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Embryo Grading Redefined: AI Innovations Shaping the Future of Fertility

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Abstract:- Fertility treatments, particularly in the context of in vitro fertilization (IVF), have seen significant advancements in recent years, revolutionizing the prospects for couples facing infertility. The quality of the embryo is a critical factor influencing the success of these treatments. Traditional methods for embryo assessment have limitations in accuracy and efficiency, prompting the need for innovative techniques. This research study explores the application of deep learning models to enhance embryo quality assessment in the field of reproductive medicine.

The study involves the collection of a large dataset of embryo images, Leveraging state-of-the-art deep learning algorithms for the automated evaluation of embryo quality. The deep learning models can accurately predict embryo quality and developmental potential, offering a valuable tool for clinicians and embryologists.

The outcomes showcase the exceptional performance of the deep learning models, markedly enhancing both the speed and accuracy of embryo quality assessment. This advancement not only enhances the efficiency of fertility treatments but also contributes to better patient outcomes by facilitating the selection of the most viable embryos for fertilization.

The findings of this research have the potential to transform the field of reproductive medicine, making fertility treatments more accessible, cost-effective, and successful. Utilizing the capabilities of deep learning, this research marks a hopeful stride in enhancing the prospects of conception for individuals and couples grappling with infertility.

Keywords:- *Fertility treatments, In vitro fertilization (IVF), Embryo quality, Embryo assessment, Convolutional Neural Network (CNN), Deep learning, Reproductive medicine, Automated assessment, Embryo viability, Reproductive health.*

I. INTRODUCTION

Infertility, a complex and multifaceted health issue, goes beyond its biological dimensions, extending into the realms of emotional and social well-being. While it is frequently underestimated in public discourse, its impact on couples around the world is profound. The inability to conceive can give rise to a range of emotional challenges, including frustration, sadness, and a sense of loss, which often manifest as emotional distress and, in severe cases, clinical depression [1]. The extensive occurrence of infertility and subfertility presents a formidable global challenge, transcending geographical boundaries. This health issue's overarching impact is profound and potentially underrepresented in reported statistics, emphasizing the need for increased awareness and attention. Over the past two decades, there has been no observable reduction in the rates of infertility and subfertility, indicating the persistent nature of this concern [2].

In vitro fertilization (IVF) is a common and widely used assisted reproductive technology (ART) that helps individuals or couples experiencing infertility to conceive a child. IVF, while advantageous for overcoming infertility, remains financially demanding. This burden is heightened by the substantial costs, with a significant portion typically not covered by insurance [2].

Adding to the financial challenges, many individuals and couples undergoing fertility treatments often find themselves undergoing multiple cycles of ART to achieve the desired outcome of a successful pregnancy. The success of these ART cycles is contingent on a multitude of factors, including maternal age, underlying medical diagnoses, gamete and embryo quality, and the receptivity of the endometrium. As a result, the intricate interplay of these variables underscores the complexity and challenges associated with assisted reproductive technologies. [1].

Embryo selection is a crucial aspect of determining the success of pregnancy following in-vitro fertilization (IVF). Researchers are investigating the application of artificial

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intelligence (AI) methods to elevate embryo selection, forecast implantation, and enhance overall pregnancy outcomes. As global fertility rates decline, many individuals and couples are increasingly relying on assisted reproduction procedures to achieve conception. The quality of embryos plays a pivotal role in the success of IVF, making the embryo selection process essential for expediting the time to pregnancy for patients. There is a compelling need to enhance the current methods of selecting embryos for transfer into the uterus during IVF [2].

In the realm of assisted reproductive technology, procedures like ovulation induction, egg retrieval, fertilization, and embryo transfer are fraught with a notably low success rate. This limited success is often attributed to suboptimal embryo quality, prompting the transfer of multiple embryos and subsequent complications for both mothers and children, as well as escalated healthcare costs. To address the risks linked to multiple pregnancies, the concept of Single Embryo Transfer (SET) has emerged. SET aims to choose the most viable embryo, maximizing the potential for a successful childbirth. However, the current method for effective embryo selection heavily relies on morphology assessments conducted in IVF laboratories. Despite numerous studies and proposed embryo grading systems, no consensus has been reached on the most accurate method. Moreover, existing grading systems predominantly hinge on subjective and visual evaluations by embryologists, resulting in significant variability among professionals of diverse backgrounds and moderate variability even among embryologists assessing the same embryo image multiple times. This current approach to embryo grading is not only time-consuming for IVF practitioners but also directly impacts the likelihood of IVF success [2].

In the past decade, significant strides in assisted reproductive technology have brought hope to countless infertile couples. The controlled ovarian stimulation (COS) process has notably improved the retrieval of high-quality oocytes during ovum pickup. Subsequent to this, embryos derived from in vitro fertilization (IVF) or intracytoplasmic sperm injection (ICSI) undergo a grading process. This grading is instrumental in selecting the most viable embryo for either immediate transfer or cryopreservation. When factored in with considerations such as the patient's health, age, fertility, and medical history, embryo grading plays a pivotal role in determining the optimal day for transfer, the appropriate number of embryos to transfer, and the specific embryos to choose—ultimately contributing to enhanced rates of pregnancy success [3].

Recent research has explored the potential of machine learning, particularly deep learning, for analysing embryo quality. While these methods have shown promise, they often require advanced embryological expertise, extensive pre-processing, and face challenges in scaling to large datasets.

Convolutional Neural Networks (CNNs) represent a specialized type of artificial neural network tailored for the processing and analysis of visual data, particularly in tasks related to computer vision. The distinctive feature that sets CNNs apart from conventional neural networks lies in their organization of neurons in three dimensions—width, height, and depth. This three-dimensional arrangement allows CNNs to effectively capture intricate features within complex medical images.

CNNs demonstrate excellence in handling medical data by leveraging their convolutional layers to perform spatial hierarchies of feature extraction. This mechanism enables the model to identify patterns at various levels of abstraction. The hierarchical feature learning exhibited by CNNs is particularly crucial in discerning complex structures and subtle patterns within medical data, making them highly suitable for applications in the field of healthcare [16].

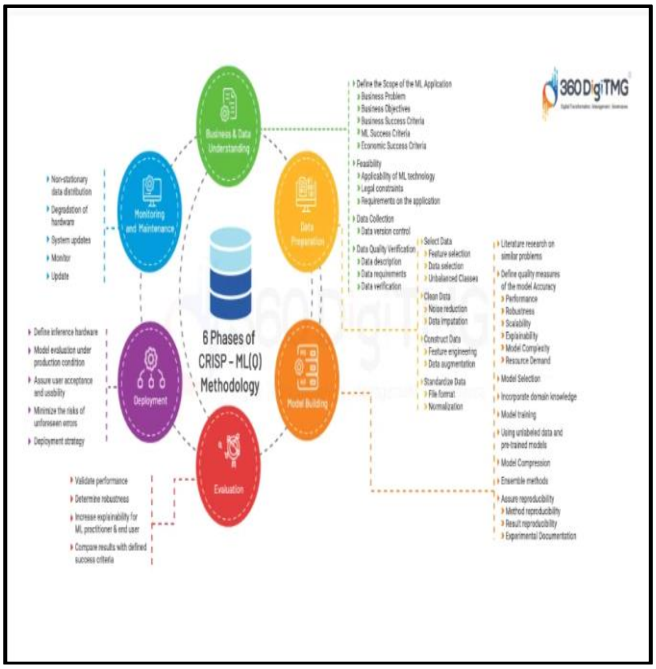

Fig.1: *CRISP-ML(Q)- approach for quality assurance for each of the six phases.(Source:CRISP-ML(Q) | 360DigiTMG)*

The CRISP-ML(Q) framework, available as an open-source tool on the 360DigiTMG website [Fig.1] has been instrumental in steering our image classification project with a meticulous and systematic approach.

The initial stage of our project, as indicated in [Fig.1], is the "Business Understanding" phase. During this phase of a project the focus is on gaining a comprehensive understanding of the business context, objectives, and requirements in image quality assessment. Progressing further, the "Data Understanding" phase, depicted in [Fig.1], involves a thorough process of collecting and analysing data tailored to our image classification project. In our efforts, we have diligently assembled an extensive dataset comprising 40,000 microscopic images. The careful curation of this dataset ensures alignment with the specific requirements of our project. Additionally, we have conducted a detailed exploration of the data, examining factors such as image quality, resolution, and domain-specific nuances. This phase is crucial in laying the foundation for our subsequent modelling endeavours.

In the Data Pre-processing & Annotation/Augmentation [Fig.1, 2] stage, we studied image quality and used domain knowledge to classify images. We annotated the datasets using Roboflow and divided them into classes like ‘good’ and ‘bad’. We also augmented our data using various techniques, increasing it from 40,000 to 100,000 images. After pre-processing and augmentation, we exported the data from Roboflow [Fig.1, 2]. We then moved to Model Building & Evaluation [Fig.1, 2], where we trained pre-trained models like VGG16, YOLOv8, ResNet50, MobileNet, InceptionV3 on the pre-processed data.

"Data mining," as depicted in [Fig.1], serves as the nucleus of our project, where we employ state-of-the-art machine learning methodologies. Our primary objective is to construct a resilient image classification model capable of accurately classifying between "good" and "bad" embryos. In this modelling stage, we harness a diverse array of algorithms, including advanced deep learning models, known for their proficiency in uncovering intricate patterns and trends within our dataset. This modelling approach is crucial to our mission of providing precise and reliable predictions regarding image quality. Achieving this involves extracting and scrutinizing significant or interesting patterns from data stored in databases [1]. Through this comprehensive analysis, we unveil hidden insights and optimize our image classification process to enhance overall performance and reliability.

The next phase of our project, denoted as the "Model Deployment" stage, as reflected in [Fig.1], represents the culmination of our efforts. In this phase, our carefully crafted image classification model seamlessly integrates into practical applications. A notable instance is the implementation of our model within the Streamlit web application, enabling real-time predictions of image quality. This tool proves invaluable for businesses aiming to elevate their quality control processes, streamline supply chain management, and optimize resource allocation. Finally, we have Monitoring & Maintenance [Fig.1, 2], where we ensure the continued performance and correctness of the deployed models and the entire system.

The CRISP-ML(Q) framework is widely acknowledged as a prominent standard in the field of data mining. It is frequently employed in various aspects, including the development of data mining solutions, analysis of business issues, and the execution of data mining projects [4]. Research studies have identified CRISP-ML(Q) as the de facto standard guiding the creation of projects related to data mining and knowledge discovery, solidifying its reputation in the field [5].

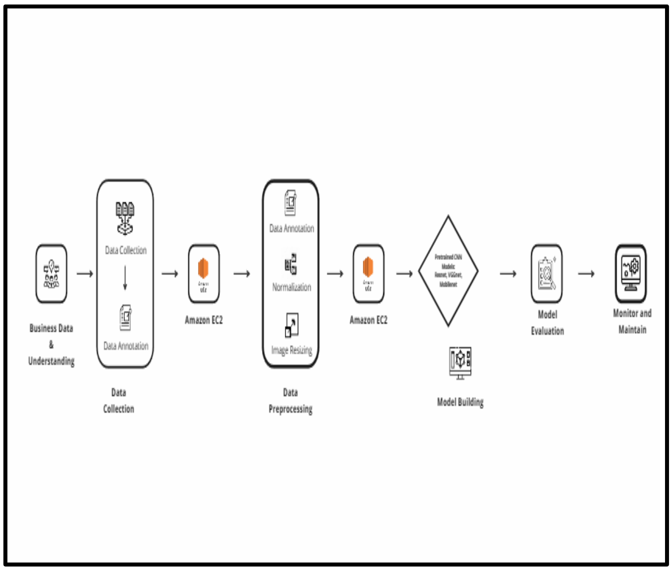

Fig.2: *Project architecture for embryo quality prediction. (Source:ML Workflow | 360DigiTMG)*

The architecture diagram [Fig.2] provides a comprehensive view of our proposed system for predicting the quality of an embryo.

II. METHODS AND TECHNIQUES

A. Data Collection:

Data Collection encompassed images sourced from the client, with patient details appropriately masked to address security considerations. The dataset contains static morphology images of human embryos from day 1 to day 5, We have taken around 40 thousand images and after augmentation the size of the dataset was increased to one lakh images. The dimensions of data used is given below [Table.1]

Type of Data	Dimensions	Format
Image Data	640*640, 512*384, 500*500, 2592*1944, 640*480	JPG, BNP

Table.1*: Dataset Details*

➢ *Stages of Embryo Development:*

Embryo development encompasses a series of stages, starting from the fertilization of an egg to the formation of a multicellular organism.

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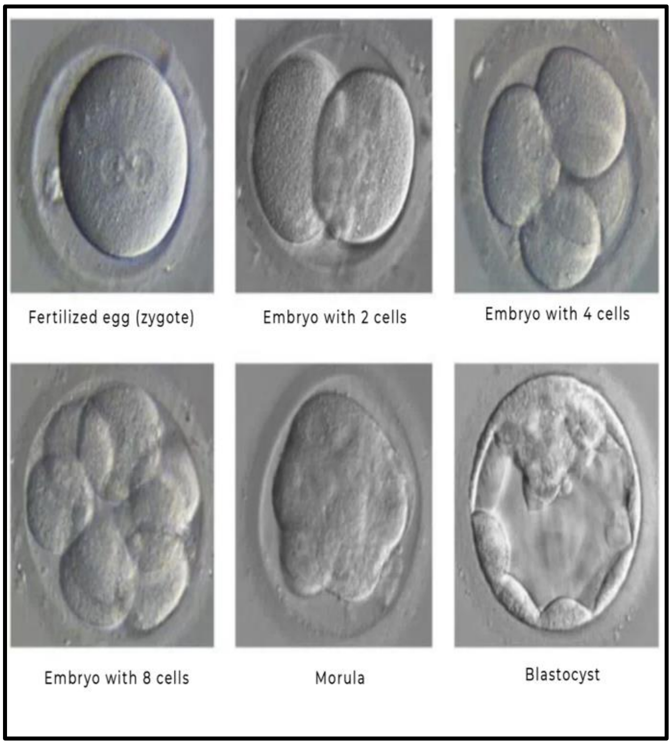

Fig.3: *Common stages of embryo development from day 1 to day 5 include images of a fertilized egg (zygote), embryo with 2 cells, embryo with 4 cells, embryo with 8 cells, morula, and a blastocyst.*
(Source:-https://www.arcfertility.com/understanding-embryo-grading/)

➢ *Fertilization:*

Fertilization is a biological process wherein male and female reproductive cells, typically sperm and egg, unite to create a new individual possessing a unique combination of genetic material. In sexual reproduction, fertilization marks the initiation of a new organism's development. This event occurs either internally within the reproductive organs or externally, depending on the species. The fusion of genetic material from male and female gametes forms a zygote, initiating the development of a new organism through subsequent cell division and differentiation. In the context of in vitro fertilization (IVF), fertilization specifically denotes the stage in the assisted reproductive technology process where the union of sperm and egg takes place outside the body, typically in a laboratory setting [7].

➢ *Cleavage Stage:*

At the cleavage stage, the fertilized egg undergoes multiple rounds of cell division, resulting in the formation of a structure known as a cleavage-stage embryo [6]. This stage typically occurs around days 2-3 post-fertilization. During this period, rapid cell divisions take place within the protective zona pellucida, leading to the creation of a multicellular structure. The grading of embryos at this stage is based on the symmetry of cells and the degree of fragmentation [8].

➢ *Development of Blastocyst:*

Shortly after fertilization, the embryo transforms from a small cluster of rapidly dividing cells into the organized structure known as the blastocyst (refer to Fig 4, 5). This cellular assembly consists of two distinct groups – inner and outer cells – interspersed with fluids [8].

➢ *Implantation of Blastocyst:*

Upon reaching the uterus, the blastocyst undergoes implantation within the endometrium, the mucous membrane lining the uterus [9].

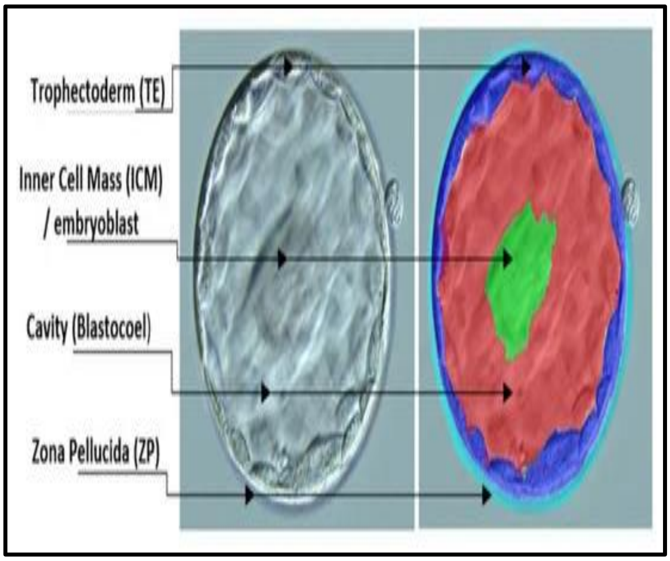

Fig.4: *Blastocyst Stage*
(Source:- Image Processing Approach for Grading IVF Blastocyst)

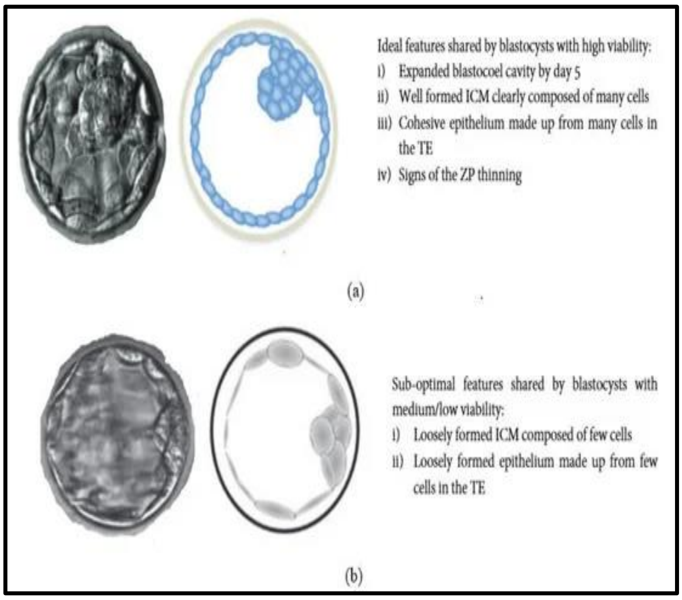

Fig.5*: Blastocyst image a) Well developed b) Poorly developed (Source:- Image Processing Approach for Grading IVF Blastocyst)*

ISSN No:-2456-2165

➢ *Embryo Development:*

Upon progressing through the final stages of implantation into the inner lining of the uterus, the blastocyst undergoes a transformative process, evolving into a distinct structure known as an embryo [10].

B. Data Pre-processing:

All embryo images were analysed underwent annotation using the Roboflow tool . The preprocessing steps like resizing and normalisation were applied in the preprocessing stage so that the data is ready to be sent to the model and subsequently, the data was categorized into testing, training, and validation sets.

➢ Roboflow:

Roboflow stands as an all-encompassing developer framework for Computer Vision, providing advanced capabilities ranging from data collection to pre-processing and model training techniques. The platform facilitates access to public datasets and allows users to upload custom data. Roboflow accommodates various annotation formats, and its data pre-processing phase involves tasks such as image orientation, resizing, contrast adjustment, and data augmentations.

➢ Augmentation Steps:

To enhance robustness and account for potential new data scenarios, a set of augmentation techniques were implemented. These include cropping (0-12%), flipping (horizontal and vertical), rotation at various angles (0-450), adding noise (0-3%), and other relevant measures.

C. Model Approach:

Various Convolutional Neural Network (CNN) architectures were employed for training and testing in the context of embryo assessments to identify the most suitable network for evaluation. Models utilized include ResNeT, Inception, YOLOv8, MobileNet, and VGG [11, 12, 13, 14,15]. Among these, the RESNET model demonstrated the most favorable results, as depicted in Table 2.

➢ *Models and Comparisons:*

Table.2*: Model Comparison between different CNN models*

Model Used	**Train Accuracy(%)**	**Test Accuracy(%)**
VGG 16	72.06	67.5
MobileNet	82	51
YOLOv8	70.1	69.8
Inception	67.3	59.8
Resnet 50	83	81
Resnet 101	73.42	54.3

We found that Resnet50 was the best model after adjusting the hyperparameters to Resnet-50, learning rate =0.01, Epochs = 100, dropout = 0.05, batch size = 64

➢ *Model Deployment:*

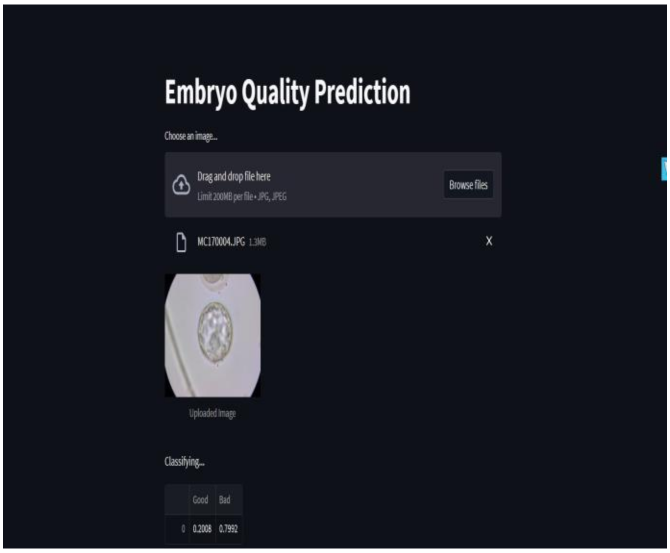

Fig.6*: Streamlit deployment of best model*

The Best model was deployed using Streamlit as shown [Fig.6]. Here the user can upload embryo images and the model predicts the quality of embryo and gives results.

III. RESULTS AND DISCUSSION

Our investigation delved into the application of various deep learning models—ResNet, MobileNet, YOLO v8, Inception, and VGG—to enhance the assessment of embryo quality in fertility treatments. The comparative analysis unearthed nuanced differences in the performance of each model, shedding light on their unique strengths and limitations. Variables such as architecture, depth, and feature extraction capabilities influenced precision, speed, and robustness across ResNet, MobileNet, YOLO v8, Inception, and VGG.

The dataset's role proved pivotal, with certain models showcasing superior generalizability. Despite disparities, all models demonstrated efficiency in automation, hinting at their potential clinical relevance. Particularly noteworthy was ResNet, striking a promising balance between precision and speed, boasting training accuracy at 83% and testing accuracy at 81%.

The diverse performances of ResNet, MobileNet, YOLOv8, Inception, and VGG underscore the importance of tailored model selection based on specific application requirements. Achieving equilibrium between precision and speed is critical, with ResNet emerging as a promising candidate. The dataset's influence on model success highlights the necessity of a diverse and representative dataset. The comparative analysis serves as a guide for the potential integration of these models into clinical practice, considering their individual strengths and limitations.

Future research avenues may explore fine-tuning parameters, optimizing architectures, and assessing real-world impact. Ethical considerations, particularly transparency and patient consent, remain paramount for responsible AI use in fertility treatments. In summary, our study furnishes valuable insights into diverse deep learning models for embryo quality assessment in reproductive medicine.

IV. CONCLUSION

Our study underscores the immense potential of employing deep learning models to refine embryo quality assessment in fertility treatments, notably within in vitro fertilization (IVF). Surpassing the limitations of traditional methods, our research leveraged a comprehensive dataset of embryo images, showcasing the effectiveness of cutting-edge deep learning algorithms in automating quality evaluations. This breakthrough expedites fertility processes, enhancing patient outcomes by facilitating the identification of the optimal embryo for fertilization.

The automated assessment, propelled by Convolutional Neural Networks (CNNs) and deep learning, signifies a transformative leap in reproductive medicine. Beyond the laboratory, our findings promise to make fertility treatments more accessible, cost-effective, and successful. By harnessing the potential of deep learning, our study represents a pivotal advancement in addressing the challenges faced by those navigating infertility. The precise prediction of embryo quality opens avenues for personalized and optimized fertility treatments, offering renewed hope to individuals and couples on the path to parenthood.

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