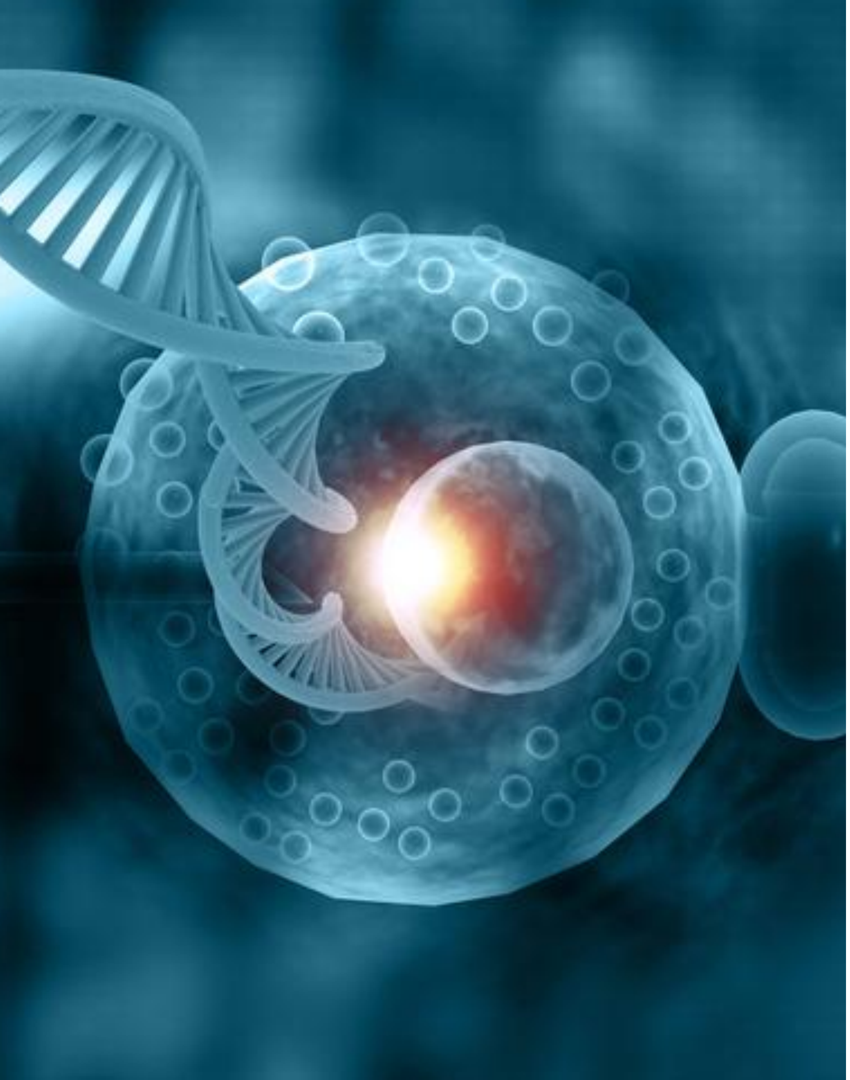

Assessing Embryo Quality from Images to Boost IVF Success

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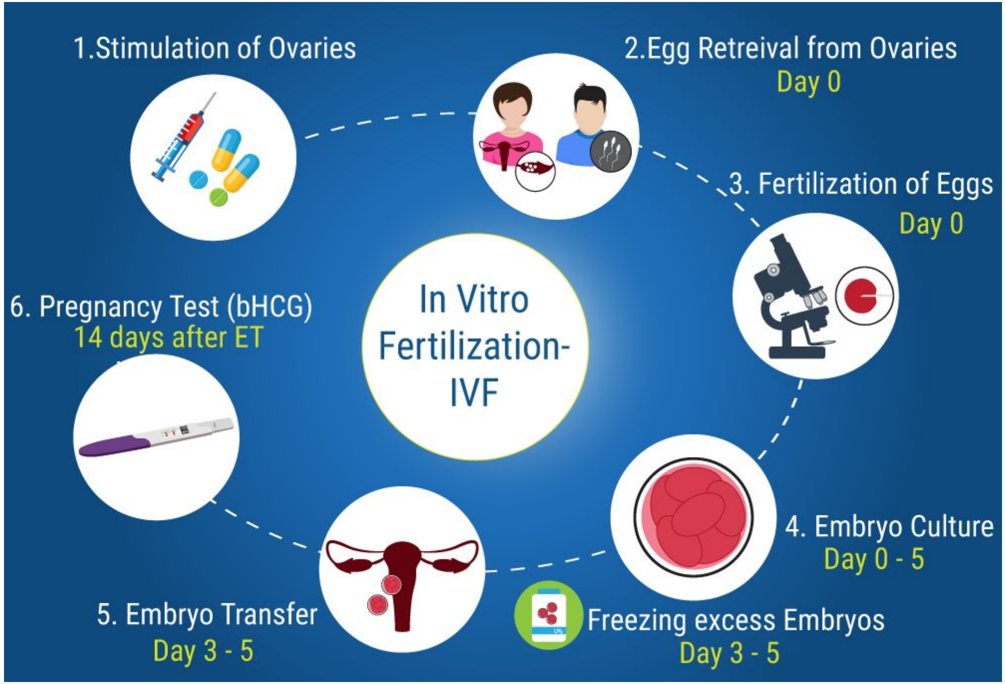
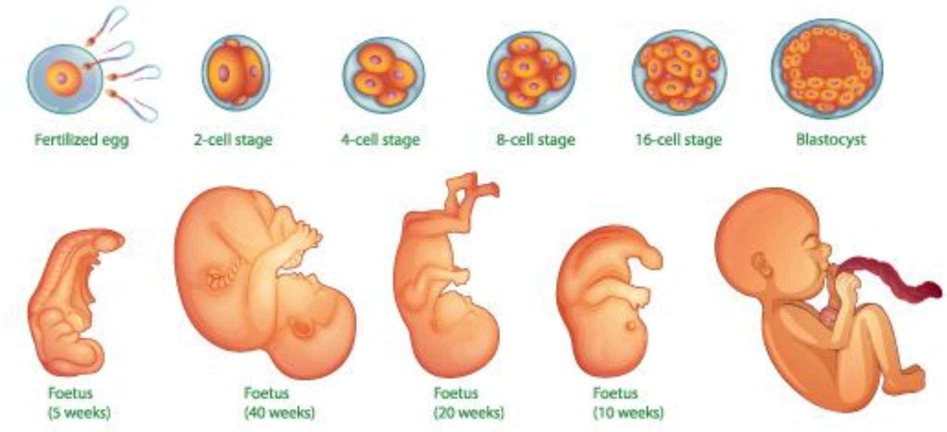
Introduction

Embryos are selected for transfer on the basis of **developmental rate and morphological features.**

A good quality embryo **increases chances of pregnancy rate** and **decreases number of embryo transfers** hence, **decreasing the cost of the IVF treatment.**



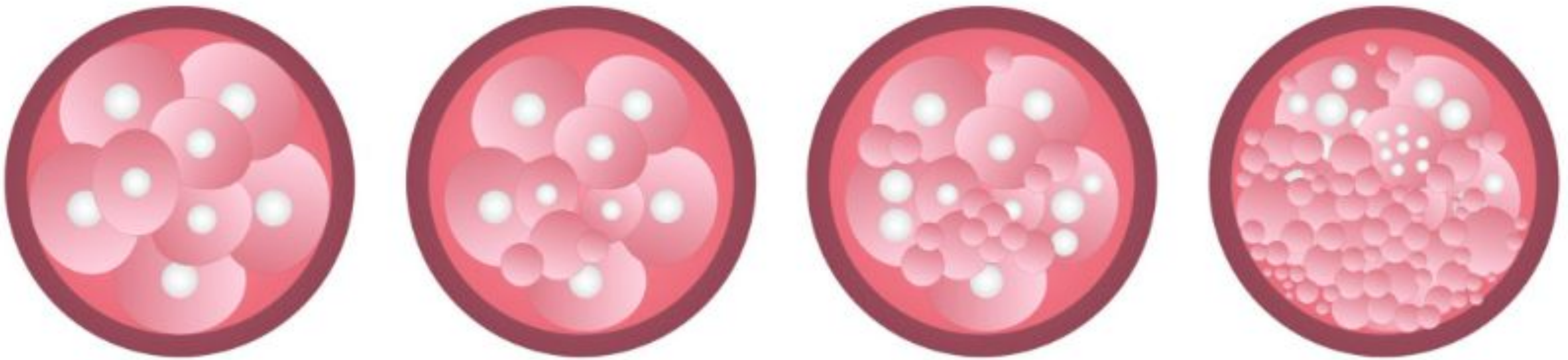
Problem Statement



In the field of in vitro fertilization (IVF), one of the critical challenges is selecting the most viable embryos for implantation to increase the chances of a successful pregnancy.

Currently, this selection process is highly subjective and relies on manual examination by embryologists, which can lead to variability in outcomes.

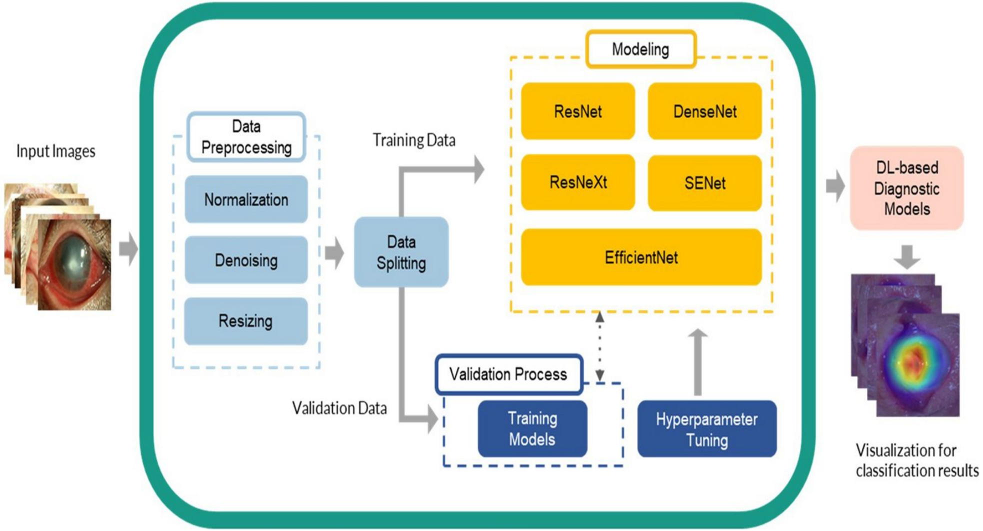
Categories of Embryo



Category A	Category B	Category C	Category D
Optimum quality embryo which has the best chance of implanting.	a good quality embryo which is very likely to implant	an embryo that is not great quality and which is unlikely to implant	a poor quality embryo which is very unlikely to implant

https://www.institutebernabeu.com/en/blog/criteria-for-embryo-classification/

Goal



This project aims to develop an advanced image analytics solution that utilizes machine learning and computer vision techniques to analyze and classify embryos.

We want to provide a more accurate, consistent, and objective method for distinguishing between embryos with higher and lower potential for successful development, thereby enhancing the overall effectiveness and success rates of IVF treatments.

What are we doing?

Exploratory Data Analysis → Convolutional Neural Network (CNN) → Structural Similarity Index (SSIM) → Conclusion & Future Scope

Data Overview

- 840 Training Images
- JPG format
- 256 x 256 Pixels
- 3-Day and 5-Day embryos images

Class Labels
- Bad; 0 (82 %)
- Good; 1 (18 %)

ID - Refers to the ID of the images in the test set.

Image - Refers to the file name of the embryo images in the train or test folder.

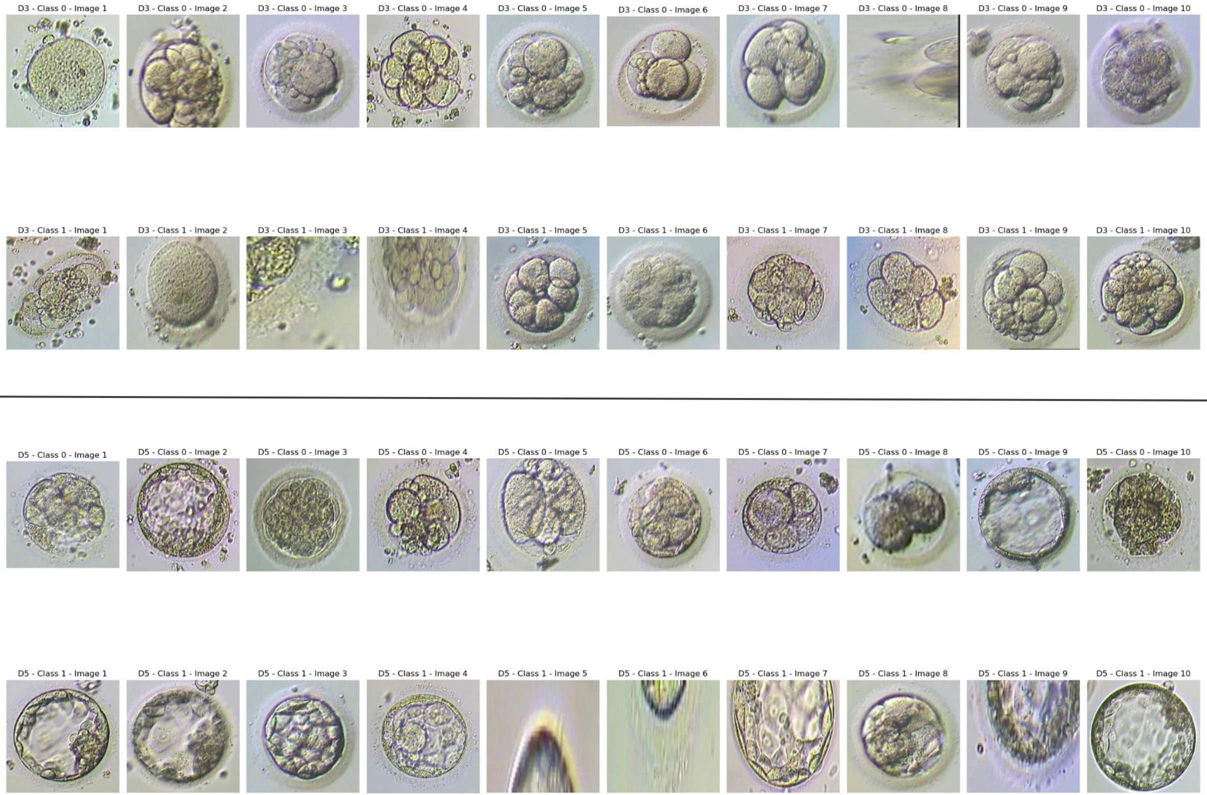
Class - Represents the evaluation of the embryo images. This column provides the ground truth label for each image, indicating whether the embryo is classified as 'good' or 'not good'

Embryo Images

Day 3

Class 0

Class 1

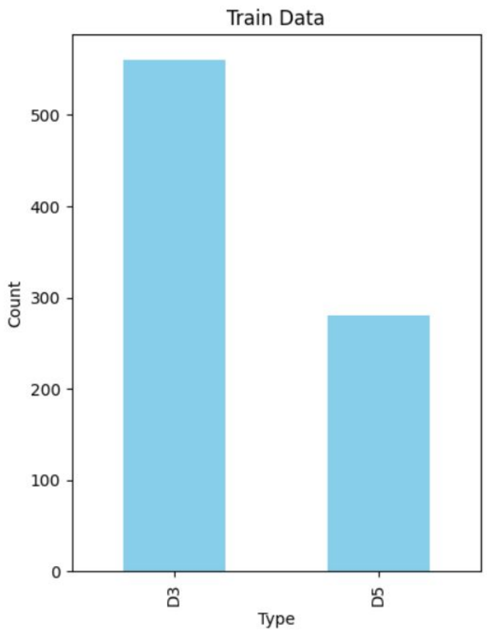


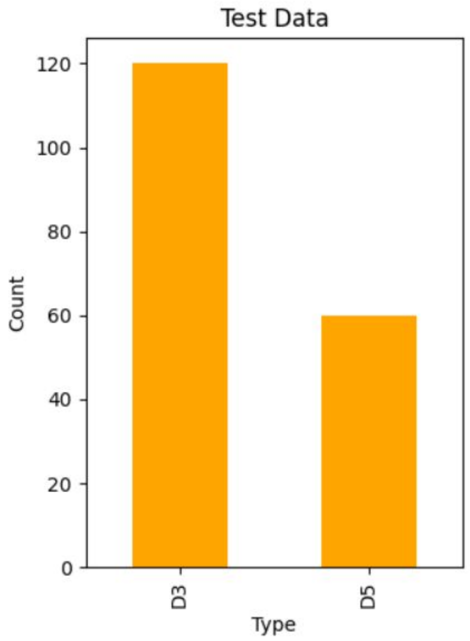
Day 5

Class 0

Class 1

EDA

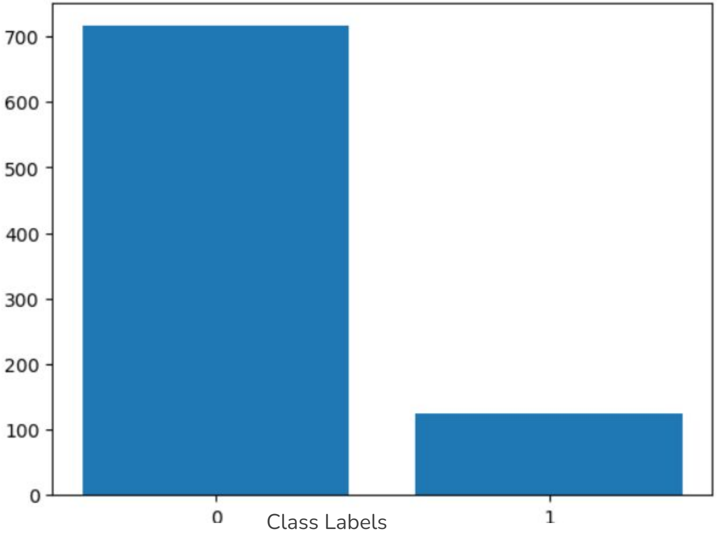


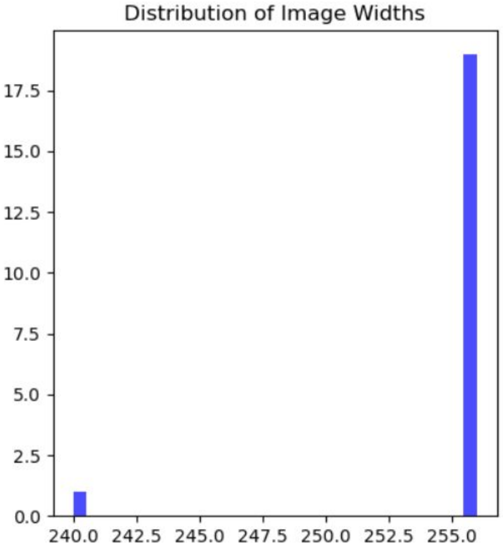


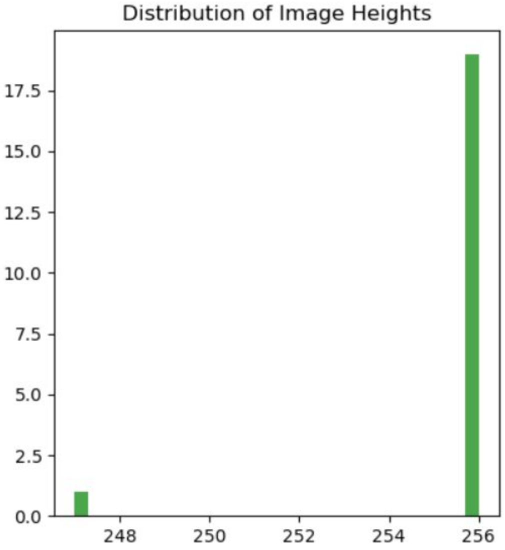
Imbalance in image type, with 'D3' having roughly twice as many samples as 'D5'

Imbalance in image is is consistent with the training data

EDA





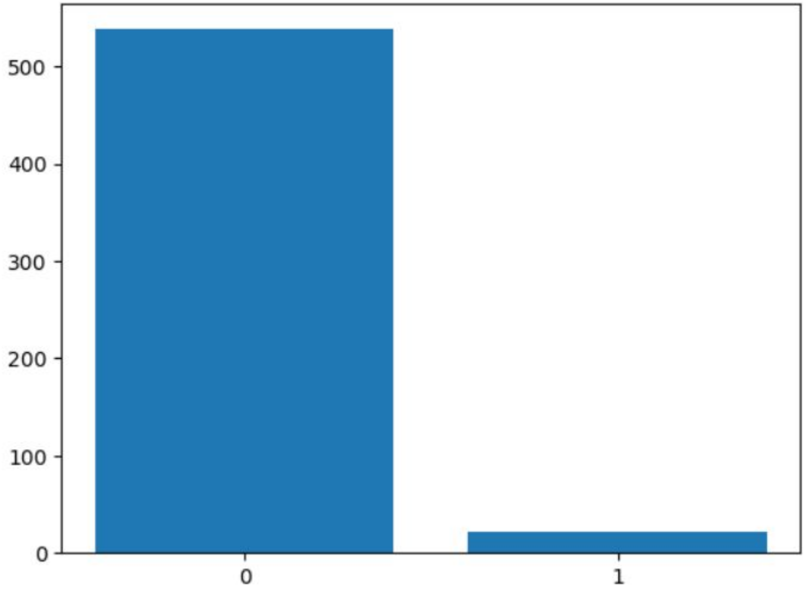


Dataset is imbalanced, with just 124 embryos out of 716 classified as 'good'

The above images show the distribution of image width and height

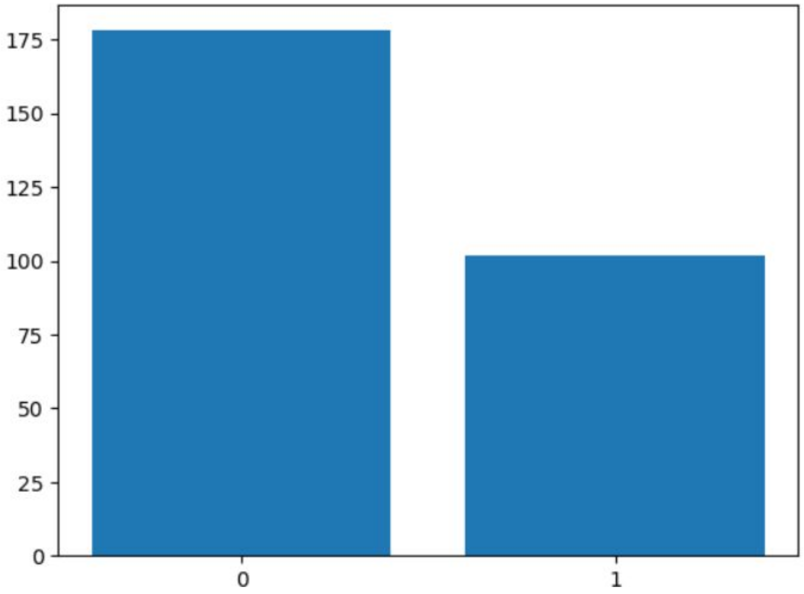
EDA

D3 Images with Class Labels



D3 images are very imbalanced, with just 22 embryos out of 560 classified as 'good'

D5 Images with Class Labels



D5 images are fairly balanced, with just 102 embryos out of 280 classified as 'good'

Image Pre-Processing

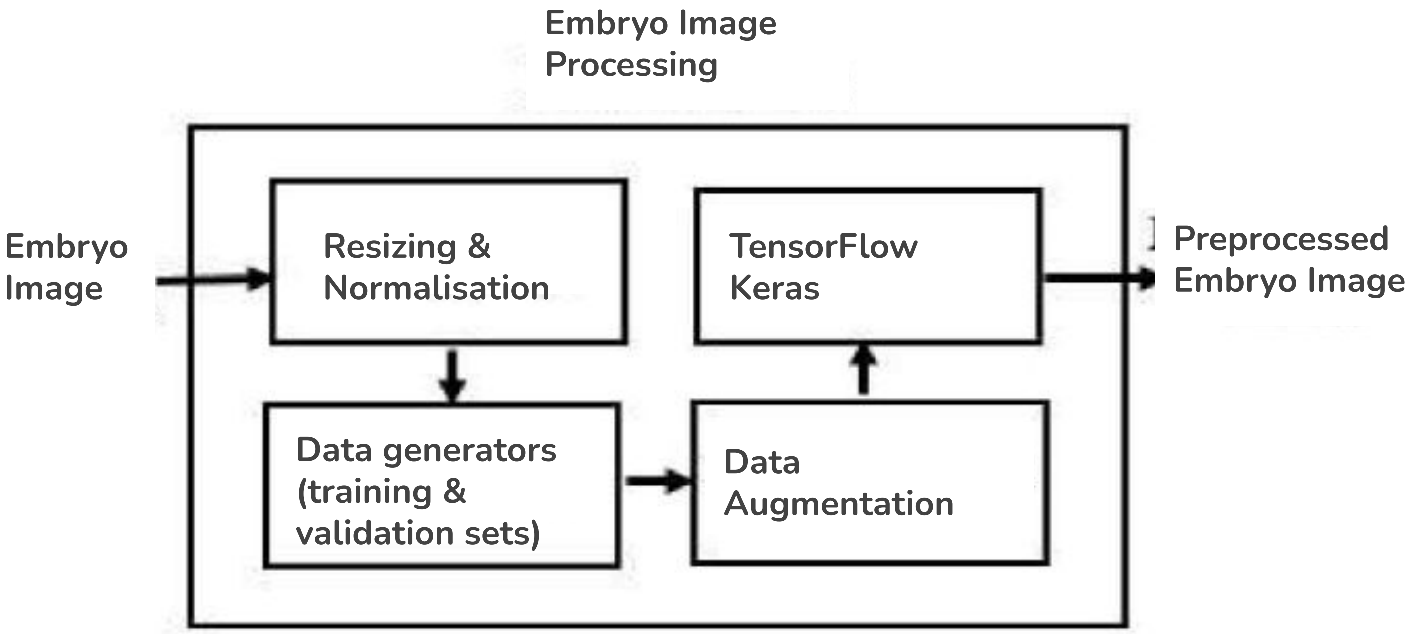
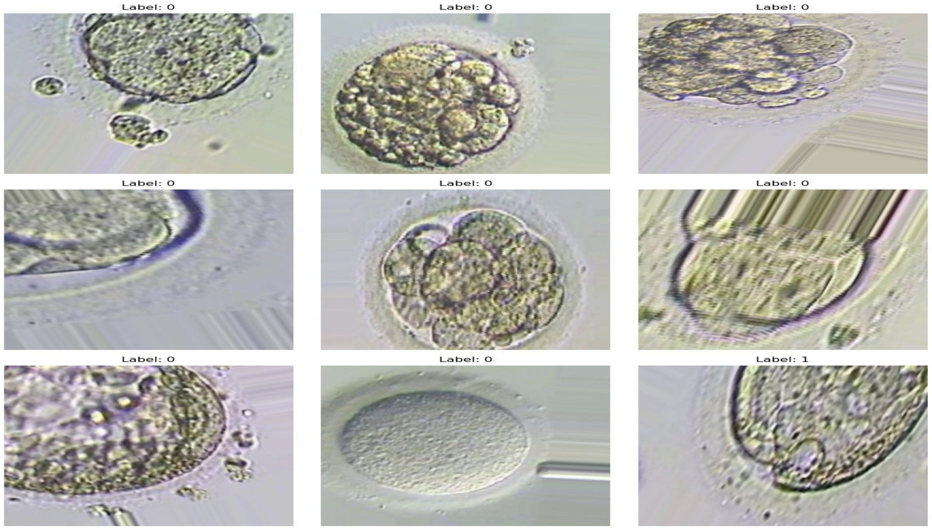


Image Pre-Processing

Labels in training and validation data generators



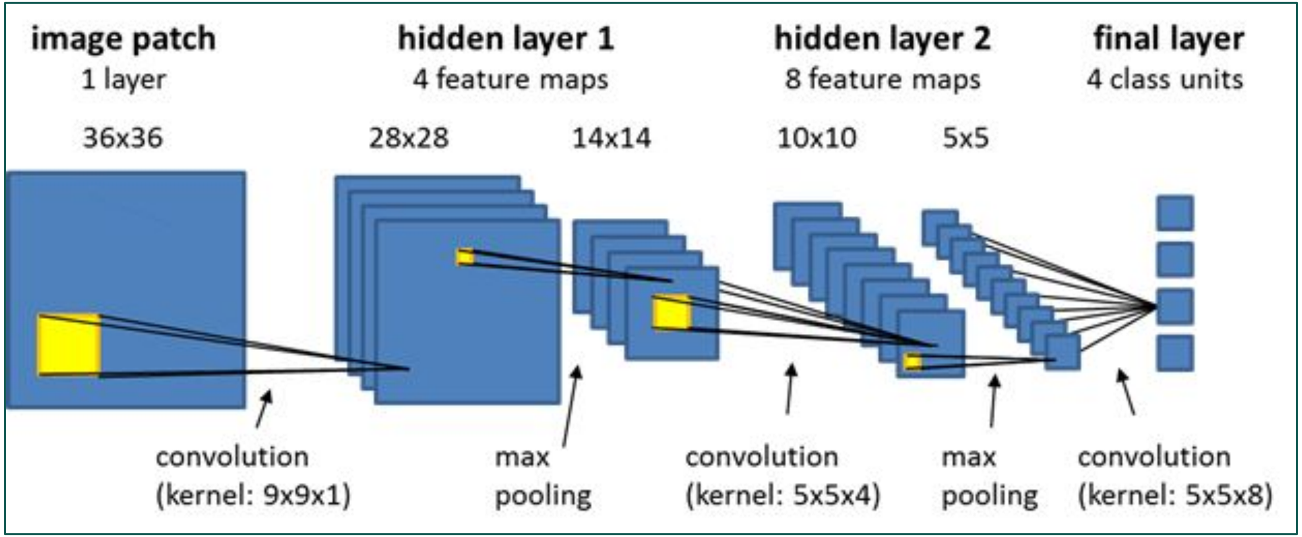
Label 0 is dominant with 666 samples, while label 1 has only 74 samples. There is a significant class imbalance in the training generator.

Validation generator appears to be balanced, with an equal number of samples (50) for both label 0 and label 1.

What are we doing?

Exploratory Data Analysis → Convolutional Neural Network (CNN) → Structural Similarity Index (SSIM) → Conclusion & Future Scope

CNN



Advantage: Efficiently captures hierarchical features in images.

Applications: Image classification, object detection, image segmentation.

Powerful for: Tasks involving visual recognition.

Convolutional Layer

- Identifies patterns using filters.
- Slides across data, creating feature maps.

Pooling Layer

- Reduces dimensionality.
- Retains essential information.

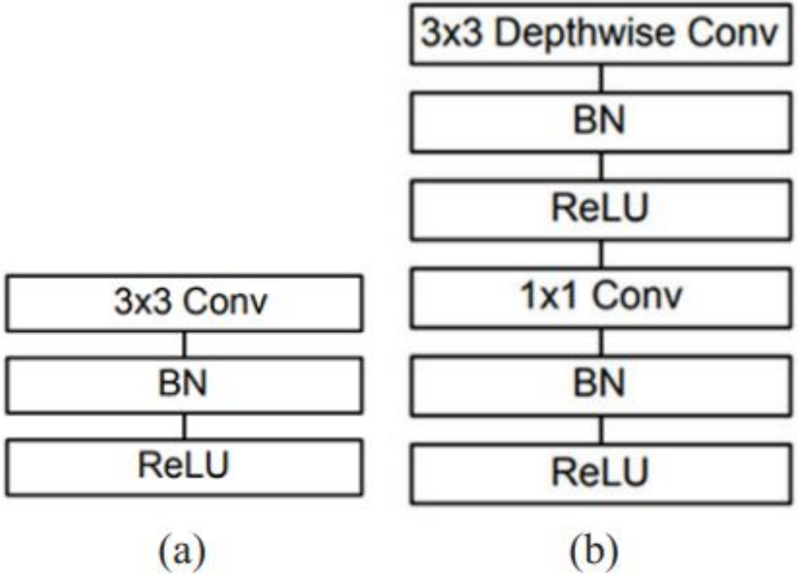
Flattening

- Converts pooled features to vectors

Fully Connected Layer

- Learns to make predictions.
- Produces final output

What is MobileNet ?



(a) Traditional single 3×3 convolution layer followed by the batch normalization and ReLU.

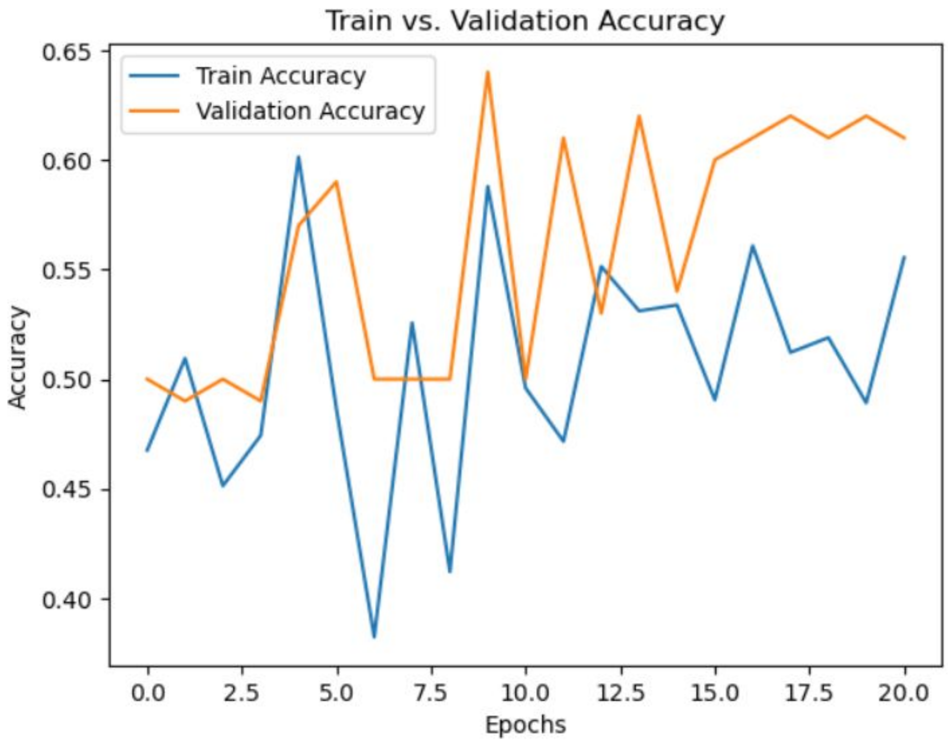
(b) 3×3 depth-wise conv and a 1×1 pointwise conv followed by batch normalization and ReLU.

- MobileNet was open-sourced by Google.
- MobileNet is a CNN architecture
- It makes use of a new kind of convolutional layers, known as Depthwise and Pointwise.
- Increases the efficiency of CNN to predict images.
- Hence, highly effective feature extractors for segmentation and object detection.

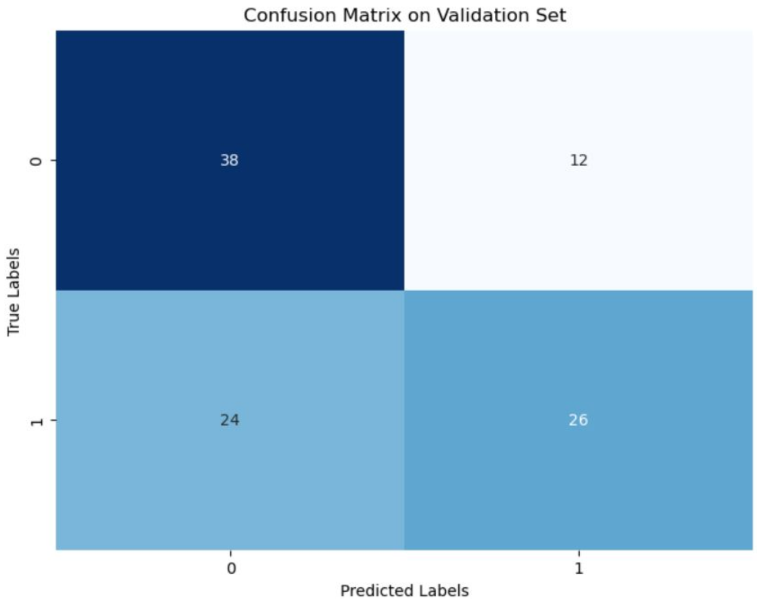
Advantages of MobileNet over other networks

- MobileNets have higher classification accuracy.
- Lesser number of parameters.
- Reduces comparison and recognition time a lot, so it provides a better response in a very short time.
- Because of the small size of the model, these models are considered very useful to be implemented on mobile and embedded devices.

Analysis for Mobile Net



Precision: 68.42 %
Recall: 52.00 %
F1 Score: 59.09 %



What are we doing?

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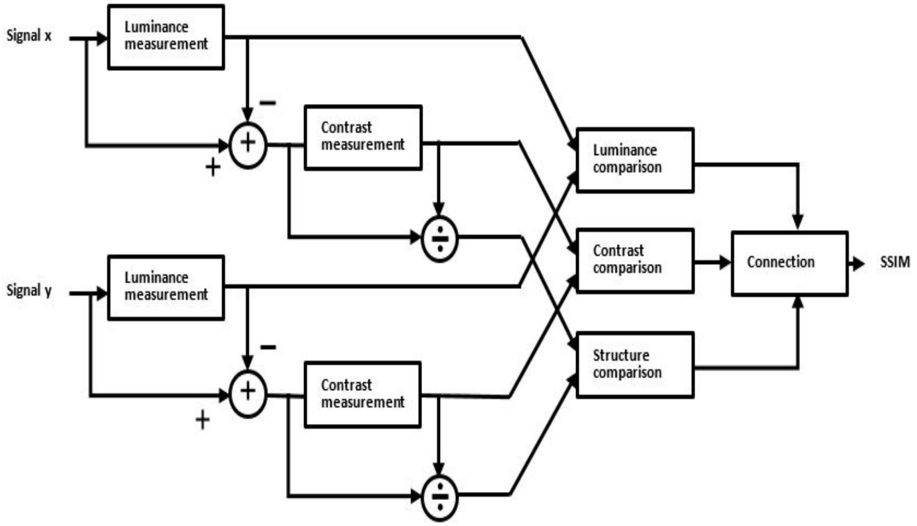
Structural Similarity Index (SSIM)

- The Structural Similarity Index (SSIM) is a metric used to quantify the similarity between two images.

- Key components of SSIM are Structure, Luminance and Contrast

- The SSIM predicts image quality based on an initial uncompressed or distortion-free image as reference. It tells us how far away an image is from its original reference image more aligned with the human perceptual system.



SSIM vs MSE

SSIM

- SSIM looks for similarities within pixels.
- Loss is between 0 and 1
- A score of 1 on SSIM means the images are very similar while a score of 0 means they are very different.

MSE

- Calculates MSE between each pixel for two images
- MSE tends to have arbitrarily high numbers, making it harder to standardize
- A higher MSE generally indicates lesser similarity but if the MSE between picture sets differs randomly, it will be harder to tell anything.

Structural Similarity Index (SSIM)

Train Test Split → Pre-processing → Find SSIM

Train Test Split

Split the data into Training and Validation set with a split of 75 % training and 25% test

Pre-processing

Augmented the images

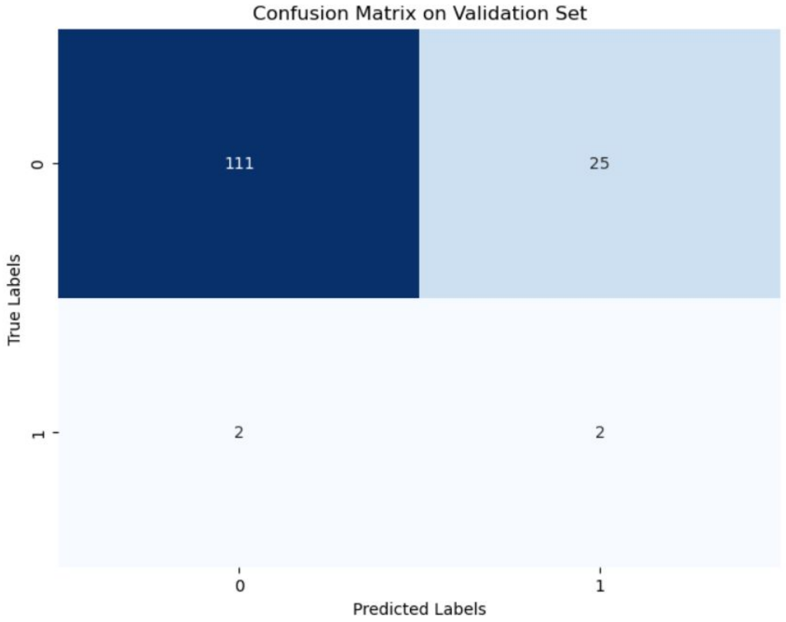
Changed the size from 256 x 256 to 11 X 11

Find SSIM

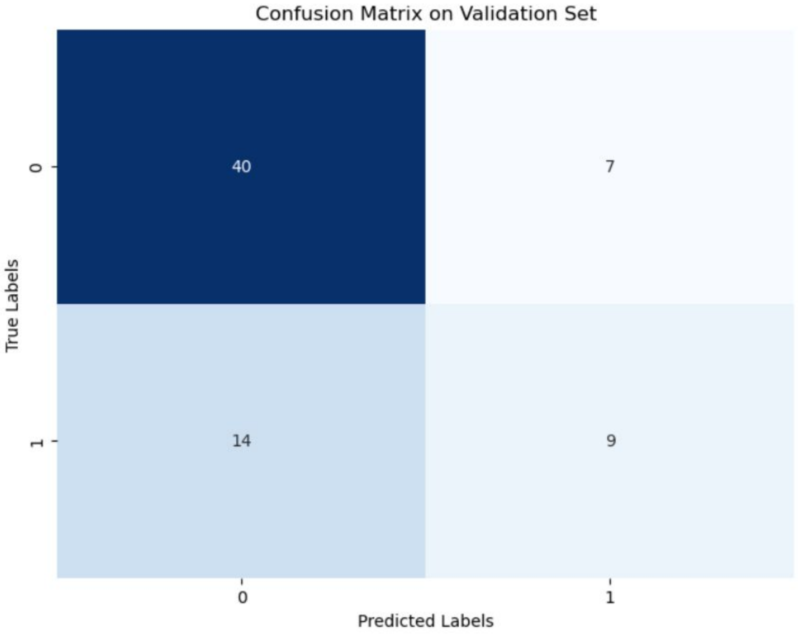
Calculated the Similarity of the Validation set with reference to Class 1 images of the Training set

Set a cut-off value of similarity at 0.25 and assigning a value of 1 above this threshold and then aggregating

Confusion Matrix



For 3-Day Embryos



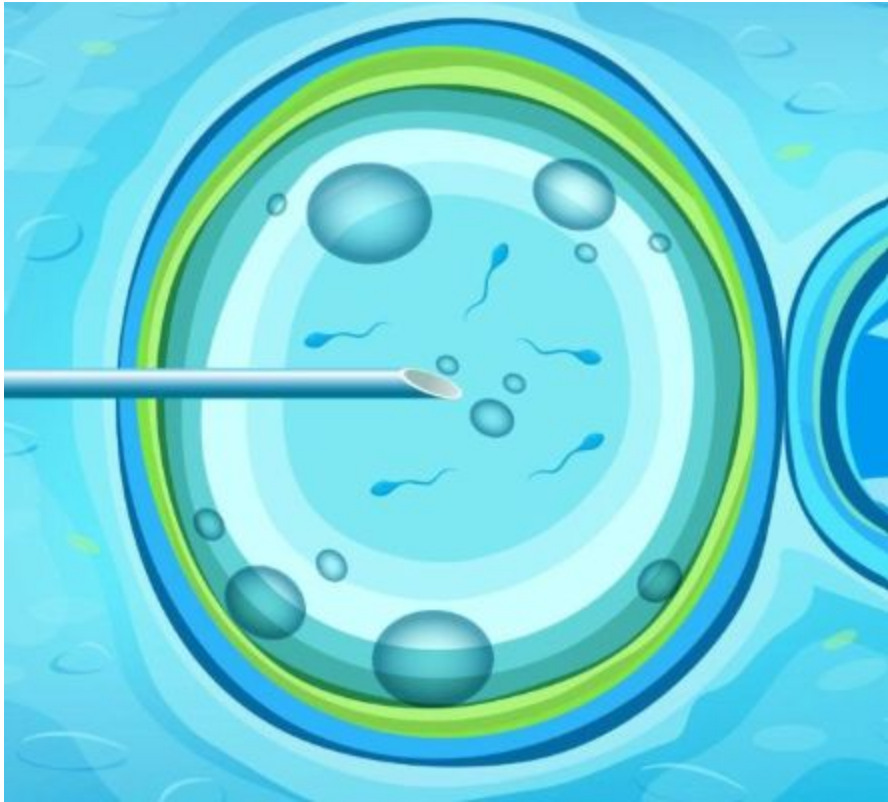
For 5-Day Embryos

What are we doing?

Exploratory Data Analysis → Convolutional Neural Network (CNN) → Structural Similarity Index (SSIM) → Conclusion & Future Scope

Real World Applications

1. Increased Success Rates in IVF Treatments
2. Cost Reduction for Patients and Clinics
3. Standardization of Embryo Selection
4. Research and Development in Reproductive Medicine
5. Global Accessibility and Equality in Treatment



Potential Ways to Expand Project

Integration with Genetic Testing

Real-time Monitoring of Embryo Development

Automated Reporting and Data Analysis

AI-Enhanced Predictive Models

Global Database for Research and Collaboration

Thank You!

Questions?

References

- https://www.kaggle.com/competitions/world-championship-2023-embryo-classification/overview
- IC-IP Lab, ISODS Competitions, Shaimaa Ali. (2023). Embryo classification based on microscopic images. Kaggle. https://kaggle.com/competitions/world-championship-2023-embryo-classification