# Head Circumference Prediction Using Deep Learning

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## Abstract

This report presents the implementation of a deep learning model for head circumference (HC) prediction from ultrasound images. A ResNet50-based regression model was trained and evaluated using the HCG18 dataset. Performance metrics such as MAE, RMSE, and R-squared score were analyzed.


## 1 Introduction

Head circumference (HC) is an essential biometric parameter in fetal growth assessment. This study employs a deep learning approach using transfer learning to predict HC values from ultrasound images.

## 2 Dataset and Preprocessing

The dataset used in this study comprises ultrasound images paired with corresponding head circumference (HC) values. The data was divided into three distinct subsets: the training set, validation set, and test set. The training set consists of 80% of the total dataset, which is used to train the deep learning model. The validation set, making up 20% of the dataset, is utilized for tuning the model's hyperparameters and monitoring its performance during training. The test set is reserved for evaluating the model's final performance after training.

Before feeding the images into the model, several preprocessing steps were performed. All images were resized to a consistent dimension of 224x224 pixels. This size was chosen to match the input size expected by the ResNet50 architecture. Additionally, the images were normalized using the same preprocessing technique applied to the ResNet50 model, ensuring that the pixel values were scaled appropriately for efficient model training. Lastly, all images were converted to RGB format to maintain consistency, even if the original ultrasound images had a different color scheme or format.

## 3 Model Architecture

The model architecture is built on a pre-trained ResNet50 network, which is utilized as a feature extractor. In order to adapt the network for regression tasks, several additional layers are incorporated. First, a Global Average Pooling layer is added to reduce the spatial dimensions of the output from the ResNet50 model, converting it into a one-dimensional vector. This step helps in extracting high-level features and reduces the number of parameters, thus preventing overfitting.

Following the pooling layer, fully connected layers with ReLU activation functions are included to enable the model to learn complex, non-linear relationships between the extracted features and the predicted output. Dropout layers are inserted between the fully connected layers as a form of regularization, which helps prevent overfitting during training by randomly setting a fraction of the output units to zero at each update during training.

Finally, the model concludes with a linear output layer, which is designed to output a continuous value representing the predicted head circumference. The linear activation function ensures that the output is not constrained within any range, which is suitable for the regression task of predicting HC values.

# 4 Training and Evaluation

The model was trained using Mean Absolute Error (MAE) loss and Adam optimizer with a learning rate of 0.0001. It was trained for 10 epochs with a batch size of 32.

# 5 Results

## 5.1 Model Performance

Performance metrics on the validation set are summarized in Table 1.

| Metric | Value |
|---|---|
| MAE (mm) | 22.69 |
| MSE | 945.79 |
| RMSE (mm) | 30.75 |
| R-squared | 0.7656 |

Table 1: Regression Model Evaluation Metrics

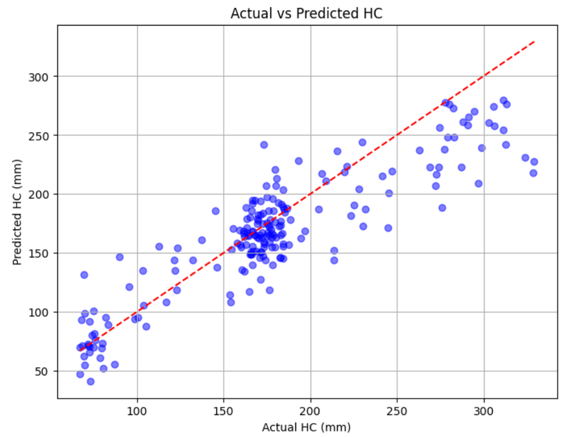


Figure 2: Actual vs Predicted HC

## 5.2 Visualization

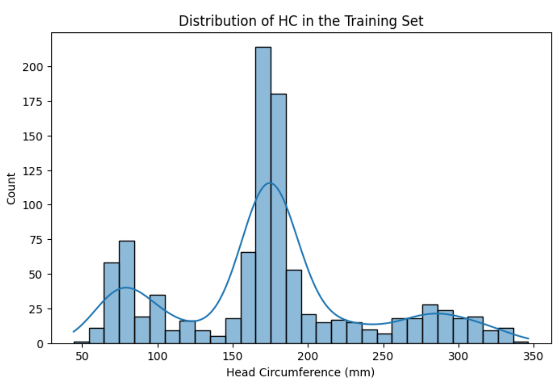


Figure 1: HC Distribution in Training Set

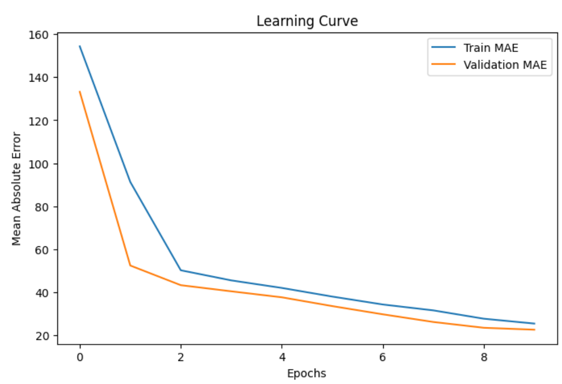


Figure 3: Training and Validation MAE

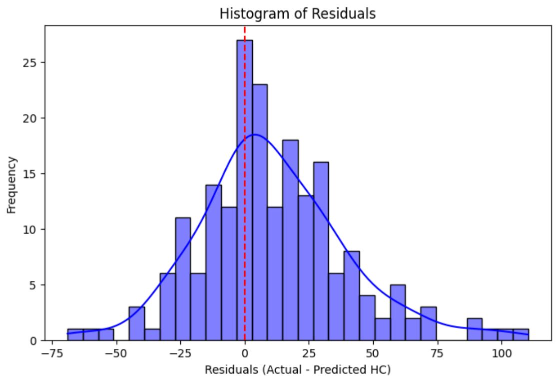


Figure 4: Residuals Distribution

# 6 Conclusion

This study demonstrated that deep learning models, particularly ResNet50-based regression, can effectively predict fetal HC. Future work includes fine-tuning and exploring alternative architectures for improved accuracy.

# References

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