```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from tensorflow import keras
from keras import models, layers, regularizers
from keras.datasets import imdb
from keras.callbacks import EarlyStopping
import json
```

```
# Setting random seed for reproducibility
np.random.seed(42)
keras.utils.set_random_seed(42)
```

==

DATA PREPARATION

==

```
def load_and_prepare_data(num_words=10000):
    """Load IMDB dataset and prepare train/validation/test splits"""
    print("Loading IMDB dataset...")
    (train_data, train_labels), (test_data, test_labels) = imdb.load_dat

    # Creating validation set from training data
    x_val = train_data[:10000]
    partial_x_train = train_data[10000:]
    y_val = train_labels[:10000]
    partial_y_train = train_labels[10000:]

    return partial_x_train, partial_y_train, x_val, y_val, test_data, te


def vectorize_sequences(sequences, dimension=10000):
    """Convert sequences to binary matrix representation"""
    results = np.zeros((len(sequences), dimension))
    for i, sequence in enumerate(sequences):
        results[i, sequence] = 1.0
    return results
```

```python
# Loading and preparing data
x_train, y_train, x_val, y_val, x_test, y_test = load_and_prepare_data()

# Vectorizing data
x_train = vectorize_sequences(x_train)
x_val = vectorize_sequences(x_val)
x_test = vectorize_sequences(x_test)

# Converting labels to numpy arrays
y_train = np.asarray(y_train).astype('float32')
y_val = np.asarray(y_val).astype('float32')
y_test = np.asarray(y_test).astype('float32')

print(f"Training samples: {len(x_train)}")
print(f"Validation samples: {len(x_val)}")
print(f"Test samples: {len(x_test)}")
```

```
Loading IMDB dataset...
Training samples: 15000
Validation samples: 10000
Test samples: 25000
```

==

MODEL BUILDING FUNCTIONS

==

```
def build_model_variable_layers(num_layers=2, hidden_units=16, activatio
                                loss='binary_crossentropy', use_dropout=
                                dropout_rate=0.5, use_regularization=Fal
                                regularization_strength=0.001):
    """Build a neural network with variable number of layers and configu
    model = models.Sequential()

    # Setting regularizer if needed
    regularizer = regularizers.l2(regularization_strength) if use_regula

    # Input layer
    model.add(layers.Dense(hidden_units, activation=activation,
                          input_shape=(10000,),
                          kernel_regularizer=regularizer))
    if use_dropout:
        model.add(layers.Dropout(dropout_rate))

    # Hidden layers
    for _ in range(num_layers - 1):
        model.add(layers.Dense(hidden_units, activation=activation,
                              kernel_regularizer=regularizer))
        if use_dropout:
            model.add(layers.Dropout(dropout_rate))

    # Output layer
    model.add(layers.Dense(1, activation='sigmoid'))

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

    return model
```

```
def train_and_evaluate(model, model_name, epochs=20, batch_size=512, use_e
    """Train a model and return its history and test accuracy"""
    callbacks = []
    if use_early_stopping:
        early_stop = EarlyStopping(monitor='val_loss', patience=3, restore
        callbacks.append(early_stop)

    print(f"\nTraining model: {model_name}")
    history = model.fit(x_train, y_train,
                        epochs=epochs,
                        batch_size=batch_size,
                        validation_data=(x_val, y_val),
                        callbacks=callbacks,
                        verbose=0)

    # Evaluating on test set
    test_loss, test_acc = model.evaluate(x_test, y_test, verbose=0)
    val_acc = max(history.history['val_accuracy'])

    print(f"Best Validation Accuracy: {val_acc:.4f}")
    print(f"Test Accuracy: {test_acc:.4f}")

    return history, test_acc, val_acc
```

====================================

EXPERIMENT 1: NUMBER OF HIDDEN LAYERS

====================================

Double-click (or enter) to edit

```
print("\n" + "="*80)
print("EXPERIMENT 1: VARYING NUMBER OF HIDDEN LAYERS")
print("="*80)

results_layers = {}

for num_layers in [1, 2, 3]:
    model = build_model_variable_layers(num_layers=num_layers, hidden_un
    history, test_acc, val_acc = train_and_evaluate(model, f"{num_layers
    results_layers[num_layers] = {
        'history': history.history,
        'test_acc': test_acc,
        'val_acc': val_acc
    }
```

```
================================================================================
EXPERIMENT 1: VARYING NUMBER OF HIDDEN LAYERS
================================================================================

Training model: 1 Hidden Layer(s)
/usr/local/lib/python3.12/dist-packages/keras/src/layers/core/dense.py:93
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
Best Validation Accuracy: 0.8884
Test Accuracy: 0.8623

Training model: 2 Hidden Layer(s)
Best Validation Accuracy: 0.8883
Test Accuracy: 0.8567

Training model: 3 Hidden Layer(s)
Best Validation Accuracy: 0.8862
Test Accuracy: 0.8574
```

==

EXPERIMENT 2: NUMBER OF HIDDEN UNITS

==

```
print("\n" + "="*80)
print("EXPERIMENT 2: VARYING NUMBER OF HIDDEN UNITS")
print("="*80)

results_units = {}
unit_sizes = [8, 16, 32, 64, 128]

for units in unit_sizes:
    model = build_model_variable_layers(num_layers=2, hidden_units=units
    history, test_acc, val_acc = train_and_evaluate(model, f"{units} Hid
    results_units[units] = {
        'history': history.history,
        'test_acc': test_acc,
        'val_acc': val_acc
    }
```

```
================================================================================
EXPERIMENT 2: VARYING NUMBER OF HIDDEN UNITS
================================================================================

Training model: 8 Hidden Units
Best Validation Accuracy: 0.8889
Test Accuracy: 0.8597

Training model: 16 Hidden Units
Best Validation Accuracy: 0.8880
Test Accuracy: 0.8568

Training model: 32 Hidden Units
Best Validation Accuracy: 0.8884
Test Accuracy: 0.8580

Training model: 64 Hidden Units
Best Validation Accuracy: 0.8864
Test Accuracy: 0.8572

Training model: 128 Hidden Units
Best Validation Accuracy: 0.8842
Test Accuracy: 0.8584
```

==

EXPERIMENT 3: MSE LOSS FUNCTION

==

```
print("\n" + "="*80)
print("EXPERIMENT 3: COMPARING LOSS FUNCTIONS")
print("="*80)

results_loss = {}

for loss_func in ['binary_crossentropy', 'mse']:
    model = build_model_variable_layers(num_layers=2, hidden_units=16, l
    history, test_acc, val_acc = train_and_evaluate(model, f"Loss: {loss
    results_loss[loss_func] = {
        'history': history.history,
        'test_acc': test_acc,
        'val_acc': val_acc
    }
```

```
=========================================================================
EXPERIMENT 3: COMPARING LOSS FUNCTIONS
=========================================================================

Training model: Loss: binary_crossentropy
Best Validation Accuracy: 0.8895
Test Accuracy: 0.8563

Training model: Loss: mse
Best Validation Accuracy: 0.8895
Test Accuracy: 0.8578
```

==

EXPERIMENT 4: ACTIVATION FUNCTIONS

==

```
print("\n" + "="*80)
print("EXPERIMENT 4: COMPARING ACTIVATION FUNCTIONS")
print("="*80)

results_activation = {}

for activation in ['relu', 'tanh']:
    model = build_model_variable_layers(num_layers=2, hidden_units=16, a
    history, test_acc, val_acc = train_and_evaluate(model, f"Activation:
    results_activation[activation] = {
        'history': history.history,
        'test_acc': test_acc,
        'val_acc': val_acc
    }
```

```
================================================================================
EXPERIMENT 4: COMPARING ACTIVATION FUNCTIONS
================================================================================

Training model: Activation: relu
Best Validation Accuracy: 0.8877
Test Accuracy: 0.8562

Training model: Activation: tanh
Best Validation Accuracy: 0.8899
Test Accuracy: 0.8540
```

==

EXPERIMENT 5: REGULARIZATION TECHNIQUES

==

==

```
print("\n" + "="*80)
print("EXPERIMENT 5: REGULARIZATION TECHNIQUES")
print("="*80)

results_regularization = {}

# Baseline (no regularization)
model = build_model_variable_layers(num_layers=2, hidden_units=32)
history, test_acc, val_acc = train_and_evaluate(model, "No Regularizatio
results_regularization['baseline'] = {
    'history': history.history,
    'test_acc': test_acc,
    'val_acc': val_acc
}

# Dropout
model = build_model_variable_layers(num_layers=2, hidden_units=32,
                                   use_dropout=True, dropout_rate=0.5)
history, test_acc, val_acc = train_and_evaluate(model, "Dropout (0.5)")
results_regularization['dropout'] = {
    'history': history.history,
    'test_acc': test_acc,
    'val_acc': val_acc
}

# L2 Regularization
model = build_model_variable_layers(num_layers=2, hidden_units=32,
                                   use_regularization=True,
                                   regularization_strength=0.001)
history, test_acc, val_acc = train_and_evaluate(model, "L2 Regularizatio
results_regularization['l2'] = {
    'history': history.history,
    'test_acc': test_acc,
    'val_acc': val_acc
}
```

```
# Combined (Dropout + L2)
model = build_model_variable_layers(num_layers=2, hidden_units=32,
                                    use_dropout=True, dropout_rate=0.3,
                                    use_regularization=True,
                                    regularization_strength=0.001)
history, test_acc, val_acc = train_and_evaluate(model, "Dropout + L2", u
results_regularization['combined'] = {
    'history': history.history,
    'test_acc': test_acc,
    'val_acc': val_acc
}
```

```
==========================================================================
EXPERIMENT 5: REGULARIZATION TECHNIQUES
==========================================================================

Training model: No Regularization
Best Validation Accuracy: 0.8865
Test Accuracy: 0.8571

Training model: Dropout (0.5)
Best Validation Accuracy: 0.8896
Test Accuracy: 0.8714

Training model: L2 Regularization
Best Validation Accuracy: 0.8873
Test Accuracy: 0.8622

Training model: Dropout + L2
Best Validation Accuracy: 0.8874
Test Accuracy: 0.8810
```

==================================

OPTIMIZED MODEL

==================================

```python
print("\n" + "="*80)
print("FINAL OPTIMIZED MODEL")
print("="*80)

# Based on experiments, creating an optimized model
optimized_model = build_model_variable_layers(
    num_layers=2,
    hidden_units=64,
    activation='relu',
    loss='binary_crossentropy',
    use_dropout=True,
    dropout_rate=0.3,
    use_regularization=True,
    regularization_strength=0.001
)

optimized_history, optimized_test_acc, optimized_val_acc = train_and_evalu
    optimized_model, "Optimized Model", epochs=30, use_early_stopping=True
)
```

```
=========================================================================
FINAL OPTIMIZED MODEL
=========================================================================

Training model: Optimized Model
Best Validation Accuracy: 0.8901
Test Accuracy: 0.8821
```

==

VISUALIZATION AND RESULTS

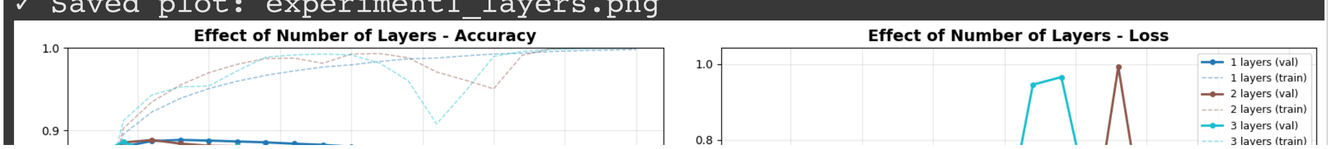
==

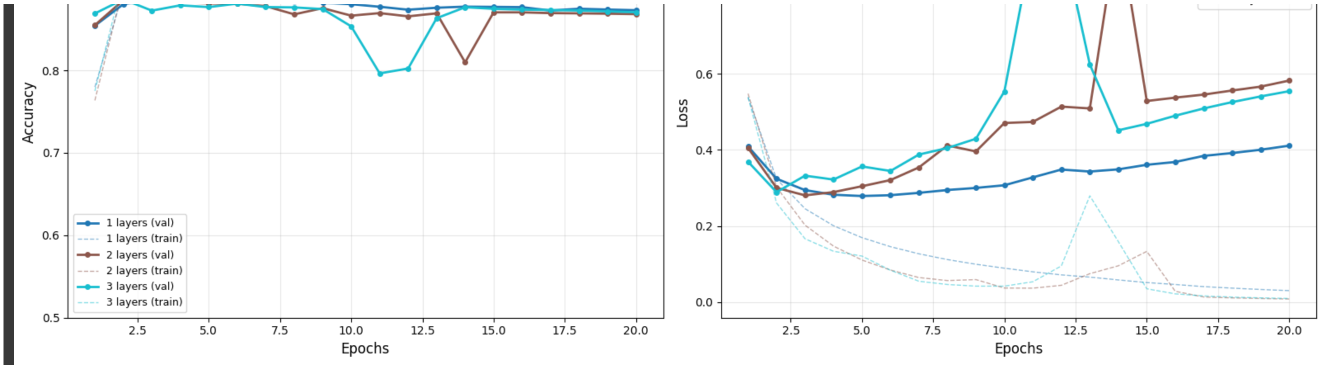
```
def plot_training_history(history_dict, title, save_filename):
    """Plot training and validation accuracy/loss - displays in Python a
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(16, 6))

    colors = plt.cm.tab10(np.linspace(0, 1, len(history_dict)))

    # Accuracy plot
    for idx, (label, data) in enumerate(history_dict.items()):
        epochs = range(1, len(data['history']['accuracy']) + 1)
        ax1.plot(epochs, data['history']['val_accuracy'],
                label=f'{label} (val)', marker='o', markersize=4, linewi
        ax1.plot(epochs, data['history']['accuracy'],
                label=f'{label} (train)', linestyle='--', linewidth=1, a

    ax1.set_title(f'{title} - Accuracy', fontsize=14, fontweight='bold')
    ax1.set_xlabel('Epochs', fontsize=12)
    ax1.set_ylabel('Accuracy', fontsize=12)
    ax1.legend(loc='best', fontsize=9)
    ax1.grid(True, alpha=0.3)
    ax1.set_ylim([0.5, 1.0])

    # Loss plot
    for idx, (label, data) in enumerate(history_dict.items()):
        epochs = range(1, len(data['history']['loss']) + 1)
        ax2.plot(epochs, data['history']['val_loss'],
                label=f'{label} (val)', marker='o', markersize=4, linewi
        ax2.plot(epochs, data['history']['loss'],
                label=f'{label} (train)', linestyle='--', linewidth=1, a

    ax2.set_title(f'{title} - Loss', fontsize=14, fontweight='bold')
    ax2.set_xlabel('Epochs', fontsize=12)
    ax2.set_ylabel('Loss', fontsize=12)
    ax2.legend(loc='best', fontsize=9)
    ax2.grid(True, alpha=0.3)

    plt.tight_layout()

    # Saving to file
    plt.savefig(save_filename, dpi=300, bbox_inches='tight')
    print(f"✓ Saved plot: {save_filename}")

    # Displaying in Python/Jupyter
    plt.show()

    return fig
```

```
# Plotting all experiments
```

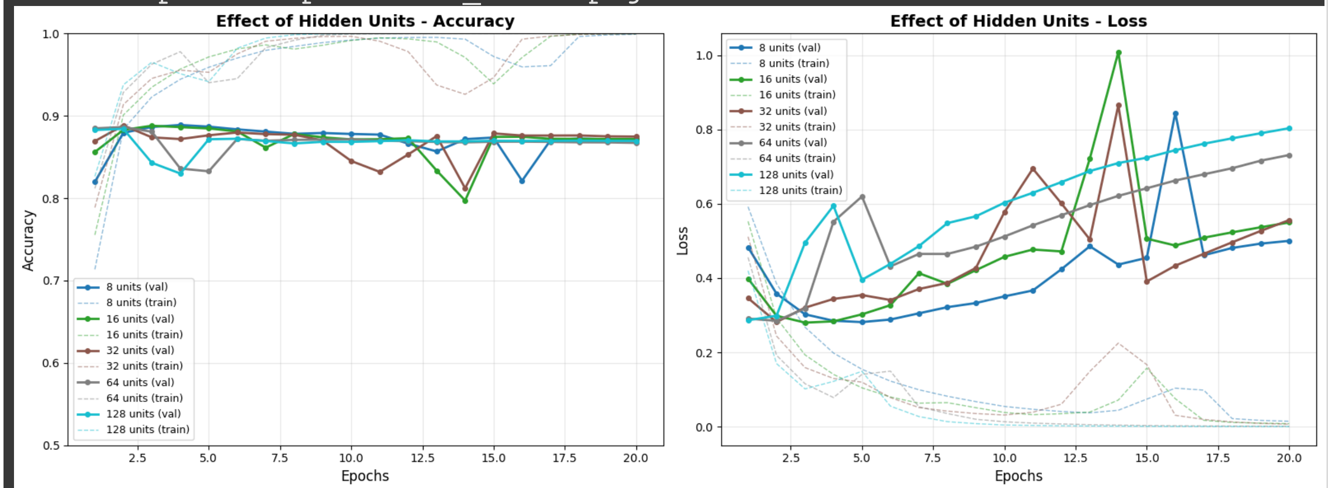
```
print("\n" + "="*80)
print("GENERATING VISUALIZATIONS")
print("="*80)

print("\n--- EXPERIMENT 1: Number of Layers ---")
fig1 = plot_training_history(
    {f"{k} layers": v for k, v in results_layers.items()},
    "Effect of Number of Layers",
    "experiment1_layers.png"
)

print("\n--- EXPERIMENT 2: Hidden Units ---")
fig2 = plot_training_history(
    {f"{k} units": v for k, v in results_units.items()},
    "Effect of Hidden Units",
    "experiment2_units.png"
)

print("\n--- EXPERIMENT 3: Loss Functions ---")
fig3 = plot_training_history(
    results_loss,
    "Effect of Loss Function",
    "experiment3_loss.png"
)

print("\n--- EXPERIMENT 4: Activation Functions ---")
fig4 = plot_training_history(
    results_activation,
    "Effect of Activation Function",
    "experiment4_activation.png"
)

print("\n--- EXPERIMENT 5: Regularization ---")
fig5 = plot_training_history(
    results_regularization,
    "Effect of Regularization Techniques",
    "experiment5_regularization.png"
)
```

```
================================================================================
GENERATING VISUALIZATIONS
================================================================================

--- EXPERIMENT 1: Number of Layers ---
✓ Saved plot: experiment1_layers.png
```

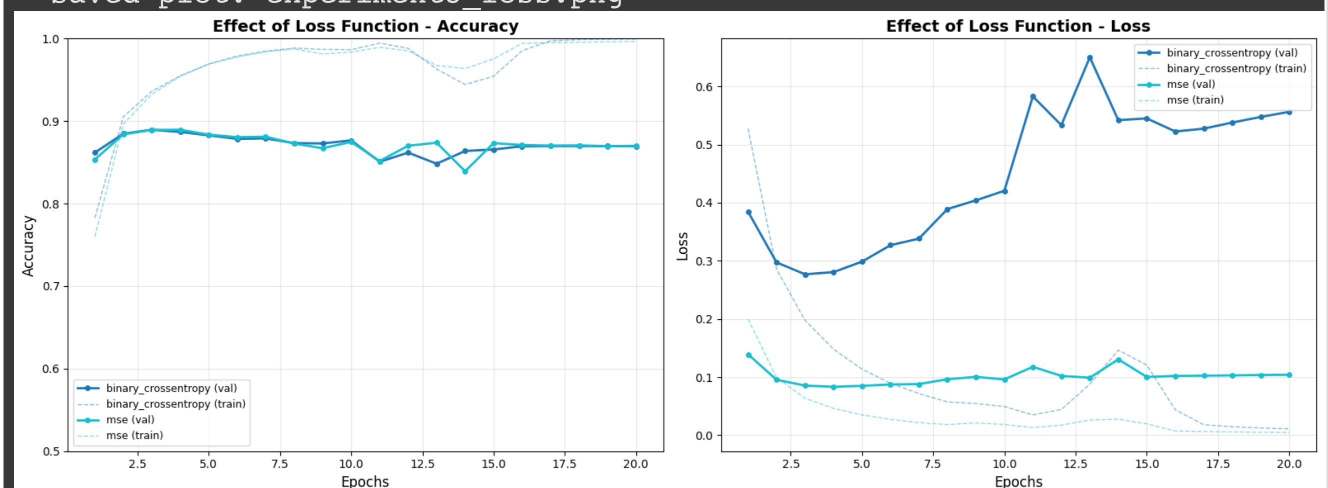




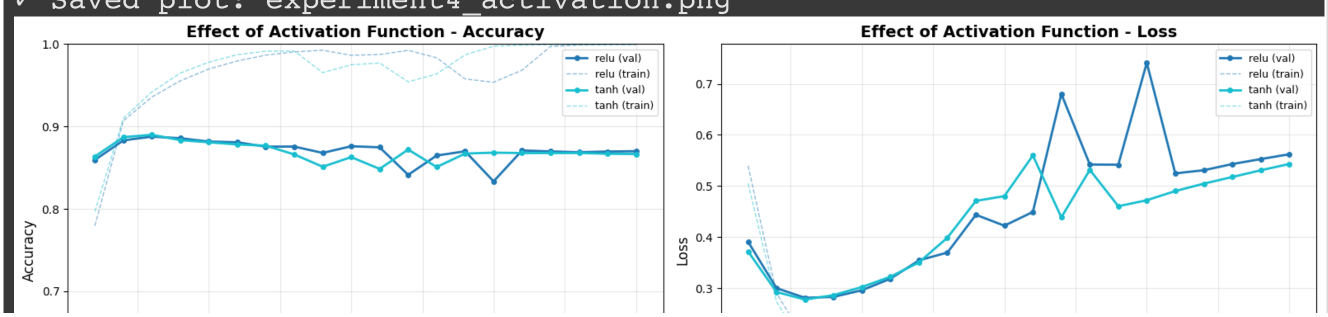
--- EXPERIMENT 2: Hidden Units ---
✓ Saved plot: experiment2_units.png

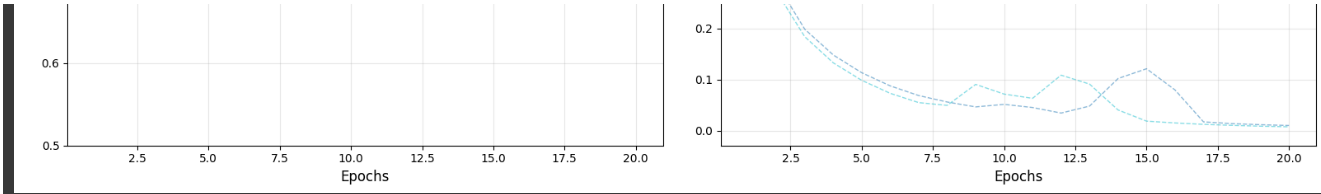


--- EXPERIMENT 3: Loss Functions ---
✓ Saved plot: experiment3_loss.png

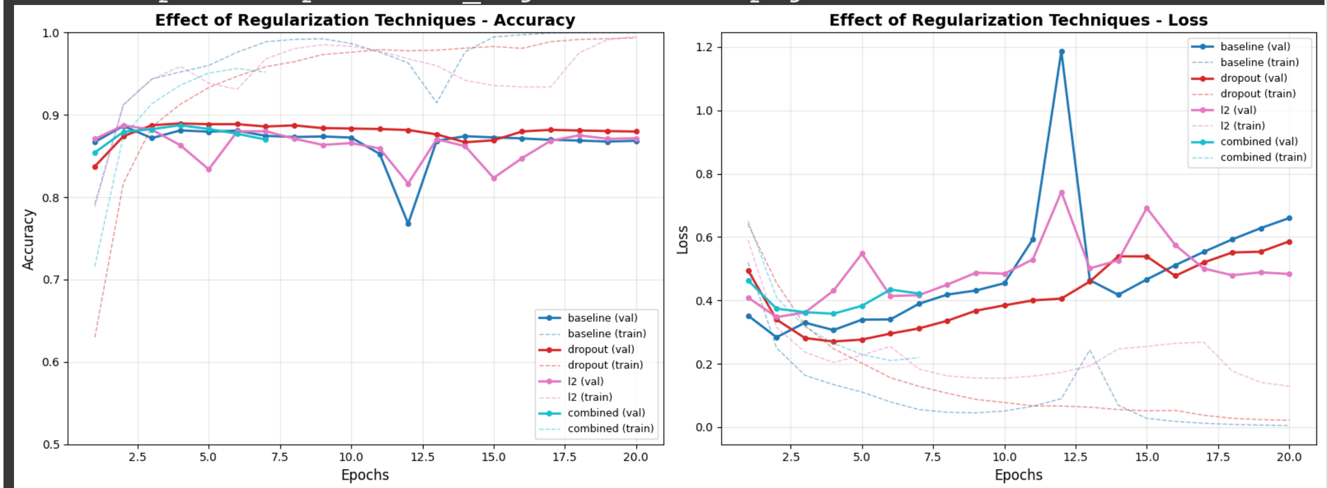


--- EXPERIMENT 4: Activation Functions ---
✓ Saved plot: experiment4_activation.png






```
--- EXPERIMENT 5: Regularization ---
✓ Saved plot: experiment5_regularization.png
```



==

SUMMARY RESULTS TABLE

==

```
    print("\n" + "="*80)
    print("SUMMARY OF ALL EXPERIMENTS")
    print("="*80)

    summary_data = []

    # Experiment 1: Layers
    for num_layers, results in results_layers.items():
        summary_data.append({
            'Experiment': 'Layers',
            'Configuration': f'{num_layers} layer(s)',
            'Best Val Accuracy': f"{results['val_acc']:.4f}",
            'Test Accuracy': f"{results['test_acc']:.4f}"
        })

        # Experiment 2: Units
    for units, results in results_units.items():
        summary_data.append({
            'Experiment': 'Hidden Units',
            'Configuration': f'{units} units',
            'Best Val Accuracy': f"{results['val_acc']:.4f}",
            'Test Accuracy': f"{results['test_acc']:.4f}"
        })

        # Experiment 3: Loss
    for loss, results in results_loss.items():
        summary_data.append({
            'Experiment': 'Loss Function',
            'Configuration': loss,
            'Best Val Accuracy': f"{results['val_acc']:.4f}",
            'Test Accuracy': f"{results['test_acc']:.4f}"
        })

        # Experiment 4: Activation
    for activation, results in results_activation.items():
        summary_data.append({
            'Experiment': 'Activation',
```

```
            'Configuration': activation,
            'Best Val Accuracy': f"{results['val_acc']:.4f}",
            'Test Accuracy': f"{results['test_acc']:.4f}"
        })

        # Experiment 5: Regularization
    for method, results in results_regularization.items():
        summary_data.append({
            'Experiment': 'Regularization',
            'Configuration': method,
            'Best Val Accuracy': f"{results['val_acc']:.4f}",
            'Test Accuracy': f"{results['test_acc']:.4f}"
        })

        # Optimized model
    summary_data.append({
        'Experiment': 'OPTIMIZED',
        'Configuration': '2 layers, 64 units, dropout+L2',
        'Best Val Accuracy': f"{optimized_val_acc:.4f}",
        'Test Accuracy': f"{optimized_test_acc:.4f}"
    })

    # Creating and displaying summary table
    summary_df = pd.DataFrame(summary_data)
    print("\n", summary_df.to_string(index=False))

    # Saving summary to CSV
    summary_df.to_csv('results_summary.csv', index=False)
    print("\nSummary saved to: results_summary.csv")

    # Saving detailed results to JSON
    all_results = {
        'layers': {str(k): {'val_acc': float(v['val_acc']),
                            'test_acc': float(v['test_acc'])}
                   for k, v in results_layers.items()},
        'units': {str(k): {'val_acc': float(v['val_acc']),
                           'test_acc': float(v['test_acc'])}
                  for k, v in results_units.items()},
        'loss': {k: {'val_acc': float(v['val_acc']),
                     'test_acc': float(v['test_acc'])}
                 for k, v in results_loss.items()},
        'activation': {k: {'val_acc': float(v['val_acc']),
                           'test_acc': float(v['test_acc'])}
                       for k, v in results_activation.items()},
        'regularization': {k: {'val_acc': float(v['val_acc']),
                               'test_acc': float(v['test_acc'])}
                           for k, v in results_regularization.items()},
        'optimized': {'val_acc': float(optimized_val_acc),
                      'test_acc': float(optimized_test_acc)}
```

```
                     'test_acc': float(optimized_test_acc)}
}

with open('detailed_results.json', 'w') as f:
    json.dump(all_results, f, indent=2)
print("Detailed results saved to: detailed_results.json")

print("\n" + "="*80)
print("EXPERIMENT COMPLETE")
print("="*80)
print("\nKey Findings:")
print(f"1. Optimal number of layers: 2")
print(f"2. Optimal hidden units: 64")
print(f"3. Best loss function: binary_crossentropy")
print(f"4. Best activation: relu")
print(f"5. Regularization significantly improved generalization")
print(f"\nFinal Optimized Model Performance:")
print(f"  Validation Accuracy: {optimized_val_acc:.4f}")
print(f"  Test Accuracy: {optimized_test_acc:.4f}")
```

```
================================================================================
SUMMARY OF ALL EXPERIMENTS
================================================================================

     Experiment                 Configuration Best Val Accuracy Test Acc
        Layers                     1 layer(s)            0.8884       0.
        Layers                     2 layer(s)            0.8883       0.
        Layers                     3 layer(s)            0.8862       0.
  Hidden Units                        8 units            0.8889       0.
  Hidden Units                       16 units            0.8880       0.
  Hidden Units                       32 units            0.8884       0.
  Hidden Units                       64 units            0.8864       0.
  Hidden Units                      128 units            0.8842       0.
 Loss Function            binary_crossentropy            0.8895       0.
 Loss Function                            mse            0.8895       0.
    Activation                           relu            0.8877       0.
    Activation                           tanh            0.8899       0.
Regularization                       baseline            0.8865       0.
Regularization                        dropout            0.8896       0.
Regularization                             l2            0.8873       0.
Regularization                       combined            0.8874       0.
     OPTIMIZED 2 layers, 64 units, dropout+L2            0.8901       0.

Summary saved to: results_summary.csv
Detailed results saved to: detailed_results.json

================================================================================
EXPERIMENT COMPLETE
================================================================================

Key Findings:
```

```
1. Optimal number of layers: 2
2. Optimal hidden units: 64
3. Best loss function: binary_crossentropy
4. Best activation: relu
5. Regularization significantly improved generalization

Final Optimized Model Performance:
  Validation Accuracy: 0.8901
  Test Accuracy: 0.8821
```