Assignment – 7 (Week -8)

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GitHub link: https://github.com/nagaphaneendra2001/Deep_Learning_Neural_Networks.git

1. Tune hyper-parameter and make necessary addition to the baseline model to improve validation accuracy and reduce validation loss.
2. Provide logical description of which steps lead to improved response and what was its impact on architecture behavior.

Program

```
s# Tune hyperparameter and make necessary addition to the baseline model to improve validation accuracy
# Provide logical description of which steps lead to improved response and what was its impact on architecture behavior
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.datasets import load_iris
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import make_pipeline
iris = load_iris()
X, y = iris.data, iris.target
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state=42)
pipeline = make_pipeline(StandardScaler(), LogisticRegression(max_iter=1000))
param_grid = {
    'logisticregression__C': [0.001, 0.01, 0.1, 1, 10, 100],
}
grid_search = GridSearchCV(pipeline, param_grid, cv=5)
grid_search.fit(X_train, y_train)
print("Best hyperparameters:", grid_search.best_params_)
val_accuracy = grid_search.score(X_val, y_val)
print("Validation Accuracy:", val_accuracy)
```

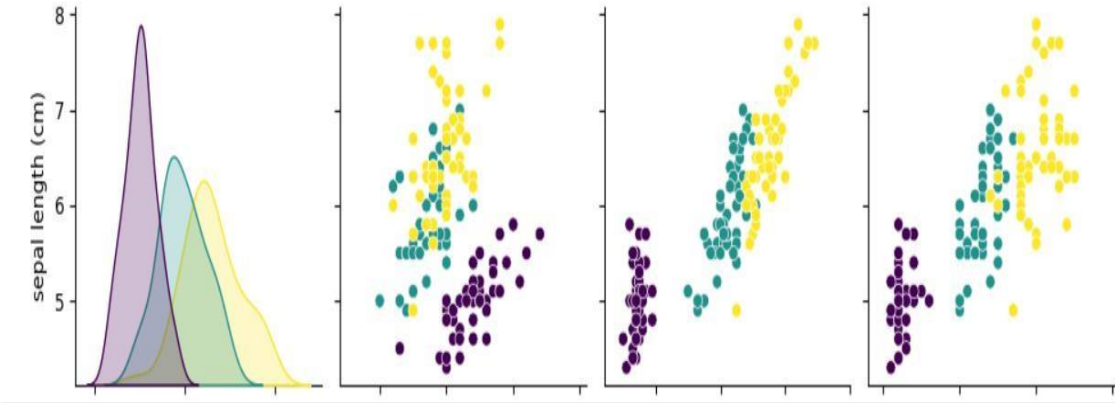
ndarray: y

ndarray with shape (150,)

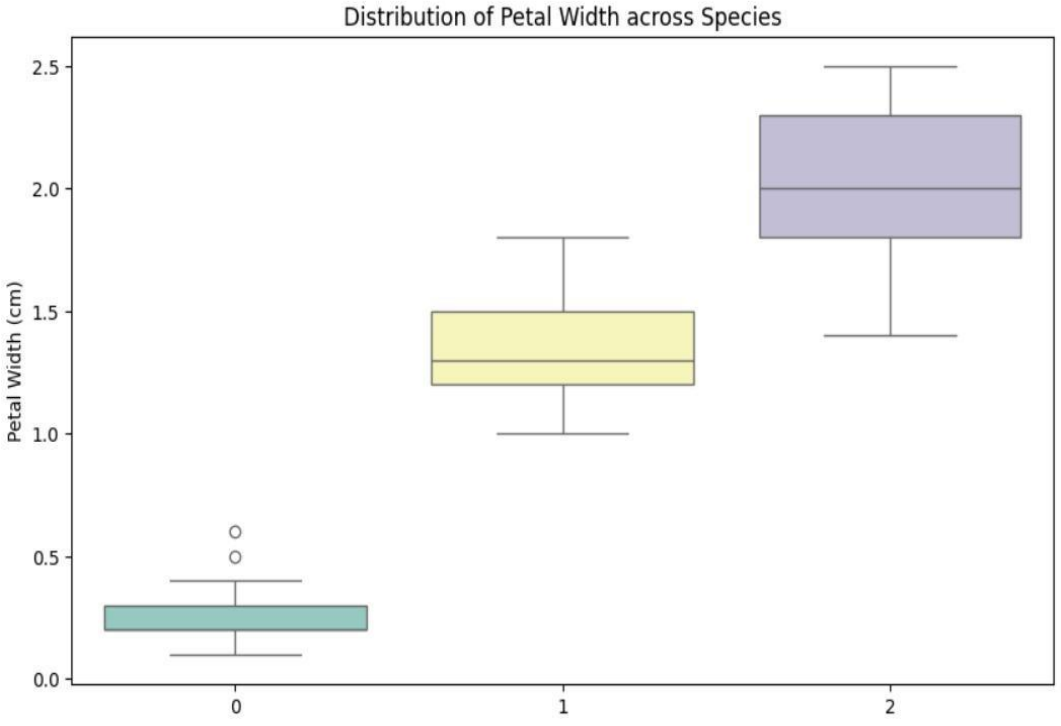
```
Best hyperparameters: {'logisticregression__C': 1}
Validation Accuracy: 1.0
```

3. Create at least two more visualizations using matplotlib (Other than provided in the source file)

```
# Create at least two more visualizations using matplotlib (Other than provided in the source file)
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
iris_df = pd.DataFrame(data=iris.data, columns=iris.feature_names)
iris_df['target'] = iris.target
sns.pairplot(iris_df, hue='target', palette='viridis')
plt.show()
plt.figure(figsize=(10, 6))
sns.boxplot(x='target', y='petal width (cm)', data=iris_df, palette='Set3')
plt.xlabel('Species')
plt.ylabel('Petal Width (cm)')
plt.title('Distribution of Petal Width across Species')
plt.show()
```




```
sns.boxplot(x='target', y='petal width (cm)', data=iris_df, palette='Set3')
```



4. Use dataset of your own choice and implement baseline models provided.

```
#Use dataset of your own choice and implement baseline models provided
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
iris = load_iris()
X, y = iris.data, iris.target
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
logistic_model = LogisticRegression(max_iter=1000)
logistic_model.fit(X_train_scaled, y_train)
y_pred = logistic_model.predict(X_test_scaled)
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy of Logistic Regression:", accuracy)
```

(module) model_selection

```
Accuracy of Logistic Regression: 1.0
```

5. Apply modified architecture to your own selected dataset and train it.

```
# Apply modified architecture to your own selected dataset and train it.
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
iris = load_iris()
X, y = iris.data, iris.target
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
model = Sequential([
    Dense(10, activation='relu', input_shape=(X_train_scaled.shape[1],)),
    Dense(20, activation='relu'),
    Dense(10, activation='relu'),
    Dense(3, activation='softmax')
])
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
model.fit(X_train_scaled, y_train, epochs=50, batch_size=8, verbose=1, validation_split=0.1)
loss, accuracy = model.evaluate(X_test_scaled, y_test, verbose=1)
print("Accuracy of Modified Neural Network:", accuracy)
```

```
Epoch 1/50
14/14 [==============================] - 3s 44ms/step - loss: 1.1511 - accuracy: 0.3333 - val_loss: 1.0949 - val_accuracy: 0.4167
Epoch 2/50
14/14 [==============================] - 0s 17ms/step - loss: 1.0962 - accuracy: 0.3333 - val_loss: 1.0629 - val_accuracy: 0.4167
1/1 [==============================] - 0s 31ms/step - loss: 0.0829 - accuracy: 1.0000
Accuracy of Modified Neural Network: 1.0
```

6. Evaluate your model on testing set.

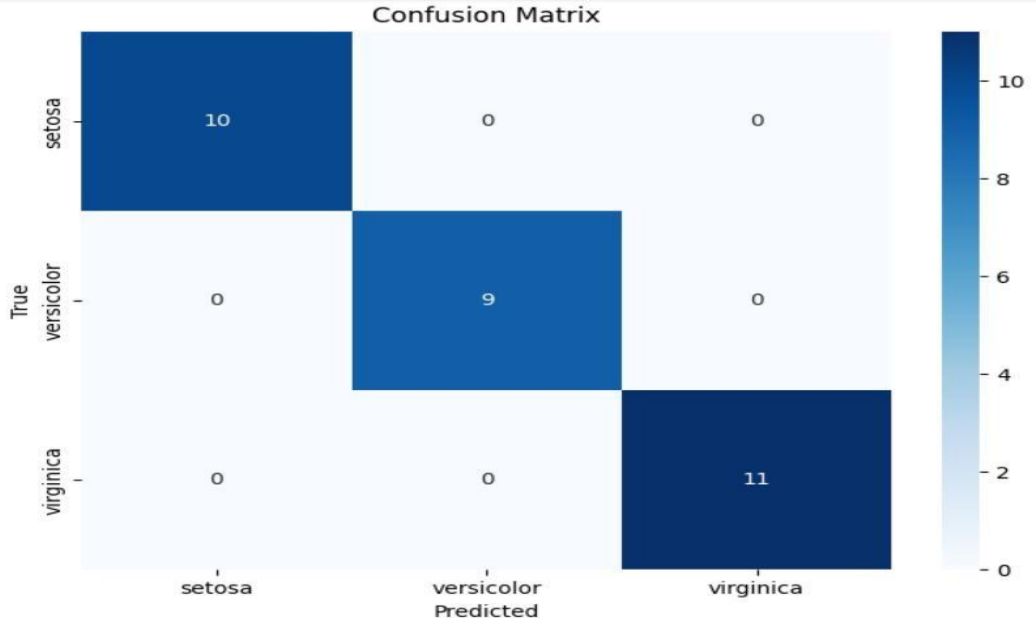
```
# Evaluate the model on the testing set
loss, accuracy = model.evaluate(X_test_scaled, y_test, verbose=1)
print("Accuracy on Testing Set:", accuracy)
```

```
1/1 [==============================] - 0s 52ms/step - loss: 0.0829 - accuracy: 1.0000
Accuracy on Testing Set: 1.0
```

7. Save the improved model and use it for prediction on testing data 8. Provide plot of confusion matric

```
# Saving the  the model and printing the first few predictions
model.save("improved_iris_model.h5")
from tensorflow.keras.models import load_model
saved_model = load_model("improved_iris_model.h5")
predictions = saved_model.predict(X_test_scaled)
print("Predictions:")
print(predictions[:5])
```

```
1/1 [==============================] - 0s 153ms/step
Predictions:
[[1.6918768e-03 9.3688971e-01 6.1418314e-02]
 [9.9732774e-01 2.6344496e-03 3.7800932e-05]
 [1.0534784e-07 7.2292364e-03 9.9277055e-01]
 [2.5175847e-03 8.1440175e-01 1.8308063e-01]
 [5.9270003e-04 7.9731899e-01 2.0212181e-01]]
```



8. Provide Training and testing Loss and accuracy plots in one plot using subplot command and history object.

```
# Training and testing Loss and accuracy plots in one plot using subplot command and history object
history = model.fit(X_train_scaled, y_train, epochs=50, batch_size=8, verbose=1, validation_split=0.1)
import matplotlib.pyplot as plt
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], label='Training Loss', color='blue')
plt.plot(history.history['val_loss'], label='Validation Loss', color='orange')
plt.title('Training and Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'], label='Training Accuracy', color='blue')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy', color='orange')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.tight_layout()
plt.show()
```

10. Provide at least two more visualizations reflecting your solution.
11. Provide logical description of which steps lead to improved response for new dataset when compared with baseline model and enhance architecture and what was its impact on architecture behavior.