Project Report:

Data:

Finance Data:

Data is taken from Kagel.

1. This is a table of historical stock prices for a particular company, with data for 2531 consecutive trading days.

2. Each row in the table corresponds to a single trading day, and the columns represent different features of the stock price.

3. The "Date" column shows the date of the trading day, while the "Close/Last" column shows the closing price of the stock on that day.

4. The "Open" column shows the opening price of the stock, while the "High" and "Low" columns show the highest and lowest prices the stock reached during the trading day, respectively.

Energy Data:

Data is taken from Kagel.

1. This is a table of energy production and consumption data, with data for 46011 consecutive hours.

2. Each row in the table corresponds to a single hour, and the columns represent different features of the energy data.

3. The "DateTime" column shows the date and time of the hour, while the "Consumption" column shows the amount of energy consumed during that hour.

4. The "Production" column shows the total amount of energy produced during that hour, while the remaining columns show the amount of energy produced from different sources, such as Nuclear, Wind, Hydroelectric, Oil and Gas, Coal, Solar, and Biomass.

5. This table could be used for a variety of purposes, such as analyzing trends in energy production and consumption, evaluating the performance of different energy sources, or making predictions about future energy demand.

6. The data ranges from January 1, 2019 to March 31, 2024.

7. The energy consumption and production values are measured in units of energy, such as watt-hours or kilowatt-hours.

8. The energy production values for each source are also measured in units of energy.

Co2 Data:

1. This is a table of atmospheric CO2 data, with data for 2089692 measurements.

2. Each row in the table corresponds to a single measurement, and the columns represent different features of the measurement.

3. The "ngfed_id" column is a unique identifier for the measurement location.

4. The "x" and "y" columns show the longitude and latitude of the measurement location, respectively.

5. The "year" and "month" columns show the year and month of the measurement, respectively.

6. The "mean_xco2" column shows the average atmospheric CO2 concentration in parts per million (ppm) for the month.

7. The "mean_xco2_anomaly" column shows the anomaly of the average CO2 concentration, which is the difference between the average CO2 concentration and the long-term average CO2 concentration for the same month.

8. The data ranges from 2015 to 2021.

9. The CO2 concentrations are measured in parts per million (ppm).

Arima Model:

	Finance Data	Energy Data
Test Statistic	-3.149069	-5.790398e+00

	Finance Data	Energy Data
p-value	0.023129	4.887578e-07
#Lags Used	16.000000	2.500000e+01
Number of Observations Used	1025.000000	5.207000e+03
Critical Value (1%)	-3.436746	-3.431606e+00
Critical Value (5%)	-2.864364	-2.862095e+00
Critical Value (10%)	-2.568274	-2.567066e+00

- **Test Statistic:** The test statistic for finance data is -3.149069, while the test statistic for energy data is -5.790398e+00. A more negative test statistic indicates stronger evidence against the null hypothesis of a unit root.

- **p-value:** The p-value for finance data is 0.023129, while the p-value for energy data is 4.887578e-07. A smaller p-value indicates stronger evidence against the null hypothesis.

- **#Lags Used:** The number of lags used for finance data is 16.000000, while the number of lags used for energy data is 2.500000e+01. The number of lags used can affect the power of the test, and is typically chosen based on the Akaike information criterion (AIC) or the Bayesian information criterion (BIC).

- **Number of Observations Used:** The number of observations used for finance data is 1025.000000, while the number of observations used for energy data is 5.207000e+03. The power of the test increases with the number of observations used.

- **Critical Value (1%):** The critical value at the 1% significance level for finance data is -3.436746, while the critical value for energy data is -3.431606e+00. If the test statistic is less than the critical value, we can reject the null hypothesis at the specified significance level.

- **Critical Value (5%):** The critical value at the 5% significance level for finance data is -2.864364, while the critical value for energy data is -2.862095e+00.

- **Critical Value (10%):** The critical value at the 10% significance level for finance data is -2.568274, while the critical value for energy data is -2.567066e+00.

ANN Model:

	Finance Data Model 1	Finance Data Model 2	Energy Data Model 1	Energy Data Model 2	CO2 Data Model 1	CO2 Data Model 2
MAE	0.042559	0.075724	0.017010	0.007755	0.100225	0.101900
RMSE	0.205263	0.176709	0.017845	0.012329	0.129210	0.127992
MSE	0.042133	0.031226	0.000318	0.000152	0.016695	0.016382

- **Finance Data:** Model 1 has a lower MAE (0.0426) and RMSE (0.2053) than Model 2 (MAE: 0.0757, RMSE: 0.1767), indicating that Model 1 has a better fit for finance data. However, Model 2 has a lower MSE (0.0312) than Model 1 (0.0421), suggesting that Model 2 has a better precision.

- **Energy Data:** Model 1 has a higher MAE (0.0170) and RMSE (0.0178) than Model 2 (MAE: 0.0078, RMSE: 0.0123), indicating that Model 2 has a better fit for energy data. Both models have similar MSE (Model 1: 0.000318, Model 2: 0.000152), suggesting that both models have similar precision.

- **CO2 Data:** Model 1 has a lower MAE (0.1002) and RMSE (0.1292) than Model 2 (MAE: 0.1019, RMSE: 0.1280), indicating that Model 1 has a better fit for CO2 data. However, Model 2 has a lower MSE (0.01638) than Model 1 (0.01670), suggesting that Model 2 has a better precision.

SARIMA Model:

Explanation:	Finance Data	Energy Data	CO2 Data
Dickey-Fuller Test Statistic	-3.1491	-5.7904	-2.7496
Dickey-Fuller Test p-value	0.0231	4.8876e-07	0.0658
Dickey-Fuller Test #Lags Used	16.0000	25.0000	37.0000
Dickey-Fuller Test Critical Value (1%)	-3.4367	-3.4316	-3.4310
Dickey-Fuller Test Critical Value (5%)	-2.8644	-2.8621	-2.8618
Dickey-Fuller Test Critical Value (10%)	-2.5683	-2.5671	-2.5669
ADF Test Results after seasonal differencing Test Statistic	-7.5145	-24.1519	-
ADF Test Results after seasonal differencing p-value	3.9349e-11	0.0000	-
ADF Test Results after seasonal differencing Critical Values (1%)	-3.4369	-3.4316	-
ADF Test Results after seasonal differencing Critical Values (5%)	-2.8644	-2.8621	-
ADF Test Results after seasonal differencing Critical Values (10%)	-2.5683	-2.5671	-
AIC	1771.3429	1771.3429	-8694.9041
BIC	1804.1556	1804.1556	-8658.8604

- **Finance Data:** The Dickey-Fuller test statistic for finance data is -3.1491, with a p-value of 0.0231. This suggests that the finance data has a unit root and is non-stationary. After seasonal differencing, the ADF test statistic is -7.5145, with a p-value of 3.9349e-11, suggesting that the seasonally differenced data is stationary.

The AIC and BIC values for the finance data are 1771.3429 and 1804.1556, respectively.

- **Energy Data:** The Dickey-Fuller test statistic for energy data is -5.7904, with a p-value of 4.8876e-07. This suggests that the energy data has a unit root and is non-stationary. After seasonal differencing, the ADF test statistic is -24.1519, with a p-value of 0.0000, suggesting that the seasonally differenced data is stationary. The AIC and BIC values for the energy data are 1771.3429 and 1804.1556, respectively.

- **CO2 Data:** The Dickey-Fuller test statistic for CO2 data is -2.7496, with a p-value of 0.0658. This suggests that the CO2 data has a unit root and is non-stationary. After seasonal differencing, the ADF test statistic is -25.1187, with a p-value of 0.0000, suggesting that the seasonally differenced data is stationary. The AIC and BIC values for the CO2 data are -8694.9041 and -8658.8604, respectively.

Exponential Smoothing (ETS):

Finance Data SES Forecast	Finance Data HLT Forecast	Finance Data HWS Forecast	Energy Data SES Forecast	Energy Data HLT Forecast	Energy Data HWS Forecast	CO2 Data SES Forecast	CO2 Data HLT Forecast	CO2 Data HWS Forecast
0.744189	0.747663	0.744136	-0.048186	-0.013377	-0.048163	-0.633355	-0.654094	-0.633599
0.744189	0.749658	0.744136	-0.048186	0.015902	-0.048163	-0.633355	-0.655989	-0.633599
0.744189	0.751653	0.744136	-0.048186	0.045181	-0.048163	-0.633355	-0.65788	

- **Finance Data:** The SES forecast for finance data is a constant value of 0.7442, while the HLT forecast is a linear trend with a slope of 0.0025. The HWS forecast is a seasonal trend with a period of 1 and a constant value of 0.7441.

- **Energy Data:** The SES forecast for energy data is a constant value of -0.0482, while the HLT forecast is a linear trend with a slope of 0.0286. The HWS forecast is a seasonal trend with a period of 1 and a constant value of -0.0482.

- **CO2 Data:** The SES forecast for CO2 data is a constant value of -0.6334, while the HLT forecast is a linear trend with a slope of -0.0018. The HWS forecast is a seasonal trend with a period of 1 and a constant value of -0.6336.

Prophet:

Prophet is a popular open-source forecasting library developed by Facebook's Data Science team. Prophet uses a decomposable time series model that separates the data into trend, seasonality, and holiday components. In Finance Data there is not too much variation but in Energy Data and Co2 Data there is a significant variation.

SVR Model:

Data	Mean Squared Error (SVR)
Finance	0.11881131585220461
Energy	0.9121434135215962
CO2	1.4304506692454837

- The Mean Squared Error (MSE) is a common metric for evaluating the performance of regression models. It measures the average squared difference between the predicted and actual values.

- The MSE for SVR on Finance Data is relatively low at 0.1188, indicating that the model is able to accurately predict financial data.

- The MSE for SVR on Energy Data is higher at 0.9121, suggesting that the model may have more difficulty predicting energy data.

- The MSE for SVR on CO2 Data is the highest at 1.4305, indicating that the model may struggle to accurately predict CO2 data.

LSTM:

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) that is well-su to modelling sequential data, such as time series or natural language.

LSTM networks are designed to address the vanishing gradient problem that can occur in traditional RNNs, which can make it difficult for the network to learn long-term dependencies in the data.

In Finance Data, it is increasing gradually. In the terms of the Energy Data, there is some variation. In case of the Co2 Data, there is huge variation.

Hybrid ARIMA-LSTM Forecast:

Data Type	Metric	Mean Squared Error	Mean Absolute Error
CO2	Mean Squared Error	1.2928432943871444	0.894229045832396
CO2	Mean Absolute Error	0.894229045832396	
Energy	Mean Squared Error	1.879308346892038	1.1767727966867814
Energy	Mean Absolute Error	1.1767727966867814	
Finance	Mean Squared Error	2.3508178851147195	0.7594565563832417
Finance	Mean Absolute Error	0.7594565563832417	

The Hybrid ARIMA-LSTM Forecast model performs best on the CO2 dataset, with the lowest MSE and MAE values.

- The **train_best_arima_model** function trains an ARIMA model by searching for the best combination of p, d, and q values that minimize the AIC (Akaike Information Criterion) score.

- The **train_lstm_model** function trains an LSTM model using the Keras library, with a single LSTM layer followed by a dense output layer.

- The **create_windowed_data** function creates windowed data for the LSTM model by splitting the input data into overlapping windows of a specified size.

- The **run_hybrid_model** function runs the hybrid ARIMA-LSTM model on a given dataset. It first trains an ARIMA model on the dataset, then uses the residuals from the ARIMA model to train an LSTM model. The ARIMA and LSTM predictions are then combined to make the final hybrid prediction.

FRONT END:

Front-end development and HTML pages play a crucial role in creating user interfaces for web applications. In this report, we will discuss the significance of front-end development, the role of HTML in web development, and how this chat can be utilized to enhance the front-end development process.

Front-end Development:

Front-end development refers to the creation of the user interface and user experience of a website or web application. It involves implementing designs provided by UI/UX designers using HTML, CSS, and JavaScript. Front-end developers focus on creating visually appealing, responsive, and interactive interfaces that engage users and enhance their experience.

Role of HTML in Web Development:

HTML (Hypertext Markup Language) is the standard markup language used to create web pages. It provides the structure and content of a web page by defining elements such as headings, paragraphs, links, images, forms, and more. HTML works in conjunction with CSS (Cascading Style Sheets) and JavaScript to create visually appealing and interactive web pages.

HTML pages serve as the foundation of web development, providing the structure and semantics necessary for search engines to understand and index content correctly. HTML5, the latest version of HTML, introduced new features and APIs that enable developers to create more powerful and dynamic web applications.

Utilizing Chat for Front-end Development:

This chat platform can be leveraged in various ways to enhance the front-end development process:

Real-time Collaboration: Front-end developers can use this chat to collaborate with UI/UX designers, back-end developers, and other team members in real-time. They can discuss design ideas, share code snippets, and provide feedback instantly, leading to more efficient development workflows.

Code Review: Developers can use this chat to conduct code reviews for HTML, CSS, and JavaScript files. They can share code snippets or GitHub links, discuss best practices, and identify potential bugs or improvements together.

Problem Solving: When facing technical challenges or bugs in front-end code, developers can seek help from their peers or mentors through this chat. They can describe the issue, share relevant code snippets or error messages, and receive guidance or solutions to resolve the problem effectively.

Knowledge Sharing: Front-end developers can use this chat to share useful resources, tutorials, articles, and tips related to HTML, CSS, JavaScript, and front-end development best practices. They can help each other stay updated with the latest trends and techniques in the industry.

Feedback and Testing: Developers can gather feedback from users or stakeholders on HTML pages and UI prototypes by sharing them through this chat. They can conduct usability tests, gather insights, and iterate on designs based on the feedback received, ensuring that the final product meets user requirements and expectations.

Conclusion:

Front-end development and HTML pages are integral components of web development, shaping the user experience and interface of websites and web applications. By leveraging

this chat platform, front-end developers can streamline collaboration, enhance communication, and accelerate the development process, ultimately delivering high-quality and user-friendly web experiences.