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Research Article

Prediction of Potential Embryos for Implantation in the IVF Treatment Using Graph Convolution Network

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ABSTRACT

Nowadays, life style changes of human beings have created multiple challenges in obtaining normal pregnancy and leading to infertility. Infertility is considered as reproductive system disorder which occurs to large human population in the world due to lifestyle changes and some medical disorder. On advancement of the technologies, it become feasible to attain pregnancy artificially especially through treatments like In Vitro Fertilization (IVF), Assisted Reproductive Technology (ART) and Intracytoplasmic Sperm Injection (ICSI). Among those treatments, In Vitro Fertilization (IVF) becomes more familiar across peoples. Despite of several advantage of the In Vitro Fertilization (IVF) treatment, there exist some challenges in success rate of identifying potential embryo for implantation. Thus , deep learning model is only solutions which can increase the success rate of embryo implantation. In this paper, a new deep learning technique represented as graph convolution network is designed and implemented to identify the potential embryo for implantation. Graph Convolution Network composed of multiple layers and it processes the clinical data on transforming it into graph format. On processing, graph structured clinical data, it is highly efficient in extracting features of egg and organizes those extracted feature in form of the feature map. Finally fully connected layer of the model obtains the feature map in order predict the potential embryo for implantation using softmax function. Especially proposed model is capable of determining the potential embryo towards its implantation in ovary region of the uterine wall. Particular model increases success rate of the fertility. Experimental analysis of the model is performed using clinical data obtained from the Apollo Hospital in the python environment. Obtained data is partitioned into training data and test data for model training and model testing. Model testing is performed as cross fold validation of the test data using confusion matrix to obtain the parameter for accuracy computation. On performance analysis, it is proved that proposed model outperforms state of art approaches.

Keywords: Deep learning, Graph Convolution Network, In Vitro Fertilization, Embryo Selection, Implantation

1. INTRODUCTION

Rapid changes on the life styles of the human beings across the world have led to increase the infertility among the couples. Infertility occurs due to reproductive system disorder which prohibits healthy pregnancy. On advancement of the technologies, it become feasible to attain pregnancy artificially especially through treatments like In Vitro Fertilization (IVF), Assisted Reproductive Technology (ART) and Intracytoplasmic Sperm Injection (ICSI). Among those treatments, In Vitro Fertilization (IVF) becomes more familiar across peoples. Despite of several advantage of the In Vitro Fertilization (IVF) treatment, there exist some challenges in success rate of identifying potential embryo for implantation. Thus, deep learning model from artificial intelligence provides increased success rate of embryo implantation[1].

In this paper, a graph convolution network is designed and implemented to identify the potential embryo for implantation. Graph Convolution Network composed of multiple layers and it processes the clinical data on transforming it into graph format. On processing, graph structured clinical data, it is highly efficient in extracting

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features of egg and organizes those extracted feature in form of the feature map. Finally fully connected layer of the model obtains the feature map in order predict the potential embryo for implantation using softmax function. Especially proposed model is capable of determining the potential embryo towards its implantation in ovary region of the uterine wall. Specified model enhances success rate of the fertility[2].

Rest of the article is organized into following sections, section 2 discuss about related works in classification of the embryo towards implantation along its experimental and performance analysis. Section 3 describes design of the new deep learning approaches represented as graph convolution network to predict potential embryo for specific IVF protocol. Section 4 provides the experimental and performance analysis of the proposed embryo selection deep learning model against the state of art approaches on basis of accuracy. Finally Section 5 concludes the article with its findings.

2. RELATED WORKS

In this section, related works in classification of the embryo towards implantation using machine learning techniques to IVF treatment mechanism has been described in detail as follows

2.1. Naïve Bayes Classifier for Classify embryo for Implantation

In this literature, Naïve bayes Classifier is employed to classify embryo for implantation on processing clinical data of the patient. Naïve Bayes classifier organizes the clinical data in form of probability distributions. Evidence function is used to determine the potential embryo to the implantation on evaluating the characteristic of the embryo. On experimental analysis, it proved that model produces 90.7% accuracy[3]

2.2. Random Forest Classifier for Classify embryo for Implantation

In this literature, Random Forest Classifier is employed to classify embryo for implantation on processing clinical data of the patient. Random Forest classifier organizes the clinical data in form of bagging and boosting mechanism. Classifier function is used to determine the potential embryo to the implantation on evaluating the characteristic of the embryo. On experimental analysis, it proved that model produces 91.4% accuracy[4]

3. PROPOSED MODEL

In this section, a design of graph convolution network model is carried out to determine the potential embryo for implantation on processing the clinical data. Design of the proposed architecture is as follows transfer order sequence of the potential embryo on basis of the uterine activity during and after embryo transfer implantation in the uterine wall is as follows

3.1. Graph Transformation

Graph Transformation function transform the clinical data into the graph structure. Graph structure contains node and vertex. Node represents the embryo and vertex represents the association between embryo sequences[5]. Figure 1 represents the architecture of the proposed model.

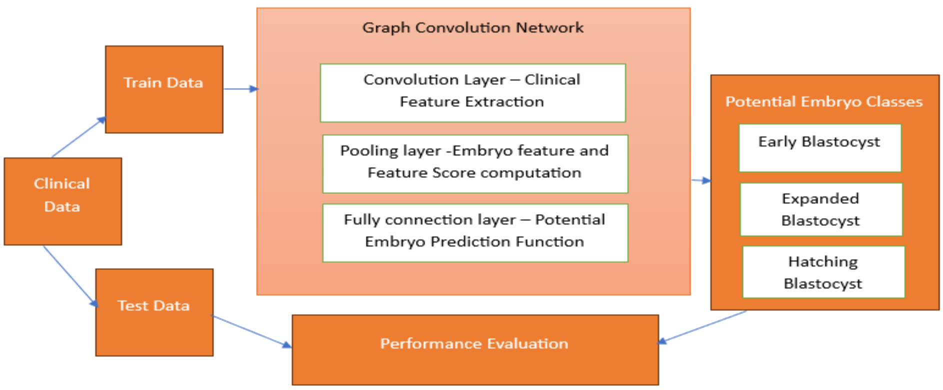

Figure 1: Proposed Architecture

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3.2. Graph Convolution layer

Graph Convolution Layer uses kernel function and activation function to filter clinical information such as ovarian simulation cycle, hormone replacement and characteristics of the egg cell. In addition, it extracts embryological data related to uterine activity including serum estrogen level and serum progesterone level. Further it is possible to compute the Embryo score and Blastocyst score on embryological morphological features such as Endometrial thickness estrogen and progesterone levels. Finally, it organizes the feature map in form of Endometrium receptive states[6].

Kernel function is represented as

$F_m = C \sum_{i=1}^{k}(u(i))$ ...Eq.1

Where C is kernel function and a(i) uterus attributes of clinical data

3.3. Pooling layer – Attention Mechanism

In this layer, attention mechanism is used to obtain the embryological features of the uterine activity. Model tuned with hyper parameter on its multiple layers to obtain better prediction result. Attention coefficient to extract optimal features is as follows

$Optimal\ embryo\ Feature\ O = \frac{e(\mathrm{ui}-\mathrm{u})\ (\mathrm{ui}-\mathrm{u})}{n-1}$...Eq.2

3.4. Fully Connected Layer

Fully connected layer uses activation function and SoftMax function to classify the optimal feature map of the embryological features of the uterine activity. Table 1 provides hyperparameter and its setting

Table 1: Model Parameter of Graph Convolution Neural Network

Parameter	Value
Batch size	25
Epoch size	45
Learning rate	10^{-6}
Loss Function	Mean Square Error
Activation function	Sigmoid

3.4.1. Activation function – Sigmoid function

Sigmoid function is used as activation function to linearize the optimal feature of embryo and linearized feature is represented in map format[7]. Algorithm 1 provides the multiple function of the proposed model.

Activation function w(f(n))= tanh(w(f(v)+b)...Eq.3

where tanh is activation function , b is bias function and w is weight function

3.4.2. SoftMax function- Support vector machine

SoftMax function uses support vector machine classifier. Support vector machine transforms the optimal features into support vector. Hyperplane is constructed using Support vector. Further decision boundary is used to classify the embryo organized in hyperplane and predict potential embryo based on embryo score for the implantation.

Classifier Function $C_f = \sum_{i=1}^{N}(y_n - f_n)^2$..Eq.4

Algorithm : Graph Convolution Network
Input: Clinical data
Output: Potential Embryo
Process()

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Graph Transformation(clinical data)
Graph (N,E)
N represents Embryo and E represents association of embryo
Convolution (Graph based Clinical data)
Feature MapF_m
Pooling Layer _Attention Mechanism
Optimal feature map OF_m
Fully Connected layer
Activation Function (OF_m)
Linear optimal feature
SoftMax function (Linear feature)
Embryo Classes = Early Blastocyst, Expanded Blastocyst and Hatching Blastocyst

4. EXPERIMENTAL ANALYSIS

Experimental analysis of the proposed model is performed using clinical data obtained from the Apollo Hospital in the python environment. Obtained data is partitioned into training data and test data for model training and model testing. Model testing is performed as cross fold validation of the test data using confusion matrix to obtain the parameter for accuracy computation[8]. Confusion matrix of the clinical data is represented in figure 3

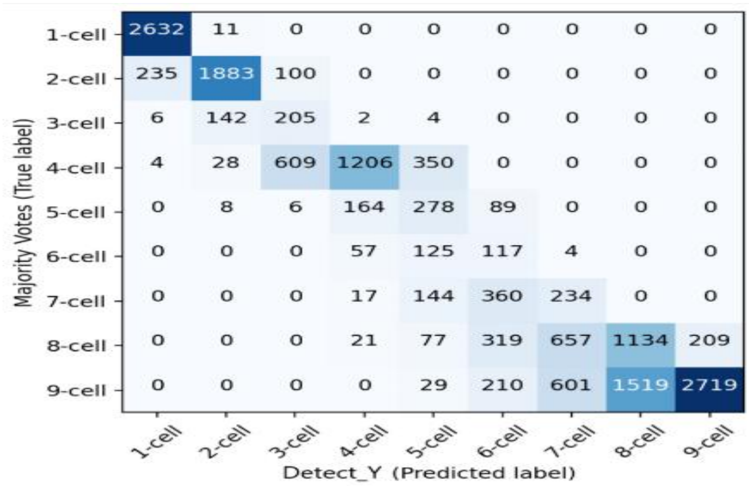

Figure 3: Confusion Matrix

4.1.1. Dataset Description

Data was obtained from 500 patients undergoing IVF treatment in Apollo Hospital, India. It composed of clinical information ovarian simulation cycle, hormone replacement therapy (HRT) cycle , egg cell extraction, fertilization, embryo transfer(blastocyst), pregnancy test results. Further embryological data related to uterine activity on embryo transfer which includes serum estrogen level (E2), serum progesterone level (P), EMT and endometrial morphology (type A or type B) type of embryo transfer [9].

4.2. Performance metrics

The model performance such as precision, recall and f measure is computed using parameter of the confusion matrix. Confusion matrix predicts embryo for successful implantation in IVF against growth stage of the embryo in uterus on basis of the cell[10].

- **Precision**

It is computed as correct embryo predicted among extracted embryo features to successful implantation in uterus on IVF treatment. In other words, it is defined as ratio of true positive to combination of true positive and false positive of prediction outcomes. It is represented as

$$\text{Precision} = \frac{\text{TP}}{TP+FP} \text{ ...Eq.5}$$

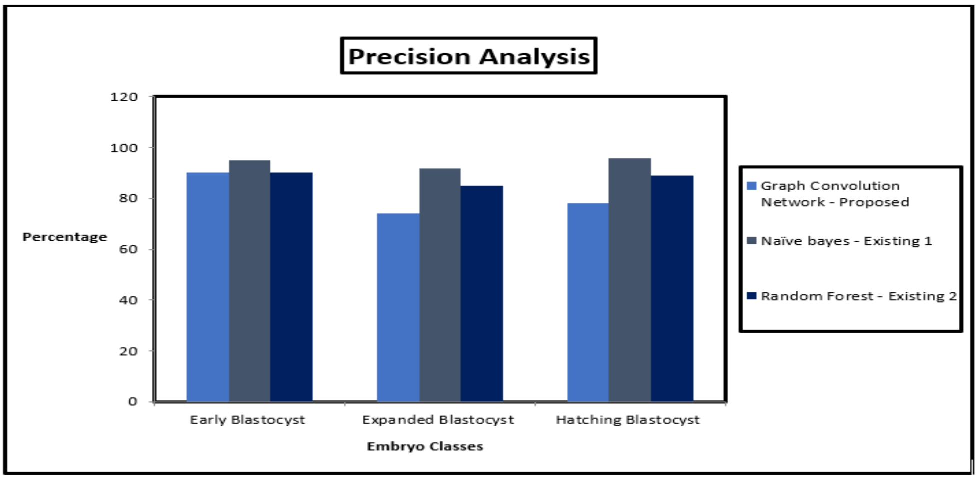

Figure 4 : Precision Analysis

Figure 4 provides precision analysis of the potential embryo prediction for implantation to IVF treatment using graph convolution network is performs better while compared to existing architectures such as naïve bayes and random forest.

- **Recall**

It is computed as incorrect embryo predicted among extracted embryo features to successful implantation in uterus on IVF treatment. In other words, it is defined as ratio of true positive to combination of true positive and false negative of prediction outcomes. It is represented as

$$\text{Recall} = \frac{\text{TP}}{TP+FN} \text{..Eq.6}$$

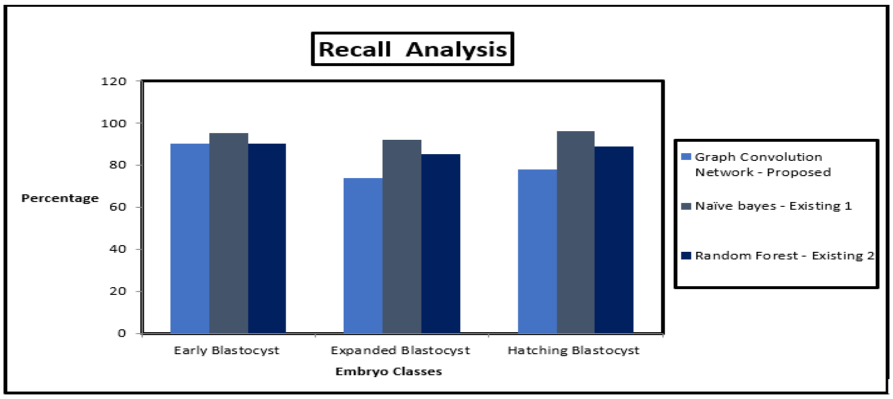

Figure 5 : Recall Analysis

Figure 5 provides recall analysis of the potential embryo prediction for implantation to IVF treatment using graph convolution network is performs better while compared to existing architectures such as naïve bayes and random forest.

- **Accuracy**

It is defined as ratio of True positive to combination of true positive and false negative embryo to uterus accurately on basis of embryological features It is represented as

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$$\text{Accuracy} = \frac{\text{TP}}{2TP+FN}..\text{Eq.7}$$

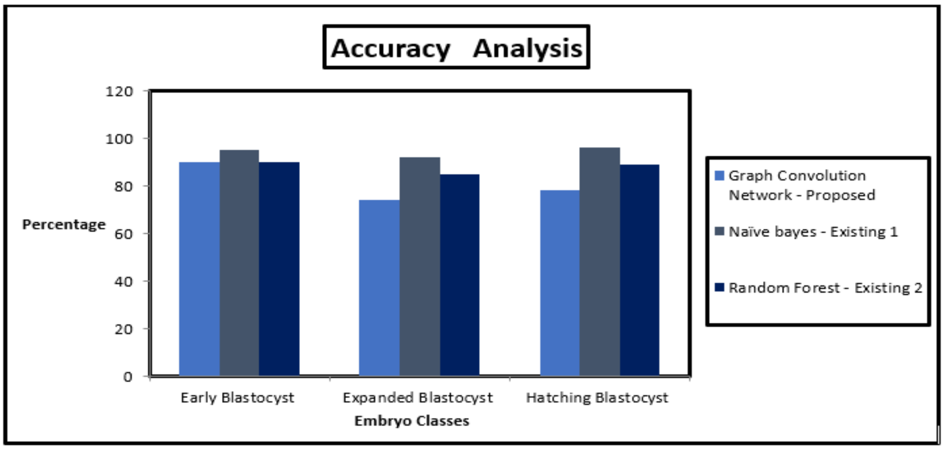

Figure 6 : Accuracy Analysis

Figure 6 provides Accuracy analysis of the potential embryo prediction for implantation to IVF treatment using graph convolution network is performs better while compared to existing architectures such as naïve bayes and random forest.

Table 2: Performance Evaluation

Embryo class	Technique	Precision	Recall	Accuracy
Early Blastocyst	Graph Convolution Network-Proposed model	98.1	96.1	98.7
	Naïve Bayes - Existing model 1	91.7	90.2	92.4
	Random forest- Existing model 2	90.6	88.4	91.0
Expanded Blastocyst	Graph Convolution Network-Proposed model	98.7	96.1	98.2
	Naïve Bayes - Existing model 1	91.8	90.5	92.7
	Random forest - Existing model 2	90.2	88.9	91.4
Hatching Blastocyst	Graph Convolution Network-Proposed model	98.7	96.4	98.9
	Naïve Bayes - Existing model 1	91.8	90.2	92.6
	Random forest - Existing model 2	90.2	88.4	91.3

The analysis on performance of graph convolution network against existing architectures such as naïve bayes and random forest. Graph convolution network produces better results represented in the table 2.

CONCLUSION

In this paper, a new graph convolution network is designed and implemented to identify the potential embryo for implantation. Initially clinical data has transformed into graph format. Those graph data processed in layer of the model towards extracting features of egg and embryos and organizes those extracted feature in form of the feature map. Next, model obtains the feature map in order predict the potential embryo for implantation using SoftMax

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function. Proposed model predicts potential embryo towards its implantation in ovary region of the uterine wall. Particular model has increased success rate of the fertility. Experimental analysis of the model and performance analysis of the model has proved that model obtain 98.4 accuracy compared to conventional approaches.

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