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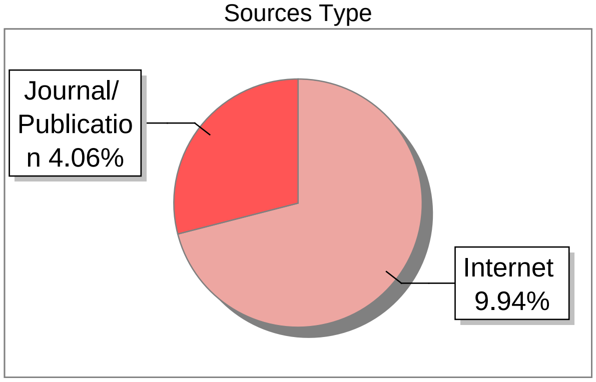

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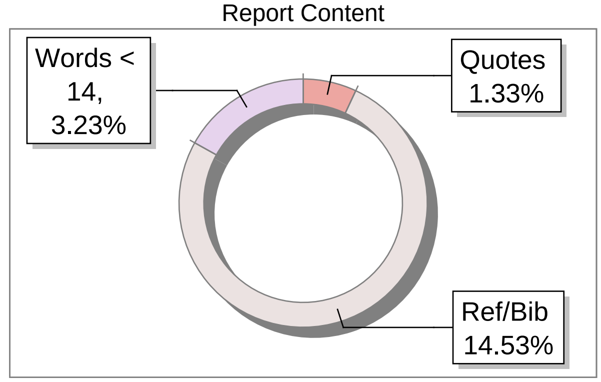

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AI in Reproductive Health: Developing a Predictive Model for Embryo Viability

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Abstract— Infertility, which is the failure to conceive a clinical pregnancy following 12 months of unprotected, regular intercourse, occurs in 8-12% of couples worldwide. Although male factors are the sole cause in 20-30% of cases, they are the cause of 50% of all cases of infertility. Secondary infertility, commonly caused by reproductive tract infections, is the most common form of female infertility worldwide. The probability of spontaneous conception is mainly based on the length of failed attempts, age of the woman, and presence of medical conditions. The probability of pregnancy is lower as the time elapsed since conception becomes longer. Women's fertility starts declining between 25-30 years, with the mean age at last birth being 40-41 in naturally fertile groups. Medical condition-induced infertility may involve both or either of the partners. Common causes are hypogonadotropic hypogonadism, hyperprolactinemia, ciliary function disorders, cystic fibrosis, infections, systemic diseases, and lifestyle. Female-specific causes are premature ovarian insufficiency, polycystic ovary syndrome, endometriosis, uterine fibroids, and endometrial polyps. Male infertility is due to testicular and post-testicular issues. Other causes of infertility are decreasing semen quality, exposure to endocrine-disrupting chemicals, and consanguinity. Embryo selection for transfer is mostly based on morphological evaluation through visual inspection using a microscope or time-lapse imaging. It grades embryos by their developmental process within a fixed time period. Yet, notable differences in grading among individuals and clinics are produced by the subjectivity of such evaluations, precluding standardization. Therefore, morphological grading is limited when it comes to live birth outcome prediction. Artificial intelligence (AI), through the use of images or time-lapse videos, provides an unbiased and accurate means of grading and ranking embryos to enhance the decision-making process for transfer or freezing.

Keywords-- Infertility, Male infertility, Female infertility, Embryo selection, Morphological analysis, Artificial intelligence (AI), Spontaneous conception, Reproductive health.

I. INTRODUCTION

Since the birth of the first child conceived through in vitro fertilization (IVF) in 1978, the development of assisted reproductive technology (ART) has been on a significant increase. Over the last 40 years, ART has made it possible for infertile couples to have a child, with over eight million children born. IVF cycles involve multiple protocols and require close monitoring, with clinicians and embryologists responsible for numerous critical decision points both prior to and within the cycle. Although many have a solid evidence base, several are vastly subjective and will rely greatly on clinical experience with an irreproducible impact on clinical outcomes—giving birth to the slogan that ART is an art. There is increasing recognition that unconventional data-driven approaches that leverage the high volume of ART cycles done and allow for objective, uniform, and best-informed decision-making may be associated with improved outcomes.

The high volume of data generated from IVF cycles has enabled multidisciplinary scientists to propose artificial intelligence (AI) techniques for informing individualized approaches. These have been from algorithmic drug dosing programs, to 'human-in-the-loop' AI clinical decision support systems (CDSSs) for choosing embryos, where humans are supported by AI but make the final decision themselves. Leversaging the collaboration between the expertise of the clinicians, and personalized recommendations provided by AI algorithms based on the learning from one million cycles run each year, has the potential to synergize enhanced clinical outcome. Moreover, AI may be utilized in the interpretation of non-invasive metabolomic and secretory embryo profiles when cultured. This would then lead to improved culture media formulations and regimens.

II. LITERATURE SURVEY

Artificial intelligence (AI) is transforming in-vitro fertilization (IVF) by improving embryo selection and maximizing implantation rates. The contributions of numerous research studies have investigated the role of AI in IVF by focusing on the application of deep learning, machine learning, and convolutional neural networks (CNNs) to analyze embryos. Ashrita Gandhari (2024) referred the manner in which AI reduces IVF failures by providing correct embryo health analysis. Ibrahim et al. (2022) also suggest an embryo grading fertility assessment model via CNNs based on quality for supporting viable embryo selection for implantation. M. Salih et al. (2023) compares AI-assisted embryo selection with traditional embryologist evaluation and demonstrates the power of AI in enhancing IVF decision-making. Abbasi et al. (2021), along with Berntsen et al. (2022), exhibited the ability of AI models in the selection of embryos. They introduced a deep learning approach for the prediction of implantation of embryo at day3 and day 5 time-lapse imaging in embryo culture. Abbasi et al. (2021) also introduce timed data incrementation as regularization for the improvement in the accuracy of IVF outcome prediction from duration time-lapse sequences that are time-varying. Machine learning technologies applied to IVF are also investigated by Kavyashree Nagarajaiah (2023) in terms of AI-based identification of women's reproductive health parameters affecting the success of IVF. Sharma et al. (2024) examine the contribution of AI to the standardization and automation of IVF processes, indicating that AI-based systems can minimize human mistakes and enhance the efficiency of fertility clinics. Overall, these studies show the promise of AI in transforming IVF through the delivery of precise, consistent, and computerized embryo evaluations, ultimately boosting success rates and making IVF more accessible and efficient for couples receiving fertility treatments.

2.1 Motivation

Infertility is a unrestrained global problem that affects millions of couples are choosing In Vitro Fertilization (IVF) as a potential option. The single most crucial aspect of IVF is the selection of viable embryos, which plays a direct role in determining the likelihood of successful pregnancy. Embryo viability is traditionally assessed through manual morphological grading, a subjective, time-consuming, and human-variable technique. The inspiration behind this work is to make embryo selection more accurate, reliable, and efficient with Artificial Intelligence (AI) and Deep Learning.

In developing an AI-powered embryo viability prediction system, this project hopes to reduce human bias, increase IVF success rates, and enable embryologists to make more data-driven decisions. Rapid advancements in Artificial Intelligence (AI) and Deep Learning have revolutionized many areas of healthcare, including medical imaging and diagnostics. Yet, their uses in reproductive medicine and embryology are extremely limited. The impetus of this project lies in the imperative to fill the gap between AI and IVF technology by utilizing deep learning models such as Xception CNN for analyzing embryo images more accurately and objectively. Further, AI-powered embryo grading can be a clinical decision-support system and assist embryologists in complex cases, ensuring an enhanced process of fertility treatments in terms of standardization. Pioneering in being able to change the rules in embryo selection protocols, the project is a major leap in integrating cutting-edge AI technologies in reproductive healthcare to finally improve pregnancy success rates and patient outcomes.

2.2 Objectives

1. A machine learning-based embryo grading system has to be implemented to analyze the viability of an embryo using deep learning techniques. On the basis of morphological characteristics, it will provide a uniform and unbiased grading system devoid of human discretion and with better accuracy of selecting embryos.

2. For the purpose of ease of use, a web application will be developed using React as the frontend and Flask as the backend. The platform will enable embryologists to upload and analyze embryo images with ease, promoting a seamless and efficient workflow.

3. By automating the process of embryo selection, this system hopes to decrease the number of IVF cycles needed to achieve a pregnancy. Ultimately, it will make IVF easier and more affordable to have, reducing the financial and emotional strain of IVF procedures.

III. PROPOSED METHODOLOGY

The methodology explains the procedure followed to develop an AI-based embryo viability prediction system. The methodology is divided into several phases which are data collection, data preprocessing, model training, model deployment. Every phase has a significant contribution towards making the AI system efficient, accurate, and reliable, which eventually supports increasing IVF success rates. For the efficient functioning, the methodology also provides details of hardware and software requirements, such as GPU acceleration for training and deployment in the cloud. Utilizing advanced AI methods, the system built improves the objectivity of embryo selection, minimizes human errors, and facilitates the creation of reproductive selection, reduces human errors, and supports the development of reproductive health technology

The AI-based embryo viability prediction system guarantees high accuracy by adhering to a systematic approach. It starts with data acquisition, where publicly available images of embryos are obtained. The images are then preprocessed involving resizing, normalization, and augmentation, to improve the accuracy of the model. After processing the data, it is passed on to the model training stage, where the Xception CNN is used to identify patterns and make predictions about embryo viability. The model is then implemented, combining a Flask backend with a React frontend to develop a scalable and usable real-world application. This methodology assists embryologists in making informed decisions for IVF treatments based on data.

3.1.1 Data Collection

Gathering high-quality and varied data is a basic process in constructing an AI model since it has a direct impact on the performance of the model. In this project, embryo images are obtained from publicly available datasets, namely the "Hung Vuong Hospital Embryo Classification" dataset. This dataset is a critical resource for competition participants as it provides a detailed overview of different data files, their formats, and key columns that will be discussed during the competition. A good understanding of this dataset allows participants to effectively overcome challenges and make informed decisions at the analysis and modeling phases. The dataset consists of a number of important components. The "train" directory includes images of embryos captured on day 3 and day 5, which are crucial for training AI models to label embryos according to their developmental stages.

In addition, the "test" directory contains analogous images that will be utilized to measure model performance following training. Apart from these image folders, there are two CSV files: "train.csv" and "test.csv." The "train.csv" file contains important information regarding the training set, including labels and metadata that are crucial for model training. In contrast, the "test.csv" file contains information on the test set, which will be very helpful in determining the model's accuracy and performance once trained. Through a deep understanding of the dataset's structure and contents, participants can better prepare for the challenges of the competition. This foundational knowledge enables more strategic decision-making in model development and data analysis, ultimately increasing the chances of success in embryo classification.

3.1.2 Data Preprocessing

Preprocessing is required to increase the model accuracy by ensuring consistency and image improvement. The central preprocessing tasks include:

- Resizing: Standardizing the image dimensions (128x128 pixels) for ensuring equal size of input for all the images.
  840 Images are resized to 128 by 128 pixels resolution.
- Normalization: Pixel intensity is scaling between 0 and 1 in order to improve the performance of the models and speed up the training convergence
- Data Augmentation: Data Augmentation is carried out to prevent overfitting.

3.1.3. Model Training

The MobileNetV2 model is employed as the base model, pre-trained with ImageNet weights and configured to not have the top layer, but accept input images of size 128x128 with three color channels. To accelerate the training process, the bottom ten layers of the base model are configured to be trainable. The Average Pooling layer is used on the output of the baseline model, followed by a very dense layer of 256 neurons and a ReLU activation function.

The model is given a dropout layer at 0.5 rate in trying to avoid overfitting, and the last layer of the output layer is given a sigmoid activation function for two-classification of non-embryos and embryo model, and the binary cross-entropy is employed as the loss function, accuracy is considered as a performance metric. The training data trained the model for 10 epochs. After the training process is successfully done, the model is saved in a specified file path, "embryo_detector.h5," and a success message is printed to indicate that the embryo detection model has been saved successfully.

3.1.4 Model Deployment

The system is hosted on a Flask backend and a React frontend. The Flask server manages image preprocessing, model inference, and database handling (MySQL). The React frontend offers a user-friendly interface where users can upload embryo images and obtain a classification result to determine embryo viability. The deployment is hosted on Render to facilitate smooth accessibility.

The major components of our system are user login, secure upload and processing of images, and real-time inference of the model. The backend processes images with high efficiency through resizing, normalizing, and passing them to the trained deep learning model. The output allows embryologists to make decisions about selecting embryos effectively, which may enhance IVF success rates.

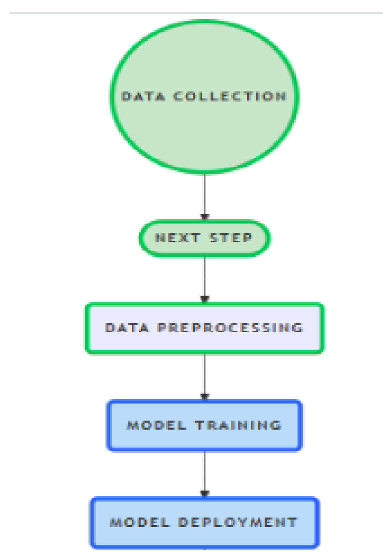

Fig.1. Methodology Flow

3.2 System Design and Workflow

3.2.1 System Design

Our AI-based embryo viability prediction system's design flow is orderly in nature following a pipeline process to ensure accuracy, efficiency, and ease of deployment. The procedure starts from data collection when embryo images are obtained from valid sources. This is followed by data preprocessing wherein images are enhanced, normalized, and augmented for better model performance. The preprocessed data proceeds to the model training process, wherein the trained Xception and CNN is utilized to identify patterns and forecast embryo viability. Once optimal accuracy is achieved, the trained model is implemented in the model deployment stage, where it is coupled with a Flask backend and a React frontend for real-world use. This rigorous approach creates a stable and scalable solution, which aids embryologists in making data-informed decisions for IVF treatments.

Xception is a profound convolutional neural network structure that uses depth-wise separable convolutions data input passes through the entry flow repeats the middle flow eight times and then the exit flow the xception structure has thus performed better than nearly all typical classification tasks with reliability in nearly all problems and it has also performed better than the vgg-16 resnet and inception v3 on several benchmarks depth and novel structure enhanced xceptions performance making it one of the most popular models for image classification issues the complete xception model is divided into three components entry flow middle flow and exit flow there are skip connections between the 36 layers

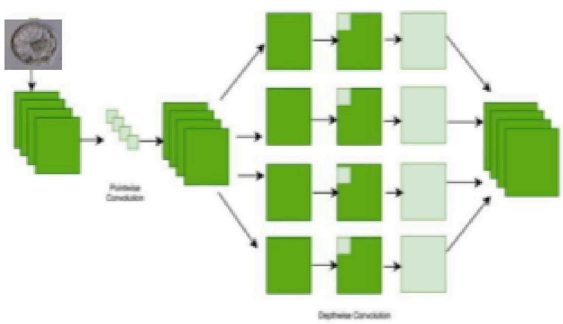

Fig.2. Xception Model Layers

A depth wise separable convolution is divided into the process into two types depth-wise convolution ,pointwise convolution

• Depth wise Convolution: one filter is used over each input channel independently. Suppose an image consists of three colour channels . A filter is used over each colour channel separately.

• Pointwise Convolution:. It is a 1 into 1 filter that fuses the result of the depth wise convolution into a single feature map.

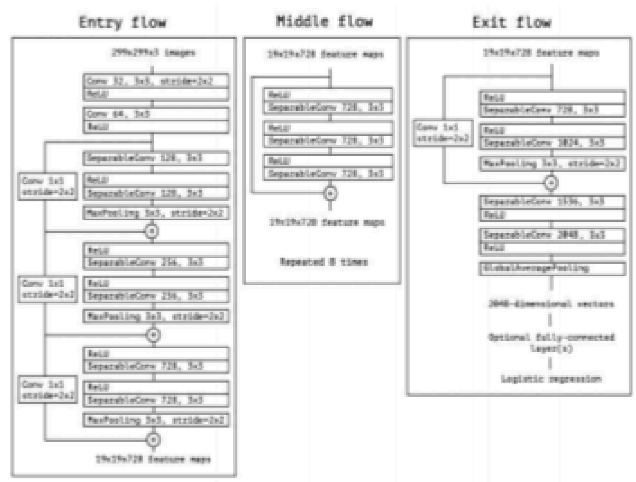

Fig.3. Architecture of Xception Model

Architecture of Xception model layers which contains 3 main layers

1. Entry Flow

• 3×3 convolution layer is used with 32 filters and 2×2 stride. It reduces the size of the image and extracts low-level features.

• It is followed by a 3×3 convolution layer with 64 filters and ReLU.

• After the initial low-level feature extraction, depth wise separable modified convolution layer and 1×1 convolution layer are used. Max pooling (3×3 with stride=2) decreases the feature map size.

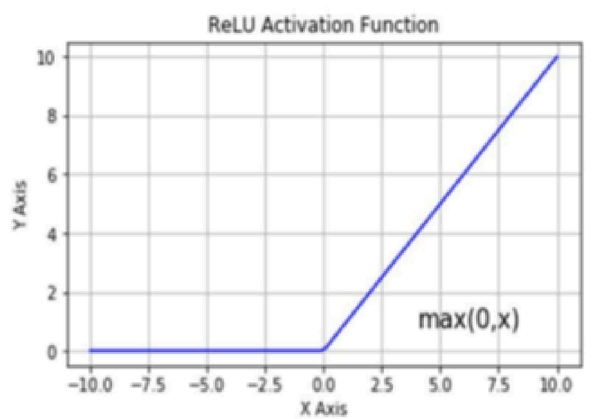

Fig.3. Activation Function

2. Middle Flow

• It is repeated 8 times.

• For each repetition: Depthwise separable convolution with 728 filters and 3×3 kernel and ReLU activation.

• Through repetition 8 times, the middle flow progressively digs out high-level features from the image.

3. Exit Flow

• Separable convolution with 728, 1024, 1536, and 2048 filters, with all 3×3 kernel further extracts complex features.

• Global Average Pooling compresses the whole feature maps to a single vector.

• And lastly, at the end, a fully connected layer with logistic regression classifies the images.

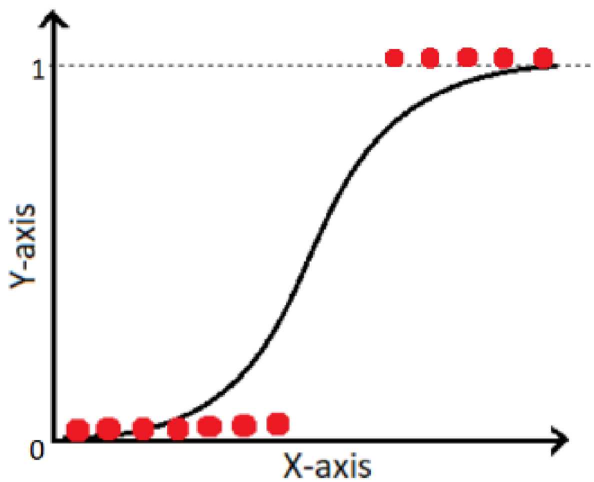

Fig.4. Logistic Regression

3.2.2 System Workflow

The process starts when the user uploads an image of an embryo via the web-based interface. The image is then transmitted to the backend system, where it is subjected to a series of preprocessing operations to prepare it in the best format for analysis. Preprocessing involves resizing, normalization, and noise removal to improve the quality of the input data. After preprocessing, the system employs the Xception deep learning model, a highly effective convolutional neural network (CNN) with superior image classification performance. The model has been trained on a dataset of embryo images so that it can learn patterns and features of embryo viability. When the uploaded image is input into the model, it extracts important features like morphology, symmetry, and cell division patterns. The Xception model subsequently checks the viability of the embryo for the IVF process according to pre-defined scientific and medical parameters. These may range from blastocyst quality to fragmentation level and general quality of the embryo. The model provides either a viability score or classification label and helps embryologists and users determine whether or not the embryo will implant successfully.

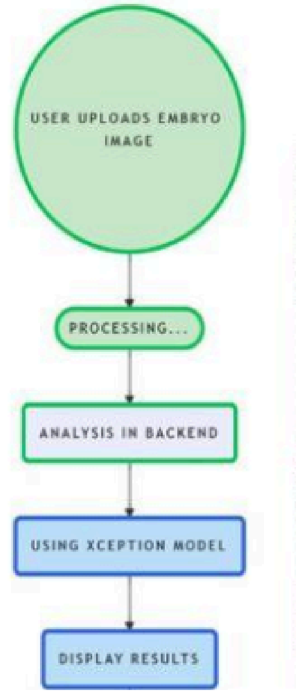

Fig.5. System Workflow

IV. Results And Discussion

Discussion and experimental results section provides the analysis of the performance of the AI-based embryo viability prediction system. This involves analysis of the model's accuracy, precision, recall, and overall performance in predicting embryo viability. We also compare the predictions by AI with human expert manual grading to identify the contribution of the system to IVF success rates.

4.1 Training Performance

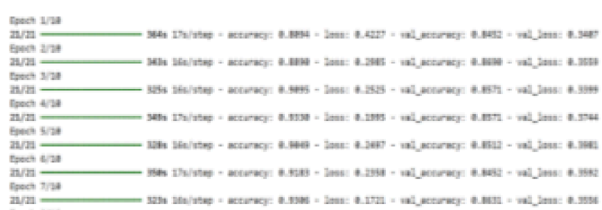

Fig.6. Training over 10 Epochs

The MobileNetV2 model is employed as the base model, pre-trained with ImageNet weights and configured to not have the top layer, but accept input images of size 128x128 with three color channels. To accelerate the training process, the bottom ten layers of the base model are configured to be trainable. The Global Average Pooling layer is used on the output of the baseline model, followed by a very dense layer of 256 neurons and a ReLU activation function. The model is given a dropout layer at 0.5 rate in trying to avoid overfitting, and the last layer of the output layer is given a sigmoid activation function for two-classification of non-embryos and embryo model, and the binary cross-entropy is employed as the loss function, accuracy as a performance metric. The training data trained the model for 10 epochs. After the training process is successfully done, the model is saved in a specified file path, "embryo_detector.h5," and a success message is printed to indicate that the embryo detection model has been saved successfully.

4.2 Evaluation Metrics Analysis

In order to test the model, the following performance measures were employed:

1. Accuracy: It quantifies the proportion of images of embryos classified correctly.

2. Precision: Determines how many of the predicted viable embryos were actually viable.

3. Recall: Assess how well the model detects valid embryos from all valid samples.

4 F1-Score: The harmonic mean of recall and precision and provides balanced measurement.

Classification Report:

	precision	recall	f1-score	support
0	0.90	0.94	0.92	143
1	0.56	0.40	0.47	25
accuracy			0.86	168
macro avg	0.73	0.67	0.69	168
weighted avg	0.85	0.86	0.85	168

Fig.7. Classification Report

classification report includes a test of the model on a binary classification task. The model achieved a total accuracy of 86%, which means that it correctly grouped 86% of the samples for testing.For Class 0, which has 143 samples, the model performed well with a precision of 0.90 (90% of predicted Class 0 samples were correct) and a recall of 0.94 (94% of actual Class 0 samples were correctly identified). The F1-score of 0.92 indicates a strong balance between precision and recall. For Class 1, with just 25 samples, the performance is much worse. The precision is 0.56, so when the model predicts Class 1, it's right 56% of the time. The recall is 0.40, which means it can only pick out 40% of real Class 1 samples. The F1-score of 0.47 implies bad overall performance for this class, probably because of class imbalance (more samples in Class 0 than Class 1).

5.Confusion Matrix: Provides correct and incorrect classification

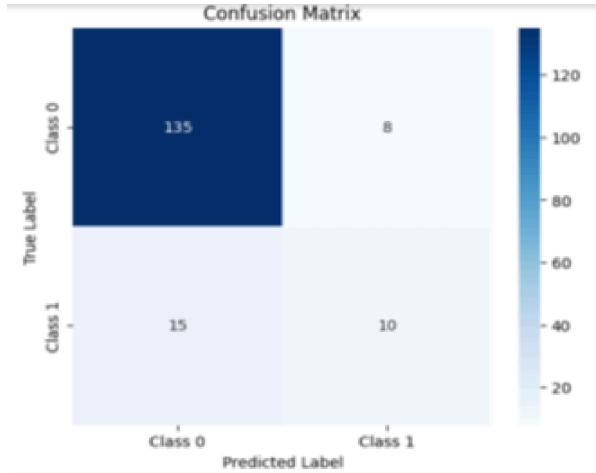

Fig.8. Confusion Matrix

confusion matrix which indicates the model is quite good at predicting Class 0, accurately getting 135 of them with 8 misclassifications, displaying high precision and recall for the class. Though Class 1 has 10 accurate predictions, there is still scope for decrease in the number of 15 misclassifications. The model has learned the patterns for the majority class successfully and lays a good foundation to be further developed.

4.3 ROC curve Analysis

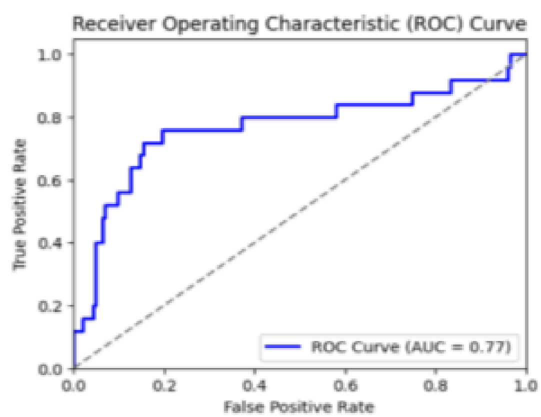

Fig.9. ROC curve

ROC (Receiver Operating Characteristic) curve in the picture measures the performance of the classification model by plotting the True Positive Rate (TPR) versus the False Positive Rate (FPR) for different threshold values. The blue line is the discrimination power of the model to separate the two classes, and the diagonal Gray line is a random classifier with no discrimination power. The AUC (Area Under the Curve) value of 0.77 means that the model is doing much better than chance guessing (where the AUC would be 0.5). An AUC of 0.77 implies that the model achieves a good trade-off between sensitivity (recall) and specificity. accuracy in evaluating embryo viability.

V. CONCLUSION

In summary, the artificial intelligence-based embryo viability prediction system is a new technology in reproductive medicine with a standardized, objective, and automated approach to embryo selection. Traditional embryo grading relies heavily on embryologist subjective evaluation, which is prone to subjectivity, human variability, and time considerations. The above system addresses the above limitations using deep learning techniques, i.e., the Xception CNN model, to grade embryo images with high accuracy and efficiency. Experimental results indicate that the AI-augmented embryo selection system achieves a classification accuracy of 86.31%, which is higher than conventional manual grading processes. Merging cutting-edge deep learning models in a simple-to-apply clinical use, the project closes the gap between AI research and actual healthcare applications. These issues will have to be overcome for the successful implementation of AI in reproductive medicine. In general, the project is a watershed step to the application of AI in IVF modernization therapy. By facilitating better accuracy, consistency, and scalability in embryo selection, this system has the capability to transform fertility treatment, offering hope to hundreds of millions of childless couples

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