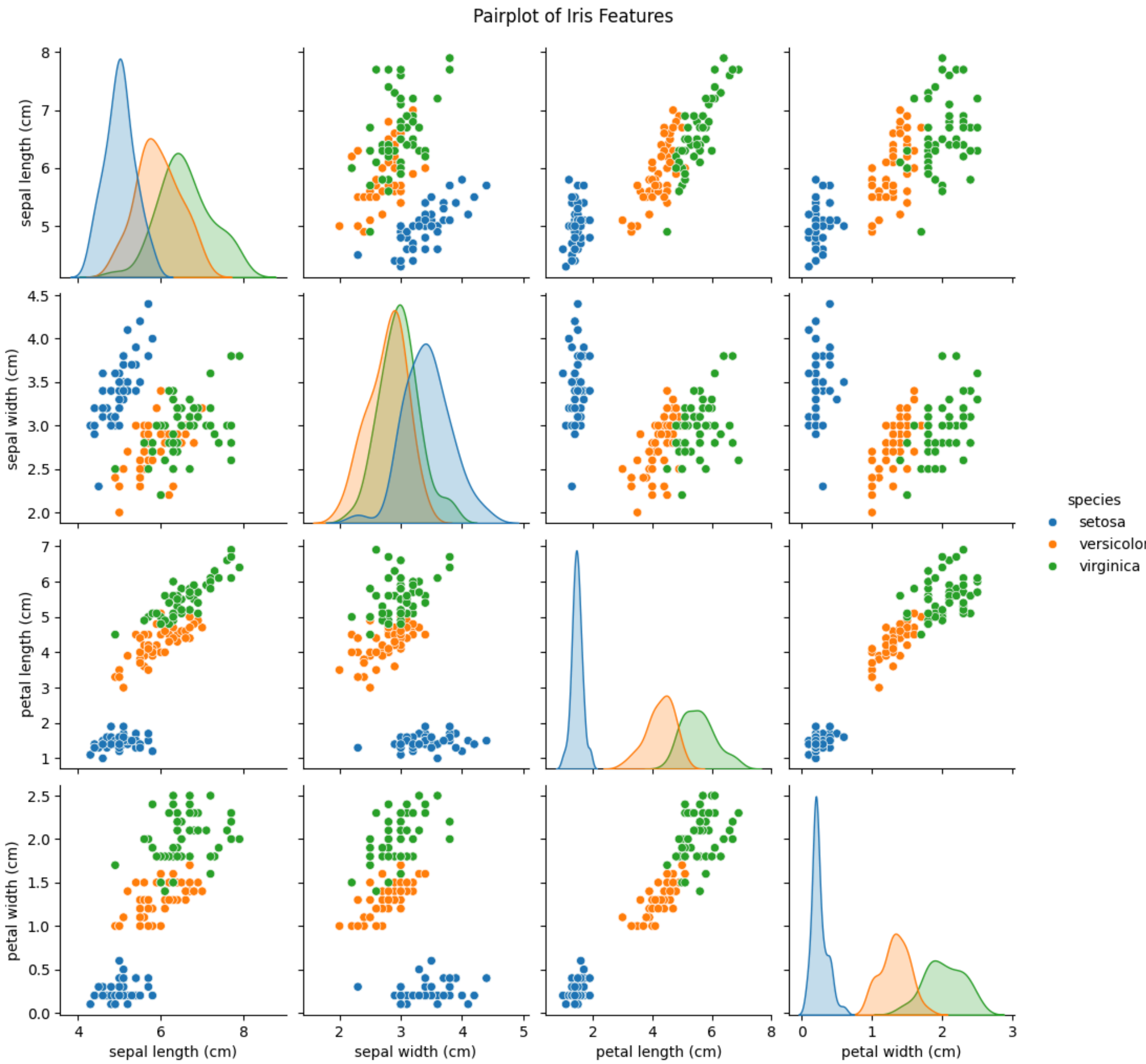
In [1]:
```python
# 🔷 Step 1: Import Necessary Libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix, accuracy_score, classification_r
```

In [2]:
```python
# 🔷 Step 2: Load the Iris Dataset
iris = load_iris()
X = pd.DataFrame(iris.data, columns=iris.feature_names)
y = pd.Series(iris.target, name='species')

# Display the first few rows
df = X.copy()
df['species'] = y
df['species'] = df['species'].map(dict(zip(range(3), iris.target_names)))
df.head()
```

Out[2]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa

In [3]:
```python
# 🔷 Step 3: Data Visualization
sns.pairplot(df, hue='species', diag_kind='kde')
plt.suptitle("Pairplot of Iris Features", y=1.02)
plt.show()
```



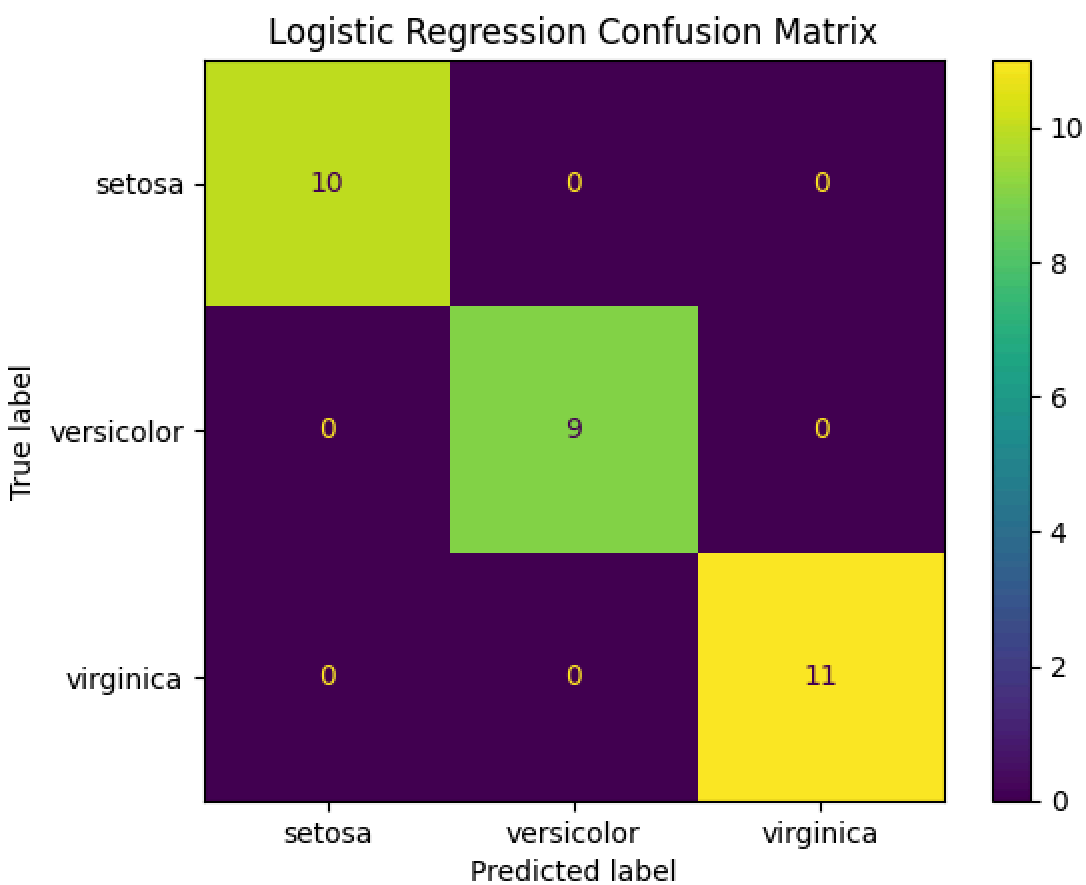
In [4]:
```
# 🔷 Step 4: Feature Scaling and Train/Test Split
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, iris.target, test_size=0.2, random_state=42
)

print("Training samples:", X_train.shape[0])
print("Test samples:", X_test.shape[0])
```

```
Training samples: 120
Test samples: 30
```

In [5]:
```
# 🔷 Logistic Regression
lr_model = LogisticRegression(max_iter=200)
lr_model.fit(X_train, y_train)
y_pred_lr = lr_model.predict(X_test)
```

```python
# Evaluation
print("Logistic Regression Accuracy:", accuracy_score(y_test, y_pred_lr))
print("\nClassification Report:\n", classification_report(y_test, y_pred_lr, t

ConfusionMatrixDisplay.from_predictions(y_test, y_pred_lr, display_labels=iris
plt.title("Logistic Regression Confusion Matrix")
plt.show()
```

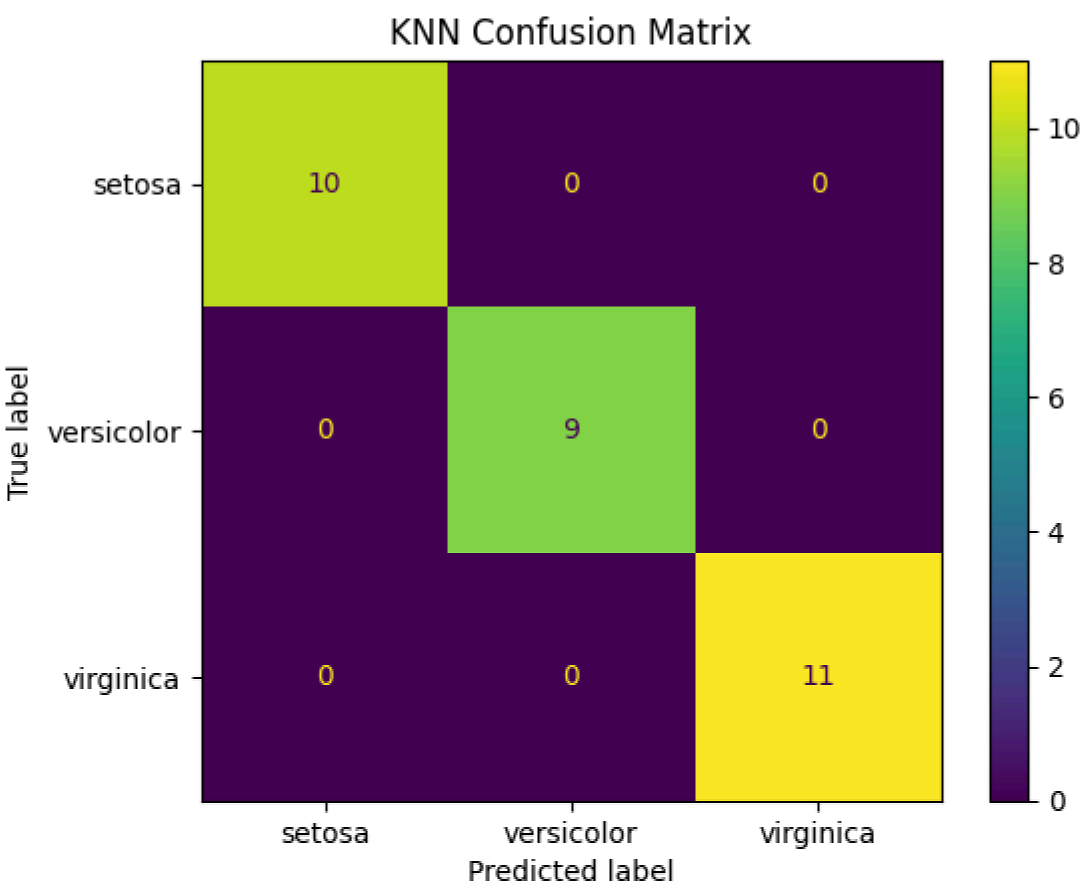
```
Logistic Regression Accuracy: 1.0

Classification Report:
               precision    recall  f1-score   support

      setosa       1.00      1.00      1.00        10
  versicolor       1.00      1.00      1.00         9
   virginica       1.00      1.00      1.00        11

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30
```



In [6]:
```python
# ◈ K-Nearest Neighbors
knn_model = KNeighborsClassifier(n_neighbors=5)
knn_model.fit(X_train, y_train)
y_pred_knn = knn_model.predict(X_test)
```

```python
# Evaluation
print("KNN Accuracy:", accuracy_score(y_test, y_pred_knn))
print("\nClassification Report:\n", classification_report(y_test, y_pred_knn,

ConfusionMatrixDisplay.from_predictions(y_test, y_pred_knn, display_labels=iri
plt.title("KNN Confusion Matrix")
plt.show()
```

```
KNN Accuracy: 1.0

Classification Report:
               precision    recall  f1-score   support

      setosa       1.00      1.00      1.00        10
  versicolor       1.00      1.00      1.00         9
   virginica       1.00      1.00      1.00        11

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30
```



In [ ]:

Model Choice & Evaluation – Task 1: Introduction to Machine Learning with Scikit-learn

In this task, we explored the Iris dataset to build and evaluate simple machine learning classification models using Scikit-learn. The Iris dataset, being small and well-balanced, is ideal for beginners and allows clear insights into classification performance.

Model Selection:

We chose two commonly used supervised learning algorithms:

- **Logistic Regression**: A linear model suitable for multiclass classification problems. It is fast, interpretable, and performs well when classes are linearly separable.
- **K-Nearest Neighbors (KNN)**: A non-parametric, instance-based algorithm that classifies data based on the majority label of its k-nearest neighbors. It works well with low-dimensional, clean datasets like Iris.

Evaluation Results:

Both models achieved **100% accuracy** on the test set of 30 samples. Performance was evaluated using:

- **Confusion Matrix**: Confirmed all samples were correctly classified across all three species: *setosa*, *versicolor*, and *virginica*.
- **Classification Report**: Precision, recall, and F1-score were all 1.00 for every class, indicating perfect classification.

Conclusion:

Both Logistic Regression and KNN performed excellently on this dataset. Logistic Regression is preferred for its simplicity and faster inference, whereas KNN offers strong performance for datasets with clearly separated clusters. The Iris dataset's well-defined structure allowed both models to achieve perfect classification results.
