation of TCN model performance through comparative analysis with the other models, assess the impact of features on TCN's predictions across both the full variant dataset and a refined version with selected features. Additionally, we probe the TCN model's generative potential across varying future time frames and scrutinize the influence of cross-validation on model efficacy.

Our extensive analysis uncovers several significant findings: First, our experiment suggests that STI Close prices do not adhere to a random walk pattern, and the data exhibits evolving dynamics over time. Notably, the TCN model outperforms its counterparts, demonstrating superior performance metrics marked by lower loss, Mean

Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Furthermore, we observe that feature selection plays a pivotal role, having the potential to either enhance or diminish predictive performance. As anticipated, our examination of cross-validation results in an enhancement in the model's ability to predict near-future data. Lastly, the model displays resilience in predicting short-term data but encounters a decrease in accuracy when forecasting over longer time horizons.

These discoveries emphasize the essentiality of precise feature curation and regular model updates to preserve predictive precision. Future research may involve the integration of sentiment analysis from news sources, presenting a compelling opportunity to enhance predictive capabilities and gain deeper insights into market dynamics. In summary, this study contributes valuable insights and methodologies, benefiting researchers and investors in navigating Singapore's intricate financial markets, making a substantial stride in financial forecasting.

Keywords: Straits Times Index (STI), Multivariate Temporal Convolutional Network (TCN), Cross-validation, Stock Price, Feature impact.

2 Introduction

In the dynamic realm of finance, the accurate prediction of stock prices stands as a formidable challenge with far-reaching implications for investors and financial institutions. However, the volatile and intricate nature of financial markets has spurred a constant quest to predict stock price movements with precision. Driven by the advent of advanced artificial intelligence and deep learning techniques, this research aims to identify and evaluate a different deep learning technique on stock price prediction within

Singapore market. This chapter introduces the study, in the sequence of overall background, the research problem, objectives, significance, and the report structure.

2.1 Background

Stock price prediction has captivated the interest of investors for many years. Fundamental analysis and technical analysis are two major debates before the development of machine learning. Fundamental analysis involves assessing the intrinsic value of an investment instrument, purchasing undervalued shares, holding them for extended periods, and selling when prices rise (Segal, 2023). Technical analysis, on the other hand, concentrates on short-term trading signals by analyzing historical data-based technical indicators (Hayes, 2022). While both these approaches are heavily dependent on the analyst's financial expertise, machine learning has emerged as a valuable tool to analyze stock price for all investors including non-financial experts. The early machine learning algorithms tailored for time series data, such as Moving Average (MA), Autoregressive Integrated Moving Average (ARIMA), and Seasonal ARIMA (SARIMA), are primarily univariate models. These models often overlook the latent dynamics inherent in the data (Selvin et al., 2017). Studies, such as those by Zhong and Enke (2017) and Hoseinzade and Haratizadeh (2019), have highlighted the impact of economic variables on stock prices. This problem could be solved by deep learning neural networks which offers nonlinearity, possess the capacity to discern concealed patterns and relationships within variables(Selvin et al., 2017).

The stock price prediction landscape predominantly centers on three leading deep learning architectures: Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN), with LSTM emerging as a prominent

variant (Mintarya et al., 2023). A relatively recent entrant is the Temporal Convolutional Network (TCN), renowned for its efficiency, minimal parameter requirements, and strong performance in sequential tasks (Bai, Kolter, and Koltun, 2018; Gridin, 2022). This exceptional performance has ignited our curiosity in utilizing TCN for stock market analysis. Kumbure et al. (2023) conducted a comprehensive review of 138 journal articles published from 2000 to 2019 on stock price prediction using machine learning, revealing that the majority of these studies were heavily concentrated on the U.S. financial market. There is a significance in the literature that few studies have been done on the Singapore financial market (Kumbure et al., 2023). Consequently, this study endeavors to address this void by evaluating the effectiveness of TCN in modeling financial data specific to the Singapore market, while also conducting comparative analyses with well-established models, including ANN, LSTM, and CNN, to provide valuable insights into stock price prediction within this unique financial landscape.

2.2 Research Questions:

With the fundamental assumption that STI exhibits predictability beyond the realm of a random walk, my research is primarily guided by following research questions:

1. How predictable on the price movements of the Straits Times Index (STI) beyond random walk behavior, and what are the associations between historical prices and additional project-specific variables contributing to this predictability?
2. How does the multivariate TCN model's predictive accuracy for STI prices compare to traditional models such as ANN, LSTM, and 1D-CNN, considering its capacity to capture longer-term patterns?

3. What is the generalization ability of the TCN model in forecasting STI stock prices on the unseen datasets across distinct time periods in future time? How could cross-validation improve model performance?

2.3 Aims and Objectives:

The overarching aim of this research is to design, develop, and assess the performance of a multivariate TCN model optimized for precise daily stock price prediction within the unique Singapore financial market landscape.

Objectives include:

1. Evaluate and rationalize the selection of datasets to be collected and the sampling strategy to ensure data completeness and representativeness.
2. Develop deep learning models capable of accurately predicting STI stock prices, including the multivariate TCN model and traditional models (ANN, LSTM, 1D-CNN), optimizing their architecture via hyperparameter tuning.
3. Conduct a comprehensive comparative analysis to contrast the performance of the TCN model and other models, assessing their predictive accuracy.
4. Examine the TCN model predictive power, evaluating their capability to generate into changing market conditions over distinct time periods. Additionally, evaluate cross-validation effectiveness in training a predictive TCN model.
5. Investigate and assess the impact of various features extracted from the multivariate dataset on the overall model performance.

2.4 Significance

This study carries substantial significance for investors, both on a global scale and within the Singapore financial market. Singapore ranks as one of the world's top destinations for Foreign Direct Investment (FDI), as well as one of the largest investor's abroad (Standard Bank Group Limited, 2023). The Straits Times Index (STI), serving as Singapore's financial barometer, underscores the critical nature of this study (Singapore Exchange Limited, 2020). The enhanced stock price prediction capabilities offered by this research hold the potential to empower investors worldwide, facilitating well-informed decision-making and potentially optimizing investment returns. Additionally, Singapore's strategic location at the heart of Southeast Asia, alongside its political and operational stability, has made it a preferred hub for businesses seeking access to regional consumer markets and cost-effective resources (The Economic Development Board Singapore, 2023). By studying the STI, this research not only benefits investors but also supports businesses in navigating the intricacies of the Singapore market, ultimately contributing to their success in the region.

2.5 Report Structure

This report begins with the above Introduction, offering an overview of stock price prediction challenges and introducing the research's focus, including research questions, aims, objectives, and significance. Moving on to the Literature Review, it summarizes existing research on stock price prediction, highlighting the growing importance of deep learning techniques and identifying the literature gap specific to Singapore's financial market. Followed by the Methodology chapter, the report explains the strategies for data collection, model development and evaluation, delving into the

creation and optimization of deep learning models, along with an outline of the comparative analysis and the exploration of model performance over time. The Results chapter summarizes key findings related to model effectiveness and efficacy of cross-validation, comparative performance, feature impact, and the TCN's predictive power over time. The discussion chapter analyzes the results in detail. The Conclusion chapter summarizes the key findings, the limitations of this project and the direction of future works.

3 Literature Review

In this project, we will review literature based on two aspects: the assessment of predictive algorithms and the exploration of different variables' impact on predictions.

In the early days of stock price prediction, statistical techniques like MA and ARIMA took center stage (Kumbure et al., 2023). However, the rise of artificial intelligence (AI) shifted the focus towards neural network models, prized for their ability to handle complex, nonlinear financial data (Kumbure et al., 2023). Among these neural network models, ANN, CNN, RNN, and their variations gained substantial recognition.

A comprehensive review by Ican and Celik (2017) found ANN to be a preferred choice in financial market prediction. Ma (2020) conducted a comparative study, pitting ANN against ARIMA and LSTM models, and discovered that ANN consistently outperformed the other models. Despite its versatility, ANN has limitations, including fixed input lengths and an inability to recognize data as ordered sequences (Gridin, 2022).

To address these issues, researchers introduced RNN, capable of capturing temporal dependencies by memorizing past values (Gridin, 2022). However, RNNs face challenges related to vanishing gradients and the effective storage of long-term

information (Gridin, 2022). Long Short-Term Memory (LSTM), a variant of RNN, has proven effective in overcoming these hurdles (Saud and Shakya, 2020). LSTM's ascendancy in practice commenced around 2015 (Mintarya et al., 2023).

Recent years have witnessed the research community acknowledging the prowess of CNNs in autonomously extracting features from time series data. Empirical research has indicated that CNNs can outperform alternative models, such as LSTM, particularly when applied to historical stock price intraday data (Selvin et al., 2017). Hoseinzade and Haratizadeh (2019) posit that CNN's strength lies in its capability to capture correlations among various features, consequently enhancing predictive accuracy. However, CNNs can suffer from a limited capacity to capture previous information, a challenge that Temporal Convolutional Networks (TCNs) effectively address by significantly expanding the input time series coverage while reducing computational costs (Gridin, 2022). Notably, Bai, Kolter, and Koltun (2018) demonstrated that TCN models outperform canonical recurrent networks such as LSTMs across various tasks and datasets, demonstrating longer effective memory. Li et al. (2022) also provides empirical evidence of the TCN model's superiority over other deep learning models, such as LSTM, and classical models like ARIMA in stock price prediction. These findings collectively inspire the investigation of TCN models in the context of the Singaporean stock market analysis.

Beyond modeling techniques, stock price prediction also involves examining independent variables' impact, including economic indicators, exchange rates, and interest rates (Zhong and Enke, 2017; Park and Shin, 2013; Hoseinzade and

Haratizadeh, 2019). These variables offer valuable insights beyond historical data and traditional stock-related metrics.

Regarding data granularity, while some studies delve into minute-wise data collection (Selvin et al., 2017), this research project centers around daily granularity data, aligning with the prevalent approach in the field (Kumbure et al., 2023).

A noticeable research gap exists concerning stock price prediction in the Singaporean financial market. Despite its significance as a major financial hub in the Asia-Pacific region, studies have barely explored this market (Kumbure et al., 2023). This research seeks to fill this gap by focusing on the applicability of the TCN model to multivariate daily data in the context of the Singaporean financial market. While TCN shows promise, this project also evaluates the performance of ANN, LSTM, and CNN models as baselines for comparison.

In summary, this literature review offers a comprehensive overview of stock price prediction methodologies, with a particular emphasis on neural network models. It underscores the importance of considering different variables and data granularity while highlighting the specific research gap in the Singaporean financial market that this project aims to address.

4 Data

4.1 Justification of Chosen Datasets

Informed by our literature review, stock price prediction could be impacted by various factors. As highlighted by Hoseinzade and Haratizadeh (2019), technical indicators, indices in different markets, the exchange rate of the U.S. dollar, commodities, the stock prices of significant U.S. companies, futures contracts, and interest rate-related

variables could play a pivotal role in stock price prediction. Consequently, these variables have been carefully justified in our dataset to ensure comprehensive coverage of potential drivers of stock price movements within the Singapore market.

4.1.1 Singapore's Export and Investment Dynamics:

Singapore's economic landscape is characterized by a reliance on exports (The Cove, 2022), and a prominent position as a hub for Foreign Direct Investment (Vinuya, 2020). Understanding the dynamics of Singapore's trade partners is crucial, which is why variables related to currency exchange rates and market indices of key trading partners, including the United States, Japan, the United Kingdom, China, Hong Kong, and Malaysia, have been meticulously included (The Observatory of Economic Complexity, 2023; Singapore Department of Statistics, 2023).

4.1.2 U.S. Economic Influence:

Considering the well-established synchronization of U.S. business cycles with the global business cycle, as indicated by (World Bank Group, 2017), it is crucial to gain insights into the broader world economy that encompasses the Singaporean market. To achieve this, we utilize multiple dimensions of the U.S. economy as a lens for understanding global economic trends. One avenue is the analysis of U.S. Treasury bonds, which serve as reliable indicators of investor sentiment toward the U.S. economy (Zucchi, 2023). These bonds offer valuable insights into market perceptions and expectations. Additionally, we explore the U.S. economy by closely examining the S&P 500, a market-capitalization-weighted index comprising 503 large-cap U.S. stocks, representing a substantial portion of the U.S. equities market and accounting for approximately 80% of its total market value (Kenton, 2023). We also investigate the top ten companies within

the S&P 500, collectively responsible for over 30% of the index's overall value (Alpert, 2023). This comprehensive approach provides a holistic view of the U.S. economic landscape, facilitating a deeper understanding of its potential impacts on the Singaporean market and global economic dynamics.

4.1.3 Gold and Crude Oil Influence:

The significance of gold and crude oil in shaping domestic and global economies cannot be understated (The Oxford Gold Group, no date; Liberto, 2023). These commodities serve as vital indicators of economic health and stability, making them crucial variables in the dataset to explore their potential influence on STI stock prices.

4.1.4 Feature Engineering:

In addition to these variables, we have undertaken feature engineering to enhance the dataset's richness. Some information in stock prices which is easy for humans to understand could be difficult for algorithms. This process includes the creation of new features, such as day of the week, price trends, and technical indicators, to provide deeper insights into stock price patterns. For example, the moving average could provide information on future prices in technical analysis. The buying and selling signals could be captured by comparing the "Close" price with moving average values. The crossing of different moving average values could form types of trading patterns. For instance, as shown in Figure 1, a “death cross” which occurs when the 50-day moving average crosses below the 200-day moving average suggests a bearish signal (Chen, 2023).

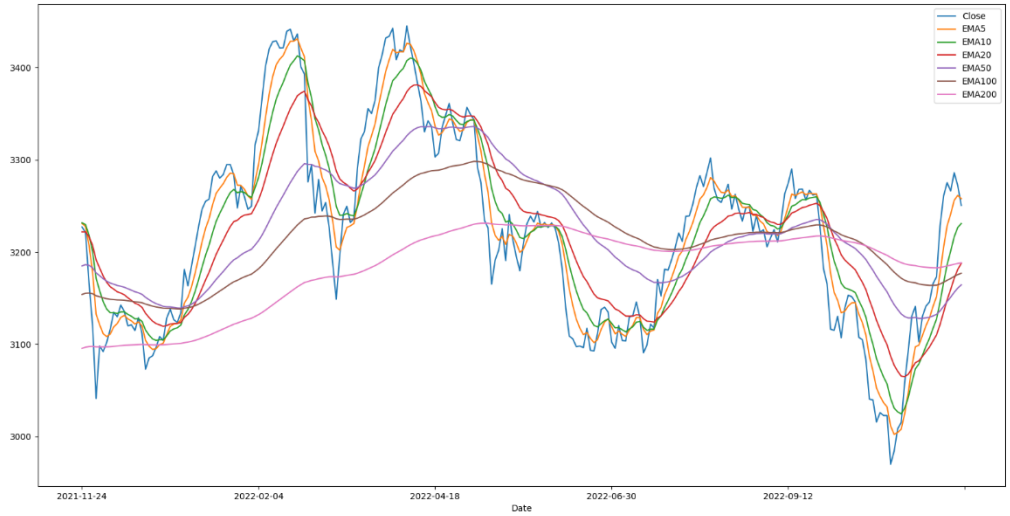

Figure 1. Moving Average

4.2 Data Sources and Collection:

The dataset utilized in this study spans from January 2013 to June 2023, encompassing daily granularity data. This dataset, comprising essential financial and economic variables, was meticulously assembled from various reputable sources. Specifically, the following sources contributed to the dataset as shown in Table 1.

Table 1 List of variables				
#	Group name	variables names	Variable Description/Calculation	source
1	prim_V	Open	STI daily Open price	Yahoo finance API
2		High	STI daily highest price	Yahoo finance API
3		Low	STI daily lowest price	Yahoo finance API
4		Close	STI daily Close price	Yahoo finance API
5		Volume	STI daily transcation volume	Yahoo finance API
6		day	which day of week	Pandas
7		trends	continuous up or down days	Manually extract from STI daily Close price
8		1st_diff	First discrete difference of Close price	Pandas
9		vola	(daily price) High - Low	Manually extract from STI daily Close price
10	TI_V	EMA5	5days Exponential Moving Average	Talib
11		EMA10	10days Exponential Moving Average	Talib
12		EMA20	20 days Exponential Moving Average	Talib
13		EMA50	50days Exponential Moving Average	Talib
14		EMA100	100days Exponential Moving Average	Talib
15		EMA200	200days Exponential Moving Average	Talib
16		rsi	Relative Strength Index	Talib
17	US_V	AAPL	Daily close price of Apple Inc	Yahoo finance API
18		MSFT	Daily close price of Microsoft Corp	Yahoo finance API
19		GOOG	Daily close price of Alphabet Inc.	Yahoo finance API
20		AMZN	Daily close price of Amazon.com, Inc.	Yahoo finance API
21		NVDA	Daily Close price of NVIDIA Corporation	Yahoo finance API
22		TSLA	Daily Close price of Tesla, Inc	Yahoo finance API
23		META	Daily Close price of Meta Platforms, Inc.	Yahoo finance API
24		BRK-A	Daily Close price of Berkshire Hathaway Inc.	Yahoo finance API
25		V	Daily Close price of Visa Inc.	Yahoo finance API
26		UNH	Daily Close price of UnitedHealth Group Incorporated	Yahoo finance API
27	Commodities_V	CL=F	Crude Oil Futures	Yahoo finance API
28		GC=F	Gold Futures	Yahoo finance API
29	indices_V	^GSPC	S&P 500	Yahoo finance API
30		^DJI	Dow Jones Industrial Average	Yahoo finance API
31		^FTSE	FTSE 100	Yahoo finance API
32		^FTMC	FTSE 250	Yahoo finance API
33		^HSI	HANG SENG INDEX	Yahoo finance API
34		000001.SS	SSE Composite Index	Yahoo finance API
35		^AEX	AEX-Index	Yahoo finance API
36		^KLSE	FTSE Bursa Malaysia KLCI	Yahoo finance API
37		^N225	Nikkei 225	Yahoo finance API
38	currencies_V	SGD	Exchange rate of Singapore dollar to U.S. dollar	Investing.com
39		EUR	Exchange rate of EURO to U.S. dollar	Investing.com
40		GBP	Exchange rate of Pound Sterling to U.S. dollar	Investing.com
41		CNY	Exchange rate of Chinese Yuan to U.S. dollar	Investing.com
42		HKD	Exchange rate of Hong Kong dollar to U.S. dollar	Investing.com
43		JPY	Exchange rate of Japanese Yen to U.S. dollar	Investing.com
44		MYR	Exchange rate of Malaysian Ringgit to U.S. dollar	Investing.com
45	TB_V	^IRX	13 Week Treasury Bill	Yahoo finance API
46		^FVX	Treasury Yield 5 Years	Yahoo finance API
47		^TNX	Treasury Yield 10 Years	Yahoo finance API
48		^TYX	Treasury Yield 30 Years	Yahoo finance API
49	ir_V	comp_sora_3m	3-month Compounded SORA for Singapore domestic interest rates	Monetary Authority of Singapore API (mas.gov.sg)

All components of this dataset are publicly accessible, ensuring transparency and openness in our research process. The data predominantly originates from transaction records and is underpinned by data providers with a distinguished reputation in the field.

4.3 Data Description:

All of our data are time series, numerical data. A summary of the data is shown in Table 2. It is easy to conclude from the summary that these variables have varying ranges which could be difficult for modelling as our neural network model prefer tensors with the range from zero to one. Also, there are many missing values as shown in Table 3.

Table 2 STI raw data statistic summary								
	count	mean	std	min	25%	50%	75%	max
Open	3118.0	3138.7	239.7	2274.4	3040.6	3200.1	3290.0	3624.2
High	3118.0	3151.1	238.0	2274.4	3056.3	3212.2	3299.6	3641.6
Low	3118.0	3125.2	241.3	2208.4	3028.4	3188.2	3278.3	3607.2
Close	3118.0	3138.0	239.7	2233.5	3040.7	3198.7	3290.4	3615.3
Volume	3118.0	216236661	132584305	0	167593825	217921000	277683150	1472751700
Dividends	3118.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Stock Splits	3118.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
day	3118.0	2.3	1.5	0.0	1.0	2.0	4.0	4.0
trends	3118.0	0.0	2.4	-10.0	-2.0	1.0	2.0	9.0
1st_diff	3117.0	0.0	24.3	-182.9	-12.7	0.2	13.6	143.4
vola	3118.0	25.9	12.9	7.0	17.5	23.0	30.7	137.2
EMA5	3113.0	3137.9	238.2	2375.0	3047.4	3199.6	3290.4	3595.6
EMA10	3107.0	3137.9	236.2	2458.2	3050.9	3195.4	3287.2	3574.7
EMA20	3095.0	3137.8	232.4	2490.6	3061.4	3197.1	3285.4	3547.7
EMA100	2994.0	3134.8	206.2	2558.0	3047.0	3190.0	3264.1	3493.2
rsi	3101.0	51.0	12.6	10.4	42.8	51.4	60.4	83.6
EMA200	2869.0	3133.1	177.9	2669.8	3005.2	3202.7	3241.2	3426.2
EMA50	3057.0	3137.0	222.3	2516.7	3062.8	3192.9	3277.5	3523.2
AAPL	3049.0	62.1	49.4	13.9	26.9	40.7	81.3	189.2
AMZN	3049.0	71.2	50.9	12.5	21.8	58.5	99.7	186.6
BRK-A	3049.0	285587.1	95094.4	139610.0	210530.0	274740.0	327440.0	539180.0
GOOG	3049.0	58.4	34.1	17.5	29.9	51.1	72.6	150.7
META	3049.0	152.6	80.6	22.9	85.7	150.2	192.5	382.2
MSFT	3049.0	121.0	90.3	26.5	47.0	84.9	186.7	348.1
NVDA	3049.0	66.9	80.9	3.0	5.5	39.8	88.8	438.1
TSLA	3049.0	68.9	96.8	2.2	14.5	18.7	59.9	407.4
UNH	3049.0	229.6	139.6	51.4	115.9	215.5	296.6	555.2
V	3049.0	126.5	64.2	38.7	69.2	112.6	192.3	250.9
CL=F	3046.0	65.7	22.2	-37.6	48.8	60.0	82.7	123.7
GC=F	3045.0	1437.4	261.9	1050.8	1241.4	1316.2	1696.5	2051.5
000001.SS	2929.0	3007.6	525.4	1950.0	2750.3	3090.8	3312.6	5166.4
^AEX	3099.0	531.2	119.6	332.2	435.7	521.9	579.3	827.6
^DJI	3049.0	23363.3	6507.2	13328.8	17554.5	23358.2	27783.6	36799.6
^FTMC	3064.0	18328.3	2382.9	12611.9	16599.8	18415.6	19949.4	24250.8
^FTSE	3063.0	6915.9	527.6	4993.9	6550.3	6954.2	7350.2	8014.3
^GSPC	3049.0	2729.3	863.8	1457.2	2048.0	2575.3	3234.9	4796.6
^HSI	3009.0	24564.8	3216.6	14687.0	22392.2	24168.7	27114.9	33154.1
^KLSE	3014.0	1668.6	128.7	1219.7	1585.8	1674.0	1773.6	1895.2
^N225	2932.0	20809.8	4838.2	10487.0	16891.2	20539.8	23421.1	33706.1
SGD	3096.0	1.3	0.1	1.2	1.3	1.4	1.4	1.5
EUR	3096.0	1.2	0.1	1.0	1.1	1.1	1.2	1.4
GBP	3096.0	1.4	0.1	1.1	1.3	1.3	1.5	1.7
CNY	3096.0	6.6	0.3	6.0	6.2	6.6	6.9	7.3
HKD	3096.0	7.8	0.0	7.7	7.8	7.8	7.8	7.9
JPY	3096.0	111.8	10.4	87.0	105.6	110.0	114.9	150.1
MYR	3096.0	4.0	0.4	3.0	3.8	4.1	4.2	4.7
^FVX	3046.0	1.7	0.9	0.2	1.2	1.6	2.1	4.4
^IRX	3046.0	0.9	1.2	-0.1	0.0	0.3	1.6	5.2
^TNX	3046.0	2.2	0.7	0.5	1.8	2.3	2.7	4.2
^TYX	3046.0	2.8	0.6	0.9	2.4	2.9	3.2	4.3
comp_sora_3m	3118.0	0.7	0.8	0.0	0.1	0.3	1.0	3.7

Table3 Missing values	
	Missing values
Open	0
High	0
Low	0
Close	0
Volume	0
day	0
trends	0
1st_diff	1
vola	0
EMA100	124
EMA20	23
EMA200	249
EMA5	5
EMA10	11
rsi	17
EMA50	61
AAPL	69
AMZN	69
BRK-A	69
GOOG	69
META	69
MSFT	69
NVDA	69
TSLA	69
UNH	69
V	69
CL=F	72
GC=F	73
000001.SS	189
^AEX	19
^DJI	69
^FTMC	54
^FTSE	55
^GSPC	69
^HSI	109
^KLSE	104
^N225	186
SGD	22
EUR	22
GBP	22
CNY	22
HKD	22
JPY	22
MYR	22
^FVX	72
^IRX	72
^TNX	72
^TYX	72
comp_sora_3m	0

Additionally, we plot each variable against timeline as shown in Figure 2. The variables of 'Dividends' and 'Stock Splits' are flat lines which would not be giving any information

to our prediction. Different variables seem to have different dynamics. However, most of the variables have fierce changes around the beginning of year 2022.

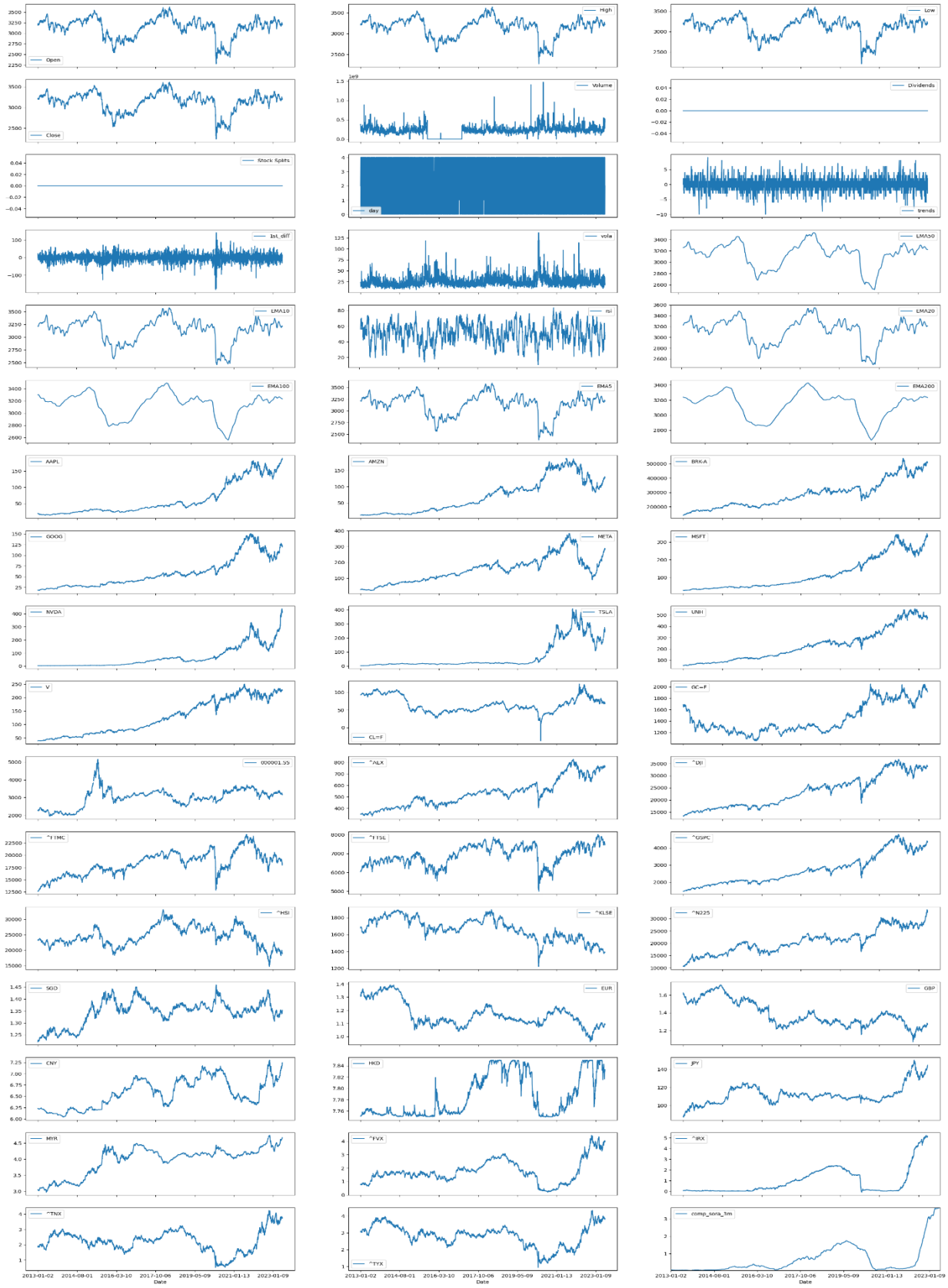

Figure 2. STI Variables Distribution Along With The Time

4.4 Data Pre-processing and Preparation

Data pre-processing was conducted with precision to prepare the dataset for analysis. Our data came from different sources. The data pre-processing focus on merging different dataset and clean the merged data. We carefully examined each of the variables on missing values, outliers. The technical indicator variables have the missing data in the beginning of the data sequence, which are caused by the computation process. Such missing data points should be removed. On the other side, missing data in other variables were addressed through random sampling for manual checks. For example, the Table 4 showed a result of a random sample of 5 dates with missing values. These missing data points were primarily due to public holidays or market closures. As time series data are usually auto-correlated, we used a forward fill method to compute the missing data. Furthermore, data normalization techniques were applied to scale variables to a range between 0 and 1 while preserving their original distributions.

Table 4: STI missing data example					
	2016-11-24	2018-11-23	2013-01-02	2013-04-19	2013-03-01
EMA200	2852.1	3245.5			
EMA50	2829.7	3099.8		3280.0	
AAPL		43.1	19.6	13.9	15.4
AMZN		75.1	12.9	13.0	13.3
BRK-A		310340.0	139610.0	157861.0	152750.0
GOOG		51.2	18.0	19.9	20.1
META		131.7	28.0	25.7	27.8
MSFT		103.1	27.6	29.8	28.0
NVDA		36.3	3.2	3.1	3.2
TSLA		21.7	2.4	3.2	2.3
UNH		261.6	54.5	60.0	53.5
V		132.9	38.8	41.0	39.5
CL=F		50.4	93.1	88.0	90.7
GC=F		1221.0	1687.9	1395.3	1571.9
000001.SS	3241.7	2579.5		2244.6	2359.5
^AEX	457.4	513.8	350.2	341.7	339.7
^DJI		24285.9	13412.5	14547.5	14089.7
^FTMC	17590.6	18533.0	12611.9	13616.7	13750.6
^FTSE	6829.2	6952.9	6027.4	6286.6	6378.6
^GSPC		2632.6	1462.4	1555.3	1518.2
^HSI	22608.5	25927.7	23312.0	22013.6	22880.2
^KLSE	1624.2	1695.9	1674.7	1706.3	1637.4
^N225	18333.4			13316.5	11606.4
SGD	1.4	1.4	1.2	1.2	1.2
EUR	1.1	1.1	1.3	1.3	1.3
GBP	1.2	1.3	1.6	1.5	1.5
CNY	6.9	6.9	6.2	6.2	6.2
HKD	7.8	7.8	7.8	7.8	7.8
JPY	113.3	113.0	87.3	99.5	93.6
MYR	4.5	4.2	3.0	3.0	3.1
^FVX		2.9	0.8	0.7	0.7
^IRX		2.3	0.1	0.0	0.1
^TNX		3.1	1.8	1.7	1.9
^TYX		3.3	3.0	2.9	3.1

Notes:

This table shows the result of a random sample of 5 dates with missing values

	missing data points highlighted as yellow
2016-11-24	Public holiday in U.S. (Thanksgiving day)
2018-11-23	Public holiday in Japan (Labor Thanksgiving Day)
2013-01-02	Public holiday. (New Year's Day)
EMA200	Technical indicator, missing value caused by calculation
EMA50	Technical indicator, missing value caused by calculation

4.5 Data Preparation:

The dataset was thoughtfully split into training, validation, and test sets, a crucial step in facilitating model development and evaluation. To account for the temporal sequence inherent in financial data and mitigate information leakage, we employed an expanding walk-forward validation approach. This method gradually extends the initial training data, allowing for a comprehensive assessment of model performance over time(Germayne,2019). Given that time series data often exhibits autocorrelation, there is a risk of information seeping into adjacent unseen data. To mitigate this, we introduced a "gap" between the training and validation segments during model training to enhance their independence and robustness. For a detailed data preparation workflow, please refer to Flowchart 1. Furthermore, you can visualize the subsets of data in Figure3.

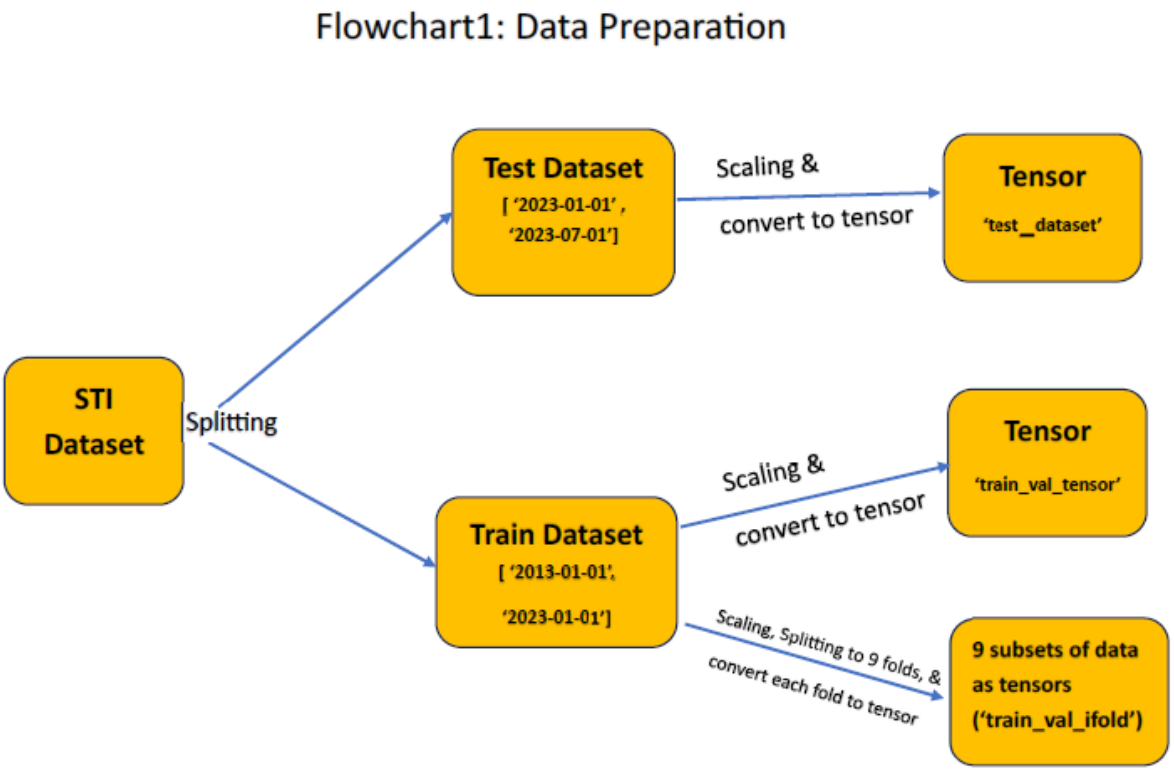

Figure 3. Flowchart1: Data Preparation

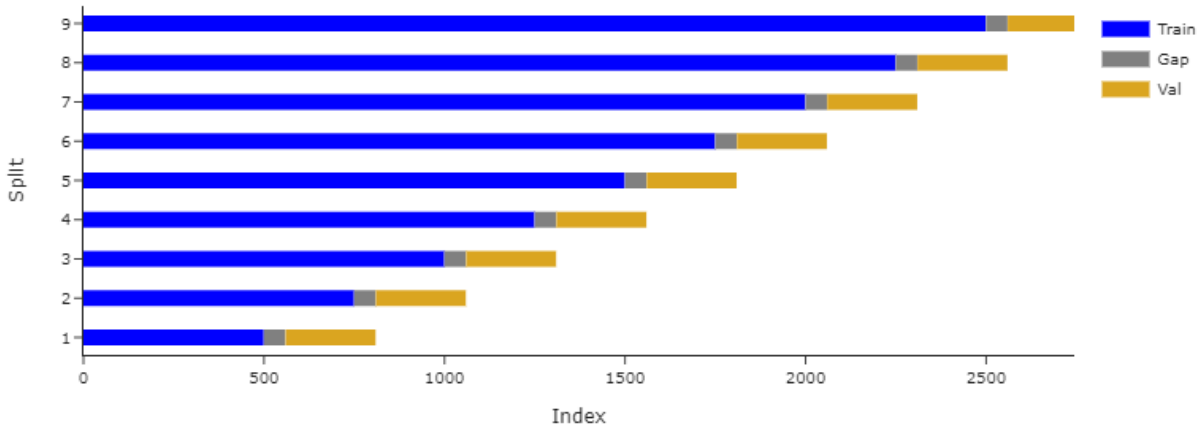

Figure 4. Walk Forward Validation

4.6 Data Exploration

Exploratory data analysis (EDA) was carried out to gain a deeper understanding of the dataset's characteristics. EDA included the generation of summary statistics and compelling visualizations. EDA unveiled significant patterns, trends, and anomalies within the data, providing valuable insights for modelling. We will elaborate our findings in the results section.

4.7 Ethical and other considerations

Ethical principles, including privacy preservation, and bias reduction, were rigorously adhered to during the data collection and analysis procedures. The dataset utilized in this research does not include any personal information, such as identity or transaction records, thereby aligning with ethical guidelines and data protection regulations. Furthermore, all datasets were obtained through a single scraping or downloading process and stored for subsequent use, demonstrating a commitment to ethical data acquisition practices. The dataset employed in this study is highly reproducible, as it originates from openly available public resources accessible to all.

5 Methodology

The methodology chapter serves as the roadmap for this research, detailing the approach and procedures undertaken for a quantitative study of the Straits Times Index (STI) utilizing a multivariate Temporal Convolutional Network (TCN), alongside comparisons with ANN, LSTM, and 1D-CNN. This chapter offers insight into data analyze methods, model validation, evaluation metrics, model architecture design, optimization, and model evaluation.

5.1 Data Analysis Method

In the data section, we carefully selected datasets based on a critical review of the literature. The methods used in data analysis for STI future price inference including:

5.1.1 Descriptive Statistics

The initial analysis includes calculating statistics such as mean, minimum, maximum, and standard deviations for each variable. While these basic statistics provide an overview, they are insufficient to uncover underlying patterns.

5.1.2 Statistical Analysis

To understand the data distribution, statistical analysis is conducted for each variable across the selected time frame. This analysis helps identify non-stationary variables, which are then converted into stationary form for further examination.

5.1.3 Hypothesis Testing

Given the assumption that STI price is not a random walk, hypothesis testing is used to validate this assumption. This analysis is critical for understanding the time-dependent behavior of STI prices.

5.1.4 Model Generalization (as shown in Flowchart2)

Recognizing the complexity and dynamics of financial data, model inference power is evaluated on datasets progressively further into the future. This approach helps assess the emergence of new dynamics in future data, and the TCN model's ability to generalize to future data.

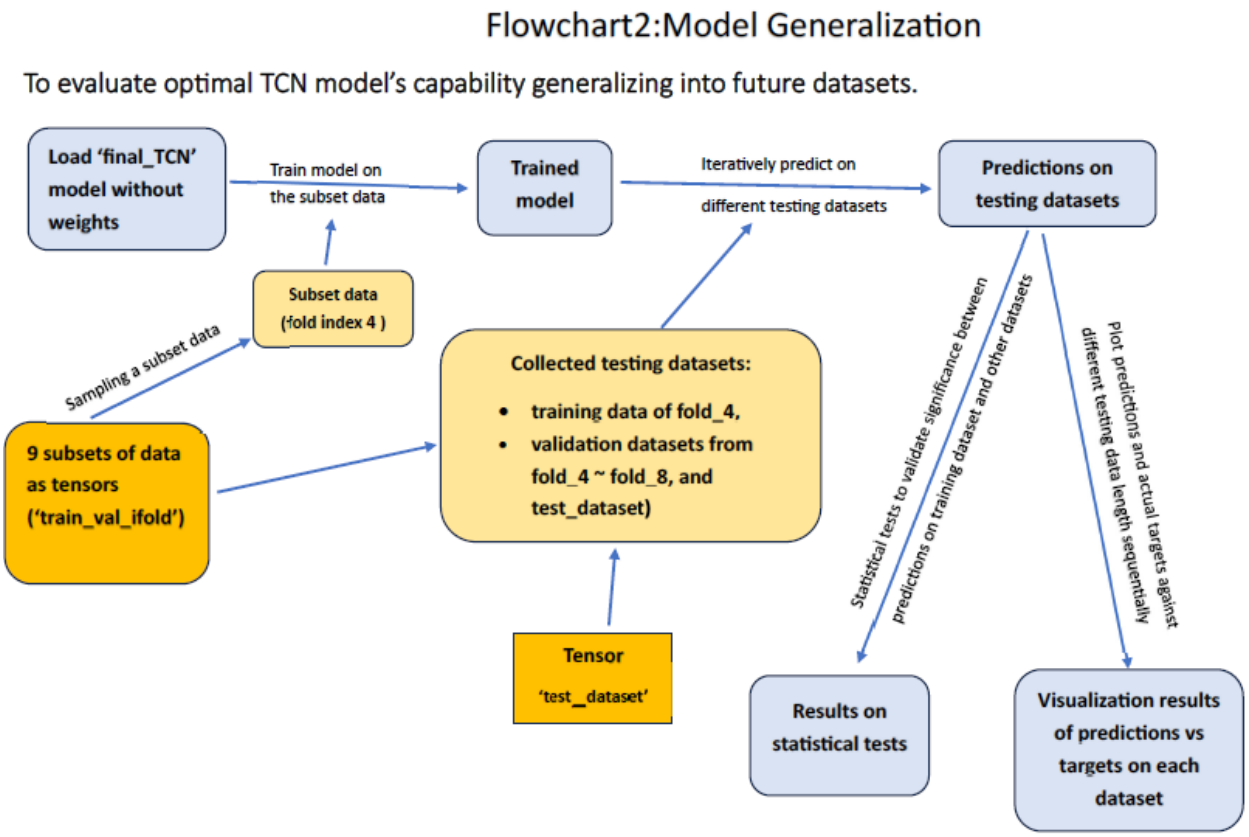

Figure 5. Flowchart2: Model Generalization (1/2)

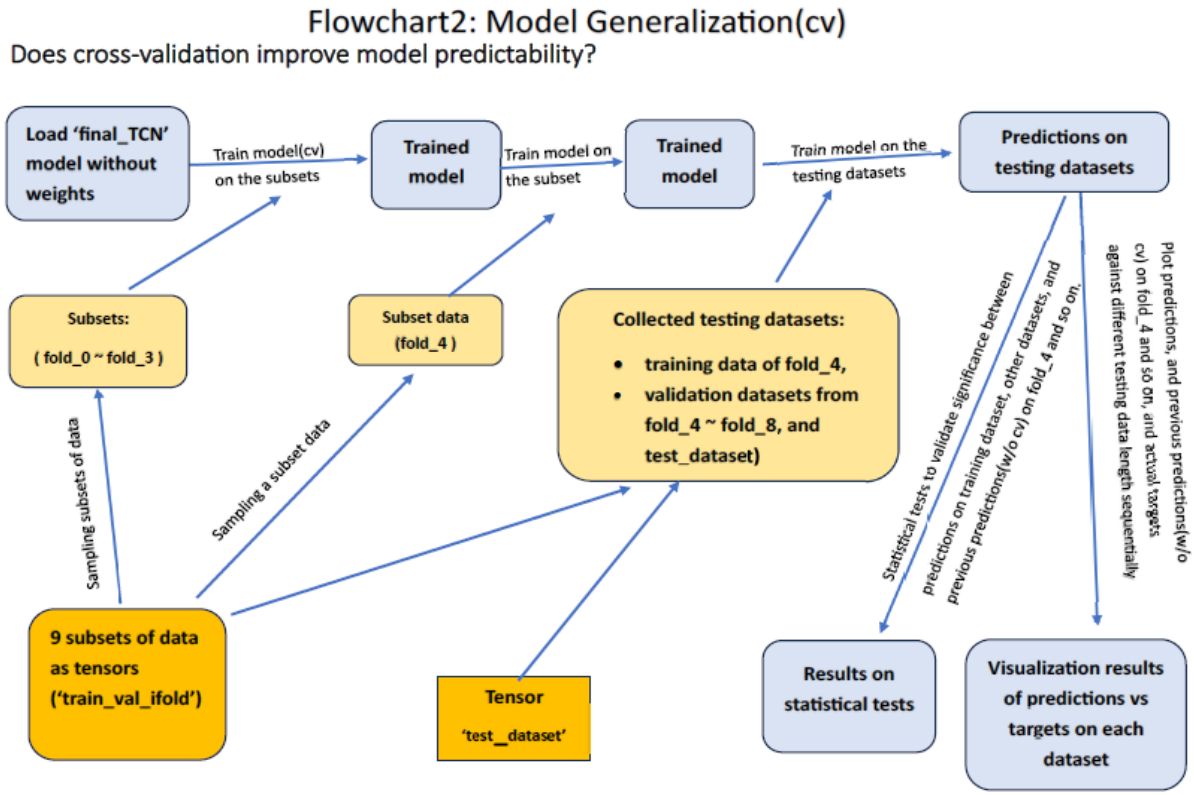

Figure 6. Flowchart2: Model Generalization(cv) (2/2)

5.1.5 Inference Analysis

Inference analysis is first used to compare performance of different models on the STI dataset (see Flowchart3). Then, it involves systematically reducing groups of features and evaluating their impact on the model's prediction of STI prices (see Flowchart4). By conducting inference analysis, we can justify predictive power of different models, and how different groups of variables influence STI prices.

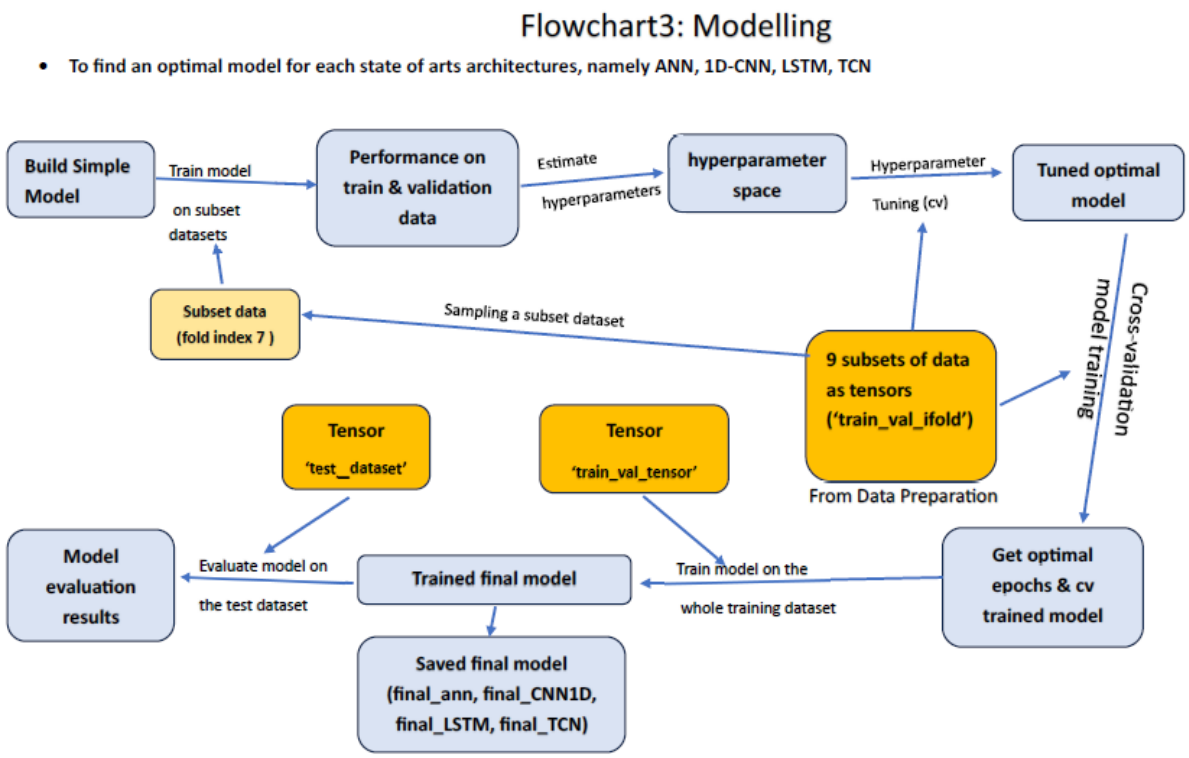

Figure 7. Flowchart3: Modelling

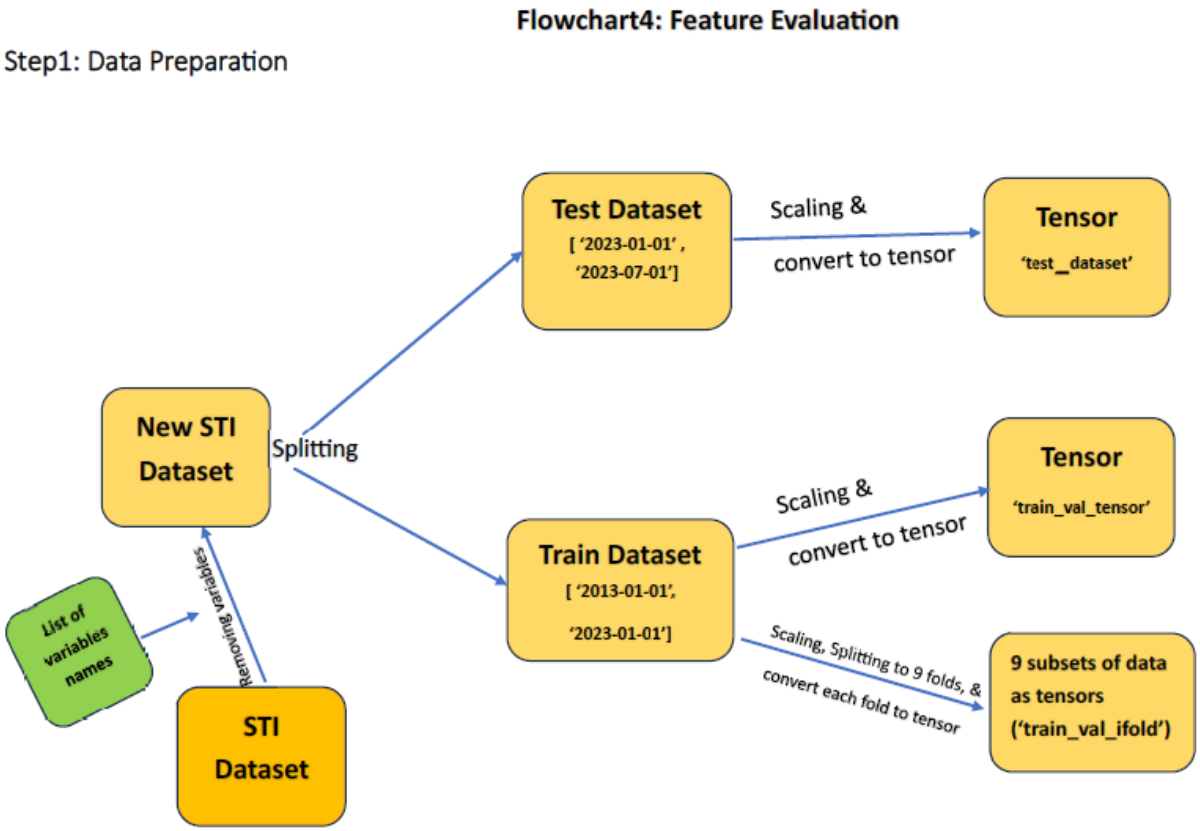

Figure 8. Flowchart4: Feature Evaluation (1/2)

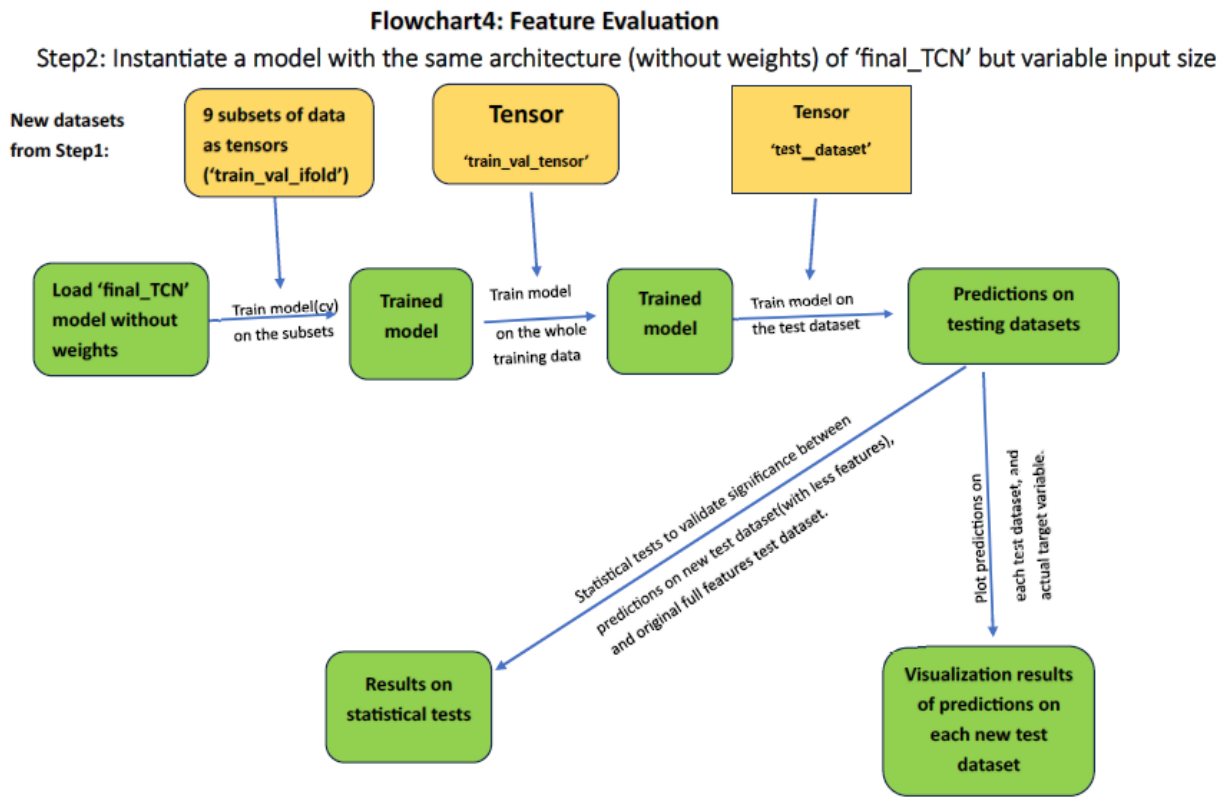

Figure 9. Flowchart4: Feature Evaluation (2/2)

5.2 Model Validation

Traditional cross-validation methods, such as hold-out validation, are often not well-suited for time series data. Hold-out validation typically involves splitting the data into a single training set and a single validation set, with no consideration for the changing dynamics of the data over time. Time series data often exhibit varying patterns and trends across different time periods. Using a single validation dataset from a specific time may not capture these evolving dynamics effectively. This limitation can result in biased model evaluations, as the chosen validation dataset may be too similar or dissimilar to the test data, depending on when it was selected.

Despite the traditional cross-validation methods could evaluate models based on different validation datasets. It splits data with random sampling strategy which often fails to account for the sequential nature of time series data. Hence, walk-forward validation is selected because it actively manages the evolving nature of time series data. This method continually expands the training dataset while keeping the validation dataset separate. By doing so, it ensures that the model is updated with the most recent data and can adapt to changing patterns over time.

However, time series data are usually autocorrelated, which can introduce information leakage from the training dataset into the adjacent validation dataset. The introduction of a "gap" between training and validation partitions could serve as a buffer to enhance the independence between the training and validation datasets. Determining the appropriate gap duration is essential. This decision is based on insights gained from the partial autocorrelation function (PACF) curve during the data exploration phase. Specifically, we set the gap duration to be 60-day time lags. This threshold is chosen because time lags of about 40 are observed to have a notable impact on the price distribution.

In this project, we start the training data by 500 data points (around 2 years), step by 250 (around 1 year), and validate on 250 data points (estimate 1 year) as shown in Figure 4.

5.3 TCN Architecture

Unlike traditional convolutional neural networks, which suffer from a limited capacity to capture previous information, TCN excels by significantly expanding the input time series coverage while reducing computational costs (Gridin, 2022).

At the core of TCN's architecture lies the concept of casual convolution, illustrated in Figure 10. This idea revolves around a convolutional network where the input and output sizes match, forming the foundational structure of TCN. Yet, TCN doesn't halt at conventional convolution; it innovatively incorporates the "dilation" principle. Dilation introduces an interval of $2^{(l-1)}$ between the input tensor, where 'l' denotes the number of network layers (Gridin, 2022). This intricate configuration is elegantly depicted in Figure 11. A typical TCN network comprises two critical components: the Temporal Casual Layers (TCLs) and a "bias" function, shown in Figure 12. As shown in Figure 12, TCL forms the heart of TCN, encompassing a casual convolution, weight normalization to mitigate gradient explosions, an activation function to infuse non-linearity, and dropout regularization to combat overfitting. The incorporation of a "bias" function, involving a low-kernel one-dimensional convolution applied to the input tensor, further amplifies TCN's performance (Gridin, 2022).

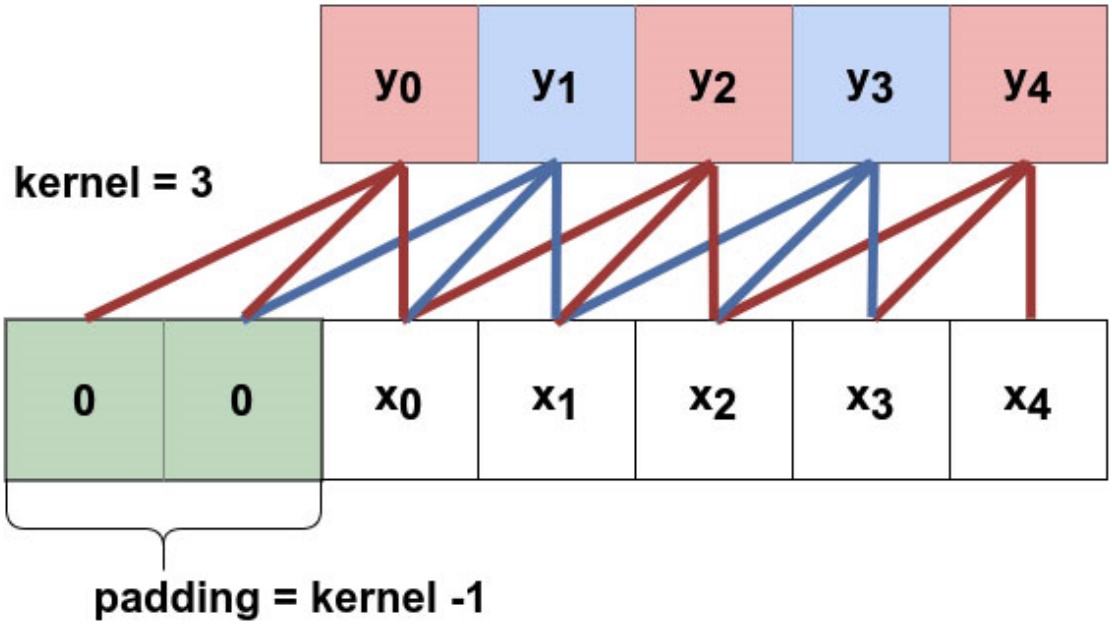

Figure 10. Casual Convolution (Gridin, 2022)

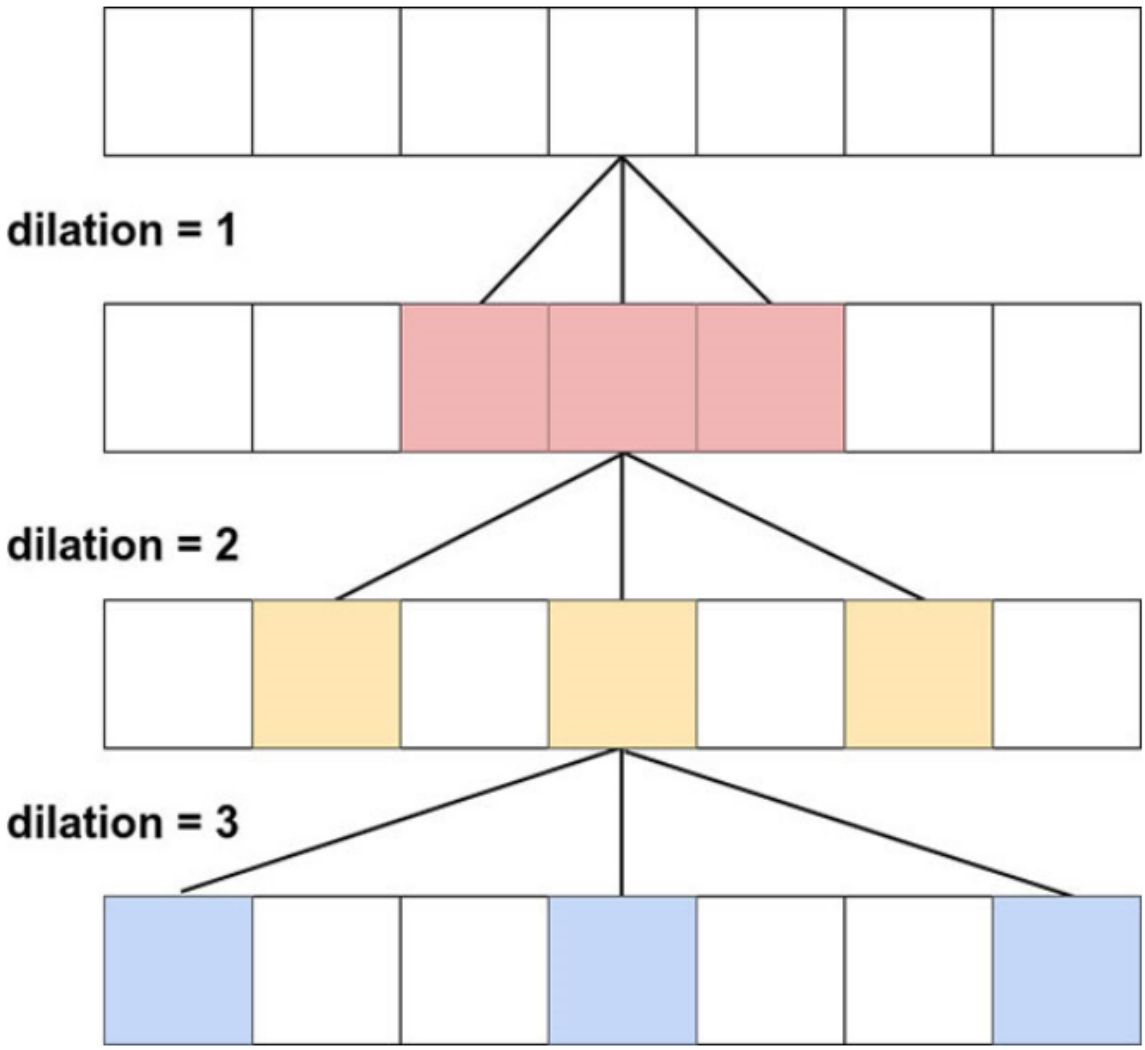

Figure 11. Dilation (Gridin, 2022)

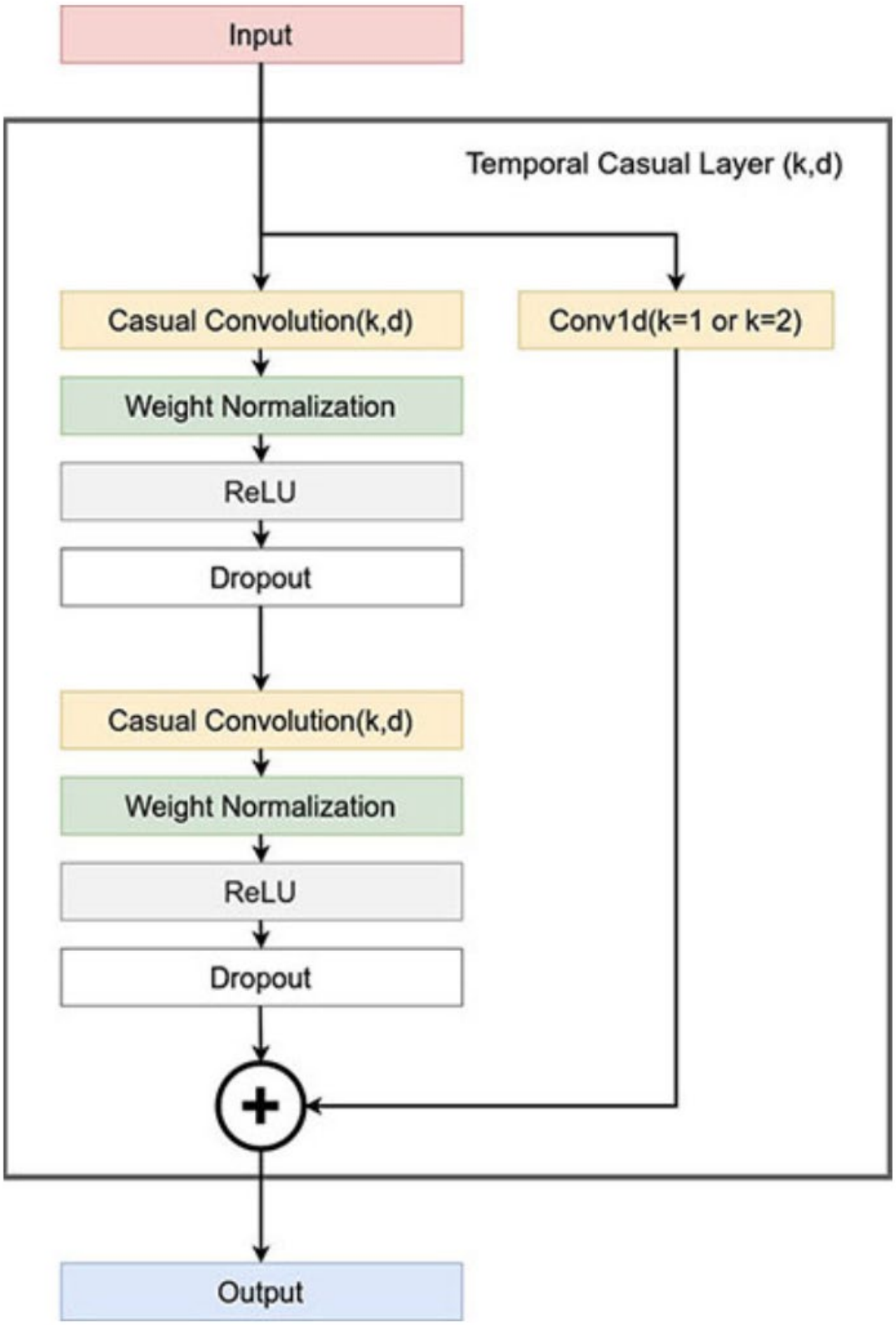

Figure 12. Temporal Casual Layer With Bias (Gridin, 2022)

5.4 Hyperparameter Tuning

Hyperparameters significantly impact machine learning model performance. Bayesian optimization is employed as a Keras Tuner to identify an optimal set of hyperparameters. This probabilistic approach conducts different trials to refine hyperparameter choices, ultimately enhancing model performance. A simple model was built for each of ANN, LSTM, 1D-CNN, and TCN to evaluate model predictive power and to estimate the possible hyperparameter space for further tuning.

5.5 Metrics and Loss Function

In our project, we are tackling a regression problem, aiming to predict the Straits Times Index price. To evaluate the performance of our predictive models, we employ a set of widely recognized metrics, namely the mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean squared error (RMSE), as shown in equation 1, equation 2, and equation 4. While both MAE and RMSE are scale-dependent, MAPE stands out as a unit-free metric, enabling us to make effective performance comparisons across different datasets. However, it's worth noting that the MAPE calculation can become unstable when the actual value approaches zero. Nonetheless, given that the STI price is unlikely to be zero, MAPE is a suitable choice for our evaluation, offering the ability not only to gauge the success of our models but also to benchmark their performance against existing studies. Apart from MAPE, our project will also take MAE as one of our metrics as it is much easier for interpretation (it is simply an average of absolute error).

Equations (Glen, no date):

Equation 1: MAE = $\frac{1}{n}\sum_{i=1}^{n} |x_i - x|$

Equation 2: MAPE = $\frac{1}{n}\sum_{i=1}^{n}\left|\frac{x_i - x}{x}\right|$

Equation 3: MSE = $\frac{1}{n}\sum_{i=1}^{n}(x_i - x)^2$

Equation 4: RMSE = $\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - x)^2}$

(Given x is the true value, x_i is the predicted value, and n is the sample size)

In the realm of neural networks, backpropagation is a fundamental technique for training models, and it relies on the differentiability of the chosen loss function. One commonly used loss function in regression problems is the mean squared error (MSE). MSE is preferred due to its ease of differentiation and its tendency to assign greater weight to larger errors. Moreover, MSE exhibits a smooth turning point during zero-point differentiation, which can be advantageous for optimizing our model during training. This choice of loss function aligns with our goal of effectively training our neural network models for precise STI price predictions.

5.6 Model evaluation

Models are evaluated on the unseen test dataset based on the metric of MAPE and MAE determined above.

This comprehensive methodology ensures a systematic and rigorous approach to the quantitative study of STI using TCN and other neural network models, considering critical aspects of data analysis, validation, architecture, hyperparameter tuning, and evaluation.

6 Results

In this chapter, we present the results of our research on daily stock price prediction in the Singapore market using a TCN model, along with comparisons to traditional models of ANN, LSTM, and 1D-CNN. We first present the findings on the STI dataset. Next, we address our research questions, assess the performance of the models, evaluate the impact of various features, and examine the TCN model's generative power on future datasets in different future timeframes.

6.1 Understanding Data Characteristics

Our investigation commenced with a thorough examination of the dataset. We unearthed diverse characteristics within the raw features (see Figure 2). Evidently, the STI price variables exhibited synchronized line curves, resembling trends observed in the stock prices of major U.S. corporations, treasury bonds, and interest rates. In contrast, stock indices, exchange rates, and commodities followed distinct curve shapes. Intriguingly, a transformative juncture surfaced in all variables at the dawn of 2020.

6.2 Exploring Variable Relationships

To unravel the intricate relationships between the STI Close price and other variables, we visualized how each variable changed along with time and compared it with STI Close price by converting them into the same scale. As shown in Figure 13, while the association between STI Close price and variable '^FTSE' appeared relatively robust, establishing significant connections with other variables proved challenging.

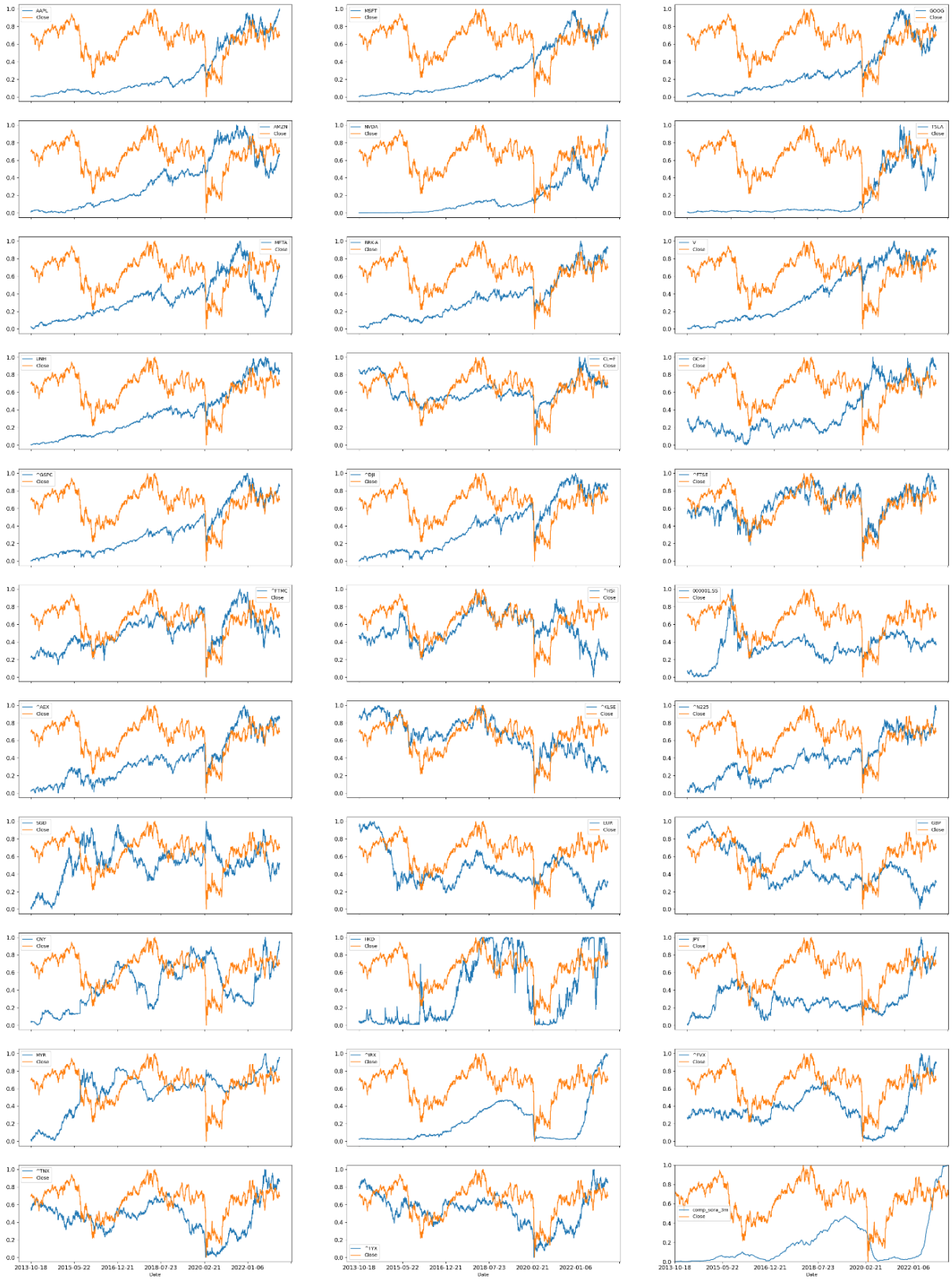

Figure 13. Compare Patterns Between STI Close Price and Each Variable

6.3 Assessing Stationarity and Distributions

Critical to our analysis was the assessment of stationarity. The Augmented Dickey-Fuller unit root test identified eight variables (['Low', 'Volume', 'day', 'trends', '1st_diff', 'vola', 'rsi', 'SGD']) as possessing stationarity. Consequently, we undertook the transformation of non-stationary variables into stationary counterparts. As shown in Figure 14, the distributions of first-differenced variables portrayed a distinct normality, converging around a mean of zero and characterized by pronounced peaks. 'trends' showed symmetry, characterized by price oscillations spanning one or two consecutive days, occasionally extending to about ten days. The volume feature exhibited rough symmetry, with one notable instance of extreme stagnation. Conversely, volatility displayed a skewed distribution, representing intermittent sharp price changes.

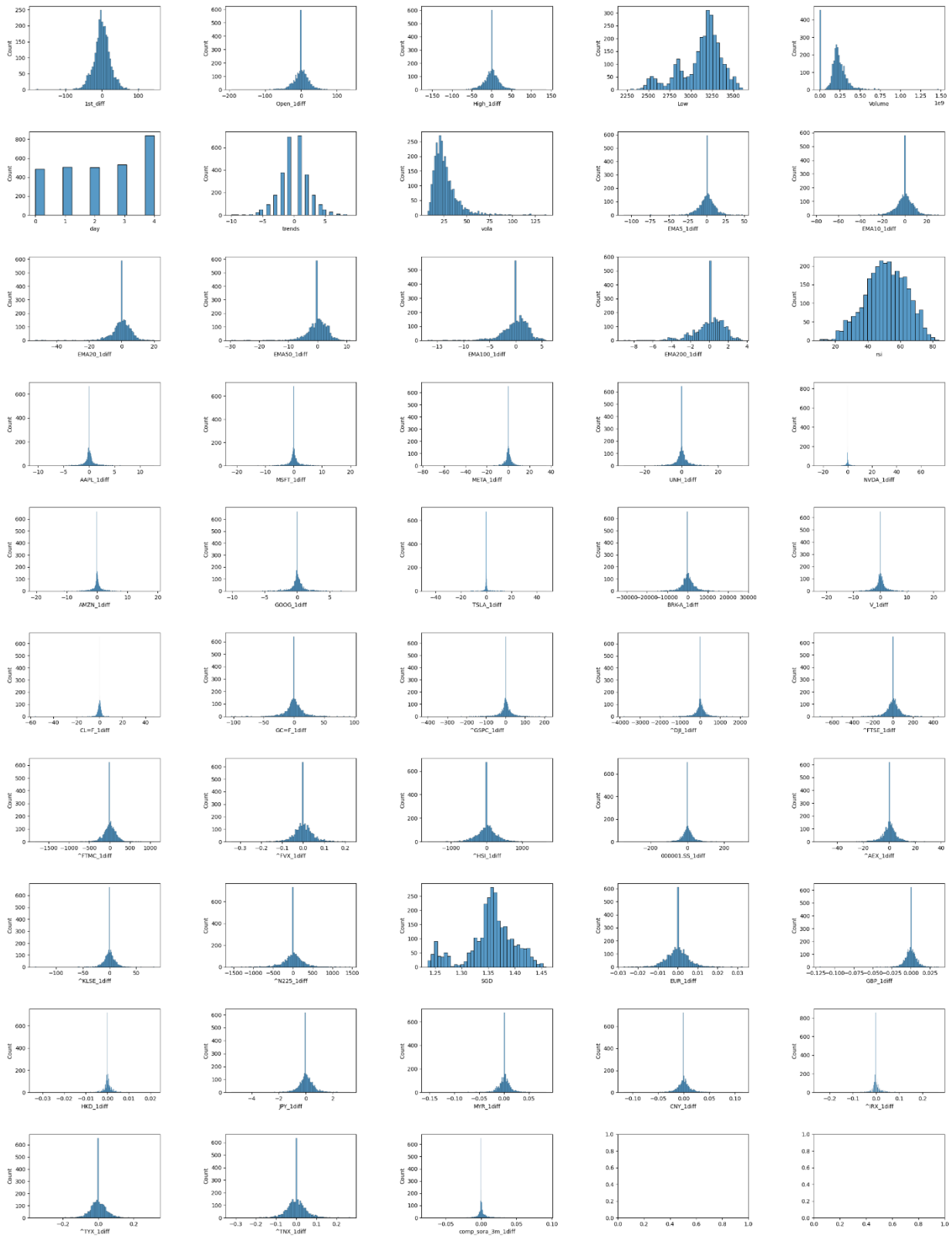

Figure14. Variable Statistical Distribution

6.4 Correlations and Patterns

When analyzing the connections between various factors and the first difference of STI Close price, we found that technical indicators displayed the highest correlation, followed by specific market indices such as '^HSI_1diff,' '^KLSE_1diff,' '^N225,' and '000001.SS_1diff' (see Figure 15). Our investigation into these variable relationships extended to examining pairwise Pearson correlations (Figure 16). Notably, robust correlations were evident within specific clusters, including U.S. companies' stock prices, market indices, currency exchange rates, and treasury bond prices. Conversely, commodities prices exhibited weak correlations with most variables.

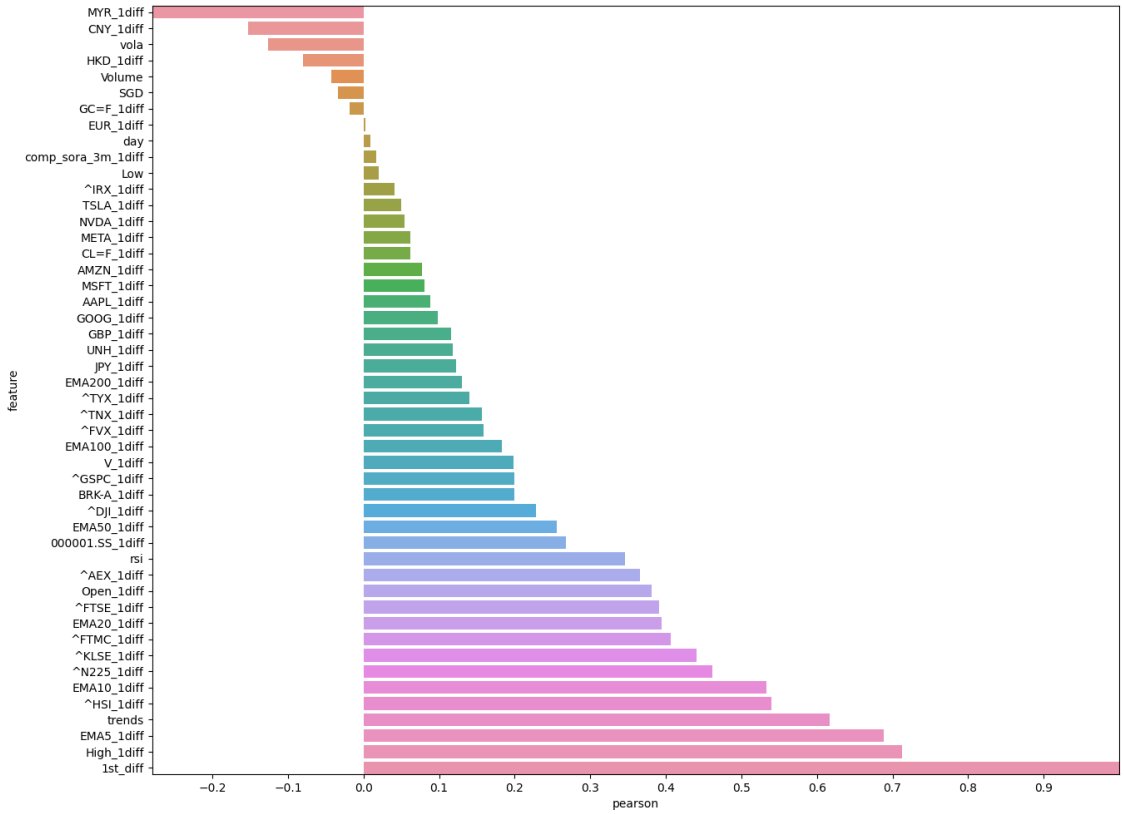

Figure 15. Pearson Correlations With The First Difference of STI Close Price

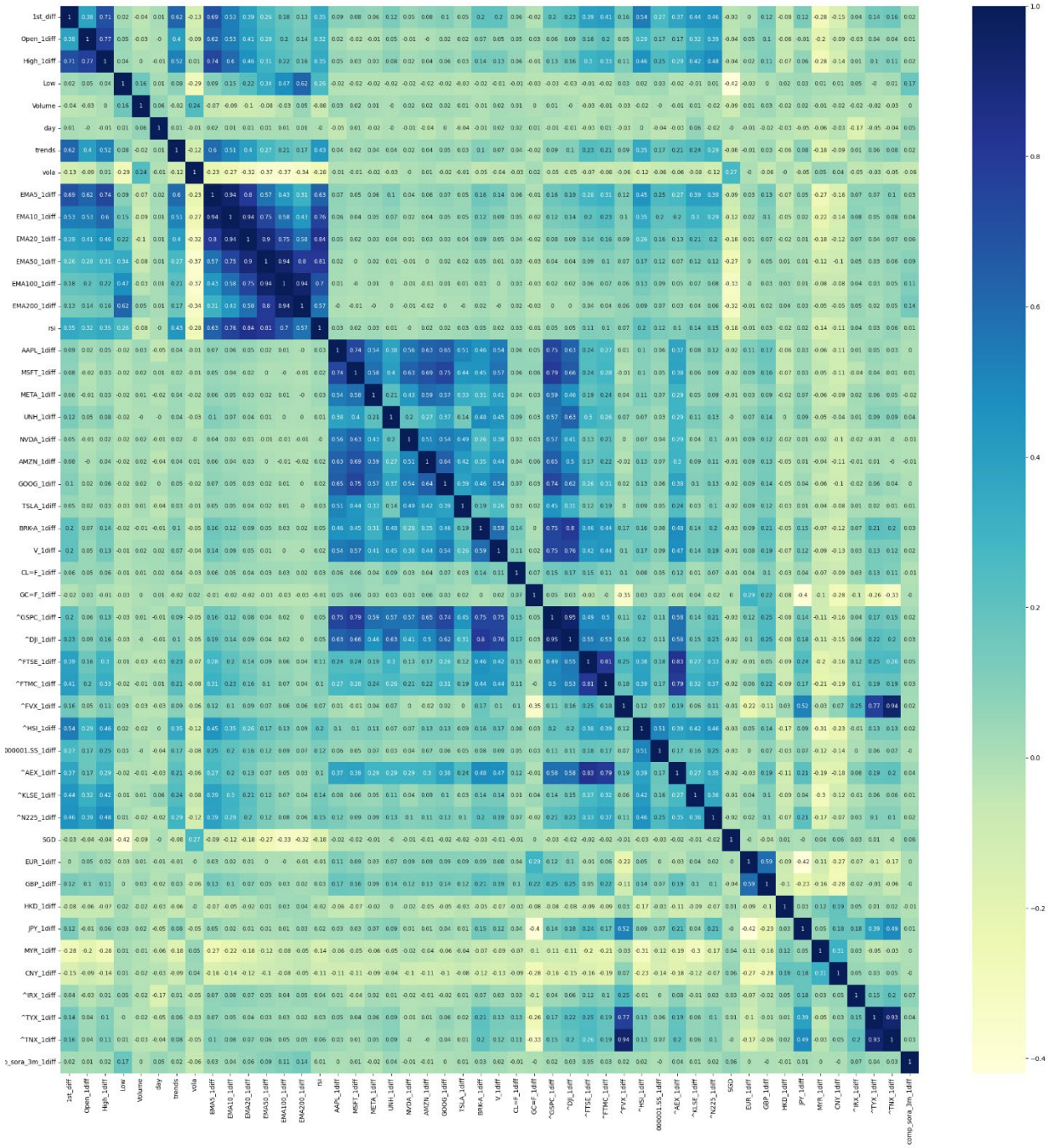

Figure 16. Pairwise Pearson Correlations

Additionally, we evaluated the autocorrelation of STI Close price in its first difference form **(**Figure17, Figure18). The autocorrelation function (ACF) and partial autocorrelation function (PACF) revealed notable correlations at lagged intervals of 1, 3, and 6 days. Some less obvious correlations were observed around day 20 and day 40.

To empower our models with more historical information, we have chosen a look-back window size of 40 days for our analysis.

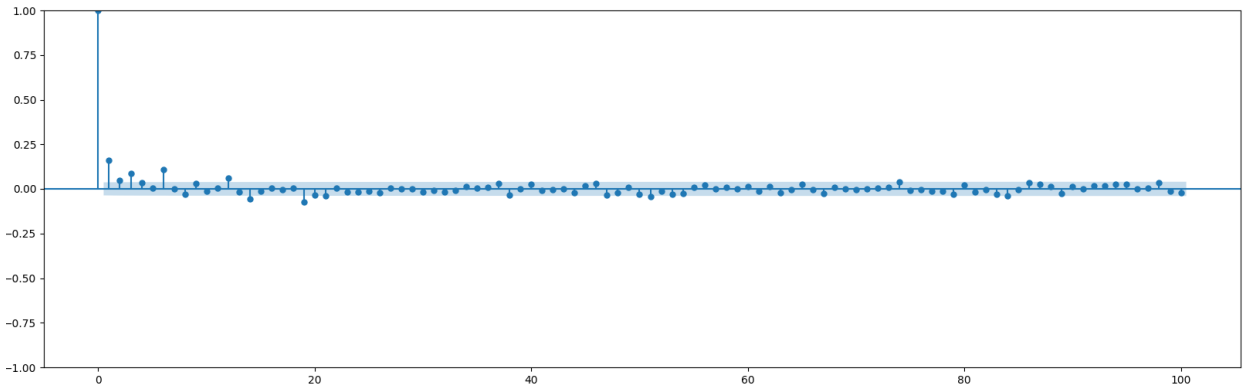

Figure 17. Autocorrelation

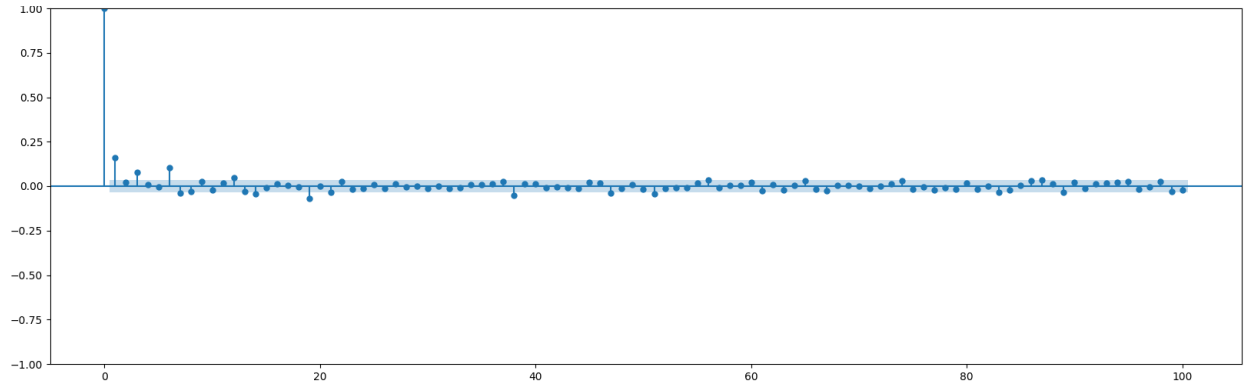

Figure 18. Partial Autocorrelation

6.5 Temporal Dynamics (Hurst Exponent)

In our endeavor to unravel temporal dynamics, we diligently computed the Hurst Exponent for varying timeframes (see results below).

- Hurst Exponent before 2015: 0.5064
- Hurst Exponent 2015~2017: 0.5720
- Hurst Exponent 2017~2019: 0.5233
- Hurst Exponent 2019~2021: 0.5373

- Hurst Exponent 2021~2023: 0.4468

Hurst Exponent quantifies the relative tendency of a time series data, exhibiting a trend when Hurst Exponent value is more than 0.5 while a tendency to reverse if less than 0.5 (Tng, 2020).

6.6 Model Performance

Our analysis encompassed a rigorous model comparison, pitting four distinct models—ANN, LSTM, 1D-CNN, and TCN—against each other (see Table 5). Keras hyperparameter tuning was used in looking for optimal candidate model. We employed Keras hyperparameter tuning and cross-validation to ensure these models withheld their optimal architecture in racing each other. Standardized experimental conditions provided to each model with batch size of 128, look back period of 40, and same input data. As per our experimental results, the TCN model emerged as the frontrunner, showing the lowest loss, mean absolute error, and mean absolute percentage error values. Welch t-tests confirmed the TCN model's statistical superiority. Visualized in Figure19, the TCN model's predictions closely tracked the actual target values.

Table 5. Model Peformance

	loss	mape	mae	stats	p_value	Significance
TCN	0.00	3.16	0.02	NaN	NaN	This is TCN model as the control group
CNN1D	0.00	5.77	0.04	3.99	0.00	Model_CNN1D is significantly worse than the optimal TCN model.
LSTM	0.01	8.49	0.06	7.79	0.00	Model_LSTM is significantly worse than the optimal TCN model.
ANN	0.01	13.19	0.10	18.13	0.00	Model_ANN is significantly worse than the optimal TCN model.

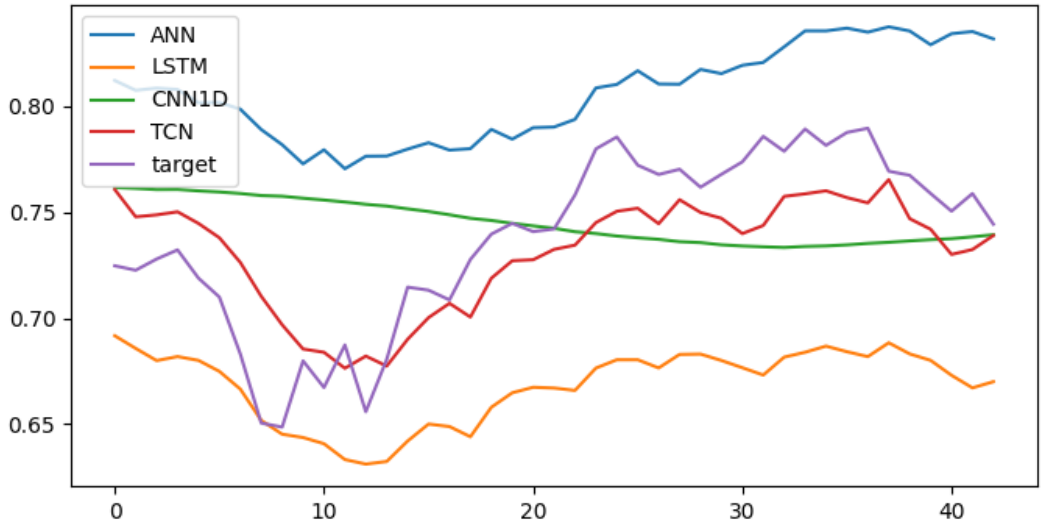

Figure 19. Model Comparison

6.7 Model generalization

6.7.1 TCN Predictions On Future Datasets

In order to evaluate the generative power of the TCN model, we re-instantiated a TCN model with same architecture and epochs and trained the model on a sampled split(fold_4) of data and evaluated its performance on the future datasets (see Table6) The model demonstrated better performance on datasets closer to the training period but showed decreasing performance as the forecast horizon extended. Our analysis suggested that the TCN model effectively forecasts up to a two-year future timespan **(**Figure 20). Additionally, the model tended to predict higher than the actual value on the future datasets.

Table 6. TCN Predictions On Future Datasets				
	MAE	stats	p_value	conclusion
0	0.06	NaN	NaN	This is training dataset as the control group
1	0.15	23.75	0.00	prediction on fold_4 is significantly worse than training dataset.
2	0.16	23.47	0.00	prediction on fold_5 is significantly worse than training dataset.
3	0.34	68.62	0.00	prediction on fold_6 is significantly worse than training dataset.
4	0.30	82.64	0.00	prediction on fold_7 is significantly worse than training dataset.
5	0.24	44.16	0.00	prediction on fold_8 is significantly worse than training dataset.
6	0.29	43.71	0.00	prediction on fold_9 is significantly worse than training dataset

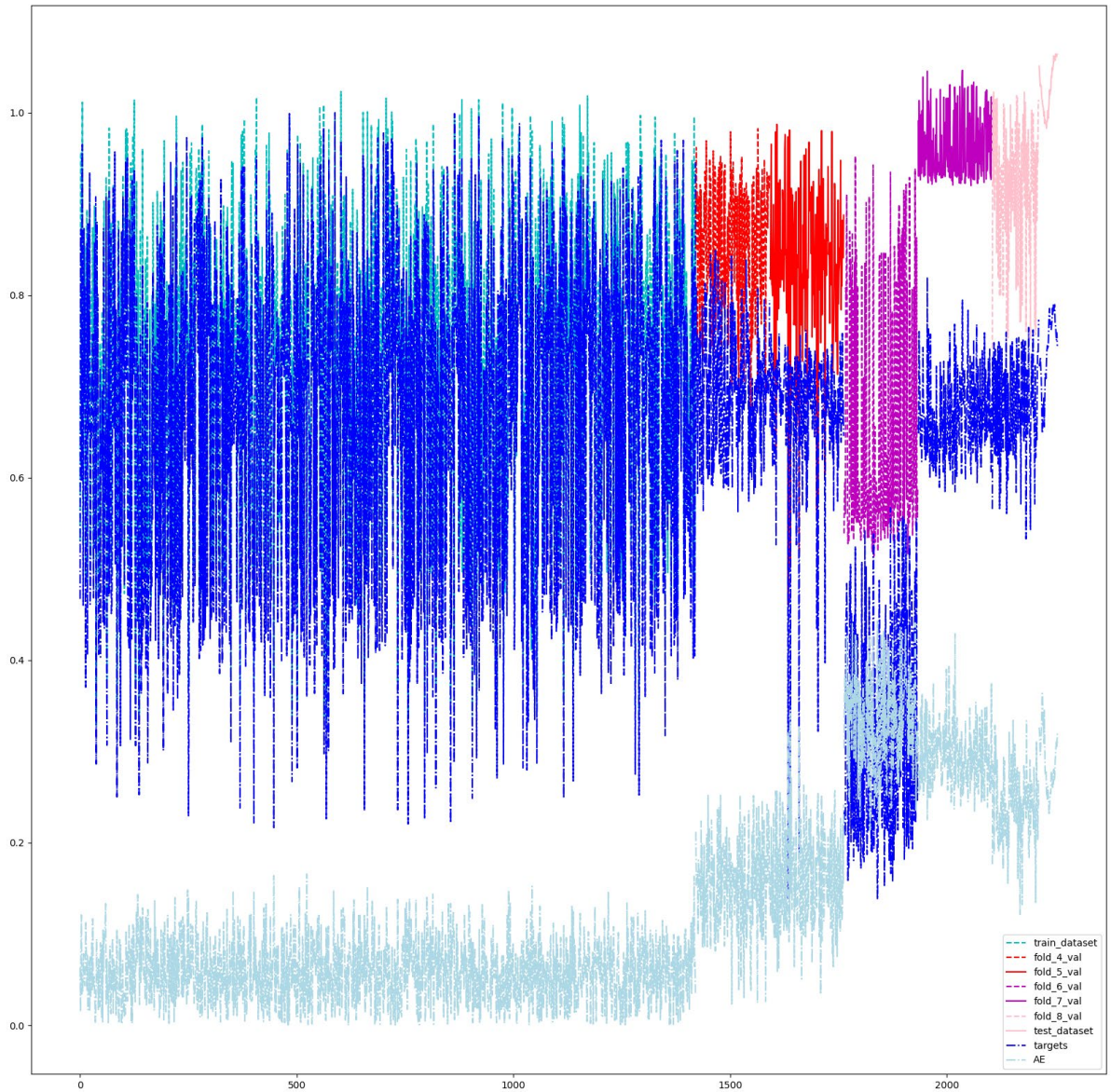

Figure 20. TCN Predictions On Future Datasets

6.7.2 Impact of Cross-Validation

To explore cross-validation's impact, we pre-trained a TCN model with cross-validation on the first four splits of data and repeat the training and evaluation process in previous model generalization experiment. As expected, the TCN model pre-trained with cross-validation demonstrated enhanced accuracy especially on datasets spanning up to a four-year timeframe. However, intriguingly, in longer-term forecasts, the model without cross-validation appeared to outperform the cross-validated TCN model (refer to Table 7, Table 8, and Figures 21, 22, and 23 for details).

Table 7. TCN (Pre-trained With Cross-validation) Predictions On Future Datasets

	mae	stats	p_value	conclusion
0	0.03	NaN	NaN	This is training dataset as the control group
1	0.06	14.34	0.00	prediction on fold_4 is significantly worse than training dataset.
2	0.09	19.58	0.00	prediction on fold_5 is significantly worse than training dataset.
3	0.15	36.56	0.00	prediction on fold_6 is significantly worse than training dataset.
4	0.26	37.06	0.00	prediction on fold_7 is significantly worse than training dataset.
5	0.34	112.17	0.00	prediction on fold_8 is significantly worse than training dataset.
6	0.49	123.91	0.00	prediction on fold_9 is significantly worse than training dataset.

Table 8. Comparison Of MAEs On Models Trained With C.V. and Without C.V.

	MAE_nonCV	MAE_CV	Significance
0	0.06	0.03	model trained with cross-validation is significantly better than the model without cross-validation on training data
1	0.15	0.06	model trained with cross-validation is significantly better than the model without cross-validation on fold_4
2	0.16	0.09	model trained with cross-validation is significantly better than the model without cross-validation on fold_5
3	0.34	0.15	model trained with cross-validation is significantly better than the model without cross-validation on fold_6
4	0.30	0.26	model trained with cross-validation is significantly better than the model without cross-validation on fold_7
5	0.24	0.34	model trained with cross-validation is significantly worse than the model without cross-validation on fold_8
6	0.29	0.49	model trained with cross-validation is significantly worse than the model without cross-validation on fold_9

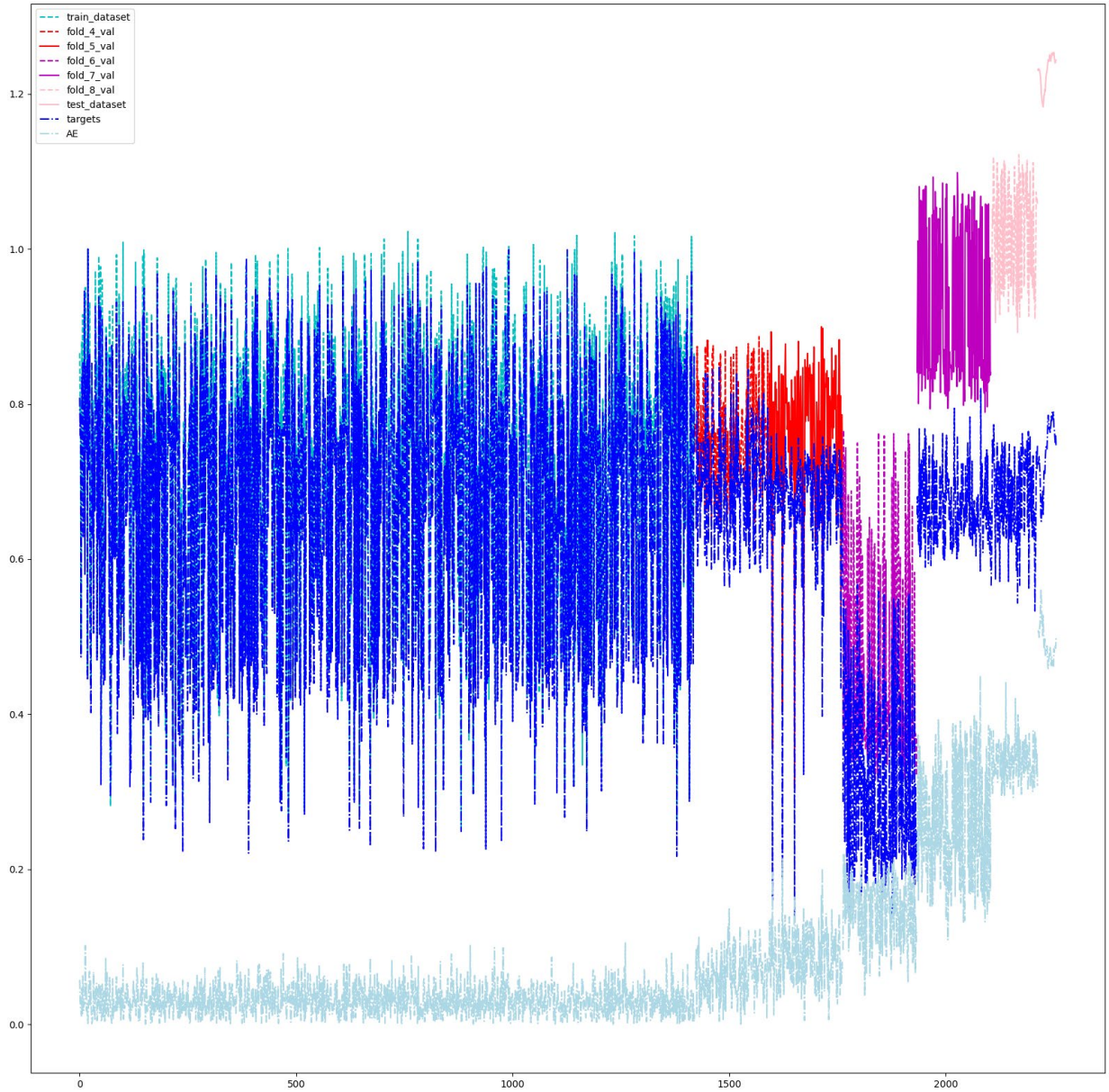

Figure 21. Predictions Of Cross-validation Pre-trained TCN On Future Datasets

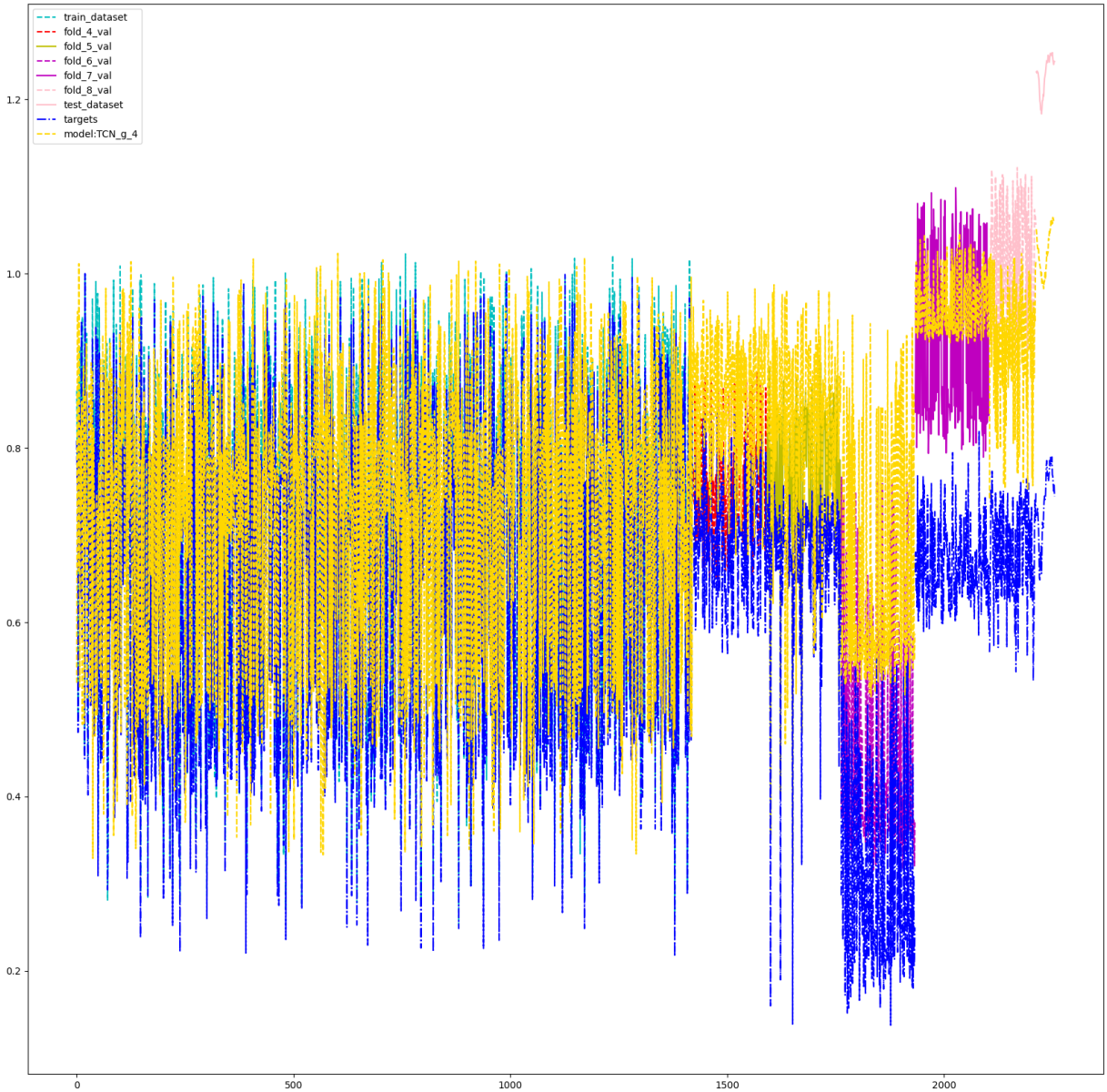

Figure 22. Predictions Of TCN Trained With C.V. vs Without C.V.

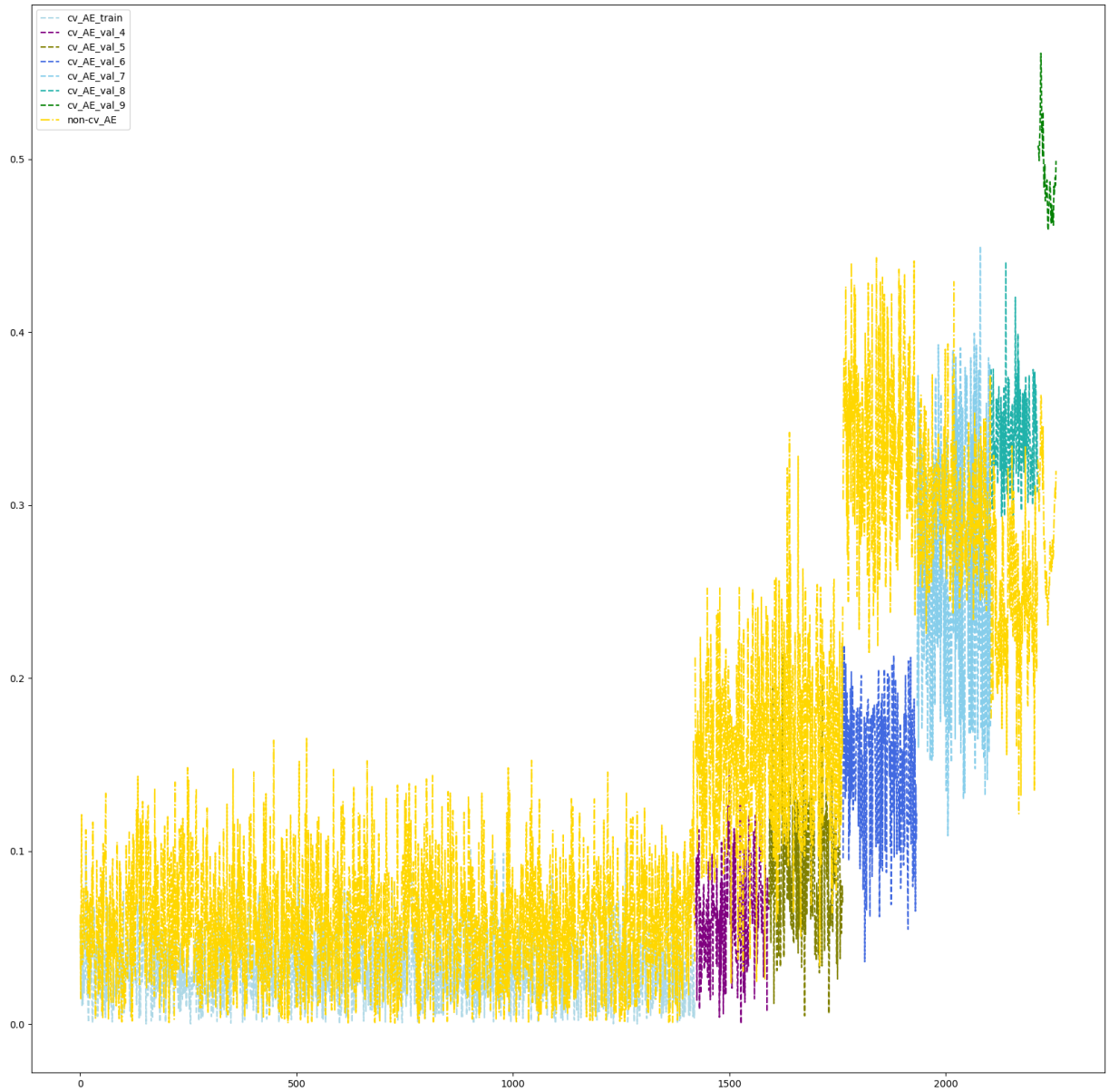

Figure 23. Absolute Errors For Predictions With C.V. And Predictions Without C.V.

6.8 Feature Influence on Predictions

Our evaluation extended to the influence of feature groups on model predictions. We compared results from models trained on dataset with fewer feature sets and on dataset with the full set of variables. Reducing feature groups of ‘ir’, ‘TB’, ‘indices’, ‘Commodities’, ‘TI’ could significantly deteriorate model prediction. While reducing

feature groups of ‘currencies’, ‘US’ showed no significant impact on model performance (see Table 9 and Figure 24).

Table 9. Predictions On Datasets With Different Features				
Group A	**MAE**	**stats**	**p_value**	**result**
(control group)	0.05	Nil	Nil	This is the control group.
reducing ir	0.08	5.18	0.00	Prediction on group A is significantly worse than the control group
reducing TB	0.12	14.07	0.00	Prediction on group A is significantly worse than the control group
reducing currencies	0.05	-0.39	0.70	Prediction on group A is NOT statistically significantly different from the control group
reducing indices	0.16	20.65	0.00	Prediction on group A is significantly worse than the control group
reducing Commodities	0.18	22.75	0.00	Prediction on group A is significantly worse than the control group
reducing US	0.05	0.30	0.77	Prediction on group A is NOT statistically significantly different from the control group
reducing TI	0.09	6.50	0.00	Prediction on group A is significantly worse than the control group

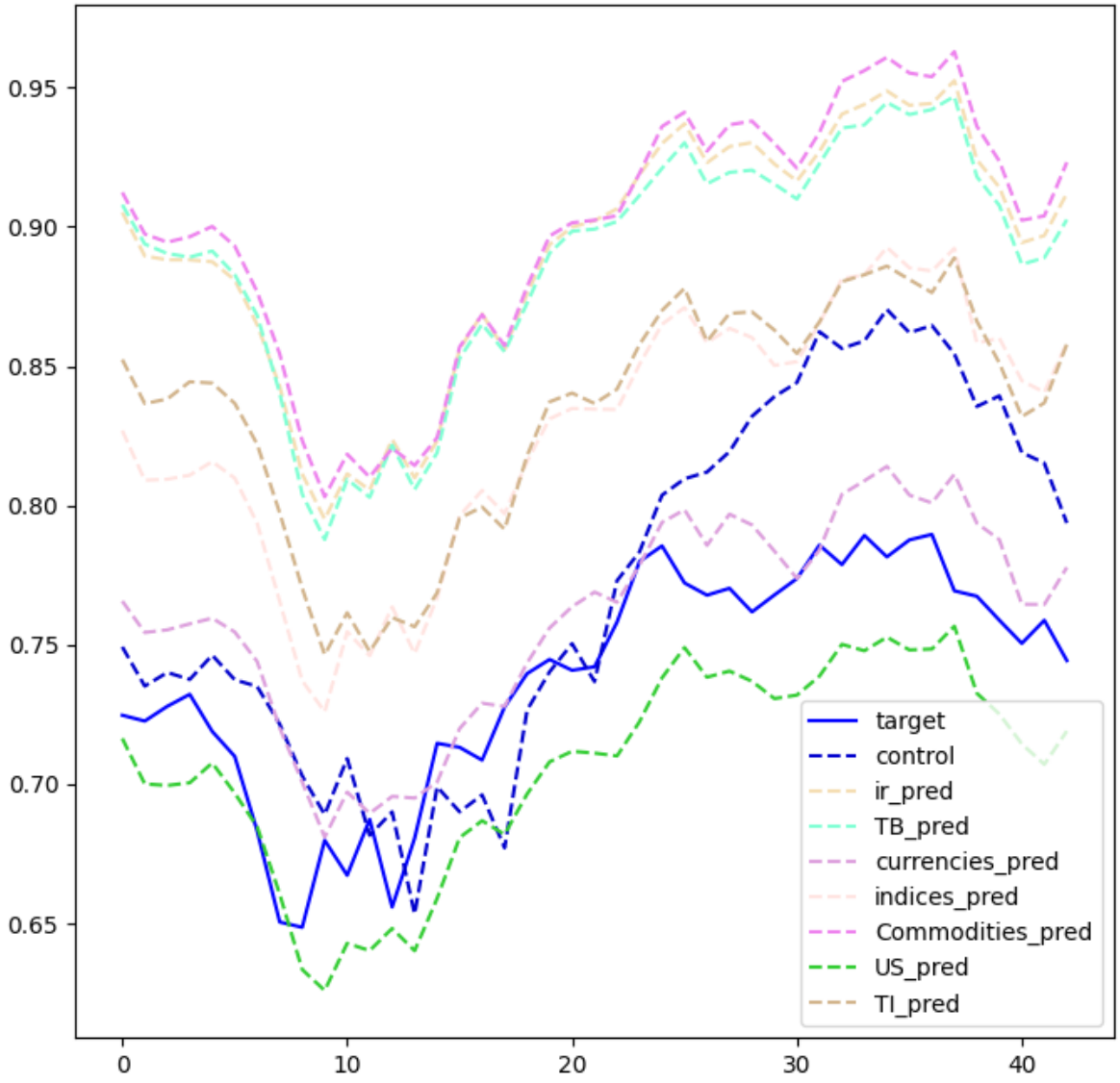

Figure 24. Predictions On Datasets With Different Features

7 Discussion

In this chapter, we delve into a comprehensive discussion of the results obtained from our research on daily stock price prediction in the Singapore market using a TCN model, along with comparisons to traditional models including ANN, LSTM, and 1D-CNN. Our analysis has been structured to address our research questions and assess

sanity of data, the performance of these models, the influence of various features, and the generalization ability of the TCN model on future datasets.

7.1 Data Sampling and Bias

Data sampling plays a pivotal role in the quality of our analysis. It is crucial to consider potential bias introduced by the choice of the time span for data selection. We have addressed this concern by selecting a time span of over 10 years, which ensures that a wide range of patterns and market conditions are included in our dataset. This extended time frame allows us to capture general patterns that repeat themselves over time. Importantly, it minimizes bias associated with selecting a short piece of time, which could lead to missing essential market dynamics.

From our literature review, we find that daily granular data is the most used for stock price prediction. Additionally, by disregarding population distribution and ensuring a sufficiently large and random sample of data points, we can reasonably assume a normal distribution within our dataset. Our plots against features that have been converted to stationary confirm this assumption, with most features exhibiting a normal distribution centered around a mean of zero and peaked high. The presence of some long tails in some variables can be attributed to significant changes in stock prices, notably the sharp changes caused by external events such as the COVID-19 pandemic in early 2020.

7.2 Hurst Exponent Analysis

Tng (2020) described the Hurst Exponent as a valuable metric that quantifies the relative tendency of a time series to either regress strongly to the mean or cluster in a particular direction. When the Hurst Exponent is greater than 0.5, it indicates a clear

trend in a certain direction. Conversely, when the Hurst Exponent is smaller than 0.5, it suggests a tendency to reverse. A Hurst Exponent equal to 0.5 indicates that the data follows a geometric random walk of changes.

Our analysis involved calculating the Hurst Exponent on data slices with a 2-year time span. The results of this analysis revealed distinct patterns in each slice of the data. Our hypothesis that the STI price does not follow a random walk is upheld by the findings, as the Hurst Exponent values consistently deviate from 0.5 across different time spans. This underscores the presence of meaningful trends and reversals in the STI price data.

7.3 Feature Associations

Exploring the associations between features and STI daily close price is essential for understanding which variables impact model performance. As shown in autocorrelation plots (ACP & PACF), historical prices indeed appear to have an impact on future prices, suggesting the presence of temporal dependencies. However, when examining the direct correlation between features and STI daily close price (as the variable '1st_diff'), no obvious correlations were visualized, except some primitive variables and the technical indicators. This prompts us to investigate further which specific features have the most significant influence on our predictive models. One noteworthy observation is that features within the same group tend to exhibit more similarity in the shapes of their curves (see Figure 2). This is supported by the pairwise correlation figures, which indicate that features within the same group generally have higher correlations than features outside of the same group. This insight inspires us to evaluate feature

importance by groups, which can not only reduce computational workload but also potentially improve the interpretability of our models.

7.4 Feature Influence on Predictions

Our evaluation of feature groups highlighted the impact of most feature groups on model predictions. The experiment suggests some features indeed contribute to the accuracy of model prediction as removing these features could deteriorate prediction. On the other side, we could remove some other features without affect the performance of the model. This suggests that careful feature selection can enhance model accuracy and efficiency.

7.5 Comparative Model Performance

The second question aimed to compare the predictive accuracy of the TCN model for STI prices with that of traditional models, such as ANN, LSTM, and 1D-CNN. Our analysis revealed that the TCN model outperformed the traditional models, demonstrating lower loss, MAE, MAPE. Statistical tests confirmed the TCN model's superiority, highlighting its potential for accurate STI price prediction.

7.6 Generalization Ability of the TCN Model

The third question focused on assessing the generalization ability of the TCN model in forecasting STI stock prices on unseen datasets across distinct future time periods. Our findings indicated that the TCN model exhibited robust performance on datasets closely aligned with the training period, while its performance decreased as the forecast horizon extended. Notably, the TCN model consistently forecasted values higher than the actual prices on future datasets. This observation could potentially be explained by two key findings. Firstly, the Hurst Exponent analysis indicated the presence of persistent trends

in most data slices, signifying enduring market patterns. Secondly, our examination of the STI Close price curves revealed a gradual upward trend over time, interspersed with sharp shorter-term downward fluctuations. Collectively, these insights suggest that the dataset likely encompasses an overall uptrend, influencing the model's tendency to predict higher values.

7.7 Impact of Cross-Validation

As anticipated, our investigation into cross-validation revealed that the TCN model, pre-trained using cross-validation, exhibited enhanced performance, especially on datasets closely aligned with the training period. Nevertheless, as we extended our focus to predict further into the future, the model trained without cross-validation showcased superior generalization performance. Therefore, it is advisable to adopt a hybrid approach, leveraging cross-validation to fine-tune the model for more accurate near-future predictions while periodically retraining the model to uphold its performance standards.

In summary, our exploration encompassed a range of aspects in daily stock price prediction. We diligently addressed data quality and bias concerns, opting for a robust 10-year dataset, and affirming a normal distribution while decisively rejecting the random walk hypothesis through the Hurst Exponent analysis. Notably, we observed that features within each group exhibited notably stronger correlations compared to features outside of their respective groups, which sparked our interest in group-based feature importance evaluation. The standout achievement was the TCN model's consistent outperformance of traditional models, supported by statistically significant lower mean absolute errors. However, the TCN model's generalization displayed

variability across forecast horizons, including a tendency to predict higher values potentially influenced by persistent trends. Lastly, cross-validation could significantly improve model performance on datasets in the near future.

8 Conclusion and future work

In this concluding chapter, we bring our study to a close by summarizing the key research findings within the context of our research aims and questions. We will also explore the value and implications of these findings, elucidating their contributions to the broader field. Additionally, we will candidly acknowledge the limitations inherent in our study and outline potential directions for future research.

This study aimed to use a multivariate TCN model to accurately predict the STI Close price. The results indicate that the TCN model has demonstrated remarkable capabilities in enhancing predictive accuracy compared to traditional models such as ANN, LSTM, and 1D-CNN. Further analysis revealed insights into the impact of specific features, with certain features enhancing predictability while others had no significant impact. Notably, the model exhibited a consistent bias towards predicting higher values than the actual targets. Moreover, predictability displayed temporal patterns, with robust performance in the immediate future and diminishing accuracy in further future datasets. As anticipated, cross-validation showed the ability to improve the model's predictive performance. These findings provide valuable insights into financial forecasting and underscore the need for meticulous feature selection and periodic model retraining in this dynamic field.

This study holds the potential to make several significant contributions to the field of financial market analysis. Firstly, it provides a comprehensive methodology for

uncovering complex financial market patterns through model comparison, generalization power assessment, feature evaluation, and validation approaches. The study demonstrates that STI Close price patterns can be effectively discovered through periodic training of a TCN model and careful evaluation of informative features. Furthermore, this research bridges a gap in the existing literature by applying the TCN model to predict the Singapore financial market, offering a novel perspective on market predictions in this specific context. Additionally, it extends the work of Hoseinzade and Haratizadeh (2019) by delving deeper into feature evaluation, shedding light on the significance of specific variables in financial forecasting. Moreover, it addresses the assertion made by Selvin et al. (2017) regarding changing dynamics in stock markets by proposing a methodology for experimenting with such dynamics through the Hurst exponent and comparing predictions on future datasets. The study's insights and methodologies could prove beneficial to global investors, particularly those interested in the Singapore market, and have the potential to be adapted for analyzing complex patterns in other financial datasets.

This study's limitations include the restricted time frame, which impeded a thorough examination of the precise effects of individual features on predictions. Moreover, due to time constraints, the study was unable to explore a wide range of model architectures within the expansive parameter space, potentially constraining the exploration of alternative modeling approaches and their implications for predictive accuracy.

Future studies could expand upon our findings by considering the impact of investor sentiment on stock prices. Incorporating sentiment analysis, potentially with the assistance of advanced AI models like ChatGPT, could provide valuable insights into

the role of market sentiment in stock price prediction. By combining sentiment analysis with our model, researchers and investors may gain a more comprehensive understanding of market dynamics and improve predictive accuracy.

In conclusion, this study enhances predictive accuracy through the TCN model, highlighting its superiority over traditional models and offering insights into feature impact. It reveals a consistent bias towards predicting higher values and temporal predictability patterns. These findings contribute by providing a comprehensive approach to financial pattern discovery and addressing literature gaps in the Singapore market context. Nonetheless, time limitations hindered in-depth feature analysis and model exploration. Future research may integrate sentiment analysis, leveraging AI models like ChatGPT, to further unravel market dynamics and enhance predictions.

Total number of words: 7187

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10 Appendices

Appendix A: Implementation code