








# DEEP LEARNING ASSIGNMENTS

## Assignment 1 – Predict Diabetes Onset with an ANN

**Dataset:** Pima Indians Diabetes (UCI)

**Task:** Build and optimise an ANN that predicts the Outcome (diagnosed diabetes).

### Steps:

 Problem framing	Define baseline metric (e.g., ROC-AUC $\geq$ 0.80).
 Data handling	Load the CSV from the URL, inspect class balance, split 60-20-20 (train/val/test).
 Pre-processing	Scale numeric features, handle any zeros as missing for medical realism.
 Modelling	1) Baseline logistic regression 2) Build a Keras ANN ( $\geq$ 2 hidden layers).
 Optimisation	Experiment with units, activation functions, dropout, learning-rate schedules, early-stopping.
 Evaluation	Accuracy, precision/recall/F1, ROC-AUC, confusion-matrix heat-map.
 Reporting	Compare ANN vs. baseline, justify architecture choices, discuss error patterns.

### Stretch ideas

- K-Fold cross-validation with `tf.keras.wrappers.scikit_learn.KerasClassifier`.
- Hyperparameter search via KerasTuner or Optuna.
- SHAP feature-importance plots.

**Starter notebook:** Provided in the assignment folder







### Submit:

Link to completed notebook with the outputs in it

## Assignment 2 – Classify Histopathology Images with a CNN

**Dataset: PathMNIST** (9-class tissue-type images, part of MedMNIST). Small (4-MB) yet realistic.

**Task:** Train a CNN in PyTorch to label pathology tiles.

 Data setup	Use <code>medmnist</code> to download <code>pathmnist</code> ; visualise a grid of images per class.
 Model	Implement a CNN ( $\geq 3$ conv blocks) from scratch or finetune a pretrained ResNet-18.
 Training loop	Leverage GPU, track loss/accuracy curves, use early stopping & LR scheduler.
 Evaluation	Overall accuracy plus macro & weighted F1, confusion matrix; discuss misclassifications.
 Explainability	Optional: Grad-CAM or Torch-CAM on a few tiles.
 Report	Describe augmentation choices, architecture reasoning, and how performance could improve with more data.

### Stretch ideas

- MixUp or CutMix augmentations.
- Class-imbalance handling with focal-loss or weighted sampling.
- Export to TorchServe or ONNX for inference demo.

### Starter notebook:

Provided with the assignment.

### Submit:








Link to completed notebook with the outputs

## Assignment 3 – Sentiment Analysis with an LSTM

**Dataset:** IMDB Movie Reviews (large movie-review corpus, 25 000 training + 25 000 test examples, balanced positive/negative)

**Task:** Build and optimise an LSTM-based sequence model that predicts sentiment from raw text.

### Steps:

 Data ingestion	Load the dataset with <code>tensorflow_datasets</code> ; create 80-20 train/validation split from the official training set.
 Text prep	Fit a <code>Tokenizer</code> (20k vocab), convert to integer sequences, and pad/trim to a fixed length (e.g., 300 tokens).
 Baseline	Implement a TF-IDF + Logistic Regression classifier and report validation accuracy.
 Modelling	Build a <b>Bidirectional LSTM</b> with an <code>Embedding</code> layer ( $\geq 128$ dims) and at least one stacked LSTM layer; add dropout/regularisation.
 Optimisation	Tune embedding size, LSTM units, learning rate, and early-stopping patience to beat the baseline.
 Evaluation	Accuracy, precision/recall/F1, and a confusion matrix on the held-out test set.
 Reporting	Compare baseline vs. LSTM, discuss misclassified examples, and propose next improvements.

### Stretch ideas

- Replace the LSTM with a 1-D CNN or Transformer encoder and compare.
- Use pre-trained GloVe or FastText embeddings.
- Quantise or prune the model for on-device inference, then measure size vs. accuracy.

### Starter notebook:

Provided with the assignment

### Submit:

Link to completed notebook with the outputs