Deep Learning for Embryo Classification in IVF: A Case Study from the World Championship 2023

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Abstract

Accurate embryo viability assessment is pivotal for in-vitro fertilization (IVF) success. The World Championship 2023 Embryo Classification challenge on Kaggle provides a platform to develop automated solutions using deep learning (1). We employ transfer learning with MobileNetV3Large, EfficientNetB0, and DenseNet121 to classify approximately 1,000 embryo images as ”Good” or ”Not Good” based on morphological features. Our pipeline includes advanced preprocessing, model fine-tuning, and rigorous evaluation, achieving an 81% validation accuracy with DenseNet121 and a public leaderboard score of 0.73333, ranking 15th globally. This paper presents our methodology, experimental outcomes, and future research directions.

1. Introduction

In-vitro fertilization (IVF) relies on selecting viable embryos to maximize pregnancy success rates, a process traditionally performed by embryologists through manual morphological assessment. This approach is subjective, timeconsuming, and prone to inter-observer variability, leading to inconsistent outcomes. The World Championship 2023 Embryo Classification competition on Kaggle offers a platform to address these challenges by automating embryo viability classification using machine learning (1). We leverage transfer learning with pre-trained convolutional neural networks (CNNs)—MobileNetV3Large, EfficientNetB0, and DenseNet121—to classify Day 3 and Day 5 embryo images as ”Good” or ”Not Good.” Our solution achieved a competitive public leaderboard score of 0.73333, ranking 15th globally despite a late submission, demonstrating its potential for clinical deployment. This paper reviews related literature, details our methodology, evaluates experimental results, and proposes future enhancements to advance automated embryo selection in reproductive medicine.

2. Previous Studies

Embryo viability assessment is central to reproductive medicine. Traditional methods, like the Gardner grading scale, evaluate blastocyst morphology based on expansion, inner cell mass, and trophectoderm quality (2), but suffer from interobserver variability. Machine learning has transformed this field. (3) Used time-lapse imaging with deep learning, achieving an AUC of 0.93 for implantation prediction. (4) Developed a CNN-based system for static embryo classification, reporting 90% accuracy on a private dataset. Transfer learning with models like ResNet, DenseNet, and EfficientNet has proven effective for small datasets (5). Combined CNNs with traditional image processing, enhancing robustness to noise. (6) Explored MobileNet for lightweight embryo classification, achieving moderate accuracy on limited data. Challenges include small annotated datasets, class imbalance, and imaging variability (e.g., microscope settings). Our work builds on these by applying MobileNetV3Large, EfficientNetB0

and DenseNet121 to a 1,000-image Kaggle dataset, optimizing for efficiency and accuracy.

3. Method

Our solution uses transfer learning with pre-trained CNNs (MobileNetV3Large, EfficientNetB0, DenseNet121) to classify embryo images as ”Good” or ”Not Good” for the World Championship 2023 Embryo Classification challenge. The pipeline, implemented in a Colab notebook (https://colab.research.google.com/drive/111za1XSWgcrBDXv7GLgxgQN0dkjR8fZY?usp=sharing), encompasses data preprocessing, model selection, hyperparameter optimization, training, and evaluation. Below, we detail each component.

3.1 Dataset Description

The Kaggle dataset contains approximately 1,000 high-resolution RGB embryo images from Day 3 and Day 5, labeled as ”Good” or ”Not Good” based on morphological features (e.g., blastocyst symmetry, fragmentation). The dataset is balanced (50% per class) but exhibits variations in illumination, focus, and microscope magnification. We split the data into 80% training (800 images) and 20% validation (200 images) sets using stratified sampling to preserve class proportions. A separate test set was used for Kaggle submissions, with predictions formatted as CSV files. Images were stored in JPEG format, requiring preprocessing to standardize inputs.

3.2 Data Preprocessing

To ensure compatibility with pre-trained models and enhance robustness, we applied:

- Resizing: Images were resized to 224x224 pixels using bilinear interpolation to match model input dimensions while preserving morphological details.
- Normalization: Pixel intensities were normalized to [0, 1] via min-max scaling:
    - $x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}$
- Data Augmentation: Using TensorFlow’s ImageDataGenerator, we applied:
    - Random rotations: Uniformly sampled from [-30°, 30°].
    - Horizontal/vertical flips: 50% probability.
    - Zoom: Scaling factor in [0.8, 1.2].
    - Brightness adjustments: Scaling in [0.8, 1.2].
    - Shear: Angle in [-10°, 10°] to simulate slight distortions.

  Augmentation increased the effective training set to 1,600 samples, mitigating overfitting on the small dataset.
- Data Cleaning: Images with low entropy (e.g., blurry or overexposed) were filtered, retaining 950 samples (95% of the dataset).

Preprocessing was performed on-the-fly during training to optimize memory in the Colab environment.

3.3 Model Architecture

We employed three pre-trained CNNs from TensorFlow’s Keras Applications, leveraging ImageNet weights:

- MobileNetV3Large: Features depthwise separable convolutions and inverted residual blocks, with 5.3 million parameters. Optimized for lightweight deployment, it uses squeeze-and-excitation modules to enhance feature representation.

- EfficientNetB0: Employs compound scaling (depth, width, resolution), with 5.3 million parameters. It uses MBConv blocks with squeeze-and-excitation, balancing efficiency and accuracy.
- DenseNet121: Comprises 121 layers with dense connectivity, promoting feature reuse, with 8 million parameters. It excels at capturing complex patterns via concatenated feature maps.

For each model:

- Base layers were frozen to retain pre-trained weights.
- A custom head was added: global average pooling to reduce spatial dimensions, a dense layer (256 units, ReLU, dropout 0.5), and an output layer (2 units, softmax for binary classification).

This transfer learning approach adapted ImageNet features to embryo morphology, minimizing training time on the small dataset.

3.4 Hyperparameter Optimization

We conducted a grid search with 5-fold cross validation on the training set:

- Learning Rate: Tested [0.01, 0.001, 0.0001]; 0.001 optimized convergence.
- Batch Size: Evaluated [8, 16, 32]; 16 balanced gradient stability and memory usage.
- Dropout Rate: Tested [0.3, 0.5, 0.7]; 0.5 minimized overfitting.
- Optimizer: Adam with beta1=0.9, beta2=0.999, epsilon=1e-8.
- Weight Initialization: Used pre-trained ImageNet weights for base layers; Glorot uniform for the custom head.

The configuration with the highest mean validation accuracy was selected for each model.

3.5 Training Algorithm

Models were trained using Adam, minimizing binary cross-entropy loss:

$$L_{BCE} = -\frac{1}{n}\sum_{i=1}^{n}(Y_i * \log y_i + (1 - Y_i) * \log(1 - y_i))$$

where n is the number of samples, Y_i is the true label, and y_i is the predicted probability. Training ran for 50 epochs on a Tesla T4 GPU in Colab (1 hour per model), with:

- Early Stopping: Halted if validation loss did not improve for 10 epochs.
- Learning Rate Scheduling: Reduced by 0.5 after 5 epochs of no improvement.
- Data Shuffling: Randomized sample order per epoch.
- L2 Regularization: Applied ($\lambda = 0.01$) to dense layers to reduce overfitting.

On-the-fly augmentation ensured diverse batches, optimizing performance on the small dataset.

3.6 Evaluation Metrics

Performance was assessed using:

- Accuracy: $\frac{T_p+T_n}{T_p+T_n+F_p+F_n}$
- Precision: $\frac{T_p}{T_p+F_p}$
- Recall: $\frac{T_p}{T_p+F_n}$
- F1-Score: $2 * \frac{Precision * Recall}{Precision + Recall}$

Metrics were computed on the 20% validation set using scikit-learn. Confusion matrices analyzed class-specific errors.

4. Experimental Results

We evaluated MobileNetV3Large, EfficientNetB0, and DenseNet121 on the validation set and Kaggle's test set.

4.1 Quantitative Results

Table 1 summarizes performance, with DenseNet121 achieving the highest validation accuracy (81%).

Model	Train acc.	Val. Acc.	Val. Loss	Generalization Gap
MobileNet	52%	68%	0.77	Small (Good Gen.)
EfficientNet	61%	53%	0.82	Large (Overfitting)
DenseNet	73%	81%	0.42	Small (Good Gen.)

Table 1: Model Performance on Validation Set

Our DenseNet121 submission achieved a Kaggle public leaderboard score of 0.73333, ranking 15th globally. Due to a late submission, our team name was not listed, but we contacted Kaggle for manual inclusion.

4.2 Qualitative Analysis

Confusion matrices (not shown due to LaTeX constraints) revealed MobileNetV3Large's balanced errors, EfficientNetB0's bias toward "Not Good" predictions (indicating overfitting), and DenseNet121's superior performance on both classes. Feature maps from DenseNet121 highlighted complex morphological features (e.g., blastocyst boundaries, inner cell mass), outperforming lighter models. MobileNetV3Large struggled with subtle features, reflecting its lower capacity.

4.3 Ablation Study

We assessed key components:

- Without Augmentation: DenseNet121's validation accuracy dropped to 74%, with increased errors on "Good" embryos.
- Without Fine-Tuning: Accuracy fell to 69%, underscoring the custom head's role.
- No L2 Regularization: EfficientNetB0's validation loss rose to 0.90, confirming overfitting.

These results validate augmentation, fine-tuning, and regularization.

4.4 Limitations

The dataset's small size (1,000 images) limited model capacity, particularly for MobileNetV3Large, which struggled to capture nuanced morphological features. EfficientNetB0's overfitting (53% validation accuracy) suggests insufficient regularization or dataset diversity, potentially exacerbated by imaging variability (e.g., differences in focus, lighting). The binary classification scheme ("Good" vs. "Not Good") may oversimplify embryo quality, omitting intermediate grades used in clinical practice. Limited computational resources in Colab restricted exploration of deeper architectures or extensive hyperparameter tuning.

5. Conclusions

This project developed a transfer learningbased solution for embryo viability classification, achieving an 81% validation accuracy with DenseNet121 and a Kaggle public leaderboard score of 0.73333, ranking 15th globally despite a late submission (1). Our contributions include a robust preprocessing pipeline, a comparative evaluation of MobileNetV3Large, EfficientNetB0, and DenseNet121, and a competitive performance on a small biomedical dataset. The results highlight

transfer learning's potential to automate IVF embryo selection, reducing subjectivity and enhancing efficiency. Future work could include:

- Collecting larger, more diverse datasets to improve model generalization.
- Implementing GradCAM to visualize decision-making for clinical trust.
- Fine-tuning base layers of pre-trained models to better adapt to embryo features.
- Developing ensemble methods to combine model strengths for higher accuracy.
- Exploring multi-class classification to align with clinical grading systems.

These advancements could further refine automated embryo selection, supporting improved IVF outcomes and broader adoption in clinical settings.

References

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