

ECGR_4105_HW6_Problem_2

November 28, 2024

```
[6]: import pandas as pd
import tensorflow as tf
import time

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

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[2]: file_path = 'https://raw.githubusercontent.com/lnguye782/ECGR-4105-Intro-to-ML/
↳refs/heads/main/HW6/cancer.csv'
cancer_data = pd.read_csv(file_path)

cancer_data.head()
```

```
[2]:
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	mean radius	mean texture	mean perimeter	mean area	mean smoothness	\
0	17.99	10.38	122.80	1001.0	0.11840	
1	20.57	17.77	132.90	1326.0	0.08474	
2	19.69	21.25	130.00	1203.0	0.10960	
3	11.42	20.38	77.58	386.1	0.14250	
4	20.29	14.34	135.10	1297.0	0.10030	

	mean compactness	mean concavity	mean concave points	mean symmetry	\
0	0.27760	0.3001	0.14710	0.2419	
1	0.07864	0.0869	0.07017	0.1812	
2	0.15990	0.1974	0.12790	0.2069	
3	0.28390	0.2414	0.10520	0.2597	
4	0.13280	0.1980	0.10430	0.1809	

	mean fractal dimension	...	worst texture	worst perimeter	worst area	\
0	0.07871	...	17.33	184.60	2019.0	
1	0.05667	...	23.41	158.80	1956.0	
2	0.05999	...	25.53	152.50	1709.0	
3	0.09744	...	26.50	98.87	567.7	
4	0.05883	...	16.67	152.20	1575.0	

	worst smoothness	worst compactness	worst concavity	worst concave points	\
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0	0.1622	0.6656	0.7119	0.2654
1	0.1238	0.1866	0.2416	0.1860
2	0.1444	0.4245	0.4504	0.2430
3	0.2098	0.8663	0.6869	0.2575
4	0.1374	0.2050	0.4000	0.1625

	worst symmetry	worst fractal dimension	target
0	0.4601	0.11890	0
1	0.2750	0.08902	0
2	0.3613	0.08758	0
3	0.6638	0.17300	0
4	0.2364	0.07678	0

[5 rows x 31 columns]

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[4]: # Separate features and target
X = cancer_data.drop(columns=["target"])
y = cancer_data["target"]

# Normalize the data
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Split the data into training (80%) and validation (20%) sets
X_train, X_val, y_train, y_val = train_test_split(X_scaled, y, test_size=0.2,
↳random_state=42, stratify=y)
```

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[7]: # Define the neural network with an explicit Input layer
model = Sequential([
    Input(shape=(X_train.shape[1],)), # Define the input shape
    Dense(32, activation='relu'),
    Dense(1, activation='sigmoid') # Binary classification output layer
])

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy',
↳metrics=['accuracy'])

# Train the model
start_time = time.time()
history = model.fit(X_train, y_train, validation_data=(X_val, y_val),
↳epochs=100, verbose=0)
training_time = time.time() - start_time

# Evaluate the model
evaluation = model.evaluate(X_val, y_val, verbose=0)
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training_loss = history.history['loss'][-1]
validation_accuracy = evaluation[1]

training_time, training_loss, validation_accuracy

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[7]: (6.114588499069214, 0.013174124993383884, 0.9561403393745422)

```

[8]: # Extend the neural network to include two additional hidden layers
model_extended = Sequential([
    Input(shape=(X_train.shape[1],)), # Explicit Input layer
    Dense(32, activation='relu'),
    Dense(32, activation='relu'), # First additional hidden layer
    Dense(32, activation='relu'), # Second additional hidden layer
    Dense(1, activation='sigmoid') # Binary classification output layer
])

# Compile the extended model
model_extended.compile(optimizer='adam', loss='binary_crossentropy',
    ↪ metrics=['accuracy'])

# Train the extended model
start_time = time.time()
history_extended = model_extended.fit(X_train, y_train, validation_data=(X_val,
    ↪ y_val), epochs=100, verbose=0)
training_time_extended = time.time() - start_time

# Evaluate the extended model
evaluation_extended = model_extended.evaluate(X_val, y_val, verbose=0)

training_loss_extended = history_extended.history['loss'][-1]
validation_accuracy_extended = evaluation_extended[1]

training_time_extended, training_loss_extended, validation_accuracy_extended

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[8]: (7.382623195648193, 0.00022640445968136191, 0.9649122953414917)