Implement XOR gate using 2-layer Neural Network

- Use Adadelta optimizer
- Plot accuracy vs epoch

In [29]:
```
import numpy as np
import tensorflow as tf
import pandas as pd
```

In [30]:
```
X = np.array([[0,0],[0,1],[1,1],[1,0]])
```

In [31]:
```
y = np.array([0,1,0,1])
```

In [32]:
```
w1 = np.random.rand(2,2)
b1 = np.random.rand(1)
w2 = np.random.rand(1,1)
b2 = np.random.rand(1)
```

In [33]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Input
```

In [34]:
```
model = Sequential([
    Input(shape=(2,)),
    Dense(2, activation='relu'),
    Dense(1, activation='sigmoid')
])
```

In [35]:
```
model.compile(optimizer='adadelta', loss='binary_crossentropy', metrics=['accuracy'])
```

In [36]:
```
history = model.fit(X, y, epochs=100)
```

```
Epoch 1/100

[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 417ms/step - accuracy:
0.7500 - loss: 0.8847
Epoch 2/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8847
Epoch 3/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 21ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 4/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 5/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 6/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 7/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 8/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 9/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 23ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 10/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 11/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 12/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 23ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 13/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 23ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 14/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 15/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 16/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 17/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 18/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 19/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 21ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 20/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 21/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 22/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
```

```
Epoch 23/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 24/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 25/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 26/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 27/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 28/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 29/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 30/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 31/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 32/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 33/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 34/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 35/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 36/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 37/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 38/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 39/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 40/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 41/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 42/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 43/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 44/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 21ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 45/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 46/100
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[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 47/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 48/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 49/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 50/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 51/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 52/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 53/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 54/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 55/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 56/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 57/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 21ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 58/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 21ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 59/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 60/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 61/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 62/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 63/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 64/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 65/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 66/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 67/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 68/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 69/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
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0.7500 - loss: 0.8846
Epoch 70/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 21ms/step - accuracy: 
0.7500 - loss: 0.8845
Epoch 71/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 21ms/step - accuracy: 
0.7500 - loss: 0.8845
Epoch 72/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy: 
0.7500 - loss: 0.8845
Epoch 73/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy: 
0.7500 - loss: 0.8845
Epoch 74/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy: 
0.7500 - loss: 0.8845
Epoch 75/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 25ms/step - accuracy: 
0.7500 - loss: 0.8845
Epoch 76/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 23ms/step - accuracy: 
0.7500 - loss: 0.8845
Epoch 77/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy: 
0.7500 - loss: 0.8845
Epoch 78/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy: 
0.7500 - loss: 0.8845
Epoch 79/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy: 
0.7500 - loss: 0.8845
Epoch 80/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy: 
0.7500 - loss: 0.8845
Epoch 81/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy: 
0.7500 - loss: 0.8845
Epoch 82/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy: 
0.7500 - loss: 0.8845
Epoch 83/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy: 
0.7500 - loss: 0.8845
Epoch 84/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy: 
0.7500 - loss: 0.8845
Epoch 85/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 21ms/step - accuracy: 
0.7500 - loss: 0.8845
Epoch 86/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy: 
0.7500 - loss: 0.8845
Epoch 87/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy: 
0.7500 - loss: 0.8845
Epoch 88/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy: 
0.7500 - loss: 0.8845
Epoch 89/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 21ms/step - accuracy: 
0.7500 - loss: 0.8845
Epoch 90/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 21ms/step - accuracy: 
0.7500 - loss: 0.8845
Epoch 91/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy: 
0.7500 - loss: 0.8845
Epoch 92/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 23ms/step - accuracy: 
0.7500 - loss: 0.8845
```
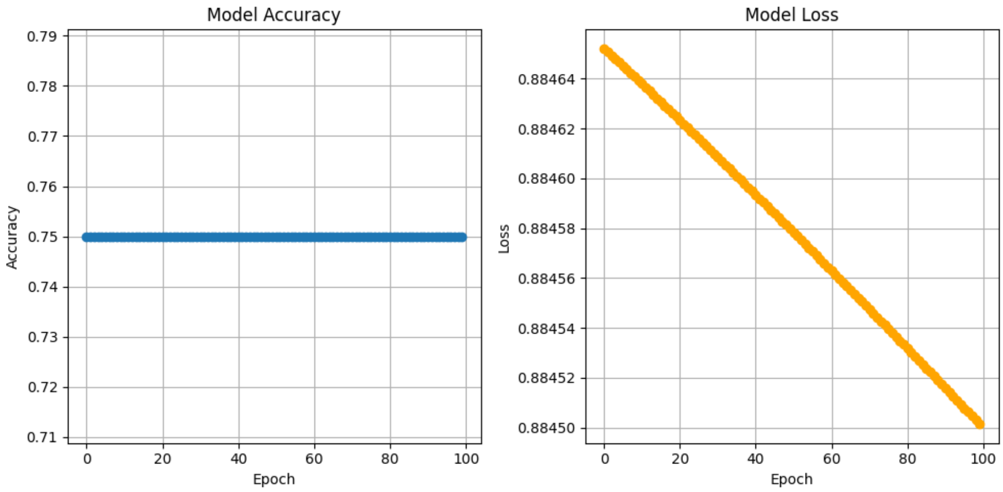

```
Epoch 93/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 94/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 95/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 96/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 24ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 97/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 21ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 98/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 23ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 99/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 29ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 100/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 31ms/step - accuracy:
0.7500 - loss: 0.8845
```

In [37]:

```
import matplotlib.pyplot as plt

# Plot accuracy vs epoch
plt.figure(figsize=(10, 5))

plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], marker='o')
plt.title('Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.grid(True)

plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], marker='o', color='orange')
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.grid(True)

plt.tight_layout()
plt.show()

# Test predictions
print("\n" + "="*40)
print("XOR Gate Predictions:")
print("="*40)
predictions = model.predict(X)
for i in range(len(X)):
    predicted = 1 if predictions[i] > 0.5 else 0
    print(f"Input: {X[i]} → Predicted: {predicted}, Actual: {y[i]}")
print("="*40)
```




```
========================================
XOR Gate Predictions:
========================================
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 84ms/step
Input: [0 0] → Predicted: 0, Actual: 0
Input: [0 1] → Predicted: 1, Actual: 1
Input: [1 1] → Predicted: 1, Actual: 0
Input: [1 0] → Predicted: 1, Actual: 1
========================================
```

Use dataset with initial values X = [1.0, 2.0], Y = [0.5, 1.5]

- Initialize neural network with random weights
- Compute output using linear activation
- Calculate MAE and MSE
- Plot loss surface (weight vs loss)

Initialize dataset and neural network

In [38]:
```
# Dataset
X_data = np.array([1.0, 2.0])
Y_data = np.array([0.5, 1.5])

# Initialize random weights and bias
np.random.seed(42)
w = np.random.randn()
b = np.random.randn()

print("Dataset:")
print(f"X = {X_data}")
print(f"Y = {Y_data}")
print(f"\nInitial weights:")
print(f"w = {w:.4f}")
print(f"b = {b:.4f}")
```

```
Dataset:
X = [1. 2.]
Y = [0.5 1.5]

Initial weights:
w = 0.4967
b = -0.1383
```

Compute output using linear activation

In [39]:
```
# Linear activation: y = w*x + b
Y_pred = w * X_data + b

print("Predictions (Linear Activation):")
print(f"Y_pred = {Y_pred}")
print(f"\nActual:")
print(f"Y = {Y_data}")
```

```
Predictions (Linear Activation):
Y_pred = [0.35844985 0.855164  ]

Actual:
Y = [0.5 1.5]
```

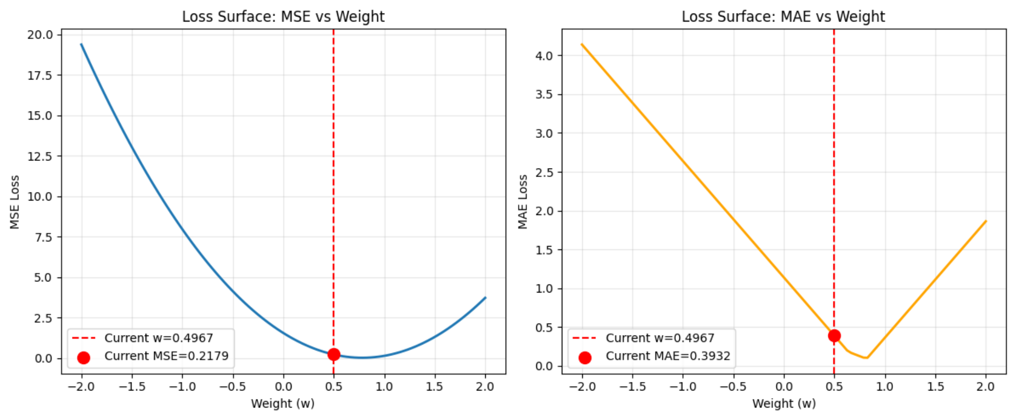
Calculate MAE and MSE

In [40]:
```
# Calculate errors
errors = Y_data - Y_pred

# Mean Absolute Error (MAE)
mae = np.mean(np.abs(errors))

# Mean Squared Error (MSE)
mse = np.mean(errors ** 2)

print("Error Metrics:")
print("="*40)
print(f"MAE (Mean Absolute Error): {mae:.4f}")
print(f"MSE (Mean Squared Error): {mse:.4f}")
print(f"RMSE (Root Mean Squared Error): {np.sqrt(mse):.4f}")
print("="*40)
```

```
Error Metrics:
========================================
MAE (Mean Absolute Error): 0.3932
MSE (Mean Squared Error): 0.2179
RMSE (Root Mean Squared Error): 0.4668
========================================
```

Plot loss surface (weight vs loss)

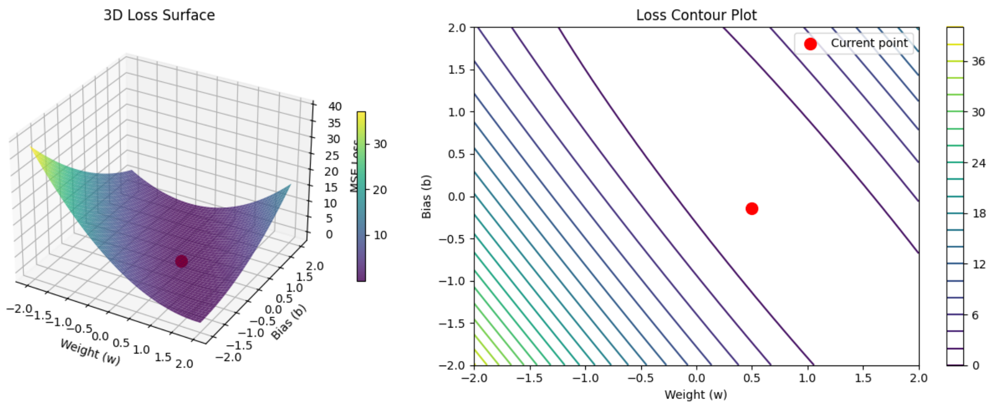
In [41]:
```
# Create a range of weight values
weights = np.linspace(-2, 2, 100)

# Calculate MSE for each weight value (keeping bias constant)
mse_values = []
for weight in weights:
    predictions = weight * X_data + b
    mse_val = np.mean((Y_data - predictions) ** 2)
    mse_values.append(mse_val)

# Plot loss surface
plt.figure(figsize=(12, 5))

# Plot 1: MSE vs Weight
plt.subplot(1, 2, 1)
plt.plot(weights, mse_values, linewidth=2)
plt.axvline(w, color='red', linestyle='--', label=f'Current w={w:.4f}')
plt.scatter([w], [mse], color='red', s=100, zorder=5, label=f'Current MSE={mse:.4f}')
plt.xlabel('Weight (w)')
plt.ylabel('MSE Loss')
plt.title('Loss Surface: MSE vs Weight')
plt.legend()
plt.grid(True, alpha=0.3)

# Plot 2: MAE vs Weight
mae_values = []
for weight in weights:
    predictions = weight * X_data + b
    mae_val = np.mean(np.abs(Y_data - predictions))
    mae_values.append(mae_val)

plt.subplot(1, 2, 2)
plt.plot(weights, mae_values, linewidth=2, color='orange')
plt.axvline(w, color='red', linestyle='--', label=f'Current w={w:.4f}')
plt.scatter([w], [mae], color='red', s=100, zorder=5, label=f'Current MAE={mae:.4f}')
plt.xlabel('Weight (w)')
plt.ylabel('MAE Loss')
plt.title('Loss Surface: MAE vs Weight')
plt.legend()
plt.grid(True, alpha=0.3)

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



3D Loss Surface (Weight vs Bias vs Loss)

In [42]:

```
# Create mesh grid for weight and bias
w_range = np.linspace(-2, 2, 50)
b_range = np.linspace(-2, 2, 50)
W_grid, B_grid = np.meshgrid(w_range, b_range)

# Calculate MSE for each combination
MSE_grid = np.zeros_like(W_grid)
for i in range(W_grid.shape[0]):
    for j in range(W_grid.shape[1]):
        predictions = W_grid[i, j] * X_data + B_grid[i, j]
        MSE_grid[i, j] = np.mean((Y_data - predictions) ** 2)

# Create 3D surface plot
from mpl_toolkits.mplot3d import Axes3D

fig = plt.figure(figsize=(14, 5))

# 3D Surface
ax1 = fig.add_subplot(121, projection='3d')
surf = ax1.plot_surface(W_grid, B_grid, MSE_grid, cmap='viridis', alpha=0.8)
ax1.scatter([w], [b], [mse], color='red', s=100, label='Current point')
ax1.set_xlabel('Weight (w)')
ax1.set_ylabel('Bias (b)')
ax1.set_zlabel('MSE Loss')
ax1.set_title('3D Loss Surface')
fig.colorbar(surf, ax=ax1, shrink=0.5)

# Contour plot
ax2 = fig.add_subplot(122)
contour = ax2.contour(W_grid, B_grid, MSE_grid, levels=20, cmap='viridis')
ax2.scatter([w], [b], color='red', s=100, zorder=5, label='Current point')
ax2.set_xlabel('Weight (w)')
ax2.set_ylabel('Bias (b)')
ax2.set_title('Loss Contour Plot')
ax2.legend()
fig.colorbar(contour, ax=ax2)

plt.tight_layout()
plt.show()

print(f"\nCurrent position: w={w:.4f}, b={b:.4f}, MSE={mse:.4f}")
```




```
Current position: w=0.4967, b=-0.1383, MSE=0.2179
```

Fashion-MNIST Classification

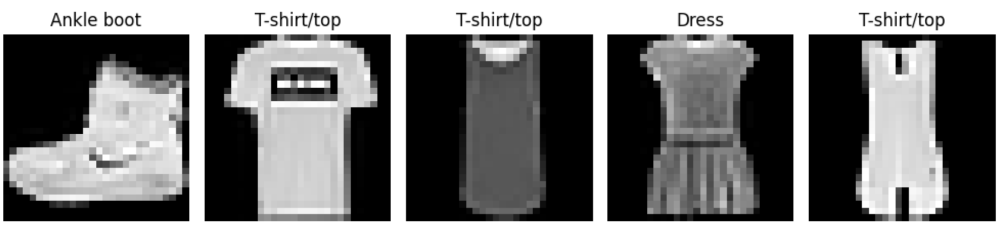
- CNN with RMSProp & Adam
- Compare confusion matrices

In [43]:
```
from tensorflow.keras.datasets import fashion_mnist
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten
from tensorflow.keras.optimizers import RMSprop, Adam
from sklearn.metrics import confusion_matrix, classification_report
import seaborn as sns

# Load Fashion-MNIST dataset
(train_images, train_labels), (test_images, test_labels) = fashion_mnist.load_data()

# Class names for Fashion-MNIST
class_names = ['T-shirt/top', 'Trouser', 'Pullover', 'Dress', 'Coat',
               'Sandal', 'Shirt', 'Sneaker', 'Bag', 'Ankle boot']

print(f"Training set shape: {train_images.shape}")
print(f"Test set shape: {test_images.shape}")
print(f"Number of classes: {len(class_names)}")
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-labels-idx1-ubyte.gz
[1m29515/29515[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-images-idx3-ubyte.gz
[1m26421880/26421880[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m3s[0m 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-labels-idx1-ubyte.gz
[1m5148/5148[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-images-idx3-ubyte.gz
[1m4422102/4422102[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 0us/step
Training set shape: (60000, 28, 28)
Test set shape: (10000, 28, 28)
Number of classes: 10
```

Preprocess data

In [44]:
```
# Normalize pixel values to [0, 1]
train_images = train_images.astype("float32") / 255.0
test_images = test_images.astype("float32") / 255.0

# Get image dimensions
img_size = train_images.shape[1]
num_classes = len(class_names)

# Display sample images
plt.figure(figsize=(10, 4))
for i in range(5):
    plt.subplot(1, 5, i+1)
    plt.imshow(train_images[i], cmap='gray')
    plt.title(f'{class_names[train_labels[i]]}')
    plt.axis('off')
plt.tight_layout()
plt.show()
```



Build and train CNN with Adam optimizer

In [45]:
```
adam_model = Sequential([
    Conv2D(32, kernel_size=(3,3), activation='relu', input_shape=(img_size, img_size,
1)),
    MaxPooling2D(pool_size=(2,2)),
    Conv2D(64, kernel_size=(3,3), activation='relu'),
    MaxPooling2D(pool_size=(2,2)),
    Flatten(),
    Dense(128, activation='relu'),
    Dense(num_classes, activation='softmax')
])

adam_model.compile(optimizer='adam', loss='sparse_categorical_crossentropy',
metrics=['accuracy'])
print("Training with Adam optimizer...")
adam_history = adam_model.fit(train_images, train_labels, epochs=10,
validation_split=0.2, verbose=1)
```

```
Training with Adam optimizer...
Epoch 1/10
```

```
/home/smayan/Desktop/AI-ML-DS/AI-and-ML-Course/.conda/lib/python3.11/site-
packages/keras/src/layers/convolutional/base_conv.py:113: UserWarning: Do not
pass an `input_shape`/`input_dim` argument to a layer. When using Sequential
models, prefer using an `Input(shape)` object as the first layer in the model
instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
2026-01-06 14:56:50.423583: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot_245', 4 bytes spill stores, 4 bytes spill
loads
```

```
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m3s[0m 1ms/step - accuracy:
0.7574 - loss: 0.6708 - val_accuracy: 0.8704 - val_loss: 0.3662
Epoch 2/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 953us/step -
accuracy: 0.8764 - loss: 0.3353 - val_accuracy: 0.8856 - val_loss: 0.3184
Epoch 3/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 918us/step -
accuracy: 0.8955 - loss: 0.2824 - val_accuracy: 0.8954 - val_loss: 0.2851
Epoch 4/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 894us/step -
accuracy: 0.9100 - loss: 0.2376 - val_accuracy: 0.8997 - val_loss: 0.2837
Epoch 5/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 915us/step -
accuracy: 0.9239 - loss: 0.2061 - val_accuracy: 0.9082 - val_loss: 0.2565
Epoch 6/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 853us/step -
accuracy: 0.9320 - loss: 0.1865 - val_accuracy: 0.9117 - val_loss: 0.2513
Epoch 7/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 893us/step -
accuracy: 0.9394 - loss: 0.1646 - val_accuracy: 0.9111 - val_loss: 0.2487
Epoch 8/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 885us/step -
accuracy: 0.9468 - loss: 0.1448 - val_accuracy: 0.9076 - val_loss: 0.2759
Epoch 9/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 905us/step -
accuracy: 0.9510 - loss: 0.1307 - val_accuracy: 0.9121 - val_loss: 0.2628
Epoch 10/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 892us/step -
accuracy: 0.9578 - loss: 0.1111 - val_accuracy: 0.9140 - val_loss: 0.2771
```

Build and train CNN with RMSProp optimizer

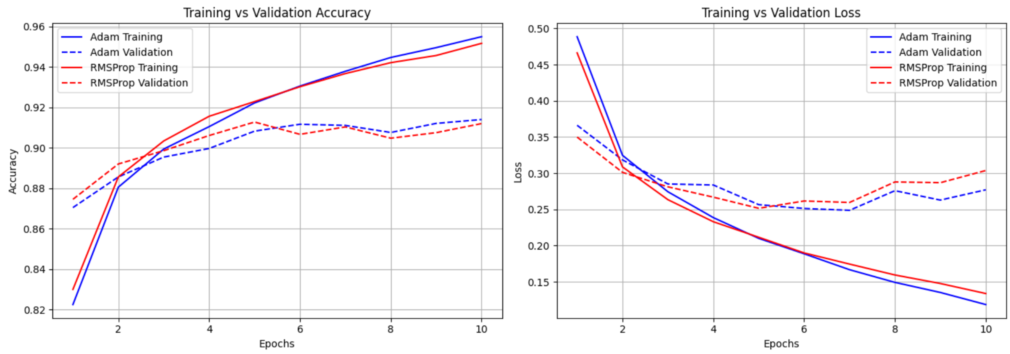
In [46]:
```
rmsprop_model = Sequential([
    Conv2D(32, kernel_size=(3,3), activation='relu', input_shape=(img_size, img_size, 1)),
    MaxPooling2D(pool_size=(2,2)),
    Conv2D(64, kernel_size=(3,3), activation='relu'),
    MaxPooling2D(pool_size=(2,2)),
    Flatten(),
    Dense(128, activation='relu'),
    Dense(num_classes, activation='softmax')
])

rmsprop_model.compile(optimizer='rmsprop', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
print("Training with RMSProp optimizer...")
rmsprop_history = rmsprop_model.fit(train_images, train_labels, epochs=10, validation_split=0.2, verbose=1)
```

```
Training with RMSProp optimizer...
Epoch 1/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy: 0.7667 - loss: 0.6443 - val_accuracy: 0.8745 - val_loss: 0.3499
Epoch 2/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 859us/step - accuracy: 0.8819 - loss: 0.3174 - val_accuracy: 0.8920 - val_loss: 0.3011
Epoch 3/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 887us/step - accuracy: 0.9011 - loss: 0.2667 - val_accuracy: 0.8986 - val_loss: 0.2811
Epoch 4/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 872us/step - accuracy: 0.9133 - loss: 0.2390 - val_accuracy: 0.9061 - val_loss: 0.2669
Epoch 5/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 866us/step - accuracy: 0.9230 - loss: 0.2129 - val_accuracy: 0.9128 - val_loss: 0.2515
Epoch 6/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 932us/step - accuracy: 0.9309 - loss: 0.1889 - val_accuracy: 0.9067 - val_loss: 0.2616
Epoch 7/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 903us/step - accuracy: 0.9386 - loss: 0.1684 - val_accuracy: 0.9103 - val_loss: 0.2596
Epoch 8/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 905us/step - accuracy: 0.9443 - loss: 0.1539 - val_accuracy: 0.9047 - val_loss: 0.2879
Epoch 9/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 891us/step - accuracy: 0.9470 - loss: 0.1424 - val_accuracy: 0.9075 - val_loss: 0.2869
Epoch 10/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 901us/step - accuracy: 0.9525 - loss: 0.1312 - val_accuracy: 0.9120 - val_loss: 0.3037
```

Compare training performance

In [47]:

```
# Extract history
adam_acc = adam_history.history['accuracy']
adam_val_acc = adam_history.history['val_accuracy']
adam_loss = adam_history.history['loss']
adam_val_loss = adam_history.history['val_loss']

rmsprop_acc = rmsprop_history.history['accuracy']
rmsprop_val_acc = rmsprop_history.history['val_accuracy']
rmsprop_loss = rmsprop_history.history['loss']
rmsprop_val_loss = rmsprop_history.history['val_loss']

epochs = range(1, len(adam_acc) + 1)

# Plot comparison
plt.figure(figsize=(14, 5))

# Accuracy comparison
plt.subplot(1, 2, 1)
plt.plot(epochs, adam_acc, 'b-', label='Adam Training')
plt.plot(epochs, adam_val_acc, 'b--', label='Adam Validation')
plt.plot(epochs, rmsprop_acc, 'r-', label='RMSProp Training')
plt.plot(epochs, rmsprop_val_acc, 'r--', label='RMSProp Validation')
plt.title('Training vs Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.grid(True)

# Loss comparison
plt.subplot(1, 2, 2)
plt.plot(epochs, adam_loss, 'b-', label='Adam Training')
plt.plot(epochs, adam_val_loss, 'b--', label='Adam Validation')
plt.plot(epochs, rmsprop_loss, 'r-', label='RMSProp Training')
plt.plot(epochs, rmsprop_val_loss, 'r--', label='RMSProp Validation')
plt.title('Training vs Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.grid(True)

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



Evaluate models on test set

In [48]:
```
# Evaluate Adam model
adam_test_loss, adam_test_acc = adam_model.evaluate(test_images, test_labels,
verbose=0)
print("Adam Model:")
print(f"  Test Accuracy: {adam_test_acc:.4f}")
print(f"  Test Loss: {adam_test_loss:.4f}")

# Evaluate RMSProp model
rmsprop_test_loss, rmsprop_test_acc = rmsprop_model.evaluate(test_images,
test_labels, verbose=0)
print("\nRMSProp Model:")
print(f"  Test Accuracy: {rmsprop_test_acc:.4f}")
print(f"  Test Loss: {rmsprop_test_loss:.4f}")
```

```
Adam Model:
  Test Accuracy: 0.9053
  Test Loss: 0.3123

RMSProp Model:
  Test Accuracy: 0.9120
  Test Loss: 0.3134
```

Generate predictions and confusion matrices

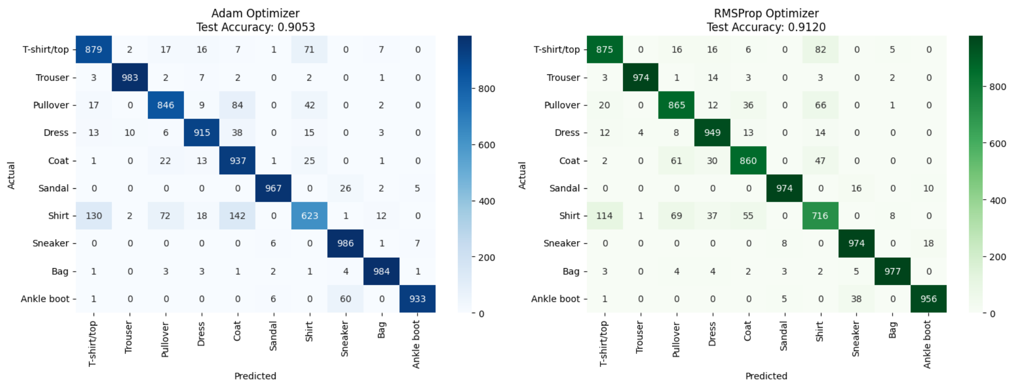
In [49]:
```
# Get predictions
adam_predictions = np.argmax(adam_model.predict(test_images), axis=1)
rmsprop_predictions = np.argmax(rmsprop_model.predict(test_images), axis=1)

# Generate confusion matrices
adam_cm = confusion_matrix(test_labels, adam_predictions)
rmsprop_cm = confusion_matrix(test_labels, rmsprop_predictions)

print("Predictions generated successfully!")
```

```
[1m313/313[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 958us/step
[1m313/313[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step
Predictions generated successfully!
```

Compare confusion matrices

In [50]:

```
# Plot confusion matrices side by side
fig, axes = plt.subplots(1, 2, figsize=(16, 6))

# Adam confusion matrix
sns.heatmap(adam_cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=class_names, yticklabels=class_names, ax=axes[0])
axes[0].set_title(f'Adam Optimizer\nTest Accuracy: {adam_test_acc:.4f}')
axes[0].set_xlabel('Predicted')
axes[0].set_ylabel('Actual')

# RMSProp confusion matrix
sns.heatmap(rmsprop_cm, annot=True, fmt='d', cmap='Greens',
            xticklabels=class_names, yticklabels=class_names, ax=axes[1])
axes[1].set_title(f'RMSProp Optimizer\nTest Accuracy: {rmsprop_test_acc:.4f}')
axes[1].set_xlabel('Predicted')
axes[1].set_ylabel('Actual')

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



Classification reports

In [51]:

```
print("="*70)
print("ADAM OPTIMIZER - CLASSIFICATION REPORT")
print("="*70)
print(classification_report(test_labels, adam_predictions, target_names=class_names))

print("\n" + "="*70)
print("RMSPROP OPTIMIZER - CLASSIFICATION REPORT")
print("="*70)
print(classification_report(test_labels, rmsprop_predictions,
target_names=class_names))

# Summary comparison
print("\n" + "="*70)
print("OPTIMIZER COMPARISON SUMMARY")
print("="*70)
print(f"Adam    - Test Accuracy: {adam_test_acc:.4f}, Test Loss:
{adam_test_loss:.4f}")
print(f"RMSProp - Test Accuracy: {rmsprop_test_acc:.4f}, Test Loss:
{rmsprop_test_loss:.4f}")
print("="*70)
```

```
======================================================================
ADAM OPTIMIZER - CLASSIFICATION REPORT
======================================================================
              precision    recall  f1-score   support

 T-shirt/top       0.84      0.88      0.86      1000
     Trouser       0.99      0.98      0.98      1000
    Pullover       0.87      0.85      0.86      1000
       Dress       0.93      0.92      0.92      1000
        Coat       0.77      0.94      0.85      1000
      Sandal       0.98      0.97      0.98      1000
       Shirt       0.80      0.62      0.70      1000
     Sneaker       0.92      0.99      0.95      1000
         Bag       0.97      0.98      0.98      1000
  Ankle boot       0.99      0.93      0.96      1000

    accuracy                           0.91     10000
   macro avg       0.91      0.91      0.90     10000
weighted avg       0.91      0.91      0.90     10000


======================================================================
RMSPROP OPTIMIZER - CLASSIFICATION REPORT
======================================================================
              precision    recall  f1-score   support

 T-shirt/top       0.85      0.88      0.86      1000
     Trouser       0.99      0.97      0.98      1000
    Pullover       0.84      0.86      0.85      1000
       Dress       0.89      0.95      0.92      1000
        Coat       0.88      0.86      0.87      1000
      Sandal       0.98      0.97      0.98      1000
       Shirt       0.77      0.72      0.74      1000
     Sneaker       0.94      0.97      0.96      1000
         Bag       0.98      0.98      0.98      1000
  Ankle boot       0.97      0.96      0.96      1000

    accuracy                           0.91     10000
   macro avg       0.91      0.91      0.91     10000
weighted avg       0.91      0.91      0.91     10000


======================================================================
OPTIMIZER COMPARISON SUMMARY
======================================================================
Adam    - Test Accuracy: 0.9053, Test Loss: 0.3123
RMSProp - Test Accuracy: 0.9120, Test Loss: 0.3134
======================================================================
```