SIMULATED ANNEALING-BASED SUPPORT VECTOR REGRESSION (SA-SVR) IN CRUDE PALM OIL PRICE PREDICTION

By

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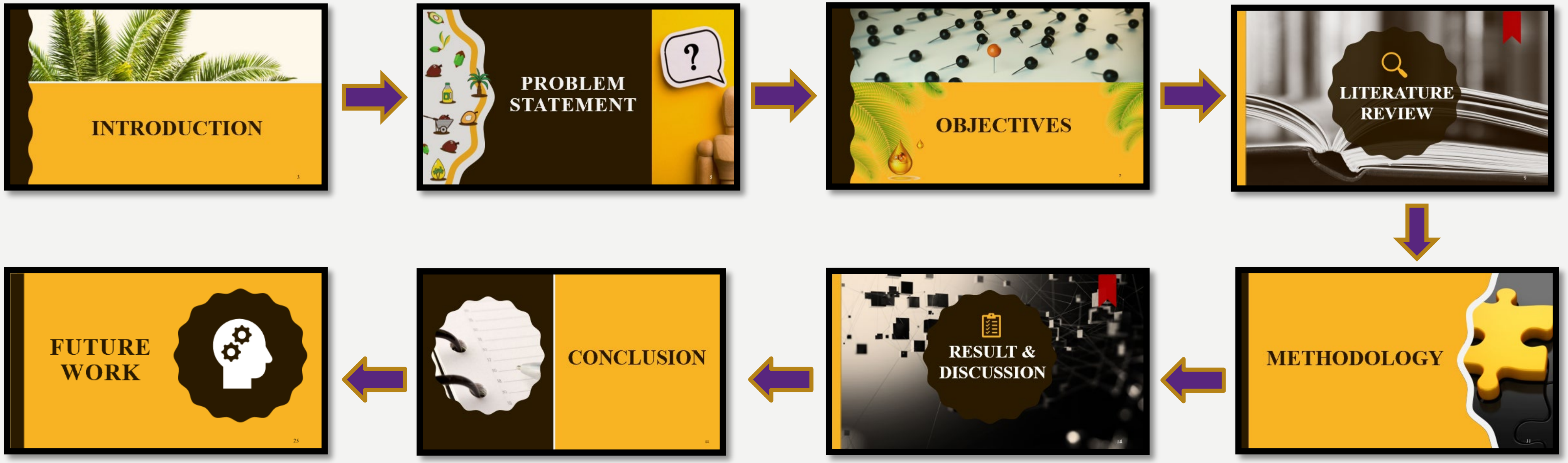
OUTLINE


INTRODUCTION
PROBLEM STATEMENT
OBJECTIVES
LITERATURE REVIEW
METHODOLOGY
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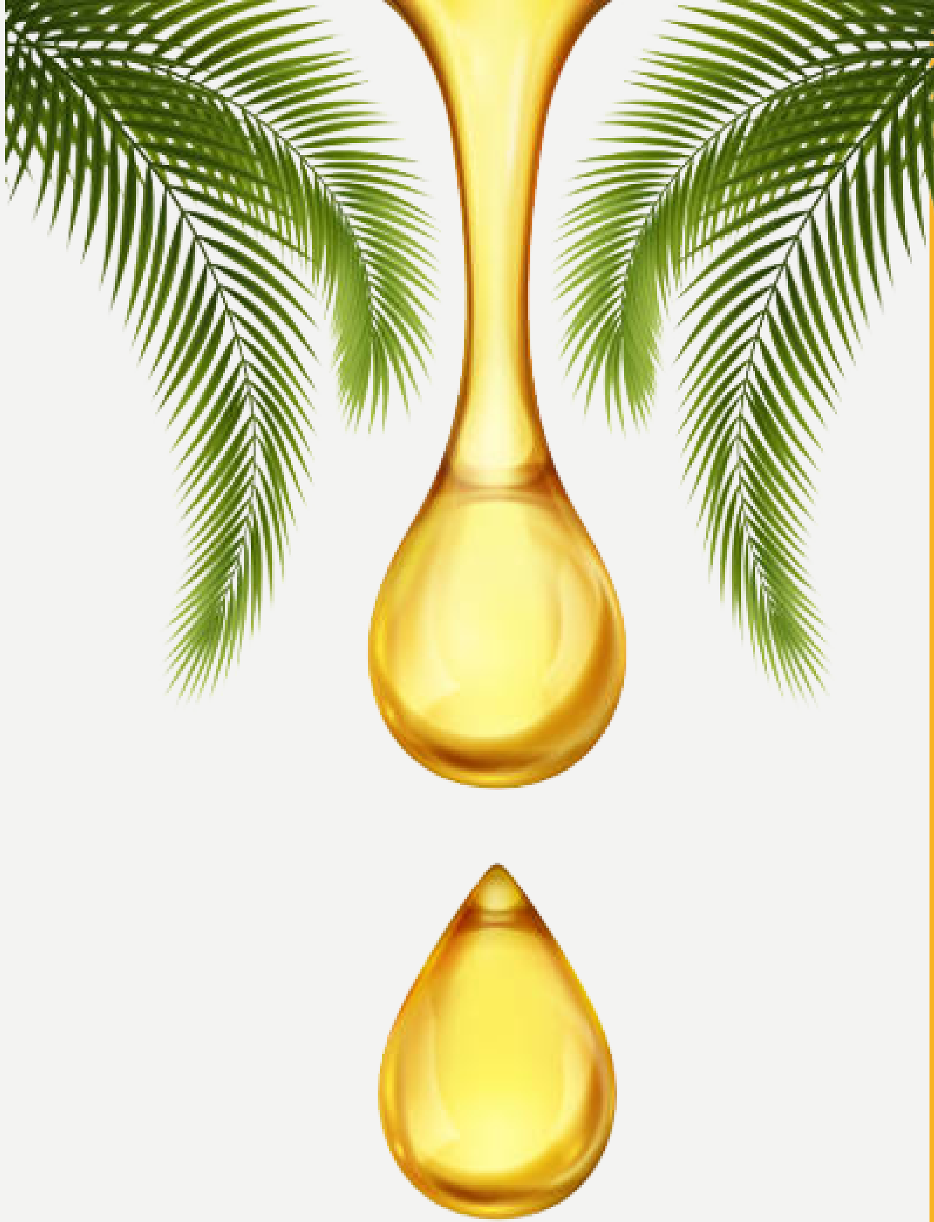
INTRODUCTION

INTRODUCTION

- **Importance of Crude Palm Oil in Malaysia**
  - **Major Export Products**
- **Usage of Futures Contract**
  - **"Financial instrument that allow market participants to offset or assume the risk of a price change of an asset over time", CME Group**
- **What is Support Vector Regression (SVR)?**
  - **Machine Learning Algorithm**
- **What is Simulated Annealing (SA)?**
  - **Metaheuristics Algorithm**



PROBLEM STATEMENT

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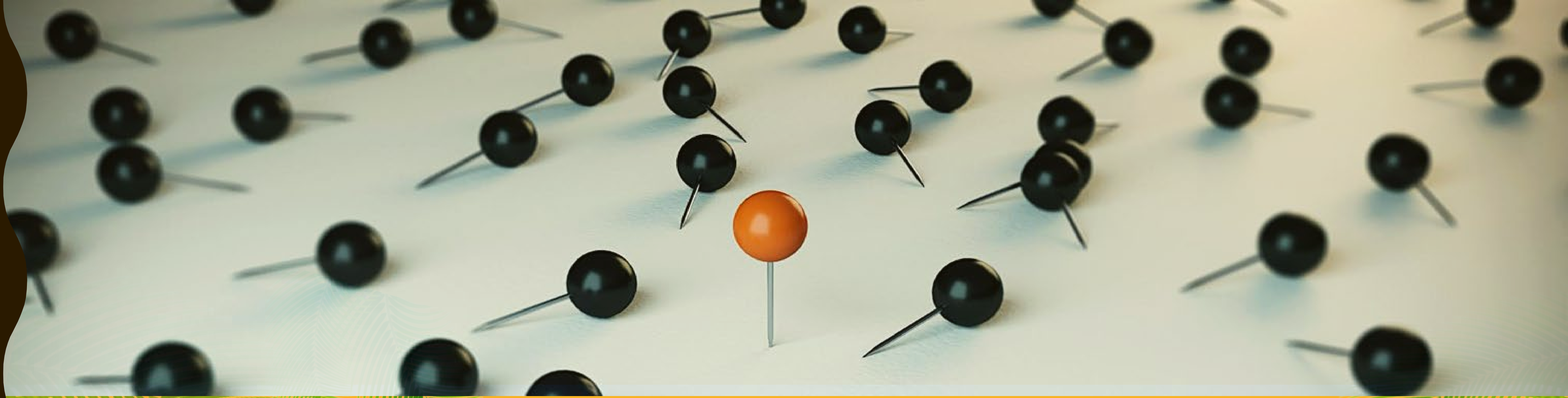
- **Uncertainties**
  - Weather - unpredictable
  - Supply and Demand - variable
- **New Methodology**
  - Simulated Annealing-based Support Vector Regression (**SA-SVR**) model



OBJECTIVES

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01 Investigate the **price prediction of FCPO** in the literature.

02 Study the usage of **SVR with hyperparameters optimized by SA** in FCPO price prediction.

03 Implement SVR and SA in **Python** for FCPO price prediction.

04 **Perform experiments** to optimize the hyperparameters of SVR using SA to better predict FCPO price.

LITERATURE REVIEW

LITERATURE REVIEW

Articles	Method	Work	Conclusion
Brooks & Morgan, 1995	Simulated Annealing (SA)	-	• Advantages of SA: - **simplicity** - **ease of implementation** - ability to **handle complex cost function & constraint**
Siddique & Adeli, 2016			• **SA** converges to a global optimality if there is **sufficient randomness** with a **slow enough cooling**
Ali Alahmari, 2020	Support Vector Regression (SVR)	Cryptocurrency future price forecasting	• **SVR** with **radial basis function (RBF) kernel** outperforms other kernel • MAE, MSE, RMSE, R^2 → **high accuracy**
Astudillo *et al.*, 2020		Copper price forecasting	• **RMSE ≤ 2.2%** → **SVR** able to **accurately predict** the data
González-Mancha, 2018	SA-SVR	Stock price forecasting	• Show **improvement** in model's prediction performance

METHODOLOGY

MAIN FLOW

Data Collection → Data Preprocessing → Exploratory Data Analysis (EDA) → Feature Engineering → Data Splitting → Data Transformation → Analysis

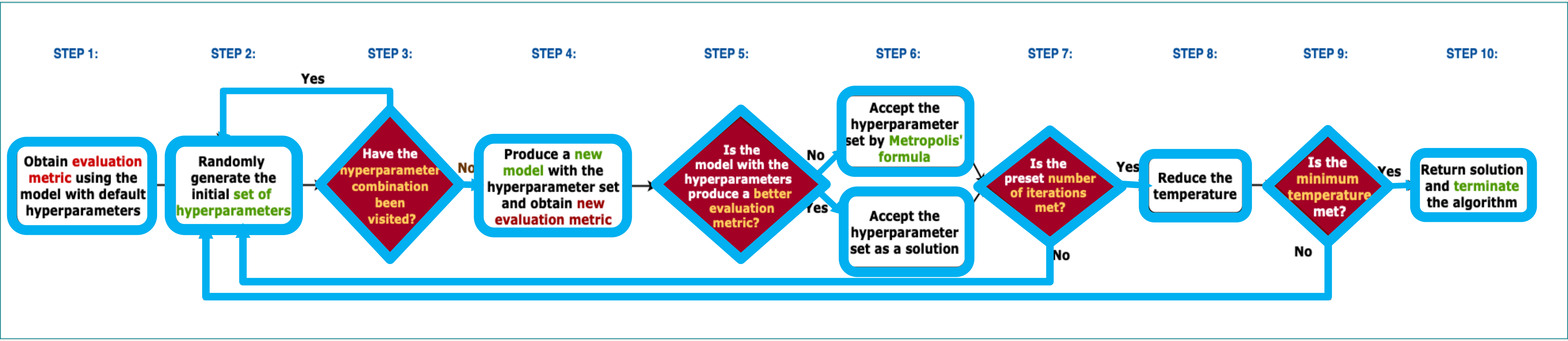
Exploratory Data Analysis (EDA)
- Descriptive statistics
- Data visualization

Feature Engineering
- Date features
- Lag features

Data Splitting
- Train set
- Test set

SIMULATED ANNEALING-BASED SUPPORT VECTOR REGRESSION (SA-SVR)

Hyperparameters of RBF kernelized SVR model: C, ε, γ



RESULT & DISCUSSION

PERFORMANCE COMPARISON

Evaluation metrics: MAE, MAPE, RMSE, R^2.

SVR

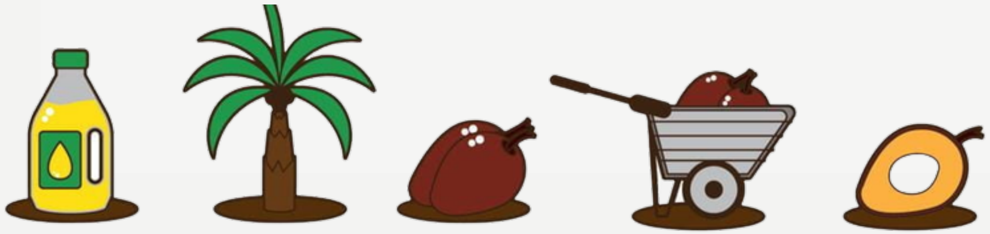
- SVR model **without** hyperparameter tuning
- **Default hyperparameter setting** in Scikit-learn library:

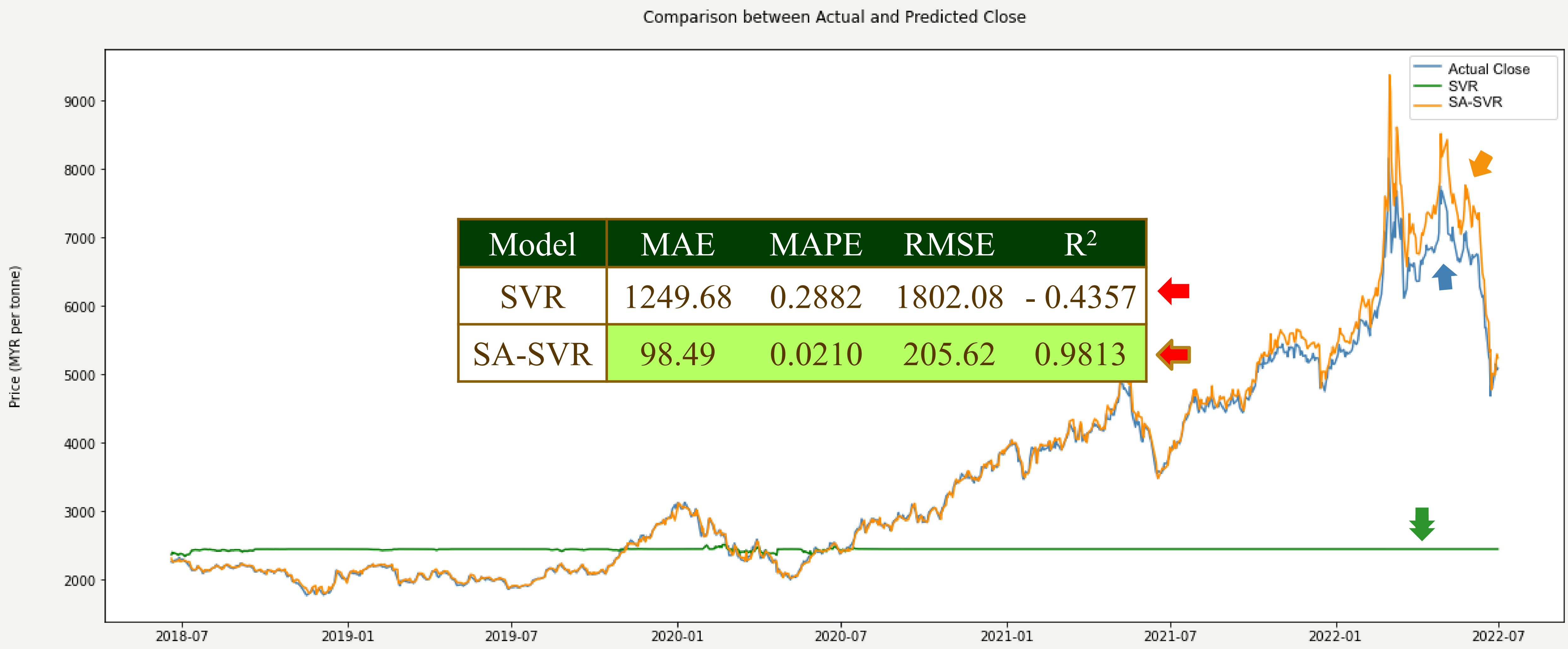
$$C = 1, \gamma = \text{‘scale’}, \varepsilon = 0.1$$

SA-SVR

- SVR model **with** hyperparameter tuning using SA
- SA searches for the **best hyperparameter values** from a pre-defined parameter space. (**30 runs**)
- Best hyperparameter combination:

$$C = 741709, \gamma = 1\text{e-}06, \varepsilon = 1\text{e-}07$$





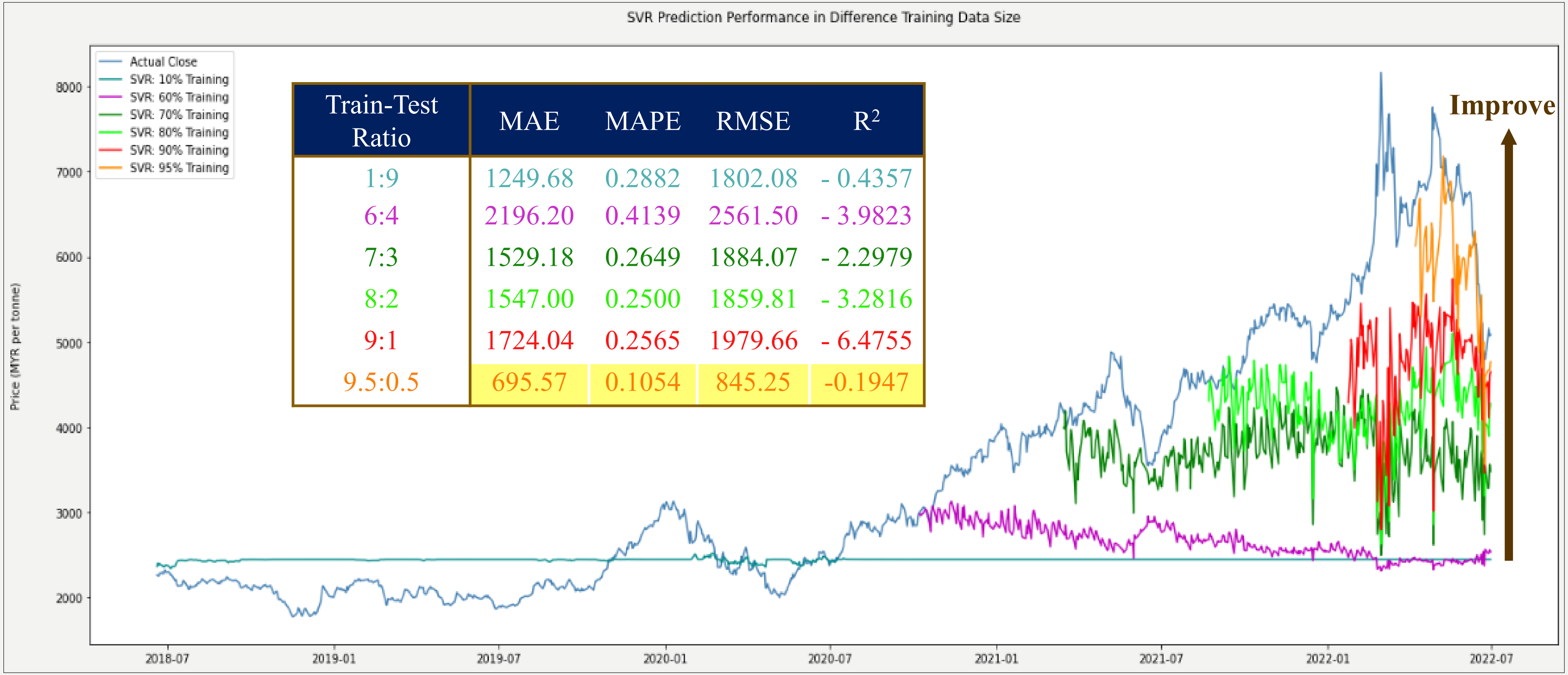
Model	MAE	MAPE	RMSE	R^2
SVR	1249.68	0.2882	1802.08	- 0.4357
SA-SVR	98.49	0.0210	205.62	0.9813

SVR vs SA-SVR

FURTHER ANALYSIS

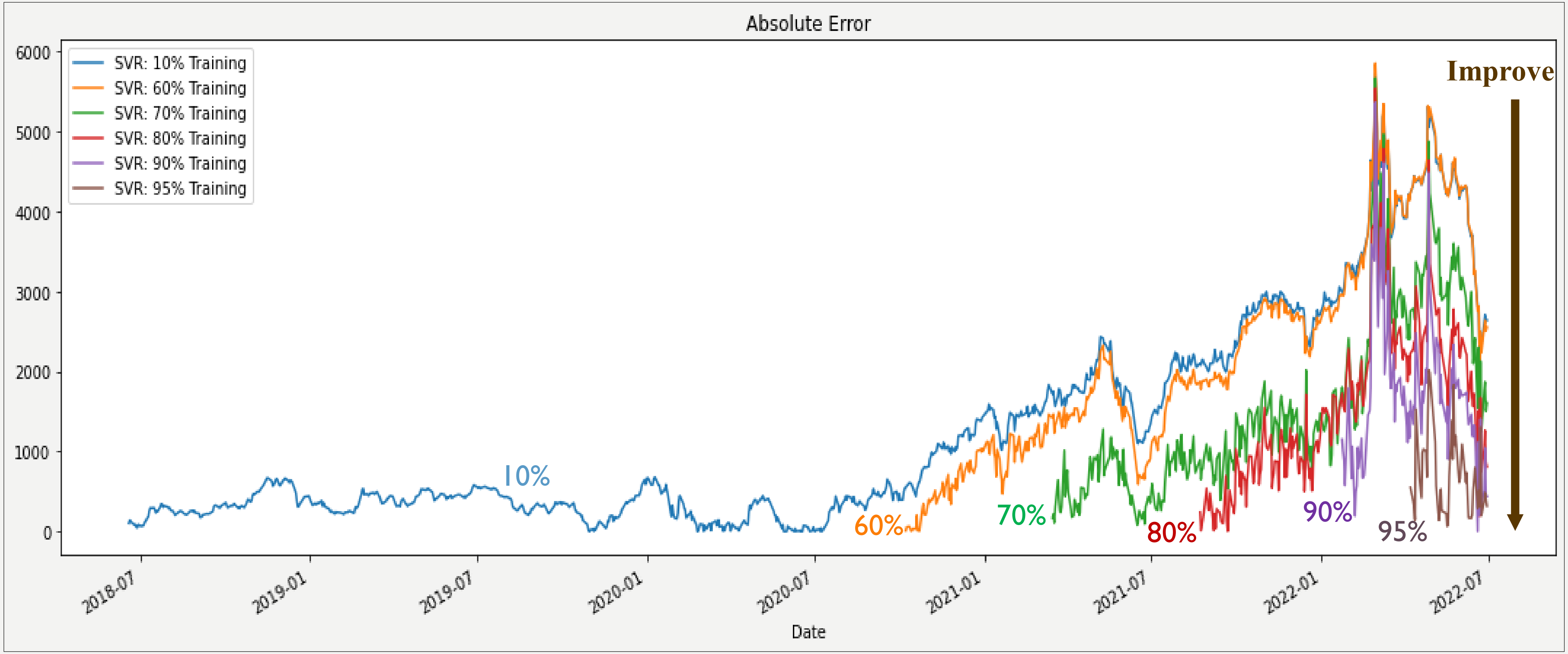
Analysis 1	Analysis 2	Analysis 3
➢ Study the effect of **training data size** - using different **train-test split ratios**	➢ Select the **temperature values** for SA: using different combination of **initial** and **minimum** temperatures	Initiate the parameter search based on the **previous best** hyperparameter set

ANALYSIS 1: DIFFERENT TRAIN-TEST SPLIT RATIO



Train-Test Ratio	MAE	MAPE	RMSE	R^2
1:9	1249.68	0.2882	1802.08	- 0.4357
6:4	2196.20	0.4139	2561.50	- 3.9823
7:3	1529.18	0.2649	1884.07	- 2.2979
8:2	1547.00	0.2500	1859.81	- 3.2816
9:1	1724.04	0.2565	1979.66	- 6.4755
9.5:0.5	695.57	0.1054	845.25	-0.1947

ANALYSIS 1: DIFFERENT TRAIN-TEST SPLIT RATIO



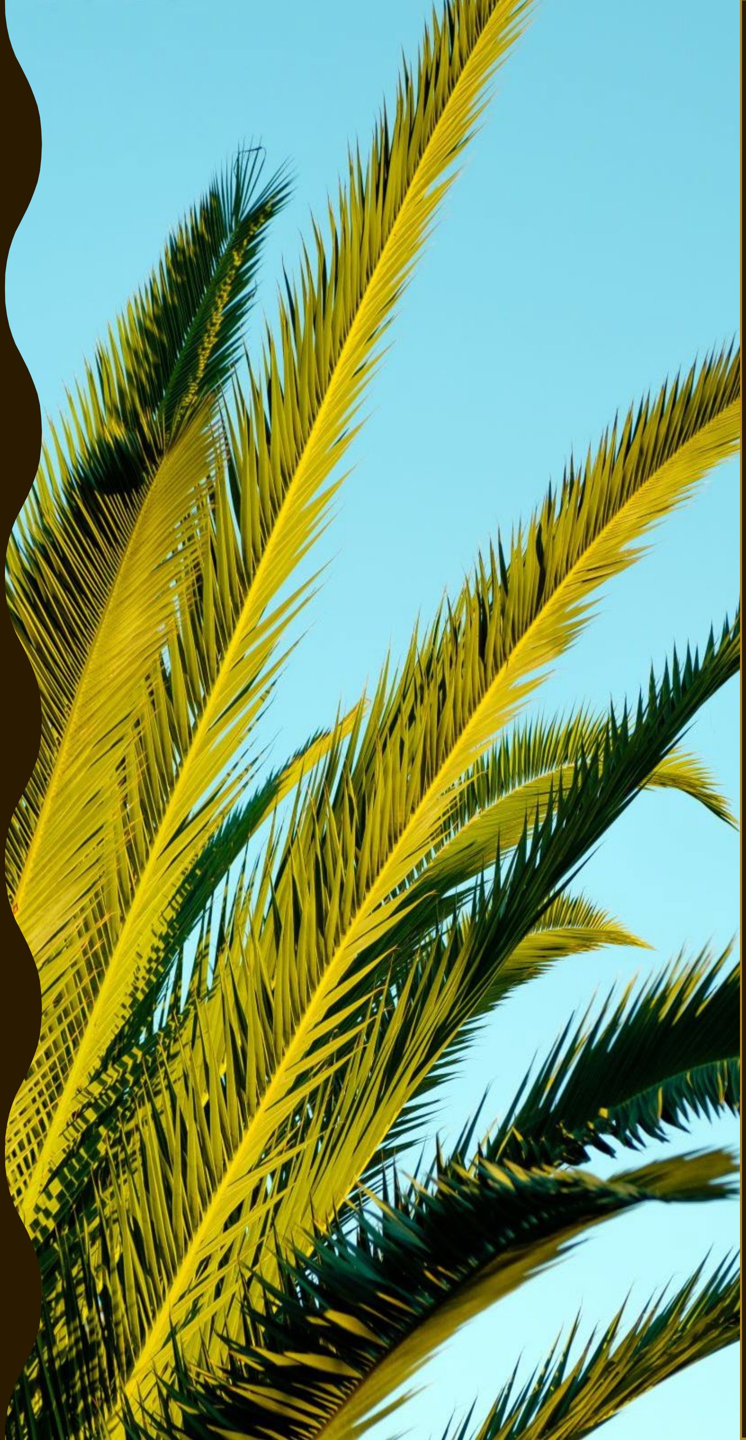
ANALYSIS 2: SA TEMPERATURE PARAMETER

T_0, T_{min}	C	γ	ε	RMSE	Average Execution Time (seconds)
50, 20	674541	1×10^{-6}	1×10^{-10}	155.12	105
50, 30	741362	1×10^{-6}	1×10^{-18}	205.65	57
50, 40	1000000	1×10^{-6}	1×10^{-12}	200.20	28
100, 20	900000	1×10^{-6}	1×10^{-12}	251.23	165
100, 30	741709	1×10^{-6}	1×10^{-7}	205.62	154
100, 40	670126	1×10^{-6}	1×10^{-16}	153.23	106
150, 20	741727	1×10^{-6}	1×10^{-8}	203.21	212
150, 30	741301	1×10^{-6}	1×10^{-6}	205.53	176
150, 40	1000000	1×10^{-6}	1×10^{-12}	200.20	135

ANALYSIS 3:
NEW PARAMETER SEARCH POINT

Analysis	Number of Temperature Reductions	Current Temperature (Best Hyperparameters)
2	3	42.19
3	0	100

CONCLUSION



CONCLUSION

- Select **appropriate** hyperparameter values → **improve** the prediction performance

- SA-SVR is a high performing model with **accurate and trustworthy** predictions

Analysis	Summary
1	▪ Fix **test set size** ▪ Extract **more historical price** data
2	▪ Different temperature combinations affect the overall optimization result ▪ If no time constraint: (1) set **higher initial temperature** (2) vary the temperature **reduction rate** (3) **tune SA parameter**
3	▪ Starting search point close to the best set → **decrease the number of temperature reductions and average execution time**

FUTURE WORK

DIRECTIONS FOR FUTURE RESEARCH

Include **more relevant dataset** for price prediction

Study **different parameters** for **SA** algorithm

Apply SA-SVR on predicting **other continuous data**

Optimize SVR hyperparameters using **other metaheuristic methods**

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Q&A

THANK YOU
FOR YOUR ATTENTION!