Deep Learning for the Automatic Classification of Congenital Lung Abnormalities using MRI Scans

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Background

- Congenital lung abnormalities are rare diseases that occur during pregnancy
- Diagnosis of congenital lung abnormalities from MRI images allows physicians to:
  - Improve clinical management during or after delivery
  - Provide information on the outcome of the pregnancy
- Currently there are no fast and fully automatic classification models
- We explore the application of Convolutional Networks with 2D and 3D kernels to fetal MRI scans to automatically diagnose abnormal fetal lungs

Goal

- Development of **fast** and **fully automatic** classification models saves physician time and provides an entry point to more complex models of lung volumetry that further improve prognostic prediction.

Data

- **4632** Single Shot Fast-Spin Echo (SSFSE) T2-weighted Fetal MRI Scans in multiple orientations
- Ground truth from radiologist with 12 yrs experience
- Collected from **2004-2017** at Stanford Hospital
- Each scan is comprised of a series of 2 dimensional grayscale values

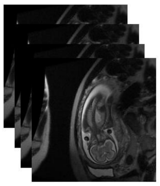


FIGURE 1: Fetal MRI slices

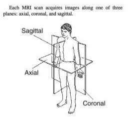


Figure 1: Scan Orientations

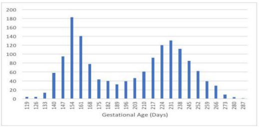
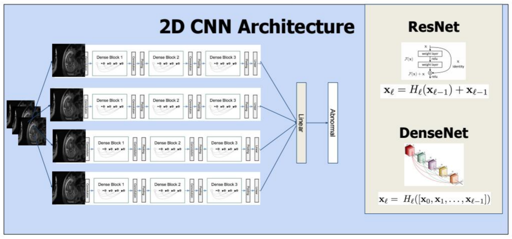
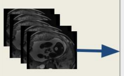


Figure 2: Age Distribution

Methods and Models



3DResnet



1x40x64x64 Volumes (n_channels=1)

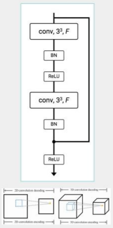
3D ResNet-18

[conv (7 × 7 × 7, 64)
temporal stride = 1
spatial stride = 2]
V

[F: 64, N: 2]
V
[F: 128, N: 2]
V
[F: 256, N: 2]
V
[F: 512, N: 3]

V
[global average pool]
[2-d fully-connected]
[softmax]

3D ResNet Block



Two convolutional layers:
-- 3 × 3 × 3
-- 3 × 3 × 3
Batch norm (**BN**) and **ReLU**

A **shortcut pass** connects the top of the block to the layer just before the last ReLU in the block

Identity connections to avoid increasing number of parameters

Results

	Training Accuracy	Test Accuracy
ResNet-18	99%	58.8%
DenseNet-121	97.1%	75%
3D ResNet-18	99.7%	67.9%

Table 1: Classification Performance for three models on Fetal MRI data set

	Predicted Negative	Predictive Positive
True Negative	163	1
True Positive	5	40

Figure 3: Densenet -121 Training Confusion Matrix

Discussion

Dataset Challenges

- Multiple Fetal Orientations and Blurring → Data Augmentation
- Class Imbalance → Weighted Cross-Entropy Loss
- # of slices varies per scan → Pad+Slice MRI Scans to fixed #
- Resolution varies per scan → Downsample each Image Slice
- Variability in scanning protocols
- Variability in scan quality and scanning equipment
- Small data set due to low incidence of the disease

2D Model Challenges

- 2D Models were unable to take advantage of series data → RNNs
- Slow training due to low batch size to fit each scan into GPU

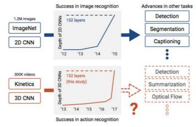


Figure 4: Kinetics for 3D CNNs as ImageNet for 2D CNNs?

3D Model Challenges

- Slow Training due to Memory Intensive Data
- Lack of 3D Pretrained Models → Recent Kinetics Challenge Model
- Overfit after 200 Epochs → Regularization+Augmentation little effect

Future Work

- Get segmentation labels and apply attention-mechanisms and segmentation algorithms to identify the area of abnormality e.g. fetus or thorax region (e.g. VNet, RADNet)
- Apply advanced featurization (e.g. SIFT, HoG) or Gaussian Mixture Models to pinpoint viable regions and slices.
- Try 2D models that process time series data (e.g. LSTMs).
- Change to a multiclass model to account for multiple types of abnormalities.
- Use architectures with other 3D data (e.g. Pointnet, VoxNet, OctNet) for MRI imaging

References

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