```
import pandas as pd
data=pd.read_csv("agricultural_yield.csv")
df=pd.DataFrame(data)
df.head()
```

| | Soil_Quality | Seed_Variety | Fertilizer_Amount_kg_per_hectare | Sunny_Days | Rainfall_mm | Irrigation_Schedule | Yield_kg_pe |
|---|---|---|---|---|---|---|---|
| 0 | 93.304721 | 0 | 132.522218 | 96.670922 | 602.386237 | 3 | |
| 1 | 83.674653 | 1 | 57.283997 | 99.007556 | 466.518251 | 8 | |
| 2 | 65.963033 | 1 | 227.895479 | 104.844272 | 510.320495 | 4 | |
| 3 | 78.692834 | 1 | 176.314126 | 90.136191 | 354.350914 | 5 | |
| 4 | 72.415684 | 1 | 160.070418 | 101.221668 | 443.993788 | 10 | |

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

---

```
print(df.columns)
```

```
Index(['Soil_Quality', 'Seed_Variety', 'Fertilizer_Amount_kg_per_hectare',
       'Sunny_Days', 'Rainfall_mm', 'Irrigation_Schedule',
       'Yield_kg_per_hectare'],
      dtype='object')
```

```
X=df[['Soil_Quality', 'Seed_Variety', 'Fertilizer_Amount_kg_per_hectare','Sunny_Days', 'Rainfall_mm', 'Irrigation_Schedule']]
y=df['Yield_kg_per_hectare'].values
```

```
X.shape[1]
```

```
6
```

```
model=Sequential([
    Dense(256,activation="relu",input_shape=(X.shape[1],)),
    Dense(128,activation="relu"),
    Dense(64,activation="relu"),
    Dense(32,activation="relu"),
    Dense(1)
])
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an `input_shape`/`in
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
scalar=StandardScaler()
x_train=scalar
```

```
x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
model.compile(optimizer='adam',loss="binary_crossentropy",metrics=['mse'])
```

```
model.summary()
```

**Model: "sequential_1"**

| Layer (type) | Output Shape | Param # |
|---|---|---|
| dense_5 (Dense) | (None, 256) | 1,792 |
| dense_6 (Dense) | (None, 128) | 32,896 |
| dense_7 (Dense) | (None, 64) | 8,256 |
| dense_8 (Dense) | (None, 32) | 2,080 |
| dense_9 (Dense) | (None, 1) | 33 |

**Total params:** 45,057 (176.00 KB)
**Trainable params:** 45,057 (176.00 KB)
**Non-trainable params:** 0 (0.00 B)

```
model.fit(x_train,y_train,batch_size=16,epochs=50)
```

```
Epoch 1/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: -10742.7168 - mse: 399179.4688
Epoch 2/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: -11344.1602 - mse: 376240.8125
Epoch 3/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: -11276.0352 - mse: 371262.2812
Epoch 4/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11327.2061 - mse: 374788.7812
Epoch 5/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11342.7793 - mse: 374231.0938
Epoch 6/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: -11246.7188 - mse: 368010.6875
Epoch 7/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: -11296.9180 - mse: 370465.3438
Epoch 8/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: -11356.5723 - mse: 376903.6562
Epoch 9/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: -11303.2520 - mse: 371787.6562
Epoch 10/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: -11255.4121 - mse: 369691.4062
Epoch 11/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 2s 11ms/step - loss: -11311.3027 - mse: 372279.5312
Epoch 12/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 2s 9ms/step - loss: -11246.8232 - mse: 368149.3438
Epoch 13/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11252.0693 - mse: 371269.3750
Epoch 14/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: -11390.0771 - mse: 379519.0938
Epoch 15/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: -11279.6592 - mse: 371769.5938
Epoch 16/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: -11228.6260 - mse: 369240.0938
Epoch 17/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: -11180.1064 - mse: 365976.4375
Epoch 18/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: -11253.7412 - mse: 367207.1875
Epoch 19/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: -11246.3926 - mse: 368646.5625
Epoch 20/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: -11174.6006 - mse: 362475.3125
Epoch 21/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - loss: -11162.2080 - mse: 362343.1562
Epoch 22/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - loss: -11212.5732 - mse: 368043.6250
Epoch 23/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: -11270.0889 - mse: 371060.6875
Epoch 24/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: -11248.7949 - mse: 368407.4688
Epoch 25/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: -11325.0479 - mse: 373739.0000
Epoch 26/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11181.5244 - mse: 364094.7188
Epoch 27/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - loss: -11333.6309 - mse: 372336.8125
Epoch 28/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - loss: -11326.6064 - mse: 373715.7812
Epoch 29/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: -11306.2314 - mse: 370983.6562
```

```
# prompt: generate different plots

import matplotlib.pyplot as plt
import seaborn as sns

# Assuming 'x_train', 'y_train', 'x_test', 'y_test' are defined from the previous code

# Plot training history
history = model.fit(x_train, y_train, batch_size=16, epochs=50, validation_data=(x_test, y_test)) #added validation data
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss') # Plot validation loss
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Training and Validation Loss')
plt.legend()
plt.show()

#Plot training history of mean squared error
plt.plot(history.history['mse'], label='Training MSE')
plt.plot(history.history['val_mse'], label='Validation MSE') # Plot validation loss
plt.xlabel('Epoch')
plt.ylabel('MSE')
plt.title('Training and Validation MSE')
plt.legend()
plt.show()


# Scatter plot of actual vs. predicted values
```

```
y_pred = model.predict(x_test)
plt.scatter(y_test, y_pred)
plt.xlabel("Actual Yield")
plt.ylabel("Predicted Yield")
plt.title("Actual vs. Predicted Yield")
plt.show()


# Distribution plots
sns.distplot(y_test, label='Actual Yield')
sns.distplot(y_pred, label='Predicted Yield')
plt.xlabel("Yield")
plt.ylabel("Density")
plt.title("Distribution of Actual and Predicted Yield")
plt.legend()
plt.show()

# Correlation Matrix Heatmap (if you want to visualize feature correlations)
correlation_matrix = df.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title("Correlation Matrix Heatmap")
plt.show()
```

```
Epoch 1/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - loss: -11269.0039 - mse: 370074.7500 - val_loss: -11264.8809 - val_mse: 37026
Epoch 2/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11323.2314 - mse: 372228.7500 - val_loss: -11264.8809 - val_mse: 37026
Epoch 3/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11397.1465 - mse: 378477.7812 - val_loss: -11264.8809 - val_mse: 37026
Epoch 4/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: -11231.3613 - mse: 366213.8438 - val_loss: -11264.8809 - val_mse: 37026
Epoch 5/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11304.7197 - mse: 372321.5000 - val_loss: -11264.8809 - val_mse: 37026
Epoch 6/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: -11323.3906 - mse: 374422.7188 - val_loss: -11264.8809 - val_mse: 37026
Epoch 7/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11303.4814 - mse: 372065.6250 - val_loss: -11264.8809 - val_mse: 37026
Epoch 8/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: -11336.8398 - mse: 377081.8125 - val_loss: -11264.8809 - val_mse: 37026
Epoch 9/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: -11367.3994 - mse: 377139.0625 - val_loss: -11264.8809 - val_mse: 37026
Epoch 10/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11272.2578 - mse: 370168.5312 - val_loss: -11264.8809 - val_mse: 37026
Epoch 11/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: -11319.3604 - mse: 373057.3438 - val_loss: -11264.8809 - val_mse: 37026
Epoch 12/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11366.1406 - mse: 376026.1562 - val_loss: -11264.8809 - val_mse: 37026
Epoch 13/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: -11287.7080 - mse: 371486.1250 - val_loss: -11264.8809 - val_mse: 37026
Epoch 14/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: -11366.0684 - mse: 377522.6875 - val_loss: -11264.8809 - val_mse: 37026
Epoch 15/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11289.5791 - mse: 370802.3750 - val_loss: -11264.8809 - val_mse: 37026
Epoch 16/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: -11355.2568 - mse: 377935.3125 - val_loss: -11264.8809 - val_mse: 37026
Epoch 17/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: -11282.0527 - mse: 372138.2500 - val_loss: -11264.8809 - val_mse: 37026
Epoch 18/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: -11427.4551 - mse: 382292.1562 - val_loss: -11264.8809 - val_mse: 37026
Epoch 19/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11275.9268 - mse: 369787.7188 - val_loss: -11264.8809 - val_mse: 37026
Epoch 20/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11285.2793 - mse: 371767.7812 - val_loss: -11264.8809 - val_mse: 37026
Epoch 21/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11311.5488 - mse: 372424.7812 - val_loss: -11264.8809 - val_mse: 37026
Epoch 22/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11298.5967 - mse: 373682.4375 - val_loss: -11264.8809 - val_mse: 37026
Epoch 23/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: -11307.1865 - mse: 373416.6250 - val_loss: -11264.8809 - val_mse: 37026
Epoch 24/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11325.7363 - mse: 375570.9062 - val_loss: -11264.8809 - val_mse: 37026
Epoch 25/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11323.5449 - mse: 374180.7500 - val_loss: -11264.8809 - val_mse: 37026
Epoch 26/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11252.2852 - mse: 368312.8125 - val_loss: -11264.8809 - val_mse: 37026
Epoch 27/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11320.8193 - mse: 375388.5625 - val_loss: -11264.8809 - val_mse: 37026
Epoch 28/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11206.9463 - mse: 365056.5312 - val_loss: -11264.8809 - val_mse: 37026
Epoch 29/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11287.2783 - mse: 369257.1250 - val_loss: -11264.8809 - val_mse: 37026
Epoch 30/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11266.1270 - mse: 369275.3125 - val_loss: -11264.8809 - val_mse: 37026
Epoch 31/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11312.2734 - mse: 374357.5000 - val_loss: -11264.8809 - val_mse: 37026
Epoch 32/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 2s 5ms/step - loss: -11354.9072 - mse: 373493.8438 - val_loss: -11264.8809 - val_mse: 37026
Epoch 33/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: -11347.5645 - mse: 375991.4375 - val_loss: -11264.8809 - val_mse: 37026
Epoch 34/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11227.3525 - mse: 368290.7812 - val_loss: -11264.8809 - val_mse: 37026
Epoch 35/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11309.4482 - mse: 373331.4375 - val_loss: -11264.8809 - val_mse: 37026
Epoch 36/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11287.1289 - mse: 372492.3125 - val_loss: -11264.8809 - val_mse: 37026
Epoch 37/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11306.2354 - mse: 370879.0625 - val_loss: -11264.8809 - val_mse: 37026
Epoch 38/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: -11382.8486 - mse: 379457.1875 - val_loss: -11264.8809 - val_mse: 37026
Epoch 39/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11181.9502 - mse: 362565.9688 - val_loss: -11264.8809 - val_mse: 37026
Epoch 40/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11326.9111 - mse: 374761.0625 - val_loss: -11264.8809 - val_mse: 37026
Epoch 41/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11267.7393 - mse: 369171.1250 - val_loss: -11264.8809 - val_mse: 37026
Epoch 42/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11302.5537 - mse: 372196.0938 - val_loss: -11264.8809 - val_mse: 37026
Epoch 43/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11334.7510 - mse: 371784.0000 - val_loss: -11264.8809 - val_mse: 37026
Epoch 44/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11269.5430 - mse: 368361.9375 - val_loss: -11264.8809 - val_mse: 37026
Epoch 45/50
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: -11350.9609 - mse: 374786.2500 - val_loss: -11264.8809 - val_mse: 37026
```