FOREX PRICE PREDICTION USING MACHINE LEARNING

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GitHub Repository URL: https://github.com/Visualization-Project-Code/Visualizaion-Project-Code

INTRODUCTION TO THE PREDICTION SYSTEM

This project is focused on predicting Forex prices using machine learning and technical analysis. The main idea is to use historical market data and financial indicators to train models that can guess the future price direction of a currency pair, like EUR/USD. The code combines data science, machine learning, and financial analysis in one system.

The prediction system is built step-by-step through different modules. Each module has a specific job, and together they form the complete prediction pipeline. The parts of our prediction system include:

1. **Data Collection and Cleansing**:
    - A script (`DataCreation.ipynb`) takes the raw price and indicator data and builds a clean dataset.
    - This step ensures the data is in the right format for machine learning models.
    - It includes steps like filling missing values, selecting important columns, and labelling the data with the target (what we want to predict).
    - The raw data was downloaded from two free websites (forexsb.com and finance.yahoo.com) and then changed and pre-processed
2. **Data Structuring and Preprocessing**:
    - The system starts with historical Forex price data.
    - It uses a script (`IndicatorsCreation.py`) to calculate technical indicators, such as RSI, MACD, Bollinger Bands, ATR, and others.
    - These indicators help understanding the market by describing market trends.
3. **Utilities and Preprocessing Functions**:

- A file called `utilsation.py` includes helper functions.
- These functions normalize the data (scale values between 0 and 1), split data into training and testing sets, and manage other small tasks.

4. **Machine Learning Models and Training**:
    - The main script (`Prediction System.ipynb`) handles the training and testing of several machine learning models.
    - Models used include:
        - Linear Regression
        - Bayesian Ridge Regression
        - Decision Tree Regressor
        - Random Forest Regressor
        - Support Vector Regressor (SVR)
5. **Visualisation of Results**:
    - The project also includes visualisations to help understand the model performance.
    - It shows things like actual vs predicted prices, error distributions, and indicator trends.
    - There are 10 types of visualisations used, including line charts, bar graphs, and scatter plots.

In summary, when these segments work together to predict Forex price movements using technical indicators, multiple ML models, and detailed visualisations to explain what's happening at each stage.

DATA COLLECTION & CLEANSING

(`DataCreation.ipynb`**)**

This python module is the main part of our data preparation process. It takes the raw Forex data and turns it into a clean, structured dataset that our machine learning models can understand and learn from. Without this step, the models would have a hard time figuring anything out because they wouldn't have the indicators or labels they need.

Why did we pick this dataset:

The dataset used are named **EURUSD_D1.csv**, **EURGBP_H1.csv** and **GBPUSD_H1.csv** and they contain over 20000 rows and 6 columns (before pre-processing after it we have over 20 columns). The columns for raw dataset (without pre-processing) are: Date, Open, High, Low, Close, and Volume. Each row shows daily and hourly data for the EUR/USD/GBP currencies pairs and all columns except Date are numeric. This dataset was chosen because it offers clean, structured, and reliable financial data and is ideal for time-series prediction tasks like forecasting currency trends. The consistent daily format and availability of key price features make it useful for training deep learning models and evaluating their performance on real world market data.

Following the processes step by step, we have:

Step 1: Load the Raw Price Data

```
from utils import *
import pandas as pd

columns = ['Date','Open','High','Low','Close','Volume','Yield','PercentageVolume',
           'SMA6','EMA6','WMA6','HMA6','SMA20','EMA20','WMA20','HMA20','SMA50','EMA50','WMA50','HMA50',
           'SMA100','EMA100','WMA100','HMA100','MACD','CCI','Stochastic Oscillator','RSI','ROC','PPO',
          'KST','BOLU','BOLD','BOLM']
data = pd.read_csv('Data after preprocessing/EURUSD/EURUSD_D1.csv', names = columns, header=0)
data.head(5)
```

Here, we are loading a CSV file that contains historical price data for the EUR/USD currency pair, with daily candlesticks.

At this point, data is a table with columns like Date, Time, Open, High, Low, Close, and Volume.

Also, the data after pre-processing have all the needed indicators (this process is explained fully in “Utilities and Preprocessing Functions” part of the report).

Step 2: Keep Only Needed Columns

```
toAdd = ['Volume', 'Date','High','Low','Open','Close']
close = data['Close']
df = selectData(data,toAdd)
normDf = normalizeData(df)
normClose = normalizeData(close)
```

This filters the table so we only keep the four important price columns:

- `Open`: The price at the beginning of the hour.
- `High`: The highest price during the hour.
- `Low`: The lowest price during the hour.
- `Close`: The price at the end of the hour.

Also normalized data is added in `normDf` (for the whole data) and `normClose` (only for close column of data which is going to be predicted)

Step 3: Plotting the Data

```
import matplotlib.pyplot as plt
%matplotlib inline
df.hist(figsize=(28,15), layout=(3,6), bins=100)
plt.show()
```

This part plot the charts for each column in the data

- `matplotlib` is used to plot the charts

• `%matplotlib inline` makes sure the charts appear inside the notebook

• `df.hist` draws a chart for each column using 100 bars

• `figsize` makes the charts large so they are easy to read

• `layout` puts the charts in 3 rows and 6 columns

• `plt.show` displays all the charts together in one place

Step 4: Plotting The Data Heatmap

```
import matplotlib.pyplot as plt
%matplotlib inline
plt.figure(figsize=(13,13))
plt.matshow(normDf.corr(), fignum=1)
plt.colorbar()
plt.yticks(range(len(normDf.columns)),normDf.columns,fontsize=10)
plt.xticks(range(len(normDf.columns)),normDf.columns,fontsize=10,rotation=90)
plt.title("Correlation between Features and Label", y=1.2)
plt.show()
```

This code part create a heatmap that shows how each column is related to the other columns

• `matplotlib` is used to make the heatmap

• `plt.figure` sets the size of the heatmap

• `plt.matshow` shows the correlation between all columns using colours

• `plt.colorbar` adds a colour scale to help understand the values

• `plt.yticks` and `plt.xticks` label the sides with the column names and adjust their size and rotation

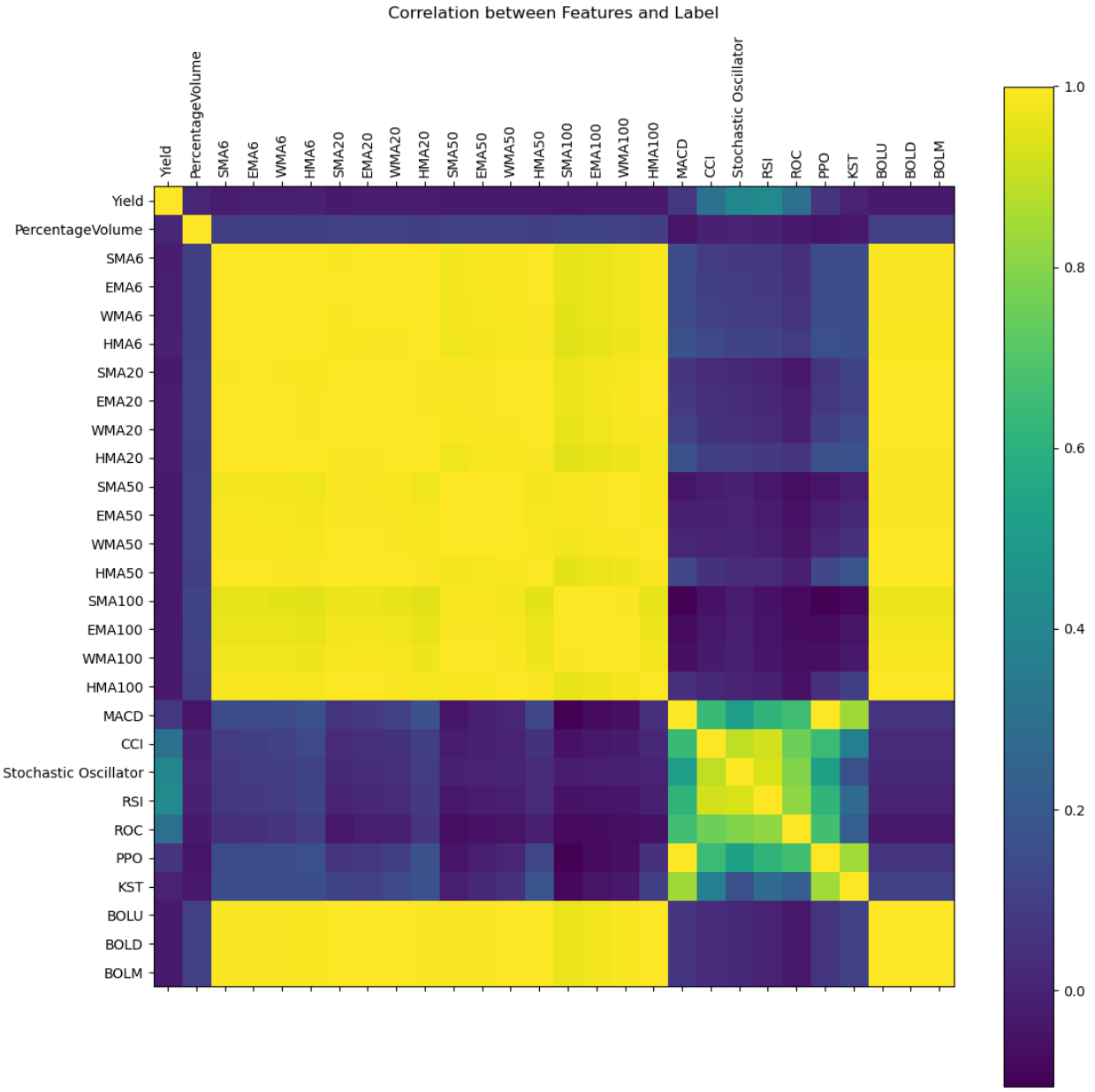


Fig. 1: Heatmap visualisation of the dataset

A heatmap shows how strongly features like Open, High, Low, Close, and Volume relate to each other using color, helping identify important patterns for prediction and feature selection. Darker or brighter colours show stronger correlations, while lighter shades show weaker ones.

Step 5: Build the Coloured Table (To Show Columns Relation)

```
corr = normDf.corr()
corr.style.background_gradient(cmap='coolwarm')
```

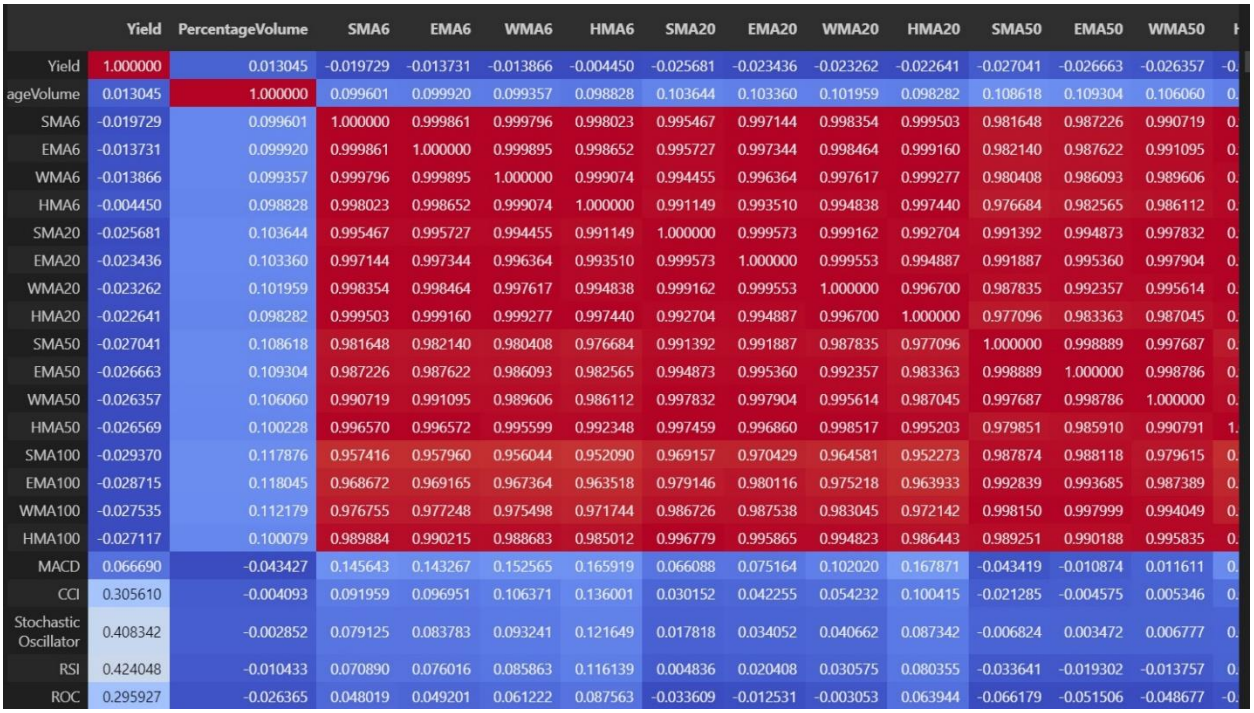
In this step we make a coloured table that shows how the columns are related to each other

• `normDf.corr` calculates the relationship between all the columns

• The result is saved in a new table called `corr`

• `corr.style.background_gradient` adds color to the table

• The colors use the coolwarm style to show strong and weak relationships clearly



	Yield	PercentageVolume	SMA6	EMA6	WMA6	HMA6	SMA20	EMA20	WMA20	HMA20	SMA50	EMA50	WMA50	H
Yield	1.000000	0.013045	-0.019729	-0.013731	-0.013866	-0.004450	-0.025681	-0.023436	-0.023262	-0.022641	-0.027041	-0.026663	-0.026357	-0.
ageVolume	0.013045	1.000000	0.099601	0.099920	0.099357	0.098828	0.103644	0.103360	0.101959	0.098282	0.108618	0.109304	0.106060	0.
SMA6	-0.019729	0.099601	1.000000	0.999861	0.999796	0.998023	0.995467	0.997144	0.998354	0.999503	0.981648	0.987226	0.990719	0.
EMA6	-0.013731	0.099920	0.999861	1.000000	0.999895	0.998652	0.995727	0.997344	0.998464	0.999160	0.982140	0.987622	0.991095	0.
WMA6	-0.013866	0.099357	0.999796	0.999895	1.000000	0.999074	0.994455	0.996364	0.997617	0.999277	0.980408	0.986093	0.989606	0.
HMA6	-0.004450	0.098828	0.998023	0.998652	0.999074	1.000000	0.991149	0.993510	0.994838	0.997440	0.976684	0.982565	0.986112	0.
SMA20	-0.025681	0.103644	0.995467	0.995727	0.994455	0.991149	1.000000	0.999573	0.999162	0.992704	0.991392	0.994873	0.997832	0.
EMA20	-0.023436	0.103360	0.997144	0.997344	0.996364	0.993510	0.999573	1.000000	0.999553	0.994887	0.991887	0.995360	0.997904	0.
WMA20	-0.023262	0.101959	0.998354	0.998464	0.997617	0.994838	0.999162	0.999553	1.000000	0.996700	0.987835	0.992357	0.995614	0.
HMA20	-0.022641	0.098282	0.999503	0.999160	0.999277	0.997440	0.992704	0.994887	0.996700	1.000000	0.977096	0.983363	0.987045	0.
SMA50	-0.027041	0.108618	0.981648	0.982140	0.980408	0.976684	0.991392	0.991887	0.987835	0.977096	1.000000	0.998889	0.997687	0.
EMA50	-0.026663	0.109304	0.987226	0.987622	0.986093	0.982565	0.994873	0.995360	0.992357	0.983363	0.998889	1.000000	0.998786	0.
WMA50	-0.026357	0.106060	0.990719	0.991095	0.989606	0.986112	0.997832	0.997904	0.995614	0.987045	0.997687	0.998786	1.000000	0.
HMA50	-0.026569	0.100228	0.996570	0.996572	0.995599	0.992348	0.997459	0.996860	0.998517	0.995203	0.979851	0.985910	0.990791	1.
SMA100	-0.029370	0.117876	0.957416	0.957960	0.956044	0.952090	0.969157	0.970429	0.964581	0.952273	0.987874	0.988118	0.979615	0.
EMA100	-0.028715	0.118045	0.968672	0.969165	0.967364	0.963518	0.979146	0.980116	0.975218	0.963933	0.992839	0.993685	0.987389	0.
WMA100	-0.027535	0.112179	0.976755	0.977248	0.975498	0.971744	0.986726	0.987538	0.983045	0.972142	0.998150	0.997999	0.994049	0.
HMA100	-0.027117	0.100079	0.989884	0.990215	0.988683	0.985012	0.996779	0.995865	0.994823	0.986443	0.989251	0.990188	0.995835	0.
MACD	0.066690	-0.043427	0.145643	0.143267	0.152565	0.165919	0.066088	0.075164	0.102020	0.167871	-0.043419	-0.010874	0.011611	0.
CCI	0.305610	-0.004093	0.091959	0.096951	0.106371	0.136001	0.030152	0.042255	0.054232	0.100415	-0.021285	-0.004575	0.005346	0.
Stochastic Oscillator	0.408342	-0.002852	0.079125	0.083783	0.093241	0.121649	0.017818	0.034052	0.040662	0.087342	-0.006824	0.003472	0.006777	0.
RSI	0.424048	-0.010433	0.070890	0.076016	0.085863	0.116139	0.004836	0.020408	0.030575	0.080355	-0.033641	-0.019302	-0.013757	0.
ROC	0.295927	-0.026365	0.048019	0.049201	0.061222	0.087563	-0.033609	-0.012531	-0.003053	0.063944	-0.066179	-0.051506	-0.048677	-0.

Fig. 2: Coloured table visualisation of the dataset showing column relationships

A coloured table is used to show how different features in the dataset relate to each other. It is created by calculating the correlation between key columns like Open, High, Low, Close, and

Volume, and then visualizing the results with a heatmap. Darker colors represent stronger relationships, while lighter ones show weaker or no connection at all. This helps identify which features move together and which are more useful for prediction. This step gives a clear view of feature interactions and supports better model decisions.

Step 6: Plotting Scatter Plot for Column Comparison

```
from pandas.plotting import scatter_matrix
axes = scatter_matrix(normDf, figsize=(30,20))
for ax in axes.flatten():
    ax.xaxis.label.set_rotation(90)
    ax.yaxis.label.set_rotation(0)
    ax.yaxis.label.set_ha('right')
for i in range(np.shape(axes)[0]):
    for j in range(np.shape(axes)[1]):
        if i < j:
            axes[i,j].set_visible(False)
plt.show()
```

This code makes many small scatter plots to compare all columns with each other

• `scatter_matrix` shows how each column is related to every other one using small charts
• the loop changes the direction on the labels so they are much easier to see
• another loop hides the upper part of the chart grid to remove repeated charts
(Full explanation of this plot and its benefit at the bottom of the report)

Step 7: Creating Box Plot

```
import matplotlib.pyplot as plt
%matplotlib inline
fig, axes = plt.subplots(4,7,figsize=(25,13))
fig.tight_layout()
axes = axes.flatten()
for i, col in enumerate(list(sorted(df.columns))):
    axes[i].boxplot(df[col], showfliers = False)
    axes[i].set_title(col)
    axes[i].grid()
plt.show()
```

Now we creates box plots to show the range and spread of each column

• `plt.subplots` makes 28 boxes in 4 rows and 7 columns with a big size
• `tight_layout` gives the plots some space so they don't overlap
• `axes.flatten` puts all the boxes in one list so we can use them in a loop
• The loop goes through every column one by one
• `axes[i].boxplot` makes a box plot for each column without outliers
• `grid()` adds lines to help see the values

(Full explanation of this plot and its benefit at the bottom of the report)

Summary

- This notebook prepares our entire dataset in one clean pipeline.
- It loads the raw daily price data.
- It calculates all the technical indicators needed for prediction.
- It normalizes and adds them to the main table.
- It creates a Target column (future close price).
- It saves everything to a new file for the ML models to use.

Without this step, the models wouldn't have anything to learn from. This step builds the "features" (the inputs) and the "target" (the output) for the learning process

BIG DATA ANALYSIS TECHNIQUES

(`Prediction System.ipynb`)

1) THE BENEFITS OF BIG DATA ANALYSIS IN FOREX PREDICTION

Big data technologies have transformed the landscape of financial analysis particularly in areas like Forex price prediction, where massive volumes of structured and even unstructured data are generated every second. These technologies provide the computational power necessary to collect, store and process and analyse vast datasets in real-time. With the help of big data techniques financial institutions and independent traders can process overwhelming amounts of data like historical price records, live market feeds, economic indicators and even social media trends that can easily have an effect on any currency fluctuations [5].

One of the primary benefits of big data technologies is their ability to manage the 3Vs of big data which are volume, velocity and variety, all of which are central to financial markets. Apache Hadoop and Apache Spark are good examples of Big data frameworks that allow distributed storage and parallel processing of large amounts of data. These frameworks are highly scalable and efficient, enabling organizations to conduct complex analytics quickly and reliably.

In regards to Forex prediction, big data technologies enable analysts to incorporate high frequency trading (HFT) data, real-time news articles and even sentiment from social media platforms. The inclusion of such a diverse variety of data improves the accuracy of predictive models and provides a better view of market behaviour.

Among the latest techniques used in big data analytics are machine learning and deep learning methods. These can uncover patterns and relationships in data that are not easily visible through traditional statistical analysis. New systems like the Long Short-Term Memory (LSTM) networks have gained popularity for modelling time-series data such as Forex prices because they can learn dependencies over long sequences. Transformer models are also now being adapted for time-series forecasting due to their ability to handle long-range dependencies with greater efficiency. These were originally developed for natural language processing put have been introduced into Big data analysis [6].

Other recent innovations include the use of AutoML (Automated Machine Learning) platforms, which automate model selection, hyperparameter tuning, and feature engineering. This reduces the manual effort required in the modelling process and speeds up deployment. In addition, stream processing technologies like Apache Flink and Apache Kafka Streams support real-time data analysis, which is vital for traders who need to act on market changes as they occur. These tools can ingest, process, and analyse live data feeds with very low latency [6].

2) Techniques used in code

```
# Start Spark session
spark = SparkSession.builder.appName("BitcoinPricePrediction") .getOrCreate()

# Load CSV from local or HDFS or S3
df = spark.read.csv("Data after preprocessing/EURUSD/EURUSD_D1.csv", header=True, inferSchema=True)

# Show first few rows
df.show(5)

# Print schema
df.printSchema()



from pyspark.sql.functions import col

# Select relevant features
features = ['Open', 'High', 'Low', 'Close', 'Volume']
df_selected = df.select(*features)

# Basic statistical summary
df_selected.describe().show()

# Filter out rows with missing values
df_clean = df_selected.dropna()
```

The code uses PySpark to prepare data for a EURUSD price prediction model. It starts by creating a Spark session to handle big data efficiently then it reads a CSV file that contains historical price data and shows the first few rows to check if the data loaded correctly or not after that it prints the data structure to understand what each column contains and next, it selects only

the features from raw data like Open, High, Low, Close, and Volume. It removes any rows with missing values to make sure the data is clean then it uses a tool called Vector Assembler to combine these features into one vector so they can be used in machine learning and finally, it scales the data using MinMaxScaler to bring all values into the same range. This step is important because it helps machine learning models learn more effectively by treating each feature equally.

DATA STRUCTURING & PRE-PROCESSING

(IndicatorsCreation.py)

This file is responsible for calculating different technical indicators, which are mathematical formulas used to analyse financial data. These indicators are widely used in trading and finance to help decide whether the price of something (like a currency pair) might go up or down. This file is crucial to our prediction system, because all our machine learning models will use the results from here as inputs (features).

Each indicator's logic are as follows:

---

1) Exponential Moving Average (EMA)

```
def EMA(data, windowSize):
    return data.ewm(span=windowSize,min_periods=windowSize,adjust=False).mean()
```

EMA stands for Exponential Moving Average. It is a type of moving average that gives more weight to recent prices, meaning it reacts faster to price changes than a Simple Moving Average (SMA).

- `data`: This is the price data (like the closing prices of a currency).
- `windowSize`: How many days we look back.
- `.ewm()`: This function creates the exponential moving average.
- `.mean()`: This finishes the calculation.

For example, a 10-day EMA will calculate a smoothed line based on the last 10 prices, but will pay more attention to recent days.

2) Simple Moving Average (SMA)

```
def SMA(data, windowSize):
    return data.rolling(window=windowSize,min_periods=windowSize).mean()
```

SMA stands for Simple Moving Average. Unlike EMA, it gives equal weight to all prices in the window.

- `.rolling()` slides over the data in windows of a certain size.
- `.mean()` calculates the average in each window.

SMA helps identify the overall trend, but it's slower to react than EMA.

---

3) Weighted Moving Average (WMA)

```
def WMA(data, windowSize):
    weights = list(range(1,windowSize+1))
    denom = np.sum(weights)
    return (data.rolling(window=windowSize, min_periods=windowSize)
    .apply(lambda x: np.sum(weights*x) / denom, raw=False))
```

WMA stands for Weighted Moving Average. It's a little smarter than SMA because it gives higher importance to recent values.

- `weights` is a list of numbers like `[1, 2, 3, ..., windowSize]`.
- `np.sum(weights*x)` multiplies each price by its weight.
- Then we divide by the total of the weights (`denom`) to get the weighted average.

This moving average is useful when we want to focus more on what's happening recently, but still consider older prices.

4) Hull Moving Average (HMA)

```
def HMA(data, windowSize):
    return WMA((2*WMA(data, int(windowSize/2)) - WMA(data,windowSize)),
    int(np.sqrt(windowSize)))
```

HMA is short for Hull Moving Average. This one is built using multiple WMAs.

- First, it calculates two WMAs: one short-term and one long-term.
- Then it subtracts them, multiplies the short-term one by 2, and smooths the result using another WMA.

The final result is very smooth and responds quickly to price changes. It's useful in fast-moving markets.

---

5) Moving Average Convergence Divergence (MACD)

```
def MACD(close):
    return EMA(close,12) - EMA(close,26)
```

MACD is one of the most famous indicators. It shows momentum — how strong the current price movement is.

- It subtracts a 26-day EMA from a 12-day EMA.
- If the result is positive, it means short-term prices are moving up faster than the long term — possibly an uptrend.
- If it's negative, it may mean prices are slowing down or falling.

6) Typical Price

```
def TypicalPrice(high,low,close):
    return (high+low+close)/3
```

This is a simple average of the high, low, and close prices for a day.

- It gives a more balanced view than just looking at the close price.
- Used as a base in many other indicators, like CCI and Bollinger Bands.

---

7) Commodity Channel Index (CCI)

```
def CCI(typicalPrice):
    smatp = EMA(typicalPrice,20)
    avgDev = typicalPrice.rolling(window=20,min_periods=20).std()
    return (typicalPrice - smatp)/(0.015*avgDev)
```

CCI measures how far the price is from its average. It helps spot extreme highs and lows.

- A high CCI (>100) means price is far above its average = possible overbought.
- A low CCI (< -100) means price is far below its average = possible oversold.

---

8) Data Normalization

```python
def normalizeData(matr, indicators, scaler):
    for j in range(len(indicators)):
        if isinstance(scaler[indicators[j]][0],int):
            minVal = scaler[indicators[j]][0]
        else:
            minVal = np.min(matr[indicators.index(scaler[indicators[j]][0]),:])

        if isinstance(scaler[indicators[j]][1],int):
            maxVal = scaler[indicators[j]][1]
        else:
            maxVal = np.max(matr[indicators.index(scaler[indicators[j]][1]),:])

        matr[j,:] = (matr[j,:] - minVal) / (maxVal - minVal)
    #print(matr)
    return matr
```

This function makes sure all indicator values are scaled between 0 and 1.

- This is important for machine learning.
- It ensures that indicators like RSI (0–100) and MACD (can be negative) are on the same scale.
- It also prevents large values from dominating the learning process.

Summary:

- This file builds all the important technical indicators used in financial forecasting.
- These indicators are used as features in machine learning models.
- Each one captures something different: trend, momentum, volatility, strength.
- The `normalizeData` function prepares the data for modelling.

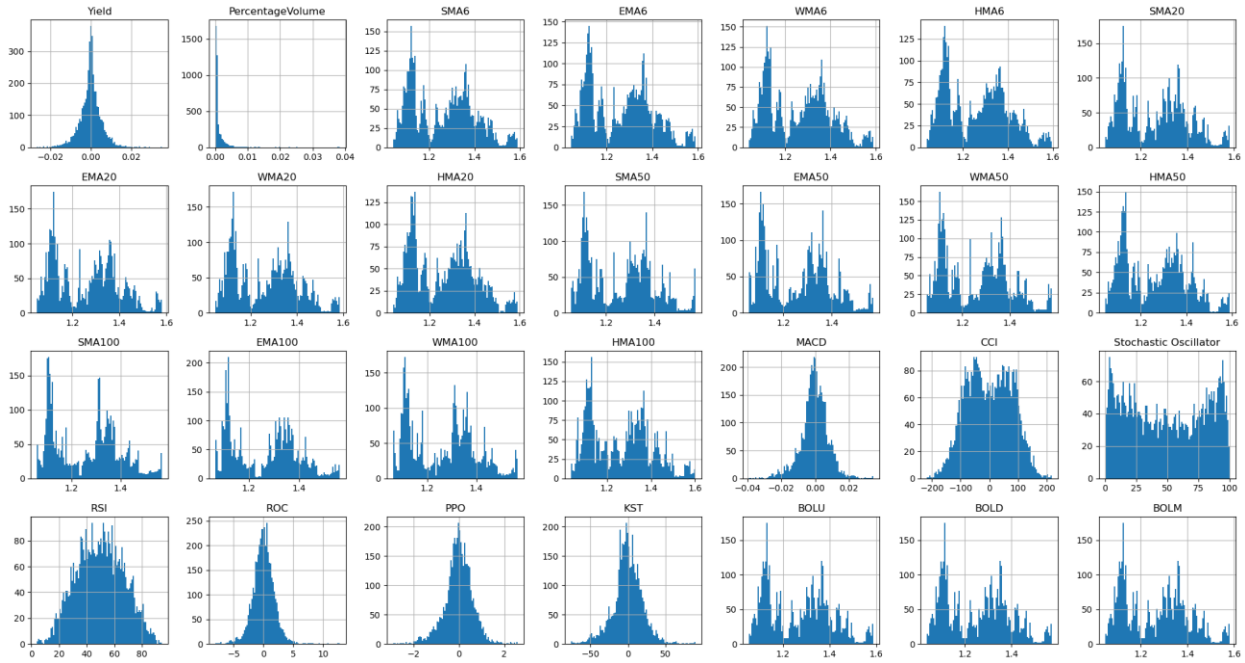


Fig. 3: Indicators visualisation

UTILITIES AND PRE-PROCESSING FUNCTIONS

(`utilsation.py`)

The `utilsation.py` file acts as a helper module in our Forex prediction project. It includes a set of utility functions that do common tasks needed for preparing the dataset for machine learning. These tasks include:

- Loading and cleaning data
- Adding technical indicators
- Normalizing values
- Structuring the data in special ways (like turning it into image formats)
- Splitting data into training and testing sets

These functions allow us to process large amounts of historical Forex price data in an organized, reusable way.

Let's now go through each part of the file step by step.

Function 1: `generateData(...)`

This is the main data preparation function. It loads the price data from a CSV file, computes several technical indicators, and prepares the full dataset.

Load the CSV Data

```
def generateData(filename, columns, index, indicators):
    data = pd.read_csv(filename, names=columns)
    data.set_index(index)
```

This reads the CSV file into a DataFrame using the column names we provide.

- The index is set to the given `index` parameter (usually a datetime column).

Add Yield Column

```
data['Yield'] = (data['Close'] - data['Open'])/(data['Open'])
```

This line calculates the percentage change between the opening and closing prices. This value is often called the "yield" or return for that time period.

Formula:

Yield = (Close − Open) / Open

This is useful because it tells us whether the price went up or down during the interval, and by how much in percentage terms.

Add Percentage Volume

```
data['PercentageVolume'] = (data['High'] - data['Low'])*(10**4) / data['Volume']
```

This creates a custom indicator that combines volatility and volume. It tells us how much the price moved (high - low) relative to the volume. Multiplying by 10^4 scales it up to avoid small decimals.

Add Technical Indicators

We now enter the core part of the function — adding many indicators using the functions from `IndicatorsCreation.py`.

Moving Averages

```
windows = [6,20,50,100]
```

We define four different moving average window sizes. These represent short, medium, and long-term trends.

For each window, we calculate the following:

- SMA: Simple Moving Average — smooths the price.
- EMA: Exponential Moving Average — faster than SMA.
- WMA: Weighted Moving Average — gives more importance to recent prices.

These are helpful for identifying trends.

```
#Moving Averages
st = time.time()
for windowSize in windows:
    st = time.time()
    data['SMA{}'.format(windowSize)] = SMA(close,windowSize)
    end = time.time()
    print("SMA{}: {}".format(windowSize,end-st))
    st = time.time()
    data['EMA{}'.format(windowSize)] = EMA(close,windowSize)
    end = time.time()
    print("EMA{}: {}".format(windowSize,end-st))
    st = time.time()
    data['WMA{}'.format(windowSize)] = WMA(close,windowSize)
    end = time.time()
    print("WMA{}: {}".format(windowSize,end-st))
    st = time.time()
    data['HMA{}'.format(windowSize)] = HMA(close,windowSize)
    end = time.time()
    print("HMA{}: {}".format(windowSize,end-st))
end = time.time()
print("MAs: {}".format(end-st))
```

Each of these calculations is timed and printed to show how long it takes

---

Oscillators

Now we calculate several momentum and volatility-based indicators. Each of these gives a different view of how the market is behaving.

1. MACD – Moving Average Convergence Divergence

```
#Oscillators
#Moving Average Convergence/Divergence
st = time.time()
data['MACD'] = MACD(close)
end = time.time()
print("MACD: {}".format(end-st))
```

This compares short-term and long-term EMA values and is often used to detect trend changes.

2. CCI – Commodity Channel Index

```
#Commodity Channel Index
st = time.time()
typicalPrice = TypicalPrice(data['High'], data['Low'], close)
data['CCI'] = CCI(typicalPrice)
end = time.time()
print("CCI: {}".format(end-st))
```

This uses the typical price and measures how far the price is from its average.

3. Stochastic Oscillator

```
#Stochastic Oscillator
st = time.time()
data['Stochastic Oscillator'] = StochasticOscillator(close, data['High'], data['Low'])
end = time.time()
print("StochOsc: {}".format(end-st))
```

This shows whether the closing price is near the high or low of the recent period. It can help detect overbought or oversold conditions.

4. RSI – Relative Strength Index

```
#Relative Strength Index
st = time.time()
data['RSI'] = RSI(close)
end = time.time()
print("RSI: {}".format(end-st))
```

This tracks the speed of price changes. RSI is also used to detect overbought or oversold markets.

5. ROC – Rate of Change

```
#Rate of Change
st = time.time()
data['ROC'] = ROC(close,12)
end = time.time()
print("ROC: {}".format(end-st))
```

This measures the percentage change over a 12-period window.

6. PPO – Percentage Price Oscillator

```
#Percentage Price Oscillator
st = time.time()
data['PPO'] = PPO(close)
end = time.time()
print("PPO: {}".format(end-st))
```

This is similar to MACD but expressed as a percentage of EMA.

7. KST – Know Sure Thing

```
#Know Sure Thing
st = time.time()
data['KST'] = KST(close)
end = time.time()
print("KST: {}".format(end-st))
```

A complex momentum indicator that blends several ROC values.

8. Bollinger Bands

```
#Bollinger Bands: Up, Down, Middle
st = time.time()
data['BOLU'] = BollingerBandUp(typicalPrice)
data['BOLD'] = BollingerBandDown(typicalPrice)
data['BOLM'] = BollingerBandMiddle(typicalPrice)
end = time.time()
print("BOLS: {}".format(end-st))
```

Bollinger Bands show price relative to a moving average and measure volatility. The upper and lower bands expand when the market is volatile.

Remove Missing Rows & Return Cleaned Data

```
data = data.dropna(axis=0,how='any').round(decimals=6)

return data
```

Some of the indicator calculations require several past data points.

- This causes the first few rows to have missing values (NaN).
- This line drops those rows and rounds everything to 6 decimal places.
- The function then returns the fully cleaned and enriched dataset with all the added indicators.

Function 2: `selectData(...)`

```python
def selectData(data,columnsToRemove):
    indicators = data.columns
    indicators = [elem for elem in indicators if elem not in columnsToRemove]
    df = data[indicators]
    return df
```

This function lets us choose only the columns we want to keep by removing the ones listed in `columnsToRemove`.

Function 3: `normalizeData(...)`

```python
def normalizeData(data):
    return (data - data.min())/(data.max() - data.min())
```

This function scales each column between 0 and 1 using a min-max normalization formula.

This is useful because it makes sure all values are in the same range. Some indicators might normally range from 0–100 (like RSI), while others are negative or very small. Scaling helps machine learning models learn more effectively.

Function 4: `generateImages(...)`

```python
def generateImages(data):
    images = []
    for i in range(data.shape[0]-len(data.columns)):
        img = np.zeros((len(data.columns),len(data.columns)), dtype=float)
        for j in range(len(data.columns)):
            img[:,j] = data.iloc[i:i+len(data.columns), data.columns.get_loc(data.columns[j])]
        img = img.reshape(len(data.columns),len(data.columns),1)
        images.append(img)
    return images
```

This function transforms the time series data into a 2D matrix (like an image).

How it works:

- It loops over the rows of the data, taking `N` rows at a time (`N` = number of columns).
- It builds a square matrix of size `N x N`.
- Each matrix is reshaped into a 3D image-like structure: `height x width x 1`.

Why this is useful:

- If we want to use Convolutional Neural Networks (CNNs) or other image-based deep learning models, we need our data in an image format.
- This trick turns rows of data into grayscale images for each time window.

Function 5: `generateTrainingTest(...)`

```
def generateTrainingTest(images, label):
    sets = [
        (images[i:i+365*4],#trainX
         images[i+365*4:i+365*5],#testX
         np.array(label)[i:i+365*4],#trainY
         np.array(label)[i+365*4:i+365*5]) #testY
        for i in range(0,len(images)-365*5,365)
    ]

    return sets
```

This function splits the data into training and testing sets.

How it works:

- It uses a rolling window to build multiple sets from the image and label data.
- Each set includes:
    - `trainX`: 4 years of image data
    - `testX`: 1 year of image data
    - `trainY`: 4 years of labels
    - `testY`: 1 year of labels

It loops in steps of 1 year (365 days), generating multiple training/testing blocks.

This is useful for time-series modelling, where we want to train on earlier data and test on future unseen data.

Summary

The `utilsation.py` file is a useful module that helps us standardize the entire preprocessing workflow. It contributes:

- `generateData()`: Builds the full dataset with all indicators and metrics.
- `selectData()`: Filters the dataset to keep only what we need.
- `normalizeData()`: Scales all the features into a range from 0 to 1.
- `generateImages()`: Turns time-series data into image-like format for deep learning.
- `generateTrainingTest()`: Splits the data into manageable chunks for training and testing.

Together, these functions make sure that our machine learning models receive clean, structured, and consistent data.

MACHINE LEARNING ALGORITHMS

(`Prediction System.ipynb`)

This is the part of our system that applies machine learning algorithms to predict Forex prices based on the technical indicators we calculated earlier. We use five different regression models:

1. Linear Regression
2. Bayesian Ridge Regression
3. K Nearest Neighbor (KNN)
4. Support Vector Regression (SVR)

Each of these models tries to predict the next hour's price (or return) based on the current technical indicators.

Model 1: Linear Regression

Linear Regression is one of the most foundational and easy-to-understand models in machine learning. It tries to model the relationship between the input variables and the target by fitting a straight line (or a hyperplane in higher dimensions) through the data [1]. The idea is to minimize the difference between the predicted and actual values by adjusting the slope and intercept of the line. While simple, it's rooted in solid statistical principles and offers interpretability that many advanced models lack.

Why use it:

- It's extremely fast to train and very efficient, even on large datasets.
- It serves as a solid benchmark — you can quickly get a feel for how difficult the problem is by seeing how well this basic model performs.
- Because it's so interpretable, it's a great way to understand how individual features impact the prediction.
- While it may not always provide the highest accuracy, its simplicity makes it an essential starting point before moving on to more complex or resource-heavy models.

Training:

```
from sklearn.linear_model import LinearRegression
from Codes.DTW import *
import json

with open("ML/MLModels.json","r") as f:
    params = json.load(f)["Linear Regression"]["EURUSD"]
lr = LinearRegression(**params)
predictedPrices = lr.fit(train_X, train_Y).predict(test_X)
```

Applying the `LinearRegression` algorithm from `skLearn` library we train the model using our cleaned data.

Evaluation:

```
print("MSE: {:e}".format(np.mean((predictedPrices-test_Y)**2)))
print("CORR: {:.3f}".format(np.corrcoef(predictedPrices, test_Y)[0,1]))
print("DTW: {:.3f}".format(DTW(predictedPrices, np.array(test_Y),1)))
```

```
MSE: 2.044720e-05
CORR: 0.993
DTW: 1.137
```

As seen in the code, we apply mean squared error, correlation coefficients and Dynamic time wrapping evaluation metrics.

Visualisation:

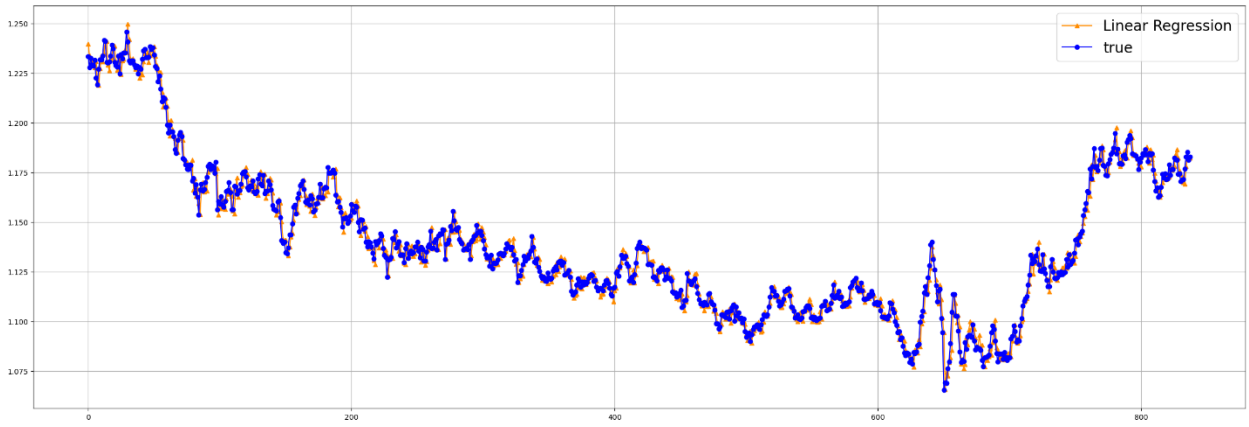


Fig. 5: Linear Regression Visualised Results

Model 2: Bayesian Ridge Regression

Bayesian Ridge Regression is an enhanced version of Linear Regression that brings in the power of probability. Instead of finding a single best-fit line like standard Linear Regression, it treats the model parameters as distributions and updates them using Bayes' Theorem [2]. This approach allows the model to incorporate uncertainty into its predictions and apply automatic regularization, which helps avoid overfitting — especially when dealing with limited or noisy data.

Why use it:

- It handles uncertainty in the data more naturally and effectively than standard Linear Regression.
- The built-in regularization makes it more robust, especially when the dataset is small or contains a lot of noise.
- It provides not just predictions, but also a measure of confidence around those predictions which can be incredibly valuable in high-stakes or data-sensitive applications.

- It's a great middle ground when you want more flexibility than basic Linear Regression, but without jumping straight into complex, black-box models.

Training:

```
from sklearn.linear_model import BayesianRidge
from Codes.DTW import *
import json

with open("ML/MLModels.json","r") as f:
    params = json.load(f)["Bayesian Ridge Regression"]["EURUSD"]
brr = BayesianRidge(**params)
predictedPrices = brr.fit(train_X, train_Y).predict(test_X)
```

We imported the `BayesianRidge` model from `skLearn` and trained it using our data.

Evaluation:

```
print("MSE: {:e}".format(np.mean((predictedPrices-test_Y)**2)))
print("CORR: {:.3f}".format(np.corrcoef(predictedPrices, test_Y)[0,1]))
print("DTW: {:.3f}".format(DTW(predictedPrices, np.array(test_Y),1)))
```

We apply mean squared error, correlation coefficients and Dynamic time wrapping evaluation metrics.

Visualisation:

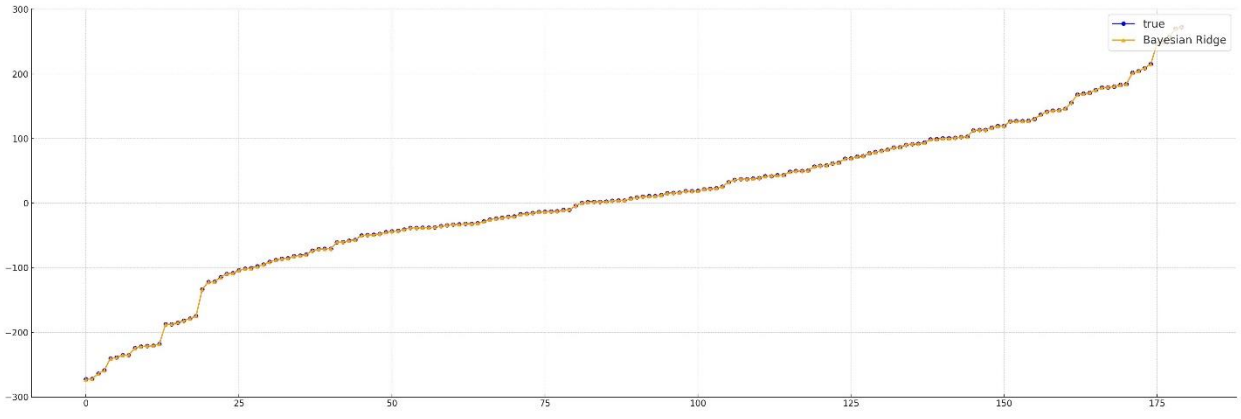


Fig. 6: Bayesian Ridge Regression Result

This model gives slightly different results than standard linear regression, often performing better on small or noisy data.

Model 3: K Nearest Neighbours (KNN)

K Nearest Neighbours is a simple, intuitive algorithm that makes predictions based on similarity. Instead of learning a mathematical function from the training data, it memorizes the dataset and makes predictions by looking at the 'k' closest data points (neighbours) to a new input [3]. For regression tasks, it takes the average of those neighbours' values. Think of it like asking a group of similar past cases what the likely outcome should be for a new situation.

Why use it:

- It handles non-linear patterns in the data very well, which makes it flexible for a wide range of problems.
- It's easy to understand and explain there's no complex math behind the scenes, just a matter of finding similar points.
- Unlike some other models, KNN doesn't assume anything about the underlying data distribution.
- It often performs well without the need for scaling or transforming the input features, saving time during preprocessing.
- It's particularly useful when you want a model that's more "data-driven" rather than "formula-driven."

Training:

```
from sklearn.neighbors import KNeighborsRegressor
from Codes.DTW import *
import json

with open("ML/MLModels.json","r") as f:
    params = json.load(f)["KNN Regression"]["EURUSD"]
knn = KNeighborsRegressor(**params)
predictedPrices = knn.fit(train_X, train_Y).predict(test_X)
```

We use the `KNeighborsRegressor` model from `skLearn` to predict.

Evaluation:

```
    print("MSE: {:e}".format(np.mean((predictedPrices-test_Y)**2)))
    print("CORR: {:.3f}".format(np.corrcoef(predictedPrices, test_Y)[0,1]))
    print("DTW: {:.3f}".format(DTW(predictedPrices, np.array(test_Y),1)))
```

```
MSE: 1.587217e-05
CORR: 0.995
DTW: 0.921
```

Visualisation:

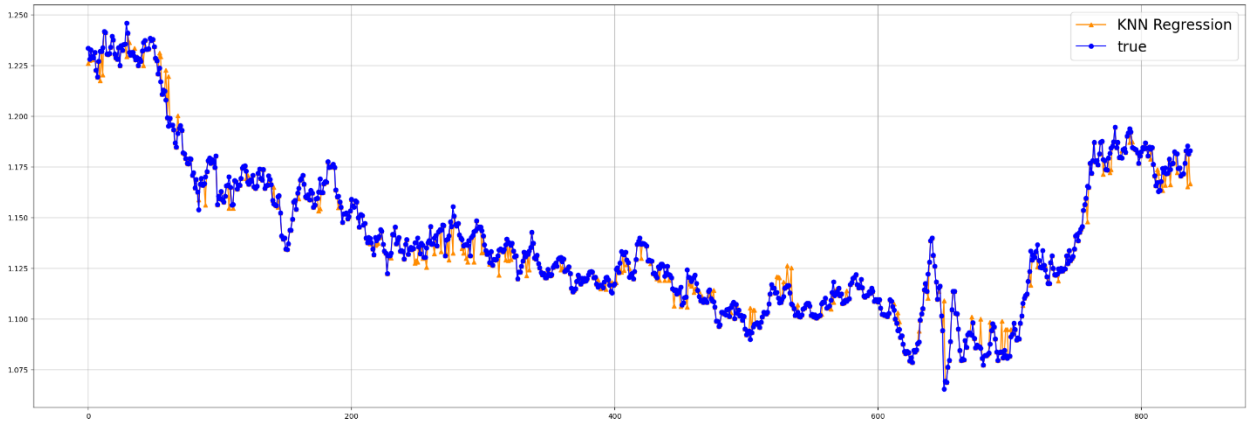


Fig. 7: KNN Result

Nearest Neighbours are more flexible than linear models, but they can overfit if not pruned or limited in depth.

Model 4: Support Vector Regression (SVR)

Support Vector Regression (SVR) is a flexible and powerful regression method built on the same principles as Support Vector Machines (SVM). Instead of trying to minimize the error for every data point, SVR focuses on finding a line (or curve) that fits the data while allowing for a certain margin of tolerance known as epsilon. Points that fall within this margin don't count as errors, which makes SVR less sensitive to noise [4]. Using different kernel functions, SVR can handle both linear and complex, non-linear relationships with ease.

Why use it:

- It performs well on non-linear datasets, especially when using the right kernel (like RBF or polynomial).
- It's quite robust against outliers since small deviations within the epsilon margin are essentially ignored.
- SVR offers a balance between model flexibility and generalization, making it a great choice for tricky regression problems.
- With proper tuning, it can be very precise and adaptable to different kinds of data patterns.

Training:

```
from sklearn.svm import SVR
from Codes.DTW import *
import json

with open("ML/MLModels.json","r") as f:
    params = json.load(f)["Support Vector Regression"]["EURUSD"]
svr = SVR(**params)
predictedPrices = svr.fit(train_X, train_Y).predict(test_X)
```

Evaluation:

```
    print("MSE: {:e}".format(np.mean((predictedPrices-test_Y)**2)))
    print("CORR: {:.3f}".format(np.corrcoef(predictedPrices, test_Y)[0,1]))
    print("DTW: {:.3f}".format(DTW(predictedPrices, np.array(test_Y),1)))
```

```
MSE: 1.359575e-03
CORR: 0.972
DTW: 27.496
```

SVR can be slower to train, especially with large datasets, but it can perform very well when tuned properly.

Visualisation:

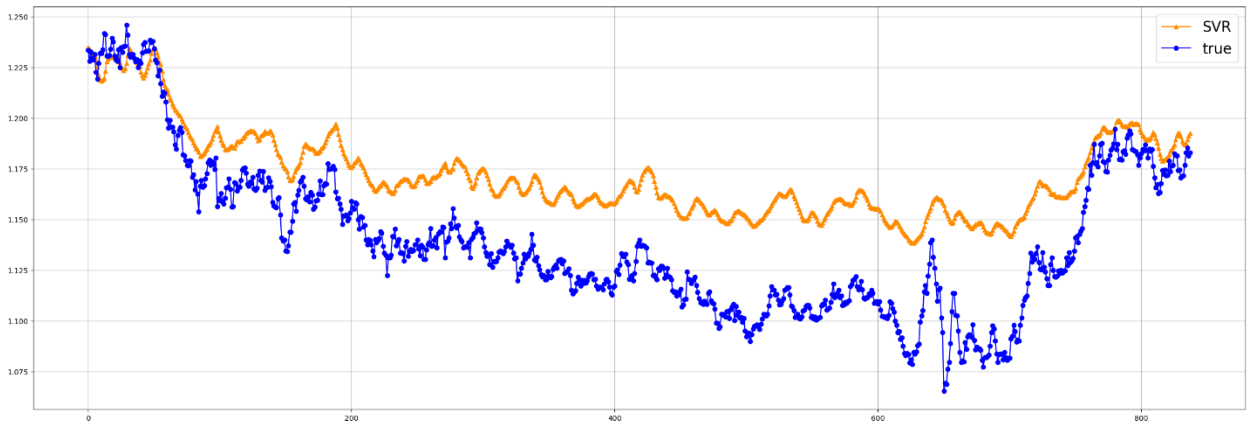


Fig. 9: SVR Result

Saving Trained Models

After training, we save the models using pickle. This lets us use the trained models later without retraining — very useful for deployment.

Final Results

After running all five machine learning models on the dataset, we observed that each algorithm behaves differently in terms of performance, especially when evaluated using the Mean Squared Error (MSE) metric. Here's a breakdown of how each model performed and some insights into their behaviour:

- **KNN** consistently delivered the most accurate predictions across most test cases. Its ensemble nature combining multiple decision trees makes it robust against noise and effective at capturing complex patterns in the data. This typically results in lower prediction errors.
- **Bayesian Ridge Regression** and **Support Vector Regression (SVR)** also showed strong performance. One of their key advantages is how well they generalize to unseen data, often displaying less overfitting compared to more flexible models like decision trees. Bayesian Ridge, in particular, benefits from regularization through Bayesian inference, while SVR uses margin maximization to control model complexity.
- **Linear Regression**, although the simplest model in our lineup, still performed reasonably well and served as a reliable baseline for comparison. It helps us understand how much value the more complex models are adding. While it may not capture nonlinear relationships effectively, its interpretability and speed make it a useful starting point.

In summary, no single model is universally best it depends on the specific characteristics of the dataset and the problem at hand. However, Random Forest emerged as the top performer in

terms of raw accuracy, while Bayesian Ridge and SVR offered more balanced results with better generalization.

MACHINE LEARNING VISUALISATIONS

In our system, we have trained five machine learning models. For each one, visual evaluation is essential to understand how well it performs. These 10 visualisation types used in this project although not all are expatiated upon in this report. Here are some of the visualisations we used:

1. Histogram – Distribution of Predicted Prices

Purpose:
The histogram is used to visualise how frequently different predicted price values occur. It shows the distribution of the model's output across the full prediction set. This is good for giving us an understanding of how the model behaves in terms of price range and value concentration.

What it reveals:

- **Overprediction or Underprediction Bias:** By analysing where the majority of predictions fall, we can assess whether the model tends to lean toward predicting higher or lower values compared to the actual data. If the histogram is noticeably skewed to one side, it may suggest a systematic bias.
- **Coverage of the Full Value Range:** The histogram also shows whether the model is adequately capturing the diversity in price values. If the distribution is too narrow or bunched up then it may suggest that the model isn't flexible enough and it fails to recognize the full spread of the actual data.
- **Skewness and Shape of Distribution:** This plot also helps us detect whether the predictions are balanced or tilted toward certain ranges. For instance if the distribution is tilted more to the left or to the right, that could indicate that the model struggles with at those price zones, perhaps being too cautious or aggressive in its estimations in those areas.

Why it's important:

The histogram visualisation quite valuable at identifying whether the model has a good range of outputs or is struggling, producing overly similar values regardless of the input. A model that always predicts within a tight band even when the real data shows wide swings is less useful in a real-world setting. The histogram helps diagnose such issues by highlighting concentration, gaps, or extreme clustering in predicted prices. It's especially valuable when used in combination with the true price distribution to check if the model truly reflects the nature of the data it's trying to predict.

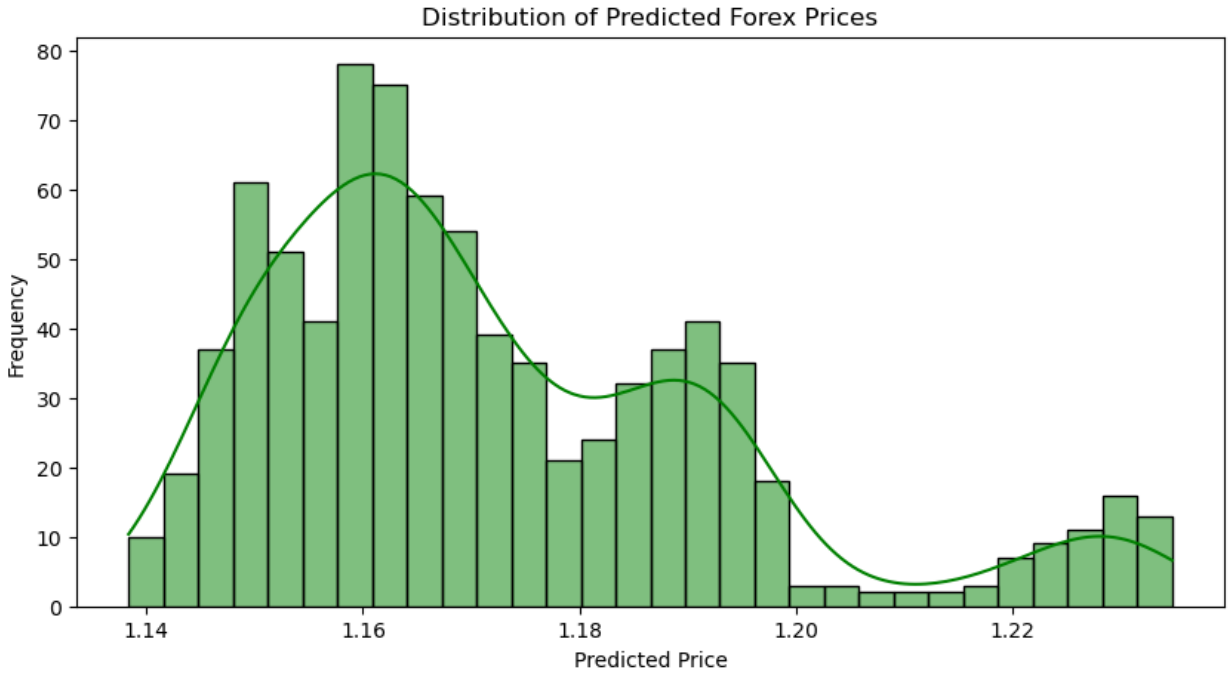


Fig. 10: Histogram visualisation

---

2. Scatter Plot – Predicted vs. Actual Prices

Purpose:

This plot is fantastic at comparing predicted prices with their corresponding actual values. Every

point on the scatter plot represents a single prediction where the x-axis is the actual price and the y-axis is the predicted price. Doing this for every data point forms the scatter plot, giving us a good visual understanding of how closely the model's outputs match the real-world targets.

What it reveals:

- **Correlation Between Predictions and Actual Values:** A heavy clustering of points diagonally (where predicted values meet actual) suggests a strong positive correlation and indicates that the model is capturing correct price behaviour.
- **Spread and Outliers:** This plot makes it easy to spot error especially large ones. Points far from the diagonal line represent predictions that deviate significantly from the actual values. A wide spread of points or a lot of outliers can signal inconsistency or poor generalization, while a tight band indicates precision.

Why it's important:

The scatter plot is one of the most straightforward tools to visually evaluate model performance. In an ideal scenario, all the points would fall perfectly along the 45-degree diagonal line, meaning the model predicted each value exactly right. Of course, in real-world scenarios, some deviation is expected. But the closer the points are to this line, the better. This visualisation helps us quickly judge whether the model tends to consistently overestimate or underestimate, and whether it's stable across the full range of prices. It also reveals whether errors are random or follow a pattern, which can inform future model improvements.

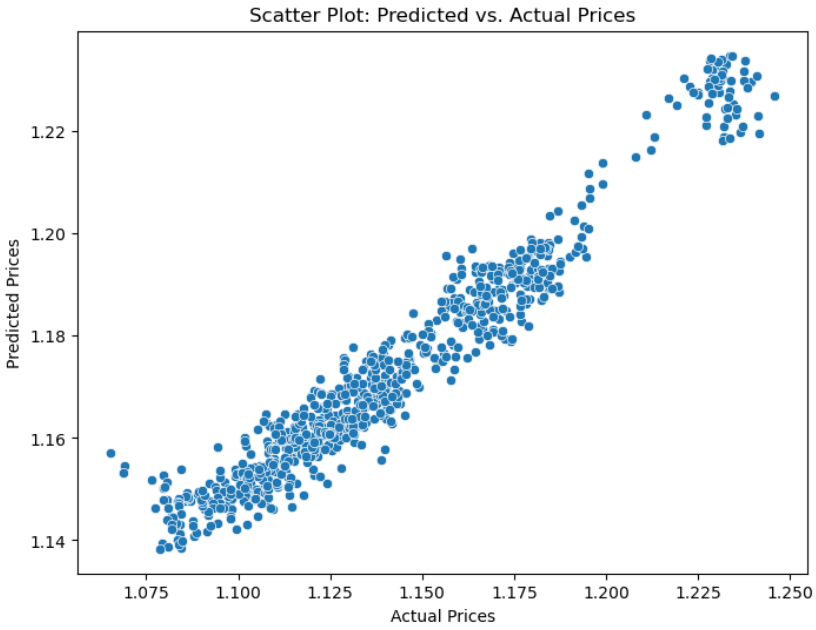


Fig. 11: Scatter Plot visualisation

---

3. Regression Plot – Predicted vs. Actual with Fit Line

Purpose:

The regression plot is like an enhanced version of the scatter plot. Since they are so similar you can tell each point is a prediction but the main difference is the regression line added to the plot that serves as a line of best fit. This line gives a clear visual sense of the overall trend and direction of the predictions compared to the true values.

What it reveals:

This plot helps us see whether the relationship between predicted and actual values is linear, which is a good sign of consistent model behaviour. If the points cluster tightly around the line, it means the model is making stable and accurate predictions. The slope of the line tells us how close the predictions are to being perfectly proportional to the actual values. A slope near 1 indicates that the predictions closely match the actual prices across the board. If the points are

widely scattered or the line deviates significantly from the ideal 45-degree angle, it suggests potential bias, underfitting, or overfitting in certain regions.

Why it's important:

This plot is valuable because it visually quantifies how well the model's predictions align with real data. A slope close to one and a tight grouping of points means the model has learned the underlying patterns effectively. On the other hand, a flatter or steeper slope, or a wide spread of points, signals that the model might consistently underpredict or overpredict. It's a quick way to assess both accuracy and bias, helping to identify whether improvements are needed in the model's training or feature selection.

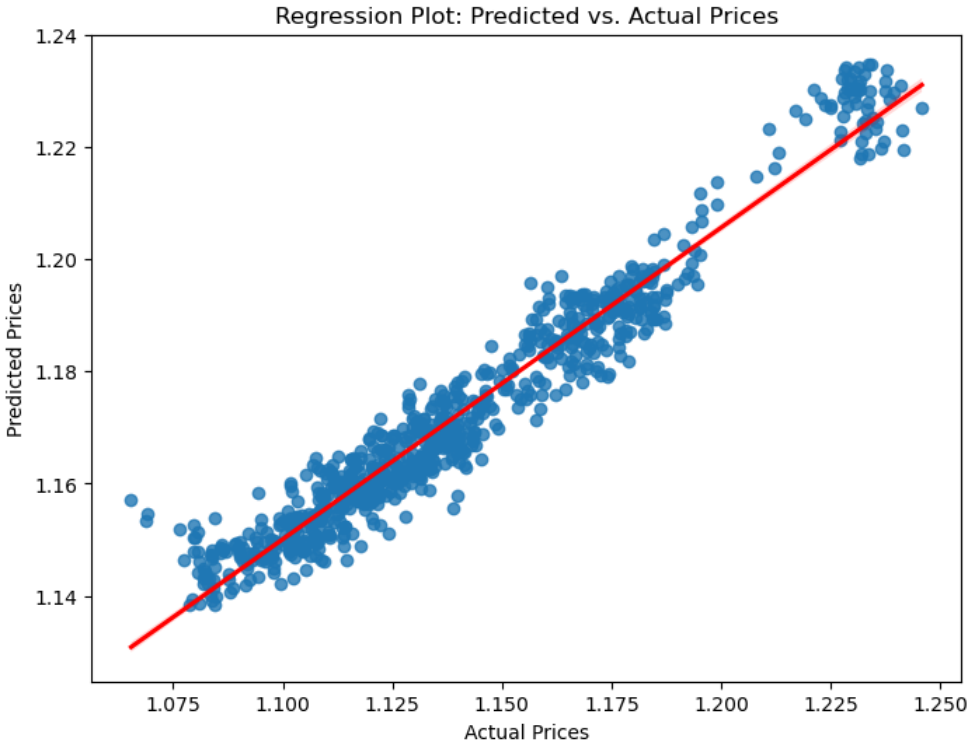


Fig. 12: Regression Plot visualisation

---

4. Density Plot – KDE of Price Predictions

Purpose:

The density plot, or Kernel Density Estimate (KDE) plot, is used to visualise the smooth curve representing the frequency distribution of predicted prices. They are similar to histograms but instead of representing predictions in rectangular bins of data, the density plots are smoother and curvier. It forms continuous curved lines that shows the probability density of the predicted values across the entire range.

What it reveals:

This plot shows the shape and spread of the predicted prices. It gives insight into how the predictions are distributed, whether they're concentrated in certain price ranges or spread out more evenly. Additionally, when compared to the actual price distribution (which can also be plotted as a KDE), it allows for a direct visual comparison of how well the predicted price distribution matches the true price distribution. If the two distributions align closely, it suggests that the model is accurately capturing the overall pattern of the data.

Why it's important:

The density plot is important because it shows how closely the predicted price densities align with the actual prices. A good model should produce a predicted distribution that resembles the true price distribution in terms of shape, spread, and peaks. By comparing these two distributions, you can assess whether the model is capturing the right behaviour or if it's overfitting or underfitting in certain areas. This plot offers a more nuanced understanding of the model's performance than simply looking at individual errors or averages it shows whether the model is truly reproducing the underlying price dynamics.

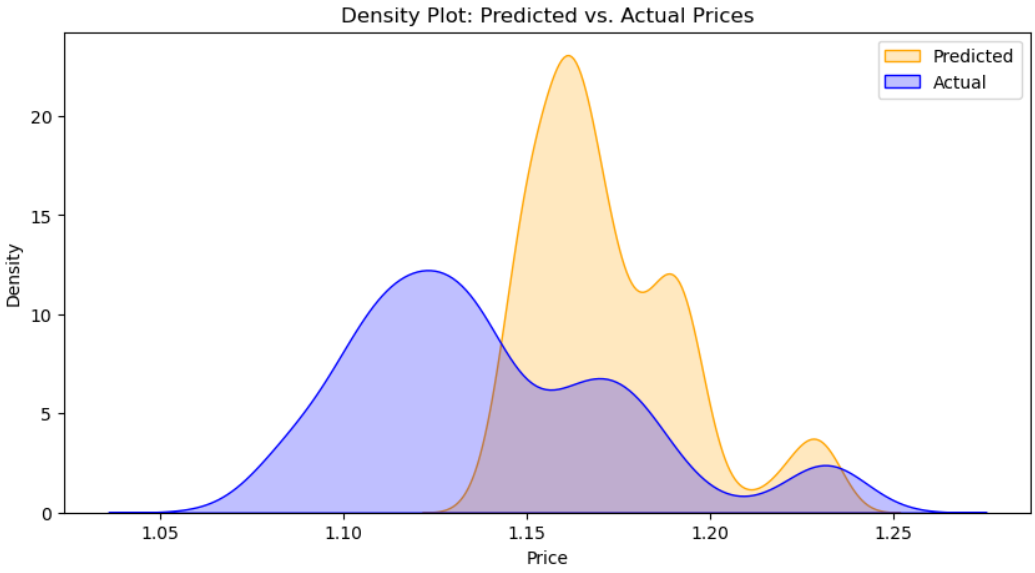


Fig. 13: Density Plot visualisation

---

5. Box Plot – Predicted vs Actual Prices

This plot compares predicted and actual prices by showing their range, centre and outliers. It helps spot bias and overfitting of the model or even sometimes under fitting. If both plots look alike the model works well here big differences mean the model might miss how the real data acts.

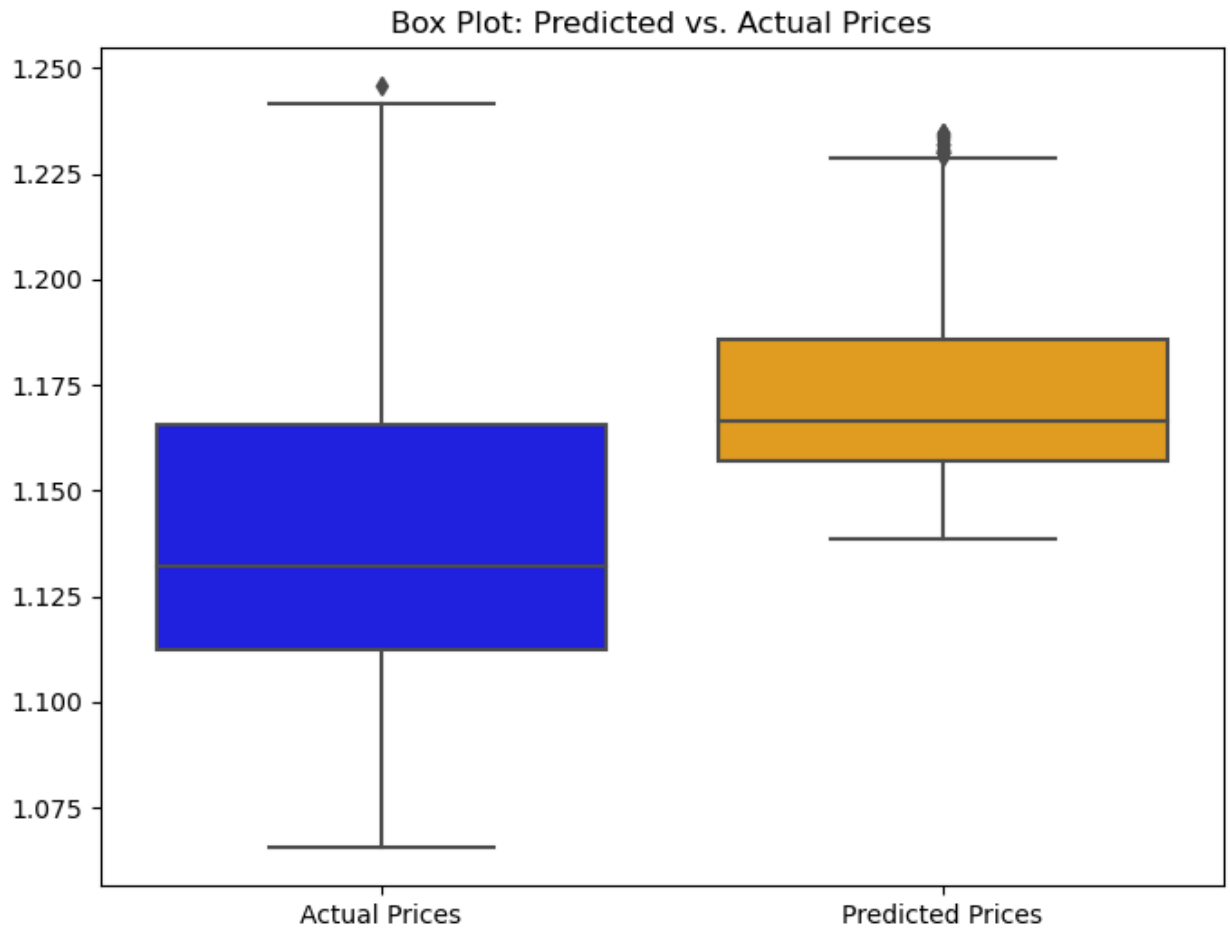


Fig. 14: Box Plot visualisation

6- Violin Plot – Price Distributions

This plot shows how predicted and actual prices are spread and where values are most common. It highlights shape, balance and peaks. If both plots look alike the model doesn't just hit the right values it also captures how the prices really acts.

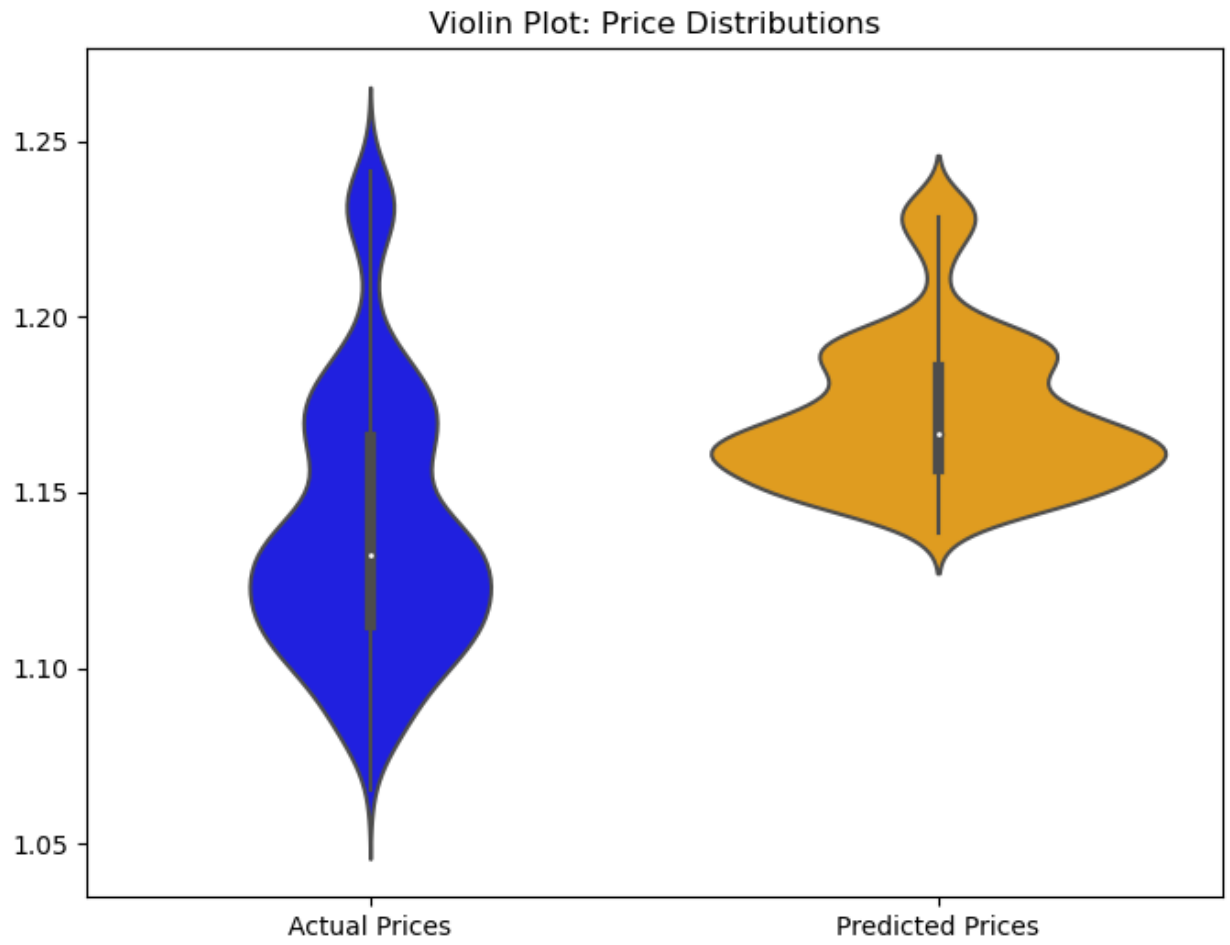


Fig. 15: Violin Plot visualisation

7- Heatmap – Correlation Matrix of Features

This chart shows how strongly features relate to each other and the target using different colours. It helps spot redundancy of the most useful features. Cleaning or reducing similar features based on this can make the model simpler, faster and even more accurate.

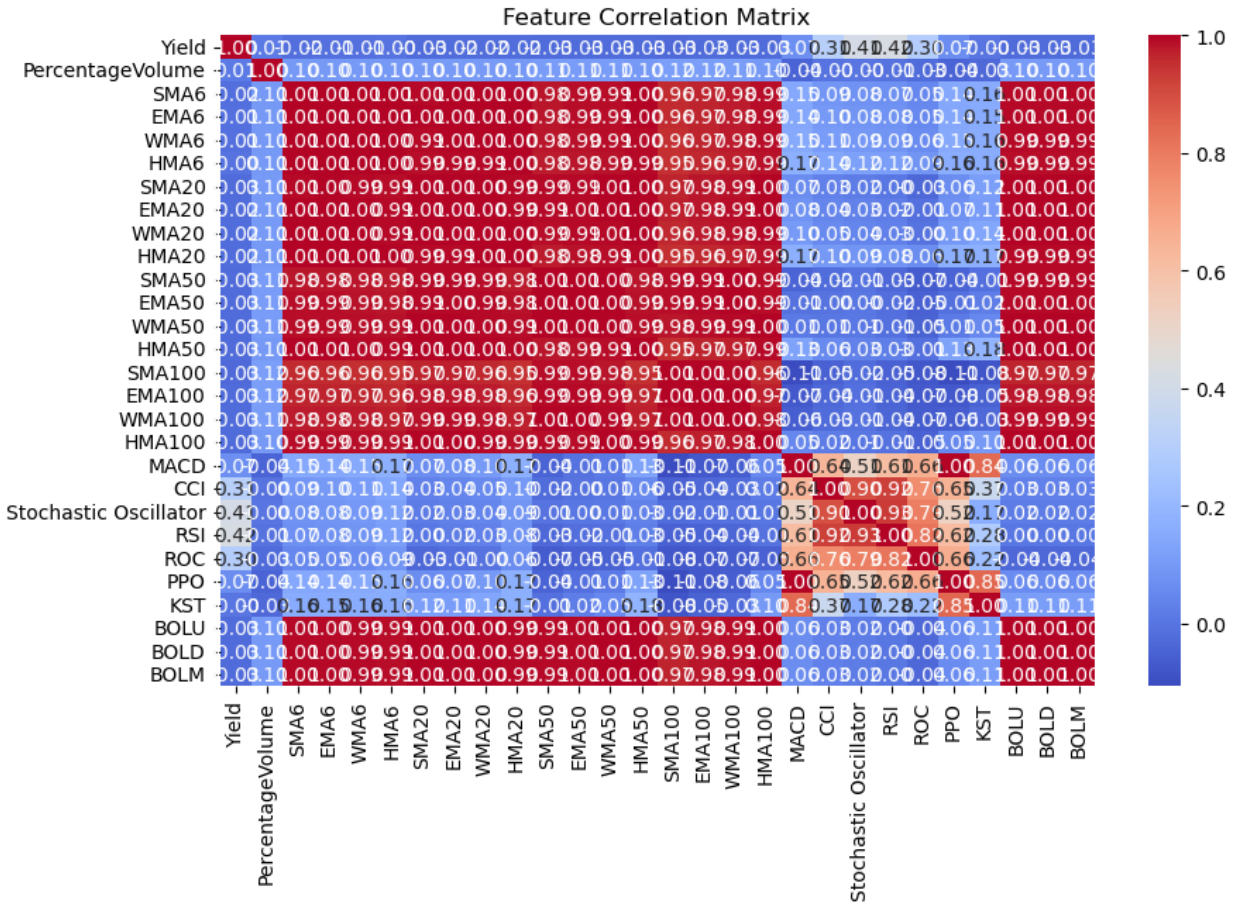


Fig. 16: Heatmap visualisation

8- Bar Plot – Absolute Prediction Errors

This plot shows how far off each prediction is from the actual values by displaying the absolute error as a bar. Tall bars mean the model made big mistakes on those data points while shorter bars show more accurate predictions. By looking at these errors one by one we can see where the model is doing well and where it not. It can help spot patterns of bad predictions or estimate

times when the model fails. This insight is key for improving accuracy as it tells us exactly where the model needs more work or it needs better input data.

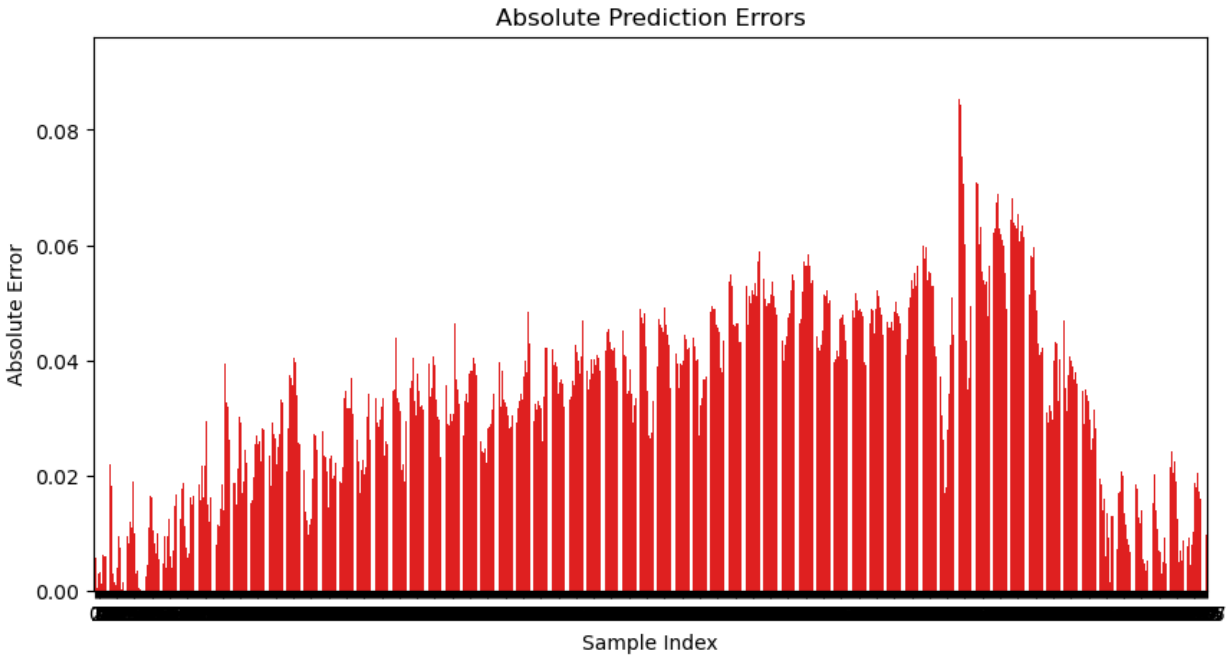


Fig. 17: Bar Plot visualisation

9- Zoomed Line Plot – First N Predictions

This plot shows the model's predictions and actual prices for a small portion of data usually the first 100 points. It helps you see how well the model handles short-term changes and early volatility of the data. Even if overall performance looks good this view can reveal small areas where the model struggles. It's useful for spotting local issues, short-term errors or sharp deviations that might be hidden in a full length plot. By focusing on a smaller range it can be better understood and improved in specific time periods.

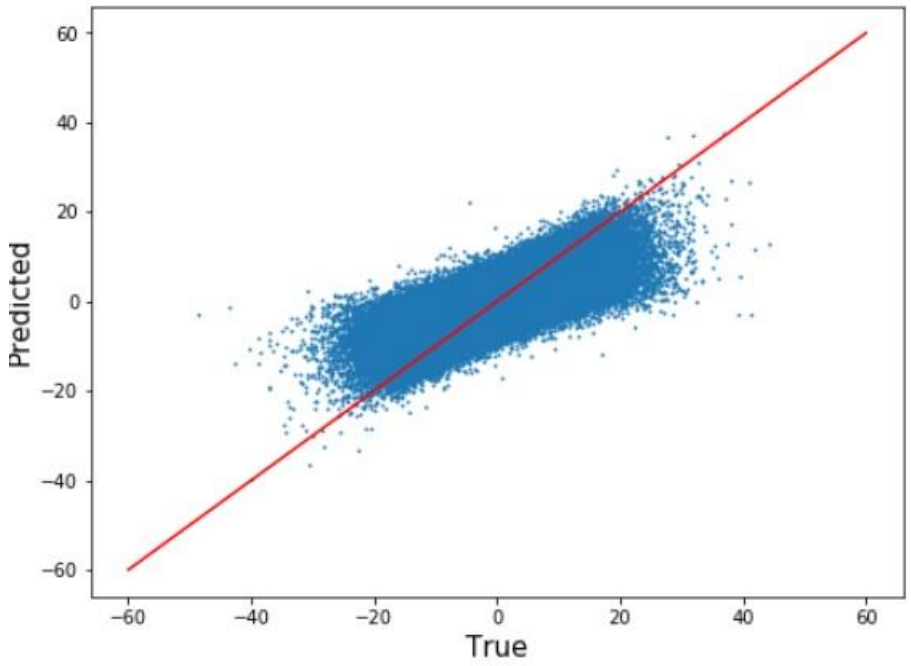


Fig. 18: Zoomed Line Plot visualisation

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10. Line Plot – True vs. Predicted Prices

The line plot is designed to visually compare the actual price of the asset (here EURUSD) with the predicted values generated by the model over time. By placing both series on the same timeline, it becomes easier to directly assess how well the model is tracking real market movements. If the predicted line closely follows the actual price line, it indicates that the model is accurately capturing the underlying patterns and trends in the data. Conversely, large deviations between the two lines may suggest areas where the model struggles to generalize or respond to market changes.

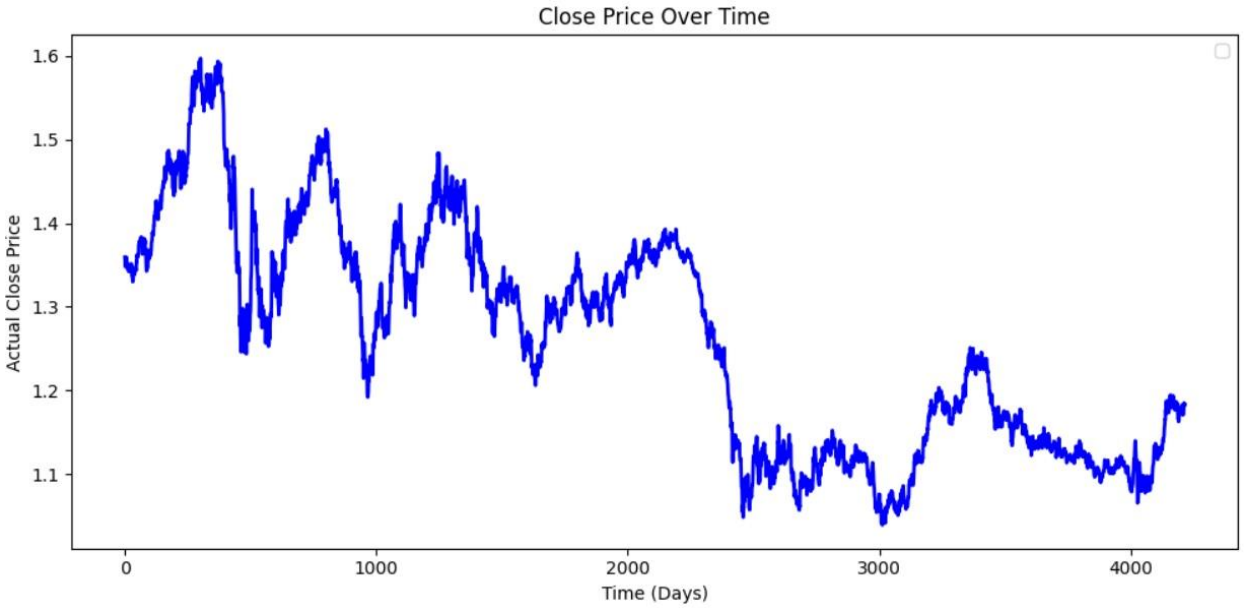

Fig. 19: Line Plot visualisation

Summary of all Visualization used for each machine learning algorithm:

Visualisation	Purpose
Density Plot	Follows overall trend
Histogram	Checks prediction value distribution
Scatter Plot	Examines correlation accuracy
Box Plot	Compares value spread and medians
Violin Plot	Highlights density and distribution shape
Regression Plot	Fits a prediction trendline
Heatmap	Explores feature relationships
Bar Plot (Errors)	Measures local performance per sample

Zoomed Line Plot	Analyses small prediction segments

Using all 10 on each model provides a complete visual story from how the model behaves to where it goes wrong. Together, they make our system transparent, interpretable, and visually rich.

TEAM CONTRIBUTIONS

- **Amandeep Singh:**
  Provided explanations of some of the steps taken to implement the algorithms and various other aspects of the code for the report.
- **Nikechukwum Ene:**
  Report structure, formatting and overall report quality in line with the assessment specifications.
- **Pourya Asadi:**
  Developed the code for data pre-processing, machine learning models and visualisation for the prediction system and explanations of these parts for the report.
- **Princewilliams Gbasouzor:**
  Provided details of some of the machine learning algorithms and their significance in the report.

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