Deep Learning Assignment Report – 2024-25

Iason-Christoforos Asproudis
Student ID: p3352318

Part 1: Image Classification

Dataset Description

We utilized two datasets for initial image classification experiments:

- **Fashion-MNIST**: 28x28 grayscale images categorized into 10 clothing item classes.
- **CIFAR-10**: 32x32 RGB images across 10 object classes such as airplanes, cats, and cars.

Both datasets are provided through `tensorflow.keras.datasets`.

Model Architectures

Fashion-MNIST (MLP):

- Fully connected neural network using Functional API
- Two hidden layers with 256 and 128 units
- ReLU activation and Dropout (0.3)
- Glorot uniform initialization

CIFAR-10 (CNN):

- Three convolutional blocks with Conv2D, BatchNormalization, MaxPooling, and Dropout
- Flatten and dense layers at the end
- Trained with EarlyStopping

Training Strategy

- Optimizer: Adam
- EarlyStopping with patience of 3
- Training epochs: 10–30
- Batch size: 128
- Dropout and BatchNormalization to reduce overfitting and stabilize training

Challenges & Solutions

- Slow convergence on CIFAR-10: Deepened architecture and added normalization layers
- Overfitting in Fashion-MNIST: Resolved with EarlyStopping and Dropout

Results Summary

Fashion-MNIST (MLP):

- Test Accuracy: 88.7%
- Validation Accuracy: 89.0%

CIFAR-10 (CNN):

- Test Accuracy: ˜71%

Part 2: X-ray Classification – MURA Dataset

Dataset Overview

The MURA dataset includes musculoskeletal radiographs categorized as either *normal* or *abnormal* across seven body parts. An analysis of the training split revealed:

- Total labeled studies: 13,456
- Normal (label 0): 8280 (61.5%)
- Abnormal (label 1): 5176 (38.5%)

Body parts are unevenly represented, with **wrist** and **shoulder** dominating the dataset. Notably, **shoulder** is the only body part where abnormal cases outnumber normal ones. This imbalance was visualized using a heatmap (Figure 1) and informed our training strategy.

Learning Approach

The pipeline was designed to support:

- Binary classification: Normal vs. Abnormal
- Multitask learning: Body part prediction as auxiliary task
- Modular design with reusable code components
- Resource optimization for Colab Pro (A100 GPU)
- Generalization using data augmentation and sample weighting

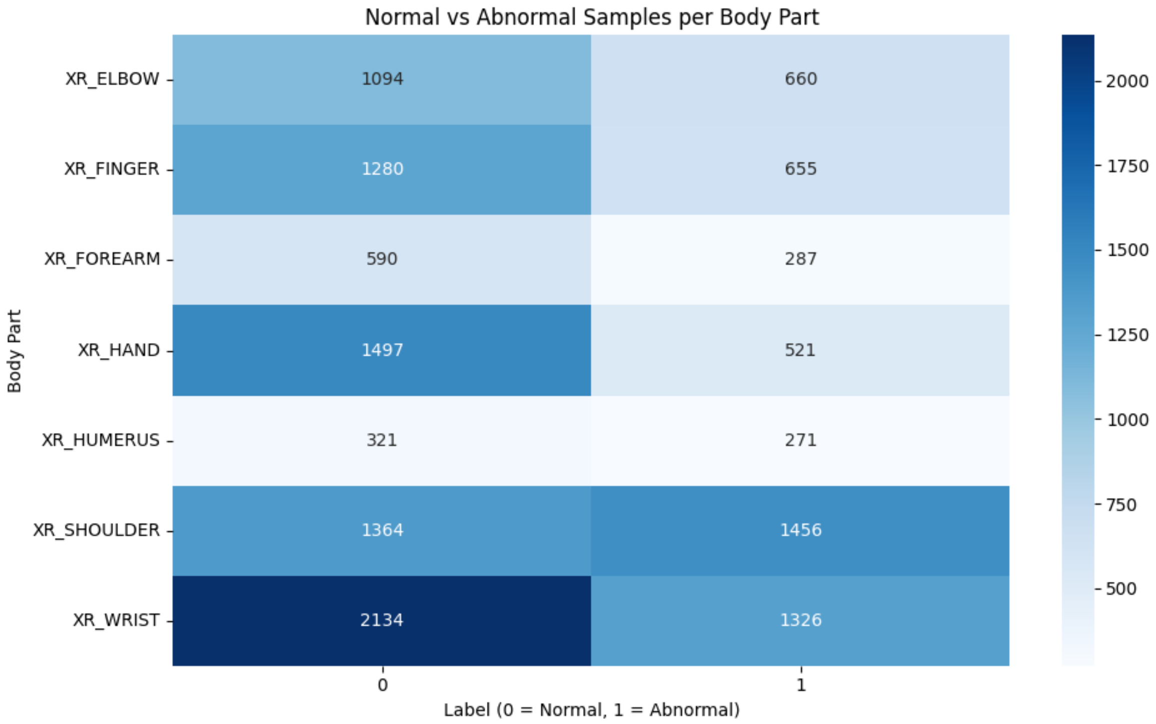

Figure 1: heatmap of MURA Dataset

Model Development

CNN from Scratch:

- Custom multitask CNN with two output heads
- Batch normalization and dropout
- Metrics: accuracy, F1-score, precision, recall, categorical accuracy

EfficientNetB0 (Transfer Learning) – Failure:

- Despite ImageNet pretraining, validation metrics remained at 0.00
- Severe overfitting: training accuracy ¿85% while val_accuracy ≈ 4.3%
- Switching to global average pooling and sigmoid did not help
- Transfer failed due to domain mismatch between natural and medical images

Switch to InceptionV3 + MaxPooling:

- Adopted InceptionV3 with max pooling and regularized custom heads
- Addressed memory and shape issues with simplified multitask setup
- Augmentation, sample weighting, and fine-tuning reused
- Validation metrics started recovering as training stabilized

Data Handling

- Grayscale to RGB conversion
- Local caching and float16 usage for memory efficiency
- Data augmentation: flip, brightness, contrast
- Sample weights using `compute_sample_weight`

Results

CNN from Scratch (Multitask):

- Binary Accuracy: 64.9%
- F1 Score (Abnormal): 0.60
- Body Part Accuracy: ∼100%
- Precision (Abnormal): 0.66
- Recall (Abnormal): 0.56

Note: InceptionV3 training still in progress. Metrics will be updated after full convergence.

Challenges and Strategy Shifts

Challenges Encountered:

- GPU memory exceeded with multitask models
- Output shape mismatch in pretrained multitask architectures
- Crashes in Colab from RAM overflow
- Grayscale inputs incompatible with EfficientNetB0
- Class weight instability in multitask setup
- TensorFlow/Keras version incompatibilities
- Functional API input mismatches
- Overfitting with frozen base models
- Path inconsistencies between local and Colab

Solutions Implemented:

- Switched to binary-only for pretrained models
- Used float16 and smaller batch sizes
- Replaced `ImageDataGenerator` with `tf.data.Dataset`

- Applied `sample_weight` over `class_weight`
- Data augmentation for robustness
- EarlyStopping and ReduceLROnPlateau
- Saved best checkpoints with timestamps
- Guided data decisions using heatmaps

Source Code

All source code, including preprocessing, training, and model definition scripts, is available at: `https://github.com/jasproudis/deep-learning-assignment`

Final Thoughts

This assignment offered valuable hands-on experience across various deep learning tasks, ranging from classic image classification to medical image analysis. Designing and debugging custom CNNs, experimenting with pretrained backbones, and handling real-world dataset challenges sharpened both our engineering and research skills.

Key takeaways include:

- Pretrained models require careful adaptation, especially in domain-shifted settings like medical imaging
- Multitask learning, although promising, introduces complexity in data flow, loss balancing, and resource usage
- Modular code and early visualizations greatly accelerate debugging and result interpretation

We believe our final models and analysis reflect a thoughtful balance of practical engineering, experimentation, and interpretability.

Future work could explore:

- Attention-based mechanisms to improve focus on abnormal regions
- Transformer-based architectures for multimodal representation
- Additional modalities (e.g., metadata, clinical notes) if available