```
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.datasets import imdb
from tensorflow.keras.preprocessing.sequence import pad_sequences

# Preparing data
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)

# Build model
model = keras.Sequential([
    layers.Embedding(max_features, 32),
    layers.Flatten(),
    layers.Dense(32, activation="relu"),
    layers.Dense(1, activation="sigmoid"),
])

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

history = model.fit(
    x_train,
    y_train,
    epochs=10,
    batch_size=512,
    validation_split=0.2
)
```

```
Epoch 1/10
40/40 ━━━━━━━━━━━━━━━━━━━━ 8s 143ms/step - accuracy: 0.5131 - loss: 0.6929 - val_accuracy: 0.5526 - val_loss: 0.6804
Epoch 2/10
40/40 ━━━━━━━━━━━━━━━━━━━━ 4s 106ms/step - accuracy: 0.5888 - loss: 0.6641 - val_accuracy: 0.7332 - val_loss: 0.5856
Epoch 3/10
40/40 ━━━━━━━━━━━━━━━━━━━━ 5s 114ms/step - accuracy: 0.7901 - loss: 0.5140 - val_accuracy: 0.6892 - val_loss: 0.5757
Epoch 4/10
40/40 ━━━━━━━━━━━━━━━━━━━━ 5s 122ms/step - accuracy: 0.8420 - loss: 0.3561 - val_accuracy: 0.8508 - val_loss: 0.3427
Epoch 5/10
40/40 ━━━━━━━━━━━━━━━━━━━━ 4s 94ms/step - accuracy: 0.9102 - loss: 0.2324 - val_accuracy: 0.8544 - val_loss: 0.3362
Epoch 6/10
40/40 ━━━━━━━━━━━━━━━━━━━━ 4s 95ms/step - accuracy: 0.9323 - loss: 0.1781 - val_accuracy: 0.8672 - val_loss: 0.3228
Epoch 7/10
40/40 ━━━━━━━━━━━━━━━━━━━━ 5s 128ms/step - accuracy: 0.9539 - loss: 0.1313 - val_accuracy: 0.8732 - val_loss: 0.3260
Epoch 8/10
40/40 ━━━━━━━━━━━━━━━━━━━━ 4s 92ms/step - accuracy: 0.9730 - loss: 0.0881 - val_accuracy: 0.8682 - val_loss: 0.3472
Epoch 9/10
40/40 ━━━━━━━━━━━━━━━━━━━━ 4s 92ms/step - accuracy: 0.9804 - loss: 0.0675 - val_accuracy: 0.8770 - val_loss: 0.3408
Epoch 10/10
40/40 ━━━━━━━━━━━━━━━━━━━━ 6s 106ms/step - accuracy: 0.9926 - loss: 0.0356 - val_accuracy: 0.8742 - val_loss: 0.3708
```

```
# 1. One vs Two vs Three Hidden Layers
# One hidden layer best training accuracy = .9994, best validation accuarcy = .8714
# Two hidden layers best training accuracy = 1.0000, best validation accuarcy = .8698
# Three hidden layers best training accuracy = .9999, best validation accuarcy = .8648

# This indicates that one layer is the best generalization compared to two hidden layers being slightly overfitting
# and three layers being the most overfitting due to also learning noise. Adding more layers increased the model
# complexity without improving generalization.


# 2. More / Fewer Hidden Units
# 16 hidden units inside Dense(), best training accuracy = .9994, best validation accuarcy = .8714
# 32 hidden units inside Dense(), best training accuracy = .9999, best validation accuarcy = .8718
# 64 hidden units inside Dense(), best training accuracy = .9999, best validation accuarcy = .8662
# 128 hidden units inside Dense(), best training accuracy = 1.0000, best validation accuarcy = .8696

# This indicates that 32 hidden units is the best balance of training and validation accuracy.
# As the number of hidden units increases the model becomes more powerful. Training accuracy stays near perfect
```

```
# As the number of hidden units increases the model becomes more powerful. Training accuracy stays near perfect
# while the validation stops impoving and begins to drop.

# 3. MSE Loss Instead of Binary Crossentropy
# binary_crossentropy, best training accuracy = .9999, best validation accuarcy = .8718
# mse, best training accuracy = .9981, best validation accuarcy = .8650

# Binary Crossentropy is the best learning signal while MSE is weaker for classification.
# The model trained with a loss function designed for classification learned more useful decision boundaries
# than one trained with a regression-style loss.

# 4. tanh Instead of relu
# relu, best training accuracy = .9999, best validation accuarcy = .8718
# tanh, best training accuracy = .9999, best validation accuarcy = .8606

# relu is better for generalization while tanh overfits and trains less effectivly.
# The difference is about how efficiently the network learns useful features and relu transferred that
# learning better to unseen data.

# 5. Regularization and Dropout
# Dropout,  best training accuracy = .7188, best validation accuarcy = .5884
#   code: layers.Dropout(0.5)
# Regularization, best training accuracy = .9984, best validation accuarcy = .8642
#   code: kernel_regularizer=keras.regularizers.l2(0.001)

# The Dropout method was underfitting while the Regularization method reduced overfitting but still did
# not have the best improvment on performance. The model struggled to learn the training data properly.
```

```
import pandas as pd
import matplotlib.pyplot as plt

# Hyperparameter Tuning Summary Table

results_data = [
    # Hidden Layers
    ["Hidden Layers", "1 layer", 0.9994, 0.8714, "Best generalization"],
    ["Hidden Layers", "2 layers", 1.0000, 0.8698, "Slight overfitting"],
    ["Hidden Layers", "3 layers", 0.9999, 0.8648, "Overfitting"],

    # Hidden Units
    ["Hidden Units", "16 units", 0.9994, 0.8714, "Strong baseline"],
    ["Hidden Units", "32 units", 0.9999, 0.8718, "Best balance"],
    ["Hidden Units", "64 units", 0.9999, 0.8662, "Overfitting"],
    ["Hidden Units", "128 units", 1.0000, 0.8696, "Overfitting"],

    # Loss Function
    ["Loss Function", "Binary Crossentropy", 0.9999, 0.8718, "Best classification performance"],
    ["Loss Function", "MSE", 0.9981, 0.8650, "Weaker learning signal"],

    # Activation
    ["Activation", "ReLU", 0.9999, 0.8718, "Better feature learning"],
    ["Activation", "tanh", 0.9999, 0.8606, "Reduced generalization"],

    # Regularization
    ["Regularization", "Dropout", 0.7188, 0.5884, "Underfitting"],
    ["Regularization", "L2", 0.9984, 0.8642, "Reduced overfitting"]
]

columns = ["Experiment", "Configuration", "Best Training Accuracy", "Best Validation Accuracy", "Interpretation"]

df_results = pd.DataFrame(results_data, columns=columns)

# Final Conclusion Row

final_model = pd.DataFrame([[
    "FINAL MODEL",
    "1 layer, 32 units, ReLU, Binary Crossentropy, No Regularization",
    0.9999,
    0.8718,
    "Best overall generalization performance"
]], columns=columns)

df_results = pd.concat([df_results, final_model], ignore_index=True)

df_results
```

	Experiment	Configuration	Best Training Accuracy	Best Validation Accuracy	Interpretation
0	Hidden Layers	1 layer	0.9994	0.8714	Best generalization
1	Hidden Layers	2 layers	1.0000	0.8698	Slight overfitting
2	Hidden Layers	3 layers	0.9999	0.8648	Overfitting
3	Hidden Units	16 units	0.9994	0.8714	Strong baseline
4	Hidden Units	32 units	0.9999	0.8718	Best balance
5	Hidden Units	64 units	0.9999	0.8662	Overfitting
6	Hidden Units	128 units	1.0000	0.8696	Overfitting
7	Loss Function	Binary Crossentropy	0.9999	0.8718	Best classification performance
8	Loss Function	MSE	0.9981	0.8650	Weaker learning signal
9	Activation	ReLU	0.9999	0.8718	Better feature learning
10	Activation	tanh	0.9999	0.8606	Reduced generalization
11	Regularization	Dropout	0.7188	0.5884	Underfitting
12	Regularization	L2	0.9984	0.8642	Reduced overfitting

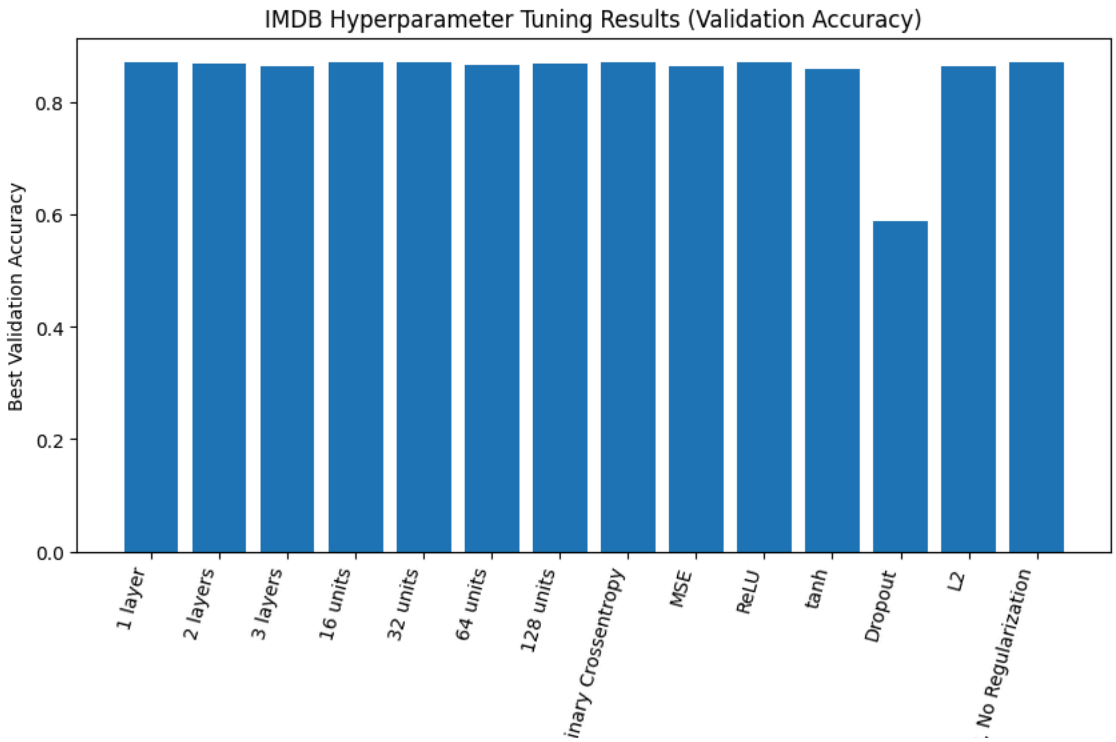
```
# Plot Validation Accuracy

plt.figure(figsize=(10, 5))

labels = df_results["Configuration"]
val_acc = df_results["Best Validation Accuracy"]

plt.bar(labels, val_acc)
plt.xticks(rotation=75, ha="right")
plt.ylabel("Best Validation Accuracy")
plt.title("IMDB Hyperparameter Tuning Results (Validation Accuracy)")

plt.show()
```



IMDB Hyperparameter Tuning Results (Validation Accuracy)
Best Validation Accuracy
0.0
0.2
0.4
0.6
0.8
1 layer
2 layers
3 layers
16 units
32 units
64 units
128 units
inary Crossentropy
MSE
ReLU
tanh
Dropout
L2
No Regularization