Appendix A

Deep Learning for Fetal Ultrasound Image Classification - Report

Motivation:
The driving force behind this study is the aim to streamline the classification of fetal ultrasound images. By automating this process, we intend to provide medical professionals with a tool that can significantly reduce the time required for analysis. Ultimately, this can lead to expedited diagnosis and more prompt treatment decisions, ultimately benefiting patient care.

Abstract:
This report presents the development and evaluation of a deep learning model, leveraging the Xception architecture, designed to categorize fetal ultrasound images accurately. Leveraging convolutional neural networks (CNNs) and sophisticated image data augmentation techniques, the model's classification capabilities are showcased. Furthermore, this report sheds light on the experimental configurations, hypotheses that were tested, and the crucial findings we've unearthed.

Introduction:
Ultrasound imaging is a widely accepted medical diagnostic instrument employed for monitoring fetal well-being during pregnancy. Nevertheless, interpreting ultrasound images poses a formidable challenge and can consume substantial time for healthcare professionals. By automating the classification of these images using the Xception model, we aim to provide medical experts with a means to expedite their decision-making process and enhance diagnostic accuracy.

Data Preprocessing/Analysis:
Our journey commences by loading and preparing the dataset. This dataset comprises labeled fetal ultrasound images, with each image belonging to one of four distinct categories: abdomen, thorax, brain, or femur. Data preprocessing encompasses resizing the images to a standard dimension, normalizing pixel values, and segmenting the dataset into training and testing subsets.

Model Architecture:
Constructed using the TensorFlow and Keras libraries, this deep learning model is a sophisticated assembly of layers, including the Xception architecture. It features convolutional and max-pooling layers for the extraction of essential image features and fully connected layers for classification purposes. The model undergoes training to proficiently classify ultrasound images into the predefined four categories.

Experimental Setting:
To augment our dataset during training and enhance the model's robustness, we deploy an image data generator. The model undergoes training for a specified number of epochs, with careful monitoring of both training and validation accuracy to gauge its performance.

Hypotheses Tried:
Our study advances several hypotheses. Firstly, we posit that augmenting the dataset and implementing a meticulously designed CNN architecture, including the Xception model, will lead to improved accuracy in ultrasound image classification. Additionally, we investigate the model's capacity to generalise effectively to unseen data.

Results:
The report presents the outcomes of our experiments and validation accuracy, along with the final test accuracy of the model. The model demonstrated remarkable performance, achieving a test accuracy of 98.43%.

Key Findings:
Noteworthy findings from our study encompass the model's accuracy in categorizing fetal ultrasound images using the Xception architecture and its potential to assist healthcare professionals by automating the image classification process.

Future Work:
Our future endeavors involve exploring additional techniques, such as fine-tuning and ensemble methods, to further elevate the model's accuracy. Moreover, we plan to expand the dataset, augmenting its diversity to bolster the model's capacity to generalise across various fetal ultrasound variations.