MultiNet: Binary Image Classifier

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1 Introduction

In the realm of machine learning, particularly in image classification tasks, the balance between model complexity and performance is crucial, especially under hardware constraints. Here, we explore the implementation of an ensemble model which we call MultiNet. The before-mentioned model leverages three ResNet architectures to improve binary classification accuracy without significantly increasing model size, since that would prevent us from training the models on consumer accessible hardware.

2 Methodology

2.1 Individual ResNet Models

We initiated our approach by training three ResNet models independently:

- **ResNet50**: Trained locally due to its smaller size and computational requirements.
- **ResNet152**: Trained on Kaggle's cloud infrastructure.
- **ResNet304**: A custom model where we doubled the layers of ResNet152, also trained on Kaggle.

2.2 Ensemble Model

After training these models, their outputs were fed into a Convolutional Neural Network (CNN) with four fully connected layers, followed by a sigmoid function to output a probability between 0 and 1, indicating the certainty of classification. Since all the models didn't fit on a single gpu we took advantage of the dual t4s offered by kaggle to train this final classifier.

2.3 CNN Model

A secondary CNN model was also implemented to help the MultiNet model reach higher accuracy. This CNN model contains three convolutional layers, each followed by Relu activation and pooling, to extract features from input images. These features are then flattened and processed through six fully connected layers, with dropout applied after most dense layers to mitigate over-fitting.

2.4 Final Decision Making

The original model plateaued at a bit under 99% so in order to improve the accuracy of MultiNet we decided to train the secondary CNN to help it assign a class to the images it was unsure of. The threshold for uncertainty was set at 15%. If it wasn't reached the output of the MultiNet model was compared with the prediction of the CNN model, with a decision mechanism in place to choose based on the confidence levels of both models.

3 Results

- **Validation Accuracy**: Post-ensemble, our model achieved around 98.5% accuracy.

- **Combined Model Accuracy**: With the integration of secondary CNN, preliminary results suggest that accuracy could exceed 99%.

The following figures illustrate the training and validation metrics of our models:

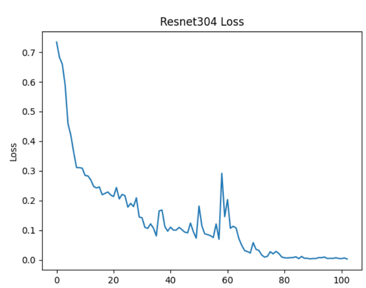


Figure 1: ResNet304 Loss

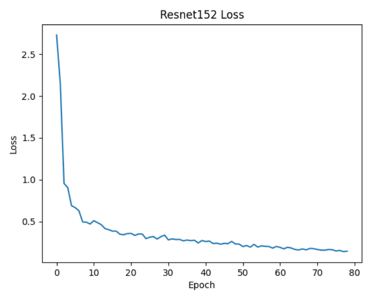
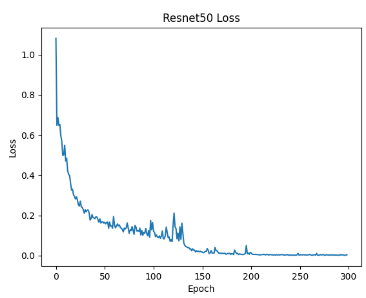
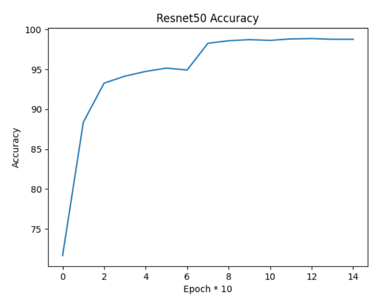


Figure 2: ResNet152 Loss

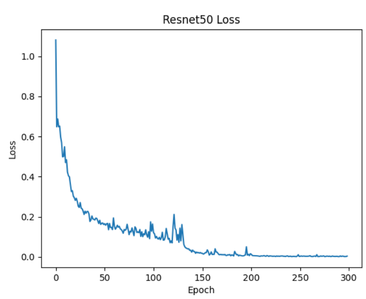


(a) ResNet50 Loss

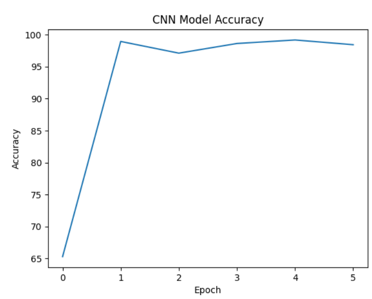


(b) ResNet50 Accuracy

Figure 3: ResNet50 Metrics



(a) CNN Loss



(b) CNN Accuracy

Figure 4: CNN Metrics

4 Analysis

The loss curves for all models indicate a decreasing trend as epochs increase, with some fluctuations in resnet304, resnet50, and in the CNN, likely due to learning rate adjustments or data shuffling. The accuracy of all models quickly plateaus near 95%, showing that if a few percentage point difference doesnt cause many issues similar effectiveness and stability in classification can be reached with much smaller models.

5 Conclusion

The MultiNet approach, combining multiple ResNet architectures and a decision-making CNN, demonstrates potential for high accuracy in binary image classification tasks. Further optimization, particularly in model integration and decision thresholds, could yield even higher performance metrics, it's also worth mentioning that if the complete automatization of the classification isn't necessary it's possible to manually analyze the results for which the model is less confident (confidence less than .02) which would further increase the accuracy of the predictions.

6 Architectures

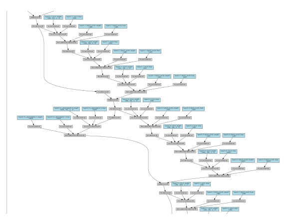


Figure 5: Partial Resnet304 Architecture

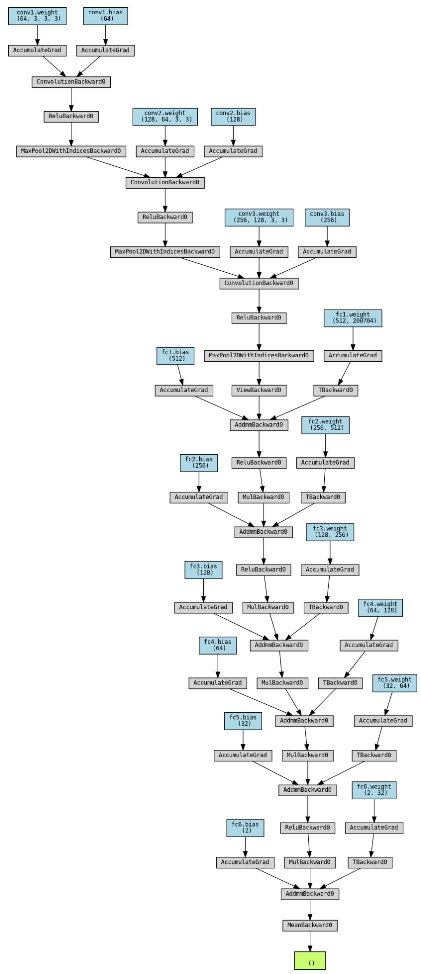


Figure 6: CNN Architecture

7 References

- **Github Repository**: https://github.com/poset26/DL_Challenge_BinaryClassifier
- **ResNEt**: https://github.com/JayPatwardhan/ResNet-PyTorch/tree/master
- **Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun Deep Residual Learning for Image Recognition**: https://arxiv.org/pdf/1512.03385.pdf