



# **Model Development Phase Template**

Date	01 December 2024
Team ID	739791
Project Title Rice Crop Monitoring-Time Series Analy	
Maximum Marks	10 Marks

# **Initial Model Training Code, Model Validation and Evaluation Report**

The initial model training code will be showcased in the future through a screenshot. The model validation and evaluation report will include a summary and training and validation performance metrics for multiple models, presented through respective screenshots.

## **Initial Model Training Code (5 marks):**

#### 1. Arima Model

```
# Function to evaluate ARIMA model
def evaluate_arima_model(train, test, order):
    model = ARIMA(train, order=order)
    model_fit = model.fit()
    predictions = model_fit.forecast(steps=len(test))
    rmse = sqrt(mean_squared_error(test, predictions))
    return rmse
# Function to optimize ARIMA
def optimize_arima(train, test, p_values, d_values, q_values):
    best_score, best_cfg = float("inf"), None
    for p, d, q in itertools.product(p_values, d_values, q_values):
        try:
            order = (p, d, q)
            rmse = evaluate_arima_model(train, test, order)
            if rmse < best_score:</pre>
                best_score, best_cfg = rmse, order
            print(f'ARIMA{order} RMSE={rmse:.4f}')
        except:
            continue
    print(f'Best ARIMA{best_cfg} RMSE={best_score:.4f}')
    return best_cfg
```





#### 2. Sarima Model

```
def evaluate_sarima_model(train, test, order, seasonal_order):
   model = SARIMAX(train, order=order, seasonal_order=seasonal_order)
   model_fit = model.fit(disp=False)
   predictions = model_fit.forecast(steps=len(test))
   rmse = sqrt(mean_squared_error(test, predictions))
   return rmse
# Function to optimize SARIMA
def optimize_sarima(train, test, p_values, d_values, q_values, P_values, D_values, Q_values, m):
   best_score, best_cfg = float("inf"), None
    for p, d, q, P, D, Q in itertools.product(p_values, d_values, q_values, P_values, D_values, Q_values):
           order = (p, d, q)
           seasonal_order = (P, D, Q, m)
           rmse = evaluate_sarima_model(train, test, order, seasonal_order)
           if rmse < best_score:</pre>
               best_score, best_cfg = rmse, (order, seasonal_order)
            print(f'SARIMA{order}x{seasonal_order} RMSE={rmse:.4f}')
    print(f'Best SARIMA{best_cfg} RMSE={best_score:.4f}')
   return best_cfg
```

## 3. Facebook Prophet Model

```
import pandas as pd
from prophet import Prophet

df = pd.read_csv('rice production across different countries from 1961 to 2021.csv')

# Replace 'your_date_column' and 'your_value_column' with the actual column names from new = df.rename(columns={'Year': 'ds', 'Value': 'y'}) # Example: Assuming 'Year' is your_value_column' with the actual column names from new = df.rename(columns={'Year': 'ds', 'Value': 'y'}) # Example: Assuming 'Year' is your_value_column' with the actual column names from new = df.rename(columns={'Year': 'ds', 'Value': 'y'}) # Example: Assuming 'Year' is your_value_column' with the actual column names from new = df.rename(columns={'Year': 'ds', 'Value': 'y'}) # Example: Assuming 'Year' is your_value_column' with the actual column names from new = df.rename(columns={'Year': 'ds', 'Value': 'y'}) # Example: Assuming 'Year' is your_value_column' with the actual column names from new = df.rename(columns={'Year': 'ds', 'Value': 'y'}) # Example: Assuming 'Year' is your_value_column' with the actual column names from new = df.rename(columns={'Year': 'ds', 'Value': 'y'}) # Example: Assuming 'Year' is your_value_column' with the actual column names from new = df.rename(columns={'Year': 'ds', 'Value': 'y'}) # Example: Assuming 'Year' is your_value_column' with the actual column names from new = df.rename(columns={'Year': 'ds', 'Value': 'y'}) # Example: Assuming 'Year' is your_value_column' with the actual column names from new = df.rename(columns={'Year': 'ds', 'Value': 'y'})
```

```
from sklearn.metrics import mean_absolute_error
# Generate predictions on test data
# Ensure y_pred contains predictions corresponding to the test data in 'new'
y_pred = model.predict(new[['ds']])['yhat'] # Predict on the 'ds' values from 'new'
# Calculate root mean squared error
mae = mean_absolute_error(new['y'].values, y_pred)
print('MAE:', mae)
```

**Model Validation and Evaluation Report (5 marks):** 





Model	Summary	Training and Validation Performance Metrics
Arima Model	<ul> <li>Combines three components:</li> <li>AR (AutoRegression), I (Integration), MA (Moving Average)</li> <li>Requires the time series to be stationary (constant mean and variance over time).</li> <li>Use Cases: <ul> <li>Works well for univariate time series with linear trends and seasonality.</li> <li>Suitable for short-term forecasting.</li> </ul> </li> </ul>	<pre>model = ARIMA(train, order=param)     model_fit = model.fit()     y_pred = model_fit.forecast(len(test))     mae = np.sqrt(mean_absolute_error(test, y_pred))     print(param, 'MAE:', mae)     if mae &lt; best_score: # Changed rmse to mae for consistency         best_score, best_cfg, bestfit = mae, param, model_fit     except:         continue     print('Best parameters: ', best_cfg)     print('mae: ', best_score)  (0, 0, 0) MAE: 1470.7437683209869 (0, 0, 1) MAE: 1449.149787698572 (0, 0, 2) MAE: 1421.740809823649 (0, 1, 0) MAE: 568.0192673267467 (0, 1, 1) MAE: 561.7140241109017 (0, 1, 2) MAE: 561.7140241109017 (0, 1, 2) MAE: 1357.7357304259974 (0, 2, 0) MAE: 1179.4161549705568 (1, 0, 0) MAE: 569.9200754175704 (1, 0, 1) MAE: 552.8654412398556 (1, 0, 2) MAE: 525.8037602469777</pre>
Sarima Model	<ul> <li>2. SARIMAX (Seasonal AutoRegressive Integrated Moving Average with eXogenous factors)</li> <li>Features the Extension of ARIMA</li> <li>Use Cases:</li> <li>Best for time series data with seasonal patterns (e.g., monthly sales).</li> <li>Incorporates external variables to improve accuracy.</li> </ul>	# Fitting the model  best_model = SARIMAX(df['Value']).fit(dis=-1)  print(best_model.summary())  SARIMAX Results  Dep. Variable: Value No. Observations: 7324  Model: SARIMAX(1, 0, 0) Log Likelihood -122781.828  Date: Sun, 01 Dec 2024 AIC 245567.655  Time: 20:16:14 BIC 245581.453  Sample: 0 HQIC 245572.399  - 7324  Covariance Type: opg  coef std err z P> z  [0.025 0.975]  ar.L1 0.9827 0.000 3426.422 0.000 0.982 0.983  sigma2 2.131e+13 6.12e-18 3.48e+30 0.000 2.13e+13 2.13e+13  Ljung-Box (L1) (Q): 0.35 Prob(JB): 0.000  Heteroskedasticity (H): 0.04 Skew: -33.16  Prob(H) (two-sided): 0.00 Kurtosis: 1475.22





#### Features:

- Developed by Facebook, designed for business forecasting with a focus on non-statisticians.
- Automatically handles:

# Facebook Prophet model

Trends (linear or logistic growth), Seasonality (daily, weekly, yearly), Holidays/events as additional regressors.

## **Use Cases:**

- Robust for time series with irregular or missing data.
- Suitable for datasets with holidays or special events.
- Highly customizable and interpretable.

```
# Instantiate and fit the Prophet model
model = Prophet(seasonality_mode='multiplicative')
model.fit(new)
```

Importing plotly failed. Interactive plots will not work. 20:18:34 - cmdstanpy - INFO - Chain [1] start processing 20:18:35 - cmdstanpy - INFO - Chain [1] done processing

ophet.forecaster.Prophet at 0x190b1046d50>