EDA_and_Prediction_Model_on_Galton_Family_Heights_Dataset

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[ ]:
```python
#This cell imports the main Python libraries used
# for data analysis and visualization - NumPy and Pandas for handling data,␣
↪Matplotlib and Seaborn for plotting, and it also hides unnecessary warning␣
↪messages to keep the output clean.
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

[ ]:
```python
#This cell loads the Galton Family Heights dataset from the given file path␣
↪into a pandas DataFrame named df
# then displays the first six rows to preview the data.
df = pd.read_csv('/Users/hatemelgenedy/Desktop/AI and Data Science Microsoft␣
↪course/Galton_Family_Heights.csv')
df.head(6)
```

[ ]:

	Father_height	Mother_height	Child_height	gender
0	78.5	67.0	73.2	1
1	78.5	67.0	69.2	0
2	78.5	67.0	69.0	0
3	78.5	67.0	69.0	0
4	75.5	66.5	73.5	1
5	75.5	66.5	72.5	1

[ ]:
```python
#This cell displays a summary of the dataset’s structure, including column␣
↪names, data types, number of non-null values, and the total number of␣
↪entries -
# helping to check for missing data or data type issues.
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 934 entries, 0 to 933
Data columns (total 4 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
```

```
 0   Father_height  934 non-null    float64
 1   Mother_height  934 non-null    float64
 2   Child_height   934 non-null    float64
 3   gender         934 non-null    int64
dtypes: float64(3), int64(1)
memory usage: 29.3 KB
```

[ ]:
```
#This cell shows the dimensions of the dataset - the number of rows and columns␣
↪- helping you understand how many records and features are in the DataFrame.
df.shape
```

[ ]:
```
(934, 4)
```

[ ]:
```
#This cell lists the data type of each column (e.g., float, int, object),␣
↪helping you identify which columns are numeric, categorical, or other types␣
↪for further analysis.
df.dtypes
```

[ ]:
```
Father_height    float64
Mother_height    float64
Child_height     float64
gender             int64
dtype: object
```

[122]:
```
#his cell identifies and separates columns in the dataset by their data types -␣
↪numeric, categorical, boolean, and datetime - then prints each list.
#It helps you understand what kinds of data  working with for analysis or␣
↪preprocessing.
num_cols = df.select_dtypes(include="number").columns
cat_cols = df.select_dtypes(include=["object", "category"]).columns
bool_cols = df.select_dtypes(include="bool").columns
dt_cols   = df.select_dtypes(include=["datetime", "datetimetz"]).columns

print("Numeric:", list(num_cols))
print("Categorical:", list(cat_cols))
print("Boolean:", list(bool_cols))
print("Datetime:", list(dt_cols))
```

```
Numeric: ['Father_height', 'Mother_height', 'Child_height', 'gender',
'Midparent_height']
Categorical: []
Boolean: []
Datetime: []
```

[ ]:
```
#This cell installs the ydata_profiling library,
# which is used to automatically generate a detailed exploratory data analysis␣
↪(EDA) report -
# summarizing data distributions, correlations, and missing values in one step.
```

```
!pip install ydata_profiling
```

```
Requirement already satisfied: ydata_profiling in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (4.17.0)
Requirement already satisfied: scipy<1.16,>=1.4.1 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
ydata_profiling) (1.13.1)
Requirement already satisfied: pandas!=1.4.0,<3.0,>1.1 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
ydata_profiling) (2.3.1)
Requirement already satisfied: matplotlib<=3.10,>=3.5 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
ydata_profiling) (3.10.0)
Requirement already satisfied: pydantic>=2 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from ydata_profiling) (2.11.7)
Requirement already satisfied: PyYAML<6.1,>=5.0.0 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
ydata_profiling) (6.0.2)
Requirement already satisfied: jinja2<3.2,>=2.11.1 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
ydata_profiling) (3.1.6)
Requirement already satisfied: visions<0.8.2,>=0.7.5 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
visions[type_image_path]<0.8.2,>=0.7.5->ydata_profiling) (0.8.1)
Requirement already satisfied: numpy<2.2,>=1.16.0 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
ydata_profiling) (1.26.4)
Requirement already satisfied: minify-html>=0.15.0 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
ydata_profiling) (0.18.1)
Requirement already satisfied: filetype>=1.0.0 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from ydata_profiling) (1.2.0)
Requirement already satisfied: phik<0.13,>=0.11.1 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
ydata_profiling) (0.12.5)
Requirement already satisfied: requests<3,>=2.24.0 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
ydata_profiling) (2.32.4)
Requirement already satisfied: tqdm<5,>=4.48.2 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from ydata_profiling) (4.67.1)
Requirement already satisfied: seaborn<0.14,>=0.10.1 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
ydata_profiling) (0.13.2)
Requirement already satisfied: multimethod<2,>=1.4 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
ydata_profiling) (1.12)
Requirement already satisfied: statsmodels<1,>=0.13.2 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
```

```
ydata_profiling) (0.14.5)
Requirement already satisfied: typeguard<5,>=3 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from ydata_profiling) (4.4.4)
Requirement already satisfied: imagehash==4.3.1 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from ydata_profiling) (4.3.1)
Requirement already satisfied: wordcloud>=1.9.3 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from ydata_profiling) (1.9.4)
Requirement already satisfied: dacite>=1.8 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from ydata_profiling) (1.9.2)
Requirement already satisfied: numba<=0.61,>=0.56.0 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
ydata_profiling) (0.61.0)
Requirement already satisfied: PyWavelets in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from imagehash==4.3.1->ydata_profiling)
(1.9.0)
Requirement already satisfied: pillow in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from imagehash==4.3.1->ydata_profiling)
(11.3.0)
Requirement already satisfied: MarkupSafe>=2.0 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from jinja2<3.2,>=2.11.1->ydata_profiling)
(3.0.2)
Requirement already satisfied: contourpy>=1.0.1 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from matplotlib<=3.10,>=3.5->ydata_profiling)
(1.3.1)
Requirement already satisfied: cycler>=0.10 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from matplotlib<=3.10,>=3.5->ydata_profiling)
(0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
matplotlib<=3.10,>=3.5->ydata_profiling) (4.55.3)
Requirement already satisfied: kiwisolver>=1.3.1 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
matplotlib<=3.10,>=3.5->ydata_profiling) (1.4.8)
Requirement already satisfied: packaging>=20.0 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from matplotlib<=3.10,>=3.5->ydata_profiling)
(24.2)
Requirement already satisfied: pyparsing>=2.3.1 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from matplotlib<=3.10,>=3.5->ydata_profiling)
(3.2.0)
Requirement already satisfied: python-dateutil>=2.7 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
matplotlib<=3.10,>=3.5->ydata_profiling) (2.9.0.post0)
Requirement already satisfied: llvmlite<0.45,>=0.44.0dev0 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
numba<=0.61,>=0.56.0->ydata_profiling) (0.44.0)
Requirement already satisfied: pytz>=2020.1 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from pandas!=1.4.0,<3.0,>1.1->ydata_profiling)
(2025.2)
```

```
Requirement already satisfied: tzdata>=2022.7 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from pandas!=1.4.0,<3.0,>1.1->ydata_profiling)
(2025.2)
Requirement already satisfied: joblib>=0.14.1 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from phik<0.13,>=0.11.1->ydata_profiling)
(1.5.1)
Requirement already satisfied: charset_normalizer<4,>=2 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
requests<3,>=2.24.0->ydata_profiling) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from requests<3,>=2.24.0->ydata_profiling)
(3.7)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
requests<3,>=2.24.0->ydata_profiling) (2.5.0)
Requirement already satisfied: certifi>=2017.4.17 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
requests<3,>=2.24.0->ydata_profiling) (2025.8.3)
Requirement already satisfied: patsy>=0.5.6 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from statsmodels<1,>=0.13.2->ydata_profiling)
(1.0.2)
Requirement already satisfied: typing_extensions>=4.14.0 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
typeguard<5,>=3->ydata_profiling) (4.15.0)
Requirement already satisfied: attrs>=19.3.0 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from
visions<0.8.2,>=0.7.5->visions[type_image_path]<0.8.2,>=0.7.5->ydata_profiling)
(24.3.0)
Requirement already satisfied: networkx>=2.4 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from
visions<0.8.2,>=0.7.5->visions[type_image_path]<0.8.2,>=0.7.5->ydata_profiling)
(3.4.2)
Requirement already satisfied: puremagic in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from
visions<0.8.2,>=0.7.5->visions[type_image_path]<0.8.2,>=0.7.5->ydata_profiling)
(1.30)
Requirement already satisfied: annotated-types>=0.6.0 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
pydantic>=2->ydata_profiling) (0.6.0)
Requirement already satisfied: pydantic-core==2.33.2 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
pydantic>=2->ydata_profiling) (2.33.2)
Requirement already satisfied: typing-inspection>=0.4.0 in
/opt/anaconda3/envs/anaconda-nlp/lib/python3.11/site-packages (from
pydantic>=2->ydata_profiling) (0.4.0)
Requirement already satisfied: six>=1.5 in /opt/anaconda3/envs/anaconda-
nlp/lib/python3.11/site-packages (from python-
dateutil>=2.7->matplotlib<=3.10,>=3.5->ydata_profiling) (1.17.0)
```

[ ]:
```python
#This cell imports the ProfileReport class from the ydata_profiling library,
#which allows you to create an automated EDA report for your dataset.
from ydata_profiling import ProfileReport
```

[ ]:
```python
#This cell reloads the Galton Family Heights dataset into the DataFrame df and␣
↪displays the first six rows to confirm that the data was loaded correctly.
df = pd.read_csv('/Users/hatemelgenedy/Desktop/AI and Data Science Microsoft␣
↪course/Galton_Family_Heights.csv')
df.head(6)
```

[ ]:

	Father_height	Mother_height	Child_height	gender
0	78.5	67.0	73.2	1
1	78.5	67.0	69.2	0
2	78.5	67.0	69.0	0
3	78.5	67.0	69.0	0
4	75.5	66.5	73.5	1
5	75.5	66.5	72.5	1

[ ]:
```python
#his cell generates an automated EDA report for the dataset using ProfileReport␣
↪and saves it as an HTML file named "Galton Family EDA.html" -
#giving a detailed summary of data patterns, distributions, and correlations.
report = ProfileReport(df , title = 'Galton Family data analysis report')
report.to_file(output_file = 'Galton Family EDA.html')
```

```
Summarize dataset:   0%|          | 0/5 [00:00<?, ?it/s]

100%|     | 4/4 [00:00<00:00, 25003.30it/s]

Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]

Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]

Export report to file:   0%|          | 0/1 [00:00<?, ?it/s]
```

#The dataset represents Father height , Mother height , Child height , Gender

[ ]:
```python
#This cell checks for missing (null) values in each column of the dataset and␣
↪displays how many are present -
# helping to identify if any data cleaning is needed.
df.isnull().sum()
```

[ ]:
```
Father_height    0
Mother_height    0
Child_height     0
gender           0
dtype: int64
```

[ ]:
```python
#This cell checks for duplicate rows in the dataset and returns a boolean␣
↪Series indicating which rows are duplicates -
df.duplicated()
```

[ ]:
```
0      False
1      False
2      False
3       True
4      False
       …
929    False
930    False
931    False
932    False
933    False
Length: 934, dtype: bool
```

[ ]:
```
#This cell shows the number of rows and columns in the dataset - helping to␣
↪confirm the dataset's overall size.
df.shape
```

[ ]:
```
(934, 4)
```

[ ]:
```
#This cell checks the dataset for duplicate rows and prints the total number␣
↪found -
#helping to identify repeated data that might need removal.
duplicates = df . duplicated().sum()
print(f"Number of duplicate rows : {duplicates}")
```

```
Number of duplicate rows : 182
```

[ ]:
```
#This cell creates a new column called Midparent_height, which calculates the␣
↪average of the father's and mother's heights -
#representing the parents' combined average height.
df["Midparent_height"] = (df["Father_height"] + df["Mother_height"]) / 2
```

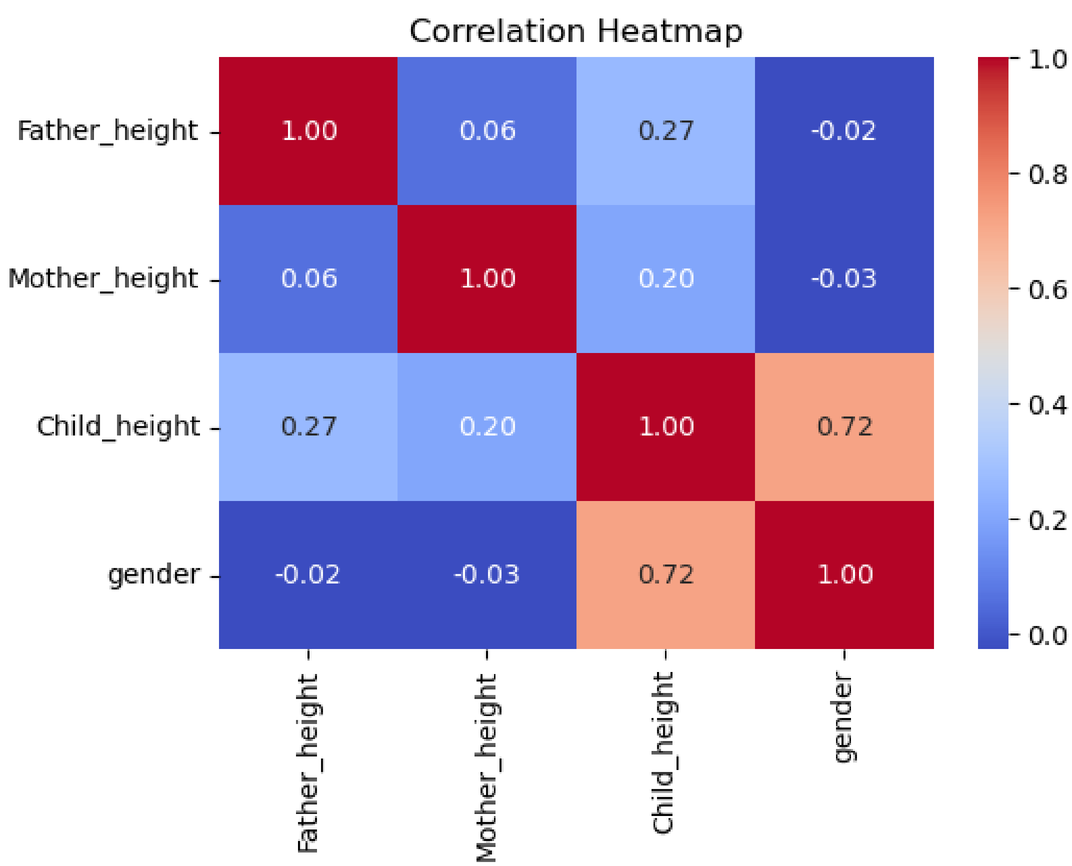
[ ]:
```
#This cell calculates the correlation matrix between all numeric columns in the␣
↪dataset and prints it - showing:
#how strongly each pair of variables (like parent and child heights) are␣
↪related.
corr = df.corr(numeric_only=True)
print("\nCorrelation Matrix:\n", corr)
```

```

Correlation Matrix:
                   Father_height  Mother_height  Child_height    gender  \
Father_height          1.000000       0.060366      0.266039 -0.024762
Mother_height          0.060366       1.000000      0.201322 -0.025216
Child_height           0.266039       0.201322      1.000000  0.716709
gender                -0.024762      -0.025216      0.716709  1.000000
Midparent_height       0.752750       0.702546      0.322443 -0.034284
```

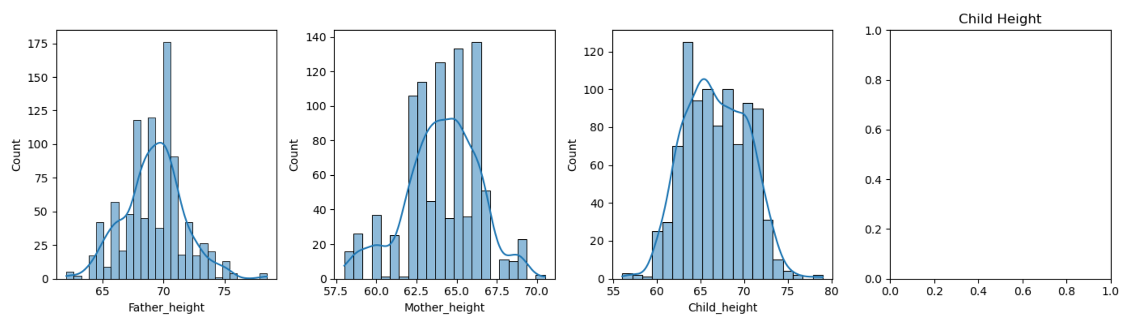
```
                   Midparent_height
Father_height              0.752750
Mother_height              0.702546
Child_height               0.322443
gender                    -0.034284
Midparent_height           1.000000
```

[ ]:
```
#This cell computes the correlation matrix for all numeric columns in the␣
↪dataset -
#measuring the strength and direction of relationships between numerical␣
↪variables.
corr = df.corr(numeric_only=True)
```

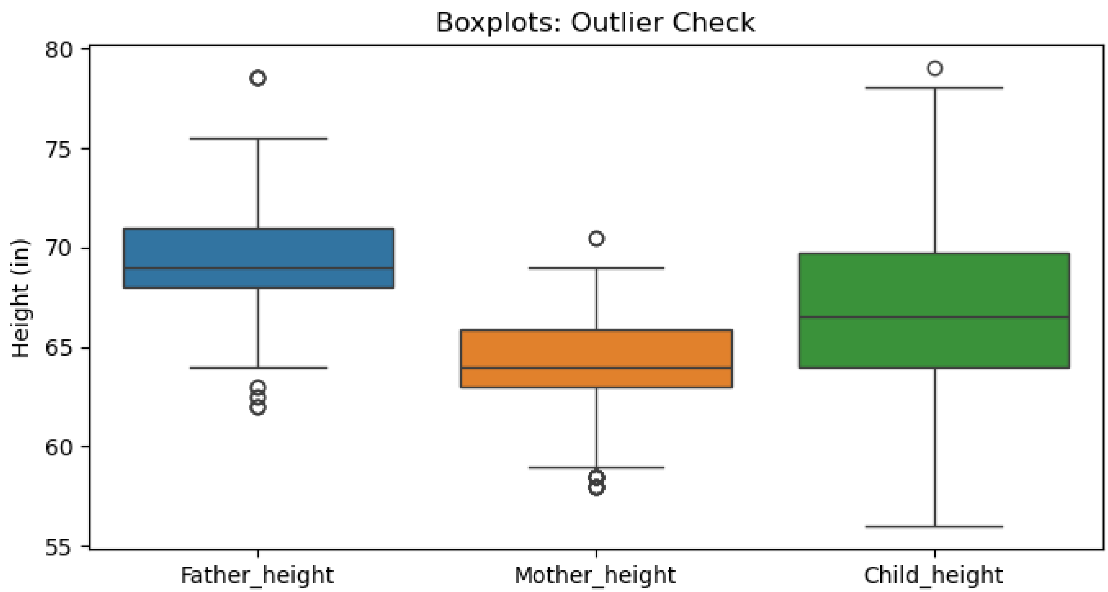
[ ]:
```
#This cell visualizes the correlation matrix as a heatmap, where colors␣
↪represent how strongly variables are related -
#with coolwarm showing positive (red) and negative (blue) correlations.
#%matplotlib inline ensures the plot appears directly in the notebook.
%matplotlib inline
plt.figure(figsize=(6,4))
sns.heatmap(corr, annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Correlation Heatmap")
plt.show()
```



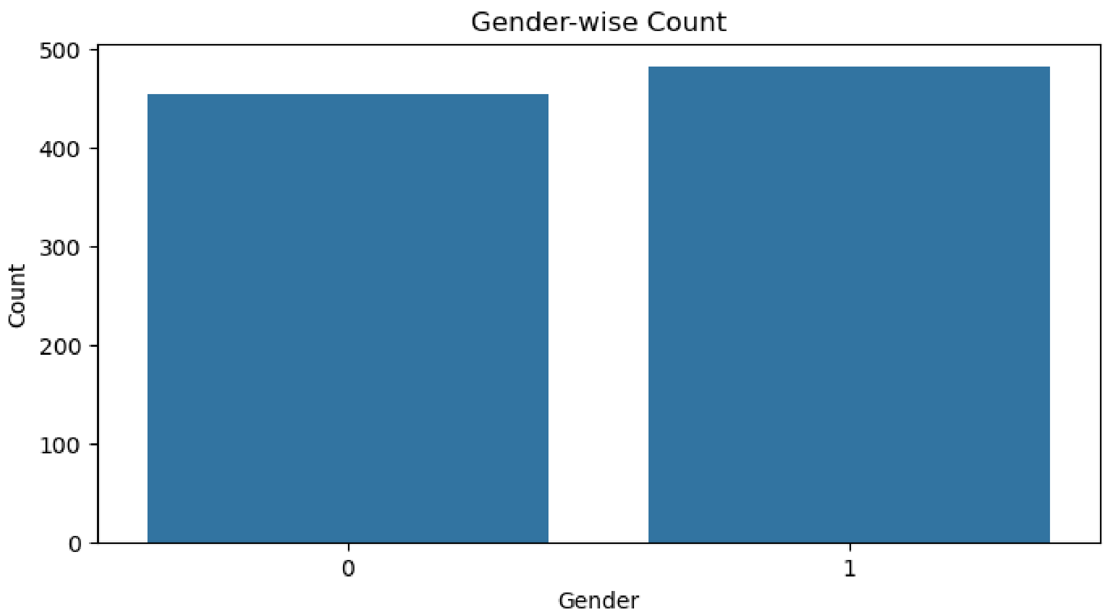
[ ]:
```
# X axis represents the height of the father,Mother , Child
# Y axis. represents how many fathers,Mothers , Childerns in this heights
#This cell creates histograms for the heights of fathers, mothers, and children␣
↪to visualize how each is distributed.
#The kde=True adds a smooth density curve, and plt.tight_layout() ensures the␣
↪plots don't overlap for a cleaner display.
fig = plt.figure(figsize=(14, 4))
axes = fig.subplots(1, 4)
sns.histplot(df["Father_height"], kde=True, ax=axes[0])
plt.title("Father Height")

sns.histplot(df["Mother_height"], kde=True, ax=axes[1])
plt.title("Mother Height")

sns.histplot(df["Child_height"], kde=True, ax=axes[2])
plt.title("Child Height")
plt.tight_layout()
plt.show()
```



[ ]:
```
#Outliers in Father,Mother,Child height
#This cell creates boxplots for father, mother, and child heights to visually␣
↪identify outliers and compare height distributions -
#The boxes show data spread,
#while points outside indicate possible outliers.
fig = plt.figure(figsize=(8, 4))
ax  = fig.subplots()
sns.boxplot(data=df[["Father_height", "Mother_height", "Child_height"]], ax=ax)
plt.title("Boxplots: Outlier Check")
plt.ylabel("Height (in)")
plt.show()
```



[ ]:
```
#Gender count
#This cell creates a count plot showing how many records belong to each gender␣
↪(e.g., male vs. female).
#It helps visualize the gender distribution in the dataset.
fig = plt.figure(figsize=(8, 4))
ax  = fig.subplots()
sns.countplot(x="gender", data=df, ax=ax)
ax.set_title("Gender-wise Count")
ax.set_xlabel("Gender")
ax.set_ylabel("Count")
plt.show()
```




```
[ ]: #This cell imports key tools from scikit-learn:
     #train_test_split to divide data into training and testing sets,
     #LinearRegression and RandomForestRegressor to build prediction models,
     #r2_score and mean_absolute_error to evaluate model accuracy and error.
     from sklearn.model_selection import train_test_split
     from sklearn.linear_model import LinearRegression
     from sklearn.ensemble import RandomForestRegressor
     from sklearn.metrics import r2_score,mean_absolute_error
```

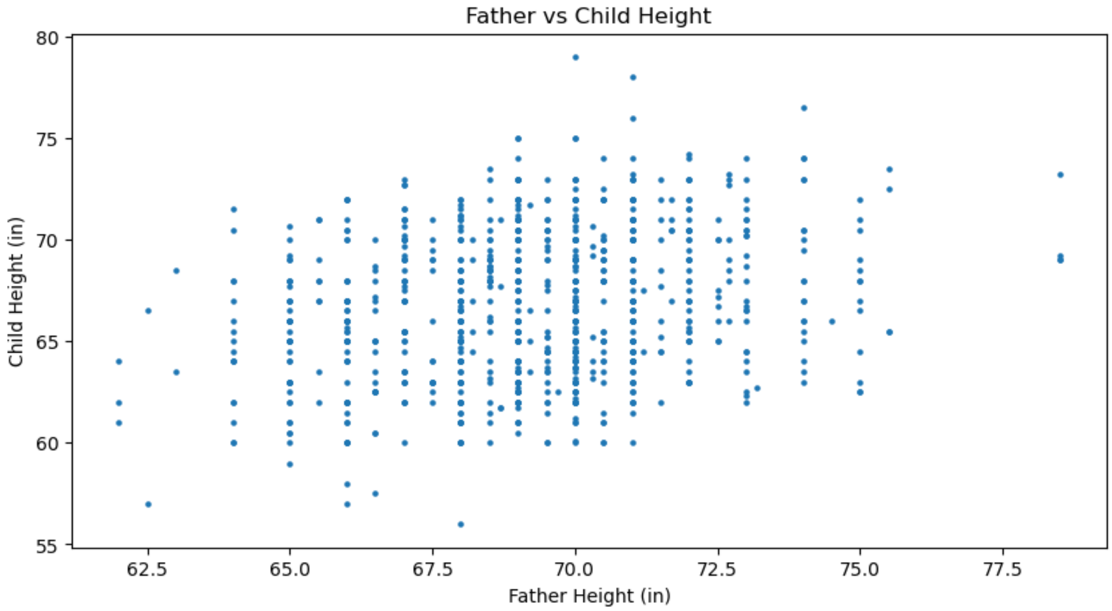
```
[ ]: #This cell displays the first few rows of the dataset to confirm that the data␣
      ↪is loaded correctly and to get an initial look at the structure and values␣
      ↪in the DataFrame.
     df.head()
```

[ ]:

	Father_height	Mother_height	Child_height	gender	Midparent_height
0	78.5	67.0	73.2	1	72.75
1	78.5	67.0	69.2	0	72.75
2	78.5	67.0	69.0	0	72.75
3	78.5	67.0	69.0	0	72.75
4	75.5	66.5	73.5	1	71.00

```
[ ]: #This scatter plot shows the relationship between father height and child␣
      ↪height - each point represents one family.
     #It helps visualize how a child's height tends to increase as the father's␣
      ↪height increases, showing a positive correlation.
     plt.figure(figsize=(10,5))
```

```
plt.show()
```

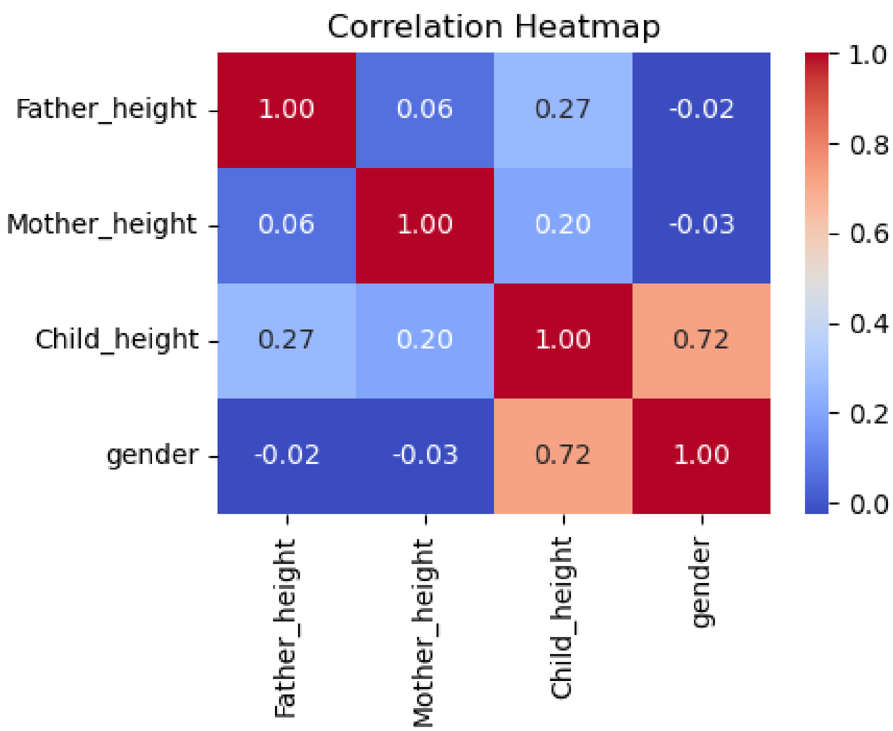



```
<Figure size 1000x500 with 0 Axes>
```

```
<Figure size 1000x500 with 0 Axes>
```

[ ]:
```
#This cell selects only the numeric columns (father, mother, child heights, and
↪gender) and computes their correlation matrix, showing how strongly these
↪variables are related to each other.
num_cols = ["Father_height", "Mother_height", "Child_height", "gender"]
corr = df[num_cols].corr(numeric_only=True)
```

[ ]:
```
#This cell creates a heatmap of the numeric columns' correlation values -
visually showing how closely each variable (father, mother, child heights, and
↪gender) is related, using color intensity to represent the correlation
↪strength.
plt.figure(figsize=(5,4))
sns.heatmap(corr, annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Correlation Heatmap")
plt.tight_layout()
plt.show()
```



[ ]:
```
#average child height by gender
#This cell groups the data by gender and calculates the average child height␣
↪for each group,
#rounding the results to two decimal places - helping compare the mean height␣
↪between males and females.
avg_by_gender = df.groupby("gender")["Child_height"].mean().round(2)
print("\nAverage Child Height by Gender:\n", avg_by_gender)
```

```
Average Child Height by Gender:
 gender
0    64.10
1    69.23
Name: Child_height, dtype: float64
```

[ ]:
```
#Model Building - Child Height Prediction
#This cell defines the features (X) - father's height, mother's height, and␣
↪gender -
#and the target variable (y), which is the child's height, preparing the data␣
↪for model training.
X = df[["Father_height", "Mother_height", "gender"]]
y = df["Child_height"]
```

[ ]:
```
#This cell splits the dataset into training and testing sets, with 80% of the␣
↪data used for training and 20% for testing.
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.20, random_state=42)
```

[ ]:
```
#This cell initializes a Linear Regression model, which will be used to predict␣
↪child heights based on the features defined in X.
linreg = LinearRegression()
```

[ ]:
```
# This cell initializes a Random Forest Regressor model, which will be used to␣
↪predict child heights based on the features defined in X.
rf = RandomForestRegressor(random_state=42, n_estimators=300)
```

[ ]:
```
#This cell fits the Linear Regression model to the training data (X_train and␣
↪y_train) and also fits the Random Forest Regressor to the same training␣
↪data, allowing both models to learn the relationships between the features␣
↪and the target variable.
linreg.fit(X_train, y_train)
rf.fit(X_train, y_train)
```

[ ]:
```
RandomForestRegressor(n_estimators=300, random_state=42)
```

[ ]:
```
#This cell uses the trained Linear Regression and Random Forest models to make␣
↪predictions on the test set (X_test), storing the predicted child heights in␣
↪y_pred_lr and y_pred_rf respectively.
y_pred_lr = linreg.predict(X_test)
y_pred_rf = rf.predict(X_test)
```

[ ]:
```
#This cell evaluates the performance of the Linear Regression model by␣
↪calculating the R-squared score and Mean Absolute Error (MAE) between the␣
↪actual child heights (y_test) and the predicted heights (y_pred_lr).
r2_lr = r2_score(y_test, y_pred_lr)
mae_lr = mean_absolute_error(y_test, y_pred_lr)
```

[ ]:
```
#This cell evaluates the performance of the Random Forest Regressor model by␣
↪calculating the R-squared score and Mean Absolute Error (MAE) between the␣
↪actual child heights (y_test) and the predicted heights (y_pred_rf).
r2_rf = r2_score(y_test, y_pred_rf)
mae_rf = mean_absolute_error(y_test, y_pred_rf)
```

[ ]:
```
#This cell prints the R-squared and MAE values for both the Linear Regression␣
↪and Random Forest models, allowing you to compare their performance in␣
↪predicting child heights.
print(f"Linear Regression R2: {r2_lr:.3f}, MAE: {mae_lr:.3f}")
print(f"Random Forest R2: {r2_rf:.3f}, MAE: {mae_rf:.3f}")
```

```
Linear Regression R2: 0.613, MAE: 1.687
Random Forest R2: 0.590, MAE: 1.670
```

```
[ ]: #This cell compares the R-squared scores of both models and prints which one␣
    ↪performed better in terms of R2, indicating which model explains more␣
    ↪variance in the child height data.
best_model_name = "Random Forest" if r2_rf >= r2_lr else "Linear Regression"
print(f"\nBetter model (by R2): {best_model_name}")
```

```
Better model (by R2): Linear Regression
```

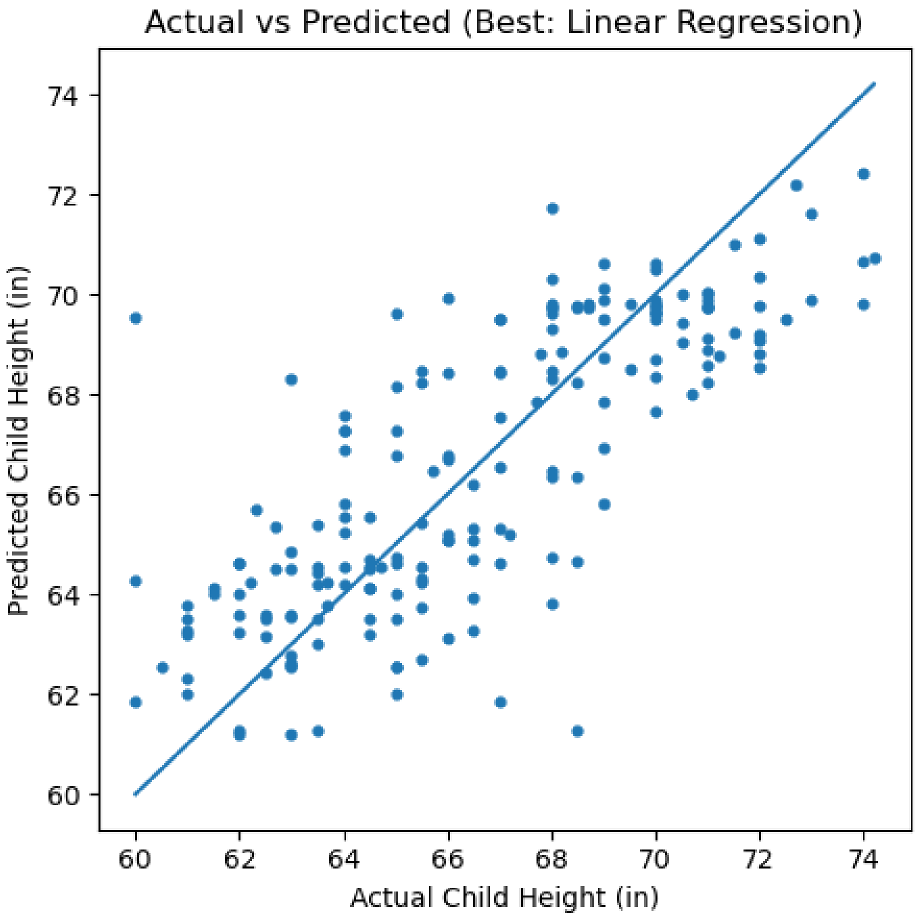
#The x-axis is the actual child height from test data. #The y-axis is the predicted height from model. #The blue line is the perfect prediction line — where Actual = Predicted.

#The closer the dots are to the diagonal line, the better the predictions. #Dots above the line → model predicted too high. #Dots below the line → model predicted too low.

#The points are mostly near the diagonal, meaning the Linear Regression model predicts well.

#Clear positive trend: as actual height increases, predicted height also increases.

```
[ ]: #Model Interpretation & Visualization
#Plot actual vs predicted (use best model)
#This cell creates a scatter plot comparing the actual child heights (y_test)␣
    ↪to the predicted heights from the best-performing model (either Random␣
    ↪Forest or Linear Regression).
if best_model_name == "Random Forest":
    y_pred_best = y_pred_rf
else:
    y_pred_best = y_pred_lr

plt.figure(figsize=(5,5))
plt.scatter(y_test, y_pred_best, s=12)
# diagonal reference line
mn, mx = min(y_test.min(), y_pred_best.min()), max(y_test.max(), y_pred_best.
    ↪max())
plt.plot([mn, mx], [mn, mx])
plt.title(f"Actual vs Predicted (Best: {best_model_name})")
plt.xlabel("Actual Child Height (in)")
plt.ylabel("Predicted Child Height (in)")
plt.tight_layout()
plt.show()
```



#The x-axis is the index of each test record. #The y-axis is the residual (error) = Actual − Predicted.

#If residual = 0 → perfect prediction.

#Dots above 0 → model under-predicted (predicted too low). #Dots below 0 → model over-predicted (predicted too high).

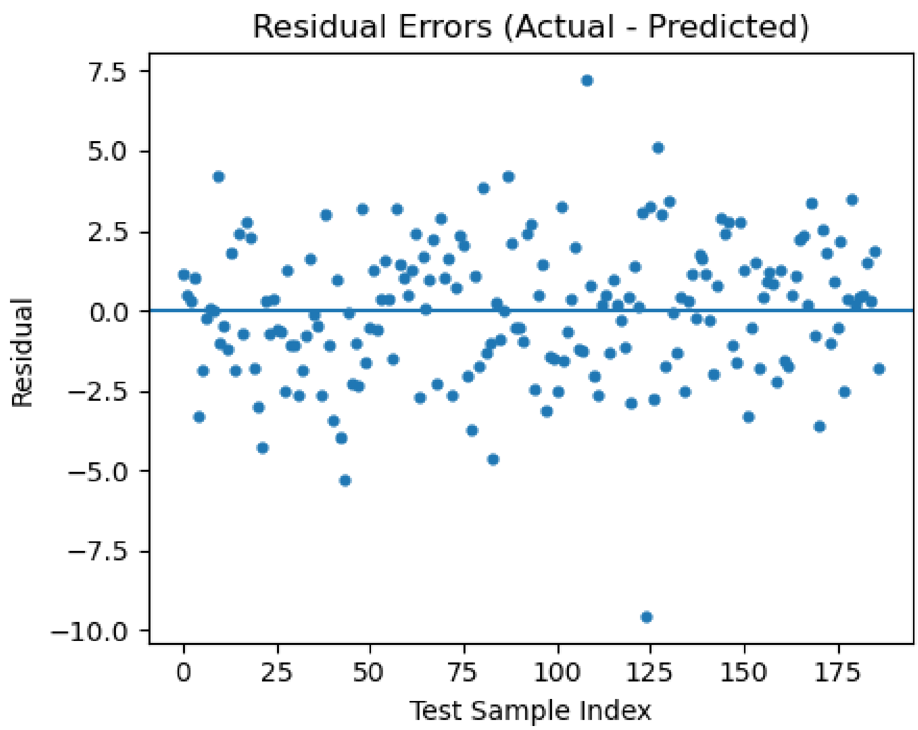
#Most residuals are centered around 0.

#No clear pattern (theyspread randomly above and below the line), which means the model doesn't have systematic bias.

#A few points are farther away from 0 — those are larger errors or outliers.

[ ]:
```
#This cell calculates the residuals (the difference between actual and␣
↪predicted values) for the best model and creates a scatter plot of these␣
↪residuals to check for patterns or biases in the predictions.
residuals = y_test - y_pred_best

plt.figure(figsize=(5,4))
```

```python
plt.scatter(range(len(residuals)), residuals, s=12)
plt.axhline(0)
plt.title("Residual Errors (Actual - Predicted)")
plt.xlabel("Test Sample Index")
plt.ylabel("Residual")
plt.tight_layout()
plt.show()
```



#Residual = Actual – Predicted #X-axis → the size of those residuals (how far off each prediction was)

#Y-axis → how many data points had that size of error

#Bars near 0 → predictions close to actual values.

#Bars farther from 0 → larger errors.

#Most residuals cluster between about –3 and +3 → predictions are close to real heights.

#The peak is near 0, showing the model is centered correctly (no consistent over/under-prediction).

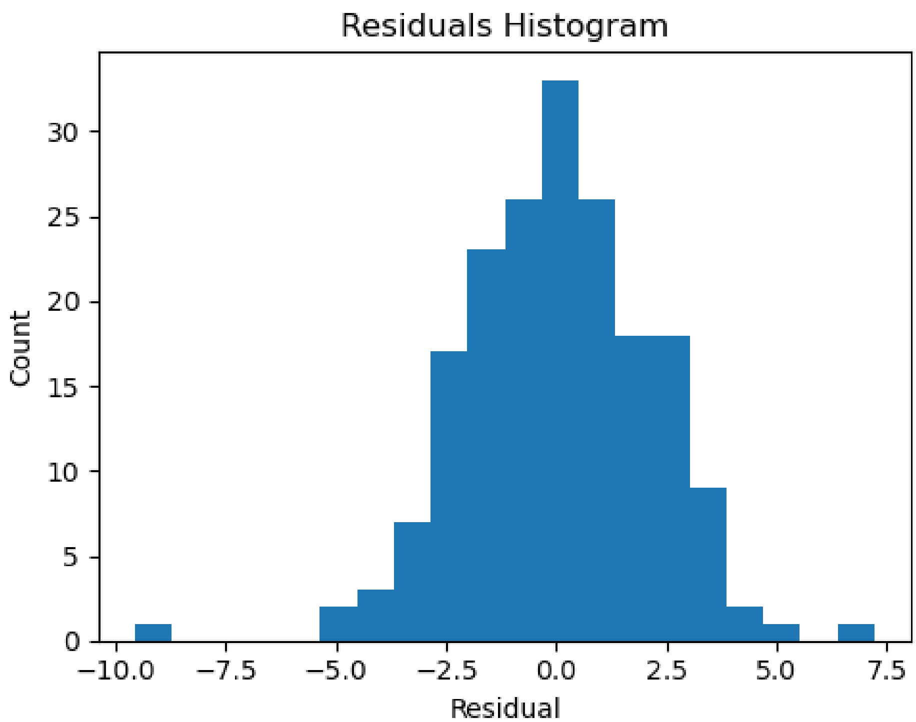
#The shape is almost normal (bell-shaped), which supports Linear Regression assumptions are reasonable.

#A few bars on the far left/right (like –10 or +7) are outliers — these are just a few cases where the model missed badly.

#This histogram shows that most prediction errors are small and evenly spread around zero.

#The model performs well overall, with only a few large outliers.

[ ]:
```
#This cell creates a histogram of the residuals to visualize their␣
↪distribution, helping to check if they are normally distributed around zero,␣
↪which is an assumption of many regression models.
plt.figure(figsize=(5,4))
plt.hist(residuals, bins=20)
plt.title("Residuals Histogram")
plt.xlabel("Residual")
plt.ylabel("Count")
plt.tight_layout()
plt.show()
```



[ ]:
```
#This cell creates a new DataFrame called comparison that contains the actual␣
↪child heights (y_test) and the predicted heights (y_pred_best) from the best␣
↪model, then prints the first 10 rows of this comparison to show how well the␣
↪predictions match the actual values.
#comparing actual vs predicted
comparison = pd.DataFrame({
    "Actual": y_test.values,
    "Predicted": y_pred_best
}).reset_index(drop=True)
```

```python
print("\nFirst 10 - Actual vs Predicted:")
print(comparison.head(10).round(2))
```

```
First 10 - Actual vs Predicted:
   Actual  Predicted
0    65.5      64.32
1    72.7      72.21
2    70.0      69.72
3    69.5      68.50
4    64.0      67.29
5    63.0      64.85
6    64.5      64.71
7    65.5      65.44
8    63.5      63.52
9    74.0      69.81
```