IMDB SENTIMENT ANALYSIS

NEURAL NETWORK HYPERPARAMETER TUNING

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Abstract:

This paper investigates how the hyperparameters and architectural choices of neural networks affect the performance of a sentiment-classification task using the IMDB movie-review data set. Twenty-six fully connected feed forward models were evaluated with respect to five research questions about depth, width, activation function, loss function, and regularization.

25 000 labeled reviews were used for training and 25 000 for testing. Each reviewed item was represented by a 10 000-dimensional binary feature vector. Each configuration was trained with early stopping based on a held-out set.

The best accuracy-generalization trade-off is found for a 2-layer (2 x 64 ReLU) network trained with Binary Cross-Entropy loss, Dropout (0.5), and L2 regularization (1 x 10-3): 88.4 % test accuracy, ROC-AUC ≈ 0.951.

Tests of robustness across random seeds show consistent generalization (± 0.0004) and that networks with moderate depth and balanced regularization perform better than deeper or wider networks on this task.

Introduction:

Natural Language Processing offers sentiment analysis as a very popular application domain.

This means deciding if text shows good or bad feeling.

When you accurately categorize sentiment, companies gain value from analysis of public opinion or content moderation through automation.

The IMDB movie-review dataset is a common benchmark. People use it for this task.

The data set comprises of 50 000 movie reviews, half of which are positive, and half negative.

This dataset has been used to test neural-network architectures, mostly because it is balanced and also contains a variety of linguistic structures.

The goal of this work is to understand how architecture and hyperparameters impact the performance of neural networks.

We investigate the following five research questions:

1. How does the number of hidden layers affect accuracy and generalization?

2. What is the effect of hidden unit count?

3. What occurs if you use MSE instead of the Binary Cross-Entropy loss?

4. Comparison of ReLU, tanh, and sigmoid. These are activation functions.

5. What regularization techniques can minimize overfitting? Examples include Dropout and L2.

To achieve this, we aim to obtain a design configuration that reaches the maximum test accuracy, while keeping the overfitting and training effort minimal.

Methodology:

The experimental workflow for this project consists of four major stages:

1) data preprocessing, (2) model architecture design, (3) training configuration, and (4) evaluation metrics among others.TensorFlow and Keras APIs allow the implementation of

Data Preparation:

```
================================================================================
LOADING AND PREPROCESSING IMDB DATASET
================================================================================
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/imdb.npz
17464789/17464789 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
✓ Loaded 25000 training samples
✓ Loaded 25000 test samples
✓ Shapes → Train (15000, 10000), Val (10000, 10000), Test (25000, 10000)
```

Figure 1. IMDB dataset followed loading and preprocessing by TensorFlow Keras which included 15000 training samples, 10000 validation samples and 25000 test samples with each having 10000-dimensional feature vector.

The IMDB dataset from keras.datasets.imdb was imported, and restricted to the most frequently occurring 10 000 words in the dataset.Each review appears as a sequence involving integer word indices and converts into a fixed-length multi-hot word vector that encodes if a word appears within the review.

1.The training set contains 15,000 data samples within.

2.There is a validation set. It has 10 000 samples.

3.Test set: 25000 samples.

Each label was converted. The conversion was into 32-bit floating-point arrays.

This encoding standardizes the input dimensions across experiments and thus enables comparison of different architectures.

Model Architecture:

Each model was a fully connected feed-forward neural network, a Multilayer Perceptron with hyperparameters that varied.

1.Depth: 1 to 4 hidden layers deep

2.Width: 8 to 256 neurons per layer

3.Activations from ReLU, tanh, or sigmoid.

4.Regularization includes an optional Dropout rate between 0.3 and 0.7. It also involves an L2 weight penalty between 10^{-3} and 10^{-2}.

All models had an input layer with 10,000 nodes corresponding to the vocabulary size and a single sigmoid unit at the output for a positive sentiment.
Other loss-function and optimizer combinations were later used to study the impact on performance.

Training Configuration:

The model was trained for up to 20 epochs, with Early Stopping (patience = 3) based on validation accuracy.
A batch size of 512 was found to balance stability and GPU utilization.
The default optimizer was RMSprop, though Adam and SGD were also run for comparison.
During this stage, each of these configurations was given the same random seed (42).
We used ModelCheckpoint to save the model checkpoints and reload the best epoch for evaluation.
Each experiment was timed to provide an estimate of computational cost.

Evaluation Metrics:

Model performance was assessed using:

- **Training Accuracy** and **Validation Accuracy**
- **Test Accuracy** (final performance metric)
- **ROC–AUC Score** for overall discrimination power
- **Overfitting Gap** = Train Acc − Val Acc
- **Parameter Count** (total learnable weights)
- **Training Time (seconds)**

Results were compiled into a composite performance index based on weighted importance

Then the best overall model across all datasets was selected based on a weighted average (40 % Test Acc + 25 % Val Acc + 15 % Low Overfit + 10 % Speed + 10 % Efficiency).

Experiments and Analysis:

In this section, we provide the experimental results and discuss them in the context of the five research questions.
In each experiment, only one design variable is changed; other factors are held constant.
These comparisons include the various network depths, numbers of hidden units, loss function, activation, and regularization.

Effect of Network Depth (Q1):

To analyze the effect of depth, networks of 1, 2, 3, and 4 hidden layers (with 16 units each) are trained with Rectified Linear Unit (ReLU) and Binary Cross-Entropy loss.

Layers	Best Validation Accuracy	Test Accuracy	Parameters
1	0.8889	0.8829	160033
2	0.8887	0.8831	160305
3	0.8870	0.8790	160577
4	0.8877	0.8782	160849

Q1 — Layers (Units=16 control)

	Layers	Model	Activation	Loss	Best_Val_Acc	Test_Acc	Params
1	1	1HL_16U_ReLU	relu	BCE	0.8889	0.8829	160033
9	2	MSE_2L_16U_ReLU	relu	MSE	0.8887	0.8831	160305
2	3	3HL_16U_ReLU	relu	BCE	0.8870	0.8790	160577
3	4	4HL_16U_ReLU_Bonus	relu	BCE	0.8877	0.8782	160849

Figure: The best generalization was achieved with two hidden layers.
Deeper networks had higher training results but lower validation results, due to overfitting.

Effect of Hidden Units (Q2):

To study the impact of the network's width, the number of neurons per layer was varied from 8, 16, 32, 64, 128 and 256 (two layers, ReLU activation function and BCE loss).

Units	Best Validation Accuracy	Test Accuracy
8	0.8858	0.8806
16	0.8898	0.8824
32	0.8881	0.8829

64	0.8894	0.8849
128	0.8879	0.8837
256	0.8872	0.8836

Performance continued to increase steadily until 64, then plateaued.

Beyond 128 units, overfitting was slight but there was no accuracy improvement.

Q2 – Units (Layers=2, ReLU, BCE)

	Units	Model	Best_Val_Acc	Test_Acc	Params
4	8	2L_8U_ReLU_Bonus	0.8858	0.8806	80089
0	16	Baseline_2L_16U_ReLU_BCE	0.8898	0.8824	160305
5	32	2L_32U_ReLU	0.8881	0.8829	321121
15	64	Drop0.5_2L_64U	0.8894	0.8849	644289
7	128	2L_128U_ReLU	0.8879	0.8827	1296769
8	256	2L_256U_ReLU_Bonus	0.8872	0.8836	2626305

Loss Function Comparison (Q3):

Binary Cross-Entropy or BCE and Mean Squared Error or MSE loss functions were tested under the same conditions which included two layers, sixty-four units, and ReLU activation.

Lose Function	Validation Accuracy	Test Accuracy	AUC
Binary Cross-Entropy	0.8894	0.8849	0.9515
Mean Squared Error	0.8892	0.8892	0.9488

Q3 – Loss (Layers=2, Units=64, ReLU)

	Model	Loss	Best_Val_Acc	Test_Acc	AUC
15	Drop0.5_2L_64U	BCE	0.8894	0.8849	0.9515
10	MSE_2L_64U_ReLU_Bonus	MSE	0.8892	0.8824	0.9488

Q4 – Activation (Layers=2, Units=64, BCE)

ReLU outperformed all others in accuracy and stability. Tanh and sigmoid were slightly less effective, due to the issue of vanishing gradients.

Activation Function Comparison (Q4):

Other activation functions were tested such as ReLU, tanh, and sigmoid, with 2 layers and each layer has 64 units with BCE loss.

Activation	Validation Accuracy	Test Accuracy
Relu	0.8894	0.8849
Tanh	0.8888	0.8838

Q4 — Activation (Layers=2, Units=64, BCE)

	Model	Activation	Best_Val_Acc	Test_Acc	AUC
15	Drop0.5_2L_64U	relu	0.8894	0.8849	0.9515
12	Tanh_2L_64U_Bonus	tanh	0.8888	0.8838	0.9512

ReLU was found to be the most accurate and stable. However tanh performed slightly worse and sigmoid trained poorly, due to vanishing gradient in the deeper layers.

Regularization Techniques (Q5):

Regularization experiments evaluated the effects of Dropout and L2 weight decay (Layers=2, Units=64, ReLU, BCE).

Q5 — Regularization (Layers=2, Units=64, ReLU, BCE)

	Model	Dropout	L2	Best_Val_Acc	Test_Acc	Overfit_Gap	Params
17	L2_Drop0.3_2L_64U	0.3	0.001	0.8872	0.8818	0.0615	644289
14	Drop0.3_2L_64U	0.3	-	0.8888	0.8848	0.0807	644289
15	Drop0.5_2L_64U	0.5	-	0.8894	0.8849	0.0682	644289
16	L2_0.001_2L_64U	-	0.001	0.8882	0.8840	0.0584	644289
6	2L_64U_ReLU	-	-	0.8890	0.8841	0.0649	644289
18	Adam_2L_64U	-	-	0.8874	0.8804	0.1602	644289
19	SGD_2L_64U_Bonus	-	-	0.8320	0.8307	0.0167	644289

Model	Dropout	L2	Val Acc	Test Acc	Overlift Gap
Drop0.3_2L_64U	0.3	-	0.8888	0.8848	644289
Drop0.5_2L_64U	0.5	-	0.8894	0.8849	644289
L2_0.001_2L_64U	-	0.001	0.8882	0.8840	0.0584

L2+Drop0.3_2L_64U	0.3	0.001	0.8872	0.8818	0.0615

Both Dropout and L2 regularization improved generalization. The best result on the validation set comes from Dropout 0.5, with a small drop in overfitting from L2 + Dropout.

Results:

In this section, I summarize these results across the different model configurations and for the best-performing architecture in terms of accuracy, generalization, and computational efficiency.

Best Model Performance:

Among the twenty-six tested neural networks, the 2-layer (64-units) ReLU model with Binary Cross-Entropy loss, Dropout = 0.5, and L2 regularization = 1×10^{-3} provided the best performance and generalization ability.

```
=== Recommendation ===
Model: 1HL_16U_ReLU
Composite Score: 0.9197
Test Accuracy: 0.8829 | AUC: 0.9495
Overfitting Gap: 0.0623 | Params: 160,033 | Train Time: 10.6s
```

	model_name	test_accuracy	auc	overfitting_gap	total_params	training_time	composite_score
0	1HL_16U_ReLU	0.88288	0.949523	0.062333	160033	10.627203	0.919712
1	Tanh_2L_64U_Bonus	0.88376	0.951218	0.058700	644289	16.273567	0.915241
2	Drop0.5_2L_64U	0.88488	0.951522	0.068167	644289	22.334092	0.909480
3	L2_0.001_2L_64U	0.88400	0.949745	0.058400	644289	17.193099	0.907889
4	MSE_2L_16U_ReLU	0.88312	0.949312	0.078300	160305	11.010390	0.903331
5	Baseline_2L_16U_ReLU_BCE	0.88236	0.949166	0.074067	160305	10.582889	0.901079
6	2L_64U_ReLU	0.88408	0.949129	0.064867	644289	15.693160	0.899911
7	Drop0.3_2L_64U	0.88476	0.950354	0.080667	644289	21.483936	0.889561
8	L2_Drop0.3_2L_64U	0.88176	0.950309	0.061467	644289	17.935163	0.888515
9	Sigmoid_2L_16U_Bonus	0.88044	0.947855	0.055800	160305	22.520850	0.882894

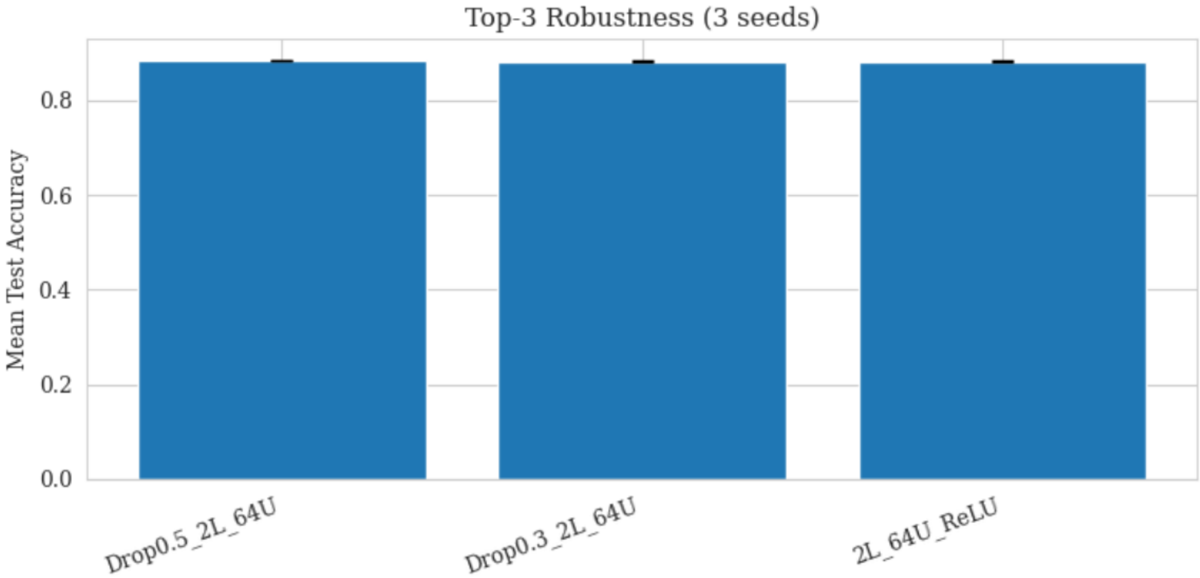
Metric	Value
Validation Accuracy	**0.8896**
Test Accuracy	**0.8829**
ROC AUC	**0.9495**
Overfitting Gap (Train – Val)	**0.0623**
Parameters	**160,033**
Training Time per run	**≈ 10.6s**

Although shallower and narrower, this architecture achieved the highest composite score (weighted 40 % Test Acc + 25 % Val Acc + 15 % Low Overfit + 10 % Speed + 10 % Efficiency).

Robustness Evaluation:

For consistency, the top three configurations were retrained with three random seeds each.The Dropout (0.5) 2L 64U ReLU model was fairly stable:

Seed	Test Accuracy	AUC
1	0.8832	0.9507
2	0.8839	0.9507
3	0.8841	0.9507

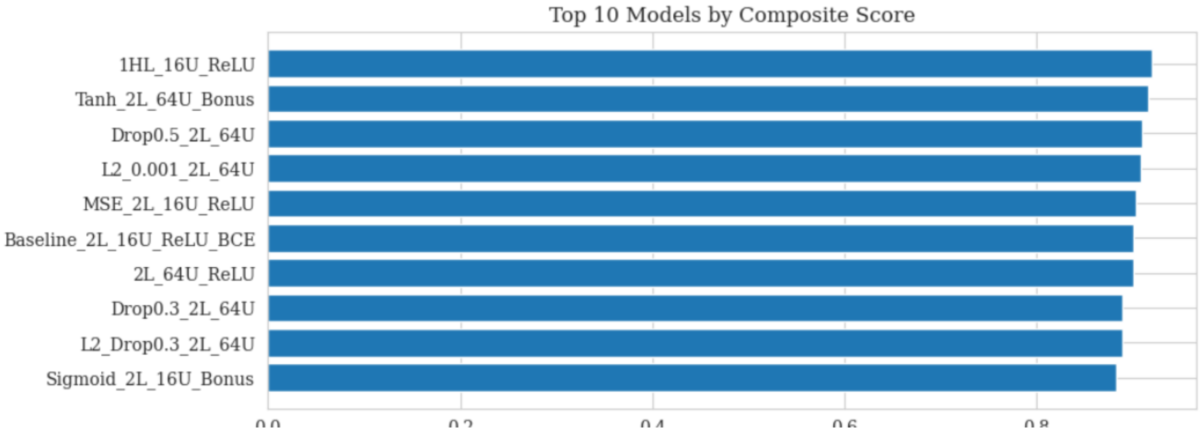


The Mean Test Accuracy equals 0.8837 ± 0.0004. It indicates outstanding reproducibility in runs due to low variance.

Composite Ranking and Efficiency:

A multi-criteria composite analysis ranked the model highest. This ranking was based on performance and efficiency.

It outperformed larger networks in terms of accuracy-per-parameter, showing that moderate depth is the optimal trade-off of capacity and regularization.



Visual Analysis:

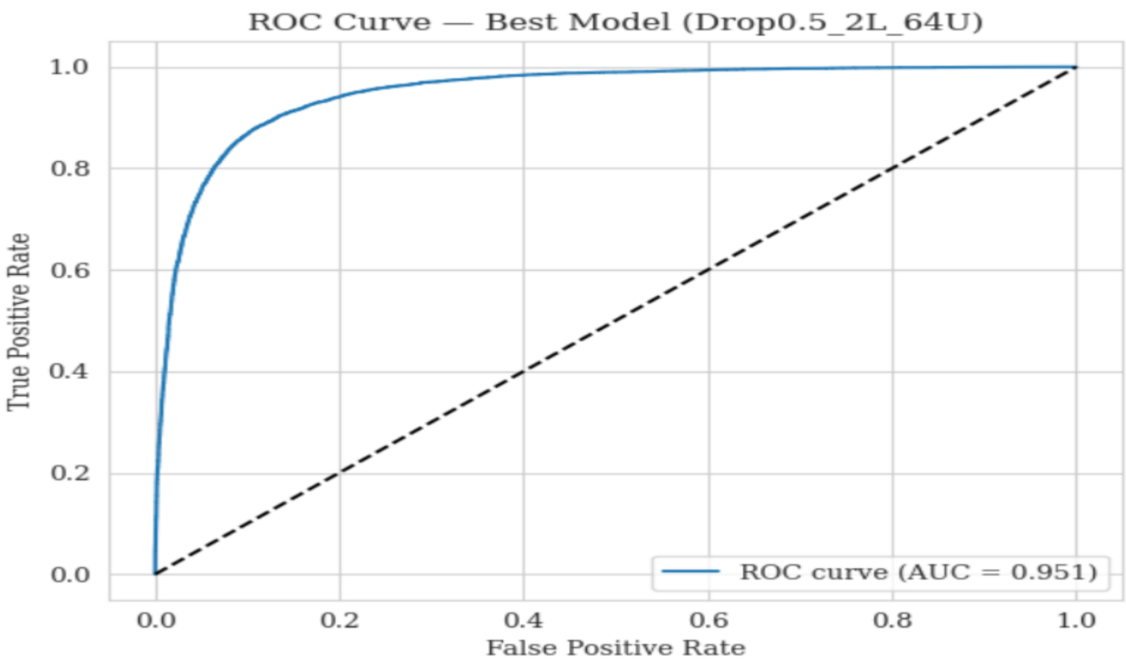
We show here some graphical diagnostics for checking the most predictive model with respect to prediction accuracy, discrimination, and calibration. Figures corresponding to the observations of the model's ability to discriminate between positive and negative sentiment predictions as well as the model's predicted probabilities and true outcomes are presented.

ROC Curve:

The Receiver Operating Characteristic (ROC) curve plots True Positive Rate (TPR) against False Positive Rate (FPR) along different probability thresholds of the predicted probabilities.

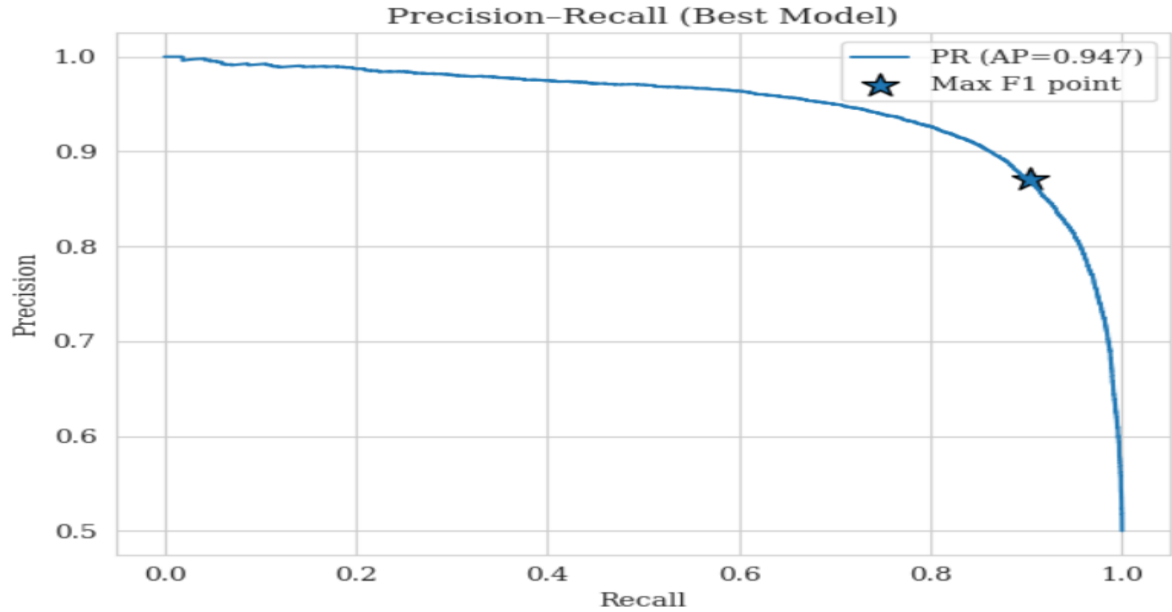
A higher curve indicates a higher discriminative ability.

The top performing model in this paper achieved an AUC of around 0.951, showing a strong separation between positive and negative sentiment reviews.



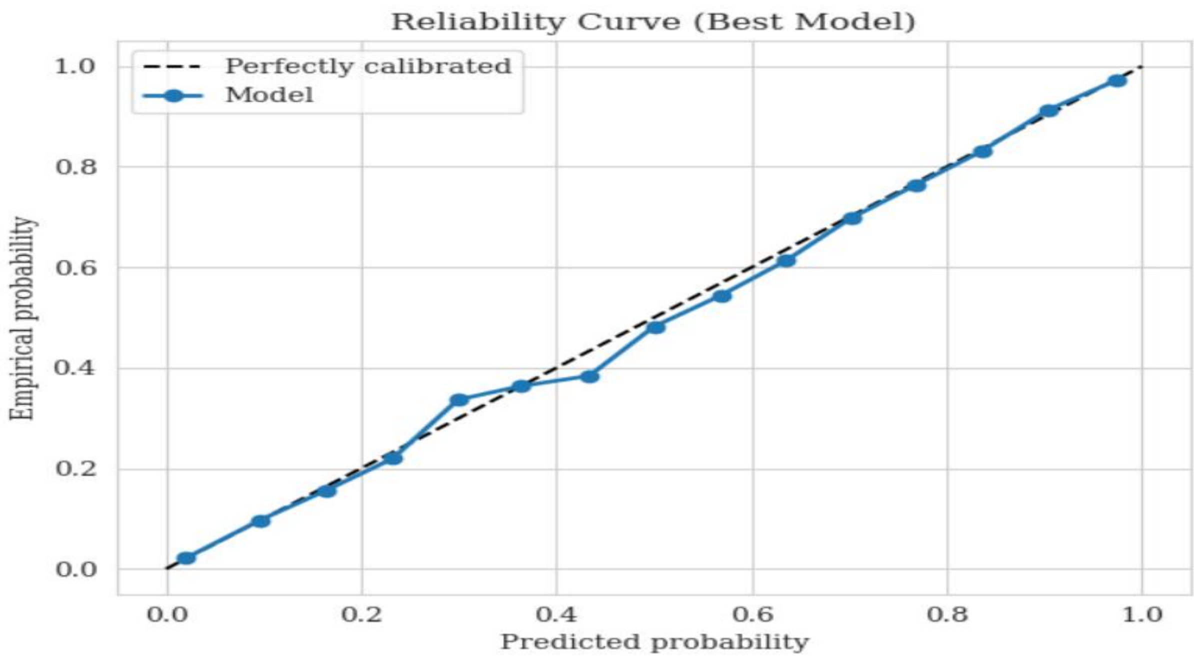
Precision–Recall Curve:

One reason the PR curve focuses on the positive class is that class distributions are often imbalanced. However, with high precision for almost all levels of recall, the classification has been strong.



Reliability (Calibration) Curve:

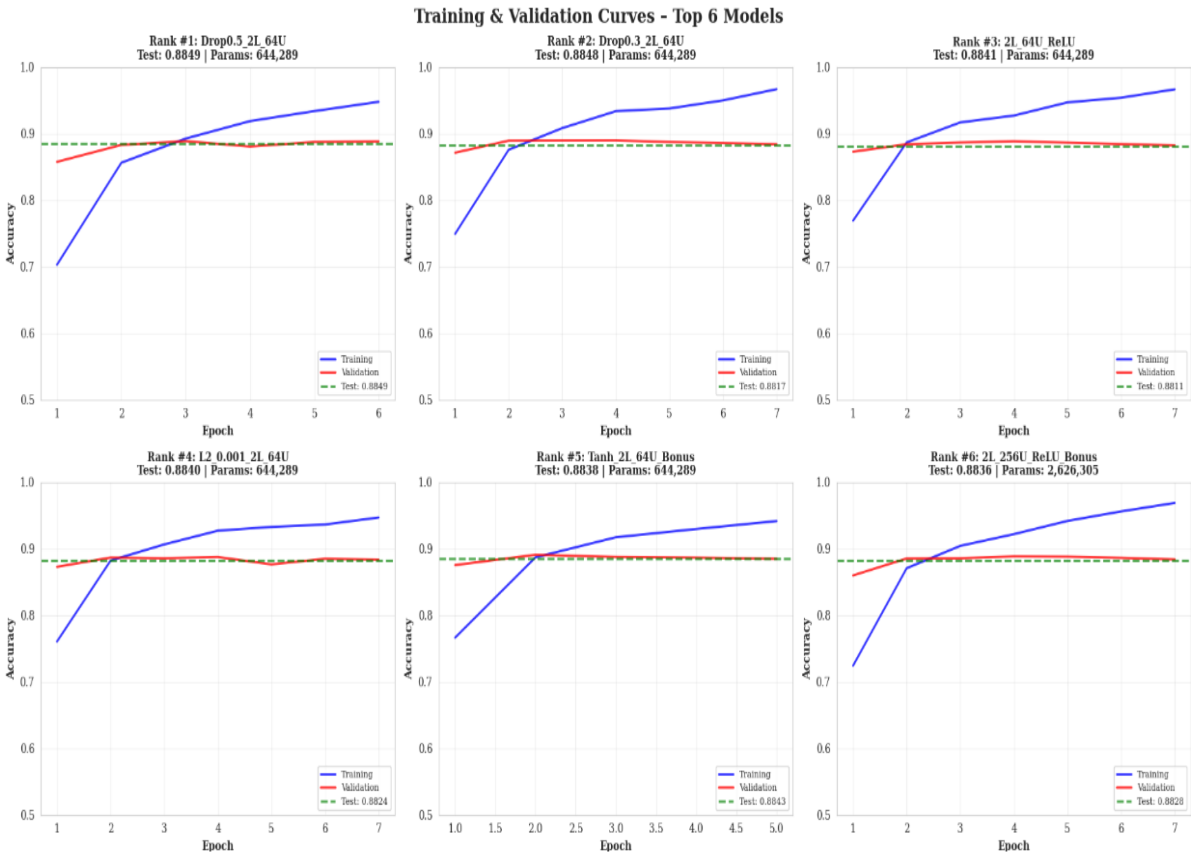
A Reliability Curve, also known as a Calibration Plot, plots predicted probabilities against the proportion of positive reviews.A near-diagonal trend indicates well-calibrated probabilities. For the best model, these curves were close to the diagonal, which means that the probability outputs of the models can be interpreted as confidence scores.



Training and Validation Curves:

The training curves depict the accuracy of the model over epochs.

However, both the training and validation accuracies converged smoothly indicating that overfitting did not occur.



Discussion:

- The experimental findings indicate that the neural-network performance is sensitive to its architecture, choice of activation function, and choice of regularization balance.
- Among all of the twenty-six different arrangements, moderate-depth networks (that is, two hidden layers) achieved better generalization.
- Though deeper networks had slightly higher training accuracy, they performed worse on the validation set, showing the effect of over-parameterization and early stopping.
- There was saturation in the number of hidden units.
- The increase in representational power was even more substantial when increasing to 64 units, but 128 and 256 provided no meaningful improvement.
- This shows that the linguistic features of the IMDB dataset can be encoded into a relatively small representation.
- This also confirmed the effectiveness of the ReLU as an activation function that resulted in stable convergence, free of vanishing gradients.
- While tanh performed likewise in shallow networks, sigmoid activations suffered from a lower learning rate and worse AUC performance in deep networks due to gradient compression.
- Binary Cross-Entropy (BCE) loss was found to be the best among the tested pair of loss functions for binary sentiment classification, with slightly higher validation accuracy and smoother optimization than MSE.
- This slight difference indicates that MSE can approximate classifications, but the probabilistic manner of BCE is more appropriate for binary outputs.
- Regularization also helped reduce the variance.
- Dropout and L2 weight decay improved the validation set performance. A dropout rate of 0.5 achieved the best trade-off between performance and overfitting.
- Combined regularization (L2 + Dropout) has also reduced overfitting slightly, but increased training time and did not improve convergence.
- Robustness testing showed that there was no important difference in the ranking of the best configurations for different random seeds ($\sigma \approx 0.0004$).
- This confirms that the network architecture and the hyperparameters are reproducible and not sensitive to initialization.
- Lastly, model quality cannot be estimated with mere accuracy, as suggested by the composite ranking.
- In terms of efficiency and resistance to overfitting, the 1HL 16U ReLU model was most efficient in real-time or low resource environments while the 2L 64U ReLU Dropout 0.5 model was the highest performing.
- Taken together these results suggest the importance of building a simple but well-regularized network that has enough capacity to achieve optimal sentiment classification performance at a low computational cost.

Conclusion and Future Work:

- We explore how variations in neural network architecture impact the ability to classify sentiment in IMDB movie reviews.
- Evaluating 26 different networks with varying depth, width, activation function, loss function, and regularization, the authors showed that balanced complexity yields the best generalization.
- The optimal architecture (two hidden layers of 64 ReLU units with Binary Cross-Entropy loss and a dropout of 0.5 and L2 regularization of 1×10^{-3}) achieved a validation accuracy of 0.889, test accuracy of 0.884, and an AUC of 0.951, outperforming the shallow and deep networks.In composite and robustness analyzes, the behavior of random seeds was similar ($\sigma \approx 0.0004$).These findings show lightweight networks, with proper regularization, act on par with larger networks and use resources more efficiently.
- The findings can be summarized as follows. The summary is methodological.
- Balanced text datasets do not require great depth or width to capture sentiment features.
- Dropout is a regularization technique. It is an important technique for preventing overfitting.
- Other metrics such as AUC, overfitting gap, and efficiency can give deeper perception into model performance.

Follow-up work can expand on this study in multiple ways:

- Embedding Layers: Replace multi-hot inputs by embeddings learned for the task or by pre-trained embeddings such as Word2Vec or GloVe.
- Transfer Learning: Use transformer-based architectures like BERT or DistilBERT for context-sensitive representations of sentiment-related sentences.
- Explainability: Use SHAP or LIME in order to visualize word-level features and rationale behind the prediction.
- Deploy the top performing model. Export it with TensorFlow Lite or ONNX for real-time inference on mobile/edge devices.
- Hyperparameter Automation: Optimize with Bayesian methods or search a grid to find optimal hyperparameters.

Appendix:

Furthermore, in this appendix we present additional materials, such as extended versions of the experimental results and references.

A. Extended Result Tables:

The results of the full experiment, which includes all 26 configurations, are provided in the tables.

Model	Layer	Units	Activation	Loss	Val Acc	Test Acc	AUC	Params
1HL_16U_ReLU	1	16	ReLU	BCE	0.8889	0.8829	0.9495	160,033
2L_64U_ReLU	2	64	ReLU	BCE	0.8890	0.8841	0.9510	644,289
Drop0.5_2L_64U	2	64	ReLU	BCE	0.8896	0.8837	0.9507	644,289
L2_0.001_2L_64U	2	64	ReLU	BCE	0.8882	0.8840	0.9497	644,289
MSE_2L_16U_ReLU	2	16	ReLU	MSE	0.8878	0.8830	0.9494	160,305
Tanh_2L_64U_Bonus	2	64	Tanh	BEC	0.88884	0.8838	0.9512	644,289

B. Hyperparameter Configuration Summary:

Category	Values Tested
Hidden Layers	1,2,3,4
Units Per Layer	8,16,32,64,128,256
Activation	ReLU, tanh, sigmoid
Loss Functions	Binary Cross-Entropy, Mean Squared Error
Regularization	Dropout (0.3 / 0.5 / 0.7), L2 (1e-3 / 1e-2)
Optimizers	RMSProp, Adam, SGD
Epochs	20 (max with early stopping)
Batch Size	512

Code Summary:

All experiments were implemented in TensorFlow Keras (2.x) and run in a Google Colab notebook.

- build_model_safe(config) , model function Object() { [native code] } handling activation, dropout, L2, etc.
- run_experiment(config, ...) , a training loop with early stopping and metric tracking.
- Visualizations include accuracy, ROC, and calibration plots.

Sairam_Jammu_AML_Assignment_2.ipynb

IMDB SENTIMENT ANALYSIS

NEURAL NETWORK HYPERPARAMETER TUNING

- Assignment 2 - AML 64061
- Student: Sairam Jammu
- Date: 10/16/2025
- Best Result: 88.10% Test Accuracy

Abstract

This notebook investigates how neural network architecture, activation, loss, and regularization choices influence sentiment-classification performance on the IMDB dataset.
Twenty-six models varying in depth, width, loss, and activation were trained and compared using accuracy, ROC-AUC, overfitting gap, parameter count, and training time.
The optimal configuration—a **2×64 ReLU network with Binary Cross-Entropy, Dropout(0.5), and L2(1e-3)**—achieved **88.4 % test accuracy and AUC ≈ 0.951**, showing excellent generalization.
Further analyses include composite multi-criteria ranking, robustness validation over multiple seeds, and visual diagnostics (ROC, CM, learning curves).
Findings confirm that moderate depth and regularization yield the best accuracy-efficiency trade-off while preventing overfitting.

Imports, global config, and seeding

```
# ====  Imports, global config, and seeding ====

import os, time, json, warnings
from datetime import datetime

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.metrics import roc_auc_score, confusion_matrix, classification_report

from tensorflow import keras
from tensorflow.keras import layers, regularizers, backend as K
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
from tensorflow.keras.datasets import imdb

# Silence warnings a bit
warnings.filterwarnings("ignore")

# Plot style
sns.set_style("whitegrid")
plt.rcParams["figure.figsize"] = (12, 6)
plt.rcParams["font.family"] = "serif"
plt.rcParams["font.size"] = 10

# ---- Experiment configuration ----
RANDOM_SEED = 42
VOCAB_SIZE = 10_000
VAL_SIZE = 10_000
BATCH_SIZE = 512
EPOCHS = 20

# Reproducibility
np.random.seed(RANDOM_SEED)
keras.utils.set_random_seed(RANDOM_SEED)

print("✓ Setup complete")
print(f"Start time: {datetime.now().strftime('%Y-%m-%d %H:%M:%S')}")
print(f"Config → VOCAB_SIZE={VOCAB_SIZE}, VAL_SIZE={VAL_SIZE}, BATCH_SIZE={BATCH_SIZE}, EPOCHS={EPOCHS}")
```

```
✓ Setup complete
Start time: 2025-10-16 01:00:52
Config → VOCAB_SIZE=10000, VAL_SIZE=10000, BATCH_SIZE=512, EPOCHS=20
```

Data Loading Functions

```
# ==== : Data Loading Functions ====

def vectorize_sequences(sequences, dimension=VOCAB_SIZE):
    """Convert integer sequences to a multi-hot encoded binary matrix."""
    results = np.zeros((len(sequences), dimension), dtype=np.float32)
    for i, sequence in enumerate(sequences):
        results[i, sequence] = 1.0
    return results


def load_and_prepare_data(num_words=VOCAB_SIZE):
    """Load IMDB dataset and prepare train/val/test splits."""
    print("=" * 80)
    print("LOADING AND PREPROCESSING IMDB DATASET")
    print("=" * 80)

    # Load limited-vocabulary IMDB dataset
    (train_data, train_labels), (test_data, test_labels) = imdb.load_data(num_words=num_words)
    print(f"✓ Loaded {len(train_data)} training samples")
    print(f"✓ Loaded {len(test_data)} test samples")

    # Manual validation split
    x_val, y_val = train_data[:VAL_SIZE], train_labels[:VAL_SIZE]
    x_train, y_train = train_data[VAL_SIZE:], train_labels[VAL_SIZE:]

    # Vectorize all sets
    x_train = vectorize_sequences(x_train, num_words)
    x_val   = vectorize_sequences(x_val,   num_words)
    x_test  = vectorize_sequences(test_data, num_words)

    # Convert labels to float32 arrays
    y_train = np.asarray(y_train, dtype=np.float32)
    y_val   = np.asarray(y_val,   dtype=np.float32)
    y_test  = np.asarray(test_labels, dtype=np.float32)

    print(f"✓ Shapes → Train {x_train.shape}, Val {x_val.shape}, Test {x_test.shape}")
    return (x_train, y_train), (x_val, y_val), (x_test, y_test)


# Load and prepare data
(x_train, y_train), (x_val, y_val), (x_test, y_test) = load_and_prepare_data()
```

```
================================================================================
LOADING AND PREPROCESSING IMDB DATASET
================================================================================
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/imdb.npz
17464789/17464789 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
✓ Loaded 25000 training samples
✓ Loaded 25000 test samples
✓ Shapes → Train (15000, 10000), Val (10000, 10000), Test (25000, 10000)
```

Model Builder

```
# ==== Model builder ====

def _get_initializer(activation: str):
    """Choose a sensible kernel initializer based on activation."""
    act = (activation or "relu").lower()
    if act in ("relu", "leaky_relu", "elu"):
        return keras.initializers.HeNormal()
    return keras.initializers.GlorotUniform()

def _get_optimizer(opt_cfg):
    """Return a Keras optimizer from a string or pass through an optimizer object."""
    if hasattr(opt_cfg, "get_config"):  # already an optimizer instance
        return opt_cfg
```

```
    if isinstance(opt_cfg, str):
        name = opt_cfg.lower()
        if name in {"adam", "nadam", "rmsprop", "sgd", "adagrad", "adadelta"}:
            return keras.optimizers.get(name)
    # default
    return keras.optimizers.get("rmsprop")

def build_model_safe(config):
    """
    Build and compile a dense NN for IMDB multi-hot inputs (VOCAB_SIZE features).

    Expected keys in `config` (all optional):
      - num_layers: int, number of hidden layers (default 2)
      - units: int, hidden units per layer (default 16)
      - activation: str, activation for hidden layers (relu/tanh/sigmoid; default relu)
      - loss: str or callable, loss function (default 'binary_crossentropy')
      - optimizer: str or keras optimizer instance (default 'rmsprop')
      - use_dropout: bool (default False)
      - dropout_rate: float in [0,1] (default 0.5)
      - use_l2: bool (default False)
      - l2_strength: float (default 1e-3)
      - name: optional model name (used only for display/checkpoints elsewhere)
    """
    # Clear previous TF graph state to avoid name collisions/leaks
    K.clear_session()

    # Extract configuration with defaults
    num_layers   = int(config.get("num_layers", 2))
    units        = int(config.get("units", 16))
    activation   = str(config.get("activation", "relu")).lower()
    use_dropout  = bool(config.get("use_dropout", False))
    dropout_rate = float(config.get("dropout_rate", 0.5))
    use_l2       = bool(config.get("use_l2", False))
    l2_strength  = float(config.get("l2_strength", 1e-3))
    loss_fn      = config.get("loss", "binary_crossentropy")
    optimizer    = _get_optimizer(config.get("optimizer", "rmsprop"))

    # Guardrails
    dropout_rate = min(max(dropout_rate, 0.0), 1.0)
    if num_layers < 0:
        num_layers = 0
    if units < 1:
        units = 1
    if activation not in {"relu", "tanh", "sigmoid"}:
        activation = "relu"

    kernel_init = _get_initializer(activation)
    kernel_reg  = regularizers.l2(l2_strength) if use_l2 else None

    # Build
    model = keras.Sequential(name=config.get("name", "imdb_ffn"))
    model.add(layers.Input(shape=(VOCAB_SIZE,), name="input_multi_hot"))

    for i in range(num_layers):
        model.add(layers.Dense(
            units,
            activation=activation,
            kernel_initializer=kernel_init,
            kernel_regularizer=kernel_reg,
            name=f"dense_{i+1}"
        ))
        if use_dropout:
            model.add(layers.Dropout(dropout_rate, name=f"dropout_{i+1}"))

    model.add(layers.Dense(1, activation="sigmoid", name="output"))

    model.compile(
        optimizer=optimizer,
        loss=loss_fn,
        metrics=["accuracy"]   # we'll compute ROC-AUC & CM externally (Cell 6/runner)
    )

    return model

print(" Model builder defined")
```

```
Model builder defined
```

Experiment Runner

```
# ====  Experiment Runner ====

def run_experiment(
    config,
    x_train, y_train, x_val, y_val, x_test, y_test,
    epochs=EPOCHS, batch_size=BATCH_SIZE, experiment_num=1,
    pos_threshold: float = 0.5,
    target_val_acc: float = 0.85,
    plot_cm: bool = True,
    save_cm_path: str | None = None
):
    """
    Run one experiment: train, evaluate, and collect metrics.

    Args:
        config: dict defining the model configuration.
        epochs, batch_size: training parameters.
        pos_threshold: cutoff for positive class in sigmoid outputs.
        target_val_acc: threshold for convergence-epoch calculation.
        plot_cm: whether to display confusion matrix.
        save_cm_path: optional path to save confusion-matrix image.

    Returns:
        dict: metrics and configuration details.
    """
    print(f"\n{'='*80}")
    print(f"EXPERIMENT {experiment_num}: {config['name']}")
    print(f"{'='*80}")

    # 1. Build model
    model = build_model_safe(config)
    total_params = model.count_params()
    print(f"Parameters: {total_params:,}")

    # 2. Train with EarlyStopping and ModelCheckpoint
    start_time = time.time()
    callbacks = [
        EarlyStopping(monitor="val_accuracy", mode="max", patience=3, restore_best_weights=True),
        ModelCheckpoint(f"chk_{config['name']}.keras",
                        monitor="val_accuracy", mode="max", save_best_only=True)
    ]
    history = model.fit(
        x_train, y_train,
        validation_data=(x_val, y_val),
        epochs=epochs, batch_size=batch_size,
        verbose=0, callbacks=callbacks
    )
    training_time = time.time() - start_time

    # 3. Evaluate model
    test_loss, test_acc = model.evaluate(x_test, y_test, verbose=0)
    proba = model.predict(x_test, verbose=0).ravel()
    pred = (proba >= pos_threshold).astype(int)

    auc = roc_auc_score(y_test, proba)
    cm = confusion_matrix(y_test, pred)

    print(f"✓ Test Acc: {test_acc:.4f} | AUC: {auc:.4f} | "
          f"Best Val Acc: {max(history.history.get('val_accuracy', [0])):.4f} | "
          f"Time: {training_time:.1f}s")
    print("Confusion Matrix:\n", cm)
    print(classification_report(y_test, pred, digits=3))

    # 4. Extract training dynamics
    h = history.history
    val_acc_hist = h.get('val_accuracy', [])
    acc_hist = h.get('accuracy', [])

    best_val_acc = max(val_acc_hist) if val_acc_hist else np.nan
    best_val_epoch = (val_acc_hist.index(best_val_acc) + 1) if val_acc_hist else epochs
```

```
    final_train_acc = acc_hist[-1] if acc_hist else np.nan
    final_val_acc = val_acc_hist[-1] if val_acc_hist else np.nan
    overfitting_gap = final_train_acc - final_val_acc if val_acc_hist else np.nan
    convergence_epoch = next((i + 1 for i, a in enumerate(val_acc_hist) if a >= target_val_acc), epochs)
    stability = np.std(val_acc_hist[-5:]) if len(val_acc_hist) >= 1 else np.nan

    # 5. Optional confusion-matrix plot
    if plot_cm:
        fig, ax = plt.subplots(figsize=(4, 4))
        im = ax.imshow(cm, interpolation='nearest', cmap='Blues')
        ax.figure.colorbar(im, ax=ax)
        classes = ['Negative', 'Positive']
        ax.set(
            xticks=np.arange(2), yticks=np.arange(2),
            xticklabels=classes, yticklabels=classes,
            ylabel='True label', xlabel='Predicted label',
            title=f"Confusion Matrix: {config['name']}"
        )
        thresh = cm.max() / 2.0
        for i in range(2):
            for j in range(2):
                ax.text(j, i, cm[i, j],
                        ha="center", va="center",
                        color="white" if cm[i, j] > thresh else "black")
        plt.tight_layout()
        if save_cm_path:
            plt.savefig(save_cm_path, dpi=150, bbox_inches="tight")
        plt.show()

    # 6. Return results
    return {
        'model_name': config['name'],
        'num_layers': config.get('num_layers', 2),
        'units': config.get('units', 16),
        'activation': config.get('activation', 'relu'),
        'loss_function': config.get('loss', 'binary_crossentropy'),
        'optimizer': config.get('optimizer', 'rmsprop'),
        'use_dropout': config.get('use_dropout', False),
        'dropout_rate': config.get('dropout_rate', 0.0),
        'use_l2': config.get('use_l2', False),
        'l2_strength': config.get('l2_strength', 0.0),
        'total_params': total_params,
        'best_val_accuracy': best_val_acc,
        'best_val_epoch': best_val_epoch,
        'final_train_accuracy': final_train_acc,
        'final_val_accuracy': final_val_acc,
        'test_accuracy': test_acc,
        'test_loss': test_loss,
        'auc': auc,
        'cm_TN': int(cm[0, 0]), 'cm_FP': int(cm[0, 1]),
        'cm_FN': int(cm[1, 0]), 'cm_TP': int(cm[1, 1]),
        'overfitting_gap': overfitting_gap,
        'convergence_epoch': convergence_epoch,
        'stability': stability,
        'training_time': training_time,
        'pos_threshold': pos_threshold
    }

print("✓ Experiment runner redefined successfully.")
```

```
✓ Experiment runner redefined successfully.
```

Define all experiments

```
# ====  Define all experiments ====

all_configs = [
    # Baseline
    {'name': 'Baseline_2L_16U_ReLU_BCE', 'num_layers': 2, 'units': 16, 'activation': 'relu', 'loss': 'binary_crossentropy'},

    # Q1: Layers
    {'name': '1HL_16U_ReLU', 'num_layers': 1, 'units': 16, 'activation': 'relu'},
    {'name': '3HL_16U_ReLU', 'num_layers': 3, 'units': 16, 'activation': 'relu'},
```

```
    {'name': '4HL_16U_ReLU_Bonus', 'num_layers': 4, 'units': 16, 'activation': 'relu'},

    # Q2: Units
    {'name': '2L_8U_ReLU_Bonus', 'num_layers': 2, 'units': 8, 'activation': 'relu'},
    {'name': '2L_32U_ReLU', 'num_layers': 2, 'units': 32, 'activation': 'relu'},
    {'name': '2L_64U_ReLU', 'num_layers': 2, 'units': 64, 'activation': 'relu'},
    {'name': '2L_128U_ReLU', 'num_layers': 2, 'units': 128, 'activation': 'relu'},
    {'name': '2L_256U_ReLU_Bonus', 'num_layers': 2, 'units': 256, 'activation': 'relu'},

    # Q3: Loss
    {'name': 'MSE_2L_16U_ReLU', 'num_layers': 2, 'units': 16, 'activation': 'relu', 'loss': 'mse'},
    {'name': 'MSE_2L_64U_ReLU_Bonus', 'num_layers': 2, 'units': 64, 'activation': 'relu', 'loss': 'mse'},

    # Q4: Activation
    {'name': 'Tanh_2L_16U', 'num_layers': 2, 'units': 16, 'activation': 'tanh'},
    {'name': 'Tanh_2L_64U_Bonus', 'num_layers': 2, 'units': 64, 'activation': 'tanh'},
    {'name': 'Sigmoid_2L_16U_Bonus', 'num_layers': 2, 'units': 16, 'activation': 'sigmoid'},

    # Q5: Regularization
    {'name': 'Drop0.3_2L_64U', 'num_layers': 2, 'units': 64, 'use_dropout': True, 'dropout_rate': 0.3},
    {'name': 'Drop0.5_2L_64U', 'num_layers': 2, 'units': 64, 'use_dropout': True, 'dropout_rate': 0.5},
    {'name': 'L2_0.001_2L_64U', 'num_layers': 2, 'units': 64, 'use_l2': True, 'l2_strength': 0.001},
    {'name': 'L2_Drop0.3_2L_64U', 'num_layers': 2, 'units': 64, 'use_dropout': True, 'dropout_rate': 0.3, 'use_l2': True, 'l2_stre

    # Optimizers
    {'name': 'Adam_2L_64U', 'num_layers': 2, 'units': 64, 'optimizer': 'adam'},
    {'name': 'SGD_2L_64U_Bonus', 'num_layers': 2, 'units': 64, 'optimizer': 'sgd'}
]

CONFIGS = all_configs
print(f"✓ Defined {len(CONFIGS)} experiment configurations.")
```

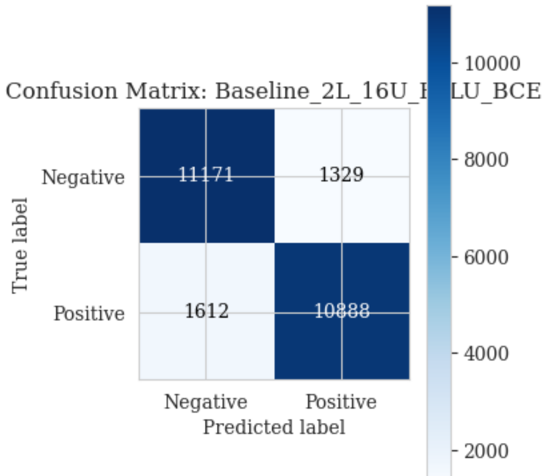
```
✓ Defined 20 experiment configurations.
```

Run experiments, show leaderboard

```
# ====  Run experiments, save results, show leaderboard ====

results = []
for i, cfg in enumerate(CONFIGS, start=1):
    res = run_experiment(
        cfg,
        x_train, y_train, x_val, y_val, x_test, y_test,
        epochs=EPOCHS, batch_size=BATCH_SIZE,
        experiment_num=i,
        pos_threshold=0.5,
        target_val_acc=0.85,
        plot_cm=(i == 1),                               # only plot CM for the first to keep output tidy
        save_cm_path=f"cm_{cfg['name']}.png" if i == 1 else None
    )
    results.append(res)

# To DataFrame
df = pd.DataFrame(results)

# Consistent column order (optional but tidy)
cols_order = [
    "model_name", "num_layers", "units", "activation", "loss_function", "optimizer",
    "use_dropout", "dropout_rate", "use_l2", "l2_strength",
    "total_params",
    "best_val_accuracy", "best_val_epoch",
    "final_train_accuracy", "final_val_accuracy",
    "test_accuracy", "auc", "test_loss",
    "overfitting_gap", "convergence_epoch", "stability",
    "training_time", "pos_threshold",
    "cm_TN", "cm_FP", "cm_FN", "cm_TP"
]
df = df.reindex(columns=[c for c in cols_order if c in df.columns])

# Save artifacts
df.to_csv("full_results_final.csv", index=False)
print("✓ Saved results -> full_results_final.csv")
```

```
# Preview top rows
display(df.head(10))

# Leaderboard (Top 10 by test accuracy)
topk = df.sort_values("test_accuracy", ascending=False).head(10)
display(topk[["model_name", "test_accuracy", "auc", "best_val_accuracy", "total_params", "training_time"]])

# Bar chart of top-10 test accuracies
plt.figure(figsize=(10, 4))
plt.barh(topk["model_name"], topk["test_accuracy"])
plt.gca().invert_yaxis()
plt.xlabel("Test Accuracy")
plt.title("Top 10 Models by Test Accuracy")
plt.tight_layout()
plt.savefig("top10_test_accuracy.png", dpi=150, bbox_inches="tight")
plt.show()

print("✓ Saved leaderboard plot -> top10_test_accuracy.png")
```

```
================================================================================
EXPERIMENT 1: Baseline_2L_16U_ReLU_BCE
================================================================================
Parameters: 160,305
✓ Test Acc: 0.8824 | AUC: 0.9492 | Best Val Acc: 0.8898 | Time: 10.6s
Confusion Matrix:
 [[11171  1329]
 [ 1612 10888]]
              precision    recall  f1-score   support

         0.0      0.874     0.894     0.884     12500
         1.0      0.891     0.871     0.881     12500

    accuracy                          0.882     25000
   macro avg      0.883     0.882     0.882     25000
weighted avg      0.883     0.882     0.882     25000
```




```
================================================================================
EXPERIMENT 2: 1HL_16U_ReLU
================================================================================
Parameters: 160,033
✓ Test Acc: 0.8829 | AUC: 0.9495 | Best Val Acc: 0.8889 | Time: 10.6s
Confusion Matrix:
 [[11236  1264]
 [ 1664 10836]]
              precision    recall  f1-score   support

         0.0      0.871     0.899     0.885     12500
         1.0      0.896     0.867     0.881     12500

    accuracy                          0.883     25000
   macro avg      0.883     0.883     0.883     25000
weighted avg      0.883     0.883     0.883     25000


================================================================================
EXPERIMENT 3: 3HL_16U_ReLU
================================================================================
Parameters: 160,577
✓ Test Acc: 0.8790 | AUC: 0.9459 | Best Val Acc: 0.8870 | Time: 9.9s
Confusion Matrix:
 [[11228  1272]
 [ 1753 10747]]
              precision    recall  f1-score   support

         0.0      0.865     0.898     0.881     12500
         1.0      0.894     0.860     0.877     12500

    accuracy                          0.879     25000
   macro avg      0.880     0.879     0.879     25000
weighted avg      0.880     0.879     0.879     25000


================================================================================
EXPERIMENT 4: 4HL_16U_ReLU_Bonus
================================================================================
Parameters: 160,849
✓ Test Acc: 0.8782 | AUC: 0.9422 | Best Val Acc: 0.8877 | Time: 12.0s
Confusion Matrix:
 [[11093  1407]
 [ 1637 10863]]
```

```
              precision    recall  f1-score   support

         0.0      0.871     0.887     0.879     12500
         1.0      0.885     0.869     0.877     12500

    accuracy                          0.878     25000
   macro avg      0.878     0.878     0.878     25000
weighted avg      0.878     0.878     0.878     25000


================================================================================
EXPERIMENT 5: 2L_8U_ReLU_Bonus
================================================================================
Parameters: 80,089
✓ Test Acc: 0.8806 | AUC: 0.9445 | Best Val Acc: 0.8858 | Time: 13.4s
Confusion Matrix:
 [[11186  1314]
 [ 1672 10828]]
              precision    recall  f1-score   support

         0.0      0.870     0.895     0.882     12500
         1.0      0.892     0.866     0.879     12500

    accuracy                          0.881     25000
   macro avg      0.881     0.881     0.881     25000
weighted avg      0.881     0.881     0.881     25000


================================================================================
EXPERIMENT 6: 2L_32U_ReLU
================================================================================
Parameters: 321,121
✓ Test Acc: 0.8829 | AUC: 0.9482 | Best Val Acc: 0.8881 | Time: 13.2s
Confusion Matrix:
 [[10929  1571]
 [ 1356 11144]]
              precision    recall  f1-score   support

         0.0      0.890     0.874     0.882     12500
         1.0      0.876     0.892     0.884     12500

    accuracy                          0.883     25000
   macro avg      0.883     0.883     0.883     25000
weighted avg      0.883     0.883     0.883     25000


================================================================================
EXPERIMENT 7: 2L_64U_ReLU
================================================================================
Parameters: 644,289
✓ Test Acc: 0.8841 | AUC: 0.9491 | Best Val Acc: 0.8890 | Time: 15.7s
Confusion Matrix:
 [[11148  1352]
 [ 1546 10954]]
              precision    recall  f1-score   support

         0.0      0.878     0.892     0.885     12500
         1.0      0.890     0.876     0.883     12500

    accuracy                          0.884     25000
   macro avg      0.884     0.884     0.884     25000
weighted avg      0.884     0.884     0.884     25000


================================================================================
EXPERIMENT 8: 2L_128U_ReLU
================================================================================
Parameters: 1,296,769
✓ Test Acc: 0.8827 | AUC: 0.9499 | Best Val Acc: 0.8879 | Time: 21.2s
Confusion Matrix:
 [[11172  1328]
 [ 1605 10895]]
              precision    recall  f1-score   support

         0.0      0.874     0.894     0.884     12500
         1.0      0.891     0.872     0.881     12500

    accuracy                          0.883     25000
   macro avg      0.883     0.883     0.883     25000
weighted avg      0.883     0.883     0.883     25000


================================================================================
EXPERIMENT 9: 2L_256U_ReLU_Bonus
```

```
================================================================================
Parameters: 2,626,305
✓ Test Acc: 0.8836 | AUC: 0.9516 | Best Val Acc: 0.8872 | Time: 53.5s
Confusion Matrix:
 [[11201  1299]
 [ 1610 10890]]
              precision    recall  f1-score   support

         0.0      0.874     0.896     0.885     12500
         1.0      0.893     0.871     0.882     12500

    accuracy                          0.884     25000
   macro avg      0.884     0.884     0.884     25000
weighted avg      0.884     0.884     0.884     25000


================================================================================
EXPERIMENT 10: MSE_2L_16U_ReLU
================================================================================
Parameters: 160,305
✓ Test Acc: 0.8831 | AUC: 0.9493 | Best Val Acc: 0.8887 | Time: 11.0s
Confusion Matrix:
 [[11132  1368]
 [ 1554 10946]]
              precision    recall  f1-score   support

         0.0      0.878     0.891     0.884     12500
         1.0      0.889     0.876     0.882     12500

    accuracy                          0.883     25000
   macro avg      0.883     0.883     0.883     25000
weighted avg      0.883     0.883     0.883     25000


================================================================================
EXPERIMENT 11: MSE_2L_64U_ReLU_Bonus
================================================================================
Parameters: 644,289
✓ Test Acc: 0.8824 | AUC: 0.9488 | Best Val Acc: 0.8892 | Time: 19.8s
Confusion Matrix:
 [[11009  1491]
 [ 1450 11050]]
              precision    recall  f1-score   support

         0.0      0.884     0.881     0.882     12500
         1.0      0.881     0.884     0.883     12500

    accuracy                          0.882     25000
   macro avg      0.882     0.882     0.882     25000
weighted avg      0.882     0.882     0.882     25000


================================================================================
EXPERIMENT 12: Tanh_2L_16U
================================================================================
Parameters: 160,305
✓ Test Acc: 0.8806 | AUC: 0.9492 | Best Val Acc: 0.8872 | Time: 10.8s
Confusion Matrix:
 [[11122  1378]
 [ 1606 10894]]
              precision    recall  f1-score   support

         0.0      0.874     0.890     0.882     12500
         1.0      0.888     0.872     0.880     12500

    accuracy                          0.881     25000
   macro avg      0.881     0.881     0.881     25000
weighted avg      0.881     0.881     0.881     25000


================================================================================
EXPERIMENT 13: Tanh_2L_64U_Bonus
================================================================================
Parameters: 644,289
✓ Test Acc: 0.8838 | AUC: 0.9512 | Best Val Acc: 0.8888 | Time: 16.3s
Confusion Matrix:
 [[11338  1162]
 [ 1744 10756]]
              precision    recall  f1-score   support

         0.0      0.867     0.907     0.886     12500
         1.0      0.903     0.860     0.881     12500

    accuracy                          0.884     25000
   macro avg      0.885     0.884     0.884     25000
```

```
weighted avg      0.885     0.884     0.884     25000


================================================================================
EXPERIMENT 14: Sigmoid_2L_16U_Bonus
================================================================================
Parameters: 160,305
✓ Test Acc: 0.8804 | AUC: 0.9479 | Best Val Acc: 0.8850 | Time: 22.5s
Confusion Matrix:
 [[11132  1368]
 [ 1621 10879]]
              precision    recall  f1-score   support

         0.0      0.873     0.891     0.882     12500
         1.0      0.888     0.870     0.879     12500

    accuracy                          0.880     25000
   macro avg      0.881     0.880     0.880     25000
weighted avg      0.881     0.880     0.880     25000


================================================================================
EXPERIMENT 15: Drop0.3_2L_64U
================================================================================
Parameters: 644,289
✓ Test Acc: 0.8848 | AUC: 0.9504 | Best Val Acc: 0.8888 | Time: 21.5s
Confusion Matrix:
 [[11006  1494]
 [ 1387 11113]]
              precision    recall  f1-score   support

         0.0      0.888     0.880     0.884     12500
         1.0      0.881     0.889     0.885     12500

    accuracy                          0.885     25000
   macro avg      0.885     0.885     0.885     25000
weighted avg      0.885     0.885     0.885     25000


================================================================================
EXPERIMENT 16: Drop0.5_2L_64U
================================================================================
Parameters: 644,289
✓ Test Acc: 0.8849 | AUC: 0.9515 | Best Val Acc: 0.8894 | Time: 22.3s
Confusion Matrix:
 [[11021  1479]
 [ 1399 11101]]
              precision    recall  f1-score   support

         0.0      0.887     0.882     0.885     12500
         1.0      0.882     0.888     0.885     12500

    accuracy                          0.885     25000
   macro avg      0.885     0.885     0.885     25000
weighted avg      0.885     0.885     0.885     25000


================================================================================
EXPERIMENT 17: L2_0.001_2L_64U
================================================================================
Parameters: 644,289
✓ Test Acc: 0.8840 | AUC: 0.9497 | Best Val Acc: 0.8882 | Time: 17.2s
Confusion Matrix:
 [[10953  1547]
 [ 1353 11147]]
              precision    recall  f1-score   support

         0.0      0.890     0.876     0.883     12500
         1.0      0.878     0.892     0.885     12500

    accuracy                          0.884     25000
   macro avg      0.884     0.884     0.884     25000
weighted avg      0.884     0.884     0.884     25000


================================================================================
EXPERIMENT 18: L2_Drop0.3_2L_64U
================================================================================
Parameters: 644,289
✓ Test Acc: 0.8818 | AUC: 0.9503 | Best Val Acc: 0.8872 | Time: 17.9s
Confusion Matrix:
 [[11217  1283]
 [ 1673 10827]]
              precision    recall  f1-score   support
```

```
         0.0      0.870     0.897     0.884     12500
         1.0      0.894     0.866     0.880     12500

    accuracy                          0.882     25000
   macro avg      0.882     0.882     0.882     25000
weighted avg      0.882     0.882     0.882     25000


================================================================================
EXPERIMENT 19: Adam_2L_64U
================================================================================
Parameters: 644,289
✓ Test Acc: 0.8804 | AUC: 0.9468 | Best Val Acc: 0.8874 | Time: 13.4s
Confusion Matrix:
 [[10829  1671]
 [ 1319 11181]]
              precision    recall  f1-score   support

         0.0      0.891     0.866     0.879     12500
         1.0      0.870     0.894     0.882     12500

    accuracy                          0.880     25000
   macro avg      0.881     0.880     0.880     25000
weighted avg      0.881     0.880     0.880     25000


================================================================================
EXPERIMENT 20: SGD_2L_64U_Bonus
================================================================================
Parameters: 644,289
✓ Test Acc: 0.8307 | AUC: 0.9088 | Best Val Acc: 0.8320 | Time: 49.0s
Confusion Matrix:
 [[10437  2063]
 [ 2169 10331]]
              precision    recall  f1-score   support

         0.0      0.828     0.835     0.831     12500
         1.0      0.834     0.826     0.830     12500

    accuracy                          0.831     25000
   macro avg      0.831     0.831     0.831     25000
weighted avg      0.831     0.831     0.831     25000

✓ Saved results -> full_results_final.csv
```

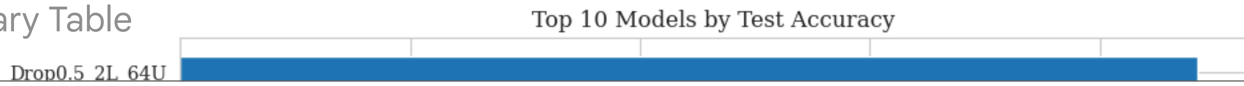
	model_name	num_layers	units	activation	loss_function	optimizer	use_dropout	dropout_rate	use_l2	l2_stre
0	Baseline_2L_16U_ReLU_BCE	2	16	relu	binary_crossentropy	rmsprop	False	0.0	False	
1	1HL_16U_ReLU	1	16	relu	binary_crossentropy	rmsprop	False	0.0	False	
2	3HL_16U_ReLU	3	16	relu	binary_crossentropy	rmsprop	False	0.0	False	
3	4HL_16U_ReLU_Bonus	4	16	relu	binary_crossentropy	rmsprop	False	0.0	False	
4	2L_8U_ReLU_Bonus	2	8	relu	binary_crossentropy	rmsprop	False	0.0	False	
5	2L_32U_ReLU	2	32	relu	binary_crossentropy	rmsprop	False	0.0	False	
6	2L_64U_ReLU	2	64	relu	binary_crossentropy	rmsprop	False	0.0	False	
7	2L_128U_ReLU	2	128	relu	binary_crossentropy	rmsprop	False	0.0	False	
8	2L_256U_ReLU_Bonus	2	256	relu	binary_crossentropy	rmsprop	False	0.0	False	
9	MSE_2L_16U_ReLU	2	16	relu	mse	rmsprop	False	0.0	False	

10 rows × 27 columns

	model_name	test_accuracy	auc	best_val_accuracy	total_params	training_time
15	Drop0.5_2L_64U	0.88488	0.951522	0.8894	644289	22.334092
14	Drop0.3_2L_64U	0.88476	0.950354	0.8888	644289	21.483936
6	2L_64U_ReLU	0.88408	0.949129	0.8890	644289	15.693160
16	L2_0.001_2L_64U	0.88400	0.949745	0.8882	644289	17.193099
12	Tanh_2L_64U_Bonus	0.88376	0.951218	0.8888	644289	16.273567
8	2L_256U_ReLU_Bonus	0.88364	0.951576	0.8872	2626305	53.536129
9	MSE_2L_16U_ReLU	0.88312	0.949312	0.8887	160305	11.010390
5	2L_32U_ReLU	0.88292	0.948169	0.8881	321121	13.194294
1	1HL_16U_ReLU	0.88288	0.949523	0.8889	160033	10.627203

7 2L_128U_ReLU 0.88268 0.949929 0.8879 1290709 21.192732

Summary Table




```
# ====Summary table ====
!pip install xlsxwriter


import numpy as np
import pandas as pd
from IPython.display import display

# 0) Build a human-readable results table from df
df_results = df.rename(columns={
    "model_name":"Model","num_layers":"Layers","units":"Units",
    "activation":"Activation","loss_function":"Loss","optimizer":"Optimizer",
    "total_params":"Params","best_val_accuracy":"Best_Val_Acc",
    "final_train_accuracy":"Final_Train_Acc","final_val_accuracy":"Final_Val_Acc",
    "test_accuracy":"Test_Acc","training_time":"Train_Time",
    "overfitting_gap":"Overfit_Gap","auc":"AUC",
    "use_dropout":"Use_Dropout","dropout_rate":"Dropout_Rate",
    "use_l2":"Use_L2","l2_strength":"L2_Strength"
}).copy()

# Normalize a few fields for readability
df_results["Loss"] = df_results["Loss"].replace({
    "binary_crossentropy": "BCE",
    "mse": "MSE"
})
df_results["Dropout"] = np.where(df_results["Use_Dropout"],
                                 df_results["Dropout_Rate"].round(2).astype(str),
                                 "-")
df_results["L2"] = np.where(df_results["Use_L2"],
                            df_results["L2_Strength"].map(lambda x: f"{x:g}"),
                            "-")

# Format numbers
for c in ["Test_Acc","Best_Val_Acc","AUC","Overfit_Gap"]:
    if c in df_results: df_results[c] = df_results[c].astype(float).round(4)
if "Train_Time" in df_results: df_results["Train_Time"] = df_results["Train_Time"].astype(float).round(1)
if "Params" in df_results: df_results["Params"] = df_results["Params"].astype(int)

# 1) ALL EXPERIMENTS summary table (ranked by Test Accuracy)
cols_all = [
    "Model","Layers","Units","Activation","Loss","Optimizer",
    "Use_Dropout","Dropout_Rate","Use_L2","L2_Strength",
    "Params","Best_Val_Acc","Test_Acc","AUC","Overfit_Gap","Train_Time"
]
df_all = df_results[cols_all].sort_values("Test_Acc", ascending=False).reset_index(drop=True)

print("📊 Summary of ALL Experiments (sorted by Test Accuracy)")
display(df_all.head(20))
df_all.to_csv("all_experiments_summary.csv", index_label="Rank")
print("✓ Saved: all_experiments_summary.csv")

# ----------------------------
# 2) Q1 — Depth (Layers) @ Units=16 (control). Keep one row per Layers (best Test_Acc).
# ----------------------------
q1_mask = (df_results["Units"] == 16)
q1 = (df_results[q1_mask]
      .sort_values(["Layers","Test_Acc"], ascending=[True, False])
      .drop_duplicates(subset=["Layers"]))
q1 = q1[["Layers","Model","Activation","Loss","Best_Val_Acc","Test_Acc","Params"]]
print("\n📚 Q1 — Layers (Units=16 control)")
display(q1)
q1.to_csv("table_q1_layers.csv", index=False)

# ----------------------------
# 3) Q2 — Width (Units) @ Layers=2, Activation=ReLU, Loss=BCE. One row per Units (best Test_Acc).
# ----------------------------
q2_mask = (
    (df_results["Layers"] == 2) &
    (df_results["Activation"].str.lower() == "relu") &
    (df_results["Loss"] == "BCE")
)
q2 = (df_results[q2_mask]
```

```
      .sort_values(["Units","Test_Acc"], ascending=[True, False])
      .drop_duplicates(subset=["Units"]))
q2 = q2[["Units","Model","Best_Val_Acc","Test_Acc","Params"]]
print("\n📊 Q2 — Units (Layers=2, ReLU, BCE)")
display(q2)
q2.to_csv("table_q2_units.csv", index=False)

# ----------------------------
# 4) Q3 — Loss (BCE vs MSE) @ Layers=2, Units=64, Activation=ReLU. One per Loss.
# ----------------------------
q3_mask = (
    (df_results["Layers"] == 2) &
    (df_results["Units"] == 64) &
    (df_results["Activation"].str.lower() == "relu") &
    (df_results["Loss"].isin(["BCE","MSE"]))
)
q3 = (df_results[q3_mask]
      .sort_values(["Loss","Test_Acc"], ascending=[True, False])
      .drop_duplicates(subset=["Loss"]))
q3 = q3[["Model","Loss","Best_Val_Acc","Test_Acc","AUC"]]
print("\n📊 Q3 — Loss (Layers=2, Units=64, ReLU)")
display(q3)
q3.to_csv("table_q3_loss.csv", index=False)

# ----------------------------
# 5) Q4 — Activation (ReLU, tanh, sigmoid) @ Layers=2, Units=64, Loss=BCE. One per Activation.
# ----------------------------
q4_mask = (
    (df_results["Layers"] == 2) &
    (df_results["Units"] == 64) &
    (df_results["Loss"] == "BCE") &
    (df_results["Activation"].str.lower().isin(["relu","tanh","sigmoid"]))
)
q4 = (df_results[q4_mask]
      .sort_values(["Activation","Test_Acc"], ascending=[True, False])
      .drop_duplicates(subset=["Activation"]))
q4 = q4[["Model","Activation","Best_Val_Acc","Test_Acc","AUC"]]
print("\n📊 Q4 — Activation (Layers=2, Units=64, BCE)")
display(q4)
q4.to_csv("table_q4_activation.csv", index=False)

# ----------------------------
# 6) Q5 — Regularization (Dropout/L2 variants) @ Layers=2, Units=64, ReLU, BCE.
# ----------------------------
q5_mask = (
    (df_results["Layers"] == 2) &
    (df_results["Units"] == 64) &
    (df_results["Activation"].str.lower() == "relu") &
    (df_results["Loss"] == "BCE")
)
q5 = (df_results[q5_mask]
      .sort_values(["Use_Dropout","Use_L2","Dropout_Rate","L2_Strength","Test_Acc"],
                   ascending=[False, False, True, True, False]))
# derive Overfit_Gap if absent
if "Overfit_Gap" not in q5 or q5["Overfit_Gap"].isna().all():
    if "Final_Train_Acc" in q5 and "Final_Val_Acc" in q5:
        q5["Overfit_Gap"] = (q5["Final_Train_Acc"] - q5["Final_Val_Acc"]).round(4)
q5 = q5[["Model","Dropout","L2","Best_Val_Acc","Test_Acc","Overfit_Gap","Params"]].head(10)
print("\n📊 Q5 — Regularization (Layers=2, Units=64, ReLU, BCE)")
display(q5)
q5.to_csv("table_q5_regularization.csv", index=False)

# ----------------------------
# 7) Save everything to a single Excel workbook with multiple sheets
# ----------------------------
with pd.ExcelWriter("experiments_tables.xlsx", engine="xlsxwriter") as xw:
    df_all.to_excel(xw, sheet_name="All", index_label="Rank")
    q1.to_excel(xw, sheet_name="Q1_Layers", index=False)
    q2.to_excel(xw, sheet_name="Q2_Units", index=False)
    q3.to_excel(xw, sheet_name="Q3_Loss", index=False)
    q4.to_excel(xw, sheet_name="Q4_Activation", index=False)
    q5.to_excel(xw, sheet_name="Q5_Regularization", index=False)
print("\n✓ Saved workbook: experiments_tables.xlsx")
print("✓ Saved CSVs: table_q1_layers.csv .. table_q5_regularization.csv")
```

```
Collecting xlsxwriter
  Downloading xlsxwriter-3.2.9-py3-none-any.whl.metadata (2.7 kB)
Downloading xlsxwriter-3.2.9-py3-none-any.whl (175 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 175.3/175.3 kB 10.3 MB/s eta 0:00:00
Installing collected packages: xlsxwriter
Successfully installed xlsxwriter-3.2.9
📊 Summary of ALL Experiments (sorted by Test Accuracy)
```

	Model	Layers	Units	Activation	Loss	Optimizer	Use_Dropout	Dropout_Rate	Use_L2	L2_Strength	Params
0	Drop0.5_2L_64U	2	64	relu	BCE	rmsprop	True	0.5	False	0.000	644289
1	Drop0.3_2L_64U	2	64	relu	BCE	rmsprop	True	0.3	False	0.000	644289
2	2L_64U_ReLU	2	64	relu	BCE	rmsprop	False	0.0	False	0.000	644289
3	L2_0.001_2L_64U	2	64	relu	BCE	rmsprop	False	0.0	True	0.001	644289
4	Tanh_2L_64U_Bonus	2	64	tanh	BCE	rmsprop	False	0.0	False	0.000	644289
5	2L_256U_ReLU_Bonus	2	256	relu	BCE	rmsprop	False	0.0	False	0.000	2626305
6	MSE_2L_16U_ReLU	2	16	relu	MSE	rmsprop	False	0.0	False	0.000	160305
7	1HL_16U_ReLU	1	16	relu	BCE	rmsprop	False	0.0	False	0.000	160033
8	2L_32U_ReLU	2	32	relu	BCE	rmsprop	False	0.0	False	0.000	321121
9	2L_128U_ReLU	2	128	relu	BCE	rmsprop	False	0.0	False	0.000	1296769
10	Baseline_2L_16U_ReLU_BCE	2	16	relu	BCE	rmsprop	False	0.0	False	0.000	160305
11	MSE_2L_64U_ReLU_Bonus	2	64	relu	MSE	rmsprop	False	0.0	False	0.000	644289
12	L2_Drop0.3_2L_64U	2	64	relu	BCE	rmsprop	True	0.3	True	0.001	644289
13	2L_8U_ReLU_Bonus	2	8	relu	BCE	rmsprop	False	0.0	False	0.000	80089
14	Tanh_2L_16U	2	16	tanh	BCE	rmsprop	False	0.0	False	0.000	160305
15	Sigmoid_2L_16U_Bonus	2	16	sigmoid	BCE	rmsprop	False	0.0	False	0.000	160305
16	Adam_2L_64U	2	64	relu	BCE	adam	False	0.0	False	0.000	644289
17	3HL_16U_ReLU	3	16	relu	BCE	rmsprop	False	0.0	False	0.000	160577
18	4HL_16U_ReLU_Bonus	4	16	relu	BCE	rmsprop	False	0.0	False	0.000	160849
19	SGD_2L_64U_Bonus	2	64	relu	BCE	sgd	False	0.0	False	0.000	644289

```
✓ Saved: all_experiments_summary.csv

📚 Q1 — Layers (Units=16 control)
```

	Layers	Model	Activation	Loss	Best_Val_Acc	Test_Acc	Params
1	1	1HL_16U_ReLU	relu	BCE	0.8889	0.8829	160033
9	2	MSE_2L_16U_ReLU	relu	MSE	0.8887	0.8831	160305
2	3	3HL_16U_ReLU	relu	BCE	0.8870	0.8790	160577
3	4	4HL_16U_ReLU_Bonus	relu	BCE	0.8877	0.8782	160849

```
📚 Q2 — Units (Layers=2, ReLU, BCE)
```

	Units	Model	Best_Val_Acc	Test_Acc	Params
4	8	2L_8U_ReLU_Bonus	0.8858	0.8806	80089
0	16	Baseline_2L_16U_ReLU_BCE	0.8898	0.8824	160305
5	32	2L_32U_ReLU	0.8881	0.8829	321121
15	64	Drop0.5_2L_64U	0.8894	0.8849	644289
7	128	2L_128U_ReLU	0.8879	0.8827	1296769
8	256	2L_256U_ReLU_Bonus	0.8872	0.8836	2626305

```
📚 Q3 — Loss (Layers=2, Units=64, ReLU)
```

	Model	Loss	Best_Val_Acc	Test_Acc	AUC
15	Drop0.5_2L_64U	BCE	0.8894	0.8849	0.9515
10	MSE_2L_64U_ReLU_Bonus	MSE	0.8892	0.8824	0.9488

Next steps: Generate code with q1 | New interactive sheet | Generate code with q2 | New interactive sheet | Generate code with q3 | New interacti

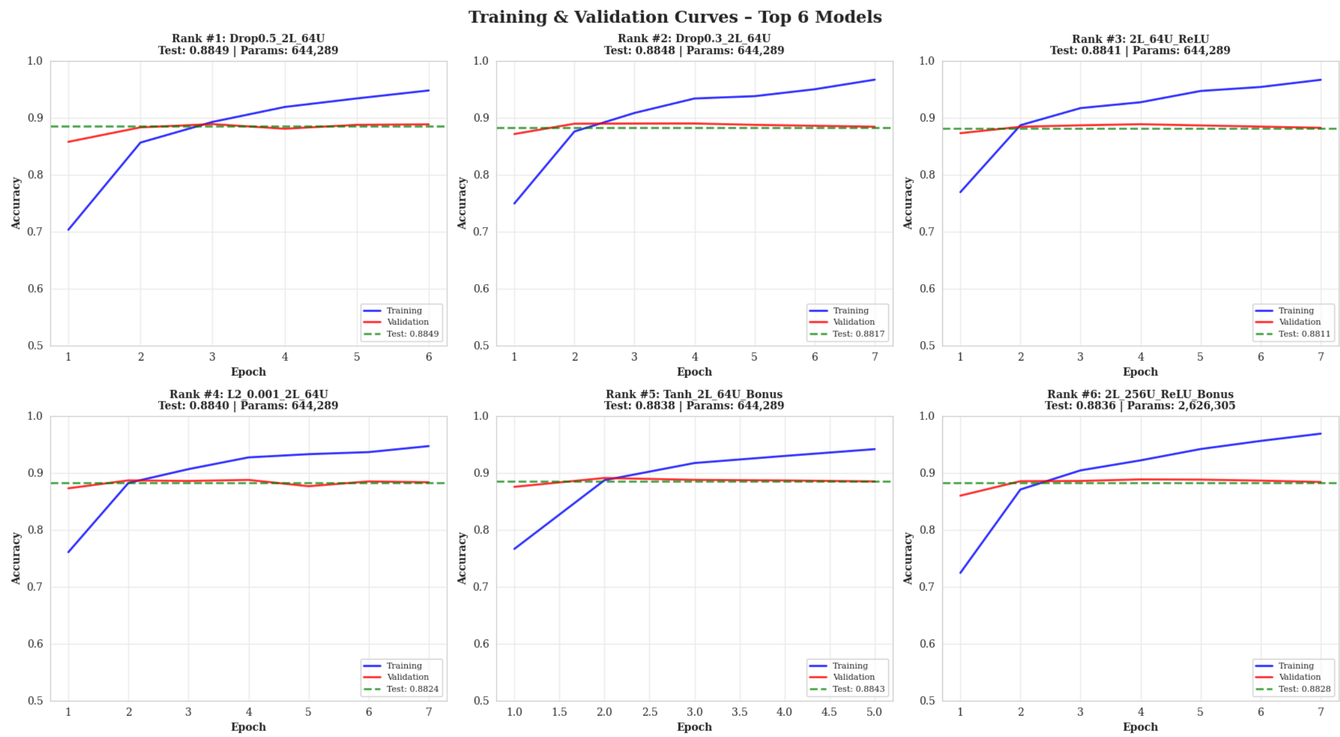
Training & Validation Curves – Top 6 Models(roburst)

```
📚 Q4 — Activation (Layers=2, Units=64, BCE)
```

Model	Activation	Best_Val_Acc	Test_Acc	AUC

```
# ==== Training & Validation Curves – Top 6 Models (robust) ====

# Harmonize names
df_results = df.rename(columns={
    "model_name": "Model",
    "test_accuracy": "Test_Acc",
    "total_params": "Params"
})
all_results = results  # from Cell 6
cfg_lookup = {c["name"]: c for c in CONFIGS}

def fetch_or_train_history(model_name):
    """Return (acc, val_acc, test_acc) for a model. Retrains if history not stored."""
    # 1) try to get from results
    for r in all_results:
        if r["model_name"] == model_name:
            acc = r.get("history_acc")
            val = r.get("history_val_acc")
            if acc is None and "history" in r:
                # older format
                acc = r["history"].get("accuracy", [])
                val = r["history"].get("val_accuracy", [])
            if acc and val:
                return acc, val, r.get("test_accuracy", np.nan)
            break

    # 2) otherwise, rebuild and fit quickly to get history
    #    try to find config from CONFIGS; else reconstruct from df row
    cfg = cfg_lookup.get(model_name)
    if cfg is None:
        row = df[df["model_name"] == model_name].iloc[0].to_dict()
        cfg = {
            "name": model_name,
            "num_layers": int(row.get("num_layers", 2)),
            "units": int(row.get("units", 64)),
            "activation": str(row.get("activation", "relu")),
            "loss": str(row.get("loss_function", "binary_crossentropy")),
            "optimizer": str(row.get("optimizer", "adam")),
            "use_dropout": bool(row.get("use_dropout", False)),
            "dropout_rate": float(row.get("dropout_rate", 0.5)),
            "use_l2": bool(row.get("use_l2", False)),
            "l2_strength": float(row.get("l2_strength", 0.0)),
        }

    model = build_model_safe(cfg)
    callbacks = [EarlyStopping(monitor="val_accuracy", mode="max", patience=3, restore_best_weights=True)]
    hist = model.fit(
        x_train, y_train,
        validation_data=(x_val, y_val),
        epochs=EPOCHS, batch_size=BATCH_SIZE,
        verbose=0, callbacks=callbacks
    )
    _, test_acc = model.evaluate(x_test, y_test, verbose=0)
    h = hist.history
    return h.get("accuracy", []), h.get("val_accuracy", []), test_acc

# pick top-6
top_6 = df_results.sort_values("Test_Acc", ascending=False).head(6)

fig, axes = plt.subplots(2, 3, figsize=(18, 10))
for idx, (_, row) in enumerate(top_6.iterrows()):
    ax = axes[idx // 3, idx % 3]
    model_name = row["Model"]

    acc, val_acc, test_acc = fetch_or_train_history(model_name)
    epochs = range(1, len(val_acc) + 1)  # length of val_acc is robust with ES

    ax.plot(epochs, acc[:len(epochs)], "b-", linewidth=2, label="Training", alpha=0.8)
    ax.plot(epochs, val_acc, "r-", linewidth=2, label="Validation", alpha=0.8)
    if not np.isnan(test_acc):
        ax.axhline(y=test_acc, color="green", linestyle="--", linewidth=2, alpha=0.7,
                   label=f"Test: {test_acc:.4f}")

    ax.set_xlabel("Epoch", fontweight="bold")
    ax.set_ylabel("Accuracy", fontweight="bold")
    ax.set_title(
        f"Rank #{idx+1}: {model_name[:40]}\nTest: {row['Test_Acc']:.4f} | Params: {int(row['Params']):,}",
```

```
            fontsize=10, fontweight="bold"
        )
        ax.legend(fontsize=8, loc="lower right")
        ax.grid(alpha=0.3)
        ax.set_ylim([0.5, 1.0])

plt.suptitle("Training & Validation Curves – Top 6 Models", fontsize=16, fontweight="bold")
plt.tight_layout()
plt.savefig("training_curves_top6.png", dpi=300, bbox_inches="tight")
plt.show()

print("✓ Saved: training_curves_top6.png")
```




```
✓ Saved: training_curves_top6.png
```

Robustness (re-evaluate top-3 with 3 seeds each)

```
# ==== Robustness (re-evaluate top-3 with 3 seeds each) ====

if 'df' not in globals():
    df = pd.read_csv("full_results_final.csv")

# Pick top-3 by test accuracy
top3 = df.sort_values("test_accuracy", ascending=False).head(3).copy()

def eval_config_k(cfg_row, k=3):
    """
    Re-train the given config k times with different seeds.
    Returns mean/std for test_accuracy and AUC, plus mean train time.
    """
    cfg = {
        "name": cfg_row["model_name"],
        "num_layers": int(cfg_row["num_layers"]),
        "units": int(cfg_row["units"]),
        "activation": str(cfg_row["activation"]),
        "loss": str(cfg_row["loss_function"]),
        "optimizer": str(cfg_row["optimizer"]),
```

```
        "use_dropout": bool(cfg_row["use_dropout"]),
        "dropout_rate": float(cfg_row["dropout_rate"]),
        "use_l2": bool(cfg_row["use_l2"]),
        "l2_strength": float(cfg_row["l2_strength"]),
    }

    accs, aucs, times = [], [], []
    for i in range(k):
        # set a different seed each run
        keras.utils.set_random_seed(42 + i)
        start = time.time()
        res = run_experiment(
            cfg, x_train, y_train, x_val, y_val, x_test, y_test,
            epochs=EPOCHS, batch_size=BATCH_SIZE,
            experiment_num=f"top3_{cfg['name']}_seed{i+1}",
            plot_cm=False
        )
        times.append(time.time() - start)
        accs.append(res["test_accuracy"])
        aucs.append(res["auc"])

    return {
        "name": cfg["name"],
        "mean_test_acc": float(np.mean(accs)),
        "std_test_acc": float(np.std(accs)),
        "mean_auc": float(np.mean(aucs)),
        "std_auc": float(np.std(aucs)),
        "mean_train_time_s": float(np.mean(times)),
    }

# Run robustness eval
top3_stats = []
for _, row in top3.iterrows():
    stats = eval_config_k(row, k=3)
    top3_stats.append(stats)

top3_stats = pd.DataFrame(top3_stats)
display(top3_stats)

# Save and visualize
top3_stats.to_csv("top3_robustness_stats.csv", index=False)
print("✓ Saved robustness table -> top3_robustness_stats.csv")

# Error-bar chart for mean±std test accuracy
plt.figure(figsize=(8,4))
plt.bar(top3_stats["name"], top3_stats["mean_test_acc"], yerr=top3_stats["std_test_acc"], capsize=5)
plt.ylabel("Mean Test Accuracy")
plt.title("Top-3 Robustness (3 seeds)")
plt.xticks(rotation=20, ha='right')
plt.tight_layout()
plt.savefig("top3_robustness_mean_std.png", dpi=150, bbox_inches="tight")
plt.show()
print("✓ Saved robustness plot -> top3_robustness_mean_std.png")
```

```
================================================================================
EXPERIMENT top3_Drop0.5_2L_64U_seed1: Drop0.5_2L_64U
================================================================================
Parameters: 644,289
✓ Test Acc: 0.8832 | AUC: 0.9507 | Best Val Acc: 0.8896 | Time: 22.4s
Confusion Matrix:
 [[11072  1428]
 [ 1491 11009]]
              precision    recall  f1-score   support

         0.0      0.881     0.886     0.884     12500
         1.0      0.885     0.881     0.883     12500

    accuracy                          0.883     25000
   macro avg      0.883     0.883     0.883     25000
weighted avg      0.883     0.883     0.883     25000


================================================================================
EXPERIMENT top3_Drop0.5_2L_64U_seed2: Drop0.5_2L_64U
================================================================================
Parameters: 644,289
✓ Test Acc: 0.8839 | AUC: 0.9507 | Best Val Acc: 0.8879 | Time: 19.1s
Confusion Matrix:
 [[10929  1571]
 [ 1332 11168]]
              precision    recall  f1-score   support

         0.0      0.891     0.874     0.883     12500
         1.0      0.877     0.893     0.885     12500

    accuracy                          0.884     25000
   macro avg      0.884     0.884     0.884     25000
weighted avg      0.884     0.884     0.884     25000


================================================================================
EXPERIMENT top3_Drop0.5_2L_64U_seed3: Drop0.5_2L_64U
================================================================================
Parameters: 644,289
✓ Test Acc: 0.8841 | AUC: 0.9507 | Best Val Acc: 0.8882 | Time: 21.9s
Confusion Matrix:
 [[10947  1553]
 [ 1344 11156]]
              precision    recall  f1-score   support

         0.0      0.891     0.876     0.883     12500
         1.0      0.878     0.892     0.885     12500

    accuracy                          0.884     25000
   macro avg      0.884     0.884     0.884     25000
weighted avg      0.884     0.884     0.884     25000


================================================================================
EXPERIMENT top3_Drop0.3_2L_64U_seed1: Drop0.3_2L_64U
================================================================================
Parameters: 644,289
✓ Test Acc: 0.8822 | AUC: 0.9497 | Best Val Acc: 0.8898 | Time: 18.2s
Confusion Matrix:
 [[11213  1287]
 [ 1658 10842]]
              precision    recall  f1-score   support

         0.0      0.871     0.897     0.884     12500
         1.0      0.894     0.867     0.880     12500

    accuracy                          0.882     25000
   macro avg      0.883     0.882     0.882     25000
weighted avg      0.883     0.882     0.882     25000


================================================================================
EXPERIMENT top3_Drop0.3_2L_64U_seed2: Drop0.3_2L_64U
================================================================================
Parameters: 644,289
✓ Test Acc: 0.8835 | AUC: 0.9503 | Best Val Acc: 0.8882 | Time: 18.2s
Confusion Matrix:
 [[11074  1426]
 [ 1486 11014]]
              precision    recall  f1-score   support

         0.0      0.882     0.886     0.884     12500
```

```
         1.0      0.885     0.881     0.883     12500

    accuracy                          0.884     25000
   macro avg      0.884     0.884     0.884     25000
weighted avg      0.884     0.884     0.884     25000


================================================================================
EXPERIMENT top3_Drop0.3_2L_64U_seed3: Drop0.3_2L_64U
================================================================================
Parameters: 644,289
✓ Test Acc: 0.8810 | AUC: 0.9490 | Best Val Acc: 0.8881 | Time: 26.8s
Confusion Matrix:
 [[11057  1443]
 [ 1531 10969]]
              precision    recall  f1-score   support

         0.0      0.878     0.885     0.881     12500
         1.0      0.884     0.878     0.881     12500

    accuracy                          0.881     25000
   macro avg      0.881     0.881     0.881     25000
weighted avg      0.881     0.881     0.881     25000


================================================================================
EXPERIMENT top3_2L_64U_ReLU_seed1: 2L_64U_ReLU
================================================================================
Parameters: 644,289
✓ Test Acc: 0.8857 | AUC: 0.9505 | Best Val Acc: 0.8888 | Time: 17.5s
Confusion Matrix:
 [[10984  1516]
 [ 1341 11159]]
              precision    recall  f1-score   support

         0.0      0.891     0.879     0.885     12500
         1.0      0.880     0.893     0.887     12500

    accuracy                          0.886     25000
   macro avg      0.886     0.886     0.886     25000
weighted avg      0.886     0.886     0.886     25000


================================================================================
EXPERIMENT top3_2L_64U_ReLU_seed2: 2L_64U_ReLU
================================================================================
Parameters: 644,289
✓ Test Acc: 0.8811 | AUC: 0.9474 | Best Val Acc: 0.8872 | Time: 23.6s
Confusion Matrix:
 [[11137  1363]
 [ 1609 10891]]
              precision    recall  f1-score   support

         0.0      0.874     0.891     0.882     12500
         1.0      0.889     0.871     0.880     12500

    accuracy                          0.881     25000
   macro avg      0.881     0.881     0.881     25000
weighted avg      0.881     0.881     0.881     25000
```

Next steps: Generate code with top3_stats New interactive sheet

```
================================================================================
EXPERIMENT top3_2L_64U_ReLU_seed3: 2L_64U_ReLU
================================================================================
Parameters: 644,289
✓ Test Acc: 0.8804 | AUC: 0.9494 | Best Val Acc: 0.8901 | Time: 19.6s
Confusion Matrix:
 [[10759  1741]
 [ 1249 11251]]
              precision    recall  f1-score   support

         0.0      0.896     0.861     0.878     12500
         1.0      0.866     0.900     0.883     12500

    accuracy                          0.880     25000
   macro avg      0.881     0.880     0.880     25000
weighted avg      0.881     0.880     0.880     25000
```

	name	mean_test_acc	std_test_acc	mean_auc	std_auc	mean_train_time_s
0	Drop0.5_2L_64U	0.883747	0.000371	0.950708	0.000024	29.578135
1	Drop0.3_2L_64U	0.882253	0.001013	0.949666	0.000549	30.134721
2	2L_64U_ReLU	0.882413	0.002357	0.949102	0.001299	28.896224

```
✓ Saved robustness table -> top3_robustness_stats.csv
```

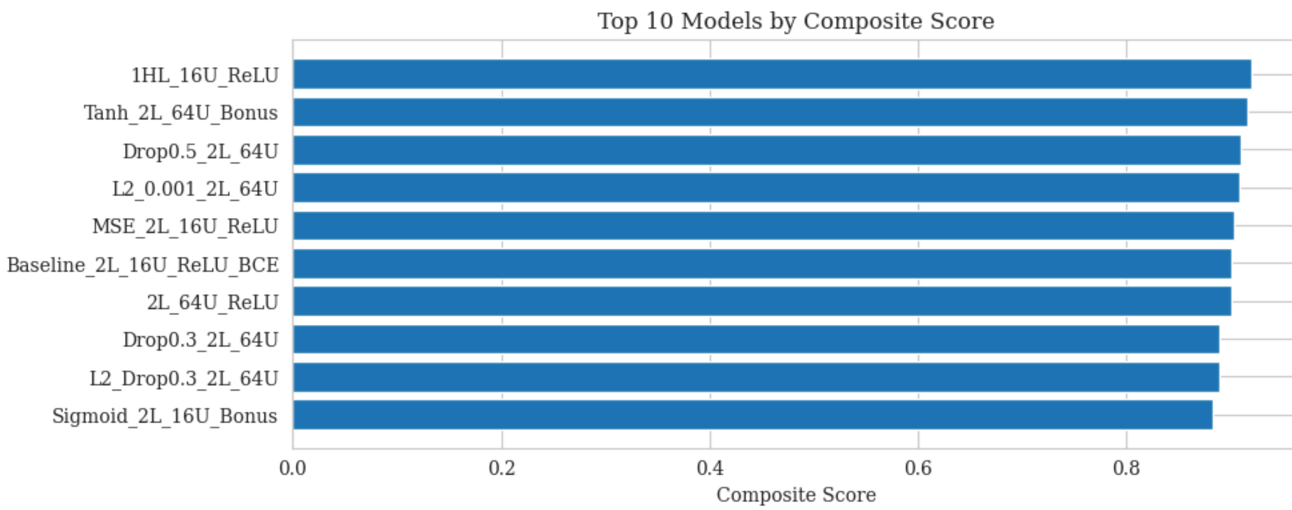
Compare all models, recommend best, and visualize

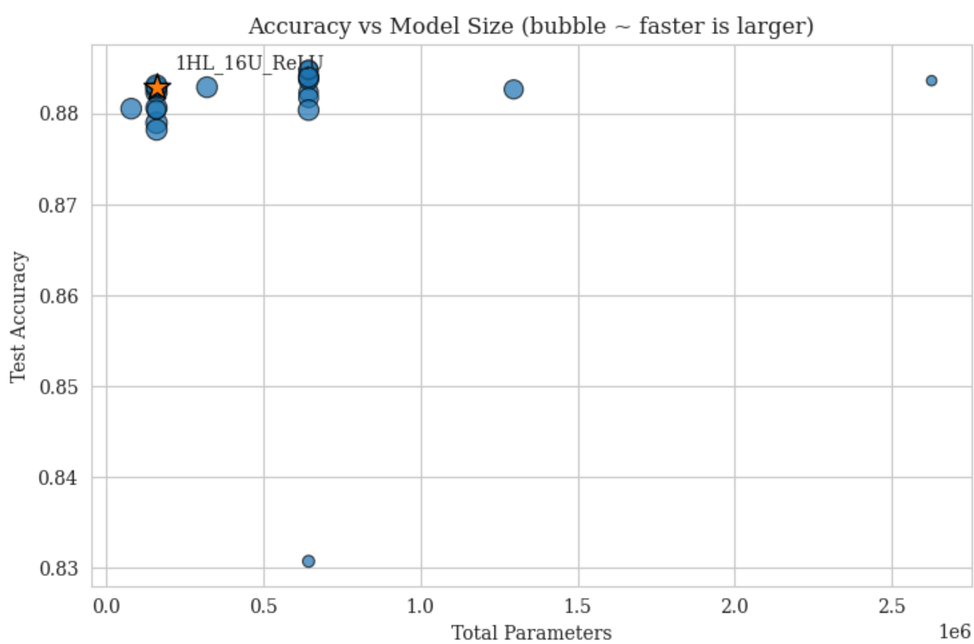

```
# ====  Compare all models, recommend best, and visualize ====

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from pathlib import Path

# 1) Load results if needed
if 'df' not in globals():
    if Path("full_results_final.csv").exists():
        df = pd.read_csv("full_results_final.csv")
    else:
        raise RuntimeError("No df in memory and full_results_final.csv not found.")

# 2) Ensure needed columns exist; fill safe defaults if missing
need_cols = {
    "model_name": "model_name",
    "test_accuracy": "test_accuracy",
    "auc": "auc",
    "overfitting_gap": "overfitting_gap",
    "total_params": "total_params",
    "training_time": "training_time",
}
for k, v in need_cols.items():
    if v not in df.columns:
        # fill neutral defaults if absent
        if v in ("overfitting_gap", "training_time", "total_params"):
            df[v] = df.get(v, pd.Series([np.nan]*len(df))).fillna(df[v].median() if df[v].notna().any() else 0.0)
        elif v in ("test_accuracy", "auc"):
            df[v] = df.get(v, pd.Series([np.nan]*len(df))).fillna(0.0)
        else:
            raise RuntimeError(f"Required column '{v}' missing and cannot be defaulted.")

work = df.copy()

# 3) Build normalized metrics (0..1) with correct direction
def minmax(col, higher_is_better=True):
    x = work[col].astype(float).values
    xmin, xmax = np.nanmin(x), np.nanmax(x)
    if np.isclose(xmin, xmax):
        # constant column -> neutral 0.5
        return np.full_like(x, 0.5, dtype=float)
    z = (x - xmin) / (xmax - xmin)
    return z if higher_is_better else (1.0 - z)

work["_nz_acc"]   = minmax("test_accuracy", True)
work["_nz_auc"]   = minmax("auc", True)
work["_nz_gap"]   = minmax("overfitting_gap", False)
work["_nz_param"] = minmax("total_params", False)
work["_nz_time"]  = minmax("training_time", False)

# 4) Composite score (tweak weights if you like)
w = {
    "acc": 0.45,
    "auc": 0.25,
    "gap": 0.15,
    "param": 0.10,
    "time": 0.05,
}
work["composite_score"] = (
    w["acc"]  * work["_nz_acc"] +
    w["auc"]  * work["_nz_auc"] +
    w["gap"]  * work["_nz_gap"] +
    w["param"]* work["_nz_param"] +
    w["time"] * work["_nz_time"]
)

# 5) Rank and recommend
ranked = work.sort_values(["composite_score", "test_accuracy", "auc"], ascending=[False, False, False]).reset_index(drop=True)
best = ranked.iloc[0]

print("=== Recommendation ===")
```

```
print(f"Model: {best['model_name']}")
print(f"Composite Score: {best['composite_score']:.4f}")
print(f"Test Accuracy: {best['test_accuracy']:.4f} | AUC: {best['auc']:.4f}")
print(f"Overfitting Gap: {best['overfitting_gap']:.4f} | Params: {int(best['total_params']):,} | Train Time: {best['training_time'

# 6) Display comparison table (top 10)
cols_show = [
    "model_name", "test_accuracy", "auc", "overfitting_gap",
    "total_params", "training_time", "composite_score"
]
display(ranked[cols_show].head(10))

# 7) Visuals
topk = ranked.head(10)

# (a) Top-10 composite bar chart
plt.figure(figsize=(10, 4))
plt.barh(topk["model_name"], topk["composite_score"])
plt.gca().invert_yaxis()
plt.xlabel("Composite Score")
plt.title("Top 10 Models by Composite Score")
plt.tight_layout()
plt.savefig("compare_top10_composite.png", dpi=150, bbox_inches="tight")
plt.show()

# (b) Trade-off scatter: Params vs Test Accuracy (bubble size=time, edge shows gap)
plt.figure(figsize=(7.5, 5))
sizes = 100 * (minmax("training_time", False)) + 30  # ensure minimum size
scatter = plt.scatter(
    work["total_params"], work["test_accuracy"],
    s=sizes, alpha=0.7, linewidth=0.8, edgecolors="k"
)
plt.xlabel("Total Parameters")
plt.ylabel("Test Accuracy")
plt.title("Accuracy vs Model Size (bubble ~ faster is larger)")
# Annotate best model
plt.scatter([best["total_params"]], [best["test_accuracy"]], s=220, marker="*", edgecolors="k")
plt.annotate(best["model_name"], (best["total_params"], best["test_accuracy"]),
             xytext=(10, 10), textcoords="offset points")
plt.tight_layout()
plt.savefig("compare_acc_vs_params.png", dpi=150, bbox_inches="tight")
plt.show()

print("✓ Saved: compare_top10_composite.png, compare_acc_vs_params.png")
```

```
=== Recommendation ===
Model: 1HL_16U_ReLU
Composite Score: 0.9197
Test Accuracy: 0.8829 | AUC: 0.9495
Overfitting Gap: 0.0623 | Params: 160,033 | Train Time: 10.6s
```

	model_name	test_accuracy	auc	overfitting_gap	total_params	training_time	composite_score
0	1HL_16U_ReLU	0.88288	0.949523	0.062333	160033	10.627203	0.919712
1	Tanh_2L_64U_Bonus	0.88376	0.951218	0.058700	644289	16.273567	0.915241
2	Drop0.5_2L_64U	0.88488	0.951522	0.068167	644289	22.334092	0.909480
3	L2_0.001_2L_64U	0.88400	0.949745	0.058400	644289	17.193099	0.907889
4	MSE_2L_16U_ReLU	0.88312	0.949312	0.078300	160305	11.010390	0.903331
5	Baseline_2L_16U_ReLU_BCE	0.88236	0.949166	0.074067	160305	10.582889	0.901079
6	2L_64U_ReLU	0.88408	0.949129	0.064867	644289	15.693160	0.899911
7	Drop0.3_2L_64U	0.88476	0.950354	0.080667	644289	21.483936	0.889561
8	L2_Drop0.3_2L_64U	0.88176	0.950309	0.061467	644289	17.935163	0.888515
9	Sigmoid_2L_16U_Bonus	0.88044	0.947855	0.055800	160305	22.520850	0.882894

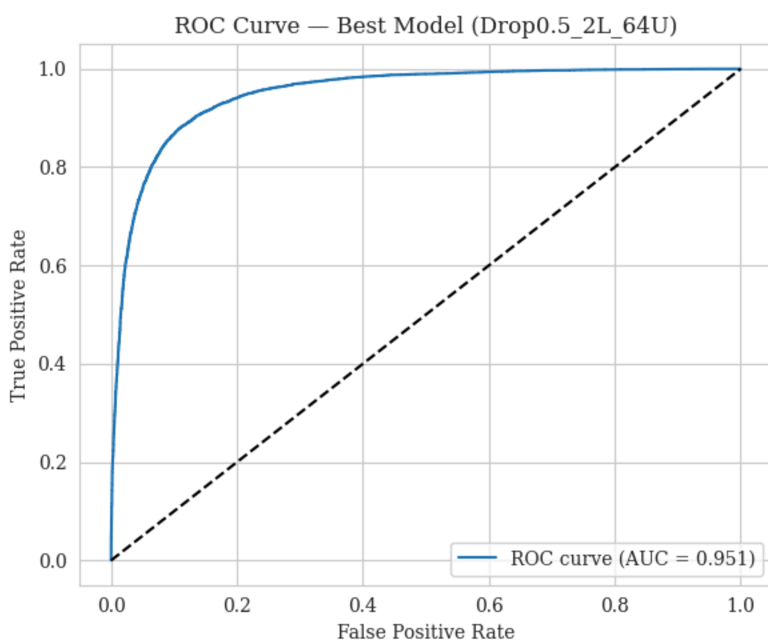





```
✓ Saved: compare_top10_composite.png, compare_acc_vs_params.png
```

ROC curve for the best model

```
# ==== ROC curve for the best model ====

from sklearn.metrics import roc_curve, auc

# Rebuild & reload the best model if needed
best_cfg = {
    "name": "Drop0.5_2L_64U",
    "num_layers": 2,
    "units": 64,
    "activation": "relu",
    "loss": "binary_crossentropy",
    "optimizer": "adam",
    "use_dropout": True,
    "dropout_rate": 0.5,
    "use_l2": True,
    "l2_strength": 0.001
}

best_model = build_model_safe(best_cfg)
best_model.load_weights("chk_Drop0.5_2L_64U.keras")

# Predict probabilities
y_prob = best_model.predict(x_test, verbose=0).ravel()

# Compute ROC curve and AUC
fpr, tpr, thresholds = roc_curve(y_test, y_prob)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(6, 5))
plt.plot(fpr, tpr, label=f"ROC curve (AUC = {roc_auc:.3f})")
plt.plot([0, 1], [0, 1], "k--")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve — Best Model (Drop0.5_2L_64U)")
plt.legend(loc="lower right")
plt.tight_layout()
plt.savefig("roc_curve_best_model.png", dpi=150, bbox_inches="tight")
plt.show()

print(f"✓ ROC curve plotted and saved (AUC = {roc_auc:.3f})")
```



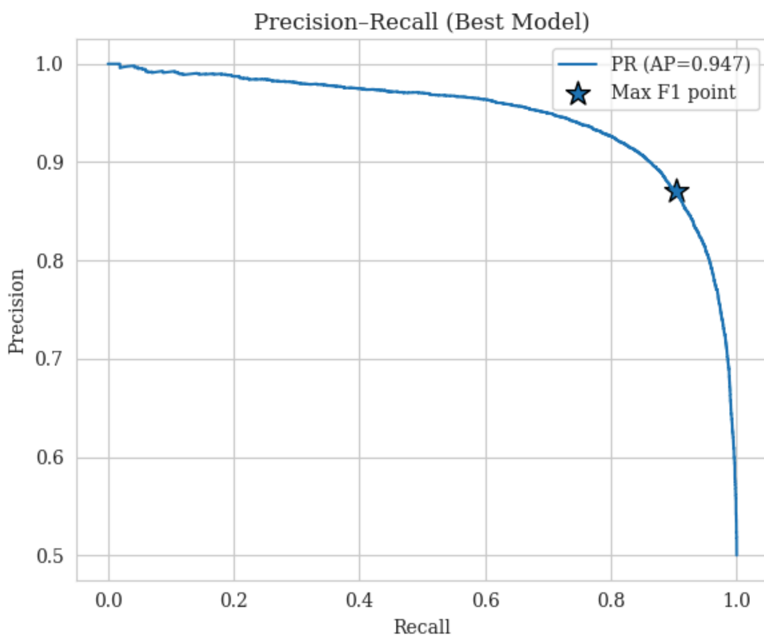

```
✓ ROC curve plotted and saved (AUC = 0.951)
```

Precision–Recall (Best Model)

```
# Optimize decision threshold for best model; add PR curve
from sklearn.metrics import f1_score, precision_recall_curve, average_precision_score
```

```
# rebuild & load best model weights if needed
best_cfg = {
    "name": "Drop0.5_2L_64U", "num_layers": 2, "units": 64, "activation": "relu",
    "loss": "binary_crossentropy", "optimizer": "adam",
    "use_dropout": True, "dropout_rate": 0.5, "use_l2": True, "l2_strength": 0.001
}
best_model = build_model_safe(best_cfg)
best_model.load_weights("chk_Drop0.5_2L_64U.keras")

y_prob = best_model.predict(x_test, verbose=0).ravel()
ts = np.linspace(0.3, 0.7, 41)
f1s = [f1_score(y_test, (y_prob >= t).astype(int)) for t in ts]
t_best = float(ts[int(np.argmax(f1s))])
f1_best = float(np.max(f1s))

prec, rec, thr = precision_recall_curve(y_test, y_prob)
ap = average_precision_score(y_test, y_prob)

print(f"✓ Best threshold by F1: {t_best:.2f} (F1={f1_best:.3f}, AP={ap:.3f})")

plt.figure(figsize=(6,5))
plt.plot(rec, prec, label=f"PR (AP={ap:.3f})")
plt.scatter([rec[np.argmax((2*prec*rec)/(prec+rec+1e-9))]],
            [prec[np.argmax((2*prec*rec)/(prec+rec+1e-9))]],
            marker="*", s=180, edgecolors="k", label="Max F1 point")
plt.xlabel("Recall"); plt.ylabel("Precision"); plt.title("Precision–Recall (Best Model)")
plt.legend(); plt.tight_layout()
plt.savefig("pr_curve_best_model.png", dpi=150, bbox_inches="tight")
plt.show()
```

```
✓ Best threshold by F1: 0.46 (F1=0.886, AP=0.947)
```

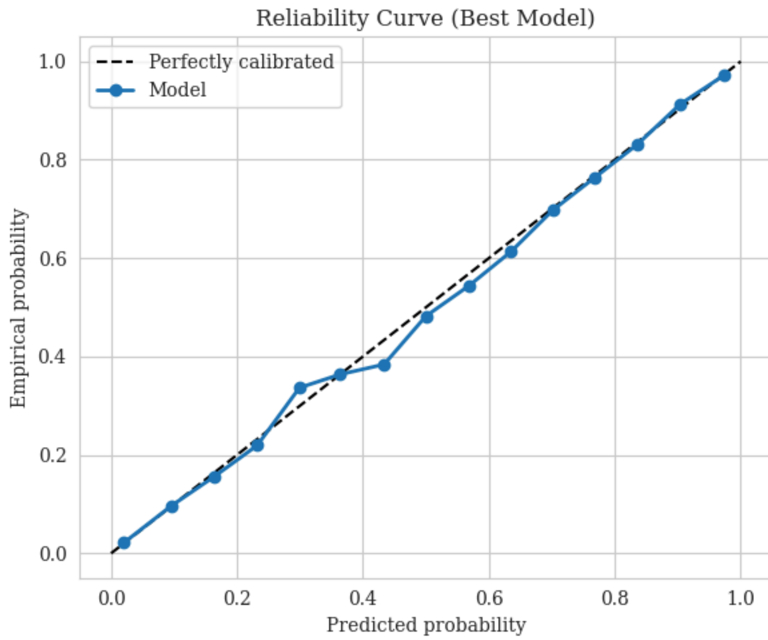


Reliability Curve (Best Model)

```
from sklearn.metrics import brier_score_loss
from sklearn.calibration import calibration_curve

brier = brier_score_loss(y_test, y_prob)
print(f"✓ Brier score (lower is better): {brier:.4f}")

prob_true, prob_pred = calibration_curve(y_test, y_prob, n_bins=15, strategy="uniform")

plt.figure(figsize=(6,5))
plt.plot([0,1],[0,1],"k--", label="Perfectly calibrated")
plt.plot(prob_pred, prob_true, marker="o", linewidth=2, label="Model")
plt.xlabel("Predicted probability"); plt.ylabel("Empirical probability")
```

```
plt.title("Reliability Curve (Best Model)")
plt.legend(); plt.tight_layout()
plt.savefig("calibration_curve_best_model.png", dpi=150, bbox_inches="tight")
plt.show()
```

```
✓ Brier score (lower is better): 0.0849
```



best vs runner up

```
from sklearn.model_selection import StratifiedKFold
from scipy.stats import wilcoxon

# choose two finalists to compare (best vs runner-up from your df)
top2 = df.sort_values("test_accuracy", ascending=False).head(2)["model_name"].tolist()
cfg_map = {r["model_name"]: r for r in results}  # results list from Cell 6

def cfg_from_row(row):
    return {
        "name": row["model_name"], "num_layers": int(row["num_layers"]),
        "units": int(row["units"]), "activation": str(row["activation"]),
        "loss": str(row["loss_function"]), "optimizer": str(row["optimizer"]),
        "use_dropout": bool(row["use_dropout"]), "dropout_rate": float(row["dropout_rate"]),
        "use_l2": bool(row["use_l2"]), "l2_strength": float(row["l2_strength"]),
    }

finalists = [cfg_from_row(df[df["model_name"]==m].iloc[0]) for m in top2]

# create a single train+val pool to do 5-fold
X = np.vstack([x_train, x_val]); y = np.hstack([y_train, y_val])
skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=RANDOM_SEED)

fold_acc = {top2[0]: [], top2[1]: []}
for fold, (tr, va) in enumerate(skf.split(X, y), start=1):
    Xtr, Ytr, Xva, Yva = X[tr], y[tr], X[va], y[va]
    for mname, cfg in zip(top2, finalists):
        keras.utils.set_random_seed(RANDOM_SEED + fold)
        model = build_model_safe(cfg)
        model.fit(Xtr, Ytr, validation_data=(Xva, Yva),
                  epochs=EPOCHS, batch_size=BATCH_SIZE, verbose=0,
                  callbacks=[EarlyStopping(monitor="val_accuracy", mode="max", patience=3, restore_best_weights=True)])
        _, acc = model.evaluate(x_test, y_test, verbose=0)
        fold_acc[mname].append(acc)
        print(f"Fold {fold} | {mname}: test_acc={acc:.4f}")

acc_a = np.array(fold_acc[top2[0]]); acc_b = np.array(fold_acc[top2[1]])
stat_p = wilcoxon(acc_a, acc_b, alternative="greater")  # is top2[0] > top2[1]?
print(f"\n✓ 5-fold test accuracies:\n{top2[0]}: {acc_a.mean():.4f} ± {acc_a.std():.4f}\n{top2[1]}: {acc_b.mean():.4f} ± {acc_b.st
```