

Math 156 Final Project

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1 Introduction

In the rapidly evolving landscape of artificial intelligence and machine learning, sequential data analysis has emerged as a pivotal area of exploration. This project delves into the heart of this domain, focusing on two powerful tools: Long Short-Term Memory (LSTM) Networks and Transformer Networks. These sophisticated models have demonstrated an aptitude for handling sequential data, making them compelling choices for forecasting financial time series.

This study conducts a comparative analysis of Long Short-Term Memory (LSTM) and Transformer models for five-day stock price forecasting. We evaluate their performance on an optimized portfolio constructed from a random selection of S&P 500 stocks by comparing two key metrics: the profitability of the predicted portfolios and the Mean Absolute Percentage Error (MAPE) of the individual price forecasts. By integrating these predictions with Modern Portfolio Theory (MPT) principles, we also construct an optimal portfolio composition for the 25 selected stocks on a weekly basis.

2 Modern Portfolio Theory

2.1 Summary

Modern Portfolio Theory is a powerful tool that can be used to build an asset portfolio which balances the acts of maximizing reward and minimizing risk. Developed by Harry Markowitz in 1952, this model is now a staple in economic theory, and is based on two main principles.

The first principle is that assets cannot be viewed in isolation. It is important to look at how the assets relate to each other and what the portfolio looks like as a whole. By looking at assets in isolation, it is possible to gloss over massive risks of the portfolio. For example, if all of the assets are extremely correlated, then it is far more likely that your portfolio is has more drastic increases and decreases which means it is more risky.

The second principle is using long-term historical returns as a means for predicting returns. This is because it is very difficult to predict future returns. By looking at the long-term historical returns we get a safe approximation on the future returns of an asset.

[6]

2.2 Key Concepts

2.2.1 Maximize Return

One key concept of Modern Portfolio Theory is maximizing the return of stock. In the context of the Modern Portfolio Theory, this occurs when it attempts to maximize the return while keeping the risk minimized. The reason why this does not just result in the highest yield stock is because the risk of that is extremely high. So, it is forced to find some combination of stocks that has a high expected return while keeping the risk under the specified value. This is a constrained optimization problem in which the objective function is the expected return and the constraints play two roles. The objective function shown below is the dot product between the w vector and the μ vector. w_i represents the percent of the stock portfolio the i^{th} stock should hold. μ_i represents the average return of the i^{th} stock. The first constraint uses the covariance matrix to calculate the risk and constrains w so that the calculated risk is under a specified value. The other constraint ensures that the w values act as percentages of the portfolio. This will output an w values that correspond to the percent of each stock it recommends in the portfolio.

$$\begin{aligned} \text{Maximize} \quad & w^T \mu \\ \text{Subject to} \quad & w^T \Sigma w \leq \sigma^2 \\ & \sum_{i=1}^n w_i = 1 \\ & w_i \geq 0 \quad \forall i \in \{1, 2, \dots, n\} \end{aligned}$$

where:

- w is the vector of portfolio weights.
- μ is the vector of expected returns of the assets.
- Σ is the covariance matrix of the asset returns.
- σ^2 is the specified risk level.
- n is the number of assets.

If this was a model that focuses solely on maximizing the expected return of a stock (unconstrained version of the problem above) then the portfolio would consist of just a single stock which would be far too risky. That is why the constraints are necessary.

2.2.2 Minimize Risk

Another key concept of the Modern Portfolio Theory is that it aims to minimize risk as well. In this context, risk is often defined as a measure of variability and volatility of the returns of the portfolio where higher values mean higher risk. One way to express how much risk a stock portfolio holds is with the equation $w^T \Sigma w$. In this equation, Σ represents the covariance matrix. By doing two dot products of it with w , we get a value that is higher when the selected stocks are positively correlated with each other and lower when they are not correlated with each other. So, diversified portfolios of uncorrelated stocks have very low risk profiles while portfolios with a small amount of stocks that

are very correlated have high risk profiles. The constrained optimization problem for minimizing risk is as follows:

$$\begin{aligned}
& \text{Minimize} && w^T \Sigma w \\
& \text{Subject to} && w^T \mu \geq \mu_p \\
& && \sum_{i=1}^n w_i = 1 \\
& && w_i \geq 0 \quad \forall i \in \{1, 2, \dots, n\}
\end{aligned}$$

where:

- w is the vector of portfolio weights.
- μ is the vector of expected returns of the assets.
- Σ is the covariance matrix of the asset returns.
- μ_p is the target return.
- n is the number of assets.

2.2.3 Covariance

In the context of building a portfolio, the covariance of possible assets is a great tool for building a low risk, high reward portfolio. Covariance is a measure of how two assets move in comparison to each other. The covariance of two random variables, X and Y , is defined as follows:

$$\begin{aligned}
\text{cov}(X, Y) &= E[(X - \mu_X)(Y - \mu_Y)] \\
&\text{Where } \mu_X = E[X] \text{ and } \mu_Y = E[Y]
\end{aligned}$$

If the covariance is positive, then it suggests that they move in the same direction. On the other hand, if the covariance is negative then they move in opposite directions.

This is an important concept of building a good portfolio and is one of the building blocks of the Modern Portfolio Theory. Covariance is a good way to eliminate multicollinearity between assets, promote diversification, and reduce the risk of the entirety of a portfolio.

2.2.4 Diversification

The Modern Portfolio Theory promotes diversification. Diversification is the spreading of investments across several different assets as a means to reduce risk. The returns of assets are not perfectly correlated so by investing in many assets, especially ones that are not correlated at all, can do a great job at decreasing the overall risk of the portfolio.

2.3 Efficient Frontier

Harry Markowitz, the founder of the Modern Portfolio Theory, also introduced the efficient frontier, represents the most return one can get at a given risk. It is a curve that essentially displays the solutions to the constrained optimization problems that were discussed above. It shows the maximum return for every chosen maximum risk as well as the minimum risk for every minimum return.

2.4 Limitations

The Modern Portfolio Theory has a strong argument and great reasoning however it is important to understand some of the limitations of this theory. First of all, it heavily relies on accurate estimates of expected returns of each stock portfolio as well as an accurate covariance matrix. We can use historical data to get a good estimate on this number that is good enough to do the job. Another limitation is that this model does not consider stuff like taxes, minimum or maximum investment limits, transaction fees, and the limit of how many different stocks one wants to invest in. These are small obstacles that can be faced when working with this theory, however, easy fixes do exist. For example, if you only want to invest in 10 assets, you can just invest in the assets that relate to the top 10 highest w values where each one takes up a proportion of your portfolio equal to that w divided by the sum of the top 10 highest w values. Lastly, it is important that this portfolio is rebalanced periodically over time as new data becomes available. Additionally, external events such as COVID can have unforeseen effects and throw the model off, because the lack of the models ability to account for big external events.

3 Long Short-Term Memory (LSTM) Networks

Long Short-Term Memory (LSTM) networks are a specialized type of Recurrent Neural Network (RNN) architecture designed to address the vanishing gradient problem that hinders traditional RNNs in processing long sequences of data. LSTMs were introduced in 1997 by Hochreiter & Schmidhuber [2] and have become a cornerstone of deep learning applications involving sequential data analysis. This section provides a detailed examination of LSTMs, encompassing their architecture, functionalities, training process, and applications to stock price predictions.

3.1 Recurrent Neural Networks (RNNs): A Brief Overview

Before delving into LSTMs, it's crucial to understand RNNs, their core concept. RNNs are a class of artificial neural networks designed to handle sequential data, where the output of a layer depends not only on the current input but also on the hidden state of the previous layer(s). This allows RNNs to capture contextual information within sequences, making them well-suited for tasks like language translation, speech recognition, and time series forecasting.

However, a significant challenge faced by RNNs is the vanishing/exploding gradient problem. In RNNs with long sequences, gradients used to update network weights during backpropagation can become vanishingly small or explode, hindering the network's ability to learn long-term dependencies within the data.

3.2 The LSTM Architecture

LSTMs address the vanishing gradient problem by introducing a memory cell that can selectively remember and propagate information over long time intervals. An LSTM unit comprises four primary components:

Cell state: This core component acts as a long-term memory, holding information relevant to the current sequence processing. It can persist over many time steps, allowing the network to learn long-term dependencies.

Forget gate: This gate regulates information flow from the previous cell state. It analyzes the prior cell state and the current input, determining what information to discard (forget) by outputting values between 0 and 1. A value closer to 1 signifies retaining information, while 0 indicates discarding it.

Input gate: This gate controls the flow of new information into the cell state. It considers the current input and the previous cell state, ultimately producing a value between 0 and 1. This value determines how much of the new information is incorporated into the cell state.

Output gate: This gate regulates the flow of information from the current cell state to the network's output. It examines the current cell state and the current input, generating a value between 0 and 1 that dictates how much information from the cell state is passed on as the output of the LSTM unit.

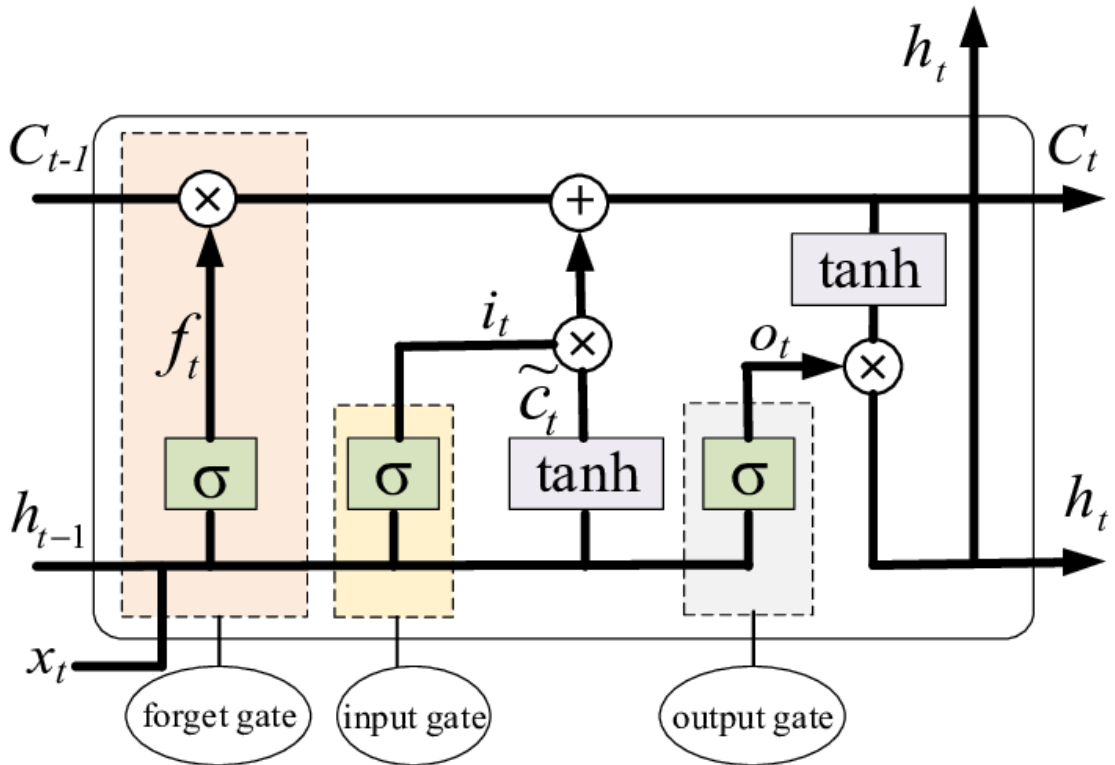


Figure 1: LSTM Architecture: [3]

3.3 Functionality of LSTMs

LSTMs operate in a step-by-step manner during sequence processing. At each time step:

The forget gate receives the previous cell state (C_{t-1}) and the current input (X_t). It outputs a forget vector (F_t) that determines which information to retain from the previous cell state.

The input gate also receives C_{t-1} and X_t . It generates an input vector (I_t) that controls how much of the new information from X_t is integrated into the cell state. Additionally, it creates a new candidate state vector (C_t) containing the information proposed for inclusion in the cell state.

The cell state is updated by combining the forgotten information from the previous cell state (multiplied by F_t) with the new candidate state (multiplied by I_t).

The output gate receives the current cell state (C_t) and the current input (X_t). It generates an output vector (O_t) that dictates how much of the information from the current cell state is used as the output of the LSTM unit for that time step.

3.4 Training LSTMs

Training LSTM networks involves a process known as backpropagation through time (BPTT), which addresses the challenge of training on sequential data by applying the standard backpropagation algorithm in a modified way. This process is essential for adjusting the weights in the network to minimize the overall error.

3.4.1 Backpropagation Through Time (BPTT)

In standard backpropagation for feedforward networks, gradients are calculated from the output layer and propagated back through the network to update weights. However, in LSTMs, the output at a given time step depends not only on the current input but also on the hidden states of previous time steps. This creates a dependency chain, making it difficult to calculate gradients for weights affecting distant time steps in the sequence. BPTT tackles this challenge by essentially "unfolding" the LSTM across various time steps, resulting in the creation of a temporary acyclic graph. This transformation enables the application of the standard backpropagation algorithm:

LSTM Unfolding: The LSTM architecture is replicated for each time step in the sequence. These replicas share identical weight parameters but operate on distinct input elements from the sequence.

Forward Pass: A standard forward pass is executed through the unfolded network. The sequence data is fed step-by-step, with the forget gate, input gate, output gate, and cell state update equations being computed at each time step.

Error Calculation: The error between the network's output (typically the hidden state of the final LSTM unit) and the desired target at the final time step is calculated.

Backpropagation: The error is propagated backward through the unfolded network in a sequential manner. Here, gradients are meticulously computed not only for the current time step’s LSTM unit parameters but also for the parameters that influence the cell state and hidden state across preceding time steps. This incorporates the impact of past inputs on the current state.

Weight Update: The accumulated gradients are ultimately used to update the shared weights across all replicas in the unfolded network. This effectively updates the weights within the actual LSTM network.

It is important to note that due to computational limitations, especially for long sequences, BPTT often employs a truncated approach. Gradients are computed only for a limited number of preceding time steps, introducing a trade-off between training accuracy and computational efficiency.

3.5 LSTMs for Predicting Stock Prices

LSTMs have proven to be an effective solution for dealing with sequence data, particularly in tasks where understanding long-term dependencies is crucial. Their unique architecture allows them to remember and retrieve information over long periods, which makes them capable of understanding complex, nonlinear dynamics of the stock market. They can automatically learn features from raw data and are well-suited for tasks where the context from earlier steps is needed to predict future steps. However, LSTMs also face challenges in predicting stock prices due to the volatile and non-stationary nature of financial markets. While LSTMs can capture historical patterns, predicting future movements in such a dynamic environment remains a complex task and continues to be an active area of research.

4 Transformer Networks

Transformer networks are a type of artificial neural network architecture that has revolutionized the field of Natural Language Processing (NLP) and beyond. Introduced in the seminal paper “Attention is All You Need” by Vaswani et al. in 2017 [7], transformers have redefined the standards in NLP and broadened their horizons to revolutionize numerous facets of artificial intelligence.

4.1 Understanding Transformers

Transformers were first developed to solve the problem of sequence transduction, which corresponds to any task that transforms an input sequence to an output sequence¹. Unlike RNNs and LSTMs, which process data sequentially, transformers process all data points in the input sequence in parallel, making them more efficient for tasks involving long sequences.

4.2 Attention Mechanism

The fundamental building block of Transformers is the attention mechanism. It allows the model to focus on specific parts of the input sequence when processing a particular word,

enabling it to capture long-range dependencies more effectively compared to recurrent architectures. The core idea behind attention is:

Representation: Each element in the input sequence (words, numbers, image patches, etc.) is transformed into a vector representation, with three vectors being generated for each element:

Query Vector: This is a representation of the current context or input that is being processed. The query vector is used to compute attention scores by comparing it with all the key vectors, where these scores determine how much focus to put on each part of the input.

Key Vector: This serves as an identifier or reference for the information stored in the memory. The model compares the query vector with all key vectors to determine the most relevant tokens for the focused token.

Value Vector: This represents the actual information associated with each element that we want to retrieve or use. The value vectors are used to create a weighted combination based on the attention scores, which is the output of the self-attention layer.

4.3 Transformer Architecture

A Transformer model typically consists of two main parts:

Encoder: This component processes the input sequence and converts it into a form that the rest of the model can use. It stacks multiple identical layers, each containing two main sub-layers:

Multi-Head Attention: This sub-layer is a key component of the Transformer model, performing multiple independent attention computations in parallel. Each “head” computes a different learned linear transformation of the input. This allows the model to focus on different aspects of the input simultaneously, which helps capture a richer set of features from the input.

Feed-Forward Network: This sub-layer is essentially a two-layer neural network that adds non-linearity to the model. It consists of two linear transformations with a ReLU activation function in between. Despite its simplicity, this sub-layer is powerful and helps the model learn complex relationships between tokens.

Residual Connection and Layer Normalization: These techniques are used in each sub-layer of the Transformer model to improve training stability and gradient flow. The residual connection allows the gradient to flow directly through the network, mitigating the problem of vanishing gradients which allows the model to be made very deep. Layer normalization is a technique that normalizes the inputs across the features dimension (as opposed to batch normalization, which normalizes across the batch dimension), improving the model’s performance and stability.

Decoder: This component generates the output sequence. Similar to the encoder, it uses stacked layers with multi-head attention and feed-forward networks. However, the decoder also incorporates a masked attention mechanism to prevent the model from "cheating" by peeking at future words in the output sequence during generation.

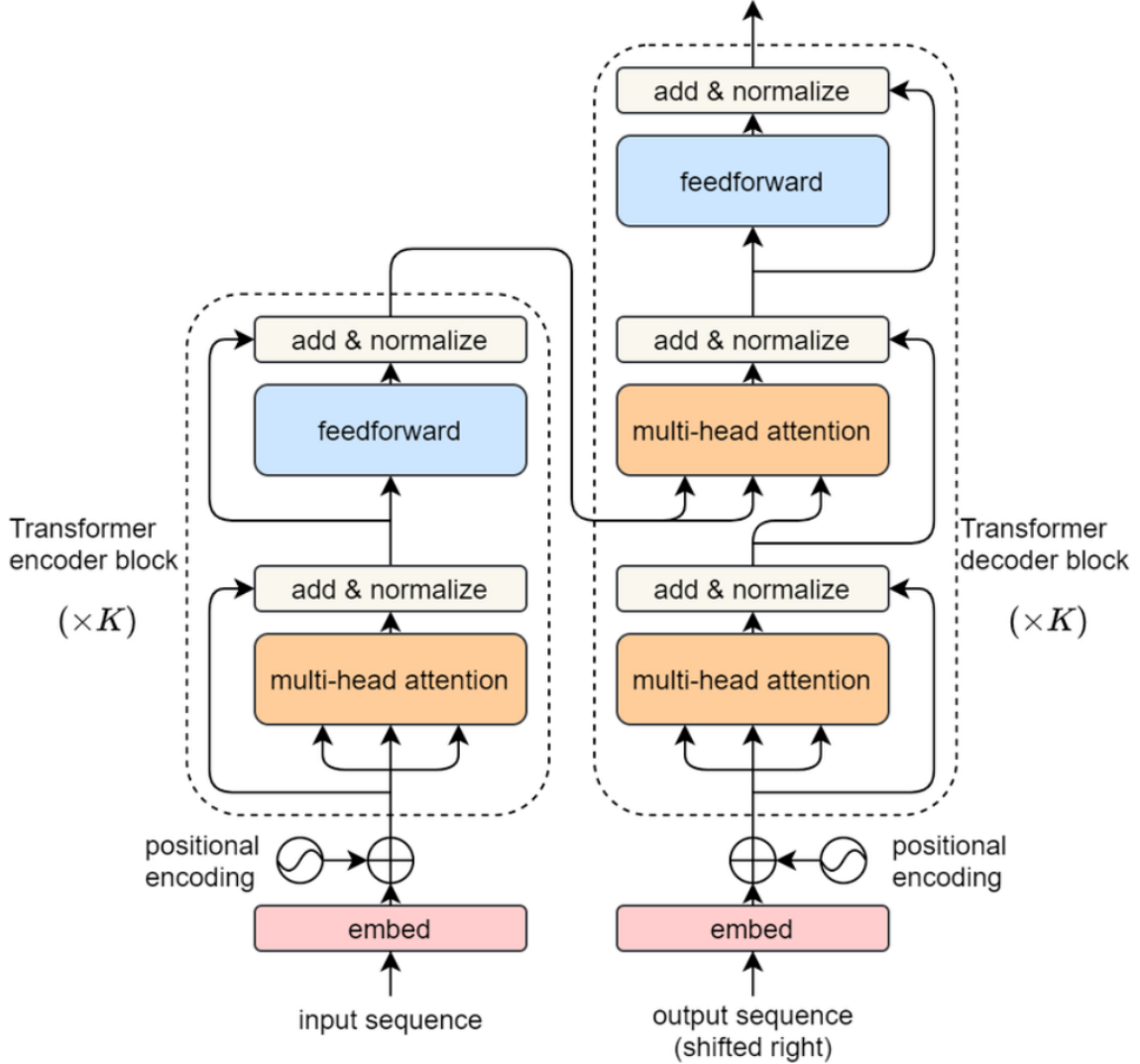


Figure 2: Transformer Architecture: [1]

4.4 Functionalities of Transformers

Transformers operate by processing the input sequence through the encoder, which generates a contextual representation for each word. This encoded representation captures information about the entire sequence and the relationships between words. The decoder then uses this encoded representation, along with a masked attention mechanism, to generate the output sequence one word at a time.

4.5 Training Transformers

Training Transformers involves the use of an optimizer (e.g., Adam) to adjust the model's weights based on the calculated loss between the generated output and the desired target.

sequence. Techniques like teacher forcing, which involves using the actual output tokens from the training dataset at each step as input to the decoder for the next step, rather than using the decoder’s own previous predictions, can be employed during training to provide guidance to the decoder, especially in the initial stages.

4.6 Advantages

Long-Range Dependency Modeling: The attention mechanism allows Transformers to effectively capture long-range dependencies between words, overcoming a limitation of recurrent architectures.

Parallelization: Transformer computations can be highly parallelized, making them suitable for training on large datasets with GPUs or TPUs.

State-of-the-Art Performance: Transformers have achieved state-of-the-art performance on various NLP benchmarks and are the foundation of many powerful Large Language Models, which have taken the AI world by storm in recent years.

4.7 Disadvantages

Computational Cost: Transformers’ exceptional performance comes with a computational price tag. Their vast number of parameters translates to demanding memory requirements and lengthy training times. Additionally, the complex attention mechanism, while enabling long-range dependency capture, involves computationally expensive calculations that scale rapidly with sequence length.

Limited Interpretability: Despite their impressive results, understanding how Transformers make decisions remains a challenge. The intricate nature of the attention mechanism makes it difficult to pinpoint the reasoning behind specific outputs. Furthermore, information within a Transformer is spread across various layers, hindering the ability to interpret how these distributed representations contribute to the final prediction. Researchers are actively exploring techniques to address both the computational cost and limited interpretability, paving the way for more efficient and trustworthy Transformer applications.

4.8 Transformers for Predicting Stock Prices

Transformers have been successfully applied to the task of predicting stock prices, demonstrating their versatility beyond the realm of natural language processing. The ability of transformers to capture long-range dependencies and handle sequences make them well-suited for modeling financial time-series data. They can also process all time steps of the input sequence in parallel while automatically extracting and learning features from raw data, making them computationally efficient for large datasets. That being said, markets are often subject to abrupt changes due to unforeseen events. While Transformers can capture historical patterns, predicting future movements in such a volatile and non-stationary environment remains a challenging task.

5 Model Building

5.1 Assumptions

In order to be able to apply our model, we needed to choose a subset of the huge number of assets that exist in this world. This project assumes that the only assets available are 25 random stocks in the S&P 500 index. We also assume that our models to predict weekly share prices are unbiased estimators for each individual ticker (we will expand on this more in the next section).

5.2 Method

5.2.1 Basic Premise

We first selected a random sample of 25 stocks off of the S&P 500 index and using historical price data, computed the covariance matrix of the share prices. The ij -th value of this 25×25 matrix represents the historical covariance between the share prices of stock i and stock j , where each of these tickers were among the 25 random tickers selected. Then, we trained both an ensemble of LSTM and transformer based models – one LSTM and one transformer for every ticker – to predict the next week’s share price for that particular ticker based on historical price data. After training these models, given historical data, we were able to determine an ”optimal” portfolio composition of these 25 stocks on a weekly basis using modern portfolio theory in conjunction with our predictive models, and pitting the LSTM models vs the transformers in terms of both the profit their predicted portfolios result in, and the mean absolute percentage error (MAPE) in predicting future prices.

5.2.2 LSTM for Share Price Prediction

We first went about training and evaluating LSTM models for each of the 25 shares we were concerned with. To do this, we obtained the share price data for each stock from Yahoo! Finance and split it into training and test data, with the last 20% of the price data being reserved for testing. We then reformulated the sequence prediction objective into a conventional supervised learning objective; at every timestep in the training data, the LSTM received the previous week’s (5 trading days) price data as input, and attempted to predict the next week’s share prices (next 5 trading days). This formulation, along with the particular code for training an LSTM in Keras were adapted from a blog post regarding a similar subject.[4]

After an individual, identically architected model was trained to predict the price of each ticker on a weekly basis for 25 epochs using backprop through time, these models were then assumed to be unbiased estimators of weekly share price of a given ticker. Thus, they were used to inform expected return on investment for a particular stock, whose values are used when applying modern portfolio theory to find a mix of stocks to invest in.

The specific architecture of the LSTM was also inspired by similar work, and consisted of an LSTM layer (built into Keras) with 200 output units, followed by two fully connected layers, the first with 50 output activations, and the second with 5 output activations.

The LSTM and first hidden layer both used the ReLU activation function, while the final layer did not have any activation layer.

5.2.3 Transformer for Share Price Prediction

The training of the transformer based model for price prediction entailed quite a similar process. As in the LSTM case, we formulated the objective as a supervised learning objective, where the previous week's share prices were the input, and the next week's (5 trading days) prices were the outputs of the model. However, in this case, we first constructed a transformer encoder block, which was defined similarly to Figure 2, i.e a multi head attention layer followed by dropout, residual connection + normalization, and feed-forward layers (mathematically equivalent to 1D convolutions used in code) followed by a residual connection. These encoder blocks were then placed in series, followed by average pooling, a fully connected layer, and the output activations.

To be more specific, each transformer encoder block consisted of a LayerNorm, a multi head self attention layer (with 4 heads, each of size 128), and a fully connected layer. To make our transformer model, 4 of these blocks were connected in series, followed by average pooling, a hidden fully connected layer with output dimension 256, and a final fully connected layer with 5 outputs (1 for the price at each day of the forthcoming week). This custom transformer model architecture was inspired by a Keras example of time-series forecasting using transformers.[5]

Clearly, in this case, since we are directly modeling a sequence of prices rather than a text sequence, there was no need to compute embeddings as described in section 4 above, and instead we simply encoded the input sequence using a transformer, and then classified the result using fully connected layer.

The transformer described above was then fit to the supervised learning objective previously described for each individual ticker. Similar to the LSTM model, we treat each individual transformer model as an unbiased estimator of the future share price of an individual ticker.

5.2.4 Application of Modern Portfolio Theory

After we trained both LSTM and transformer predictive models for each of the 25 tickers we were concerned with, we then applied the principles of modern portfolio theory to determine an optimal mix to operate within certain risk constraints and still maximize expected return. Our percentage expected returns were defined as the percentage change from the closing price of a share on the last day of the previous week to the last day of the next week (i.e. the difference in price between the last days of successive weeks). We also used a slightly alternate formulation of Modern portfolio theory and defined the following optimization problem:

$$\begin{aligned}
& \text{Minimize} && w^T \Sigma w - q \mu^T w \\
& \text{Subject to} && \sum_{i=1}^n w_i = 1 \\
& && 0 \leq w_i \leq 0.25 \quad \forall i \in \{1, 2, \dots, n\}
\end{aligned}$$

where:

- $q \in [0, \infty)$ is the risk tolerance hyperparameter.
- w is the vector of portfolio weights.
- μ is the vector of expected returns of the assets.
- Σ is the covariance matrix of the asset returns.
- μ_p is the target return.
- n is the number of assets.

This optimization problem attempts to find a portfolio weighting on the efficient frontier for a user-specified hyperparameter for risk tolerance q . Essentially, the objective is to minimize variance in portfolio return (the first term) as well as maximize the regularized expected portfolio profit (the second term). In our case, we obtained the covariance matrix Σ using the historical correlation between the prices of individual stocks, and (separately) used our LSTM and transformer models to compute the expected return μ on a per-week basis. Thus, our results for a portfolio weighting apply on a per-week timescale. We then used the cvxpy Python package to determine the optimal w which minimizes this expression, for each of the past 52 weeks. For each week, we predicted the subsequent week’s price using either the LSTM or transformer model and then for the next week, performed a prediction using the true prices for that week. That is, we did not successively use the model’s predictions of prices for a week to inform the next week’s prices. Rather, we assumed that the investor could completely rebalance their portfolio at the end of every week and use the previous week’s pricing to determine the expected return over the next week for each ticker.

6 Results

6.1 Next Week Price Prediction Results

6.1.1 LSTM

First, we tested the differences between the LSTM and the transformer models for each ticker in terms of how accurate they were at predicting prices for the next week. Over all of the 25 tickers we were considering, the average mean absolute percentage error (MAPE) for the LSTM models was 3.16%. That is, for our test set consisting of the last 20% of price data for each ticker, the average MAPE for each ticker was 3.16%, implying that over our 25 shares, the LSTM models were on average 3.16% off true share prices.

6.1.2 Transformer

On the other hand, the average MAPE for the ensemble of transformer models was 3.03%, a slight improvement over the LSTM models, meaning that over 25 tickers, the transformer based models were on average 3.03% off of true share prices.

6.2 Cumulative Return Using MPT

6.2.1 LSTM

As described in section 5.2.4 (how we applied Modern Portfolio Theory), we used the LSTM models as unbiased estimators of μ , the expected weekly returns of each of the 25 assets we were concerned with. We then performed the minimization formulated in section 5.2.4 for each of the past 52 weeks, computing an optimal portfolio with the maximal asset consisting of no more than 25% of the portfolio, no short selling, and a risk factor of 0.5. Assuming the investor can rebalance their portfolio every week, we obtained a cumulative return of 26% over the course of these 52 weeks, assuming the investor rebalanced their entire portfolio every week exactly to the ratio defined by the portfolio weights w computed in the minimization, in accordance with MPT.

6.2.2 Transformer

Once again, we apply the same method as above for LSTM, only this time using our trained transformer models for each ticker. In this case, we assume each transformer model can be used to infer an unbiased estimator of the next week's prices of each individual asset. From these predictions, we compute μ and perform the optimization step in 5.2.4 once again for each of the past 52 weeks, resulting in a cumulative profit of 26% once again, under the same assumptions as for the LSTM case.

7 Conclusion

7.1 Price Prediction

We observed in our results that the transformer based models, on average, outperformed the LSTM models, potentially due to the ability for the transformer models to retain a better representation of earlier values in the input sequence (since there is no hidden state, and each value in the sequence can "attend" to each other value). However, in this case, the difference was very slight, especially compared to the advantages that transformers tend to have over LSTMs and RNNs in other sequence modeling tasks (e.g. language modeling). This very slight advantage could be explained by our relatively short input sequence length (5 previous prices), since even the LSTM is able to keep track of input values in previous timesteps quite easily.

However, in both cases, when we unpack the $\approx 3\%$ MAPE, we can understand that neither of these models are quite performant. Consider that a 3% fluctuation of a stock price over the course of a week is considered significant, and this is simply the average error of either models' predictions. Thus, if we potentially had better estimators of future stock prices, our returns from portfolio optimization might be greater, or we may be able to operate better under a specified risk framework. There may be two potential ways

to distinctly improve the models, the first being longer input sequence length, and the second being some sort of feature engineering. A longer sequence length would give the model more information upon which to base a prediction at every time step, which could improve the model’s predictive ability. Furthermore, adding additional features and technical indicators in conjunction with external features could also improve the performance of the model, since the movements of share prices tend to be informed by new (earnings reports, etc) as well as certain technical indicators (various moving averages, mean reversions, etc). These methods could potentially improve the predictive accuracy of both the transformer and LSTM models, which subsequently could improve returns when applied to portfolio optimization, since our expected return estimates would theoretically be better, allowing for us to operate under our risk constraints better.

7.2 Portfolio Optimization

We observe reasonable results when observing the final return from the portfolio optimization steps. Operating under a very conservative risk factor of 0.5, we still see $\approx 26\%$ return over the course of a full year, in the case of both the LSTM and the Transformer. Potentially raising the risk factor and/or allowing the portfolio to consist of a greater proportion of a single share could lead to higher return, but at the expense of a more risky, less fundamentally sound portfolio. Our returns of 26% slightly outpace that of the S&P 500 over the past year; the index itself has risen 24%. However, that rise is monumental and underpinned by a categorical boom in AI and the stocks of chip manufacturers (companies whose stocks purely randomly were not included in our bag of 25 stocks).

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MATH156_project_code

June 7, 2024

```
[ ]: import pandas as pd
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
import yfinance as yf
from sklearn.metrics import mean_absolute_percentage_error
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from keras import layers
import time
import timeit
```

```
[ ]: # sourced from https://medium.com/@mskmay66/transformers-vs-lstm-for-stock-price-time-series-prediction-3a26fcc1a782
class ETL:
    """
    ticker: str
    period: string
    test_size: float betwee 0 and 1
    n_input: int
    timestep: int
    Extracts data for stock with ticker `ticker` from yf api,
    splits the data into train and test sets by date,
    reshapes the data into np.array of shape [#weeks, 5, 1],
    converts our problem into supervised learning problem.
    """
    def __init__(self, ticker, test_size=0.2, period='max', n_input=5, timestep=5) -> None:
        self.ticker = ticker
        self.period = period
        self.test_size = test_size
        self.n_input = n_input
        self.df = self.extract_historic_data()
        self.timestep = timestep
        self.train, self.test = self.etl()
        self.X_train, self.y_train = self.to_supervised(self.train)
```



```

        self.X_test, self.y_test = self.to_supervised(self.test)

def extract_historic_data(self) -> pd.Series:
    """
    gets historical data from yf api.
    """
    t = yf.Ticker(self.ticker)
    history = t.history(period=self.period)
    return history.Close

def split_data(self) -> tuple:
    """
    Splits our pd.Series into train and test series with
    test series representing test_size * 100 % of data.
    """
    data = self.extract_historic_data()
    if len(data) != 0:
        train_idx = round(len(data) * (1-self.test_size))
        train = data[:train_idx]
        test = data[train_idx:]
        train = np.array(train)
        test = np.array(test)
        return train[:, np.newaxis], test[:, np.newaxis]
    else:
        raise Exception('Data set is empty, cannot split.')

def window_and_reshape(self, data) -> np.array:
    """
    Reformats data into shape our model needs,
    namely, [# samples, timestep, # feautures]
    samples
    """
    NUM_FEATURES = 1
    samples = int(data.shape[0] / self.timestep)
    result = np.array(np.array_split(data, samples))
    return result.reshape((samples, self.timestep, NUM_FEATURES))

def transform(self, train, test) -> np.array:
    train_remainder = train.shape[0] % self.timestep
    test_remainder = test.shape[0] % self.timestep
    if train_remainder != 0 and test_remainder != 0:
        train = train[train_remainder:]
        test = test[test_remainder:]
    elif train_remainder != 0:
        train = train[train_remainder:]
    elif test_remainder != 0:
        test = test[test_remainder:]

```

```

        return self.window_and_reshape(train), self.window_and_reshape(test)

def etl(self) -> tuple[np.array, np.array]:
    """
    Runs complete ETL
    """
    train, test = self.split_data()
    return self.transform(train, test)

def to_supervised(self, train, n_out=5) -> tuple:
    """
    Converts our time series prediction problem to a
    supervised learning problem.
    """
    # flatted the data
    data = train.reshape((train.shape[0]*train.shape[1], train.shape[2]))
    X, y = [], []
    in_start = 0
    # step over the entire history one time step at a time
    for _ in range(len(data)):
        # define the end of the input sequence
        in_end = in_start + self.n_input
        out_end = in_end + n_out
        # ensure we have enough data for this instance
        if out_end <= len(data):
            x_input = data[in_start:in_end, 0]
            x_input = x_input.reshape((len(x_input), 1))
            X.append(x_input)
            y.append(data[in_end:out_end, 0])
            # move along one time step
            in_start += 1
    return np.array(X), np.array(y)

```

```

[ ]: class PredictAndForecast:
    """
    model: tf.keras.Model
    train: np.array
    test: np.array
    Takes a trained model, train, and test datasets and returns predictions
    of len(test) with same shape.
    """
    def __init__(self, model, train, test, n_input=5) -> None:
        self.model = model
        self.train = train
        self.test = test
        self.n_input = n_input
        # self.predictions = self.get_predictions()

```

```

def forecast(self, history) -> np.array:
    """
    Given last weeks actual data, forecasts next weeks prices.
    """
    # flatten data
    data = np.array(history)
    data = data.reshape((data.shape[0]*data.shape[1], data.shape[2]))
    # retrieve last observations for input data
    input_x = data[-self.n_input:, :]
    # reshape into [1, n_input, 1]
    input_x = input_x.reshape((1, len(input_x), input_x.shape[1]))
    # forecast the next week
    yhat = self.model.predict(input_x, verbose=0)
    # we only want the vector forecast
    yhat = yhat[0]
    return yhat

def get_predictions(self) -> np.array:
    """
    compiles models predictions week by week over entire
    test set.
    """
    # history is a list of weekly data
    history = [x for x in self.train]
    # walk-forward validation over each week
    predictions = []
    for i in range(len(self.test)):
        yhat_sequence = self.forecast(history)
        # store the predictions
        predictions.append(yhat_sequence)
    # get real observation and add to history for predicting the next week
    history.append(self.test[i, :]) # CHANGE TO use yhat as prior
    # history.append(np.expand_dims(yhat_sequence, axis=1))
    return np.array(predictions)

```

```

[ ]: class Evaluate:

    def __init__(self, actual, predictions) -> None:
        self.actual = actual
        self.predictions = predictions
        self.var_ratio = self.compare_var()
        self.mape = self.evaluate_model_with_mape()

    def compare_var(self):
        return abs( 1 - (np.var(self.predictions) / np.var(self.actual)))

```

```
def evaluate_model_with_mape(self):
    return mean_absolute_percentage_error(self.actual.flatten(), self.
↳ predictions.flatten())
```

```
[ ]: def build_lstm(etl: ETL, epochs=25, batch_size=32, fit=True) -> tf.keras.Model:
    """
    Builds, compiles, and fits our LSTM baseline model.
    """
    n_timesteps, n_features, n_outputs = 5, 1, 5
    callbacks = [tf.keras.callbacks.EarlyStopping(patience=10,
↳ restore_best_weights=True)]
    model = Sequential()
    model.add(LSTM(200, activation='relu', input_shape=(n_timesteps, n_features)))
    model.add(Dense(50, activation='relu'))
    model.add(Dense(n_outputs))
    print('compiling baseline model...')
    model.compile(optimizer='adam', loss='mse', metrics=['mae', 'mape'])
    if fit:
        print('fitting model...')
        start = time.time()
        history = model.fit(etl.X_train, etl.y_train, batch_size=batch_size,
↳ epochs=epochs, validation_data=(etl.X_test, etl.y_test), verbose=1,
↳ callbacks=callbacks)
        print(time.time() - start)
    return model
```

```
[ ]: def transformer_encoder(inputs, head_size, num_heads, ff_dim, dropout=0,
↳ epsilon=1e-6, attention_axes=None, kernel_size=1):
    """
    Creates a single transformer block.
    """
    x = layers.LayerNormalization(epsilon=epsilon)(inputs)
    x = layers.MultiHeadAttention(
        key_dim=head_size, num_heads=num_heads, dropout=dropout,
        attention_axes=attention_axes
    )(x, x)
    x = layers.Dropout(dropout)(x)
    res = x + inputs

    # Feed Forward Part
    x = layers.LayerNormalization(epsilon=epsilon)(res)
    x = layers.Conv1D(filters=ff_dim, kernel_size=kernel_size,
↳ activation="relu")(x)
    x = layers.Dropout(dropout)(x)
    x = layers.Conv1D(filters=inputs.shape[-1], kernel_size=kernel_size)(x)
    return x + res
```

```

def build_transformer(head_size, num_heads, ff_dim, num_trans_blocks,
    ↪mlp_units, dropout=0, mlp_dropout=0, attention_axes=None, epsilon=1e-6,
    ↪kernel_size=1):
    """
    Creates final model by building many transformer blocks.
    """
    n_timesteps, n_features, n_outputs = 5, 1, 5
    inputs = tf.keras.Input(shape=(n_timesteps, n_features))
    x = inputs
    for _ in range(num_trans_blocks):
        x = transformer_encoder(x, head_size=head_size, num_heads=num_heads,
    ↪ff_dim=ff_dim, dropout=dropout, attention_axes=attention_axes,
    ↪kernel_size=kernel_size, epsilon=epsilon)

    x = layers.GlobalAveragePooling1D(data_format="channels_first")(x)
    for dim in mlp_units:
        x = layers.Dense(dim, activation="relu")(x)
        x = layers.Dropout(mlp_dropout)(x)

    outputs = layers.Dense(n_outputs)(x)
    return tf.keras.Model(inputs, outputs)

```

```

[ ]: def fit_transformer(transformer: tf.keras.Model, data):
    """
    Compiles and fits our transformer.
    """
    transformer.compile(
        loss="mse",
        optimizer=tf.keras.optimizers.Adam(learning_rate=1e-3),
        metrics=["mae", 'mape'])

    callbacks = [tf.keras.callbacks.EarlyStopping(monitor='loss', patience=10,
    ↪restore_best_weights=True)]
    start = time.time()
    hist = transformer.fit(data.X_train, data.y_train, batch_size=32, epochs=25,
    ↪verbose=1, callbacks=callbacks)
    print(time.time() - start)
    return hist

```

```

[ ]: def plot_results(test, preds, df, image_path=None, title_suffix=None,
    ↪xlabel='AAPL stock Price'):
    """
    Plots training data in blue, actual values in red, and predictions in green,
    over time.
    """
    fig, ax = plt.subplots(figsize=(20,6))
    # x = df.Close[-498:].index

```

```

plot_test = test[1:]
plot_preds = preds[1:]
x = df[-(plot_test.shape[0]*plot_test.shape[1]):].index
plot_test = plot_test.reshape((plot_test.shape[0]*plot_test.shape[1], 1))
plot_preds = plot_preds.reshape((plot_test.shape[0]*plot_test.shape[1], 1))
ax.plot(x, plot_test, label='actual')
ax.plot(x, plot_preds, label='preds')
if title_suffix==None:
    ax.set_title('Predictions vs. Actual')
else:
    ax.set_title(f'Predictions vs. Actual, {title_suffix}')
ax.set_xlabel('Date')
ax.set_ylabel(xlabel)
ax.legend()
if image_path != None:
    imagedir = '/content/drive/MyDrive/Colab Notebooks/images'
    plt.savefig(f'{imagedir}/{image_path}.png')
plt.show()

```

```

[ ]: # Get 25 random tickers from the S and P 500
import bs4 as bs
import requests
import datetime
import random
# Scrape the list of all tickers on the S and P 500 Wikipedia Page
resp = requests.get('http://en.wikipedia.org/wiki/List_of_S%26P_500_companies')
soup = bs.BeautifulSoup(resp.text, 'lxml')
table = soup.find('table', {'class': 'wikitable sortable'})

tickers = []
# HTML parsing the table
for row in table.findAll('tr')[1:]:
    ticker = row.findAll('td')[0].text
    tickers.append(ticker)
tickers = [s.replace('\n', '') for s in tickers]
# Getting a random reproducible sample of 25 tickers
random.seed(42)
tickers = random.sample(tickers, 25)

```

```

[ ]: data = yf.download(tickers, start="2019-06-04", end="2024-06-04")

```

```

[*****100%*****] 25 of 25 completed

```

```

[ ]: prices = data['Adj Close']

```

```

[ ]: returns = prices.pct_change().dropna()

```

```

[ ]: data = {ticker: ETL(ticker) for ticker in tickers}

```

```
[ ]: LSTM_models = {ticker: build_lstm(data[ticker]) for ticker in tickers}
```

```
compiling baseline model...
```

```
fitting model...
```

```
Epoch 1/25
```

```
243/243 [=====] - 7s 21ms/step - loss: 2.9806 - mae: 0.4520 - mape: 96.5381 - val_loss: 18.2176 - val_mae: 3.3473 - val_mape: 7.5821
```

```
Epoch 2/25
```

```
243/243 [=====] - 6s 26ms/step - loss: 0.1305 - mae: 0.1449 - mape: 39.9861 - val_loss: 10.6022 - val_mae: 2.6131 - val_mape: 6.0896
```

```
Epoch 3/25
```

```
243/243 [=====] - 7s 27ms/step - loss: 0.1050 - mae: 0.1300 - mape: 31.5771 - val_loss: 8.5215 - val_mae: 2.3602 - val_mape: 5.6172
```

```
Epoch 4/25
```

```
243/243 [=====] - 6s 23ms/step - loss: 0.1337 - mae: 0.1448 - mape: 32.1664 - val_loss: 5.8145 - val_mae: 1.8814 - val_mape: 4.4756
```

```
Epoch 5/25
```

```
243/243 [=====] - 4s 16ms/step - loss: 0.1108 - mae: 0.1329 - mape: 29.3126 - val_loss: 2.4893 - val_mae: 1.1873 - val_mape: 3.0530
```

```
Epoch 6/25
```

```
243/243 [=====] - 6s 23ms/step - loss: 0.1088 - mae: 0.1336 - mape: 32.7143 - val_loss: 12.0073 - val_mae: 2.9014 - val_mape: 6.9068
```

```
Epoch 7/25
```

```
243/243 [=====] - 4s 17ms/step - loss: 0.0918 - mae: 0.1219 - mape: 33.7765 - val_loss: 3.0263 - val_mae: 1.3235 - val_mape: 3.3023
```

```
Epoch 8/25
```

```
243/243 [=====] - 4s 16ms/step - loss: 0.0961 - mae: 0.1264 - mape: 33.9940 - val_loss: 9.6064 - val_mae: 2.5719 - val_mape: 6.1311
```

```
Epoch 9/25
```

```
243/243 [=====] - 3s 13ms/step - loss: 0.0923 - mae: 0.1185 - mape: 25.5268 - val_loss: 5.4666 - val_mae: 1.8161 - val_mape: 4.2619
```

```
Epoch 10/25
```

```
243/243 [=====] - 3s 14ms/step - loss: 0.0954 - mae: 0.1233 - mape: 28.9798 - val_loss: 4.8273 - val_mae: 1.6851 - val_mape: 3.9852
```

```
Epoch 11/25
```

```
243/243 [=====] - 5s 20ms/step - loss: 0.1208 - mae: 0.1372 - mape: 28.0791 - val_loss: 3.6171 - val_mae: 1.4342 - val_mape: 3.4697
```

```
Epoch 12/25
```

```
243/243 [=====] - 4s 15ms/step - loss: 0.0809 - mae: 0.1104 - mape: 22.5533 - val_loss: 4.1302 - val_mae: 1.5491 - val_mape: 3.6733
```

```
Epoch 13/25
```

```
243/243 [=====] - 3s 14ms/step - loss: 0.0883 - mae: 0.1149 - mape: 19.2660 - val_loss: 2.0039 - val_mae: 1.0952 - val_mape: 3.0295
```

```
Epoch 14/25
```

```
243/243 [=====] - 3s 14ms/step - loss: 0.0875 - mae: 0.1153 - mape: 21.9221 - val_loss: 5.5760 - val_mae: 1.8574 - val_mape: 4.3383
```

```
Epoch 15/25
```

```
243/243 [=====] - 5s 20ms/step - loss: 0.0908 - mae:
```

0.1185 - mape: 24.0170 - val_loss: 3.9181 - val_mae: 1.5306 - val_mape: 3.6294
Epoch 16/25
243/243 [=====] - 3s 13ms/step - loss: 0.0808 - mae:
0.1126 - mape: 21.2431 - val_loss: 1.6544 - val_mae: 0.9983 - val_mape: 2.8336
Epoch 17/25
243/243 [=====] - 4s 15ms/step - loss: 0.0761 - mae:
0.1060 - mape: 15.8372 - val_loss: 14.3610 - val_mae: 3.2176 - val_mape: 7.6403
Epoch 18/25
243/243 [=====] - 5s 23ms/step - loss: 0.0829 - mae:
0.1099 - mape: 15.8130 - val_loss: 3.2102 - val_mae: 1.3688 - val_mape: 3.2716
Epoch 19/25
243/243 [=====] - 4s 16ms/step - loss: 0.0960 - mae:
0.1200 - mape: 18.6075 - val_loss: 7.6235 - val_mae: 2.2830 - val_mape: 5.4162
Epoch 20/25
243/243 [=====] - 4s 17ms/step - loss: 0.0753 - mae:
0.1036 - mape: 15.6130 - val_loss: 3.2952 - val_mae: 1.3860 - val_mape: 3.3114
Epoch 21/25
243/243 [=====] - 3s 14ms/step - loss: 0.0672 - mae:
0.0994 - mape: 15.2197 - val_loss: 4.0729 - val_mae: 1.5488 - val_mape: 3.6530
Epoch 22/25
243/243 [=====] - 5s 20ms/step - loss: 0.0692 - mae:
0.0984 - mape: 11.1653 - val_loss: 1.8438 - val_mae: 1.0250 - val_mape: 2.6055
Epoch 23/25
243/243 [=====] - 4s 15ms/step - loss: 0.0735 - mae:
0.1032 - mape: 12.7438 - val_loss: 4.5200 - val_mae: 1.6873 - val_mape: 3.9935
Epoch 24/25
243/243 [=====] - 3s 14ms/step - loss: 0.0803 - mae:
0.1083 - mape: 17.1995 - val_loss: 5.1506 - val_mae: 1.8395 - val_mape: 4.3764
Epoch 25/25
243/243 [=====] - 6s 24ms/step - loss: 0.0733 - mae:
0.1012 - mape: 12.5564 - val_loss: 3.1733 - val_mae: 1.3803 - val_mape: 3.2968
144.31452918052673
compiling baseline model...
fitting model...
Epoch 1/25
324/324 [=====] - 8s 19ms/step - loss: 8.2659 - mae:
0.9858 - mape: 17.1909 - val_loss: 1.3228 - val_mae: 0.8090 - val_mape: 3.3204
Epoch 2/25
324/324 [=====] - 6s 19ms/step - loss: 0.4130 - mae:
0.3281 - mape: 4.7458 - val_loss: 1.9354 - val_mae: 1.0888 - val_mape: 4.3792
Epoch 3/25
324/324 [=====] - 8s 25ms/step - loss: 0.4100 - mae:
0.3284 - mape: 4.5596 - val_loss: 1.1005 - val_mae: 0.7340 - val_mape: 2.9594
Epoch 4/25
324/324 [=====] - 6s 20ms/step - loss: 0.4029 - mae:
0.3268 - mape: 4.4060 - val_loss: 1.1187 - val_mae: 0.7508 - val_mape: 2.9984
Epoch 5/25
324/324 [=====] - 7s 22ms/step - loss: 0.4087 - mae:

0.3344 - mape: 4.7024 - val_loss: 1.0695 - val_mae: 0.7225 - val_mape: 2.9135
Epoch 6/25
324/324 [=====] - 6s 18ms/step - loss: 0.3782 - mae:
0.3150 - mape: 4.3604 - val_loss: 2.2949 - val_mae: 1.1831 - val_mape: 4.9316
Epoch 7/25
324/324 [=====] - 6s 19ms/step - loss: 0.3621 - mae:
0.3105 - mape: 4.2019 - val_loss: 1.0333 - val_mae: 0.7227 - val_mape: 2.8856
Epoch 8/25
324/324 [=====] - 6s 17ms/step - loss: 0.3512 - mae:
0.3048 - mape: 4.3337 - val_loss: 1.2639 - val_mae: 0.8301 - val_mape: 3.5935
Epoch 9/25
324/324 [=====] - 5s 14ms/step - loss: 0.3209 - mae:
0.2845 - mape: 3.9681 - val_loss: 1.0252 - val_mae: 0.7482 - val_mape: 3.0128
Epoch 10/25
324/324 [=====] - 6s 18ms/step - loss: 0.3149 - mae:
0.2835 - mape: 3.9178 - val_loss: 0.8577 - val_mae: 0.6470 - val_mape: 2.7304
Epoch 11/25
324/324 [=====] - 4s 14ms/step - loss: 0.3544 - mae:
0.3114 - mape: 4.4078 - val_loss: 0.9632 - val_mae: 0.7073 - val_mape: 2.8614
Epoch 12/25
324/324 [=====] - 4s 13ms/step - loss: 0.3197 - mae:
0.2859 - mape: 3.7531 - val_loss: 0.8601 - val_mae: 0.6382 - val_mape: 2.5561
Epoch 13/25
324/324 [=====] - 7s 21ms/step - loss: 0.3105 - mae:
0.2820 - mape: 3.8537 - val_loss: 0.7689 - val_mae: 0.6021 - val_mape: 2.5171
Epoch 14/25
324/324 [=====] - 5s 14ms/step - loss: 0.3203 - mae:
0.2905 - mape: 3.9871 - val_loss: 1.0073 - val_mae: 0.7350 - val_mape: 2.9235
Epoch 15/25
324/324 [=====] - 6s 20ms/step - loss: 0.2959 - mae:
0.2724 - mape: 3.8534 - val_loss: 0.8022 - val_mae: 0.6086 - val_mape: 2.4733
Epoch 16/25
324/324 [=====] - 6s 17ms/step - loss: 0.3023 - mae:
0.2791 - mape: 3.9443 - val_loss: 0.7969 - val_mae: 0.6081 - val_mape: 2.5075
Epoch 17/25
324/324 [=====] - 4s 14ms/step - loss: 0.2976 - mae:
0.2720 - mape: 3.5988 - val_loss: 1.9298 - val_mae: 1.1240 - val_mape: 4.4309
Epoch 18/25
324/324 [=====] - 6s 18ms/step - loss: 0.3175 - mae:
0.2863 - mape: 3.8164 - val_loss: 0.8060 - val_mae: 0.6135 - val_mape: 2.5221
Epoch 19/25
324/324 [=====] - 5s 15ms/step - loss: 0.2911 - mae:
0.2682 - mape: 3.5103 - val_loss: 0.7442 - val_mae: 0.5793 - val_mape: 2.3610
Epoch 20/25
324/324 [=====] - 5s 17ms/step - loss: 0.2801 - mae:
0.2620 - mape: 3.5814 - val_loss: 0.7507 - val_mae: 0.5850 - val_mape: 2.3900
Epoch 21/25
324/324 [=====] - 6s 20ms/step - loss: 0.2764 - mae:

0.2578 - mape: 3.4402 - val_loss: 0.8339 - val_mae: 0.6235 - val_mape: 2.4856
Epoch 22/25
324/324 [=====] - 5s 14ms/step - loss: 0.2784 - mae:
0.2586 - mape: 3.4496 - val_loss: 0.9214 - val_mae: 0.7034 - val_mape: 2.8542
Epoch 23/25
324/324 [=====] - 5s 15ms/step - loss: 0.2945 - mae:
0.2700 - mape: 3.5325 - val_loss: 0.8432 - val_mae: 0.6536 - val_mape: 2.7932
Epoch 24/25
324/324 [=====] - 6s 18ms/step - loss: 0.2829 - mae:
0.2623 - mape: 3.5375 - val_loss: 0.7489 - val_mae: 0.5811 - val_mape: 2.3705
Epoch 25/25
324/324 [=====] - 4s 14ms/step - loss: 0.2829 - mae:
0.2604 - mape: 3.4177 - val_loss: 0.9519 - val_mae: 0.7244 - val_mape: 2.9680
142.44335889816284
compiling baseline model...
fitting model...
Epoch 1/25
155/155 [=====] - 4s 19ms/step - loss: 221.8080 - mae:
6.0048 - mape: 19.0352 - val_loss: 20.3227 - val_mae: 3.3792 - val_mape: 3.4436
Epoch 2/25
155/155 [=====] - 3s 21ms/step - loss: 40.7579 - mae:
3.0851 - mape: 9.0951 - val_loss: 55.2658 - val_mae: 6.3195 - val_mape: 6.2241
Epoch 3/25
155/155 [=====] - 2s 14ms/step - loss: 39.2018 - mae:
2.9787 - mape: 8.1800 - val_loss: 26.2425 - val_mae: 4.1583 - val_mape: 4.1293
Epoch 4/25
155/155 [=====] - 2s 15ms/step - loss: 38.9098 - mae:
2.9185 - mape: 7.9398 - val_loss: 18.5181 - val_mae: 3.4283 - val_mape: 3.3967
Epoch 5/25
155/155 [=====] - 2s 14ms/step - loss: 43.0624 - mae:
3.0729 - mape: 8.4641 - val_loss: 33.0067 - val_mae: 4.9536 - val_mape: 4.8758
Epoch 6/25
155/155 [=====] - 2s 15ms/step - loss: 36.7091 - mae:
2.7446 - mape: 7.7982 - val_loss: 37.6329 - val_mae: 5.0071 - val_mape: 5.0717
Epoch 7/25
155/155 [=====] - 3s 20ms/step - loss: 39.1142 - mae:
3.0485 - mape: 8.4472 - val_loss: 69.5380 - val_mae: 7.6967 - val_mape: 7.5649
Epoch 8/25
155/155 [=====] - 3s 19ms/step - loss: 35.4907 - mae:
2.8130 - mape: 7.9183 - val_loss: 52.2834 - val_mae: 5.8212 - val_mape: 5.8746
Epoch 9/25
155/155 [=====] - 2s 14ms/step - loss: 34.7941 - mae:
2.5785 - mape: 7.1639 - val_loss: 34.0749 - val_mae: 4.7942 - val_mape: 4.8641
Epoch 10/25
155/155 [=====] - 2s 14ms/step - loss: 39.3476 - mae:
3.0426 - mape: 8.2060 - val_loss: 32.2214 - val_mae: 4.6514 - val_mape: 4.7310
Epoch 11/25
155/155 [=====] - 2s 15ms/step - loss: 32.0510 - mae:

2.5718 - mape: 7.0370 - val_loss: 34.1296 - val_mae: 4.9394 - val_mape: 4.8475
Epoch 12/25
155/155 [=====] - 2s 14ms/step - loss: 33.8682 - mae: 2.5956 - mape: 7.1294 - val_loss: 14.4195 - val_mae: 2.8850 - val_mape: 2.8800
Epoch 13/25
155/155 [=====] - 3s 20ms/step - loss: 35.1785 - mae: 2.7304 - mape: 7.3483 - val_loss: 84.8085 - val_mae: 8.6199 - val_mape: 8.4928
Epoch 14/25
155/155 [=====] - 3s 17ms/step - loss: 35.3012 - mae: 2.7726 - mape: 7.4680 - val_loss: 21.4880 - val_mae: 3.7530 - val_mape: 3.7169
Epoch 15/25
155/155 [=====] - 2s 14ms/step - loss: 33.2235 - mae: 2.6350 - mape: 7.3872 - val_loss: 50.4396 - val_mae: 6.5120 - val_mape: 6.4208
Epoch 16/25
155/155 [=====] - 2s 15ms/step - loss: 31.5071 - mae: 2.4056 - mape: 6.6009 - val_loss: 17.2288 - val_mae: 3.2843 - val_mape: 3.2725
Epoch 17/25
155/155 [=====] - 3s 17ms/step - loss: 34.6529 - mae: 2.6440 - mape: 7.0489 - val_loss: 15.0420 - val_mae: 2.9126 - val_mape: 2.8970
Epoch 18/25
155/155 [=====] - 2s 15ms/step - loss: 33.1949 - mae: 2.7497 - mape: 7.4568 - val_loss: 27.5104 - val_mae: 4.2829 - val_mape: 4.3403
Epoch 19/25
155/155 [=====] - 3s 22ms/step - loss: 35.1391 - mae: 2.6005 - mape: 6.7148 - val_loss: 43.2358 - val_mae: 5.8844 - val_mape: 5.7850
Epoch 20/25
155/155 [=====] - 2s 14ms/step - loss: 31.2449 - mae: 2.5046 - mape: 6.6387 - val_loss: 12.7019 - val_mae: 2.6331 - val_mape: 2.6317
Epoch 21/25
155/155 [=====] - 2s 14ms/step - loss: 33.0144 - mae: 2.6109 - mape: 6.9703 - val_loss: 18.2391 - val_mae: 3.3660 - val_mape: 3.3351
Epoch 22/25
155/155 [=====] - 2s 15ms/step - loss: 28.2866 - mae: 2.2003 - mape: 5.9444 - val_loss: 12.9365 - val_mae: 2.6727 - val_mape: 2.7046
Epoch 23/25
155/155 [=====] - 2s 15ms/step - loss: 30.6151 - mae: 2.5018 - mape: 6.6538 - val_loss: 17.0808 - val_mae: 3.2514 - val_mape: 3.2598
Epoch 24/25
155/155 [=====] - 3s 17ms/step - loss: 31.2394 - mae: 2.4819 - mape: 6.5592 - val_loss: 24.6250 - val_mae: 4.2705 - val_mape: 4.2059
Epoch 25/25
155/155 [=====] - 3s 22ms/step - loss: 29.6873 - mae: 2.3423 - mape: 6.2767 - val_loss: 28.7234 - val_mae: 4.5472 - val_mape: 4.4719
83.44734144210815
compiling baseline model...
fitting model...
Epoch 1/25
143/143 [=====] - 4s 20ms/step - loss: 80.0207 - mae:

4.0441 - mape: 15.4760 - val_loss: 9.5606 - val_mae: 2.3921 - val_mape: 4.1632
Epoch 2/25
143/143 [=====] - 3s 21ms/step - loss: 1.3925 - mae: 0.8079 - mape: 3.5394 - val_loss: 7.8550 - val_mae: 2.1321 - val_mape: 3.8108
Epoch 3/25
143/143 [=====] - 2s 15ms/step - loss: 1.3454 - mae: 0.7977 - mape: 3.4687 - val_loss: 7.3004 - val_mae: 1.9993 - val_mape: 3.7066
Epoch 4/25
143/143 [=====] - 2s 15ms/step - loss: 1.3280 - mae: 0.7914 - mape: 3.4274 - val_loss: 11.6253 - val_mae: 2.7579 - val_mape: 4.6979
Epoch 5/25
143/143 [=====] - 2s 14ms/step - loss: 1.4332 - mae: 0.8412 - mape: 3.5872 - val_loss: 13.2024 - val_mae: 2.9883 - val_mape: 5.0212
Epoch 6/25
143/143 [=====] - 2s 15ms/step - loss: 1.4543 - mae: 0.8426 - mape: 3.5740 - val_loss: 7.2792 - val_mae: 2.0674 - val_mape: 3.6751
Epoch 7/25
143/143 [=====] - 2s 17ms/step - loss: 1.3160 - mae: 0.7981 - mape: 3.3956 - val_loss: 7.2844 - val_mae: 2.0563 - val_mape: 3.6501
Epoch 8/25
143/143 [=====] - 3s 22ms/step - loss: 1.2292 - mae: 0.7636 - mape: 3.2746 - val_loss: 6.5672 - val_mae: 1.8989 - val_mape: 3.4364
Epoch 9/25
143/143 [=====] - 2s 15ms/step - loss: 1.2057 - mae: 0.7603 - mape: 3.2513 - val_loss: 6.6196 - val_mae: 1.9455 - val_mape: 3.4648
Epoch 10/25
143/143 [=====] - 2s 15ms/step - loss: 1.2530 - mae: 0.7852 - mape: 3.3390 - val_loss: 7.9187 - val_mae: 2.1616 - val_mape: 3.7744
Epoch 11/25
143/143 [=====] - 3s 18ms/step - loss: 1.0823 - mae: 0.7169 - mape: 3.0752 - val_loss: 12.1797 - val_mae: 2.9401 - val_mape: 4.9170
Epoch 12/25
143/143 [=====] - 3s 23ms/step - loss: 1.1814 - mae: 0.7517 - mape: 3.1964 - val_loss: 10.7441 - val_mae: 2.7476 - val_mape: 4.6029
Epoch 13/25
143/143 [=====] - 3s 22ms/step - loss: 1.1115 - mae: 0.7321 - mape: 3.1120 - val_loss: 5.8613 - val_mae: 1.7736 - val_mape: 3.2721
Epoch 14/25
143/143 [=====] - 3s 18ms/step - loss: 1.0456 - mae: 0.7039 - mape: 3.0151 - val_loss: 4.7409 - val_mae: 1.5884 - val_mape: 2.9044
Epoch 15/25
143/143 [=====] - 2s 14ms/step - loss: 1.0584 - mae: 0.7134 - mape: 3.0374 - val_loss: 6.2107 - val_mae: 1.8275 - val_mape: 3.3512
Epoch 16/25
143/143 [=====] - 2s 15ms/step - loss: 1.1032 - mae: 0.7362 - mape: 3.1149 - val_loss: 4.9109 - val_mae: 1.6111 - val_mape: 2.9430
Epoch 17/25
143/143 [=====] - 2s 15ms/step - loss: 1.0391 - mae:

0.7062 - mape: 2.9923 - val_loss: 9.0612 - val_mae: 2.4882 - val_mape: 4.2397
Epoch 18/25
143/143 [=====] - 2s 16ms/step - loss: 1.1247 - mae: 0.7465 - mape: 3.1429 - val_loss: 5.1438 - val_mae: 1.6439 - val_mape: 3.0350
Epoch 19/25
143/143 [=====] - 3s 22ms/step - loss: 1.0790 - mae: 0.7272 - mape: 3.0700 - val_loss: 5.1174 - val_mae: 1.7181 - val_mape: 3.0807
Epoch 20/25
143/143 [=====] - 3s 18ms/step - loss: 1.0667 - mae: 0.7186 - mape: 3.0240 - val_loss: 7.9131 - val_mae: 2.1814 - val_mape: 3.7686
Epoch 21/25
143/143 [=====] - 2s 15ms/step - loss: 0.9661 - mae: 0.6712 - mape: 2.8706 - val_loss: 5.1292 - val_mae: 1.6268 - val_mape: 3.0005
Epoch 22/25
143/143 [=====] - 2s 15ms/step - loss: 1.0594 - mae: 0.7186 - mape: 3.0502 - val_loss: 10.8484 - val_mae: 2.6919 - val_mape: 4.4944
Epoch 23/25
143/143 [=====] - 2s 15ms/step - loss: 1.0231 - mae: 0.7031 - mape: 2.9776 - val_loss: 4.9523 - val_mae: 1.6825 - val_mape: 3.0248
Epoch 24/25
143/143 [=====] - 2s 16ms/step - loss: 0.9414 - mae: 0.6617 - mape: 2.8319 - val_loss: 12.4295 - val_mae: 2.9410 - val_mape: 4.9143
60.47201609611511
compiling baseline model...
fitting model...
Epoch 1/25
183/183 [=====] - 6s 21ms/step - loss: 55.2892 - mae: 2.6397 - mape: 14.1750 - val_loss: 24.0752 - val_mae: 3.4415 - val_mape: 3.3912
Epoch 2/25
183/183 [=====] - 3s 15ms/step - loss: 1.4527 - mae: 0.7537 - mape: 3.9124 - val_loss: 26.8621 - val_mae: 3.7959 - val_mape: 3.6382
Epoch 3/25
183/183 [=====] - 3s 14ms/step - loss: 1.3090 - mae: 0.7114 - mape: 3.7071 - val_loss: 26.8736 - val_mae: 3.6854 - val_mape: 3.6254
Epoch 4/25
183/183 [=====] - 3s 14ms/step - loss: 1.3508 - mae: 0.7253 - mape: 3.7658 - val_loss: 41.9505 - val_mae: 5.2359 - val_mape: 4.7857
Epoch 5/25
183/183 [=====] - 4s 22ms/step - loss: 1.4793 - mae: 0.7633 - mape: 3.9270 - val_loss: 28.3368 - val_mae: 3.9832 - val_mape: 3.7828
Epoch 6/25
183/183 [=====] - 3s 15ms/step - loss: 1.3292 - mae: 0.7231 - mape: 3.7957 - val_loss: 22.7470 - val_mae: 3.3392 - val_mape: 3.2959
Epoch 7/25
183/183 [=====] - 3s 15ms/step - loss: 1.2010 - mae: 0.6780 - mape: 3.4897 - val_loss: 24.8649 - val_mae: 3.5211 - val_mape: 3.4624
Epoch 8/25
183/183 [=====] - 3s 14ms/step - loss: 1.1665 - mae:

0.6723 - mape: 3.5175 - val_loss: 25.4633 - val_mae: 3.7318 - val_mape: 3.5764
Epoch 9/25
183/183 [=====] - 3s 17ms/step - loss: 1.2751 - mae:
0.7051 - mape: 3.6526 - val_loss: 36.1666 - val_mae: 4.7887 - val_mape: 4.4003
Epoch 10/25
183/183 [=====] - 4s 20ms/step - loss: 1.5095 - mae:
0.7675 - mape: 3.8541 - val_loss: 21.5475 - val_mae: 3.2484 - val_mape: 3.1985
Epoch 11/25
183/183 [=====] - 3s 14ms/step - loss: 1.3090 - mae:
0.7134 - mape: 3.6263 - val_loss: 21.5239 - val_mae: 3.2246 - val_mape: 3.1957
Epoch 12/25
183/183 [=====] - 3s 14ms/step - loss: 1.1987 - mae:
0.6805 - mape: 3.5815 - val_loss: 22.5020 - val_mae: 3.4124 - val_mape: 3.3008
Epoch 13/25
183/183 [=====] - 3s 15ms/step - loss: 1.1441 - mae:
0.6664 - mape: 3.4530 - val_loss: 20.3865 - val_mae: 3.1548 - val_mape: 3.1080
Epoch 14/25
183/183 [=====] - 3s 19ms/step - loss: 1.4652 - mae:
0.7456 - mape: 3.7341 - val_loss: 26.5754 - val_mae: 3.9380 - val_mape: 3.7257
Epoch 15/25
183/183 [=====] - 4s 19ms/step - loss: 1.2232 - mae:
0.7026 - mape: 3.6476 - val_loss: 36.9050 - val_mae: 4.9580 - val_mape: 4.5124
Epoch 16/25
183/183 [=====] - 3s 14ms/step - loss: 1.2288 - mae:
0.6902 - mape: 3.5297 - val_loss: 20.4872 - val_mae: 3.2134 - val_mape: 3.1286
Epoch 17/25
183/183 [=====] - 3s 15ms/step - loss: 1.1032 - mae:
0.6476 - mape: 3.3011 - val_loss: 19.2858 - val_mae: 3.0659 - val_mape: 3.0102
Epoch 18/25
183/183 [=====] - 3s 15ms/step - loss: 1.1141 - mae:
0.6584 - mape: 3.4498 - val_loss: 23.3387 - val_mae: 3.6107 - val_mape: 3.4332
Epoch 19/25
183/183 [=====] - 4s 20ms/step - loss: 1.0323 - mae:
0.6253 - mape: 3.2573 - val_loss: 22.3690 - val_mae: 3.4814 - val_mape: 3.3035
Epoch 20/25
183/183 [=====] - 3s 19ms/step - loss: 1.1502 - mae:
0.6690 - mape: 3.3984 - val_loss: 19.1592 - val_mae: 3.0719 - val_mape: 2.9943
Epoch 21/25
183/183 [=====] - 3s 15ms/step - loss: 1.1007 - mae:
0.6510 - mape: 3.3628 - val_loss: 24.1090 - val_mae: 3.6705 - val_mape: 3.4460
Epoch 22/25
183/183 [=====] - 3s 15ms/step - loss: 0.9761 - mae:
0.6065 - mape: 3.1846 - val_loss: 25.0561 - val_mae: 3.8227 - val_mape: 3.5205
Epoch 23/25
183/183 [=====] - 3s 15ms/step - loss: 0.9220 - mae:
0.5895 - mape: 3.0708 - val_loss: 18.6745 - val_mae: 3.0980 - val_mape: 2.9968
Epoch 24/25
183/183 [=====] - 4s 22ms/step - loss: 1.0423 - mae:

0.6292 - mape: 3.2439 - val_loss: 24.2742 - val_mae: 3.6036 - val_mape: 3.4844
 Epoch 25/25
 183/183 [=====] - 3s 15ms/step - loss: 0.9545 - mae:
 0.6070 - mape: 3.2398 - val_loss: 17.2857 - val_mae: 2.8575 - val_mape: 2.8205
 77.79245519638062
 compiling baseline model...
 fitting model...
 Epoch 1/25
 203/203 [=====] - 5s 17ms/step - loss: 179.2549 - mae:
 3.4338 - mape: 16.9489 - val_loss: 55.5528 - val_mae: 5.5280 - val_mape: 2.7877
 Epoch 2/25
 203/203 [=====] - 4s 18ms/step - loss: 2.5724 - mae:
 0.8050 - mape: 3.7695 - val_loss: 64.2557 - val_mae: 5.8928 - val_mape: 2.9978
 Epoch 3/25
 203/203 [=====] - 4s 20ms/step - loss: 2.4161 - mae:
 0.7965 - mape: 3.7507 - val_loss: 60.9932 - val_mae: 5.8087 - val_mape: 2.9558
 Epoch 4/25
 203/203 [=====] - 3s 15ms/step - loss: 2.6460 - mae:
 0.8272 - mape: 3.9031 - val_loss: 62.2919 - val_mae: 6.1073 - val_mape: 3.0507
 Epoch 5/25
 203/203 [=====] - 3s 15ms/step - loss: 2.8444 - mae:
 0.8448 - mape: 3.7742 - val_loss: 68.5302 - val_mae: 6.1920 - val_mape: 3.1293
 Epoch 6/25
 203/203 [=====] - 3s 15ms/step - loss: 2.4985 - mae:
 0.7966 - mape: 3.6785 - val_loss: 64.1445 - val_mae: 5.8181 - val_mape: 2.9510
 Epoch 7/25
 203/203 [=====] - 5s 23ms/step - loss: 2.4661 - mae:
 0.7942 - mape: 3.7805 - val_loss: 56.5876 - val_mae: 5.4582 - val_mape: 2.7748
 Epoch 8/25
 203/203 [=====] - 3s 14ms/step - loss: 3.0717 - mae:
 0.8963 - mape: 4.1886 - val_loss: 69.7674 - val_mae: 6.4942 - val_mape: 3.2277
 Epoch 9/25
 203/203 [=====] - 3s 15ms/step - loss: 2.9919 - mae:
 0.8625 - mape: 3.8186 - val_loss: 59.5903 - val_mae: 5.7412 - val_mape: 2.9121
 Epoch 10/25
 203/203 [=====] - 3s 14ms/step - loss: 2.8076 - mae:
 0.8462 - mape: 3.7893 - val_loss: 54.3782 - val_mae: 5.3070 - val_mape: 2.6988
 Epoch 11/25
 203/203 [=====] - 4s 20ms/step - loss: 2.4892 - mae:
 0.7934 - mape: 3.7147 - val_loss: 71.7693 - val_mae: 6.4984 - val_mape: 3.2709
 Epoch 12/25
 203/203 [=====] - 3s 17ms/step - loss: 2.4936 - mae:
 0.8058 - mape: 3.8706 - val_loss: 51.1996 - val_mae: 5.2325 - val_mape: 2.6470
 Epoch 13/25
 203/203 [=====] - 3s 14ms/step - loss: 3.1623 - mae:
 0.8833 - mape: 3.8599 - val_loss: 87.2298 - val_mae: 7.3581 - val_mape: 3.6903
 Epoch 14/25
 203/203 [=====] - 3s 15ms/step - loss: 2.3329 - mae:

0.7712 - mape: 3.5904 - val_loss: 52.8758 - val_mae: 5.3689 - val_mape: 2.7213
Epoch 15/25
203/203 [=====] - 5s 24ms/step - loss: 2.7331 - mae:
0.8330 - mape: 3.7458 - val_loss: 48.2964 - val_mae: 4.9456 - val_mape: 2.5219
Epoch 16/25
203/203 [=====] - 4s 18ms/step - loss: 2.8059 - mae:
0.8501 - mape: 4.0553 - val_loss: 52.3592 - val_mae: 5.2596 - val_mape: 2.6725
Epoch 17/25
203/203 [=====] - 3s 15ms/step - loss: 2.5801 - mae:
0.8152 - mape: 3.7829 - val_loss: 50.3229 - val_mae: 5.0977 - val_mape: 2.5938
Epoch 18/25
203/203 [=====] - 3s 15ms/step - loss: 2.4979 - mae:
0.7978 - mape: 3.6192 - val_loss: 45.7244 - val_mae: 4.8390 - val_mape: 2.4639
Epoch 19/25
203/203 [=====] - 3s 16ms/step - loss: 2.2865 - mae:
0.7700 - mape: 3.6148 - val_loss: 47.1211 - val_mae: 4.9580 - val_mape: 2.5178
Epoch 20/25
203/203 [=====] - 4s 21ms/step - loss: 3.2770 - mae:
0.8970 - mape: 3.9236 - val_loss: 46.8849 - val_mae: 4.8992 - val_mape: 2.4966
Epoch 21/25
203/203 [=====] - 3s 15ms/step - loss: 2.1355 - mae:
0.7378 - mape: 3.4116 - val_loss: 46.2560 - val_mae: 4.8427 - val_mape: 2.4704
Epoch 22/25
203/203 [=====] - 3s 14ms/step - loss: 2.1549 - mae:
0.7439 - mape: 3.4583 - val_loss: 46.4979 - val_mae: 4.9562 - val_mape: 2.5111
Epoch 23/25
203/203 [=====] - 3s 15ms/step - loss: 2.6074 - mae:
0.8049 - mape: 3.6484 - val_loss: 44.7847 - val_mae: 4.7388 - val_mape: 2.4171
Epoch 24/25
203/203 [=====] - 4s 22ms/step - loss: 2.3663 - mae:
0.7773 - mape: 3.6583 - val_loss: 44.1061 - val_mae: 4.7622 - val_mape: 2.4223
Epoch 25/25
203/203 [=====] - 3s 15ms/step - loss: 2.3757 - mae:
0.7652 - mape: 3.5189 - val_loss: 48.4987 - val_mae: 5.1873 - val_mape: 2.6151
87.13969802856445
compiling baseline model...
fitting model...
Epoch 1/25
324/324 [=====] - 7s 16ms/step - loss: 15.4513 - mae:
1.0806 - mape: 11.9775 - val_loss: 17.9084 - val_mae: 2.9326 - val_mape: 2.2725
Epoch 2/25
324/324 [=====] - 7s 20ms/step - loss: 0.4788 - mae:
0.3686 - mape: 3.6478 - val_loss: 18.1531 - val_mae: 2.9493 - val_mape: 2.2136
Epoch 3/25
324/324 [=====] - 5s 15ms/step - loss: 0.5597 - mae:
0.4111 - mape: 4.4017 - val_loss: 23.6546 - val_mae: 3.6797 - val_mape: 2.8086
Epoch 4/25
324/324 [=====] - 5s 16ms/step - loss: 0.6041 - mae:

0.4161 - mape: 3.7239 - val_loss: 38.0883 - val_mae: 5.1108 - val_mape: 3.9860
Epoch 5/25
324/324 [=====] - 6s 18ms/step - loss: 0.5048 - mae:
0.3803 - mape: 3.8179 - val_loss: 16.8270 - val_mae: 2.7921 - val_mape: 2.1439
Epoch 6/25
324/324 [=====] - 5s 15ms/step - loss: 0.4449 - mae:
0.3572 - mape: 3.5182 - val_loss: 15.7072 - val_mae: 2.7158 - val_mape: 2.0789
Epoch 7/25
324/324 [=====] - 6s 17ms/step - loss: 0.4629 - mae:
0.3720 - mape: 4.0912 - val_loss: 28.2925 - val_mae: 3.9921 - val_mape: 3.0941
Epoch 8/25
324/324 [=====] - 5s 17ms/step - loss: 0.4506 - mae:
0.3632 - mape: 3.8813 - val_loss: 29.5436 - val_mae: 4.1014 - val_mape: 3.1701
Epoch 9/25
324/324 [=====] - 5s 14ms/step - loss: 0.4430 - mae:
0.3572 - mape: 3.4573 - val_loss: 15.9884 - val_mae: 2.6574 - val_mape: 2.0162
Epoch 10/25
324/324 [=====] - 6s 19ms/step - loss: 0.4116 - mae:
0.3466 - mape: 3.5316 - val_loss: 16.4042 - val_mae: 2.7007 - val_mape: 2.0542
Epoch 11/25
324/324 [=====] - 5s 15ms/step - loss: 0.3989 - mae:
0.3426 - mape: 3.5422 - val_loss: 14.7468 - val_mae: 2.5817 - val_mape: 1.9494
Epoch 12/25
324/324 [=====] - 5s 14ms/step - loss: 0.4306 - mae:
0.3539 - mape: 3.5091 - val_loss: 17.9473 - val_mae: 3.0183 - val_mape: 2.2670
Epoch 13/25
324/324 [=====] - 6s 19ms/step - loss: 0.4084 - mae:
0.3456 - mape: 3.2917 - val_loss: 14.5759 - val_mae: 2.5742 - val_mape: 1.9571
Epoch 14/25
324/324 [=====] - 5s 14ms/step - loss: 0.3989 - mae:
0.3379 - mape: 3.2600 - val_loss: 13.3482 - val_mae: 2.4233 - val_mape: 1.8277
Epoch 15/25
324/324 [=====] - 5s 14ms/step - loss: 0.3489 - mae:
0.3177 - mape: 3.5058 - val_loss: 15.1338 - val_mae: 2.6544 - val_mape: 1.9804
Epoch 16/25
324/324 [=====] - 6s 19ms/step - loss: 0.3620 - mae:
0.3203 - mape: 3.0210 - val_loss: 16.6541 - val_mae: 2.8669 - val_mape: 2.1314
Epoch 17/25
324/324 [=====] - 4s 14ms/step - loss: 0.3678 - mae:
0.3216 - mape: 3.0054 - val_loss: 31.2731 - val_mae: 4.5778 - val_mape: 3.5078
Epoch 18/25
324/324 [=====] - 5s 16ms/step - loss: 0.3554 - mae:
0.3180 - mape: 2.9633 - val_loss: 39.7972 - val_mae: 5.2752 - val_mape: 4.0210
Epoch 19/25
324/324 [=====] - 6s 17ms/step - loss: 0.3513 - mae:
0.3123 - mape: 2.9754 - val_loss: 16.7979 - val_mae: 2.9488 - val_mape: 2.2116
Epoch 20/25
324/324 [=====] - 4s 14ms/step - loss: 0.3549 - mae:

0.3185 - mape: 3.1752 - val_loss: 12.0494 - val_mae: 2.3020 - val_mape: 1.7453
Epoch 21/25
324/324 [=====] - 5s 17ms/step - loss: 0.3748 - mae:
0.3296 - mape: 3.3480 - val_loss: 12.5428 - val_mae: 2.3420 - val_mape: 1.7757
Epoch 22/25
324/324 [=====] - 5s 16ms/step - loss: 0.3468 - mae:
0.3118 - mape: 2.8456 - val_loss: 13.4671 - val_mae: 2.5662 - val_mape: 2.0137
Epoch 23/25
324/324 [=====] - 4s 14ms/step - loss: 0.3191 - mae:
0.2964 - mape: 2.7614 - val_loss: 30.9146 - val_mae: 4.5475 - val_mape: 3.4489
Epoch 24/25
324/324 [=====] - 6s 17ms/step - loss: 0.3644 - mae:
0.3207 - mape: 2.9765 - val_loss: 15.4481 - val_mae: 2.8028 - val_mape: 2.1452
Epoch 25/25
324/324 [=====] - 6s 18ms/step - loss: 0.3545 - mae:
0.3184 - mape: 3.1686 - val_loss: 12.7791 - val_mae: 2.4171 - val_mape: 1.8055
143.49213004112244
compiling baseline model...
fitting model...
Epoch 1/25
194/194 [=====] - 5s 16ms/step - loss: 22.2464 - mae:
1.8260 - mape: 16.9432 - val_loss: 2.7957 - val_mae: 1.2903 - val_mape: 3.9075
Epoch 2/25
194/194 [=====] - 3s 16ms/step - loss: 0.7488 - mae:
0.5245 - mape: 3.9101 - val_loss: 2.7117 - val_mae: 1.2823 - val_mape: 3.8559
Epoch 3/25
194/194 [=====] - 4s 21ms/step - loss: 0.7764 - mae:
0.5396 - mape: 4.0432 - val_loss: 2.8980 - val_mae: 1.3157 - val_mape: 3.9934
Epoch 4/25
194/194 [=====] - 3s 15ms/step - loss: 0.7425 - mae:
0.5207 - mape: 3.8359 - val_loss: 2.6167 - val_mae: 1.2594 - val_mape: 3.7880
Epoch 5/25
194/194 [=====] - 3s 14ms/step - loss: 0.7281 - mae:
0.5198 - mape: 3.9023 - val_loss: 3.4106 - val_mae: 1.4936 - val_mape: 4.4077
Epoch 6/25
194/194 [=====] - 3s 15ms/step - loss: 0.8090 - mae:
0.5474 - mape: 4.0415 - val_loss: 2.9426 - val_mae: 1.3257 - val_mape: 4.0227
Epoch 7/25
194/194 [=====] - 4s 19ms/step - loss: 0.7048 - mae:
0.5096 - mape: 3.8220 - val_loss: 2.5397 - val_mae: 1.2465 - val_mape: 3.7294
Epoch 8/25
194/194 [=====] - 4s 19ms/step - loss: 0.7439 - mae:
0.5255 - mape: 3.9428 - val_loss: 2.3626 - val_mae: 1.1785 - val_mape: 3.5668
Epoch 9/25
194/194 [=====] - 3s 14ms/step - loss: 0.6608 - mae:
0.4899 - mape: 3.6471 - val_loss: 2.6047 - val_mae: 1.2844 - val_mape: 3.8377
Epoch 10/25
194/194 [=====] - 3s 14ms/step - loss: 0.6470 - mae:

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0.4866 - mape: 3.6202 - val_loss: 3.0717 - val_mae: 1.3628 - val_mape: 4.1236
Epoch 11/25
194/194 [=====] - 3s 14ms/step - loss: 0.6779 - mae:
0.4985 - mape: 3.6654 - val_loss: 2.2900 - val_mae: 1.1779 - val_mape: 3.5174
Epoch 12/25
194/194 [=====] - 4s 22ms/step - loss: 0.8217 - mae:
0.5539 - mape: 4.0022 - val_loss: 2.2412 - val_mae: 1.1399 - val_mape: 3.4561
Epoch 13/25
194/194 [=====] - 3s 14ms/step - loss: 0.6291 - mae:
0.4836 - mape: 3.7156 - val_loss: 4.5876 - val_mae: 1.8460 - val_mape: 5.3751
Epoch 14/25
194/194 [=====] - 3s 14ms/step - loss: 0.6168 - mae:
0.4741 - mape: 3.5004 - val_loss: 2.0529 - val_mae: 1.0881 - val_mape: 3.2961
Epoch 15/25
194/194 [=====] - 3s 14ms/step - loss: 0.5816 - mae:
0.4589 - mape: 3.4234 - val_loss: 1.9938 - val_mae: 1.0891 - val_mape: 3.2841
Epoch 16/25
194/194 [=====] - 3s 16ms/step - loss: 0.5690 - mae:
0.4541 - mape: 3.3610 - val_loss: 2.5874 - val_mae: 1.2465 - val_mape: 3.7668
Epoch 17/25
194/194 [=====] - 4s 21ms/step - loss: 0.5533 - mae:
0.4480 - mape: 3.3402 - val_loss: 2.2044 - val_mae: 1.1722 - val_mape: 3.4896
Epoch 18/25
194/194 [=====] - 3s 14ms/step - loss: 0.5447 - mae:
0.4445 - mape: 3.3847 - val_loss: 2.3514 - val_mae: 1.1734 - val_mape: 3.5470
Epoch 19/25
194/194 [=====] - 3s 14ms/step - loss: 0.5912 - mae:
0.4614 - mape: 3.4048 - val_loss: 1.8549 - val_mae: 1.0293 - val_mape: 3.1067
Epoch 20/25
194/194 [=====] - 3s 14ms/step - loss: 0.5271 - mae:
0.4359 - mape: 3.2662 - val_loss: 2.1887 - val_mae: 1.1727 - val_mape: 3.4821
Epoch 21/25
194/194 [=====] - 4s 19ms/step - loss: 0.5374 - mae:
0.4411 - mape: 3.2845 - val_loss: 1.8863 - val_mae: 1.0251 - val_mape: 3.1054
Epoch 22/25
194/194 [=====] - 3s 16ms/step - loss: 0.5590 - mae:
0.4504 - mape: 3.3504 - val_loss: 2.6213 - val_mae: 1.3308 - val_mape: 3.9019
Epoch 23/25
194/194 [=====] - 3s 14ms/step - loss: 0.5430 - mae:
0.4364 - mape: 3.2071 - val_loss: 1.7858 - val_mae: 1.0152 - val_mape: 3.0447
Epoch 24/25
194/194 [=====] - 3s 14ms/step - loss: 0.5204 - mae:
0.4322 - mape: 3.2387 - val_loss: 1.8272 - val_mae: 1.0436 - val_mape: 3.1326
Epoch 25/25
194/194 [=====] - 3s 15ms/step - loss: 0.5591 - mae:
0.4508 - mape: 3.3500 - val_loss: 1.8917 - val_mae: 1.0367 - val_mape: 3.1345
83.4941987991333
compiling baseline model...

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fitting model...

Epoch 1/25

279/279 [=====] - 6s 15ms/step - loss: 23.7230 - mae: 1.4251 - mape: 11.9618 - val_loss: 16.0112 - val_mae: 2.8492 - val_mape: 2.5581

Epoch 2/25

279/279 [=====] - 6s 21ms/step - loss: 0.6976 - mae: 0.4815 - mape: 3.7799 - val_loss: 25.8098 - val_mae: 3.9661 - val_mape: 3.4712

Epoch 3/25

279/279 [=====] - 4s 14ms/step - loss: 0.7061 - mae: 0.4821 - mape: 3.4952 - val_loss: 16.0310 - val_mae: 2.8612 - val_mape: 2.5867

Epoch 4/25

279/279 [=====] - 4s 14ms/step - loss: 0.7587 - mae: 0.4983 - mape: 3.5210 - val_loss: 16.4335 - val_mae: 2.9452 - val_mape: 2.6207

Epoch 5/25

279/279 [=====] - 5s 19ms/step - loss: 0.8422 - mae: 0.5291 - mape: 4.0195 - val_loss: 27.8831 - val_mae: 4.1864 - val_mape: 3.6493

Epoch 6/25

279/279 [=====] - 4s 15ms/step - loss: 0.8068 - mae: 0.5183 - mape: 3.7506 - val_loss: 15.7416 - val_mae: 2.8439 - val_mape: 2.5283

Epoch 7/25

279/279 [=====] - 4s 15ms/step - loss: 0.7229 - mae: 0.4940 - mape: 3.7087 - val_loss: 17.4246 - val_mae: 3.0423 - val_mape: 2.6757

Epoch 8/25

279/279 [=====] - 5s 18ms/step - loss: 1.0049 - mae: 0.5658 - mape: 4.1648 - val_loss: 21.2685 - val_mae: 3.4650 - val_mape: 3.0380

Epoch 9/25

279/279 [=====] - 4s 15ms/step - loss: 0.7960 - mae: 0.5050 - mape: 3.4889 - val_loss: 16.2293 - val_mae: 2.8789 - val_mape: 2.5557

Epoch 10/25

279/279 [=====] - 4s 16ms/step - loss: 0.7447 - mae: 0.4923 - mape: 3.3553 - val_loss: 15.8010 - val_mae: 2.8537 - val_mape: 2.5278

Epoch 11/25

279/279 [=====] - 5s 19ms/step - loss: 0.6838 - mae: 0.4765 - mape: 3.5219 - val_loss: 17.1081 - val_mae: 3.0726 - val_mape: 2.7183

Epoch 12/25

279/279 [=====] - 4s 15ms/step - loss: 0.6386 - mae: 0.4637 - mape: 3.5520 - val_loss: 14.7953 - val_mae: 2.7539 - val_mape: 2.4791

Epoch 13/25

279/279 [=====] - 4s 14ms/step - loss: 0.6402 - mae: 0.4570 - mape: 3.2279 - val_loss: 14.4327 - val_mae: 2.7116 - val_mape: 2.4492

Epoch 14/25

279/279 [=====] - 5s 17ms/step - loss: 0.7151 - mae: 0.4901 - mape: 3.5261 - val_loss: 14.9504 - val_mae: 2.7866 - val_mape: 2.4827

Epoch 15/25

279/279 [=====] - 5s 17ms/step - loss: 0.6917 - mae: 0.4775 - mape: 3.3673 - val_loss: 14.0965 - val_mae: 2.6593 - val_mape: 2.4025

Epoch 16/25

279/279 [=====] - 4s 14ms/step - loss: 0.6832 - mae:

0.4694 - mape: 3.3264 - val_loss: 14.1165 - val_mae: 2.6669 - val_mape: 2.3958
Epoch 17/25
279/279 [=====] - 4s 16ms/step - loss: 0.6905 - mae:
0.4719 - mape: 3.3674 - val_loss: 16.2063 - val_mae: 2.9620 - val_mape: 2.6200
Epoch 18/25
279/279 [=====] - 6s 20ms/step - loss: 0.7368 - mae:
0.4915 - mape: 3.5974 - val_loss: 16.5225 - val_mae: 3.0164 - val_mape: 2.7437
Epoch 19/25
279/279 [=====] - 4s 14ms/step - loss: 0.6277 - mae:
0.4504 - mape: 3.1836 - val_loss: 14.5423 - val_mae: 2.7515 - val_mape: 2.4522
Epoch 20/25
279/279 [=====] - 4s 15ms/step - loss: 0.6595 - mae:
0.4692 - mape: 3.3313 - val_loss: 28.4867 - val_mae: 4.3587 - val_mape: 3.9604
Epoch 21/25
279/279 [=====] - 6s 22ms/step - loss: 0.7155 - mae:
0.4792 - mape: 3.2378 - val_loss: 13.6766 - val_mae: 2.6195 - val_mape: 2.3573
Epoch 22/25
279/279 [=====] - 4s 15ms/step - loss: 0.6020 - mae:
0.4429 - mape: 3.1396 - val_loss: 13.7866 - val_mae: 2.6308 - val_mape: 2.3621
Epoch 23/25
279/279 [=====] - 4s 16ms/step - loss: 0.6555 - mae:
0.4541 - mape: 3.1593 - val_loss: 14.4487 - val_mae: 2.7370 - val_mape: 2.4268
Epoch 24/25
279/279 [=====] - 6s 21ms/step - loss: 0.6187 - mae:
0.4465 - mape: 3.2399 - val_loss: 13.5585 - val_mae: 2.6058 - val_mape: 2.3414
Epoch 25/25
279/279 [=====] - 4s 16ms/step - loss: 0.5781 - mae:
0.4322 - mape: 3.1097 - val_loss: 13.3780 - val_mae: 2.5944 - val_mape: 2.3409
143.94008994102478
compiling baseline model...
fitting model...
Epoch 1/25
191/191 [=====] - 6s 25ms/step - loss: 275.2345 - mae:
5.3292 - mape: 11.6369 - val_loss: 38.7670 - val_mae: 4.4876 - val_mape: 2.6574
Epoch 2/25
191/191 [=====] - 3s 15ms/step - loss: 4.2419 - mae:
1.3177 - mape: 2.6603 - val_loss: 49.7674 - val_mae: 5.5283 - val_mape: 3.2347
Epoch 3/25
191/191 [=====] - 3s 14ms/step - loss: 4.2836 - mae:
1.3229 - mape: 2.6695 - val_loss: 37.0553 - val_mae: 4.3613 - val_mape: 2.5845
Epoch 4/25
191/191 [=====] - 3s 15ms/step - loss: 4.2729 - mae:
1.3151 - mape: 2.7057 - val_loss: 37.1620 - val_mae: 4.3992 - val_mape: 2.6064
Epoch 5/25
191/191 [=====] - 4s 19ms/step - loss: 4.1801 - mae:
1.2972 - mape: 2.5884 - val_loss: 40.6343 - val_mae: 4.7384 - val_mape: 2.7934
Epoch 6/25
191/191 [=====] - 4s 19ms/step - loss: 4.1092 - mae:

1.2885 - mape: 2.5858 - val_loss: 71.7727 - val_mae: 7.1325 - val_mape: 4.1349
Epoch 7/25
191/191 [=====] - 3s 15ms/step - loss: 4.4051 - mae:
1.3371 - mape: 2.7369 - val_loss: 38.0894 - val_mae: 4.4740 - val_mape: 2.6427
Epoch 8/25
191/191 [=====] - 3s 15ms/step - loss: 4.1762 - mae:
1.3040 - mape: 2.6400 - val_loss: 137.9771 - val_mae: 10.6335 - val_mape: 6.1228
Epoch 9/25
191/191 [=====] - 3s 15ms/step - loss: 4.7663 - mae:
1.3694 - mape: 2.7034 - val_loss: 81.2978 - val_mae: 7.7049 - val_mape: 4.4555
Epoch 10/25
191/191 [=====] - 4s 23ms/step - loss: 4.9587 - mae:
1.4219 - mape: 2.8649 - val_loss: 33.0495 - val_mae: 3.8700 - val_mape: 2.3181
Epoch 11/25
191/191 [=====] - 3s 15ms/step - loss: 4.6749 - mae:
1.3768 - mape: 2.8033 - val_loss: 33.7141 - val_mae: 3.8660 - val_mape: 2.3231
Epoch 12/25
191/191 [=====] - 3s 15ms/step - loss: 4.0590 - mae:
1.2698 - mape: 2.5070 - val_loss: 37.8923 - val_mae: 4.5557 - val_mape: 2.6878
Epoch 13/25
191/191 [=====] - 3s 15ms/step - loss: 4.2891 - mae:
1.3138 - mape: 2.6008 - val_loss: 64.3772 - val_mae: 6.6103 - val_mape: 3.8368
Epoch 14/25
191/191 [=====] - 4s 20ms/step - loss: 4.2954 - mae:
1.3187 - mape: 2.6190 - val_loss: 54.7290 - val_mae: 5.9982 - val_mape: 3.4953
Epoch 15/25
191/191 [=====] - 4s 18ms/step - loss: 4.4870 - mae:
1.3438 - mape: 2.6586 - val_loss: 36.0906 - val_mae: 4.3985 - val_mape: 2.5974
Epoch 16/25
191/191 [=====] - 3s 15ms/step - loss: 4.1200 - mae:
1.2809 - mape: 2.5627 - val_loss: 61.2546 - val_mae: 6.0210 - val_mape: 3.5964
Epoch 17/25
191/191 [=====] - 3s 14ms/step - loss: 4.2133 - mae:
1.3040 - mape: 2.6047 - val_loss: 110.8179 - val_mae: 9.0323 - val_mape: 5.3381
Epoch 18/25
191/191 [=====] - 3s 15ms/step - loss: 4.3217 - mae:
1.3259 - mape: 2.6628 - val_loss: 33.0858 - val_mae: 3.8708 - val_mape: 2.3304
Epoch 19/25
191/191 [=====] - 4s 22ms/step - loss: 3.7946 - mae:
1.2292 - mape: 2.4375 - val_loss: 31.3361 - val_mae: 3.8436 - val_mape: 2.2931
Epoch 20/25
191/191 [=====] - 3s 16ms/step - loss: 3.8934 - mae:
1.2517 - mape: 2.4748 - val_loss: 361.1347 - val_mae: 17.9103 - val_mape:
10.4533
Epoch 21/25
191/191 [=====] - 3s 15ms/step - loss: 9.6503 - mae:
1.7652 - mape: 3.4273 - val_loss: 34.4461 - val_mae: 3.9023 - val_mape: 2.3475
Epoch 22/25

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191/191 [=====] - 3s 15ms/step - loss: 4.1742 - mae:
1.2919 - mape: 2.5318 - val_loss: 37.5059 - val_mae: 4.1557 - val_mape: 2.5007
Epoch 23/25
191/191 [=====] - 3s 17ms/step - loss: 3.8489 - mae:
1.2368 - mape: 2.4499 - val_loss: 31.9270 - val_mae: 3.7629 - val_mape: 2.2611
Epoch 24/25
191/191 [=====] - 4s 21ms/step - loss: 3.8344 - mae:
1.2415 - mape: 2.4962 - val_loss: 101.8513 - val_mae: 8.8491 - val_mape: 5.1125
Epoch 25/25
191/191 [=====] - 3s 15ms/step - loss: 4.3840 - mae:
1.3007 - mape: 2.5682 - val_loss: 31.9979 - val_mae: 3.9447 - val_mape: 2.3495
83.51802802085876
compiling baseline model...
fitting model...
Epoch 1/25
72/72 [=====] - 3s 19ms/step - loss: 190.7377 - mae:
7.6408 - mape: 19.4252 - val_loss: 2.4442 - val_mae: 1.2181 - val_mape: 7.7483
Epoch 2/25
72/72 [=====] - 1s 14ms/step - loss: 5.3886 - mae:
1.5871 - mape: 4.8167 - val_loss: 1.9593 - val_mae: 1.0797 - val_mape: 6.8692
Epoch 3/25
72/72 [=====] - 1s 16ms/step - loss: 5.1717 - mae:
1.5555 - mape: 4.6930 - val_loss: 2.4665 - val_mae: 1.2291 - val_mape: 7.9645
Epoch 4/25
72/72 [=====] - 1s 19ms/step - loss: 5.0805 - mae:
1.5487 - mape: 4.6714 - val_loss: 1.9146 - val_mae: 1.0756 - val_mape: 6.9286
Epoch 5/25
72/72 [=====] - 2s 22ms/step - loss: 4.8765 - mae:
1.5261 - mape: 4.5618 - val_loss: 2.9304 - val_mae: 1.4128 - val_mape: 9.3664
Epoch 6/25
72/72 [=====] - 2s 23ms/step - loss: 4.8666 - mae:
1.5421 - mape: 4.5707 - val_loss: 1.5639 - val_mae: 0.9550 - val_mape: 5.9664
Epoch 7/25
72/72 [=====] - 1s 18ms/step - loss: 4.5021 - mae:
1.4710 - mape: 4.3777 - val_loss: 1.4408 - val_mae: 0.9066 - val_mape: 5.7654
Epoch 8/25
72/72 [=====] - 1s 15ms/step - loss: 4.5466 - mae:
1.4953 - mape: 4.4089 - val_loss: 1.5697 - val_mae: 0.9557 - val_mape: 6.2292
Epoch 9/25
72/72 [=====] - 1s 15ms/step - loss: 4.6408 - mae:
1.5259 - mape: 4.4651 - val_loss: 1.6314 - val_mae: 0.9857 - val_mape: 6.5074
Epoch 10/25
72/72 [=====] - 1s 15ms/step - loss: 4.1496 - mae:
1.4473 - mape: 4.2411 - val_loss: 1.3763 - val_mae: 0.8836 - val_mape: 5.5193
Epoch 11/25
72/72 [=====] - 1s 15ms/step - loss: 3.8844 - mae:
1.3745 - mape: 4.0627 - val_loss: 1.3508 - val_mae: 0.8685 - val_mape: 5.5793
Epoch 12/25

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72/72 [=====] - 1s 16ms/step - loss: 3.8255 - mae:
1.3776 - mape: 4.0477 - val_loss: 1.5565 - val_mae: 0.9530 - val_mape: 6.2639
Epoch 13/25

72/72 [=====] - 1s 15ms/step - loss: 3.6996 - mae:
1.3576 - mape: 3.9881 - val_loss: 1.8020 - val_mae: 1.0609 - val_mape: 7.0409
Epoch 14/25

72/72 [=====] - 1s 15ms/step - loss: 3.6221 - mae:
1.3460 - mape: 3.9521 - val_loss: 1.3261 - val_mae: 0.8809 - val_mape: 5.5699
Epoch 15/25

72/72 [=====] - 1s 15ms/step - loss: 3.9611 - mae:
1.4240 - mape: 4.1700 - val_loss: 1.2774 - val_mae: 0.8445 - val_mape: 5.3401
Epoch 16/25

72/72 [=====] - 1s 21ms/step - loss: 3.4996 - mae:
1.3105 - mape: 3.8558 - val_loss: 2.0300 - val_mae: 1.1229 - val_mape: 7.5492
Epoch 17/25

72/72 [=====] - 2s 23ms/step - loss: 3.5907 - mae:
1.3381 - mape: 3.9115 - val_loss: 1.3944 - val_mae: 0.8846 - val_mape: 5.7131
Epoch 18/25

72/72 [=====] - 2s 23ms/step - loss: 3.6606 - mae:
1.3525 - mape: 3.9426 - val_loss: 1.2833 - val_mae: 0.8584 - val_mape: 5.3875
Epoch 19/25

72/72 [=====] - 1s 17ms/step - loss: 3.4881 - mae:
1.3167 - mape: 3.8553 - val_loss: 1.2577 - val_mae: 0.8319 - val_mape: 5.2639
Epoch 20/25

72/72 [=====] - 1s 16ms/step - loss: 3.6117 - mae:
1.3468 - mape: 3.9245 - val_loss: 1.3806 - val_mae: 0.9063 - val_mape: 5.6459
Epoch 21/25

72/72 [=====] - 2s 22ms/step - loss: 3.7131 - mae:
1.3906 - mape: 4.0262 - val_loss: 1.2646 - val_mae: 0.8475 - val_mape: 5.3224
Epoch 22/25

72/72 [=====] - 2s 22ms/step - loss: 3.5186 - mae:
1.3316 - mape: 3.8730 - val_loss: 1.3301 - val_mae: 0.8769 - val_mape: 5.6906
Epoch 23/25

72/72 [=====] - 2s 22ms/step - loss: 3.5089 - mae:
1.3268 - mape: 3.8504 - val_loss: 1.5027 - val_mae: 0.9469 - val_mape: 6.2756
Epoch 24/25

72/72 [=====] - 1s 14ms/step - loss: 3.3985 - mae:
1.3007 - mape: 3.8143 - val_loss: 1.3242 - val_mae: 0.8718 - val_mape: 5.4187
Epoch 25/25

72/72 [=====] - 1s 15ms/step - loss: 3.2750 - mae:
1.2781 - mape: 3.7460 - val_loss: 1.2424 - val_mae: 0.8316 - val_mape: 5.2204
34.27662110328674
compiling baseline model...
fitting model...
Epoch 1/25

322/322 [=====] - 8s 19ms/step - loss: 2.9477 - mae:
0.5484 - mape: 15.0250 - val_loss: 2.1682 - val_mae: 1.0336 - val_mape: 2.6821
Epoch 2/25

322/322 [=====] - 5s 15ms/step - loss: 0.1803 - mae: 0.2110 - mape: 4.4949 - val_loss: 2.0617 - val_mae: 1.0198 - val_mape: 2.6445
Epoch 3/25

322/322 [=====] - 6s 18ms/step - loss: 0.1676 - mae: 0.2048 - mape: 5.1574 - val_loss: 2.8169 - val_mae: 1.3349 - val_mape: 3.4446
Epoch 4/25

322/322 [=====] - 5s 17ms/step - loss: 0.1736 - mae: 0.2082 - mape: 5.0630 - val_loss: 1.8990 - val_mae: 0.9407 - val_mape: 2.4580
Epoch 5/25

322/322 [=====] - 5s 15ms/step - loss: 0.1804 - mae: 0.2173 - mape: 5.3582 - val_loss: 1.8006 - val_mae: 0.9092 - val_mape: 2.3782
Epoch 6/25

322/322 [=====] - 6s 20ms/step - loss: 0.1585 - mae: 0.1984 - mape: 4.1833 - val_loss: 1.9321 - val_mae: 1.0051 - val_mape: 2.6186
Epoch 7/25

322/322 [=====] - 5s 15ms/step - loss: 0.1616 - mae: 0.2048 - mape: 5.3297 - val_loss: 1.6982 - val_mae: 0.8906 - val_mape: 2.3265
Epoch 8/25

322/322 [=====] - 5s 15ms/step - loss: 0.1477 - mae: 0.1914 - mape: 4.5840 - val_loss: 1.7104 - val_mae: 0.8837 - val_mape: 2.3074
Epoch 9/25

322/322 [=====] - 7s 20ms/step - loss: 0.1655 - mae: 0.2068 - mape: 4.7105 - val_loss: 1.7145 - val_mae: 0.8981 - val_mape: 2.3446
Epoch 10/25

322/322 [=====] - 5s 14ms/step - loss: 0.1419 - mae: 0.1871 - mape: 4.0348 - val_loss: 2.6200 - val_mae: 1.1958 - val_mape: 3.0896
Epoch 11/25

322/322 [=====] - 5s 16ms/step - loss: 0.1403 - mae: 0.1861 - mape: 4.0002 - val_loss: 1.8177 - val_mae: 0.9891 - val_mape: 2.5825
Epoch 12/25

322/322 [=====] - 6s 18ms/step - loss: 0.1407 - mae: 0.1878 - mape: 4.0358 - val_loss: 1.6823 - val_mae: 0.9274 - val_mape: 2.4185
Epoch 13/25

322/322 [=====] - 5s 15ms/step - loss: 0.1321 - mae: 0.1813 - mape: 4.2847 - val_loss: 1.6009 - val_mae: 0.8960 - val_mape: 2.3447
Epoch 14/25

322/322 [=====] - 6s 17ms/step - loss: 0.1304 - mae: 0.1794 - mape: 4.2013 - val_loss: 1.9604 - val_mae: 0.9586 - val_mape: 2.4981
Epoch 15/25

322/322 [=====] - 6s 18ms/step - loss: 0.1227 - mae: 0.1715 - mape: 3.9933 - val_loss: 1.6031 - val_mae: 0.8980 - val_mape: 2.3430
Epoch 16/25

322/322 [=====] - 5s 15ms/step - loss: 0.1264 - mae: 0.1742 - mape: 3.7532 - val_loss: 2.1654 - val_mae: 1.1695 - val_mape: 3.0338
Epoch 17/25

322/322 [=====] - 6s 19ms/step - loss: 0.1241 - mae: 0.1738 - mape: 4.0870 - val_loss: 1.5368 - val_mae: 0.8295 - val_mape: 2.1762
Epoch 18/25

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322/322 [=====] - 5s 17ms/step - loss: 0.1190 - mae:
0.1675 - mape: 3.7113 - val_loss: 1.4848 - val_mae: 0.8496 - val_mape: 2.2186
Epoch 19/25
322/322 [=====] - 5s 16ms/step - loss: 0.1250 - mae:
0.1736 - mape: 4.0825 - val_loss: 1.4690 - val_mae: 0.8096 - val_mape: 2.1331
Epoch 20/25
322/322 [=====] - 7s 21ms/step - loss: 0.1178 - mae:
0.1669 - mape: 3.8937 - val_loss: 1.5668 - val_mae: 0.8450 - val_mape: 2.2304
Epoch 21/25
322/322 [=====] - 5s 15ms/step - loss: 0.1258 - mae:
0.1756 - mape: 3.9745 - val_loss: 1.4116 - val_mae: 0.8159 - val_mape: 2.1340
Epoch 22/25
322/322 [=====] - 5s 16ms/step - loss: 0.1235 - mae:
0.1723 - mape: 3.8174 - val_loss: 1.4586 - val_mae: 0.8201 - val_mape: 2.1617
Epoch 23/25
322/322 [=====] - 6s 19ms/step - loss: 0.1197 - mae:
0.1670 - mape: 3.4911 - val_loss: 1.7631 - val_mae: 0.9497 - val_mape: 2.5298
Epoch 24/25
322/322 [=====] - 5s 15ms/step - loss: 0.1209 - mae:
0.1700 - mape: 3.6531 - val_loss: 1.6537 - val_mae: 0.9123 - val_mape: 2.4234
Epoch 25/25
322/322 [=====] - 6s 18ms/step - loss: 0.1284 - mae:
0.1786 - mape: 4.0440 - val_loss: 2.2142 - val_mae: 1.1400 - val_mape: 2.9913
139.46725749969482
compiling baseline model...
fitting model...
Epoch 1/25
84/84 [=====] - 3s 18ms/step - loss: 39.9961 - mae:
3.4724 - mape: 21.7892 - val_loss: 0.2692 - val_mae: 0.3890 - val_mape: 2.4297
Epoch 2/25
84/84 [=====] - 1s 15ms/step - loss: 0.4610 - mae:
0.4711 - mape: 3.1030 - val_loss: 0.2655 - val_mae: 0.3855 - val_mape: 2.4215
Epoch 3/25
84/84 [=====] - 1s 15ms/step - loss: 0.4248 - mae:
0.4468 - mape: 2.9408 - val_loss: 0.3333 - val_mae: 0.4569 - val_mape: 2.8146
Epoch 4/25
84/84 [=====] - 1s 15ms/step - loss: 0.4041 - mae:
0.4362 - mape: 2.8619 - val_loss: 0.2593 - val_mae: 0.3858 - val_mape: 2.3994
Epoch 5/25
84/84 [=====] - 1s 16ms/step - loss: 0.4036 - mae:
0.4379 - mape: 2.8714 - val_loss: 0.2835 - val_mae: 0.4091 - val_mape: 2.5311
Epoch 6/25
84/84 [=====] - 1s 16ms/step - loss: 0.3993 - mae:
0.4373 - mape: 2.8685 - val_loss: 0.2675 - val_mae: 0.3965 - val_mape: 2.4616
Epoch 7/25
84/84 [=====] - 2s 22ms/step - loss: 0.3927 - mae:
0.4324 - mape: 2.8265 - val_loss: 0.2508 - val_mae: 0.3748 - val_mape: 2.3558
Epoch 8/25

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84/84 [=====] - 2s 23ms/step - loss: 0.4018 - mae: 0.4441 - mape: 2.8997 - val_loss: 0.2445 - val_mae: 0.3680 - val_mape: 2.3090
Epoch 9/25

84/84 [=====] - 2s 22ms/step - loss: 0.3927 - mae: 0.4363 - mape: 2.8532 - val_loss: 0.2528 - val_mae: 0.3764 - val_mape: 2.3708
Epoch 10/25

84/84 [=====] - 1s 15ms/step - loss: 0.3794 - mae: 0.4303 - mape: 2.8103 - val_loss: 0.2893 - val_mae: 0.4203 - val_mape: 2.5950
Epoch 11/25

84/84 [=====] - 1s 15ms/step - loss: 0.3893 - mae: 0.4372 - mape: 2.8548 - val_loss: 0.2506 - val_mae: 0.3766 - val_mape: 2.3702
Epoch 12/25

84/84 [=====] - 1s 15ms/step - loss: 0.3733 - mae: 0.4245 - mape: 2.7783 - val_loss: 0.2455 - val_mae: 0.3771 - val_mape: 2.3387
Epoch 13/25

84/84 [=====] - 1s 15ms/step - loss: 0.4115 - mae: 0.4565 - mape: 2.9689 - val_loss: 0.2572 - val_mae: 0.3834 - val_mape: 2.4107
Epoch 14/25

84/84 [=====] - 1s 16ms/step - loss: 0.3691 - mae: 0.4254 - mape: 2.7802 - val_loss: 0.3051 - val_mae: 0.4398 - val_mape: 2.7082
Epoch 15/25

84/84 [=====] - 1s 16ms/step - loss: 0.3518 - mae: 0.4111 - mape: 2.6928 - val_loss: 0.3034 - val_mae: 0.4387 - val_mape: 2.7012
Epoch 16/25

84/84 [=====] - 1s 16ms/step - loss: 0.3820 - mae: 0.4405 - mape: 2.8543 - val_loss: 0.3518 - val_mae: 0.4838 - val_mape: 2.9659
Epoch 17/25

84/84 [=====] - 2s 21ms/step - loss: 0.3869 - mae: 0.4369 - mape: 2.8477 - val_loss: 0.3447 - val_mae: 0.4794 - val_mape: 2.9439
Epoch 18/25

84/84 [=====] - 2s 24ms/step - loss: 0.3577 - mae: 0.4176 - mape: 2.7247 - val_loss: 0.2148 - val_mae: 0.3450 - val_mape: 2.1594
Epoch 19/25

84/84 [=====] - 2s 19ms/step - loss: 0.3607 - mae: 0.4232 - mape: 2.7563 - val_loss: 0.3039 - val_mae: 0.4360 - val_mape: 2.6848
Epoch 20/25

84/84 [=====] - 1s 16ms/step - loss: 0.3614 - mae: 0.4268 - mape: 2.7829 - val_loss: 0.2074 - val_mae: 0.3392 - val_mape: 2.1166
Epoch 21/25

84/84 [=====] - 1s 16ms/step - loss: 0.3349 - mae: 0.4056 - mape: 2.6460 - val_loss: 0.2668 - val_mae: 0.4062 - val_mape: 2.5082
Epoch 22/25

84/84 [=====] - 1s 15ms/step - loss: 0.3236 - mae: 0.3956 - mape: 2.5861 - val_loss: 0.2064 - val_mae: 0.3406 - val_mape: 2.1215
Epoch 23/25

84/84 [=====] - 1s 15ms/step - loss: 0.3082 - mae: 0.3804 - mape: 2.4943 - val_loss: 0.2025 - val_mae: 0.3356 - val_mape: 2.0975
Epoch 24/25

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84/84 [=====] - 1s 15ms/step - loss: 0.3398 - mae:
0.4105 - mape: 2.6735 - val_loss: 0.2614 - val_mae: 0.4003 - val_mape: 2.4672
Epoch 25/25
84/84 [=====] - 1s 15ms/step - loss: 0.3063 - mae:
0.3805 - mape: 2.4944 - val_loss: 0.3374 - val_mae: 0.4716 - val_mape: 2.9014
37.79146957397461
compiling baseline model...
fitting model...
Epoch 1/25
63/63 [=====] - 4s 28ms/step - loss: 1005.3027 - mae:
18.2373 - mape: 35.5824 - val_loss: 151.3403 - val_mae: 8.9149 - val_mape:
4.8269
Epoch 2/25
63/63 [=====] - 1s 23ms/step - loss: 13.0564 - mae:
2.2532 - mape: 4.5237 - val_loss: 151.3230 - val_mae: 8.9977 - val_mape: 4.8472
Epoch 3/25
63/63 [=====] - 1s 20ms/step - loss: 12.6677 - mae:
2.1797 - mape: 4.3237 - val_loss: 135.1754 - val_mae: 8.4502 - val_mape: 4.6082
Epoch 4/25
63/63 [=====] - 1s 16ms/step - loss: 13.2806 - mae:
2.2974 - mape: 4.5595 - val_loss: 151.3202 - val_mae: 9.0124 - val_mape: 4.8483
Epoch 5/25
63/63 [=====] - 1s 15ms/step - loss: 12.6495 - mae:
2.2048 - mape: 4.3874 - val_loss: 147.6025 - val_mae: 8.9399 - val_mape: 4.8249
Epoch 6/25
63/63 [=====] - 1s 16ms/step - loss: 13.2048 - mae:
2.2742 - mape: 4.4880 - val_loss: 186.4201 - val_mae: 10.2206 - val_mape: 5.4127
Epoch 7/25
63/63 [=====] - 1s 16ms/step - loss: 17.1856 - mae:
2.6886 - mape: 5.2756 - val_loss: 169.8808 - val_mae: 9.6640 - val_mape: 5.1762
Epoch 8/25
63/63 [=====] - 1s 16ms/step - loss: 12.2924 - mae:
2.1869 - mape: 4.3326 - val_loss: 178.7134 - val_mae: 10.1792 - val_mape: 5.4926
Epoch 9/25
63/63 [=====] - 1s 16ms/step - loss: 15.4844 - mae:
2.5631 - mape: 5.0960 - val_loss: 151.2182 - val_mae: 9.0196 - val_mape: 4.8636
Epoch 10/25
63/63 [=====] - 1s 17ms/step - loss: 12.3033 - mae:
2.1521 - mape: 4.2638 - val_loss: 150.1166 - val_mae: 9.0591 - val_mape: 4.9011
Epoch 11/25
63/63 [=====] - 1s 17ms/step - loss: 12.1373 - mae:
2.1805 - mape: 4.3289 - val_loss: 119.3132 - val_mae: 7.8832 - val_mape: 4.3482
Epoch 12/25
63/63 [=====] - 1s 15ms/step - loss: 11.4783 - mae:
2.1050 - mape: 4.2082 - val_loss: 117.8243 - val_mae: 7.9137 - val_mape: 4.3564
Epoch 13/25
63/63 [=====] - 1s 22ms/step - loss: 12.4855 - mae:
2.2234 - mape: 4.4317 - val_loss: 168.5896 - val_mae: 9.7647 - val_mape: 5.2700

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Epoch 14/25
63/63 [=====] - 1s 23ms/step - loss: 11.6312 - mae:
2.1246 - mape: 4.2257 - val_loss: 133.5025 - val_mae: 8.5661 - val_mape: 4.7199
Epoch 15/25
63/63 [=====] - 1s 24ms/step - loss: 14.4061 - mae:
2.4545 - mape: 4.8802 - val_loss: 236.1254 - val_mae: 11.9642 - val_mape: 6.3771
Epoch 16/25
63/63 [=====] - 1s 17ms/step - loss: 12.1662 - mae:
2.1509 - mape: 4.2555 - val_loss: 158.2962 - val_mae: 9.4144 - val_mape: 5.0752
Epoch 17/25
63/63 [=====] - 1s 16ms/step - loss: 12.6490 - mae:
2.2644 - mape: 4.5053 - val_loss: 151.4655 - val_mae: 9.2149 - val_mape: 5.0235
Epoch 18/25
63/63 [=====] - 1s 16ms/step - loss: 11.5805 - mae:
2.0970 - mape: 4.1620 - val_loss: 98.6905 - val_mae: 7.1466 - val_mape: 4.0576
Epoch 19/25
63/63 [=====] - 1s 17ms/step - loss: 13.1488 - mae:
2.3200 - mape: 4.6394 - val_loss: 106.9785 - val_mae: 7.5097 - val_mape: 4.1785
Epoch 20/25
63/63 [=====] - 1s 16ms/step - loss: 11.4071 - mae:
2.0989 - mape: 4.1223 - val_loss: 95.5322 - val_mae: 6.9981 - val_mape: 3.9706
Epoch 21/25
63/63 [=====] - 1s 16ms/step - loss: 12.2032 - mae:
2.1500 - mape: 4.2208 - val_loss: 199.3451 - val_mae: 11.0073 - val_mape: 5.9488
Epoch 22/25
63/63 [=====] - 1s 15ms/step - loss: 11.2693 - mae:
2.1029 - mape: 4.1485 - val_loss: 139.9100 - val_mae: 8.8050 - val_mape: 4.7955
Epoch 23/25
63/63 [=====] - 1s 15ms/step - loss: 11.0241 - mae:
2.0680 - mape: 4.1014 - val_loss: 170.2301 - val_mae: 9.8920 - val_mape: 5.2856
Epoch 24/25
63/63 [=====] - 1s 16ms/step - loss: 11.6642 - mae:
2.1470 - mape: 4.2674 - val_loss: 124.4261 - val_mae: 8.1823 - val_mape: 4.4689
Epoch 25/25
63/63 [=====] - 1s 15ms/step - loss: 11.0505 - mae:
2.0657 - mape: 4.1151 - val_loss: 149.0682 - val_mae: 9.1861 - val_mape: 4.9642
30.21232295036316
compiling baseline model...
fitting model...
Epoch 1/25
165/165 [=====] - 6s 21ms/step - loss: 131.7375 - mae:
4.0643 - mape: 12.1610 - val_loss: 58.2844 - val_mae: 5.8536 - val_mape: 4.1415
Epoch 2/25
165/165 [=====] - 3s 16ms/step - loss: 2.7723 - mae:
1.0766 - mape: 3.3505 - val_loss: 50.8278 - val_mae: 5.4002 - val_mape: 3.8779
Epoch 3/25
165/165 [=====] - 3s 16ms/step - loss: 3.0652 - mae:
1.1494 - mape: 3.5675 - val_loss: 52.5256 - val_mae: 5.5171 - val_mape: 3.9317

Epoch 4/25
165/165 [=====] - 3s 16ms/step - loss: 3.0085 - mae: 1.1392 - mape: 3.5385 - val_loss: 50.5703 - val_mae: 5.4339 - val_mape: 3.8925

Epoch 5/25
165/165 [=====] - 3s 21ms/step - loss: 2.9682 - mae: 1.1214 - mape: 3.4479 - val_loss: 48.6864 - val_mae: 5.2860 - val_mape: 3.7992

Epoch 6/25
165/165 [=====] - 3s 19ms/step - loss: 2.8454 - mae: 1.1000 - mape: 3.4014 - val_loss: 59.1629 - val_mae: 6.0488 - val_mape: 4.2277

Epoch 7/25
165/165 [=====] - 3s 16ms/step - loss: 3.1362 - mae: 1.1485 - mape: 3.5281 - val_loss: 45.3731 - val_mae: 4.9407 - val_mape: 3.6573

Epoch 8/25
165/165 [=====] - 2s 15ms/step - loss: 2.7476 - mae: 1.0722 - mape: 3.3007 - val_loss: 45.1896 - val_mae: 4.9876 - val_mape: 3.6452

Epoch 9/25
165/165 [=====] - 3s 15ms/step - loss: 2.7453 - mae: 1.0910 - mape: 3.3570 - val_loss: 43.6915 - val_mae: 4.8751 - val_mape: 3.5865

Epoch 10/25
165/165 [=====] - 3s 19ms/step - loss: 3.3595 - mae: 1.1877 - mape: 3.5799 - val_loss: 43.9109 - val_mae: 4.8731 - val_mape: 3.5974

Epoch 11/25
165/165 [=====] - 4s 21ms/step - loss: 2.6688 - mae: 1.0575 - mape: 3.2622 - val_loss: 75.7843 - val_mae: 6.9271 - val_mape: 4.7242

Epoch 12/25
165/165 [=====] - 3s 15ms/step - loss: 3.2277 - mae: 1.1754 - mape: 3.5597 - val_loss: 42.6501 - val_mae: 4.8105 - val_mape: 3.5373

Epoch 13/25
165/165 [=====] - 3s 15ms/step - loss: 2.7523 - mae: 1.0768 - mape: 3.2988 - val_loss: 42.5250 - val_mae: 4.8092 - val_mape: 3.5329

Epoch 14/25
165/165 [=====] - 3s 16ms/step - loss: 3.3424 - mae: 1.1835 - mape: 3.5576 - val_loss: 50.3190 - val_mae: 5.3649 - val_mape: 3.8008

Epoch 15/25
165/165 [=====] - 3s 17ms/step - loss: 3.2152 - mae: 1.1573 - mape: 3.5013 - val_loss: 46.0117 - val_mae: 5.1592 - val_mape: 3.6851

Epoch 16/25
165/165 [=====] - 4s 24ms/step - loss: 2.8239 - mae: 1.0771 - mape: 3.2773 - val_loss: 40.9413 - val_mae: 4.7124 - val_mape: 3.4630

Epoch 17/25
165/165 [=====] - 3s 16ms/step - loss: 2.6532 - mae: 1.0512 - mape: 3.2478 - val_loss: 42.1768 - val_mae: 4.7469 - val_mape: 3.5228

Epoch 18/25
165/165 [=====] - 3s 16ms/step - loss: 2.7359 - mae: 1.0816 - mape: 3.3354 - val_loss: 43.9317 - val_mae: 4.9472 - val_mape: 3.5444

Epoch 19/25
165/165 [=====] - 3s 16ms/step - loss: 2.6275 - mae: 1.0601 - mape: 3.2684 - val_loss: 45.1974 - val_mae: 5.1496 - val_mape: 3.6649

Epoch 20/25
165/165 [=====] - 3s 18ms/step - loss: 2.3497 - mae: 0.9985 - mape: 3.1014 - val_loss: 44.8352 - val_mae: 5.1094 - val_mape: 3.6197
Epoch 21/25
165/165 [=====] - 4s 23ms/step - loss: 2.9785 - mae: 1.1256 - mape: 3.3759 - val_loss: 43.9133 - val_mae: 5.0452 - val_mape: 3.6285
Epoch 22/25
165/165 [=====] - 3s 16ms/step - loss: 2.6856 - mae: 1.0563 - mape: 3.2304 - val_loss: 39.4071 - val_mae: 4.5913 - val_mape: 3.3873
Epoch 23/25
165/165 [=====] - 3s 16ms/step - loss: 2.5694 - mae: 1.0357 - mape: 3.1660 - val_loss: 79.7506 - val_mae: 7.4264 - val_mape: 5.0537
Epoch 24/25
165/165 [=====] - 3s 16ms/step - loss: 2.8381 - mae: 1.1087 - mape: 3.3847 - val_loss: 39.3375 - val_mae: 4.6304 - val_mape: 3.3794
Epoch 25/25
165/165 [=====] - 3s 19ms/step - loss: 2.4515 - mae: 1.0045 - mape: 3.0705 - val_loss: 39.4053 - val_mae: 4.6117 - val_mape: 3.4026
84.1632752418518
compiling baseline model...
fitting model...
Epoch 1/25
393/393 [=====] - 10s 21ms/step - loss: 10.6180 - mae: 0.7834 - mape: 15.4576 - val_loss: 19.9283 - val_mae: 3.0309 - val_mape: 2.1530
Epoch 2/25
393/393 [=====] - 6s 16ms/step - loss: 0.6206 - mae: 0.3535 - mape: 6.5409 - val_loss: 25.2125 - val_mae: 3.4712 - val_mape: 2.2996
Epoch 3/25
393/393 [=====] - 8s 20ms/step - loss: 0.5490 - mae: 0.3238 - mape: 5.9475 - val_loss: 24.8226 - val_mae: 3.4847 - val_mape: 2.3468
Epoch 4/25
393/393 [=====] - 7s 18ms/step - loss: 0.6174 - mae: 0.3554 - mape: 7.4258 - val_loss: 28.5767 - val_mae: 3.7562 - val_mape: 2.4366
Epoch 5/25
393/393 [=====] - 8s 22ms/step - loss: 0.6014 - mae: 0.3430 - mape: 5.9768 - val_loss: 22.2774 - val_mae: 3.2969 - val_mape: 2.1695
Epoch 6/25
393/393 [=====] - 6s 16ms/step - loss: 0.5198 - mae: 0.3202 - mape: 5.2400 - val_loss: 25.7554 - val_mae: 3.5853 - val_mape: 2.3874
Epoch 7/25
393/393 [=====] - 8s 20ms/step - loss: 0.4954 - mae: 0.3155 - mape: 5.5037 - val_loss: 30.5711 - val_mae: 4.0395 - val_mape: 2.6662
Epoch 8/25
393/393 [=====] - 6s 16ms/step - loss: 0.4941 - mae: 0.3125 - mape: 5.2486 - val_loss: 99.6423 - val_mae: 8.2691 - val_mape: 5.2794
Epoch 9/25
393/393 [=====] - 8s 20ms/step - loss: 0.4723 - mae: 0.3084 - mape: 5.3110 - val_loss: 71.0373 - val_mae: 6.6161 - val_mape: 4.0753

Epoch 10/25
393/393 [=====] - 6s 16ms/step - loss: 0.4985 - mae:
0.3189 - mape: 5.4389 - val_loss: 47.9510 - val_mae: 5.4764 - val_mape: 3.6032
Epoch 11/25
393/393 [=====] - 8s 19ms/step - loss: 0.4558 - mae:
0.3015 - mape: 5.2690 - val_loss: 26.5777 - val_mae: 3.8130 - val_mape: 2.5235
81.79249477386475
compiling baseline model...
fitting model...
Epoch 1/25
67/67 [=====] - 3s 21ms/step - loss: 926.9507 - mae:
15.9440 - mape: 20.0800 - val_loss: 19.1514 - val_mae: 3.4449 - val_mape: 3.1852
Epoch 2/25
67/67 [=====] - 1s 16ms/step - loss: 10.2164 - mae:
2.2064 - mape: 2.7259 - val_loss: 17.7018 - val_mae: 3.3246 - val_mape: 3.0769
Epoch 3/25
67/67 [=====] - 1s 16ms/step - loss: 10.1009 - mae:
2.1825 - mape: 2.6988 - val_loss: 19.0957 - val_mae: 3.4554 - val_mape: 3.2108
Epoch 4/25
67/67 [=====] - 1s 16ms/step - loss: 9.9082 - mae:
2.1785 - mape: 2.6934 - val_loss: 18.8224 - val_mae: 3.4290 - val_mape: 3.1860
Epoch 5/25
67/67 [=====] - 1s 16ms/step - loss: 9.7764 - mae:
2.1466 - mape: 2.6488 - val_loss: 18.0468 - val_mae: 3.3281 - val_mape: 3.0483
Epoch 6/25
67/67 [=====] - 1s 16ms/step - loss: 9.5217 - mae:
2.0855 - mape: 2.5686 - val_loss: 18.1611 - val_mae: 3.3327 - val_mape: 3.0511
Epoch 7/25
67/67 [=====] - 1s 17ms/step - loss: 9.2994 - mae:
2.0705 - mape: 2.5567 - val_loss: 18.0967 - val_mae: 3.3420 - val_mape: 3.0581
Epoch 8/25
67/67 [=====] - 1s 22ms/step - loss: 9.8742 - mae:
2.1809 - mape: 2.6910 - val_loss: 19.9894 - val_mae: 3.5199 - val_mape: 3.2172
Epoch 9/25
67/67 [=====] - 2s 22ms/step - loss: 10.0482 - mae:
2.2028 - mape: 2.7298 - val_loss: 20.2870 - val_mae: 3.5231 - val_mape: 3.2077
Epoch 10/25
67/67 [=====] - 2s 23ms/step - loss: 9.5184 - mae:
2.1252 - mape: 2.6214 - val_loss: 26.0870 - val_mae: 4.0919 - val_mape: 3.6996
Epoch 11/25
67/67 [=====] - 1s 21ms/step - loss: 9.9744 - mae:
2.2106 - mape: 2.7326 - val_loss: 16.0712 - val_mae: 3.1520 - val_mape: 2.9028
Epoch 12/25
67/67 [=====] - 1s 16ms/step - loss: 8.7912 - mae:
2.0188 - mape: 2.4908 - val_loss: 16.8400 - val_mae: 3.2032 - val_mape: 2.9358
Epoch 13/25
67/67 [=====] - 1s 16ms/step - loss: 10.4632 - mae:
2.2895 - mape: 2.8336 - val_loss: 19.6161 - val_mae: 3.5171 - val_mape: 3.2667

Epoch 14/25
67/67 [=====] - 1s 15ms/step - loss: 9.5231 - mae:
2.1259 - mape: 2.6336 - val_loss: 17.5401 - val_mae: 3.2953 - val_mape: 3.0598
Epoch 15/25
67/67 [=====] - 1s 17ms/step - loss: 8.9388 - mae:
2.0429 - mape: 2.5156 - val_loss: 24.2076 - val_mae: 3.9735 - val_mape: 3.6933
Epoch 16/25
67/67 [=====] - 1s 16ms/step - loss: 9.7986 - mae:
2.1716 - mape: 2.6774 - val_loss: 15.5292 - val_mae: 3.0904 - val_mape: 2.8491
Epoch 17/25
67/67 [=====] - 1s 17ms/step - loss: 9.3905 - mae:
2.1206 - mape: 2.6099 - val_loss: 19.7310 - val_mae: 3.5432 - val_mape: 3.2932
Epoch 18/25
67/67 [=====] - 1s 17ms/step - loss: 9.8299 - mae:
2.1976 - mape: 2.7162 - val_loss: 21.2679 - val_mae: 3.6664 - val_mape: 3.3337
Epoch 19/25
67/67 [=====] - 1s 17ms/step - loss: 9.4201 - mae:
2.1214 - mape: 2.6246 - val_loss: 15.5203 - val_mae: 3.0741 - val_mape: 2.8287
Epoch 20/25
67/67 [=====] - 1s 19ms/step - loss: 9.4392 - mae:
2.1242 - mape: 2.6190 - val_loss: 15.2077 - val_mae: 3.0637 - val_mape: 2.8347
Epoch 21/25
67/67 [=====] - 2s 23ms/step - loss: 8.4973 - mae:
1.9970 - mape: 2.4696 - val_loss: 15.3191 - val_mae: 3.0662 - val_mape: 2.8436
Epoch 22/25
67/67 [=====] - 2s 23ms/step - loss: 8.7800 - mae:
2.0255 - mape: 2.4975 - val_loss: 16.8352 - val_mae: 3.2378 - val_mape: 3.0042
Epoch 23/25
67/67 [=====] - 1s 21ms/step - loss: 9.5387 - mae:
2.1492 - mape: 2.6564 - val_loss: 23.2868 - val_mae: 3.9029 - val_mape: 3.6299
Epoch 24/25
67/67 [=====] - 1s 15ms/step - loss: 9.5619 - mae:
2.1855 - mape: 2.7027 - val_loss: 28.7104 - val_mae: 4.3714 - val_mape: 3.9466
Epoch 25/25
67/67 [=====] - 1s 16ms/step - loss: 9.3105 - mae:
2.1286 - mape: 2.6161 - val_loss: 16.4776 - val_mae: 3.1461 - val_mape: 2.8751
42.521421670913696
compiling baseline model...
fitting model...
Epoch 1/25
147/147 [=====] - 4s 18ms/step - loss: 1070.5652 - mae:
9.3787 - mape: 21.1882 - val_loss: 634.3154 - val_mae: 17.6535 - val_mape:
5.1416
Epoch 2/25
147/147 [=====] - 2s 16ms/step - loss: 52.6652 - mae:
2.9426 - mape: 6.6789 - val_loss: 701.4633 - val_mae: 19.1715 - val_mape: 5.3663
Epoch 3/25
147/147 [=====] - 2s 15ms/step - loss: 45.6720 - mae:

2.8178 - mape: 6.8184 - val_loss: 1871.2869 - val_mae: 35.1731 - val_mape: 9.4519

Epoch 4/25

147/147 [=====] - 3s 22ms/step - loss: 49.5499 - mae: 2.9633 - mape: 6.9065 - val_loss: 677.4218 - val_mae: 18.4914 - val_mape: 5.3642

Epoch 5/25

147/147 [=====] - 3s 22ms/step - loss: 47.4011 - mae: 2.8644 - mape: 6.6160 - val_loss: 605.9606 - val_mae: 17.4037 - val_mape: 4.9459

Epoch 6/25

147/147 [=====] - 2s 16ms/step - loss: 41.3235 - mae: 2.6405 - mape: 6.3800 - val_loss: 577.9230 - val_mae: 16.7781 - val_mape: 4.8216

Epoch 7/25

147/147 [=====] - 2s 16ms/step - loss: 38.7724 - mae: 2.4682 - mape: 5.7958 - val_loss: 1068.0867 - val_mae: 24.8811 - val_mape: 6.6804

Epoch 8/25

147/147 [=====] - 2s 16ms/step - loss: 47.7437 - mae: 2.8729 - mape: 6.5032 - val_loss: 604.5875 - val_mae: 17.3325 - val_mape: 4.9990

Epoch 9/25

147/147 [=====] - 2s 16ms/step - loss: 43.7342 - mae: 2.7211 - mape: 6.2100 - val_loss: 564.4574 - val_mae: 16.5230 - val_mape: 4.7775

Epoch 10/25

147/147 [=====] - 3s 22ms/step - loss: 43.6423 - mae: 2.6961 - mape: 6.2560 - val_loss: 805.0975 - val_mae: 21.2238 - val_mape: 5.8029

Epoch 11/25

147/147 [=====] - 3s 19ms/step - loss: 40.4763 - mae: 2.6013 - mape: 6.0131 - val_loss: 593.1223 - val_mae: 17.2816 - val_mape: 5.0629

Epoch 12/25

147/147 [=====] - 2s 16ms/step - loss: 47.5221 - mae: 2.9913 - mape: 7.1815 - val_loss: 1013.4514 - val_mae: 24.4523 - val_mape: 7.0748

Epoch 13/25

147/147 [=====] - 2s 16ms/step - loss: 43.8661 - mae: 2.7159 - mape: 6.1240 - val_loss: 537.4086 - val_mae: 16.0726 - val_mape: 4.6299

Epoch 14/25

147/147 [=====] - 2s 16ms/step - loss: 36.4066 - mae: 2.3472 - mape: 5.3284 - val_loss: 704.7366 - val_mae: 19.1106 - val_mape: 5.5730

Epoch 15/25

147/147 [=====] - 3s 18ms/step - loss: 41.5524 - mae: 2.6213 - mape: 5.9003 - val_loss: 555.5264 - val_mae: 16.4711 - val_mape: 4.7845

Epoch 16/25

147/147 [=====] - 3s 23ms/step - loss: 44.4254 - mae: 2.7669 - mape: 6.2882 - val_loss: 747.8137 - val_mae: 20.3877 - val_mape: 5.6046

Epoch 17/25

147/147 [=====] - 2s 17ms/step - loss: 36.1427 - mae: 2.4572 - mape: 5.8221 - val_loss: 544.5390 - val_mae: 16.4668 - val_mape: 4.7978

Epoch 18/25

147/147 [=====] - 2s 15ms/step - loss: 35.8086 - mae:

2.4243 - mape: 5.5119 - val_loss: 516.3315 - val_mae: 15.6992 - val_mape: 4.4811
Epoch 19/25
147/147 [=====] - 2s 16ms/step - loss: 32.8974 - mae:
2.2586 - mape: 5.3002 - val_loss: 611.0509 - val_mae: 17.3141 - val_mape: 4.8195
Epoch 20/25
147/147 [=====] - 2s 15ms/step - loss: 35.1703 - mae:
2.4328 - mape: 5.6176 - val_loss: 719.4583 - val_mae: 19.4142 - val_mape: 5.6168
Epoch 21/25
147/147 [=====] - 3s 19ms/step - loss: 36.7197 - mae:
2.4307 - mape: 5.5754 - val_loss: 579.1429 - val_mae: 17.0545 - val_mape: 4.9746
Epoch 22/25
147/147 [=====] - 3s 23ms/step - loss: 37.8960 - mae:
2.4800 - mape: 5.5774 - val_loss: 506.4459 - val_mae: 15.3139 - val_mape: 4.3810
Epoch 23/25
147/147 [=====] - 2s 17ms/step - loss: 47.7755 - mae:
2.9466 - mape: 6.5302 - val_loss: 870.5408 - val_mae: 21.8308 - val_mape: 6.0212
Epoch 24/25
147/147 [=====] - 2s 15ms/step - loss: 38.3496 - mae:
2.4574 - mape: 5.5301 - val_loss: 595.8035 - val_mae: 17.2228 - val_mape: 5.0014
Epoch 25/25
147/147 [=====] - 2s 17ms/step - loss: 41.9996 - mae:
2.6359 - mape: 5.8079 - val_loss: 627.1155 - val_mae: 18.3902 - val_mape: 5.1526
83.4506528377533
compiling baseline model...
fitting model...
Epoch 1/25
256/256 [=====] - 6s 17ms/step - loss: 1.9473 - mae:
0.5566 - mape: 15.5007 - val_loss: 0.4859 - val_mae: 0.5712 - val_mape: 3.3640
Epoch 2/25
256/256 [=====] - 4s 17ms/step - loss: 0.0359 - mae:
0.1217 - mape: 2.7578 - val_loss: 0.2714 - val_mae: 0.3704 - val_mape: 2.2438
Epoch 3/25
256/256 [=====] - 5s 21ms/step - loss: 0.0376 - mae:
0.1253 - mape: 2.8263 - val_loss: 0.3092 - val_mae: 0.4189 - val_mape: 2.4989
Epoch 4/25
256/256 [=====] - 4s 17ms/step - loss: 0.0354 - mae:
0.1213 - mape: 2.7050 - val_loss: 0.2499 - val_mae: 0.3600 - val_mape: 2.1694
Epoch 5/25
256/256 [=====] - 4s 16ms/step - loss: 0.0362 - mae:
0.1223 - mape: 2.7569 - val_loss: 0.5437 - val_mae: 0.6067 - val_mape: 3.6844
Epoch 6/25
256/256 [=====] - 4s 17ms/step - loss: 0.0420 - mae:
0.1314 - mape: 2.8791 - val_loss: 0.2456 - val_mae: 0.3577 - val_mape: 2.1535
Epoch 7/25
256/256 [=====] - 5s 20ms/step - loss: 0.0354 - mae:
0.1211 - mape: 2.6608 - val_loss: 0.2500 - val_mae: 0.3720 - val_mape: 2.2278
Epoch 8/25
256/256 [=====] - 4s 16ms/step - loss: 0.0335 - mae:

0.1179 - mape: 2.6409 - val_loss: 0.2284 - val_mae: 0.3389 - val_mape: 2.0482
Epoch 9/25
256/256 [=====] - 4s 16ms/step - loss: 0.0338 - mae:
0.1194 - mape: 2.7477 - val_loss: 0.2853 - val_mae: 0.4102 - val_mape: 2.4445
Epoch 10/25
256/256 [=====] - 6s 22ms/step - loss: 0.0343 - mae:
0.1192 - mape: 2.6479 - val_loss: 0.2123 - val_mae: 0.3257 - val_mape: 1.9613
Epoch 11/25
256/256 [=====] - 4s 15ms/step - loss: 0.0294 - mae:
0.1088 - mape: 2.4121 - val_loss: 0.2105 - val_mae: 0.3258 - val_mape: 1.9587
Epoch 12/25
256/256 [=====] - 4s 15ms/step - loss: 0.0322 - mae:
0.1154 - mape: 2.5202 - val_loss: 0.2702 - val_mae: 0.3787 - val_mape: 2.3010
Epoch 13/25
256/256 [=====] - 5s 19ms/step - loss: 0.0329 - mae:
0.1164 - mape: 2.5251 - val_loss: 0.2093 - val_mae: 0.3220 - val_mape: 1.9438
Epoch 14/25
256/256 [=====] - 5s 18ms/step - loss: 0.0278 - mae:
0.1056 - mape: 2.3336 - val_loss: 0.2102 - val_mae: 0.3144 - val_mape: 1.9086
Epoch 15/25
256/256 [=====] - 4s 15ms/step - loss: 0.0273 - mae:
0.1042 - mape: 2.3343 - val_loss: 0.1941 - val_mae: 0.3053 - val_mape: 1.8459
Epoch 16/25
256/256 [=====] - 4s 17ms/step - loss: 0.0286 - mae:
0.1075 - mape: 2.3461 - val_loss: 0.1984 - val_mae: 0.3126 - val_mape: 1.8870
Epoch 17/25
256/256 [=====] - 5s 21ms/step - loss: 0.0314 - mae:
0.1138 - mape: 2.5243 - val_loss: 0.2216 - val_mae: 0.3520 - val_mape: 2.1004
Epoch 18/25
256/256 [=====] - 4s 16ms/step - loss: 0.0277 - mae:
0.1052 - mape: 2.3501 - val_loss: 0.1964 - val_mae: 0.3027 - val_mape: 1.8350
Epoch 19/25
256/256 [=====] - 4s 15ms/step - loss: 0.0295 - mae:
0.1089 - mape: 2.3583 - val_loss: 0.1911 - val_mae: 0.3017 - val_mape: 1.8219
Epoch 20/25
256/256 [=====] - 5s 20ms/step - loss: 0.0267 - mae:
0.1024 - mape: 2.2072 - val_loss: 0.2291 - val_mae: 0.3463 - val_mape: 2.1073
Epoch 21/25
256/256 [=====] - 4s 17ms/step - loss: 0.0280 - mae:
0.1056 - mape: 2.2775 - val_loss: 0.3068 - val_mae: 0.4474 - val_mape: 2.6598
Epoch 22/25
256/256 [=====] - 4s 15ms/step - loss: 0.0304 - mae:
0.1118 - mape: 2.4891 - val_loss: 0.1999 - val_mae: 0.3089 - val_mape: 1.8755
Epoch 23/25
256/256 [=====] - 5s 18ms/step - loss: 0.0301 - mae:
0.1098 - mape: 2.4093 - val_loss: 0.2066 - val_mae: 0.3171 - val_mape: 1.9260
Epoch 24/25
256/256 [=====] - 5s 21ms/step - loss: 0.0276 - mae:

0.1046 - mape: 2.2814 - val_loss: 0.2092 - val_mae: 0.3399 - val_mape: 2.0387
 Epoch 25/25
 256/256 [=====] - 4s 16ms/step - loss: 0.0267 - mae:
 0.1036 - mape: 2.2873 - val_loss: 0.2510 - val_mae: 0.3730 - val_mape: 2.2613
 143.92073369026184
 compiling baseline model...
 fitting model...
 Epoch 1/25
 216/216 [=====] - 6s 17ms/step - loss: 16.9078 - mae:
 1.6013 - mape: 22.8805 - val_loss: 2.0112 - val_mae: 1.0474 - val_mape: 2.4740
 Epoch 2/25
 216/216 [=====] - 3s 16ms/step - loss: 0.8975 - mae:
 0.5551 - mape: 7.0726 - val_loss: 2.1647 - val_mae: 1.0874 - val_mape: 2.6023
 Epoch 3/25
 216/216 [=====] - 5s 23ms/step - loss: 0.8382 - mae:
 0.5357 - mape: 6.7248 - val_loss: 2.6437 - val_mae: 1.2204 - val_mape: 2.9125
 Epoch 4/25
 216/216 [=====] - 3s 15ms/step - loss: 0.8336 - mae:
 0.5352 - mape: 6.6070 - val_loss: 2.0337 - val_mae: 1.0722 - val_mape: 2.5236
 Epoch 5/25
 216/216 [=====] - 3s 16ms/step - loss: 0.8309 - mae:
 0.5316 - mape: 6.1525 - val_loss: 2.6480 - val_mae: 1.3098 - val_mape: 3.0531
 Epoch 6/25
 216/216 [=====] - 4s 18ms/step - loss: 0.7096 - mae:
 0.4908 - mape: 5.6854 - val_loss: 2.2339 - val_mae: 1.1624 - val_mape: 2.6977
 Epoch 7/25
 216/216 [=====] - 5s 22ms/step - loss: 0.7891 - mae:
 0.5219 - mape: 6.2997 - val_loss: 1.9085 - val_mae: 1.0223 - val_mape: 2.4147
 Epoch 8/25
 216/216 [=====] - 3s 16ms/step - loss: 0.7024 - mae:
 0.4862 - mape: 5.3858 - val_loss: 2.8127 - val_mae: 1.3413 - val_mape: 3.0937
 Epoch 9/25
 216/216 [=====] - 3s 16ms/step - loss: 0.6823 - mae:
 0.4810 - mape: 5.2611 - val_loss: 1.8042 - val_mae: 1.0338 - val_mape: 2.4239
 Epoch 10/25
 216/216 [=====] - 4s 18ms/step - loss: 0.6960 - mae:
 0.4899 - mape: 5.1350 - val_loss: 1.6115 - val_mae: 0.9242 - val_mape: 2.1872
 Epoch 11/25
 216/216 [=====] - 5s 22ms/step - loss: 0.7133 - mae:
 0.4939 - mape: 5.9701 - val_loss: 1.8371 - val_mae: 1.0159 - val_mape: 2.3757
 Epoch 12/25
 216/216 [=====] - 3s 16ms/step - loss: 0.6721 - mae:
 0.4792 - mape: 4.9809 - val_loss: 1.5575 - val_mae: 0.9322 - val_mape: 2.1843
 Epoch 13/25
 216/216 [=====] - 3s 16ms/step - loss: 0.6375 - mae:
 0.4614 - mape: 5.2724 - val_loss: 7.8356 - val_mae: 2.5608 - val_mape: 5.8846
 Epoch 14/25
 216/216 [=====] - 4s 16ms/step - loss: 0.6188 - mae:

0.4449 - mape: 4.8579 - val_loss: 1.7327 - val_mae: 1.0182 - val_mape: 2.3772
Epoch 15/25
216/216 [=====] - 5s 24ms/step - loss: 0.6499 - mae:
0.4748 - mape: 5.0703 - val_loss: 5.3792 - val_mae: 1.9452 - val_mape: 4.4598
Epoch 16/25
216/216 [=====] - 3s 16ms/step - loss: 0.6343 - mae:
0.4538 - mape: 5.0899 - val_loss: 2.3941 - val_mae: 1.2653 - val_mape: 2.9177
Epoch 17/25
216/216 [=====] - 3s 16ms/step - loss: 0.6185 - mae:
0.4497 - mape: 4.9277 - val_loss: 1.5449 - val_mae: 0.8898 - val_mape: 2.1009
Epoch 18/25
216/216 [=====] - 4s 18ms/step - loss: 0.6292 - mae:
0.4567 - mape: 5.1599 - val_loss: 2.9918 - val_mae: 1.3497 - val_mape: 3.1910
Epoch 19/25
216/216 [=====] - 5s 22ms/step - loss: 0.6615 - mae:
0.4696 - mape: 5.1546 - val_loss: 1.5504 - val_mae: 0.9329 - val_mape: 2.1890
Epoch 20/25
216/216 [=====] - 3s 16ms/step - loss: 0.5858 - mae:
0.4319 - mape: 4.9398 - val_loss: 1.7525 - val_mae: 0.9900 - val_mape: 2.3558
Epoch 21/25
216/216 [=====] - 3s 16ms/step - loss: 0.5843 - mae:
0.4300 - mape: 4.5147 - val_loss: 1.6051 - val_mae: 0.9671 - val_mape: 2.2461
Epoch 22/25
216/216 [=====] - 4s 18ms/step - loss: 0.6032 - mae:
0.4429 - mape: 4.6341 - val_loss: 3.0414 - val_mae: 1.4086 - val_mape: 3.3217
Epoch 23/25
216/216 [=====] - 5s 21ms/step - loss: 0.5423 - mae:
0.4090 - mape: 4.6743 - val_loss: 1.5256 - val_mae: 0.8838 - val_mape: 2.1037
Epoch 24/25
216/216 [=====] - 3s 15ms/step - loss: 0.6080 - mae:
0.4488 - mape: 4.8258 - val_loss: 2.2915 - val_mae: 1.2569 - val_mape: 2.8949
Epoch 25/25
216/216 [=====] - 3s 16ms/step - loss: 0.6121 - mae:
0.4503 - mape: 5.0317 - val_loss: 2.3006 - val_mae: 1.1818 - val_mape: 2.8046
144.09084558486938
compiling baseline model...
fitting model...
Epoch 1/25
322/322 [=====] - 8s 20ms/step - loss: 8.1009 - mae:
0.8462 - mape: 16.9297 - val_loss: 3.5211 - val_mae: 1.4168 - val_mape: 2.1913
Epoch 2/25
322/322 [=====] - 5s 16ms/step - loss: 0.1995 - mae:
0.2389 - mape: 3.6824 - val_loss: 2.5905 - val_mae: 1.2316 - val_mape: 1.9002
Epoch 3/25
322/322 [=====] - 5s 16ms/step - loss: 0.2125 - mae:
0.2478 - mape: 3.8012 - val_loss: 4.2581 - val_mae: 1.7250 - val_mape: 2.6600
Epoch 4/25
322/322 [=====] - 7s 21ms/step - loss: 0.2116 - mae:

0.2483 - mape: 4.1545 - val_loss: 2.2077 - val_mae: 1.0991 - val_mape: 1.6946
Epoch 5/25
322/322 [=====] - 5s 16ms/step - loss: 0.2182 - mae:
0.2496 - mape: 3.8082 - val_loss: 2.1896 - val_mae: 1.0845 - val_mape: 1.6715
Epoch 6/25
322/322 [=====] - 5s 16ms/step - loss: 0.2319 - mae:
0.2561 - mape: 3.7259 - val_loss: 2.2127 - val_mae: 1.0888 - val_mape: 1.6760
Epoch 7/25
322/322 [=====] - 7s 20ms/step - loss: 0.2421 - mae:
0.2621 - mape: 4.1018 - val_loss: 2.5382 - val_mae: 1.1788 - val_mape: 1.8243
Epoch 8/25
322/322 [=====] - 5s 16ms/step - loss: 0.2375 - mae:
0.2636 - mape: 4.6120 - val_loss: 3.1405 - val_mae: 1.3514 - val_mape: 2.0976
Epoch 9/25
322/322 [=====] - 6s 18ms/step - loss: 0.2200 - mae:
0.2496 - mape: 3.6781 - val_loss: 2.6126 - val_mae: 1.2608 - val_mape: 1.9372
Epoch 10/25
322/322 [=====] - 6s 19ms/step - loss: 0.2486 - mae:
0.2699 - mape: 4.2190 - val_loss: 2.8268 - val_mae: 1.3416 - val_mape: 2.0721
Epoch 11/25
322/322 [=====] - 5s 16ms/step - loss: 0.2371 - mae:
0.2611 - mape: 3.7096 - val_loss: 2.0959 - val_mae: 1.0611 - val_mape: 1.6351
Epoch 12/25
322/322 [=====] - 7s 20ms/step - loss: 0.2112 - mae:
0.2440 - mape: 3.4071 - val_loss: 2.8985 - val_mae: 1.2918 - val_mape: 2.0039
Epoch 13/25
322/322 [=====] - 5s 17ms/step - loss: 0.2174 - mae:
0.2495 - mape: 3.5887 - val_loss: 3.5680 - val_mae: 1.4773 - val_mape: 2.2917
Epoch 14/25
322/322 [=====] - 5s 16ms/step - loss: 0.2245 - mae:
0.2560 - mape: 3.8327 - val_loss: 2.1748 - val_mae: 1.0653 - val_mape: 1.6479
Epoch 15/25
322/322 [=====] - 7s 22ms/step - loss: 0.1835 - mae:
0.2283 - mape: 3.3585 - val_loss: 2.7245 - val_mae: 1.2522 - val_mape: 1.9451
Epoch 16/25
322/322 [=====] - 5s 16ms/step - loss: 0.2158 - mae:
0.2442 - mape: 3.3581 - val_loss: 3.7049 - val_mae: 1.5348 - val_mape: 2.3879
Epoch 17/25
322/322 [=====] - 6s 18ms/step - loss: 0.1951 - mae:
0.2350 - mape: 3.2983 - val_loss: 2.2498 - val_mae: 1.1405 - val_mape: 1.7481
Epoch 18/25
322/322 [=====] - 6s 19ms/step - loss: 0.1876 - mae:
0.2326 - mape: 3.4844 - val_loss: 3.7908 - val_mae: 1.6170 - val_mape: 2.4644
Epoch 19/25
322/322 [=====] - 5s 16ms/step - loss: 0.2056 - mae:
0.2448 - mape: 3.5989 - val_loss: 4.8752 - val_mae: 1.8425 - val_mape: 2.8765
Epoch 20/25
322/322 [=====] - 6s 19ms/step - loss: 0.2219 - mae:

0.2533 - mape: 3.9082 - val_loss: 2.1232 - val_mae: 1.0602 - val_mape: 1.6430
 Epoch 21/25
 322/322 [=====] - 6s 17ms/step - loss: 0.1849 - mae:
 0.2296 - mape: 3.4768 - val_loss: 2.4039 - val_mae: 1.1986 - val_mape: 1.8320
 122.69381642341614
 compiling baseline model...
 fitting model...
 Epoch 1/25
 197/197 [=====] - 5s 17ms/step - loss: 102.4443 - mae:
 3.2513 - mape: 13.2110 - val_loss: 408.8391 - val_mae: 15.2958 - val_mape:
 3.9002
 Epoch 2/25
 197/197 [=====] - 3s 16ms/step - loss: 2.9635 - mae:
 1.0604 - mape: 4.4948 - val_loss: 403.2753 - val_mae: 15.4003 - val_mape: 3.9586
 Epoch 3/25
 197/197 [=====] - 5s 24ms/step - loss: 2.9468 - mae:
 1.0577 - mape: 4.4529 - val_loss: 411.8928 - val_mae: 15.7558 - val_mape: 4.0854
 Epoch 4/25
 197/197 [=====] - 6s 31ms/step - loss: 3.0980 - mae:
 1.0937 - mape: 4.5407 - val_loss: 323.9511 - val_mae: 13.3492 - val_mape: 3.4304
 Epoch 5/25
 197/197 [=====] - 4s 19ms/step - loss: 2.8333 - mae:
 1.0461 - mape: 4.4188 - val_loss: 303.9059 - val_mae: 12.9358 - val_mape: 3.3855
 Epoch 6/25
 197/197 [=====] - 4s 22ms/step - loss: 2.9826 - mae:
 1.0665 - mape: 4.3706 - val_loss: 290.3390 - val_mae: 11.8362 - val_mape: 3.1108
 Epoch 7/25
 197/197 [=====] - 4s 18ms/step - loss: 3.1251 - mae:
 1.1068 - mape: 4.5319 - val_loss: 287.1730 - val_mae: 12.4553 - val_mape: 3.2390
 Epoch 8/25
 197/197 [=====] - 3s 16ms/step - loss: 2.7808 - mae:
 1.0289 - mape: 4.2655 - val_loss: 294.2455 - val_mae: 12.4906 - val_mape: 3.2464
 Epoch 9/25
 197/197 [=====] - 3s 16ms/step - loss: 2.9868 - mae:
 1.0799 - mape: 4.5709 - val_loss: 289.5334 - val_mae: 12.1167 - val_mape: 3.1534
 Epoch 10/25
 197/197 [=====] - 4s 21ms/step - loss: 3.2593 - mae:
 1.1047 - mape: 4.4456 - val_loss: 281.5163 - val_mae: 11.6751 - val_mape: 3.0702
 Epoch 11/25
 197/197 [=====] - 4s 19ms/step - loss: 2.7795 - mae:
 1.0188 - mape: 4.2351 - val_loss: 283.2442 - val_mae: 11.6812 - val_mape: 3.0619
 Epoch 12/25
 197/197 [=====] - 3s 16ms/step - loss: 2.7754 - mae:
 1.0138 - mape: 4.1183 - val_loss: 351.3686 - val_mae: 13.1156 - val_mape: 3.4786
 Epoch 13/25
 197/197 [=====] - 3s 16ms/step - loss: 2.8471 - mae:
 1.0522 - mape: 4.2735 - val_loss: 311.2166 - val_mae: 13.1707 - val_mape: 3.3786
 Epoch 14/25


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197/197 [=====] - 3s 18ms/step - loss: 2.7028 - mae:
1.0130 - mape: 4.2548 - val_loss: 490.6993 - val_mae: 17.4946 - val_mape: 4.4758
Epoch 15/25
197/197 [=====] - 5s 23ms/step - loss: 2.5962 - mae:
0.9922 - mape: 4.1039 - val_loss: 278.0109 - val_mae: 11.5238 - val_mape: 3.0230
Epoch 16/25
197/197 [=====] - 3s 17ms/step - loss: 2.8522 - mae:
1.0529 - mape: 4.2199 - val_loss: 268.3246 - val_mae: 11.4618 - val_mape: 3.0136
Epoch 17/25
197/197 [=====] - 3s 16ms/step - loss: 2.5543 - mae:
0.9790 - mape: 4.0729 - val_loss: 291.2288 - val_mae: 11.7465 - val_mape: 3.1031
Epoch 18/25
197/197 [=====] - 3s 16ms/step - loss: 2.6183 - mae:
0.9957 - mape: 4.1310 - val_loss: 275.6026 - val_mae: 11.5156 - val_mape: 3.0258
Epoch 19/25
197/197 [=====] - 4s 22ms/step - loss: 2.6008 - mae:
0.9856 - mape: 3.9618 - val_loss: 383.4843 - val_mae: 15.0193 - val_mape: 3.8802
Epoch 20/25
197/197 [=====] - 4s 20ms/step - loss: 2.5437 - mae:
0.9754 - mape: 3.9632 - val_loss: 269.3123 - val_mae: 11.5450 - val_mape: 3.0182
Epoch 21/25
197/197 [=====] - 3s 16ms/step - loss: 2.6819 - mae:
0.9941 - mape: 3.9629 - val_loss: 266.2090 - val_mae: 11.9814 - val_mape: 3.1300
Epoch 22/25
197/197 [=====] - 3s 16ms/step - loss: 2.4746 - mae:
0.9454 - mape: 3.8340 - val_loss: 262.0930 - val_mae: 11.5537 - val_mape: 2.9954
Epoch 23/25
197/197 [=====] - 4s 18ms/step - loss: 2.3669 - mae:
0.9276 - mape: 3.8491 - val_loss: 428.9417 - val_mae: 16.2748 - val_mape: 4.1802
Epoch 24/25
197/197 [=====] - 5s 24ms/step - loss: 2.5482 - mae:
0.9722 - mape: 3.9547 - val_loss: 284.2469 - val_mae: 12.3384 - val_mape: 3.1755
Epoch 25/25
197/197 [=====] - 3s 16ms/step - loss: 2.4067 - mae:
0.9397 - mape: 3.7685 - val_loss: 233.0759 - val_mae: 10.8022 - val_mape: 2.8398
94.86834955215454
compiling baseline model...
fitting model...
Epoch 1/25
324/324 [=====] - 7s 18ms/step - loss: 3.0201 - mae:
0.5125 - mape: 18.4880 - val_loss: 7.9987 - val_mae: 2.0354 - val_mape: 2.9903
Epoch 2/25
324/324 [=====] - 7s 20ms/step - loss: 0.0571 - mae:
0.1268 - mape: 3.3906 - val_loss: 25.1601 - val_mae: 4.1498 - val_mape: 6.2139
Epoch 3/25
324/324 [=====] - 5s 16ms/step - loss: 0.0644 - mae:
0.1411 - mape: 4.5415 - val_loss: 8.9091 - val_mae: 2.2070 - val_mape: 3.2323
Epoch 4/25

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324/324 [=====] - 6s 19ms/step - loss: 0.0659 - mae:
0.1369 - mape: 4.0025 - val_loss: 5.1226 - val_mae: 1.5871 - val_mape: 2.4189
Epoch 5/25
324/324 [=====] - 6s 18ms/step - loss: 0.0621 - mae:
0.1377 - mape: 4.1949 - val_loss: 25.7096 - val_mae: 4.3505 - val_mape: 6.7825
Epoch 6/25
324/324 [=====] - 5s 16ms/step - loss: 0.0758 - mae:
0.1506 - mape: 4.1981 - val_loss: 4.2190 - val_mae: 1.4302 - val_mape: 2.3618
Epoch 7/25
324/324 [=====] - 7s 21ms/step - loss: 0.0617 - mae:
0.1357 - mape: 4.2532 - val_loss: 4.3115 - val_mae: 1.5227 - val_mape: 2.6620
Epoch 8/25
324/324 [=====] - 5s 16ms/step - loss: 0.0579 - mae:
0.1292 - mape: 3.8028 - val_loss: 6.4797 - val_mae: 1.8637 - val_mape: 2.7983
Epoch 9/25
324/324 [=====] - 5s 16ms/step - loss: 0.0676 - mae:
0.1430 - mape: 4.4315 - val_loss: 4.4623 - val_mae: 1.4597 - val_mape: 2.2534
Epoch 10/25
324/324 [=====] - 7s 21ms/step - loss: 0.0658 - mae:
0.1386 - mape: 3.7680 - val_loss: 4.4770 - val_mae: 1.5151 - val_mape: 2.5356
Epoch 11/25
324/324 [=====] - 5s 15ms/step - loss: 0.0629 - mae:
0.1375 - mape: 3.8919 - val_loss: 4.6625 - val_mae: 1.5204 - val_mape: 2.3397
Epoch 12/25
324/324 [=====] - 6s 17ms/step - loss: 0.0552 - mae:
0.1241 - mape: 3.3271 - val_loss: 4.4132 - val_mae: 1.4747 - val_mape: 2.4731
Epoch 13/25
324/324 [=====] - 6s 20ms/step - loss: 0.0568 - mae:
0.1271 - mape: 3.6778 - val_loss: 13.0373 - val_mae: 2.9732 - val_mape: 4.6348
Epoch 14/25
324/324 [=====] - 5s 15ms/step - loss: 0.0515 - mae:
0.1237 - mape: 3.9267 - val_loss: 4.4557 - val_mae: 1.4593 - val_mape: 2.2364
Epoch 15/25
324/324 [=====] - 6s 18ms/step - loss: 0.0608 - mae:
0.1323 - mape: 3.8120 - val_loss: 5.0115 - val_mae: 1.5543 - val_mape: 2.3757
Epoch 16/25
324/324 [=====] - 6s 19ms/step - loss: 0.0598 - mae:
0.1313 - mape: 3.7450 - val_loss: 3.5830 - val_mae: 1.2814 - val_mape: 2.0272
Epoch 17/25
324/324 [=====] - 5s 16ms/step - loss: 0.0609 - mae:
0.1291 - mape: 3.4679 - val_loss: 6.5723 - val_mae: 1.9175 - val_mape: 2.9351
Epoch 18/25
324/324 [=====] - 7s 20ms/step - loss: 0.0533 - mae:
0.1236 - mape: 3.4812 - val_loss: 3.3773 - val_mae: 1.2385 - val_mape: 1.9903
Epoch 19/25
324/324 [=====] - 5s 17ms/step - loss: 0.0547 - mae:
0.1249 - mape: 3.5033 - val_loss: 10.2591 - val_mae: 2.5439 - val_mape: 3.9477
Epoch 20/25

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324/324 [=====] - 5s 16ms/step - loss: 0.0494 - mae:
0.1190 - mape: 3.2609 - val_loss: 5.1499 - val_mae: 1.6462 - val_mape: 2.5005
Epoch 21/25
324/324 [=====] - 7s 22ms/step - loss: 0.0515 - mae:
0.1209 - mape: 3.3376 - val_loss: 3.3705 - val_mae: 1.2364 - val_mape: 1.9635
Epoch 22/25
324/324 [=====] - 5s 16ms/step - loss: 0.0512 - mae:
0.1214 - mape: 3.4143 - val_loss: 3.3261 - val_mae: 1.2323 - val_mape: 1.9729
Epoch 23/25
324/324 [=====] - 6s 17ms/step - loss: 0.0453 - mae:
0.1131 - mape: 2.9569 - val_loss: 5.0303 - val_mae: 1.6079 - val_mape: 2.4293
Epoch 24/25
324/324 [=====] - 6s 19ms/step - loss: 0.0537 - mae:
0.1226 - mape: 3.3144 - val_loss: 6.4701 - val_mae: 1.8625 - val_mape: 2.7843
Epoch 25/25
324/324 [=====] - 5s 16ms/step - loss: 0.0434 - mae:
0.1104 - mape: 2.8674 - val_loss: 4.5476 - val_mae: 1.4983 - val_mape: 2.2551
146.24763870239258
compiling baseline model...
fitting model...
Epoch 1/25
191/191 [=====] - 6s 24ms/step - loss: 104.0726 - mae:
3.5895 - mape: 16.0500 - val_loss: 131.1752 - val_mae: 8.0064 - val_mape: 5.2264
Epoch 2/25
191/191 [=====] - 3s 15ms/step - loss: 3.5758 - mae:
1.0958 - mape: 4.1632 - val_loss: 162.9801 - val_mae: 8.9520 - val_mape: 5.7885
Epoch 3/25
191/191 [=====] - 3s 16ms/step - loss: 3.3219 - mae:
1.0457 - mape: 3.9517 - val_loss: 122.2084 - val_mae: 7.7293 - val_mape: 5.1130
Epoch 4/25
191/191 [=====] - 3s 16ms/step - loss: 3.2609 - mae:
1.0274 - mape: 3.8703 - val_loss: 119.4227 - val_mae: 7.6468 - val_mape: 5.1016
Epoch 5/25
191/191 [=====] - 4s 22ms/step - loss: 3.3625 - mae:
1.0553 - mape: 4.0501 - val_loss: 120.1701 - val_mae: 7.6556 - val_mape: 5.0267
Epoch 6/25
191/191 [=====] - 4s 20ms/step - loss: 3.3263 - mae:
1.0449 - mape: 3.9414 - val_loss: 125.2708 - val_mae: 7.9420 - val_mape: 5.4220
Epoch 7/25
191/191 [=====] - 3s 15ms/step - loss: 3.1280 - mae:
1.0050 - mape: 3.7109 - val_loss: 121.5593 - val_mae: 7.6815 - val_mape: 5.2238
Epoch 8/25
191/191 [=====] - 3s 16ms/step - loss: 3.5375 - mae:
1.0964 - mape: 4.1069 - val_loss: 108.8162 - val_mae: 7.2059 - val_mape: 4.7764
Epoch 9/25
191/191 [=====] - 3s 16ms/step - loss: 3.1432 - mae:
1.0093 - mape: 3.7784 - val_loss: 126.1755 - val_mae: 7.9104 - val_mape: 5.4266
Epoch 10/25

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191/191 [=====] - 5s 24ms/step - loss: 3.6004 - mae:
1.1035 - mape: 4.1121 - val_loss: 111.8402 - val_mae: 7.2610 - val_mape: 4.7368
Epoch 11/25

191/191 [=====] - 3s 15ms/step - loss: 2.8711 - mae:
0.9612 - mape: 3.6097 - val_loss: 116.6740 - val_mae: 7.4631 - val_mape: 4.8443
Epoch 12/25

191/191 [=====] - 3s 16ms/step - loss: 2.9606 - mae:
0.9757 - mape: 3.6266 - val_loss: 108.6143 - val_mae: 7.1891 - val_mape: 4.8028
Epoch 13/25

191/191 [=====] - 3s 15ms/step - loss: 2.8795 - mae:
0.9638 - mape: 3.5927 - val_loss: 135.1550 - val_mae: 8.0656 - val_mape: 5.2139
Epoch 14/25

191/191 [=====] - 4s 22ms/step - loss: 2.8979 - mae:
0.9618 - mape: 3.5297 - val_loss: 169.2888 - val_mae: 9.2343 - val_mape: 5.9589
Epoch 15/25

191/191 [=====] - 4s 19ms/step - loss: 3.4893 - mae:
1.0792 - mape: 3.9744 - val_loss: 104.9827 - val_mae: 7.0799 - val_mape: 4.7101
Epoch 16/25

191/191 [=====] - 3s 15ms/step - loss: 3.4151 - mae:
1.0658 - mape: 3.9002 - val_loss: 101.4922 - val_mae: 6.9018 - val_mape: 4.6257
Epoch 17/25

191/191 [=====] - 3s 15ms/step - loss: 2.7989 - mae:
0.9570 - mape: 3.5952 - val_loss: 129.4466 - val_mae: 7.8738 - val_mape: 5.0899
Epoch 18/25

191/191 [=====] - 4s 22ms/step - loss: 2.9835 - mae:
0.9837 - mape: 3.6870 - val_loss: 99.5385 - val_mae: 6.8681 - val_mape: 4.5880
Epoch 19/25

191/191 [=====] - 5s 24ms/step - loss: 2.7463 - mae:
0.9395 - mape: 3.4870 - val_loss: 96.0823 - val_mae: 6.7122 - val_mape: 4.5138
Epoch 20/25

191/191 [=====] - 4s 19ms/step - loss: 2.3424 - mae:
0.8527 - mape: 3.1957 - val_loss: 131.1130 - val_mae: 7.7865 - val_mape: 4.9516
Epoch 21/25

191/191 [=====] - 3s 16ms/step - loss: 2.4262 - mae:
0.8709 - mape: 3.2292 - val_loss: 98.0138 - val_mae: 6.8001 - val_mape: 4.6028
Epoch 22/25

191/191 [=====] - 3s 16ms/step - loss: 2.7257 - mae:
0.9454 - mape: 3.4732 - val_loss: 98.4970 - val_mae: 6.8183 - val_mape: 4.5911
Epoch 23/25

191/191 [=====] - 4s 19ms/step - loss: 2.7918 - mae:
0.9499 - mape: 3.4349 - val_loss: 99.8383 - val_mae: 6.7755 - val_mape: 4.4099
Epoch 24/25

191/191 [=====] - 5s 24ms/step - loss: 2.8729 - mae:
0.9757 - mape: 3.6305 - val_loss: 104.2721 - val_mae: 7.0642 - val_mape: 4.7862
Epoch 25/25

191/191 [=====] - 3s 16ms/step - loss: 2.4318 - mae:
0.8903 - mape: 3.3409 - val_loss: 101.8985 - val_mae: 6.8227 - val_mape: 4.4249
143.65227270126343

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compiling baseline model...
fitting model...
Epoch 1/25
123/123 [=====] - 5s 20ms/step - loss: 148.8984 - mae:
5.6849 - mape: 16.3030 - val_loss: 5.8096 - val_mae: 1.8652 - val_mape: 4.1027
Epoch 2/25
123/123 [=====] - 2s 16ms/step - loss: 5.8866 - mae:
1.6934 - mape: 5.5115 - val_loss: 5.8122 - val_mae: 1.8628 - val_mape: 4.0454
Epoch 3/25
123/123 [=====] - 2s 15ms/step - loss: 5.6997 - mae:
1.6801 - mape: 5.3976 - val_loss: 5.0366 - val_mae: 1.7108 - val_mape: 3.7574
Epoch 4/25
123/123 [=====] - 2s 16ms/step - loss: 5.2746 - mae:
1.6067 - mape: 5.2000 - val_loss: 5.5800 - val_mae: 1.8406 - val_mape: 4.0602
Epoch 5/25
123/123 [=====] - 2s 15ms/step - loss: 5.4375 - mae:
1.6433 - mape: 5.2360 - val_loss: 5.5670 - val_mae: 1.8497 - val_mape: 4.0582
Epoch 6/25
123/123 [=====] - 3s 22ms/step - loss: 4.9987 - mae:
1.5691 - mape: 5.0950 - val_loss: 6.1506 - val_mae: 1.9693 - val_mape: 4.2311
Epoch 7/25
123/123 [=====] - 3s 22ms/step - loss: 5.0950 - mae:
1.6063 - mape: 5.1218 - val_loss: 5.9448 - val_mae: 1.9290 - val_mape: 4.1401
Epoch 8/25
123/123 [=====] - 2s 17ms/step - loss: 4.7287 - mae:
1.5230 - mape: 4.9295 - val_loss: 4.3663 - val_mae: 1.5868 - val_mape: 3.5187
Epoch 9/25
123/123 [=====] - 2s 17ms/step - loss: 4.7140 - mae:
1.5224 - mape: 4.9420 - val_loss: 4.1670 - val_mae: 1.5384 - val_mape: 3.3938
Epoch 10/25
123/123 [=====] - 2s 16ms/step - loss: 4.6678 - mae:
1.5045 - mape: 4.8101 - val_loss: 4.3584 - val_mae: 1.5825 - val_mape: 3.4715
Epoch 11/25
123/123 [=====] - 2s 16ms/step - loss: 4.5083 - mae:
1.4748 - mape: 4.7264 - val_loss: 5.4610 - val_mae: 1.8192 - val_mape: 4.0162
Epoch 12/25
123/123 [=====] - 2s 16ms/step - loss: 4.4384 - mae:
1.4687 - mape: 4.7496 - val_loss: 4.7033 - val_mae: 1.6792 - val_mape: 3.6296
Epoch 13/25
123/123 [=====] - 3s 21ms/step - loss: 4.2471 - mae:
1.4237 - mape: 4.6014 - val_loss: 6.5144 - val_mae: 2.0345 - val_mape: 4.3526
Epoch 14/25
123/123 [=====] - 3s 23ms/step - loss: 4.5318 - mae:
1.4916 - mape: 4.7371 - val_loss: 4.4226 - val_mae: 1.5949 - val_mape: 3.4811
Epoch 15/25
123/123 [=====] - 2s 18ms/step - loss: 4.4745 - mae:
1.4766 - mape: 4.6984 - val_loss: 4.6835 - val_mae: 1.6727 - val_mape: 3.6914
Epoch 16/25

```

```

123/123 [=====] - 2s 16ms/step - loss: 4.2867 - mae:
1.4360 - mape: 4.6145 - val_loss: 4.4758 - val_mae: 1.6218 - val_mape: 3.5836
Epoch 17/25
123/123 [=====] - 2s 16ms/step - loss: 4.2258 - mae:
1.4167 - mape: 4.5718 - val_loss: 4.1139 - val_mae: 1.5219 - val_mape: 3.3355
Epoch 18/25
123/123 [=====] - 2s 16ms/step - loss: 4.1733 - mae:
1.4162 - mape: 4.5659 - val_loss: 4.2317 - val_mae: 1.5526 - val_mape: 3.4316
Epoch 19/25
123/123 [=====] - 2s 16ms/step - loss: 4.4538 - mae:
1.4754 - mape: 4.6969 - val_loss: 4.7373 - val_mae: 1.6764 - val_mape: 3.6228
Epoch 20/25
123/123 [=====] - 3s 22ms/step - loss: 4.4236 - mae:
1.4629 - mape: 4.6858 - val_loss: 3.9748 - val_mae: 1.4900 - val_mape: 3.2810
Epoch 21/25
123/123 [=====] - 3s 23ms/step - loss: 4.2639 - mae:
1.4251 - mape: 4.5387 - val_loss: 4.2965 - val_mae: 1.5495 - val_mape: 3.3807
Epoch 22/25
123/123 [=====] - 2s 18ms/step - loss: 4.2736 - mae:
1.4357 - mape: 4.5542 - val_loss: 4.1225 - val_mae: 1.5302 - val_mape: 3.3603
Epoch 23/25
123/123 [=====] - 2s 15ms/step - loss: 4.2533 - mae:
1.4340 - mape: 4.5540 - val_loss: 4.0541 - val_mae: 1.4978 - val_mape: 3.2800
Epoch 24/25
123/123 [=====] - 2s 17ms/step - loss: 4.1891 - mae:
1.4196 - mape: 4.5172 - val_loss: 5.4472 - val_mae: 1.8174 - val_mape: 3.9150
Epoch 25/25
123/123 [=====] - 2s 16ms/step - loss: 4.0070 - mae:
1.3706 - mape: 4.4208 - val_loss: 3.8862 - val_mae: 1.4680 - val_mape: 3.2432
57.310579776763916

```

```

[ ]: transformer_models = {ticker: build_transformer(head_size=128, num_heads=4,
↪ff_dim=2, num_trans_blocks=4, mlp_units=[256], mlp_dropout=0.10, dropout=0.
↪10, attention_axes=1) for ticker in tickers}

```

```

[ ]: for ticker, model in transformer_models.items():
    print(f"-----\n{ticker}-----")
    fit_transformer(model, data[ticker])

```

MNST-----

```

Epoch 1/25
243/243 [=====] - 16s 25ms/step - loss: 1.5536 - mae:
0.4400 - mape: 333.2908
Epoch 2/25
243/243 [=====] - 8s 32ms/step - loss: 0.2987 - mae:
0.2139 - mape: 42.0083
Epoch 3/25

```

243/243 [=====] - 6s 25ms/step - loss: 0.2581 - mae:
 0.2040 - mape: 49.2718
 Epoch 4/25
 243/243 [=====] - 8s 33ms/step - loss: 0.2303 - mae:
 0.1974 - mape: 63.0157
 Epoch 5/25
 243/243 [=====] - 6s 26ms/step - loss: 0.2053 - mae:
 0.1841 - mape: 51.2932
 Epoch 6/25
 243/243 [=====] - 8s 32ms/step - loss: 0.1852 - mae:
 0.1756 - mape: 50.4974
 Epoch 7/25
 243/243 [=====] - 6s 26ms/step - loss: 0.1728 - mae:
 0.1682 - mape: 46.0025
 Epoch 8/25
 243/243 [=====] - 8s 33ms/step - loss: 0.1725 - mae:
 0.1674 - mape: 45.1194
 Epoch 9/25
 243/243 [=====] - 6s 26ms/step - loss: 0.1827 - mae:
 0.1697 - mape: 42.6971
 Epoch 10/25
 243/243 [=====] - 8s 34ms/step - loss: 0.1719 - mae:
 0.1667 - mape: 43.8732
 Epoch 11/25
 243/243 [=====] - 6s 27ms/step - loss: 0.1604 - mae:
 0.1567 - mape: 38.1884
 Epoch 12/25
 243/243 [=====] - 8s 33ms/step - loss: 0.1522 - mae:
 0.1555 - mape: 38.1628
 Epoch 13/25
 243/243 [=====] - 8s 33ms/step - loss: 0.1492 - mae:
 0.1541 - mape: 34.3500
 Epoch 14/25
 243/243 [=====] - 9s 35ms/step - loss: 0.1474 - mae:
 0.1512 - mape: 35.1685
 Epoch 15/25
 243/243 [=====] - 6s 26ms/step - loss: 0.1535 - mae:
 0.1563 - mape: 35.3733
 Epoch 16/25
 243/243 [=====] - 8s 33ms/step - loss: 0.1519 - mae:
 0.1536 - mape: 32.5640
 Epoch 17/25
 243/243 [=====] - 6s 26ms/step - loss: 0.1297 - mae:
 0.1407 - mape: 31.1927
 Epoch 18/25
 243/243 [=====] - 8s 35ms/step - loss: 0.1422 - mae:
 0.1474 - mape: 32.2466
 Epoch 19/25

```

243/243 [=====] - 6s 26ms/step - loss: 0.1385 - mae:
0.1457 - mape: 31.6008
Epoch 20/25
243/243 [=====] - 8s 33ms/step - loss: 0.1424 - mae:
0.1513 - mape: 37.0005
Epoch 21/25
243/243 [=====] - 6s 26ms/step - loss: 0.1330 - mae:
0.1447 - mape: 36.3180
Epoch 22/25
243/243 [=====] - 8s 33ms/step - loss: 0.1612 - mae:
0.1552 - mape: 34.3946
Epoch 23/25
243/243 [=====] - 6s 26ms/step - loss: 0.1280 - mae:
0.1405 - mape: 31.8417
Epoch 24/25
243/243 [=====] - 8s 33ms/step - loss: 0.1249 - mae:
0.1395 - mape: 32.4860
Epoch 25/25
243/243 [=====] - 6s 26ms/step - loss: 0.1458 - mae:
0.1530 - mape: 46.5026
211.65211415290833
-----
BAC-----
Epoch 1/25
324/324 [=====] - 18s 27ms/step - loss: 5.0050 - mae:
0.9792 - mape: 18.3564
Epoch 2/25
324/324 [=====] - 9s 29ms/step - loss: 1.1135 - mae:
0.5781 - mape: 7.2136
Epoch 3/25
324/324 [=====] - 10s 31ms/step - loss: 0.8961 - mae:
0.5220 - mape: 6.8549
Epoch 4/25
324/324 [=====] - 9s 27ms/step - loss: 0.7789 - mae:
0.4814 - mape: 6.2593
Epoch 5/25
324/324 [=====] - 9s 29ms/step - loss: 0.7120 - mae:
0.4583 - mape: 5.9555
Epoch 6/25
324/324 [=====] - 10s 31ms/step - loss: 0.6633 - mae:
0.4409 - mape: 5.6744
Epoch 7/25
324/324 [=====] - 8s 26ms/step - loss: 0.6262 - mae:
0.4332 - mape: 5.5465
Epoch 8/25
324/324 [=====] - 10s 30ms/step - loss: 0.6042 - mae:
0.4220 - mape: 5.2308
Epoch 9/25

```


324/324 [=====] - 10s 31ms/step - loss: 0.6020 - mae: 0.4211 - mape: 5.2114
Epoch 10/25
324/324 [=====] - 8s 25ms/step - loss: 0.6119 - mae: 0.4204 - mape: 5.1276
Epoch 11/25
324/324 [=====] - 10s 31ms/step - loss: 0.5657 - mae: 0.4029 - mape: 4.8110
Epoch 12/25
324/324 [=====] - 10s 31ms/step - loss: 0.5454 - mae: 0.3974 - mape: 4.7457
Epoch 13/25
324/324 [=====] - 8s 26ms/step - loss: 0.5618 - mae: 0.4014 - mape: 4.6420
Epoch 14/25
324/324 [=====] - 10s 31ms/step - loss: 0.5389 - mae: 0.3962 - mape: 4.7564
Epoch 15/25
324/324 [=====] - 11s 35ms/step - loss: 0.5541 - mae: 0.3982 - mape: 4.6678
Epoch 16/25
324/324 [=====] - 8s 26ms/step - loss: 0.5299 - mae: 0.3832 - mape: 4.3994
Epoch 17/25
324/324 [=====] - 10s 31ms/step - loss: 0.5251 - mae: 0.3838 - mape: 4.4153
Epoch 18/25
324/324 [=====] - 10s 31ms/step - loss: 0.5209 - mae: 0.3849 - mape: 4.4647
Epoch 19/25
324/324 [=====] - 8s 26ms/step - loss: 0.5145 - mae: 0.3821 - mape: 4.3997
Epoch 20/25
324/324 [=====] - 10s 31ms/step - loss: 0.5055 - mae: 0.3766 - mape: 4.3380
Epoch 21/25
324/324 [=====] - 10s 31ms/step - loss: 0.4968 - mae: 0.3741 - mape: 4.4006
Epoch 22/25
324/324 [=====] - 8s 26ms/step - loss: 0.5007 - mae: 0.3741 - mape: 4.3480
Epoch 23/25
324/324 [=====] - 10s 30ms/step - loss: 0.4942 - mae: 0.3692 - mape: 4.2963
Epoch 24/25
324/324 [=====] - 10s 31ms/step - loss: 0.5112 - mae: 0.3780 - mape: 4.3609
Epoch 25/25

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324/324 [=====] - 8s 26ms/step - loss: 0.4990 - mae:
0.3768 - mape: 4.4784
244.83335161209106
-----
AKAM-----
Epoch 1/25
155/155 [=====] - 13s 26ms/step - loss: 146.1824 - mae:
5.9070 - mape: 19.4130
Epoch 2/25
155/155 [=====] - 5s 33ms/step - loss: 47.6157 - mae:
3.5161 - mape: 9.6714
Epoch 3/25
155/155 [=====] - 4s 29ms/step - loss: 43.4754 - mae:
3.4445 - mape: 10.4596
Epoch 4/25
155/155 [=====] - 4s 25ms/step - loss: 43.4391 - mae:
3.2172 - mape: 8.5698
Epoch 5/25
155/155 [=====] - 5s 30ms/step - loss: 40.9267 - mae:
3.1271 - mape: 9.3610
Epoch 6/25
155/155 [=====] - 5s 32ms/step - loss: 39.9904 - mae:
3.0620 - mape: 9.2697
Epoch 7/25
155/155 [=====] - 4s 25ms/step - loss: 40.0201 - mae:
3.0084 - mape: 8.5898
Epoch 8/25
155/155 [=====] - 4s 26ms/step - loss: 39.5776 - mae:
3.0330 - mape: 8.5974
Epoch 9/25
155/155 [=====] - 6s 36ms/step - loss: 36.8975 - mae:
3.0207 - mape: 8.7563
Epoch 10/25
155/155 [=====] - 4s 25ms/step - loss: 36.7432 - mae:
2.9422 - mape: 8.4409
Epoch 11/25
155/155 [=====] - 4s 25ms/step - loss: 37.0442 - mae:
2.9076 - mape: 8.5843
Epoch 12/25
155/155 [=====] - 6s 37ms/step - loss: 41.2027 - mae:
3.1121 - mape: 8.8780
Epoch 13/25
155/155 [=====] - 4s 25ms/step - loss: 33.1085 - mae:
2.7687 - mape: 8.2509
Epoch 14/25
155/155 [=====] - 4s 25ms/step - loss: 33.0649 - mae:
2.8248 - mape: 8.9669
Epoch 15/25

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155/155 [=====] - 5s 35ms/step - loss: 32.2039 - mae:
2.6822 - mape: 8.7174
Epoch 16/25
155/155 [=====] - 4s 27ms/step - loss: 34.7405 - mae:
2.7931 - mape: 8.9897
Epoch 17/25
155/155 [=====] - 4s 25ms/step - loss: 32.4591 - mae:
2.7256 - mape: 8.3869
Epoch 18/25
155/155 [=====] - 5s 33ms/step - loss: 30.7941 - mae:
2.5787 - mape: 7.8516
Epoch 19/25
155/155 [=====] - 5s 31ms/step - loss: 32.8814 - mae:
2.7119 - mape: 8.4939
Epoch 20/25
155/155 [=====] - 4s 26ms/step - loss: 32.7877 - mae:
2.8805 - mape: 8.2970
Epoch 21/25
155/155 [=====] - 4s 28ms/step - loss: 35.1409 - mae:
2.6897 - mape: 7.2369
Epoch 22/25
155/155 [=====] - 5s 34ms/step - loss: 32.4863 - mae:
2.6466 - mape: 7.5346
Epoch 23/25
155/155 [=====] - 4s 26ms/step - loss: 32.7783 - mae:
2.6798 - mape: 7.2608
Epoch 24/25
155/155 [=====] - 4s 26ms/step - loss: 31.1946 - mae:
2.6128 - mape: 7.8282
Epoch 25/25
155/155 [=====] - 6s 37ms/step - loss: 31.9933 - mae:
2.6131 - mape: 7.2389
122.00462913513184
-----
PFG-----
Epoch 1/25
143/143 [=====] - 13s 38ms/step - loss: 55.2588 - mae:
4.0476 - mape: 15.1811
Epoch 2/25
143/143 [=====] - 4s 26ms/step - loss: 6.2893 - mae:
1.8623 - mape: 7.1025
Epoch 3/25
143/143 [=====] - 4s 26ms/step - loss: 5.4638 - mae:
1.7257 - mape: 6.5310
Epoch 4/25
143/143 [=====] - 5s 32ms/step - loss: 4.7126 - mae:
1.6073 - mape: 6.1552
Epoch 5/25

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143/143 [=====] - 5s 31ms/step - loss: 4.1603 - mae:
 1.5054 - mape: 5.7915
 Epoch 6/25
 143/143 [=====] - 4s 25ms/step - loss: 3.7531 - mae:
 1.4360 - mape: 5.5658
 Epoch 7/25
 143/143 [=====] - 5s 32ms/step - loss: 3.5181 - mae:
 1.3852 - mape: 5.3727
 Epoch 8/25
 143/143 [=====] - 6s 43ms/step - loss: 3.2194 - mae:
 1.3260 - mape: 5.1746
 Epoch 9/25
 143/143 [=====] - 4s 26ms/step - loss: 3.2121 - mae:
 1.3195 - mape: 5.1278
 Epoch 10/25
 143/143 [=====] - 4s 26ms/step - loss: 3.0249 - mae:
 1.2848 - mape: 5.0193
 Epoch 11/25
 143/143 [=====] - 5s 32ms/step - loss: 2.9288 - mae:
 1.2498 - mape: 4.8804
 Epoch 12/25
 143/143 [=====] - 4s 31ms/step - loss: 2.8342 - mae:
 1.2371 - mape: 4.8098
 Epoch 13/25
 143/143 [=====] - 4s 26ms/step - loss: 2.7397 - mae:
 1.2147 - mape: 4.7619
 Epoch 14/25
 143/143 [=====] - 4s 26ms/step - loss: 2.5432 - mae:
 1.1721 - mape: 4.5842
 Epoch 15/25
 143/143 [=====] - 5s 36ms/step - loss: 2.5656 - mae:
 1.1700 - mape: 4.5580
 Epoch 16/25
 143/143 [=====] - 4s 26ms/step - loss: 2.5063 - mae:
 1.1616 - mape: 4.5582
 Epoch 17/25
 143/143 [=====] - 4s 26ms/step - loss: 2.4512 - mae:
 1.1510 - mape: 4.5013
 Epoch 18/25
 143/143 [=====] - 5s 35ms/step - loss: 2.3794 - mae:
 1.1381 - mape: 4.4547
 Epoch 19/25
 143/143 [=====] - 4s 29ms/step - loss: 2.3494 - mae:
 1.1246 - mape: 4.4279
 Epoch 20/25
 143/143 [=====] - 4s 26ms/step - loss: 2.3600 - mae:
 1.1333 - mape: 4.4417
 Epoch 21/25

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143/143 [=====] - 4s 27ms/step - loss: 2.2983 - mae:
1.1125 - mape: 4.3722
Epoch 22/25
143/143 [=====] - 5s 35ms/step - loss: 2.2586 - mae:
1.0998 - mape: 4.3112
Epoch 23/25
143/143 [=====] - 4s 26ms/step - loss: 2.1926 - mae:
1.0846 - mape: 4.2603
Epoch 24/25
143/143 [=====] - 4s 25ms/step - loss: 2.2512 - mae:
1.1007 - mape: 4.3255
Epoch 25/25
143/143 [=====] - 5s 36ms/step - loss: 2.1297 - mae:
1.0669 - mape: 4.2021
115.24501991271973
-----
DRI-----
Epoch 1/25
183/183 [=====] - 16s 36ms/step - loss: 67.8904 - mae:
3.6032 - mape: 16.9260
Epoch 2/25
183/183 [=====] - 5s 26ms/step - loss: 6.5515 - mae:
1.5853 - mape: 7.2919
Epoch 3/25
183/183 [=====] - 5s 26ms/step - loss: 5.9403 - mae:
1.4959 - mape: 6.8089
Epoch 4/25
183/183 [=====] - 6s 35ms/step - loss: 4.8789 - mae:
1.3574 - mape: 6.1547
Epoch 5/25
183/183 [=====] - 5s 26ms/step - loss: 4.4685 - mae:
1.3062 - mape: 5.9772
Epoch 6/25
183/183 [=====] - 6s 30ms/step - loss: 3.8932 - mae:
1.2253 - mape: 5.6425
Epoch 7/25
183/183 [=====] - 6s 30ms/step - loss: 3.6712 - mae:
1.1904 - mape: 5.4207
Epoch 8/25
183/183 [=====] - 5s 25ms/step - loss: 3.3119 - mae:
1.1345 - mape: 5.2244
Epoch 9/25
183/183 [=====] - 6s 35ms/step - loss: 3.1358 - mae:
1.1064 - mape: 5.1062
Epoch 10/25
183/183 [=====] - 5s 26ms/step - loss: 3.0565 - mae:
1.0814 - mape: 4.9761
Epoch 11/25

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183/183 [=====] - 5s 26ms/step - loss: 2.9686 - mae:
1.0673 - mape: 4.9156
Epoch 12/25
183/183 [=====] - 6s 35ms/step - loss: 2.7674 - mae:
1.0378 - mape: 4.8342
Epoch 13/25
183/183 [=====] - 5s 26ms/step - loss: 2.8712 - mae:
1.0488 - mape: 4.7990
Epoch 14/25
183/183 [=====] - 5s 29ms/step - loss: 2.7756 - mae:
1.0427 - mape: 4.8242
Epoch 15/25
183/183 [=====] - 6s 32ms/step - loss: 2.5939 - mae:
1.0131 - mape: 4.7105
Epoch 16/25
183/183 [=====] - 5s 26ms/step - loss: 2.3709 - mae:
0.9706 - mape: 4.5854
Epoch 17/25
183/183 [=====] - 6s 34ms/step - loss: 2.3146 - mae:
0.9537 - mape: 4.4307
Epoch 18/25
183/183 [=====] - 5s 27ms/step - loss: 2.4333 - mae:
0.9694 - mape: 4.5058
Epoch 19/25
183/183 [=====] - 5s 26ms/step - loss: 2.3489 - mae:
0.9491 - mape: 4.3945
Epoch 20/25
183/183 [=====] - 6s 35ms/step - loss: 2.3107 - mae:
0.9484 - mape: 4.4140
Epoch 21/25
183/183 [=====] - 5s 26ms/step - loss: 2.3474 - mae:
0.9569 - mape: 4.4435
Epoch 22/25
183/183 [=====] - 5s 29ms/step - loss: 2.3934 - mae:
0.9667 - mape: 4.4715
Epoch 23/25
183/183 [=====] - 6s 33ms/step - loss: 2.1572 - mae:
0.9149 - mape: 4.2450
Epoch 24/25
183/183 [=====] - 5s 26ms/step - loss: 2.2845 - mae:
0.9313 - mape: 4.3046
Epoch 25/25
183/183 [=====] - 6s 35ms/step - loss: 2.3150 - mae:
0.9517 - mape: 4.4098
151.06021523475647
-----
STZ-----
Epoch 1/25

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203/203 [=====] - 16s 32ms/step - loss: 205.0094 - mae: 4.4892 - mape: 17.5459
Epoch 2/25
203/203 [=====] - 7s 35ms/step - loss: 20.7848 - mae: 2.1076 - mape: 7.6590
Epoch 3/25
203/203 [=====] - 5s 26ms/step - loss: 16.5834 - mae: 1.8863 - mape: 6.9563
Epoch 4/25
203/203 [=====] - 7s 33ms/step - loss: 13.7688 - mae: 1.7565 - mape: 6.4767
Epoch 5/25
203/203 [=====] - 6s 27ms/step - loss: 12.4859 - mae: 1.6555 - mape: 6.0039
Epoch 6/25
203/203 [=====] - 5s 27ms/step - loss: 10.8012 - mae: 1.5516 - mape: 5.7018
Epoch 7/25
203/203 [=====] - 7s 33ms/step - loss: 10.8807 - mae: 1.5381 - mape: 5.6188
Epoch 8/25
203/203 [=====] - 5s 26ms/step - loss: 9.7783 - mae: 1.4689 - mape: 5.3955
Epoch 9/25
203/203 [=====] - 7s 34ms/step - loss: 9.2606 - mae: 1.4216 - mape: 5.2493
Epoch 10/25
203/203 [=====] - 5s 26ms/step - loss: 8.4390 - mae: 1.3745 - mape: 5.1816
Epoch 11/25
203/203 [=====] - 6s 28ms/step - loss: 8.5041 - mae: 1.3737 - mape: 5.0758
Epoch 12/25
203/203 [=====] - 6s 30ms/step - loss: 7.7663 - mae: 1.3189 - mape: 4.9017
Epoch 13/25
203/203 [=====] - 5s 26ms/step - loss: 7.8513 - mae: 1.3387 - mape: 4.9862
Epoch 14/25
203/203 [=====] - 7s 34ms/step - loss: 7.2626 - mae: 1.2910 - mape: 4.8363
Epoch 15/25
203/203 [=====] - 5s 26ms/step - loss: 7.9927 - mae: 1.3375 - mape: 4.8934
Epoch 16/25
203/203 [=====] - 6s 31ms/step - loss: 7.1135 - mae: 1.2687 - mape: 4.7927
Epoch 17/25

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203/203 [=====] - 6s 28ms/step - loss: 7.7056 - mae:
1.2965 - mape: 4.6883
Epoch 18/25
203/203 [=====] - 5s 25ms/step - loss: 6.5000 - mae:
1.2196 - mape: 4.5726
Epoch 19/25
203/203 [=====] - 7s 34ms/step - loss: 6.8189 - mae:
1.2311 - mape: 4.5789
Epoch 20/25
203/203 [=====] - 5s 25ms/step - loss: 6.2274 - mae:
1.1802 - mape: 4.4279
Epoch 21/25
203/203 [=====] - 7s 33ms/step - loss: 6.1248 - mae:
1.1710 - mape: 4.4129
Epoch 22/25
203/203 [=====] - 6s 27ms/step - loss: 6.6812 - mae:
1.2263 - mape: 4.5148
Epoch 23/25
203/203 [=====] - 5s 26ms/step - loss: 6.2523 - mae:
1.1862 - mape: 4.3402
Epoch 24/25
203/203 [=====] - 7s 34ms/step - loss: 6.0111 - mae:
1.1731 - mape: 4.3304
Epoch 25/25
203/203 [=====] - 5s 26ms/step - loss: 5.8607 - mae:
1.1599 - mape: 4.2702
211.44623374938965
-----
CLX-----
Epoch 1/25
324/324 [=====] - 18s 31ms/step - loss: 30.4837 - mae:
2.0800 - mape: 27.3477
Epoch 2/25
324/324 [=====] - 10s 30ms/step - loss: 3.1698 - mae:
0.9594 - mape: 8.4505
Epoch 3/25
324/324 [=====] - 10s 32ms/step - loss: 2.3014 - mae:
0.8216 - mape: 7.8166
Epoch 4/25
324/324 [=====] - 10s 30ms/step - loss: 1.8152 - mae:
0.7372 - mape: 7.1317
Epoch 5/25
324/324 [=====] - 10s 31ms/step - loss: 1.6364 - mae:
0.6986 - mape: 6.8158
Epoch 6/25
324/324 [=====] - 9s 27ms/step - loss: 1.5057 - mae:
0.6729 - mape: 6.6614
Epoch 7/25

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324/324 [=====] - 10s 31ms/step - loss: 1.4251 - mae:
 0.6540 - mape: 6.3595
 Epoch 8/25
 324/324 [=====] - 10s 31ms/step - loss: 1.3364 - mae:
 0.6360 - mape: 6.3362
 Epoch 9/25
 324/324 [=====] - 9s 27ms/step - loss: 1.2828 - mae:
 0.6156 - mape: 5.7886
 Epoch 10/25
 324/324 [=====] - 10s 30ms/step - loss: 1.2290 - mae:
 0.6052 - mape: 5.6264
 Epoch 11/25
 324/324 [=====] - 10s 30ms/step - loss: 1.2075 - mae:
 0.5995 - mape: 5.3684
 Epoch 12/25
 324/324 [=====] - 9s 28ms/step - loss: 1.1558 - mae:
 0.5840 - mape: 5.2390
 Epoch 13/25
 324/324 [=====] - 10s 31ms/step - loss: 1.1543 - mae:
 0.5827 - mape: 5.0814
 Epoch 14/25
 324/324 [=====] - 10s 31ms/step - loss: 1.1455 - mae:
 0.5852 - mape: 5.0251
 Epoch 15/25
 324/324 [=====] - 9s 27ms/step - loss: 1.1521 - mae:
 0.5842 - mape: 4.9512
 Epoch 16/25
 324/324 [=====] - 10s 30ms/step - loss: 1.1404 - mae:
 0.5787 - mape: 4.8449
 Epoch 17/25
 324/324 [=====] - 10s 31ms/step - loss: 1.0752 - mae:
 0.5617 - mape: 4.7020
 Epoch 18/25
 324/324 [=====] - 9s 27ms/step - loss: 1.0338 - mae:
 0.5517 - mape: 4.6288
 Epoch 19/25
 324/324 [=====] - 10s 30ms/step - loss: 0.9890 - mae:
 0.5419 - mape: 4.5134
 Epoch 20/25
 324/324 [=====] - 10s 31ms/step - loss: 1.0332 - mae:
 0.5522 - mape: 4.5719
 Epoch 21/25
 324/324 [=====] - 8s 26ms/step - loss: 1.0414 - mae:
 0.5525 - mape: 4.5929
 Epoch 22/25
 324/324 [=====] - 10s 31ms/step - loss: 0.9654 - mae:
 0.5358 - mape: 4.4259
 Epoch 23/25

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324/324 [=====] - 10s 31ms/step - loss: 0.9887 - mae:
0.5395 - mape: 4.4811
Epoch 24/25
324/324 [=====] - 8s 26ms/step - loss: 1.0077 - mae:
0.5452 - mape: 4.3657
Epoch 25/25
324/324 [=====] - 10s 31ms/step - loss: 0.9896 - mae:
0.5409 - mape: 4.3465
269.67156410217285
-----
BWA-----
Epoch 1/25
194/194 [=====] - 14s 33ms/step - loss: 29.4665 - mae:
2.3847 - mape: 18.4723
Epoch 2/25
194/194 [=====] - 5s 25ms/step - loss: 3.2262 - mae:
1.0781 - mape: 7.3063
Epoch 3/25
194/194 [=====] - 6s 33ms/step - loss: 2.7145 - mae:
0.9920 - mape: 6.7930
Epoch 4/25
194/194 [=====] - 5s 25ms/step - loss: 2.3854 - mae:
0.9229 - mape: 6.3059
Epoch 5/25
194/194 [=====] - 5s 26ms/step - loss: 2.2123 - mae:
0.8889 - mape: 6.0502
Epoch 6/25
194/194 [=====] - 7s 34ms/step - loss: 1.9797 - mae:
0.8495 - mape: 5.8828
Epoch 7/25
194/194 [=====] - 5s 26ms/step - loss: 1.8990 - mae:
0.8313 - mape: 5.7164
Epoch 8/25
194/194 [=====] - 6s 33ms/step - loss: 1.7213 - mae:
0.7889 - mape: 5.4872
Epoch 9/25
194/194 [=====] - 5s 27ms/step - loss: 1.7121 - mae:
0.7889 - mape: 5.4777
Epoch 10/25
194/194 [=====] - 5s 26ms/step - loss: 1.6470 - mae:
0.7686 - mape: 5.2872
Epoch 11/25
194/194 [=====] - 7s 35ms/step - loss: 1.5923 - mae:
0.7589 - mape: 5.2131
Epoch 12/25
194/194 [=====] - 5s 26ms/step - loss: 1.4918 - mae:
0.7398 - mape: 5.1351
Epoch 13/25

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194/194 [=====] - 6s 32ms/step - loss: 1.3397 - mae:
0.6934 - mape: 4.7915
Epoch 14/25
194/194 [=====] - 5s 27ms/step - loss: 1.3609 - mae:
0.7002 - mape: 4.8928
Epoch 15/25
194/194 [=====] - 5s 26ms/step - loss: 1.2865 - mae:
0.6883 - mape: 4.7826
Epoch 16/25
194/194 [=====] - 7s 35ms/step - loss: 1.3444 - mae:
0.6972 - mape: 4.8556
Epoch 17/25
194/194 [=====] - 5s 26ms/step - loss: 1.2936 - mae:
0.6883 - mape: 4.7638
Epoch 18/25
194/194 [=====] - 6s 32ms/step - loss: 1.2742 - mae:
0.6776 - mape: 4.7178
Epoch 19/25
194/194 [=====] - 6s 29ms/step - loss: 1.3955 - mae:
0.7073 - mape: 4.8264
Epoch 20/25
194/194 [=====] - 5s 26ms/step - loss: 1.2381 - mae:
0.6665 - mape: 4.6202
Epoch 21/25
194/194 [=====] - 7s 35ms/step - loss: 1.1866 - mae:
0.6620 - mape: 4.5822
Epoch 22/25
194/194 [=====] - 5s 26ms/step - loss: 1.2223 - mae:
0.6629 - mape: 4.5259
Epoch 23/25
194/194 [=====] - 6s 31ms/step - loss: 1.1507 - mae:
0.6401 - mape: 4.3543
Epoch 24/25
194/194 [=====] - 6s 30ms/step - loss: 1.1205 - mae:
0.6366 - mape: 4.3929
Epoch 25/25
194/194 [=====] - 5s 26ms/step - loss: 1.1549 - mae:
0.6448 - mape: 4.4255
149.6717507839203
-----
PPG-----
Epoch 1/25
279/279 [=====] - 17s 31ms/step - loss: 32.5820 - mae:
2.1542 - mape: 20.3453
Epoch 2/25
279/279 [=====] - 8s 27ms/step - loss: 4.1238 - mae:
1.0947 - mape: 7.3484
Epoch 3/25

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279/279 [=====] - 9s 32ms/step - loss: 3.6327 - mae: 1.0091 - mape: 6.7442
Epoch 4/25
279/279 [=====] - 7s 26ms/step - loss: 2.9445 - mae: 0.9160 - mape: 6.0918
Epoch 5/25
279/279 [=====] - 9s 32ms/step - loss: 2.4112 - mae: 0.8429 - mape: 5.6055
Epoch 6/25
279/279 [=====] - 9s 32ms/step - loss: 2.2140 - mae: 0.8146 - mape: 5.5098
Epoch 7/25
279/279 [=====] - 9s 32ms/step - loss: 2.0049 - mae: 0.7685 - mape: 5.0720
Epoch 8/25
279/279 [=====] - 8s 30ms/step - loss: 1.9509 - mae: 0.7571 - mape: 5.0046
Epoch 9/25
279/279 [=====] - 8s 28ms/step - loss: 1.9061 - mae: 0.7521 - mape: 4.9217
Epoch 10/25
279/279 [=====] - 9s 32ms/step - loss: 1.8452 - mae: 0.7349 - mape: 4.8967
Epoch 11/25
279/279 [=====] - 7s 26ms/step - loss: 1.7418 - mae: 0.7088 - mape: 4.5246
Epoch 12/25
279/279 [=====] - 9s 32ms/step - loss: 1.7182 - mae: 0.7079 - mape: 4.6439
Epoch 13/25
279/279 [=====] - 7s 26ms/step - loss: 1.7935 - mae: 0.7297 - mape: 4.6392
Epoch 14/25
279/279 [=====] - 9s 32ms/step - loss: 1.6991 - mae: 0.7083 - mape: 4.5649
Epoch 15/25
279/279 [=====] - 8s 30ms/step - loss: 1.5096 - mae: 0.6692 - mape: 4.1689
Epoch 16/25
279/279 [=====] - 8s 28ms/step - loss: 1.6353 - mae: 0.6935 - mape: 4.4736
Epoch 17/25
279/279 [=====] - 9s 32ms/step - loss: 1.6127 - mae: 0.6914 - mape: 4.1938
Epoch 18/25
279/279 [=====] - 7s 26ms/step - loss: 1.4927 - mae: 0.6524 - mape: 3.9715
Epoch 19/25

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279/279 [=====] - 9s 32ms/step - loss: 1.5222 - mae:
0.6652 - mape: 4.1450
Epoch 20/25
279/279 [=====] - 7s 26ms/step - loss: 1.5465 - mae:
0.6701 - mape: 4.0838
Epoch 21/25
279/279 [=====] - 9s 32ms/step - loss: 1.4560 - mae:
0.6534 - mape: 3.9449
Epoch 22/25
279/279 [=====] - 8s 28ms/step - loss: 1.6124 - mae:
0.6795 - mape: 4.3703
Epoch 23/25
279/279 [=====] - 8s 30ms/step - loss: 1.4805 - mae:
0.6596 - mape: 4.0888
Epoch 24/25
279/279 [=====] - 9s 32ms/step - loss: 1.4796 - mae:
0.6472 - mape: 3.9042
Epoch 25/25
279/279 [=====] - 7s 27ms/step - loss: 1.5131 - mae:
0.6518 - mape: 3.9658
270.74586367607117
-----
AVB-----
Epoch 1/25
191/191 [=====] - 15s 33ms/step - loss: 262.5980 - mae:
7.2223 - mape: 14.6664
Epoch 2/25
191/191 [=====] - 5s 26ms/step - loss: 30.4756 - mae:
3.4183 - mape: 6.3861
Epoch 3/25
191/191 [=====] - 7s 34ms/step - loss: 24.4259 - mae:
3.0613 - mape: 5.7460
Epoch 4/25
191/191 [=====] - 5s 27ms/step - loss: 21.4619 - mae:
2.8877 - mape: 5.3803
Epoch 5/25
191/191 [=====] - 5s 27ms/step - loss: 19.0984 - mae:
2.7151 - mape: 5.0425
Epoch 6/25
191/191 [=====] - 7s 36ms/step - loss: 16.2413 - mae:
2.5299 - mape: 4.7665
Epoch 7/25
191/191 [=====] - 5s 26ms/step - loss: 15.1237 - mae:
2.4353 - mape: 4.5832
Epoch 8/25
191/191 [=====] - 6s 33ms/step - loss: 15.6810 - mae:
2.4783 - mape: 4.6244
Epoch 9/25

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191/191 [=====] - 6s 29ms/step - loss: 14.2810 - mae:
 2.3696 - mape: 4.4445
 Epoch 10/25
 191/191 [=====] - 5s 27ms/step - loss: 13.3849 - mae:
 2.3006 - mape: 4.3648
 Epoch 11/25
 191/191 [=====] - 7s 35ms/step - loss: 12.1272 - mae:
 2.2100 - mape: 4.2035
 Epoch 12/25
 191/191 [=====] - 5s 26ms/step - loss: 12.2919 - mae:
 2.2087 - mape: 4.1635
 Epoch 13/25
 191/191 [=====] - 6s 31ms/step - loss: 11.9427 - mae:
 2.1655 - mape: 4.0647
 Epoch 14/25
 191/191 [=====] - 6s 30ms/step - loss: 11.4376 - mae:
 2.1205 - mape: 4.0344
 Epoch 15/25
 191/191 [=====] - 5s 27ms/step - loss: 11.5709 - mae:
 2.1321 - mape: 4.0173
 Epoch 16/25
 191/191 [=====] - 7s 35ms/step - loss: 11.7638 - mae:
 2.1511 - mape: 4.0518
 Epoch 17/25
 191/191 [=====] - 5s 26ms/step - loss: 10.6162 - mae:
 2.0572 - mape: 3.9231
 Epoch 18/25
 191/191 [=====] - 6s 29ms/step - loss: 10.9317 - mae:
 2.0729 - mape: 3.9277
 Epoch 19/25
 191/191 [=====] - 6s 32ms/step - loss: 10.5037 - mae:
 2.0270 - mape: 3.8309
 Epoch 20/25
 191/191 [=====] - 5s 26ms/step - loss: 9.9293 - mae:
 1.9824 - mape: 3.7848
 Epoch 21/25
 191/191 [=====] - 7s 34ms/step - loss: 10.1779 - mae:
 2.0200 - mape: 3.7899
 Epoch 22/25
 191/191 [=====] - 5s 26ms/step - loss: 10.8298 - mae:
 2.0742 - mape: 3.9290
 Epoch 23/25
 191/191 [=====] - 5s 27ms/step - loss: 10.6764 - mae:
 2.0435 - mape: 3.8414
 Epoch 24/25
 191/191 [=====] - 7s 34ms/step - loss: 10.0612 - mae:
 1.9994 - mape: 3.7946
 Epoch 25/25

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191/191 [=====] - 5s 26ms/step - loss: 10.1166 - mae:
2.0072 - mape: 3.7889
210.9606969356537
-----
NCLH-----
Epoch 1/25
72/72 [=====] - 11s 27ms/step - loss: 226.5149 - mae:
9.2180 - mape: 23.3413
Epoch 2/25
72/72 [=====] - 2s 26ms/step - loss: 16.4694 - mae:
3.0577 - mape: 8.1895
Epoch 3/25
72/72 [=====] - 2s 26ms/step - loss: 15.6996 - mae:
3.0120 - mape: 8.0369
Epoch 4/25
72/72 [=====] - 2s 28ms/step - loss: 14.3162 - mae:
2.8353 - mape: 7.5736
Epoch 5/25
72/72 [=====] - 3s 42ms/step - loss: 13.7817 - mae:
2.7781 - mape: 7.4114
Epoch 6/25
72/72 [=====] - 2s 30ms/step - loss: 12.7222 - mae:
2.6821 - mape: 7.1602
Epoch 7/25
72/72 [=====] - 2s 26ms/step - loss: 12.0793 - mae:
2.6246 - mape: 7.0029
Epoch 8/25
72/72 [=====] - 2s 26ms/step - loss: 11.1422 - mae:
2.5155 - mape: 6.7118
Epoch 9/25
72/72 [=====] - 2s 26ms/step - loss: 10.3111 - mae:
2.4212 - mape: 6.5338
Epoch 10/25
72/72 [=====] - 2s 26ms/step - loss: 10.3471 - mae:
2.4127 - mape: 6.4233
Epoch 11/25
72/72 [=====] - 2s 34ms/step - loss: 9.2801 - mae:
2.2872 - mape: 6.1949
Epoch 12/25
72/72 [=====] - 3s 42ms/step - loss: 9.3216 - mae:
2.3019 - mape: 6.1738
Epoch 13/25
72/72 [=====] - 2s 27ms/step - loss: 8.7451 - mae:
2.2261 - mape: 6.0335
Epoch 14/25
72/72 [=====] - 2s 26ms/step - loss: 8.5988 - mae:
2.2007 - mape: 5.9662
Epoch 15/25

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72/72 [=====] - 2s 27ms/step - loss: 8.0144 - mae:
2.1204 - mape: 5.7585
Epoch 16/25
72/72 [=====] - 2s 27ms/step - loss: 8.2559 - mae:
2.1637 - mape: 5.8029
Epoch 17/25
72/72 [=====] - 2s 27ms/step - loss: 8.0161 - mae:
2.1343 - mape: 5.7575
Epoch 18/25
72/72 [=====] - 3s 37ms/step - loss: 7.5282 - mae:
2.0656 - mape: 5.5921
Epoch 19/25
72/72 [=====] - 3s 39ms/step - loss: 7.5015 - mae:
2.0707 - mape: 5.6058
Epoch 20/25
72/72 [=====] - 2s 27ms/step - loss: 7.9889 - mae:
2.1374 - mape: 5.7620
Epoch 21/25
72/72 [=====] - 2s 27ms/step - loss: 7.4064 - mae:
2.0696 - mape: 5.5909
Epoch 22/25
72/72 [=====] - 2s 26ms/step - loss: 7.4597 - mae:
2.0580 - mape: 5.5718
Epoch 23/25
72/72 [=====] - 2s 26ms/step - loss: 7.4910 - mae:
2.0460 - mape: 5.5433
Epoch 24/25
72/72 [=====] - 2s 27ms/step - loss: 6.9685 - mae:
1.9886 - mape: 5.4044
Epoch 25/25
72/72 [=====] - 3s 42ms/step - loss: 6.6477 - mae:
1.9385 - mape: 5.2553
90.93046641349792
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USB-----
Epoch 1/25
322/322 [=====] - 19s 27ms/step - loss: 1.9474 - mae:
0.6296 - mape: 31.0560
Epoch 2/25
322/322 [=====] - 10s 32ms/step - loss: 0.5054 - mae:
0.3801 - mape: 9.7859
Epoch 3/25
322/322 [=====] - 10s 32ms/step - loss: 0.3947 - mae:
0.3365 - mape: 9.1475
Epoch 4/25
322/322 [=====] - 9s 28ms/step - loss: 0.3593 - mae:
0.3233 - mape: 8.8752
Epoch 5/25

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322/322 [=====] - 10s 32ms/step - loss: 0.3427 - mae:
 0.3164 - mape: 8.7285
 Epoch 6/25
 322/322 [=====] - 10s 32ms/step - loss: 0.3281 - mae:
 0.3096 - mape: 8.5345
 Epoch 7/25
 322/322 [=====] - 9s 29ms/step - loss: 0.2855 - mae:
 0.2862 - mape: 7.8551
 Epoch 8/25
 322/322 [=====] - 10s 31ms/step - loss: 0.2807 - mae:
 0.2818 - mape: 7.2863
 Epoch 9/25
 322/322 [=====] - 12s 37ms/step - loss: 0.2760 - mae:
 0.2801 - mape: 7.0703
 Epoch 10/25
 322/322 [=====] - 9s 29ms/step - loss: 0.2814 - mae:
 0.2805 - mape: 6.5225
 Epoch 11/25
 322/322 [=====] - 10s 31ms/step - loss: 0.2591 - mae:
 0.2671 - mape: 6.1192
 Epoch 12/25
 322/322 [=====] - 11s 33ms/step - loss: 0.2585 - mae:
 0.2684 - mape: 5.8871
 Epoch 13/25
 322/322 [=====] - 9s 29ms/step - loss: 0.2546 - mae:
 0.2649 - mape: 5.6949
 Epoch 14/25
 322/322 [=====] - 10s 31ms/step - loss: 0.2617 - mae:
 0.2659 - mape: 5.6479
 Epoch 15/25
 322/322 [=====] - 10s 32ms/step - loss: 0.2464 - mae:
 0.2594 - mape: 5.3088
 Epoch 16/25
 322/322 [=====] - 9s 29ms/step - loss: 0.2468 - mae:
 0.2583 - mape: 5.1977
 Epoch 17/25
 322/322 [=====] - 10s 31ms/step - loss: 0.2374 - mae:
 0.2519 - mape: 5.1883
 Epoch 18/25
 322/322 [=====] - 10s 32ms/step - loss: 0.2557 - mae:
 0.2620 - mape: 5.0973
 Epoch 19/25
 322/322 [=====] - 9s 29ms/step - loss: 0.2425 - mae:
 0.2546 - mape: 5.1106
 Epoch 20/25
 322/322 [=====] - 10s 30ms/step - loss: 0.2539 - mae:
 0.2628 - mape: 5.2019
 Epoch 21/25

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322/322 [=====] - 10s 32ms/step - loss: 0.2380 - mae:
0.2512 - mape: 5.0595
Epoch 22/25
322/322 [=====] - 9s 29ms/step - loss: 0.2364 - mae:
0.2523 - mape: 5.0213
Epoch 23/25
322/322 [=====] - 9s 29ms/step - loss: 0.2351 - mae:
0.2500 - mape: 4.8619
Epoch 24/25
322/322 [=====] - 10s 32ms/step - loss: 0.2435 - mae:
0.2551 - mape: 5.2267
Epoch 25/25
322/322 [=====] - 9s 28ms/step - loss: 0.2279 - mae:
0.2460 - mape: 4.7245
272.20594549179077
-----
KMI-----
Epoch 1/25
84/84 [=====] - 12s 49ms/step - loss: 46.1305 - mae:
4.2663 - mape: 26.4057
Epoch 2/25
84/84 [=====] - 4s 44ms/step - loss: 2.3723 - mae:
1.1817 - mape: 7.4622
Epoch 3/25
84/84 [=====] - 3s 31ms/step - loss: 2.1576 - mae:
1.1216 - mape: 7.0530
Epoch 4/25
84/84 [=====] - 2s 26ms/step - loss: 1.9452 - mae:
1.0603 - mape: 6.6783
Epoch 5/25
84/84 [=====] - 2s 26ms/step - loss: 1.9290 - mae:
1.0569 - mape: 6.6081
Epoch 6/25
84/84 [=====] - 2s 26ms/step - loss: 1.7528 - mae:
1.0139 - mape: 6.3725
Epoch 7/25
84/84 [=====] - 3s 31ms/step - loss: 1.6811 - mae:
0.9875 - mape: 6.1892
Epoch 8/25
84/84 [=====] - 3s 39ms/step - loss: 1.5715 - mae:
0.9563 - mape: 5.9986
Epoch 9/25
84/84 [=====] - 2s 26ms/step - loss: 1.4524 - mae:
0.9126 - mape: 5.7502
Epoch 10/25
84/84 [=====] - 2s 26ms/step - loss: 1.4436 - mae:
0.9163 - mape: 5.7708
Epoch 11/25

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84/84 [=====] - 2s 27ms/step - loss: 1.3434 - mae:
0.8845 - mape: 5.5864
Epoch 12/25
84/84 [=====] - 2s 26ms/step - loss: 1.2715 - mae:
0.8583 - mape: 5.4100
Epoch 13/25
84/84 [=====] - 3s 35ms/step - loss: 1.2681 - mae:
0.8533 - mape: 5.3829
Epoch 14/25
84/84 [=====] - 3s 38ms/step - loss: 1.2037 - mae:
0.8370 - mape: 5.2999
Epoch 15/25
84/84 [=====] - 2s 26ms/step - loss: 1.1645 - mae:
0.8198 - mape: 5.1818
Epoch 16/25
84/84 [=====] - 2s 27ms/step - loss: 1.1253 - mae:
0.8112 - mape: 5.1447
Epoch 17/25
84/84 [=====] - 2s 27ms/step - loss: 1.0531 - mae:
0.7778 - mape: 4.9193
Epoch 18/25
84/84 [=====] - 2s 27ms/step - loss: 1.0567 - mae:
0.7800 - mape: 4.9151
Epoch 19/25
84/84 [=====] - 3s 38ms/step - loss: 1.0335 - mae:
0.7805 - mape: 4.9530
Epoch 20/25
84/84 [=====] - 3s 36ms/step - loss: 1.0424 - mae:
0.7735 - mape: 4.8755
Epoch 21/25
84/84 [=====] - 2s 27ms/step - loss: 1.0163 - mae:
0.7637 - mape: 4.8219
Epoch 22/25
84/84 [=====] - 2s 26ms/step - loss: 0.9883 - mae:
0.7518 - mape: 4.7409
Epoch 23/25
84/84 [=====] - 2s 27ms/step - loss: 0.9698 - mae:
0.7418 - mape: 4.6812
Epoch 24/25
84/84 [=====] - 2s 26ms/step - loss: 0.9888 - mae:
0.7528 - mape: 4.7705
Epoch 25/25
84/84 [=====] - 3s 41ms/step - loss: 0.9164 - mae:
0.7228 - mape: 4.5549
73.64928007125854
-----
ANET-----
Epoch 1/25

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63/63 [=====] - 10s 27ms/step - loss: 593.0589 - mae: 14.4772 - mape: 29.0309
Epoch 2/25
63/63 [=====] - 2s 34ms/step - loss: 37.1946 - mae: 4.2025 - mape: 8.3574
Epoch 3/25
63/63 [=====] - 3s 43ms/step - loss: 36.8182 - mae: 4.0628 - mape: 7.9351
Epoch 4/25
63/63 [=====] - 2s 29ms/step - loss: 33.4119 - mae: 3.8850 - mape: 7.6265
Epoch 5/25
63/63 [=====] - 2s 27ms/step - loss: 31.9093 - mae: 3.8197 - mape: 7.4160
Epoch 6/25
63/63 [=====] - 2s 28ms/step - loss: 29.8753 - mae: 3.6648 - mape: 7.1402
Epoch 7/25
63/63 [=====] - 2s 27ms/step - loss: 28.3978 - mae: 3.5821 - mape: 6.9636
Epoch 8/25
63/63 [=====] - 2s 27ms/step - loss: 28.9337 - mae: 3.5603 - mape: 6.8883
Epoch 9/25
63/63 [=====] - 2s 28ms/step - loss: 26.7933 - mae: 3.4616 - mape: 6.6522
Epoch 10/25
63/63 [=====] - 3s 41ms/step - loss: 26.2804 - mae: 3.3417 - mape: 6.4574
Epoch 11/25
63/63 [=====] - 2s 39ms/step - loss: 23.9924 - mae: 3.2478 - mape: 6.3257
Epoch 12/25
63/63 [=====] - 2s 27ms/step - loss: 25.7712 - mae: 3.3700 - mape: 6.4970
Epoch 13/25
63/63 [=====] - 2s 27ms/step - loss: 22.2080 - mae: 3.1688 - mape: 6.1875
Epoch 14/25
63/63 [=====] - 2s 27ms/step - loss: 22.4489 - mae: 3.1257 - mape: 6.0520
Epoch 15/25
63/63 [=====] - 2s 27ms/step - loss: 22.2782 - mae: 3.1054 - mape: 6.0462
Epoch 16/25
63/63 [=====] - 2s 27ms/step - loss: 20.6912 - mae: 3.0221 - mape: 5.8880
Epoch 17/25

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63/63 [=====] - 2s 34ms/step - loss: 21.1794 - mae:
3.0311 - mape: 5.8805
Epoch 18/25
63/63 [=====] - 3s 42ms/step - loss: 19.1354 - mae:
2.9483 - mape: 5.8023
Epoch 19/25
63/63 [=====] - 2s 34ms/step - loss: 19.7711 - mae:
2.9403 - mape: 5.6992
Epoch 20/25
63/63 [=====] - 2s 27ms/step - loss: 19.9480 - mae:
2.9618 - mape: 5.7235
Epoch 21/25
63/63 [=====] - 2s 27ms/step - loss: 18.5830 - mae:
2.8665 - mape: 5.6309
Epoch 22/25
63/63 [=====] - 2s 28ms/step - loss: 19.2989 - mae:
2.8763 - mape: 5.5876
Epoch 23/25
63/63 [=====] - 2s 27ms/step - loss: 18.4909 - mae:
2.8196 - mape: 5.4879
Epoch 24/25
63/63 [=====] - 2s 27ms/step - loss: 18.8730 - mae:
2.8657 - mape: 5.5945
Epoch 25/25
63/63 [=====] - 2s 40ms/step - loss: 18.5674 - mae:
2.8248 - mape: 5.5260
89.8281614780426
-----
MAR-----
Epoch 1/25
165/165 [=====] - 13s 27ms/step - loss: 147.9346 - mae:
5.6589 - mape: 15.7402
Epoch 2/25
165/165 [=====] - 6s 38ms/step - loss: 17.0113 - mae:
2.5682 - mape: 7.0506
Epoch 3/25
165/165 [=====] - 5s 28ms/step - loss: 14.1871 - mae:
2.3666 - mape: 6.5588
Epoch 4/25
165/165 [=====] - 7s 40ms/step - loss: 12.5960 - mae:
2.2157 - mape: 6.1139
Epoch 5/25
165/165 [=====] - 6s 35ms/step - loss: 11.1933 - mae:
2.0904 - mape: 5.7816
Epoch 6/25
165/165 [=====] - 4s 27ms/step - loss: 9.8913 - mae:
1.9681 - mape: 5.4491
Epoch 7/25

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165/165 [=====] - 5s 31ms/step - loss: 9.4637 - mae: 1.9359 - mape: 5.3750
Epoch 8/25
165/165 [=====] - 5s 32ms/step - loss: 8.2467 - mae: 1.8278 - mape: 5.1353
Epoch 9/25
165/165 [=====] - 4s 27ms/step - loss: 8.0190 - mae: 1.7816 - mape: 4.9841
Epoch 10/25
165/165 [=====] - 5s 33ms/step - loss: 7.4581 - mae: 1.7116 - mape: 4.8100
Epoch 11/25
165/165 [=====] - 5s 30ms/step - loss: 7.1542 - mae: 1.7030 - mape: 4.8062
Epoch 12/25
165/165 [=====] - 4s 27ms/step - loss: 6.9408 - mae: 1.6753 - mape: 4.7410
Epoch 13/25
165/165 [=====] - 6s 34ms/step - loss: 7.2407 - mae: 1.7146 - mape: 4.8387
Epoch 14/25
165/165 [=====] - 5s 29ms/step - loss: 6.6703 - mae: 1.6426 - mape: 4.6452
Epoch 15/25
165/165 [=====] - 4s 27ms/step - loss: 6.1566 - mae: 1.5991 - mape: 4.5626
Epoch 16/25
165/165 [=====] - 6s 36ms/step - loss: 6.7322 - mae: 1.6473 - mape: 4.6401
Epoch 17/25
165/165 [=====] - 5s 28ms/step - loss: 6.5191 - mae: 1.6084 - mape: 4.5049
Epoch 18/25
165/165 [=====] - 4s 27ms/step - loss: 6.1445 - mae: 1.5766 - mape: 4.4346
Epoch 19/25
165/165 [=====] - 6s 37ms/step - loss: 5.9930 - mae: 1.5564 - mape: 4.3797
Epoch 20/25
165/165 [=====] - 5s 28ms/step - loss: 6.1085 - mae: 1.5766 - mape: 4.4608
Epoch 21/25
165/165 [=====] - 4s 27ms/step - loss: 5.9834 - mae: 1.5442 - mape: 4.3404
Epoch 22/25
165/165 [=====] - 6s 38ms/step - loss: 6.0377 - mae: 1.5673 - mape: 4.4228
Epoch 23/25

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165/165 [=====] - 5s 27ms/step - loss: 5.3724 - mae:
1.4768 - mape: 4.2118
Epoch 24/25
165/165 [=====] - 4s 27ms/step - loss: 5.8312 - mae:
1.5233 - mape: 4.3069
Epoch 25/25
165/165 [=====] - 6s 37ms/step - loss: 5.3994 - mae:
1.4893 - mape: 4.2541
137.37717819213867
-----
GD-----
Epoch 1/25
393/393 [=====] - 20s 32ms/step - loss: 12.9702 - mae:
1.1736 - mape: 39.9173
Epoch 2/25
393/393 [=====] - 12s 31ms/step - loss: 1.9206 - mae:
0.6235 - mape: 12.2821
Epoch 3/25
393/393 [=====] - 12s 32ms/step - loss: 1.5075 - mae:
0.5568 - mape: 11.0912
Epoch 4/25
393/393 [=====] - 12s 30ms/step - loss: 1.3127 - mae:
0.5177 - mape: 10.3950
Epoch 5/25
393/393 [=====] - 14s 35ms/step - loss: 1.1869 - mae:
0.4935 - mape: 9.8666
Epoch 6/25
393/393 [=====] - 12s 30ms/step - loss: 1.1863 - mae:
0.4918 - mape: 9.1094
Epoch 7/25
393/393 [=====] - 13s 32ms/step - loss: 1.0867 - mae:
0.4706 - mape: 8.4140
Epoch 8/25
393/393 [=====] - 12s 32ms/step - loss: 1.0585 - mae:
0.4620 - mape: 8.1188
Epoch 9/25
393/393 [=====] - 13s 32ms/step - loss: 0.9974 - mae:
0.4486 - mape: 7.7061
Epoch 10/25
393/393 [=====] - 12s 31ms/step - loss: 1.0028 - mae:
0.4441 - mape: 7.3909
Epoch 11/25
393/393 [=====] - 11s 28ms/step - loss: 1.0413 - mae:
0.4577 - mape: 7.5400
Epoch 12/25
393/393 [=====] - 12s 31ms/step - loss: 1.0519 - mae:
0.4519 - mape: 7.1157
Epoch 13/25

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393/393 [=====] - 12s 31ms/step - loss: 1.0031 - mae:
0.4508 - mape: 7.3368
Epoch 14/25
393/393 [=====] - 12s 31ms/step - loss: 1.0118 - mae:
0.4469 - mape: 6.7299
Epoch 15/25
393/393 [=====] - 12s 31ms/step - loss: 0.8473 - mae:
0.4169 - mape: 6.5207
Epoch 16/25
393/393 [=====] - 11s 29ms/step - loss: 0.9509 - mae:
0.4361 - mape: 6.7639
Epoch 17/25
393/393 [=====] - 12s 30ms/step - loss: 0.9282 - mae:
0.4305 - mape: 6.6757
Epoch 18/25
393/393 [=====] - 12s 32ms/step - loss: 1.0199 - mae:
0.4529 - mape: 7.9643
Epoch 19/25
393/393 [=====] - 14s 36ms/step - loss: 0.9210 - mae:
0.4312 - mape: 6.5561
Epoch 20/25
393/393 [=====] - 12s 32ms/step - loss: 0.8414 - mae:
0.4099 - mape: 6.2353
Epoch 21/25
393/393 [=====] - 11s 28ms/step - loss: 0.8998 - mae:
0.4282 - mape: 7.4298
Epoch 22/25
393/393 [=====] - 12s 29ms/step - loss: 0.9401 - mae:
0.4312 - mape: 6.4662
Epoch 23/25
393/393 [=====] - 12s 32ms/step - loss: 0.9419 - mae:
0.4354 - mape: 6.7756
Epoch 24/25
393/393 [=====] - 12s 31ms/step - loss: 0.8674 - mae:
0.4141 - mape: 6.8815
Epoch 25/25
393/393 [=====] - 12s 31ms/step - loss: 0.8954 - mae:
0.4214 - mape: 6.8881
329.67749857902527
-----
ALLE-----
Epoch 1/25
67/67 [=====] - 10s 28ms/step - loss: 926.9208 - mae:
19.5952 - mape: 24.4042
Epoch 2/25
67/67 [=====] - 2s 27ms/step - loss: 53.2753 - mae:
5.4912 - mape: 6.8640
Epoch 3/25

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67/67 [=====] - 2s 27ms/step - loss: 48.2260 - mae: 5.2490 - mape: 6.5415
Epoch 4/25
67/67 [=====] - 2s 28ms/step - loss: 45.1699 - mae: 5.0245 - mape: 6.2597
Epoch 5/25
67/67 [=====] - 2s 32ms/step - loss: 42.6555 - mae: 4.8774 - mape: 6.0492
Epoch 6/25
67/67 [=====] - 3s 42ms/step - loss: 39.6260 - mae: 4.7137 - mape: 5.8762
Epoch 7/25
67/67 [=====] - 2s 35ms/step - loss: 37.1917 - mae: 4.5250 - mape: 5.6150
Epoch 8/25
67/67 [=====] - 2s 27ms/step - loss: 35.2679 - mae: 4.4489 - mape: 5.5386
Epoch 9/25
67/67 [=====] - 2s 27ms/step - loss: 33.5354 - mae: 4.3034 - mape: 5.3409
Epoch 10/25
67/67 [=====] - 2s 27ms/step - loss: 30.9073 - mae: 4.1542 - mape: 5.1507
Epoch 11/25
67/67 [=====] - 2s 27ms/step - loss: 31.1119 - mae: 4.1348 - mape: 5.1352
Epoch 12/25
67/67 [=====] - 2s 28ms/step - loss: 30.0839 - mae: 4.0885 - mape: 5.0570
Epoch 13/25
67/67 [=====] - 3s 40ms/step - loss: 29.6727 - mae: 4.0493 - mape: 5.0114
Epoch 14/25
67/67 [=====] - 3s 38ms/step - loss: 26.0991 - mae: 3.8203 - mape: 4.7632
Epoch 15/25
67/67 [=====] - 2s 27ms/step - loss: 26.7579 - mae: 3.8299 - mape: 4.7651
Epoch 16/25
67/67 [=====] - 2s 27ms/step - loss: 24.5314 - mae: 3.6913 - mape: 4.6033
Epoch 17/25
67/67 [=====] - 2s 27ms/step - loss: 26.0528 - mae: 3.7757 - mape: 4.6831
Epoch 18/25
67/67 [=====] - 2s 27ms/step - loss: 25.2559 - mae: 3.7304 - mape: 4.6410
Epoch 19/25

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67/67 [=====] - 2s 27ms/step - loss: 23.5039 - mae:
3.6122 - mape: 4.4906
Epoch 20/25
67/67 [=====] - 3s 38ms/step - loss: 24.7162 - mae:
3.7080 - mape: 4.5839
Epoch 21/25
67/67 [=====] - 3s 41ms/step - loss: 22.5882 - mae:
3.5264 - mape: 4.3736
Epoch 22/25
67/67 [=====] - 2s 26ms/step - loss: 21.6757 - mae:
3.4787 - mape: 4.3207
Epoch 23/25
67/67 [=====] - 2s 27ms/step - loss: 21.7111 - mae:
3.4652 - mape: 4.2787
Epoch 24/25
67/67 [=====] - 2s 26ms/step - loss: 22.0644 - mae:
3.4852 - mape: 4.3347
Epoch 25/25
67/67 [=====] - 2s 26ms/step - loss: 21.8455 - mae:
3.4864 - mape: 4.3475
90.51765894889832
-----
ALGN-----
Epoch 1/25
147/147 [=====] - 13s 36ms/step - loss: 679.5035 - mae:
8.8411 - mape: 20.4422
Epoch 2/25
147/147 [=====] - 4s 27ms/step - loss: 97.2965 - mae:
4.2484 - mape: 8.4370
Epoch 3/25
147/147 [=====] - 4s 27ms/step - loss: 86.8083 - mae:
4.0157 - mape: 8.0511
Epoch 4/25
147/147 [=====] - 6s 39ms/step - loss: 80.2023 - mae:
3.8858 - mape: 7.8889
Epoch 5/25
147/147 [=====] - 4s 27ms/step - loss: 72.3777 - mae:
3.6750 - mape: 7.6501
Epoch 6/25
147/147 [=====] - 4s 27ms/step - loss: 70.4886 - mae:
3.6196 - mape: 7.5231
Epoch 7/25
147/147 [=====] - 5s 37ms/step - loss: 65.3101 - mae:
3.4687 - mape: 7.2354
Epoch 8/25
147/147 [=====] - 4s 28ms/step - loss: 61.4192 - mae:
3.3191 - mape: 7.1088
Epoch 9/25

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147/147 [=====] - 4s 27ms/step - loss: 59.7610 - mae:
 3.2847 - mape: 6.9035
 Epoch 10/25
 147/147 [=====] - 5s 33ms/step - loss: 56.4304 - mae:
 3.2058 - mape: 6.8326
 Epoch 11/25
 147/147 [=====] - 5s 32ms/step - loss: 51.8032 - mae:
 3.1514 - mape: 6.7039
 Epoch 12/25
 147/147 [=====] - 4s 27ms/step - loss: 54.9082 - mae:
 3.0867 - mape: 6.6788
 Epoch 13/25
 147/147 [=====] - 4s 27ms/step - loss: 53.7242 - mae:
 3.0735 - mape: 6.5726
 Epoch 14/25
 147/147 [=====] - 6s 38ms/step - loss: 51.3205 - mae:
 3.0503 - mape: 6.5002
 Epoch 15/25
 147/147 [=====] - 4s 25ms/step - loss: 54.8806 - mae:
 3.0921 - mape: 6.4657
 Epoch 16/25
 147/147 [=====] - 4s 26ms/step - loss: 52.2885 - mae:
 3.0271 - mape: 6.4876
 Epoch 17/25
 147/147 [=====] - 5s 35ms/step - loss: 54.3950 - mae:
 3.1118 - mape: 6.4531
 Epoch 18/25
 147/147 [=====] - 4s 30ms/step - loss: 48.6885 - mae:
 2.9370 - mape: 6.3425
 Epoch 19/25
 147/147 [=====] - 4s 27ms/step - loss: 46.3019 - mae:
 2.9337 - mape: 6.2746
 Epoch 20/25
 147/147 [=====] - 4s 30ms/step - loss: 45.1488 - mae:
 2.8220 - mape: 6.0394
 Epoch 21/25
 147/147 [=====] - 5s 35ms/step - loss: 45.8053 - mae:
 2.8434 - mape: 6.0442
 Epoch 22/25
 147/147 [=====] - 4s 27ms/step - loss: 50.2726 - mae:
 3.0358 - mape: 6.4167
 Epoch 23/25
 147/147 [=====] - 4s 27ms/step - loss: 46.5878 - mae:
 2.8743 - mape: 6.2129
 Epoch 24/25
 147/147 [=====] - 6s 38ms/step - loss: 48.7526 - mae:
 2.9651 - mape: 6.2637
 Epoch 25/25

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147/147 [=====] - 4s 27ms/step - loss: 45.9059 - mae:
2.8800 - mape: 6.2267
149.99240493774414
-----
T-----
Epoch 1/25
256/256 [=====] - 16s 33ms/step - loss: 2.7477 - mae:
0.7282 - mape: 17.8648
Epoch 2/25
256/256 [=====] - 7s 27ms/step - loss: 0.2164 - mae:
0.3004 - mape: 6.3272
Epoch 3/25
256/256 [=====] - 8s 33ms/step - loss: 0.1709 - mae:
0.2681 - mape: 5.8891
Epoch 4/25
256/256 [=====] - 7s 26ms/step - loss: 0.1419 - mae:
0.2468 - mape: 5.4757
Epoch 5/25
256/256 [=====] - 9s 34ms/step - loss: 0.1317 - mae:
0.2368 - mape: 5.2780
Epoch 6/25
256/256 [=====] - 7s 27ms/step - loss: 0.1135 - mae:
0.2207 - mape: 4.8658
Epoch 7/25
256/256 [=====] - 8s 33ms/step - loss: 0.1074 - mae:
0.2143 - mape: 4.6778
Epoch 8/25
256/256 [=====] - 7s 26ms/step - loss: 0.1007 - mae:
0.2086 - mape: 4.7032
Epoch 9/25
256/256 [=====] - 9s 33ms/step - loss: 0.0997 - mae:
0.2072 - mape: 4.5437
Epoch 10/25
256/256 [=====] - 7s 26ms/step - loss: 0.0937 - mae:
0.2009 - mape: 4.3589
Epoch 11/25
256/256 [=====] - 8s 33ms/step - loss: 0.0987 - mae:
0.2049 - mape: 4.4159
Epoch 12/25
256/256 [=====] - 7s 27ms/step - loss: 0.0956 - mae:
0.2005 - mape: 4.2943
Epoch 13/25
256/256 [=====] - 8s 33ms/step - loss: 0.0867 - mae:
0.1916 - mape: 4.0577
Epoch 14/25
256/256 [=====] - 7s 27ms/step - loss: 0.0840 - mae:
0.1892 - mape: 3.9529
Epoch 15/25

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256/256 [=====] - 9s 33ms/step - loss: 0.0873 - mae:
0.1926 - mape: 4.0339
Epoch 16/25
256/256 [=====] - 7s 27ms/step - loss: 0.0826 - mae:
0.1844 - mape: 3.8140
Epoch 17/25
256/256 [=====] - 8s 33ms/step - loss: 0.0756 - mae:
0.1795 - mape: 3.7219
Epoch 18/25
256/256 [=====] - 7s 27ms/step - loss: 0.0832 - mae:
0.1867 - mape: 3.8030
Epoch 19/25
256/256 [=====] - 9s 34ms/step - loss: 0.0852 - mae:
0.1882 - mape: 3.8443
Epoch 20/25
256/256 [=====] - 10s 38ms/step - loss: 0.0783 - mae:
0.1806 - mape: 3.6910
Epoch 21/25
256/256 [=====] - 7s 27ms/step - loss: 0.0807 - mae:
0.1823 - mape: 3.6783
Epoch 22/25
256/256 [=====] - 9s 33ms/step - loss: 0.0765 - mae:
0.1789 - mape: 3.6333
Epoch 23/25
256/256 [=====] - 7s 27ms/step - loss: 0.0769 - mae:
0.1787 - mape: 3.5865
Epoch 24/25
256/256 [=====] - 9s 33ms/step - loss: 0.0753 - mae:
0.1778 - mape: 3.6027
Epoch 25/25
256/256 [=====] - 7s 26ms/step - loss: 0.0745 - mae:
0.1767 - mape: 3.5550
202.01312851905823
-----
CSC0-----
Epoch 1/25
216/216 [=====] - 15s 27ms/step - loss: 12.5421 - mae:
1.7791 - mape: 60.0388
Epoch 2/25
216/216 [=====] - 7s 34ms/step - loss: 1.9370 - mae:
0.8820 - mape: 10.4643
Epoch 3/25
216/216 [=====] - 6s 26ms/step - loss: 1.5788 - mae:
0.7977 - mape: 11.8133
Epoch 4/25
216/216 [=====] - 7s 34ms/step - loss: 1.4796 - mae:
0.7548 - mape: 10.3339
Epoch 5/25

```

216/216 [=====] - 6s 28ms/step - loss: 1.2684 - mae:
 0.7052 - mape: 10.4932
 Epoch 6/25
 216/216 [=====] - 7s 32ms/step - loss: 1.1746 - mae:
 0.6745 - mape: 10.4482
 Epoch 7/25
 216/216 [=====] - 7s 30ms/step - loss: 1.1004 - mae:
 0.6622 - mape: 11.4765
 Epoch 8/25
 216/216 [=====] - 6s 29ms/step - loss: 1.0806 - mae:
 0.6401 - mape: 9.4874
 Epoch 9/25
 216/216 [=====] - 7s 33ms/step - loss: 1.0764 - mae:
 0.6426 - mape: 10.0195
 Epoch 10/25
 216/216 [=====] - 6s 27ms/step - loss: 1.0024 - mae:
 0.6172 - mape: 8.7835
 Epoch 11/25
 216/216 [=====] - 8s 35ms/step - loss: 1.0411 - mae:
 0.6213 - mape: 9.1180
 Epoch 12/25
 216/216 [=====] - 6s 27ms/step - loss: 0.9097 - mae:
 0.5904 - mape: 8.4622
 Epoch 13/25
 216/216 [=====] - 8s 35ms/step - loss: 0.9455 - mae:
 0.6001 - mape: 9.6217
 Epoch 14/25
 216/216 [=====] - 6s 27ms/step - loss: 0.9172 - mae:
 0.5842 - mape: 8.4402
 Epoch 15/25
 216/216 [=====] - 7s 32ms/step - loss: 0.9134 - mae:
 0.5794 - mape: 7.9794
 Epoch 16/25
 216/216 [=====] - 7s 30ms/step - loss: 0.8990 - mae:
 0.5776 - mape: 8.6802
 Epoch 17/25
 216/216 [=====] - 7s 33ms/step - loss: 0.8967 - mae:
 0.5774 - mape: 7.8988
 Epoch 18/25
 216/216 [=====] - 8s 38ms/step - loss: 0.8974 - mae:
 0.5692 - mape: 7.4317
 Epoch 19/25
 216/216 [=====] - 6s 28ms/step - loss: 0.8812 - mae:
 0.5695 - mape: 7.5443
 Epoch 20/25
 216/216 [=====] - 8s 35ms/step - loss: 0.9622 - mae:
 0.5908 - mape: 7.4820
 Epoch 21/25

```

216/216 [=====] - 6s 28ms/step - loss: 0.9219 - mae:
0.5870 - mape: 7.4084
Epoch 22/25
216/216 [=====] - 8s 35ms/step - loss: 0.8942 - mae:
0.5718 - mape: 7.0784
Epoch 23/25
216/216 [=====] - 6s 28ms/step - loss: 0.8192 - mae:
0.5493 - mape: 6.7266
Epoch 24/25
216/216 [=====] - 7s 32ms/step - loss: 0.9489 - mae:
0.5933 - mape: 7.2007
Epoch 25/25
216/216 [=====] - 7s 30ms/step - loss: 0.8459 - mae:
0.5585 - mape: 6.6454
211.72756052017212
-----
CL-----
Epoch 1/25
322/322 [=====] - 18s 30ms/step - loss: 9.4797 - mae:
1.1696 - mape: 31.2042
Epoch 2/25
322/322 [=====] - 10s 32ms/step - loss: 1.1025 - mae:
0.5520 - mape: 7.6101
Epoch 3/25
322/322 [=====] - 9s 29ms/step - loss: 0.8934 - mae:
0.4990 - mape: 7.4703
Epoch 4/25
322/322 [=====] - 10s 30ms/step - loss: 0.7423 - mae:
0.4641 - mape: 7.3868
Epoch 5/25
322/322 [=====] - 10s 32ms/step - loss: 0.6780 - mae:
0.4422 - mape: 7.2593
Epoch 6/25
322/322 [=====] - 10s 30ms/step - loss: 0.6145 - mae:
0.4232 - mape: 7.0764
Epoch 7/25
322/322 [=====] - 11s 35ms/step - loss: 0.6204 - mae:
0.4266 - mape: 7.2083
Epoch 8/25
322/322 [=====] - 10s 32ms/step - loss: 0.5792 - mae:
0.4076 - mape: 6.4151
Epoch 9/25
322/322 [=====] - 10s 30ms/step - loss: 0.5565 - mae:
0.4012 - mape: 6.2357
Epoch 10/25
322/322 [=====] - 9s 29ms/step - loss: 0.5266 - mae:
0.3880 - mape: 5.9084
Epoch 11/25

```

```

322/322 [=====] - 10s 32ms/step - loss: 0.5114 - mae:
0.3849 - mape: 5.7810
Epoch 12/25
322/322 [=====] - 10s 30ms/step - loss: 0.5441 - mae:
0.3938 - mape: 5.5815
Epoch 13/25
322/322 [=====] - 9s 29ms/step - loss: 0.5182 - mae:
0.3835 - mape: 5.3783
Epoch 14/25
322/322 [=====] - 10s 32ms/step - loss: 0.4814 - mae:
0.3681 - mape: 4.9876
Epoch 15/25
322/322 [=====] - 9s 27ms/step - loss: 0.4882 - mae:
0.3736 - mape: 5.1132
Epoch 16/25
322/322 [=====] - 10s 30ms/step - loss: 0.5238 - mae:
0.3803 - mape: 5.0200
Epoch 17/25
322/322 [=====] - 10s 32ms/step - loss: 0.5105 - mae:
0.3765 - mape: 4.7768
Epoch 18/25
322/322 [=====] - 9s 26ms/step - loss: 0.5063 - mae:
0.3735 - mape: 4.6893
Epoch 19/25
322/322 [=====] - 10s 32ms/step - loss: 0.4753 - mae:
0.3637 - mape: 4.5440
Epoch 20/25
322/322 [=====] - 10s 33ms/step - loss: 0.4756 - mae:
0.3602 - mape: 4.5381
Epoch 21/25
322/322 [=====] - 9s 27ms/step - loss: 0.4296 - mae:
0.3471 - mape: 4.3826
Epoch 22/25
322/322 [=====] - 11s 33ms/step - loss: 0.4644 - mae:
0.3580 - mape: 4.4160
Epoch 23/25
322/322 [=====] - 12s 38ms/step - loss: 0.4929 - mae:
0.3683 - mape: 4.4673
Epoch 24/25
322/322 [=====] - 9s 29ms/step - loss: 0.4461 - mae:
0.3519 - mape: 4.3451
Epoch 25/25
322/322 [=====] - 10s 31ms/step - loss: 0.4638 - mae:
0.3566 - mape: 4.4469
269.9306848049164
-----
INTU-----
Epoch 1/25

```


197/197 [=====] - 14s 27ms/step - loss: 183.8653 - mae: 5.6587 - mape: 18.6094
Epoch 2/25
197/197 [=====] - 7s 36ms/step - loss: 16.4842 - mae: 2.3968 - mape: 7.7472
Epoch 3/25
197/197 [=====] - 5s 26ms/step - loss: 13.9569 - mae: 2.2211 - mape: 7.1512
Epoch 4/25
197/197 [=====] - 6s 30ms/step - loss: 11.7185 - mae: 2.0496 - mape: 6.7197
Epoch 5/25
197/197 [=====] - 6s 32ms/step - loss: 11.0584 - mae: 1.9812 - mape: 6.3945
Epoch 6/25
197/197 [=====] - 5s 27ms/step - loss: 9.9310 - mae: 1.8697 - mape: 6.1258
Epoch 7/25
197/197 [=====] - 7s 36ms/step - loss: 9.1756 - mae: 1.8044 - mape: 5.9269
Epoch 8/25
197/197 [=====] - 5s 27ms/step - loss: 8.3401 - mae: 1.7376 - mape: 5.7583
Epoch 9/25
197/197 [=====] - 6s 30ms/step - loss: 8.5392 - mae: 1.7460 - mape: 5.7688
Epoch 10/25
197/197 [=====] - 6s 31ms/step - loss: 7.7630 - mae: 1.6985 - mape: 5.6688
Epoch 11/25
197/197 [=====] - 5s 27ms/step - loss: 7.6457 - mae: 1.6690 - mape: 5.6303
Epoch 12/25
197/197 [=====] - 7s 35ms/step - loss: 7.2087 - mae: 1.6287 - mape: 5.4611
Epoch 13/25
197/197 [=====] - 5s 27ms/step - loss: 7.3056 - mae: 1.6239 - mape: 5.4449
Epoch 14/25
197/197 [=====] - 6s 29ms/step - loss: 7.3022 - mae: 1.6164 - mape: 5.3621
Epoch 15/25
197/197 [=====] - 6s 32ms/step - loss: 7.3849 - mae: 1.6360 - mape: 5.4529
Epoch 16/25
197/197 [=====] - 5s 27ms/step - loss: 7.1881 - mae: 1.6107 - mape: 5.3984
Epoch 17/25

```

197/197 [=====] - 7s 35ms/step - loss: 6.4783 - mae:
1.5392 - mape: 5.1383
Epoch 18/25
197/197 [=====] - 7s 36ms/step - loss: 6.7149 - mae:
1.5714 - mape: 5.2404
Epoch 19/25
197/197 [=====] - 7s 34ms/step - loss: 6.5396 - mae:
1.5447 - mape: 5.1784
Epoch 20/25
197/197 [=====] - 6s 28ms/step - loss: 6.1362 - mae:
1.5039 - mape: 5.0354
Epoch 21/25
197/197 [=====] - 5s 27ms/step - loss: 6.6813 - mae:
1.5631 - mape: 5.1550
Epoch 22/25
197/197 [=====] - 7s 35ms/step - loss: 6.2940 - mae:
1.5232 - mape: 5.0762
Epoch 23/25
197/197 [=====] - 5s 27ms/step - loss: 6.1340 - mae:
1.4879 - mape: 4.9920
Epoch 24/25
197/197 [=====] - 7s 34ms/step - loss: 6.1183 - mae:
1.4930 - mape: 4.9872
Epoch 25/25
197/197 [=====] - 5s 27ms/step - loss: 6.2514 - mae:
1.4811 - mape: 4.9158
159.14528226852417
-----
MKC-----
Epoch 1/25
324/324 [=====] - 17s 27ms/step - loss: 2.3905 - mae:
0.6038 - mape: 28.7297
Epoch 2/25
324/324 [=====] - 10s 32ms/step - loss: 0.3770 - mae:
0.3158 - mape: 8.5326
Epoch 3/25
324/324 [=====] - 10s 32ms/step - loss: 0.2721 - mae:
0.2734 - mape: 7.8221
Epoch 4/25
324/324 [=====] - 9s 27ms/step - loss: 0.2371 - mae:
0.2610 - mape: 8.3677
Epoch 5/25
324/324 [=====] - 11s 33ms/step - loss: 0.2142 - mae:
0.2482 - mape: 7.7953
Epoch 6/25
324/324 [=====] - 11s 33ms/step - loss: 0.1957 - mae:
0.2331 - mape: 6.7851
Epoch 7/25

```

324/324 [=====] - 9s 28ms/step - loss: 0.1944 - mae: 0.2347 - mape: 7.0158
Epoch 8/25
324/324 [=====] - 11s 33ms/step - loss: 0.1810 - mae: 0.2239 - mape: 6.3173
Epoch 9/25
324/324 [=====] - 11s 33ms/step - loss: 0.1724 - mae: 0.2191 - mape: 6.0924
Epoch 10/25
324/324 [=====] - 9s 28ms/step - loss: 0.1644 - mae: 0.2123 - mape: 5.4298
Epoch 11/25
324/324 [=====] - 11s 34ms/step - loss: 0.1614 - mae: 0.2103 - mape: 5.4078
Epoch 12/25
324/324 [=====] - 12s 37ms/step - loss: 0.1614 - mae: 0.2075 - mape: 5.0428
Epoch 13/25
324/324 [=====] - 9s 28ms/step - loss: 0.1570 - mae: 0.2050 - mape: 4.9417
Epoch 14/25
324/324 [=====] - 10s 32ms/step - loss: 0.1553 - mae: 0.2038 - mape: 4.7594
Epoch 15/25
324/324 [=====] - 10s 32ms/step - loss: 0.1571 - mae: 0.2028 - mape: 4.6681
Epoch 16/25
324/324 [=====] - 9s 27ms/step - loss: 0.1345 - mae: 0.1905 - mape: 4.4877
Epoch 17/25
324/324 [=====] - 10s 32ms/step - loss: 0.1472 - mae: 0.1990 - mape: 4.7061
Epoch 18/25
324/324 [=====] - 10s 31ms/step - loss: 0.1451 - mae: 0.1990 - mape: 4.7416
Epoch 19/25
324/324 [=====] - 9s 27ms/step - loss: 0.1422 - mae: 0.1922 - mape: 4.4229
Epoch 20/25
324/324 [=====] - 10s 32ms/step - loss: 0.1401 - mae: 0.1913 - mape: 4.4541
Epoch 21/25
324/324 [=====] - 10s 31ms/step - loss: 0.1299 - mae: 0.1860 - mape: 4.5201
Epoch 22/25
324/324 [=====] - 9s 27ms/step - loss: 0.1416 - mae: 0.1934 - mape: 4.7803
Epoch 23/25

```

324/324 [=====] - 10s 32ms/step - loss: 0.1435 - mae:
0.1959 - mape: 4.6755
Epoch 24/25
324/324 [=====] - 10s 30ms/step - loss: 0.1354 - mae:
0.1886 - mape: 4.5065
Epoch 25/25
324/324 [=====] - 9s 28ms/step - loss: 0.1213 - mae:
0.1809 - mape: 4.4038
270.46970653533936
-----
ALB-----
Epoch 1/25
191/191 [=====] - 15s 29ms/step - loss: 81.8521 - mae:
3.9752 - mape: 16.1707
Epoch 2/25
191/191 [=====] - 6s 34ms/step - loss: 10.2752 - mae:
1.8676 - mape: 6.5309
Epoch 3/25
191/191 [=====] - 5s 27ms/step - loss: 8.8421 - mae:
1.7512 - mape: 6.1260
Epoch 4/25
191/191 [=====] - 7s 36ms/step - loss: 7.5780 - mae:
1.6192 - mape: 5.6633
Epoch 5/25
191/191 [=====] - 6s 29ms/step - loss: 7.3563 - mae:
1.5832 - mape: 5.5534
Epoch 6/25
191/191 [=====] - 6s 29ms/step - loss: 6.7129 - mae:
1.5181 - mape: 5.3585
Epoch 7/25
191/191 [=====] - 7s 35ms/step - loss: 6.2107 - mae:
1.4535 - mape: 5.1343
Epoch 8/25
191/191 [=====] - 5s 28ms/step - loss: 6.1283 - mae:
1.4323 - mape: 5.0267
Epoch 9/25
191/191 [=====] - 7s 34ms/step - loss: 5.5835 - mae:
1.3716 - mape: 4.7988
Epoch 10/25
191/191 [=====] - 6s 29ms/step - loss: 5.4768 - mae:
1.3721 - mape: 4.8933
Epoch 11/25
191/191 [=====] - 5s 27ms/step - loss: 5.5252 - mae:
1.3753 - mape: 4.7967
Epoch 12/25
191/191 [=====] - 7s 35ms/step - loss: 5.2885 - mae:
1.3277 - mape: 4.6575
Epoch 13/25

```

```

191/191 [=====] - 5s 27ms/step - loss: 4.8465 - mae:
1.2834 - mape: 4.5828
Epoch 14/25
191/191 [=====] - 6s 32ms/step - loss: 4.6860 - mae:
1.2660 - mape: 4.4590
Epoch 15/25
191/191 [=====] - 6s 30ms/step - loss: 4.9523 - mae:
1.2794 - mape: 4.4767
Epoch 16/25
191/191 [=====] - 5s 27ms/step - loss: 4.8113 - mae:
1.2832 - mape: 4.5344
Epoch 17/25
191/191 [=====] - 7s 35ms/step - loss: 4.7601 - mae:
1.2746 - mape: 4.5495
Epoch 18/25
191/191 [=====] - 5s 26ms/step - loss: 4.7430 - mae:
1.2538 - mape: 4.3976
Epoch 19/25
191/191 [=====] - 6s 29ms/step - loss: 4.3674 - mae:
1.2155 - mape: 4.3199
Epoch 20/25
191/191 [=====] - 6s 32ms/step - loss: 4.2382 - mae:
1.2005 - mape: 4.2416
Epoch 21/25
191/191 [=====] - 5s 27ms/step - loss: 4.3035 - mae:
1.1992 - mape: 4.2488
Epoch 22/25
191/191 [=====] - 7s 36ms/step - loss: 4.2562 - mae:
1.1877 - mape: 4.1787
Epoch 23/25
191/191 [=====] - 5s 27ms/step - loss: 4.1929 - mae:
1.1821 - mape: 4.1446
Epoch 24/25
191/191 [=====] - 5s 27ms/step - loss: 4.1886 - mae:
1.1725 - mape: 4.0882
Epoch 25/25
191/191 [=====] - 6s 34ms/step - loss: 4.4739 - mae:
1.2275 - mape: 4.3404
211.3607475757599
-----
LVS-----
Epoch 1/25
123/123 [=====] - 11s 28ms/step - loss: 210.9750 - mae:
8.2169 - mape: 22.5650
Epoch 2/25
123/123 [=====] - 5s 40ms/step - loss: 16.3725 - mae:
2.9917 - mape: 8.8983
Epoch 3/25

```

123/123 [=====] - 3s 27ms/step - loss: 14.5058 - mae: 2.7979 - mape: 7.9499
Epoch 4/25
123/123 [=====] - 3s 26ms/step - loss: 13.2269 - mae: 2.6785 - mape: 7.5345
Epoch 5/25
123/123 [=====] - 3s 26ms/step - loss: 12.4716 - mae: 2.5963 - mape: 7.3008
Epoch 6/25
123/123 [=====] - 5s 41ms/step - loss: 11.4638 - mae: 2.4882 - mape: 7.0546
Epoch 7/25
123/123 [=====] - 3s 28ms/step - loss: 10.6908 - mae: 2.3917 - mape: 6.7337
Epoch 8/25
123/123 [=====] - 3s 27ms/step - loss: 10.2079 - mae: 2.3237 - mape: 6.5501
Epoch 9/25
123/123 [=====] - 3s 27ms/step - loss: 9.6453 - mae: 2.2812 - mape: 6.4738
Epoch 10/25
123/123 [=====] - 5s 40ms/step - loss: 9.2418 - mae: 2.2272 - mape: 6.3863
Epoch 11/25
123/123 [=====] - 3s 27ms/step - loss: 9.0934 - mae: 2.2026 - mape: 6.3275
Epoch 12/25
123/123 [=====] - 3s 27ms/step - loss: 8.8444 - mae: 2.1795 - mape: 6.2776
Epoch 13/25
123/123 [=====] - 3s 27ms/step - loss: 8.7778 - mae: 2.1500 - mape: 6.2283
Epoch 14/25
123/123 [=====] - 5s 39ms/step - loss: 8.1633 - mae: 2.1011 - mape: 6.1463
Epoch 15/25
123/123 [=====] - 3s 28ms/step - loss: 8.3807 - mae: 2.1042 - mape: 6.0573
Epoch 16/25
123/123 [=====] - 3s 26ms/step - loss: 8.0467 - mae: 2.0570 - mape: 5.9158
Epoch 17/25
123/123 [=====] - 3s 26ms/step - loss: 8.1040 - mae: 2.0580 - mape: 5.9433
Epoch 18/25
123/123 [=====] - 5s 37ms/step - loss: 7.7357 - mae: 2.0458 - mape: 5.9528
Epoch 19/25

```

123/123 [=====] - 4s 30ms/step - loss: 7.8033 - mae:
2.0253 - mape: 5.8668
Epoch 20/25
123/123 [=====] - 3s 27ms/step - loss: 7.7888 - mae:
2.0431 - mape: 5.9560
Epoch 21/25
123/123 [=====] - 3s 27ms/step - loss: 7.5972 - mae:
1.9969 - mape: 5.7956
Epoch 22/25
123/123 [=====] - 4s 36ms/step - loss: 7.2099 - mae:
1.9570 - mape: 5.7330
Epoch 23/25
123/123 [=====] - 4s 31ms/step - loss: 7.5202 - mae:
1.9929 - mape: 5.7619
Epoch 24/25
123/123 [=====] - 3s 26ms/step - loss: 7.2526 - mae:
1.9528 - mape: 5.6408
Epoch 25/25
123/123 [=====] - 3s 26ms/step - loss: 7.1433 - mae:
1.9422 - mape: 5.6308
149.81605553627014

```

```

[ ]: for ticker in tickers:
    transformer_models[ticker].save_weights(f"{ticker}_transformer_weights.h5")
    LSTM_models[ticker][0].save_weights(f"{ticker}_LSTM_weights.h5")

```

```

[ ]: !mkdir checkpoints
    !mkdir checkpoints/LSTM
    !mkdir checkpoints/transformer
    !mv *_transformer_weights.h5 checkpoints/transformer
    !mv *_LSTM_weights.h5 checkpoints/LSTM

```

```

[ ]: !zip -r checkpoints.zip checkpoints

```

```

adding: checkpoints/ (stored 0%)
adding: checkpoints/transformer/ (stored 0%)
adding: checkpoints/transformer/KMI_transformer_weights.h5 (deflated 60%)
adding: checkpoints/transformer/INTU_transformer_weights.h5 (deflated 60%)
adding: checkpoints/transformer/BWA_transformer_weights.h5 (deflated 60%)
adding: checkpoints/transformer/ANET_transformer_weights.h5 (deflated 61%)
adding: checkpoints/transformer/ALGN_transformer_weights.h5 (deflated 60%)
adding: checkpoints/transformer/AVB_transformer_weights.h5 (deflated 60%)
adding: checkpoints/transformer/T_transformer_weights.h5 (deflated 60%)
adding: checkpoints/transformer/PPG_transformer_weights.h5 (deflated 60%)
adding: checkpoints/transformer/MNST_transformer_weights.h5 (deflated 60%)
adding: checkpoints/transformer/CL_transformer_weights.h5 (deflated 60%)
adding: checkpoints/transformer/ALB_transformer_weights.h5 (deflated 60%)
adding: checkpoints/transformer/PFG_transformer_weights.h5 (deflated 60%)

```

```

adding: checkpoints/transformer/STZ_transformer_weights.h5 (deflated 60%)
adding: checkpoints/transformer/USB_transformer_weights.h5 (deflated 60%)
adding: checkpoints/transformer/ALLE_transformer_weights.h5 (deflated 61%)
adding: checkpoints/transformer/BAC_transformer_weights.h5 (deflated 60%)
adding: checkpoints/transformer/CSCO_transformer_weights.h5 (deflated 60%)
adding: checkpoints/transformer/GD_transformer_weights.h5 (deflated 60%)
adding: checkpoints/transformer/NCLH_transformer_weights.h5 (deflated 60%)
adding: checkpoints/transformer/MKC_transformer_weights.h5 (deflated 60%)
adding: checkpoints/transformer/AKAM_transformer_weights.h5 (deflated 60%)
adding: checkpoints/transformer/DRI_transformer_weights.h5 (deflated 60%)
adding: checkpoints/transformer/LVS_transformer_weights.h5 (deflated 60%)
adding: checkpoints/transformer/MAR_transformer_weights.h5 (deflated 60%)
adding: checkpoints/transformer/CLX_transformer_weights.h5 (deflated 60%)
adding: checkpoints/LSTM/ (stored 0%)
adding: checkpoints/LSTM/T_LSTM_weights.h5 (deflated 9%)
adding: checkpoints/LSTM/ALLE_LSTM_weights.h5 (deflated 9%)
adding: checkpoints/LSTM/KMI_LSTM_weights.h5 (deflated 9%)
adding: checkpoints/LSTM/BWA_LSTM_weights.h5 (deflated 9%)
adding: checkpoints/LSTM/BAC_LSTM_weights.h5 (deflated 9%)
adding: checkpoints/LSTM/INTU_LSTM_weights.h5 (deflated 9%)
adding: checkpoints/LSTM/ALGN_LSTM_weights.h5 (deflated 9%)
adding: checkpoints/LSTM/CL_LSTM_weights.h5 (deflated 9%)
adding: checkpoints/LSTM/GD_LSTM_weights.h5 (deflated 9%)
adding: checkpoints/LSTM/ANET_LSTM_weights.h5 (deflated 9%)
adding: checkpoints/LSTM/AVB_LSTM_weights.h5 (deflated 9%)
adding: checkpoints/LSTM/PPG_LSTM_weights.h5 (deflated 9%)
adding: checkpoints/LSTM/LVS_LSTM_weights.h5 (deflated 9%)
adding: checkpoints/LSTM/STZ_LSTM_weights.h5 (deflated 9%)
adding: checkpoints/LSTM/ALB_LSTM_weights.h5 (deflated 9%)
adding: checkpoints/LSTM/MKC_LSTM_weights.h5 (deflated 9%)
adding: checkpoints/LSTM/CLX_LSTM_weights.h5 (deflated 9%)
adding: checkpoints/LSTM/CSCO_LSTM_weights.h5 (deflated 9%)
adding: checkpoints/LSTM/PFG_LSTM_weights.h5 (deflated 9%)
adding: checkpoints/LSTM/AKAM_LSTM_weights.h5 (deflated 9%)
adding: checkpoints/LSTM/MAR_LSTM_weights.h5 (deflated 9%)
adding: checkpoints/LSTM/NCLH_LSTM_weights.h5 (deflated 9%)
adding: checkpoints/LSTM/MNST_LSTM_weights.h5 (deflated 9%)
adding: checkpoints/LSTM/DRI_LSTM_weights.h5 (deflated 9%)
adding: checkpoints/LSTM/USB_LSTM_weights.h5 (deflated 9%)

```

```
[ ]: import cvxpy as cp
```

```
[ ]: cov_df = returns.cov()
     cov_matrix = cov_df.values
```

```
[ ]: np.concatenate((data['PPG'].train, data['PPG'].test), axis=0).shape
```

```
[ ]: (2230, 5, 1)
```



```
[ ]: week_index = -1 # past week's data
expected_return_LSTM = np.zeros(shape=25)
expected_return_transformer = np.zeros(shape=25)
true_return = np.zeros(shape=25)
for i, ticker in enumerate(cov_df.columns):
    lstm_forecaster = PredictAndForecast(LSTM_models[ticker], data[ticker].
    ↪train, data[ticker].test)
    transformer_forecaster = PredictAndForecast(transformer_models[ticker],
    ↪data[ticker].train, data[ticker].test)
    concat_data = np.concatenate((data[ticker].train, data[ticker].test),
    ↪axis=0)
    expected_return_LSTM[i] = (lstm_forecaster.forecast(concat_data[:
    ↪week_index])[-1] - concat_data[week_index-1][-1]) /
    ↪concat_data[week_index-1][-1]
    expected_return_transformer[i] = (transformer_forecaster.
    ↪forecast(concat_data[:week_index])[-1] - concat_data[week_index-1][-1]) /
    ↪concat_data[week_index-1][-1]
    true_return[i] = (concat_data[week_index][-1] -
    ↪concat_data[week_index-1][-1]) / concat_data[week_index-1][-1]
```

<ipython-input-244-b0dd24ddda3e>:9: DeprecationWarning: Conversion of an array with ndim > 0 to a scalar is deprecated, and will error in future. Ensure you extract a single element from your array before performing this operation.

(Deprecated NumPy 1.25.)

```
    expected_return_LSTM[i] =
    (lstm_forecaster.forecast(concat_data[:week_index])[-1] -
    concat_data[week_index-1][-1]) / concat_data[week_index-1][-1]
```

<ipython-input-244-b0dd24ddda3e>:10: DeprecationWarning: Conversion of an array with ndim > 0 to a scalar is deprecated, and will error in future. Ensure you extract a single element from your array before performing this operation.

(Deprecated NumPy 1.25.)

```
    expected_return_transformer[i] =
    (transformer_forecaster.forecast(concat_data[:week_index])[-1] -
    concat_data[week_index-1][-1]) / concat_data[week_index-1][-1]
```

<ipython-input-244-b0dd24ddda3e>:11: DeprecationWarning: Conversion of an array with ndim > 0 to a scalar is deprecated, and will error in future. Ensure you extract a single element from your array before performing this operation.

(Deprecated NumPy 1.25.)

```
    true_return[i] = (concat_data[week_index][-1] - concat_data[week_index-1][-1])
    / concat_data[week_index-1][-1]
```

```
[ ]: n_stocks = 25
q = 0.5

weights = cp.Variable(n_stocks)
portfolio_variance = cp.quad_form(weights, cov_matrix)
expected_portfolio_return = expected_return_transformer @ weights
```

```

objective = cp.Minimize(portfolio_variance - q * expected_portfolio_return)
constraints = [
    cp.sum(weights) == 1, # Sum of weights must be 1
    weights >= 0.0,
    weights <= 0.25
]

prob = cp.Problem(objective, constraints)

```

```

[ ]: prob.solve()

# Get the optimal weights
optimal_weights = weights.value

```

```

[ ]: optimal_weights

```

```

[ ]: array([ 2.50000268e-01, -7.83303999e-09,  1.25012032e-08, -3.04540204e-08,
           2.49999978e-01,  6.70834433e-09,  8.37013469e-09, -1.58008886e-08,
           1.49975376e-07, -9.24299826e-08, -5.84185725e-08,  2.11498458e-08,
          -3.78016027e-08, -7.64824528e-08,  8.17944351e-09, -1.05224764e-10,
           5.61012675e-09, -8.84051545e-08,  2.49999945e-01,  2.50000000e-01,
           9.78600867e-09,  1.10464854e-08,  3.90470567e-08, -6.77176044e-08,
           1.28430462e-08])

```

```

[ ]: expected_return_transformer @ optimal_weights

```

```

[ ]: 0.025389962873822374

```

```

[ ]: true_return @ optimal_weights

```

```

[ ]: 0.014536526960099294

```

```

[ ]: def get_return(week_index, q, max_single_stock, model):
    expected_return = np.zeros(shape=25)
    true_return = np.zeros(shape=25)
    for i, ticker in enumerate(cov_df.columns):
        forecaster = None
        if model == "transformer":
            forecaster = PredictAndForecast(transformer_models[ticker],
↳data[ticker].train, data[ticker].test)
        elif model == "LSTM":
            forecaster = PredictAndForecast(LSTM_models[ticker], data[ticker].
↳train, data[ticker].test)
        else:
            raise Exception("Invalid model")
        concat_data = np.concatenate((data[ticker].train, data[ticker].test),
↳axis=0)

```

```

        expected_return[i] = (forecaster.forecast(concat_data[:week_index])[-1] -
        ↪ concat_data[week_index-1][-1]) / concat_data[week_index-1][-1]
        true_return[i] = (concat_data[week_index][-1] -
        ↪ concat_data[week_index-1][-1]) / concat_data[week_index-1][-1]

weights = cp.Variable(n_stocks)
portfolio_variance = cp.quad_form(weights, cov_matrix)
expected_portfolio_return = expected_return_transformer @ weights
objective = cp.Minimize(portfolio_variance - q * expected_portfolio_return)
constraints = [
    cp.sum(weights) == 1, # Sum of weights must be 1
    weights >= 0.0,
    weights <= 0.25
]

prob = cp.Problem(objective, constraints)
prob.solve()
optimal_weights = weights.value
return true_return @ optimal_weights, expected_return @ optimal_weights

```

```
[ ]: get_return(-1, 0.5, 0.25, "transformer")
```

<ipython-input-254-a7d33e7b151a>:13: DeprecationWarning: Conversion of an array with ndim > 0 to a scalar is deprecated, and will error in future. Ensure you extract a single element from your array before performing this operation. (Deprecated NumPy 1.25.)

```

        expected_return[i] = (forecaster.forecast(concat_data[:week_index])[-1] -
concat_data[week_index-1][-1]) / concat_data[week_index-1][-1]

```

<ipython-input-254-a7d33e7b151a>:14: DeprecationWarning: Conversion of an array with ndim > 0 to a scalar is deprecated, and will error in future. Ensure you extract a single element from your array before performing this operation. (Deprecated NumPy 1.25.)

```

        true_return[i] = (concat_data[week_index][-1] - concat_data[week_index-1][-1])
/ concat_data[week_index-1][-1]

```

```
[ ]: (0.014536526960099294, 0.025389962873822374)
```

```

[ ]: weekly_return_transformer = np.ones(shape=52)
weekly_return_lstm = np.ones(shape=52)
for i in range(1, 53):
    print(f"Week {i}")
    weekly_return_transformer[i-1] += get_return(-i, 0.5, 0.25,
    ↪ "transformer")[0]
    weekly_return_lstm[i-1] += get_return(-i, 0.5, 0.25, "LSTM")[0]

```

Week 1

<ipython-input-254-a7d33e7b151a>:13: DeprecationWarning: Conversion of an array with ndim > 0 to a scalar is deprecated, and will error in future. Ensure you

extract a single element from your array before performing this operation.
(Deprecated NumPy 1.25.)

```
expected_return[i] = (forecaster.forecast(concat_data[:week_index])[-1] -  
concat_data[week_index-1][-1]) / concat_data[week_index-1][-1]  
<ipython-input-254-a7d33e7b151a>:14: DeprecationWarning: Conversion of an array  
with ndim > 0 to a scalar is deprecated, and will error in future. Ensure you  
extract a single element from your array before performing this operation.  
(Deprecated NumPy 1.25.)
```

```
true_return[i] = (concat_data[week_index][-1] - concat_data[week_index-1][-1])  
/ concat_data[week_index-1][-1]
```

Week 2
Week 3
Week 4
Week 5
Week 6
Week 7
Week 8
Week 9
Week 10
Week 11
Week 12
Week 13
Week 14
Week 15
Week 16
Week 17
Week 18
Week 19
Week 20
Week 21
Week 22
Week 23
Week 24
Week 25
Week 26
Week 27
Week 28
Week 29
Week 30
Week 31
Week 32
Week 33
Week 34
Week 35
Week 36
Week 37
Week 38

```

Week 39
Week 40
Week 41
Week 42
Week 43
Week 44
Week 45
Week 46
Week 47
Week 48
Week 49
Week 50
Week 51
Week 52

```

```
[ ]: np.prod(weekly_return_transformer)
```

```
[ ]: 1.2614059586150694
```

```
[ ]: np.prod(weekly_return_lstm)
```

```
[ ]: 1.2614057962921046
```

```
[ ]: get_return(1, 0.5, 0.25, "transformer")
```

```

<ipython-input-254-a7d33e7b151a>:13: DeprecationWarning: Conversion of an array
with ndim > 0 to a scalar is deprecated, and will error in future. Ensure you
extract a single element from your array before performing this operation.
(Deprecated NumPy 1.25.)

```

```

    expected_return[i] = (forecaster.forecast(concat_data[:week_index])[-1] -
concat_data[week_index-1][-1]) / concat_data[week_index-1][-1]

```

```

<ipython-input-254-a7d33e7b151a>:14: DeprecationWarning: Conversion of an array
with ndim > 0 to a scalar is deprecated, and will error in future. Ensure you
extract a single element from your array before performing this operation.
(Deprecated NumPy 1.25.)

```

```

    true_return[i] = (concat_data[week_index][-1] - concat_data[week_index-1][-1])
/ concat_data[week_index-1][-1]

```

```
[ ]: (0.007244986497494349, 0.05128917717296181)
```

```

[ ]: lstm_mapes = []
transformer_mapes = []
for i, ticker in enumerate(cov_df.columns):
    transformer_forecaster = PredictAndForecast(transformer_models[ticker],
↪data[ticker].train, data[ticker].test)
    lstm_forecaster = PredictAndForecast(LSTM_models[ticker], data[ticker].
↪train, data[ticker].test)

```

```
transformer_evals = Evaluate(data[ticker].test, transformer_forecaster.  
↪get_predictions())  
lstm_evals = Evaluate(data[ticker].test, lstm_forecaster.get_predictions())  
  
lstm_mapes.append(lstm_evals.mape)  
transformer_mapes.append(transformer_evals.mape)
```

```
[ ]: print(sum(lstm_mapes) / len(lstm_mapes))  
      print(sum(transformer_mapes) / len(transformer_mapes))
```

```
0.03159652042084545  
0.030376104397765596
```

```
[ ]:
```