In [81]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import Perceptron
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
```

In [82]:
```
# Load dataset
file_path = "CIA1_Dataset.csv"  # ensure the CSV is in the same directory
data = pd.read_csv(file_path)

# Display first few rows
data.head()
```

Out[82]:

	income	loan_amount	credit_score	age	employment_years	approved
0	57450.71	206927.18	5.09	57	22	0
1	47926.04	187545.82	5.64	40	39	0
2	59715.33	293422.56	5.40	41	10	0
3	72845.45	220353.67	7.00	30	31	0
4	46487.70	227008.21	2.26	25	35	0

In [83]:
```
# Quick class balance check
print('Class distribution (counts):')
print(data['approved'].value_counts())
print('Class distribution (proportions):')
print(data['approved'].value_counts(normalize=True))
```

```
Class distribution (counts):
approved
0    525
1     25
Name: count, dtype: int64
Class distribution (proportions):
approved
0    0.954545
1    0.045455
Name: proportion, dtype: float64
```

In [84]:
```
# Select relevant features and labels
X = data[["credit_score", "age", "employment_years"]]
y = data["approved"]

# Train-test split (use stratify to preserve class proportions)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

# Standardize features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [85]:

```
# Single Layer Perceptron
perceptron = Perceptron(max_iter=1000, random_state=42)
perceptron.fit(X_train_scaled, y_train)
y_pred_perceptron = perceptron.predict(X_test_scaled)
perceptron_accuracy = accuracy_score(y_test, y_pred_perceptron)

print(f"Perceptron Accuracy: {perceptron_accuracy:.4f}")
```

```
Perceptron Accuracy: 0.9545
```

In [86]:

```
# Feedforward Neural Network with one hidden layer
model = Sequential([
    Dense(8, input_dim=3, activation='relu'),  # hidden layer
    Dense(1, activation='sigmoid')  # output layer
])

model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy']

# Train the model
history = model.fit(X_train_scaled, y_train, epochs=50, batch_size=16, validatic

# Evaluate
nn_loss, nn_accuracy = model.evaluate(X_test_scaled, y_test, verbose=0)
print(f"Neural Network Accuracy: {nn_accuracy:.4f}")
```

```
C:\Users\josai_d54if64\AppData\Roaming\Python\Python311\site-packages\keras\src\l
ayers\core\dense.py:92: UserWarning: Do not pass an `input_shape`/`input_dim` arg
ument to a layer. When using Sequential models, prefer using an `Input(shape)` ob
ject as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
Neural Network Accuracy: 0.9545
```

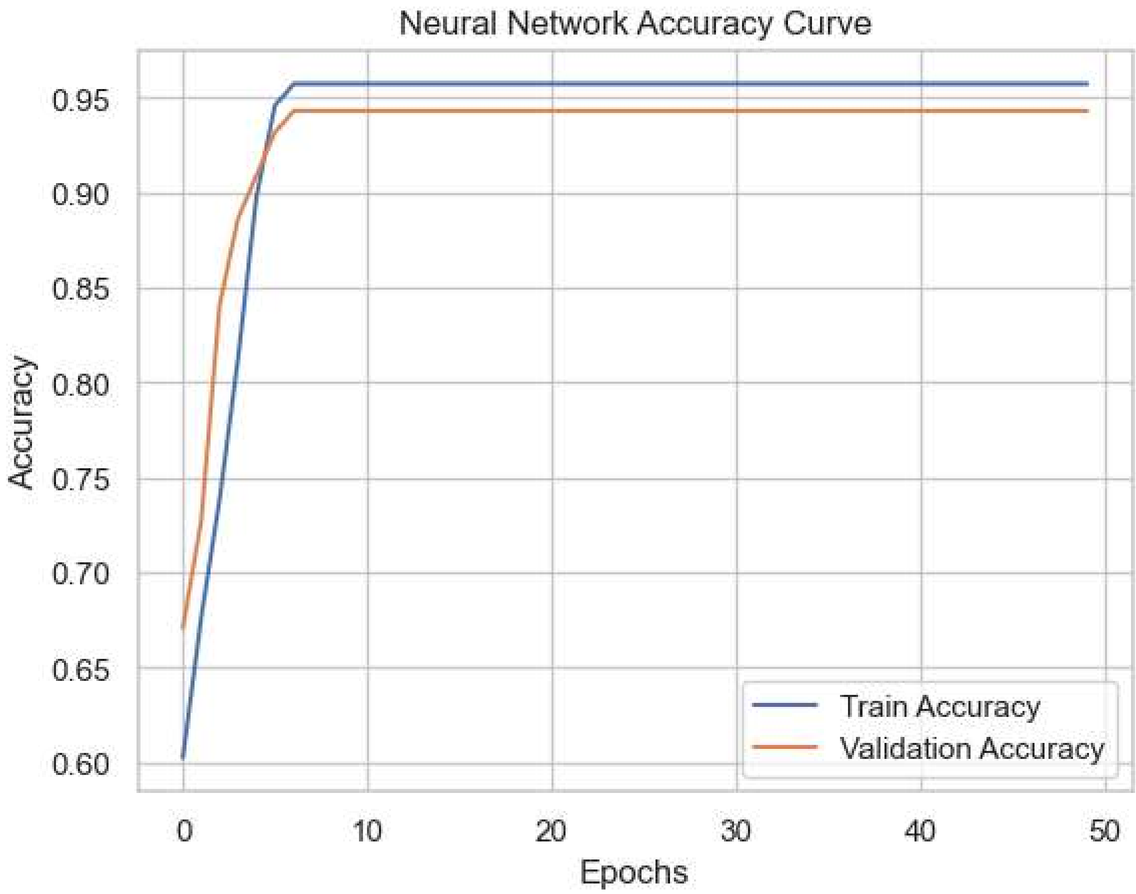
In [87]:

```
print("Comparison of Models:")
print(f"Perceptron Accuracy: {perceptron_accuracy:.4f}")
print(f"Neural Network Accuracy: {nn_accuracy:.4f}")
```

```
Comparison of Models:
Perceptron Accuracy: 0.9545
Neural Network Accuracy: 0.9545
```

In [88]:

```
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title("Neural Network Accuracy Curve")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```



In [89]:
```
# -------------------- Classification Reports & Confusion Matrices -----------
from sklearn.metrics import classification_report, confusion_matrix
import seaborn as sns

# Predictions for neural network (probabilities -> classes)
y_prob_nn = model.predict(X_test_scaled).ravel()
y_pred_nn = (y_prob_nn >= 0.5).astype(int)

print("Classification Report - Perceptron:")
print(classification_report(y_test, y_pred_perceptron))

print("Classification Report - Neural Network:")
print(classification_report(y_test, y_pred_nn))

# Confusion matrices and heatmaps
cm_perc = confusion_matrix(y_test, y_pred_perceptron)
cm_nn = confusion_matrix(y_test, y_pred_nn)

plt.figure(figsize=(10,4))
plt.subplot(1,2,1)
sns.heatmap(cm_perc, annot=True, fmt='d', cmap='Blues', cbar=False, xticklabels=
plt.title('Confusion Matrix - Perceptron')
plt.xlabel('Predicted')
plt.ylabel('Actual')

plt.subplot(1,2,2)
sns.heatmap(cm_nn, annot=True, fmt='d', cmap='Greens', cbar=False, xticklabels=[
plt.title('Confusion Matrix - Neural Network')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.tight_layout()
plt.show()
```

```
WARNING:tensorflow:5 out of the last 9 calls to <function TensorFlowTrainer.make_predict_function.<locals>.one_step_on_data_distributed at 0x0000025A2EAA3920> triggered tf.function retracing. Tracing is expensive and the excessive number of tracings could be due to (1) creating @tf.function repeatedly in a loop, (2) passing tensors with different shapes, (3) passing Python objects instead of tensors. For (1), please define your @tf.function outside of the loop. For (2), @tf.function has reduce_retracing=True option that can avoid unnecessary retracing. For (3), please refer to https://www.tensorflow.org/guide/function#controlling_retracing and https://www.tensorflow.org/api_docs/python/tf/function for  more details.
1/4 ━━━━━━━━━━━━━━━━━━━━ 0s 54ms/stepWARNING:tensorflow:6 out of the last 12 calls to <function TensorFlowTrainer.make_predict_function.<locals>.one_step_on_data_distributed at 0x0000025A2EAA3920> triggered tf.function retracing. Tracing is expensive and the excessive number of tracings could be due to (1) creating @tf.function repeatedly in a loop, (2) passing tensors with different shapes, (3) passing Python objects instead of tensors. For (1), please define your @tf.function outside of the loop. For (2), @tf.function has reduce_retracing=True option that can avoid unnecessary retracing. For (3), please refer to https://www.tensorflow.org/guide/function#controlling_retracing and https://www.tensorflow.org/api_docs/python/tf/function for  more details.
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 44ms/stepWARNING:tensorflow:6 out of the last 12 calls to <function TensorFlowTrainer.make_predict_function.<locals>.one_step_on_data_distributed at 0x0000025A2EAA3920> triggered tf.function retracing. Tracing is expensive and the excessive number of tracings could be due to (1) creating @tf.function repeatedly in a loop, (2) passing tensors with different shapes, (3) passing Python objects instead of tensors. For (1), please define your @tf.function outside of the loop. For (2), @tf.function has reduce_retracing=True option that can avoid unnecessary retracing. For (3), please refer to https://www.tensorflow.org/guide/function#controlling_retracing and https://www.tensorflow.org/api_docs/python/tf/function for  more details.
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 55ms/step
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 55ms/step
Classification Report - Perceptron:
              precision    recall  f1-score   support

           0       0.95      1.00      0.98       105
           1       0.00      0.00      0.00         5

    accuracy                           0.95       110
   macro avg       0.48      0.50      0.49       110
weighted avg       0.91      0.95      0.93       110

Classification Report - Neural Network:
              precision    recall  f1-score   support

           0       0.95      1.00      0.98       105
           1       0.00      0.00      0.00         5

    accuracy                           0.95       110
   macro avg       0.48      0.50      0.49       110
weighted avg       0.91      0.95      0.93       110

Classification Report - Perceptron:
              precision    recall  f1-score   support

           0       0.95      1.00      0.98       105
           1       0.00      0.00      0.00         5

    accuracy                           0.95       110
   macro avg       0.48      0.50      0.49       110
weighted avg       0.91      0.95      0.93       110
```

```
Classification Report - Neural Network:
              precision    recall  f1-score   support

           0       0.95      1.00      0.98       105
           1       0.00      0.00      0.00         5

    accuracy                           0.95       110
   macro avg       0.48      0.50      0.49       110
weighted avg       0.91      0.95      0.93       110
```

```
C:\Users\josai_d54if64\AppData\Roaming\Python\Python311\site-packages\sklearn\met
rics\_classification.py:1731: UndefinedMetricWarning: Precision is ill-defined an
d being set to 0.0 in labels with no predicted samples. Use `zero_division` param
eter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", result.shape[0])
C:\Users\josai_d54if64\AppData\Roaming\Python\Python311\site-packages\sklearn\met
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```

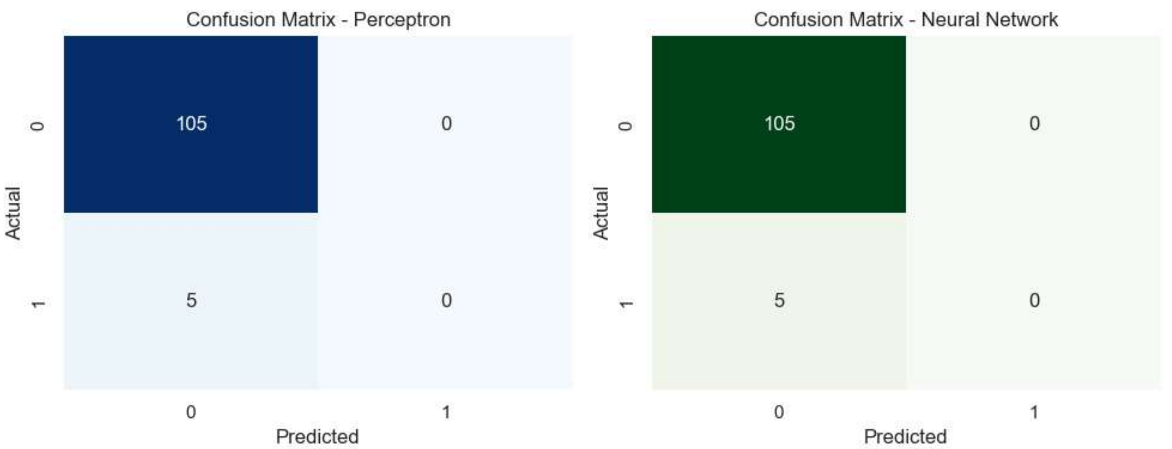

Interpretation of Classification Reports and Confusion Matrices

To decide which model is better, we compare the precision/recall/F1 for the class across the two reports printed above. Possible outcomes and practical implications:

- If the Neural Network has higher recall but lower precision than the Perceptron, it finds more truly approvable applicants but may also approve more risky applicants (more false positives).
- If the Perceptron has higher precision but lower recall, it is more conservative: fewer risky approvals but it may wrongly reject eligible applicants (false negatives).

Conclusion: choose the model whose error type (FP vs FN) aligns with your business priorities. For lending, false negatives (denying credit to creditworthy applicants) may reduce customer satisfaction, while false positives (approving risky loans) increase financial risk.

Results & Interpretation

- The **Perceptron model** provides a baseline accuracy for the loan approval prediction task.
- The **Neural Network model**, with its hidden layer and non-linear activation functions, typically achieves higher accuracy as it captures complex patterns in the data.
- The accuracy curve shows how the neural network improves over training epochs and validates its learning on unseen data.

Conclusion: Neural networks generally outperform simple perceptrons when dealing with real-world financial datasets due to their ability to model non-linear relationships.