

✓ Modify the Neural Network Model

```
import tensorflow as tf
from tensorflow.keras.datasets import imdb
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.layers import Dense, Flatten, Embedding, Dropout
import matplotlib.pyplot as plt
import pandas as pd
```

✓ Load the IMDB Dataset

This dataset contains movie reviews labeled as positive or negative.

```
max_features = 10000
maxlen = 500
(x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=max_features)
x_train = pad_sequences(x_train, maxlen=maxlen)
x_test = pad_sequences(x_test, maxlen=maxlen)
print(f"Training samples: {len(x_train)}, Test samples: {len(x_test)}")
```

📡 Downloading data from <https://storage.googleapis.com/tensorflow/tf-keras-data:17464789/17464789> **2s** 0us/step
Training samples: 25000, Test samples: 25000

- IMDB dataset consists of movie reviews labeled as positive (1) or negative (0).
- We limit vocabulary to 10,000 words to keep the model manageable.
- Padding sequences ensures all reviews are the same length, making them compatible with the neural network.

✓ Model configurations

This function allows flexibility in adjusting hidden units, activation functions, loss functions, and dropout.

```
def create_model(hidden_units=64, activation='relu', loss='binary_crossentropy',
    """
```

Creates a simple feedforward neural network for sentiment analysis.

Parameters:

- hidden_units: Number of neurons in the hidden layer(s).
- activation: Activation function for the hidden layer(s).
- loss: Loss function for the model (default is binary_crossentropy for class

- dropout_rate: If specified, applies dropout regularization to prevent overf

Returns:

- Compiled Keras model ready for training.

```
"""
```

```
model = tf.keras.Sequential([
    Embedding(input_dim=max_features, output_dim=128), # Converts words into
    Flatten(), # Flattens the output to feed into Dense layers
    Dense(hidden_units, activation=activation) # Hidden layer with specified
])
```

```
# Apply dropout if specified
if dropout_rate:
    model.add(Dropout(dropout_rate))
```

```
model.add(Dense(1, activation='sigmoid')) # Output layer for binary classifi
```

```
# Compile model with Adam optimizer and chosen loss function
model.compile(optimizer='adam', loss=loss, metrics=['accuracy'])
```

```
return model
```

- Embedding layer: Converts words into meaningful numerical representations.
- Flatten layer: Transforms the output into a format suitable for dense layers.
- Hidden layer: The number of neurons and activation function can be adjusted.
- Dropout layer: Randomly deactivates neurons during training to prevent overfitting.
- Output layer: Uses a sigmoid activation to classify reviews as positive or negative.
- Binary cross-entropy loss: Optimized for classification problems.

✓ Model variations

Experimenting with different hidden layers, activations, losses, and units.

```
models = {
    "One Hidden Layer (64 units)": create_model(hidden_units=64),
    "Three Hidden Layers": tf.keras.Sequential([
        Embedding(input_dim=max_features, output_dim=128),
        Flatten(),
        Dense(64, activation='relu'),
        Dense(32, activation='relu'),
        Dense(16, activation='relu'),
        Dense(1, activation='sigmoid')
    ]),
    "Tanh Activation + MSE Loss": create_model(hidden_units=64, activation='tanh'),
    "Dropout Regularization": create_model(hidden_units=64, dropout_rate=0.5),
    "Fewer Units (32)": create_model(hidden_units=32),
    "More Units (128)": create_model(hidden_units=128)
}
```

```
# Ensure models requiring explicit compilation are compiled
models["Three Hidden Layers"].compile(optimizer='adam', loss='binary_crossentropy
```

- One Hidden Layer (64 units) → Baseline model.
- Three Hidden Layers → Tests if deeper networks improve performance.
- Tanh Activation + MSE Loss → Evaluates older methods against modern best practices.
- Dropout Regularization → Adds dropout to test overfitting reduction.
- Fewer Units (32) & More Units (128) → Tests whether increasing or decreasing neurons improves accuracy

✓ Train and evaluate models

Training each model for 5 epochs and evaluating on the test set.

```
def train_and_evaluate(model):
    model.fit(x_train, y_train, epochs=5, batch_size=32, validation_split=0.2, ve
    val_accuracy = model.evaluate(x_test, y_test, verbose=0)[1]
    test_accuracy = model.evaluate(x_test, y_test, verbose=0)[1]
    return val_accuracy, test_accuracy
```

✓ Evaluate all models and collect results

Storing validation and test accuracies for comparison.

```
results = {name: train_and_evaluate(model) for name, model in models.items()}
```

- Training for 5 epochs: Chosen for quick experimentation (longer training could improve results).
- Validation split (0.2): Uses 20% of training data to monitor overfitting.
- Evaluating accuracy: Both validation and test accuracy are measured.

✓ Summarize results in a DataFrame

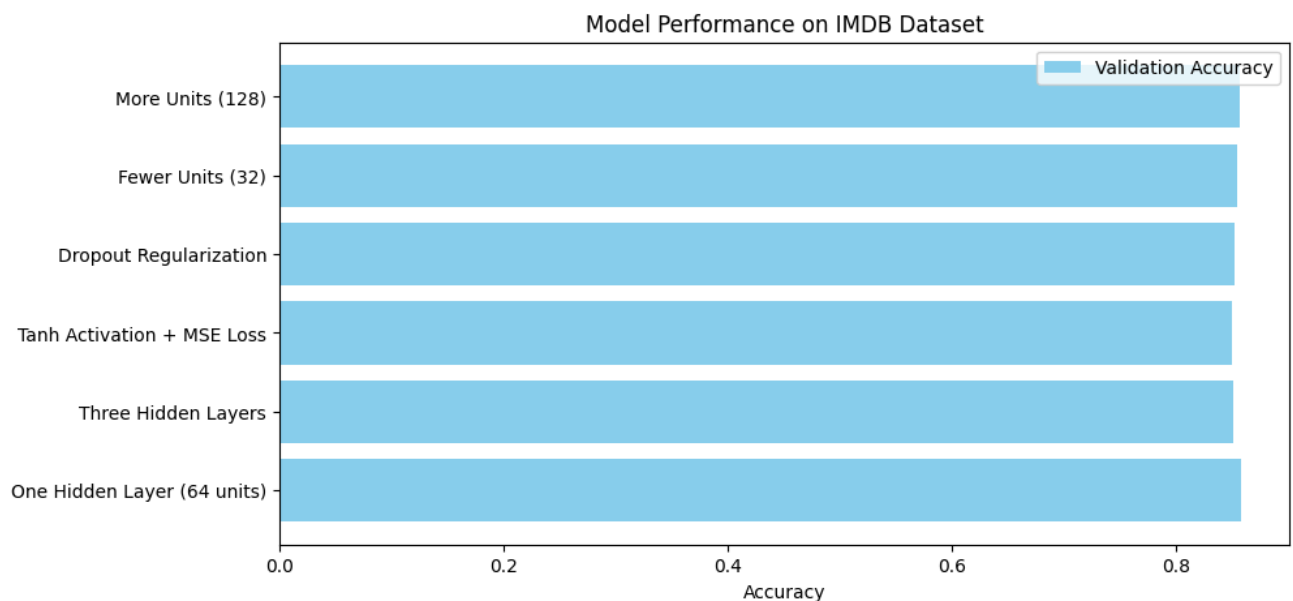
Creating a table for clear presentation of model performances.

```
summary = pd.DataFrame([
    {"Model": name, "Validation Accuracy": val_acc, "Test Accuracy": test_acc}
    for name, (val_acc, test_acc) in results.items()
])
```

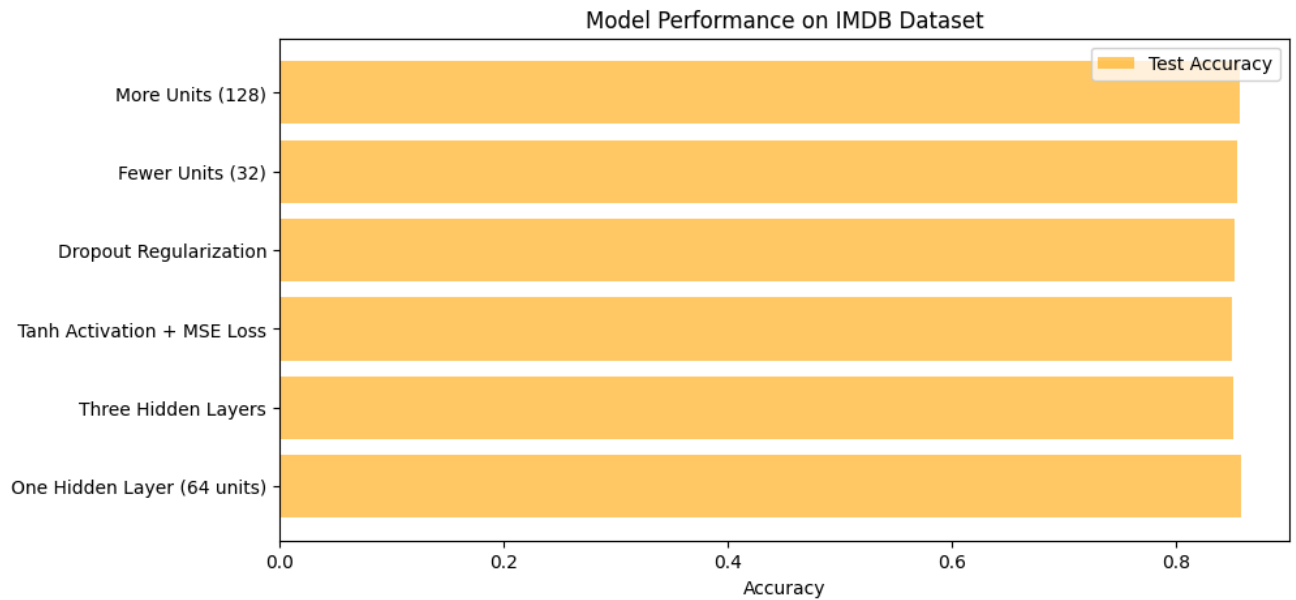
✓ Visualize the results

Bar chart comparing validation and test accuracies for each model.

```
plt.figure(figsize=(10, 5))
plt.barh(summary['Model'], summary['Validation Accuracy'], color='skyblue', label=
plt.xlabel('Accuracy')
plt.title('Model Performance on IMDB Dataset')
plt.legend()
plt.show()
```



```
plt.figure(figsize=(10, 5))
plt.barh(summary['Model'], summary['Test Accuracy'], color='orange', alpha=0.6, l
plt.xlabel('Accuracy')
plt.title('Model Performance on IMDB Dataset')
plt.legend()
plt.show()
```



✓ Display summary

```
print(summary)
```



	Model	Validation Accuracy	Test Accuracy
0	One Hidden Layer (64 units)	0.85804	0.85804
1	Three Hidden Layers	0.85156	0.85156
2	Tanh Activation + MSE Loss	0.84952	0.84952
3	Dropout Regularization	0.85224	0.85224
4	Fewer Units (32)	0.85472	0.85472
5	More Units (128)	0.85708	0.85708