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DESIGNING AN ADVANCED MACHINE LEARNING-BASED PATIENT-CENTRIC DECISION SUPPORT MODEL FOR OPTIMIZED IVF TREATMENT RECOMMENDATION

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ABSTRACT

In Vitro Fertilization (IVF) is a key assisted reproductive technique designed for individuals facing difficulties in natural conception. Due to IVF's complexity, personalized treatment recommendations are essential to maximize success rates while considering each patient's unique health profile. This study aims to create a machine learning-based, patient-centric Decision Support System (DSS) to optimize IVF treatment. By analyzing extensive patient data, including clinical and lifestyle factors, the study employs advanced algorithms such as Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), Light Gradient Boosting Machine (LightGBM), and Multi-Layer Perceptron (MLP), achieving notable prediction accuracies. Light GBM stands out with an accuracy of 84.97%, precision of 86.95%, and recall of 86.43%, demonstrating its reliability in IVF treatment recommendations. This proposed model not only advances decision-making in IVF treatments but also promotes a personalized, data-driven approach, offering clinicians accurate, consistent insights into each patient's IVF needs, which can significantly improve treatment outcomes. Future work includes enhancing model robustness across diverse populations.

Keywords: *IVF, MLP, DSS, LightGBM, CNN.*

Introduction

IVF is a pivotal assisted reproductive technology widely used for individuals facing challenges in conceiving naturally [1]. As one of the most complex processes in fertility treatment, IVF involves multiple carefully monitored steps, starting with ovarian stimulation, followed by oocyte maturation, egg retrieval, fertilization, and embryo transfer. Each step requires precise clinical assessment and meticulous execution to maximize the chances of a successful pregnancy[2,3]. Given the physical, emotional, and financial commitments associated with IVF, patient-centered approaches have gained importance, emphasizing the need for personalized treatment plans tailored to each individual [4,5]. Therefore, optimizing IVF treatment recommendations is essential not only for improving success rates but also for providing a holistic experience that addresses each patient's unique physiological and psychological profile. This patient-focused approach can enhance outcomes and support patients through the challenges of the IVF journey [6].Figure 1 illustrates the step-by-step process of IVF, from consultation through to pregnancy testing.

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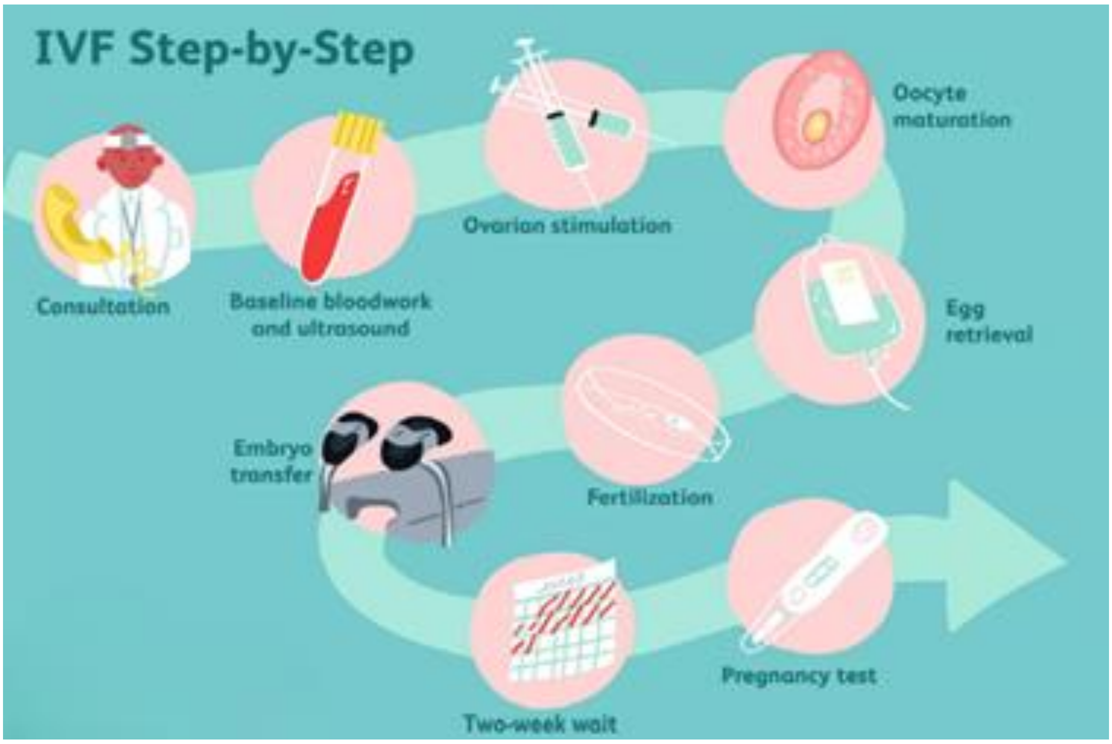

Figure 1: Stages of In vitro Fertilization Procedure [7]

The emergence of Machine Learning (ML) in healthcare has paved the way for innovative solutions that can improve clinical decision-making and personalized care, especially in fertility treatments [8]. ML algorithms, with their ability to process vast amounts of patient data and identify complex patterns, offer an unprecedented opportunity to develop highly individualized treatment recommendations in IVF[9,10]. By analyzing historical data, these models can uncover subtle correlations and predict patient responses to different treatment protocols, ultimately leading to more informed and accurate recommendations [11]. Advanced ML techniques, such as deep learning and ensemble methods, go beyond traditional statistical approaches, providing granular insights that could significantly refine IVF treatment personalization and success rates [12].

However, current IVF treatment recommendations often rely on subjective factors and general clinical guidelines, which might not fully account for the unique characteristics of each patient [13]. Traditional methods frequently lack consistency, as treatment decisions can vary considerably among clinicians based on individual expertise and experience [14]. This variability can lead to disparate outcomes and does not align with the precision required for patient-centric healthcare. Moreover, traditional approaches might overlook individual differences, such as genetic markers, lifestyle factors, and hormonal variations, which are essential for predicting responses to IVF protocols [15,16].

In light of these limitations, there is an increasing need for a patient-centric decision-support model driven by advanced machine learning to assist clinicians in recommending the most suitable IVF treatments [17]. Such a model could integrate multi-dimensional patient data, including clinical, genetic, and lifestyle factors, to create a personalized profile for each individual undergoing IVF [18]. By leveraging ML algorithms, this approach would provide clinicians with data-driven insights that go beyond conventional recommendations, facilitating more accurate, consistent, and tailored IVF treatment strategies. Ultimately, this ML-based decision support model would not only enhance IVF success rates but also promote a more empathetic, patient-centered approach to fertility care, improving both the experience and outcomes for patients seeking fertility assistance [19,20].

This research aims to design and evaluate an MLbased decision support model that can optimize patient outcomes in IVF treatment by providing personalized, data-driven recommendations for treatment protocols.

The scope of this research involves the design and evaluation of an advanced ML based patient-centric decision support model for IVF treatment. It covers the integration of patient data, algorithmic model development, optimization of treatment recommendations, and assessment of clinical outcomes, aiming to improve IVF success rates and personalization.

The significance of this research lies in developing an advanced ML based decision support model to optimize IVF treatment recommendations, enhancing personalized care and improving success rates. By leveraging patient-specific data, this model aims to assist clinicians in providing more accurate, efficient, and individualized IVF treatments, promoting better patient outcomes.

This research has the following contributions:

- This research contributes to the development of an advanced machine learning-based patient-centric decision support model for optimizing IVF treatment recommendations, enhancing personalized care and improving IVF success rates.
- The research applies advanced machine learning techniques to predict IVF treatment outcomes, improving the precision of success rate estimations and reducing variability in clinical recommendations.
- The study addresses the limitations of traditional IVF treatment methods by reducing subjectivity and providing a data-driven approach to optimize treatment protocols for each patient.
- The model is rigorously evaluated for clinical effectiveness, ensuring that it offers reliable and actionable insights that enhance IVF treatment recommendations and decision-making processes.

Section 1 of this research presents an overview of the subject matter. Section 2 delineates the pertinent contributions of numerous researchers. Section 3 delineates the proposed methodology. Section 4 outlines the result based on the proposed methodology. Section 5 describes the Conclusion and Future Scope.

Review of Literature

This section presents a comprehensive review of related studies by various authors focused on Designing an Advanced Machine Learning-Based Patient-Centric Decision Support model for Optimized IVF Treatment Recommendation.

Yao et al., (2024) [21] analyzed the rates of IVF utilization associated with prognostic reports based on machine learning during pre-treatment counseling. A retrospective cohort analysis was performed with 24,238 patients from seven reproductive institutions in the United States and Ontario, Canada. The findings indicated that the utilization of the Univfy report correlated with an increased direct IVF conversion, evidenced by odds ratios of 3.13, 2.89, and 2.04 for the 180-day, 360-day, and Ever analyses, respectively. The overall conversion rates for IVF, regardless of priorIntra-Uterine Insemination(IUI), demonstrated odds ratios of 3.41, 3.81, and 2.78, all of which were statistically significant ($p < 0.05$).

Khan et al., (2024) [22]employed sophisticated machine learning approaches to create an innovative technique for forecasting female infertility. A comprehensive analysis was performed on a dataset containing medical attributes related to reproductive health, utilizing logistic regression, Naive Bayes, Support Vector Machines (SVM), and Random Forest algorithms. The Random Forest algorithm demonstrated a remarkable accuracy rate of 93%. The results indicated that this model has potential applications for early infertility diagnosis and tailored treatment suggestions in the future.

Rathinaeaswar and Santhi (2023)[23]introduced an Efficient and Privacy-Preserving Patient-centric Clinical Decision Support System (EPPCD) aimed at assisting clinicians in predicting patient illness risks while maintaining privacy protection. This technology was designed to address the privacy challenges inherent in theClinical Decision Support System(CDSS). The suggested system stores historical data of prior patients in the cloud, which could be utilized to develop the hybrid Rotation Forest and AdaBoost classifier.The findings indicated that the suggested RandRotBoost attained a 95% F1 Score, surpassing the performance of alternative approaches.

Niraula et al., (2022) [24]developedan AI-driven decision-making framework to support oncologists in Decision-Theoretic Radiotherapy (DTR). The framework, known as Adaptive Radiotherapy Clinical Decision Support (ARCliDS), consisted of two components: Artificial RT Environment (ARTE) and Optimal Decision Maker (ODM). The structure of ARTE was designed as a Markov decision process utilizing supervised learning, while a dual Graph Neural Network (GNN) architecture was implemented to correct unphysical dose-response trends. The framework led to improved clinical decisions, resulting in 36% and 50% favorable clinical outcomes for NSCLC and HCC, respectively, and enhanced 74% and 30% of previously suboptimal decisions.

Xi et al., (2021) [25]customized embryo selection strategy and a pregnancy prediction model were created using a stacked machine learning approach. The hierarchical model, constructed with eXtreme Gradient Boosting (XGBoost), was designed to assess embryo implantation potential alongside the concurrent effects of Double Embryo Transfer (DET). Analysis using multiple regression on 19 chosen features revealed variations between the significance of prediction features and their statistical associations with outcomes. After the completion of 30 experimental iterations, the model produced average Area Under the Curves (AUCs) of 0.79 for Single Embryo Transfer (SET) pregnancy, 0.83 for DET pregnancy, and 0.72 for the risk of DET twins, indicated that XGBoost outperformed both logistic regression and classification and regression tree models.

Li et al. (2021)[26]developed and validated a predictive model for assessing clinical pregnancy failure in Poor Ovarian Responders (PORs) during IVF procedures. Researchers analyzed data from 281 patients with POR, divided into a training set (179 patients) and a validation set (102 patients). They identified factors like age over 35, BMI above 24 kg/m², elevated basal Follicle-Stimulating Hormone (FSH), and fewer than two high-quality embryos as significant predictors of pregnancy failure. The study employed logistic regression to develop a nomogram that demonstrated robust predictive accuracy, achieving an AUC of 0.786 in the group receiving training and 0.748 in the set used for validation.

Hassan et al., (2020) [27]designed a hill-climbing feature selection approach combined with automated classification employing machine learning techniques to enhance the accuracy of IVF pregnancy forecasts. An assessment was performed utilizing 25 characteristics to evaluate the prediction capabilities of five machine learning models: MLP, SVM, C4.5, Classification and Regression Trees (CART), and Random Forests (RF). The feature selection method resulted in a reduction of significant attributes, producing 19 for MLP, 16 for RF, 17 for SVM, 12 for C4.5, and 8 for CART. The results indicated that incorporating hill-climbing feature selection with classifiers like SVM, MLP, or RF improved predictive performance, offering significant insights for practitioners assessing IVF outcomes.

Qiu et al., (2019)[28]developed a predictive model employing ML techniques to evaluate the likelihood of live birth before the initiation of the first IVF operation. Retrospective clinical data were acquired from 7,188 women who underwent their initial IVF treatment. Nested cross-validation was employed to achieve an impartial assessment of the adaption efficacy of the ML algorithms. The XGBoost model attained an area under the Receiver Operating Characteristic (ROC) curve of 0.73 on the dataset used for validation and demonstrated superior calibration relative to other machine learning techniques.

Research Methodology

This study provides a comprehensive examination of the employed strategy, detailing the dataset, methods and the recommendation approach as follows:

- **Dataset Description**

This study uses a primary dataset of 850 responses organized in an Excel file. Each entry provides essential information for developing an IVF treatment recommendation model, including name, contact, age group (under 35, 35-40, over 45), fertility, and medical history. Key data include fertility attempts, reproductive issues, health metrics, and past conditions like hypertension or diabetes. It also covers ovarian reserve, uterine health, interest in genetic analysis, embryo transfer history, and outcomes. This comprehensive dataset supports the development of precise ML algorithms, ensuring personalized IVF recommendations based on diverse, relevant data.

- **Techniques Used**

This section delineates the procedures employed, encompassing data preparation, feature extraction and selection, and evaluation of the machine learning model's performance, as follows:

- **Principal Component Analysis (PCA)**

Feature extraction is essential in pattern recognition and data analysis, focusing on selecting relevant attributes from original data to reduce training time and simplify space complexity, thereby achieving dimensionality reduction. This process transforms input data into a condensed attribute set that retains significant details from the original dataset [29,30]. PCA is a robust technique for identifying patterns in high-dimensional data and extracting relevant features [31]. In PCA, components are arranged by variance, with the first few components capturing the most variability. Strong correlations among original components further reduce input dimensions, retaining only the key components with the highest variance [32]. Figure 2 illustrates the diagrammatic representation of PCA.

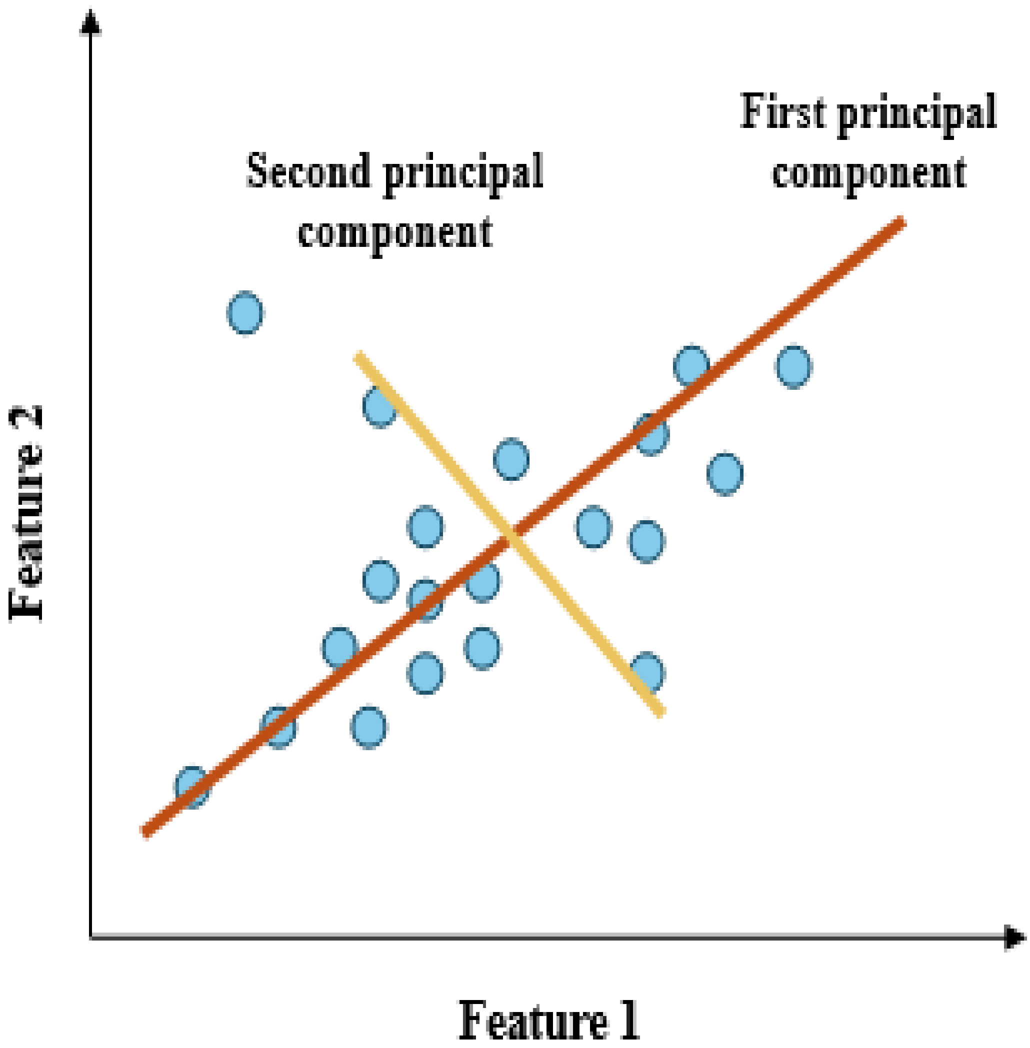

Figure 2: PCA [33]

- **Recursive Feature Elimination (RFE)**

Feature selection is crucial for identifying relevant attributes across various fields [34]. RFEis a widely used method that selects optimal features based on model learning and classification accuracy. In large datasets, irrelevant features can hinder classification efficiency and accuracy [35]. RFE mitigates this by iteratively ranking and removing less important features, preserving those essential for accurate predictions. This approach reduces dimensionality while retaining key characteristics, enhancing both model performance and interpretability [36]. Using ML classifiers, RFE refines the feature set, continuously retraining until an optimal subset is achieved. Figure 3 illustrates the RFE workflow. In this methodology, RFE is utilized to identify pertinent features, enhancing both the accuracy and clarity of the suggested treatment recommendation models.

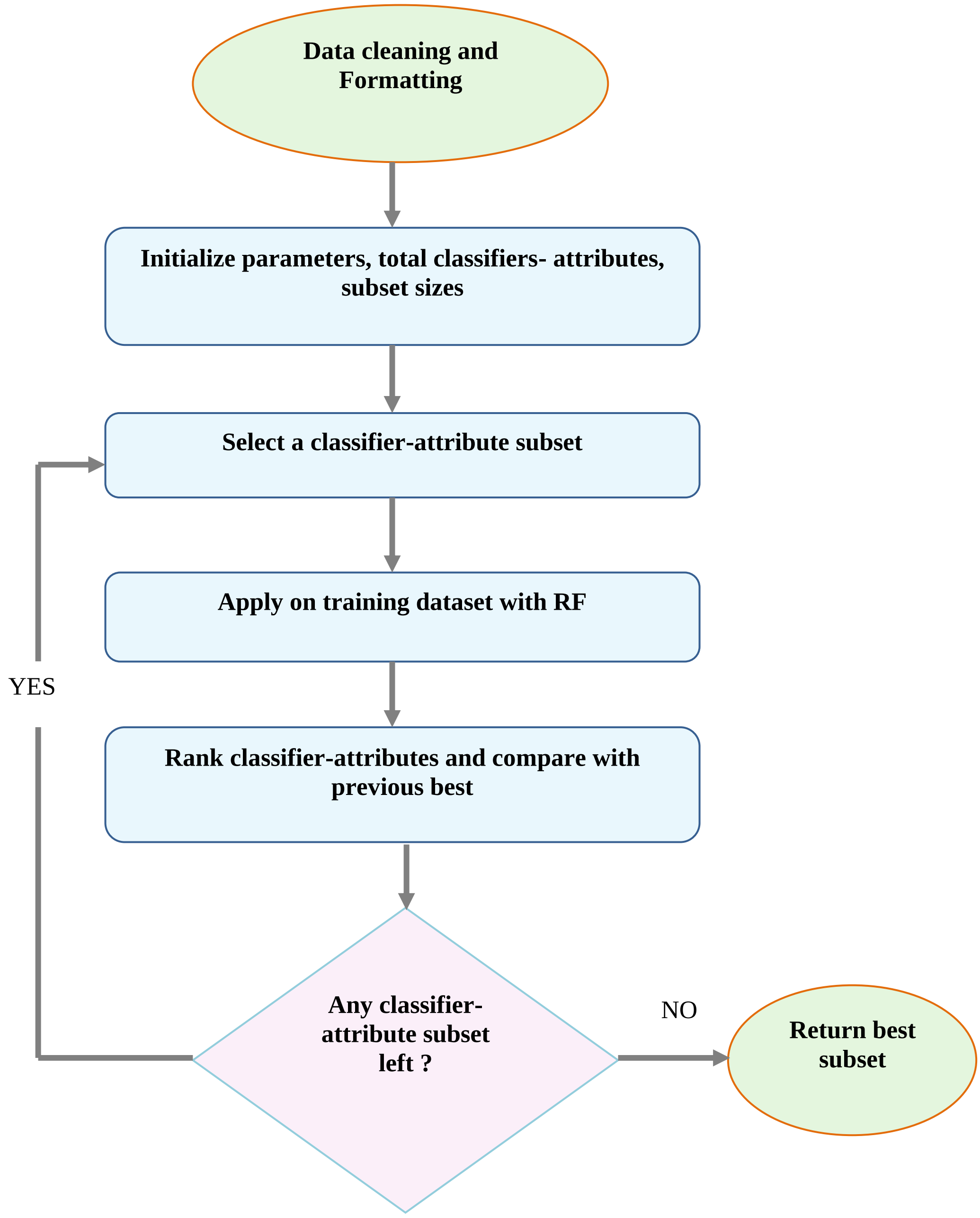

Figure 3: The working architecture of the RFE algorithm [37]

- **CNN**

CNNs use spectral layers to effectively capture both low- and high-level information, making them highly efficient for statistical forecasting and complex modeling tasks. Key principles like local filters, max-pooling, and weight distribution enhance CNNs' effectiveness over traditional Deep Neural Networks (DNNs). The CNN architecture used for treatment prediction, shown in Figure4, includes multiple convolutional and max-pooling layers, with pooling layers following each convolutional layer to improve variability handling [38,39]. Max-pooling is commonly applied in the frequency domain, yielding robust results. Fully connected layers then combine inputs into a one-dimensional feature vector, followed by a SoftMax activation layer for final classification [40].

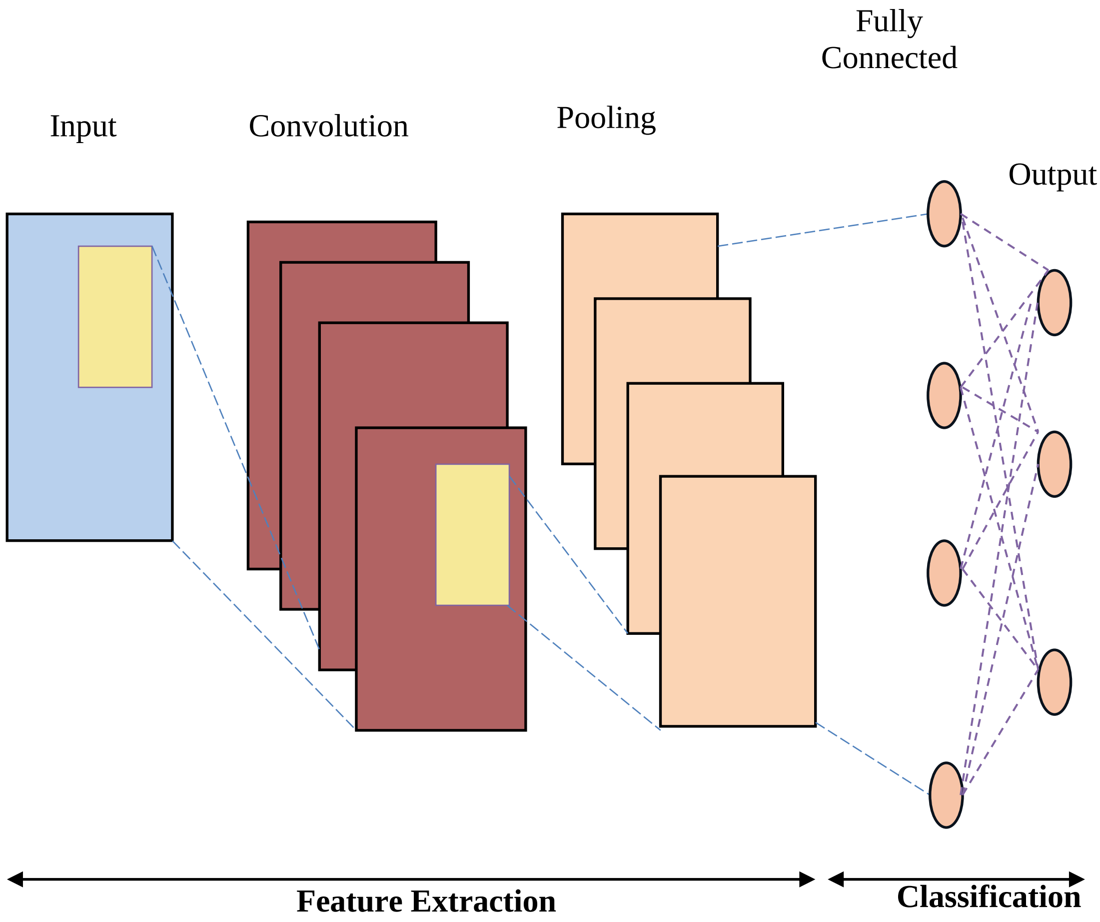

Figure 4: CNN [41]

- **LSTM**

The LSTM model is a powerful Recurrent Neural Network (RNN) designed to manage sequential data, making it ideal for patient-centric decision support in IVF treatment [42]. By retaining information across long sequences, LSTM captures essential patterns in patient histories, including previous treatment cycles and health metrics [43]. This enables precise, personalized recommendations by identifying trends crucial to treatment success. Through advanced mechanisms like attention layers, the model can emphasize significant data points, improving accuracy in forecasting optimal IVF treatment paths and ultimately enhancing success rates tailored to individual patient profiles [44].

- **LightGBM**

LightGBM, a gradient-boosting framework, is effective in handling large-scale, high-dimensional data, making it suitable for patient-centric decision support in IVF treatment [45]. By leveraging decision tree-based learning, LightGBM captures complex interactions among patient health metrics, prior treatments, and outcomes. Its efficiency and speed in training allow rapid model tuning, ensuring optimized predictions for treatment recommendations [46]. LightGBM's ability to handle categorical and continuous features enhances its accuracy, making it adept at predicting IVF success rates by identifying key factors in patient data. This ultimately enables precise, personalized IVF treatment pathways tailored to individual patient profiles [47].

- **MLP**

The MLP model, a type of feedforward neural network, is applied to create a patient-centric DSSfor optimized IVF treatment recommendations [48]. MLP effectively captures complex, non-linear relationships within patient data by processing multiple layers of nodes [49]. In this context, it learns from diverse patient metricssuch as age, hormone levels, and treatment historyto predict success rates and recommend personalized treatment paths. Through backpropagation, MLP optimizes its weight structures, allowing it to make accurate recommendations by focusing on key patient features that impact IVF outcomes, thus improving decision-making for tailored treatment plans [50].

- **Proposed Methodology**

The suggested methodology for creating a model to prescribe IVF treatment encompasses several essential elements. Figure 5 delineates a systematic methodology for data management, model training, and assessment, culminating in precise treatment recommendations. This technique delineates a concise and unambiguous method for suggesting IVF treatment. The following are the essential phases outlining the suggested methodology:

Step 1. Gathering Data

- **Collect Embryo Information**: Start by gathering all the necessary details about embryos. This information is crucial as it would be used to build and evaluate the model.

Step 2. Data preprocessing

- **Clean the Data**: Remove any mistakes or missing information from the dataset to ensure everything is accurate and reliable.
- **Standardize the Data**: Adjust the data so that all information is on the same scale. This helps the model treat each factor equally during analysis.

Step 3. Features engineering

- **Simplify the Data with PCA**: Use PCA to reduce the number of variables by combining related ones. This makes the data easier to work with without losing important information.
- **Select Key Features with RFE**: Apply RFE to pick out the most important factors. This step ensures that only the most relevant information is used for making predictions.

Step 4. Splitting the Data

- **Divide into Training and Testing Sets**: Split the pre-processed data into two parts. One part is used for the learning of the model (training), and the other is used to check how well the model works (testing).

Step 5. Building the Model

- **Create Different Models**: Develop several types of machine learning models, such as LSTM, CNN, LightGBM, and MLP. Each model has its strengths for predicting whether IVF is needed.

Step 6. Training the Model

- **Train the Models**: Use the training data to help each model learn how to make accurate predictions. Adjust the models to reduce any errors in their predictions.

Step 7. Evaluating the Model

- **Test the Models**: Use the testing data to see how well each model performs. Compare their results to find out which model is the most reliable and accurate.

Step 8. Making Recommendations

- **Provide IVF Advice**: Use the best-performing model to decide whether IVF treatment is necessary based on the input data. This helps doctors make informed decisions for their patients.

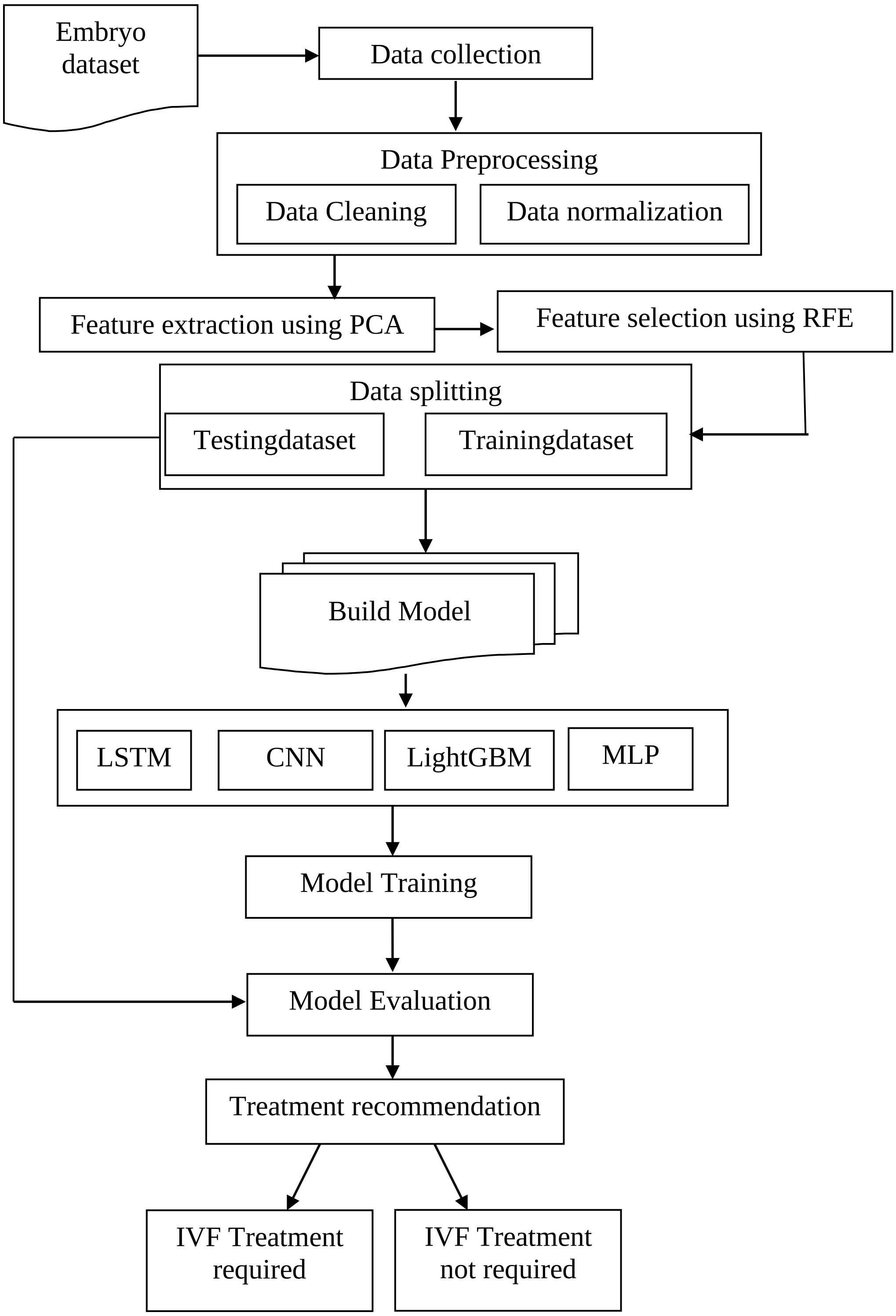

Figure 5: Proposed Methodology

- **Proposed Algorithm**

Algorithm: Treatment recommendation model

Start

Step 1: Data Collection

Collect the embryo dataset, denoted as D.

Step 2: Data Preprocessing

- **Data Cleaning**

Removing unrelated or noisy data.

- **Data Normalization**

Normalize the data to ensure consistency and increase the performance of the models.

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

Where x represents the initial data point, min(x) represents the least values in the entire data set, and max(x) represents the highest value in the data set.

Step 3: Feature Engineering

- **Feature Extraction using PCA**

Z = XWZ

X represents the data matrix, W represents a matrix of eigenvalues, and Z represents the matrices of main elements.

3.2 Feature Selection using RFE:

$$REF(X, y) = arg \min_{s \subseteq X} \sum_{i}^{n} (y_i - \hat{y}_i)^2$$

X is the feature, y represents the target variable, and $\hat{y}_i$ represents predicted value.

Step 4: Data Splitting

Split the dataset into training and testing datasets:

$$(X_{train}, y_{train}), (X_{test}, y_{test})$$

Where X and y are the features and labels, respectively.

Step 5: Model Building

Develop multiple models using different algorithms:

- **LSTM Model**
  - Forget gate :$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f)$
  - Cell state :$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$
  - Output gate :$h_t = o_t \tan h\, c_t$
- **CNN Model**
  - Convolutional layers: $conv(x, W, b) = ReLU(W * x + b)$
  - Max- Pooling layers: $MaxPool(x) = max(x)$
  - Fully Connected layers: FC$(x, W, b) = ReLU(W * x + b)$
  - SoftMax Output layers: $SoftMax(x_i) = \frac{e^{x_i}}{\sum je^{x_j}}$
- **LightGBM Model**
  - Gradient Boosting framework with decision trees as base learners.

***Objective function*:**$y_i = f(X_i) + \varepsilon_i$

Where f is the learned function, X_i is the input features and ε_i is the error term.

Binary Cross-Entropy Loss = $-\frac{1}{N}\sum_{i=1}^{N}[y_i \log(p_i) + (1 - y_i)\log(1 - p_i)]$

where y_i is the true label and p_i is the estimated probability.

- **MLP model**

Dense Layer

$$Dense\ (x) = ReLU(W \cdot x + b)$$

Output Layer

$$Output\ (x) = \sigma(W \cdot x + b)$$

Step 6: Model Training

Train each model using the training dataset.

$$\theta^* = arg \min_{\theta} \mathcal{L}\ (y, \hat{y})$$

Where $\mathcal{L}$ represents loss function, y represents true value, $\hat{y}$refers to the predicted value, and θ is the model parameters.

Step 7: Model Evaluation

Evaluate the performance of each model using the testing dataset

$$Accuarcy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1\ Score = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}$$

Step 8: Treatment Recommendation

Based on the evaluation results, recommend whether IVF treatment is required or not.

End

Results and Discussion

This section examines the results of IVF treatment prediction models, including LSTM, CNN, LightGBM, and MLP. The effectiveness of the ML model is evaluated using key indicators that illustrate the algorithm's capacity to forecast the necessity for IVF treatment. The merits and drawbacks of each model are analyzed, and a comparative study is provided to determine the most successful model for IVF treatment recommendations. The discourse delineates the distinctions among several models and provides recommendations for those that have enhanced efficacy in predicting IVF treatment results.

- **Results based on LSTM**

The IVF treatment recommendation system's LSTM model outperformed expectations across all relevant performance parameters. About three-quarters of the patients were properly predicted by the algorithm as requiring IVF therapy, with an accuracy rate of 74.51%. As shown in Figure 6, the model's recommendation of IVF therapy was accurate in the vast majority of cases 78.23% precision, reducing the number of false positives.

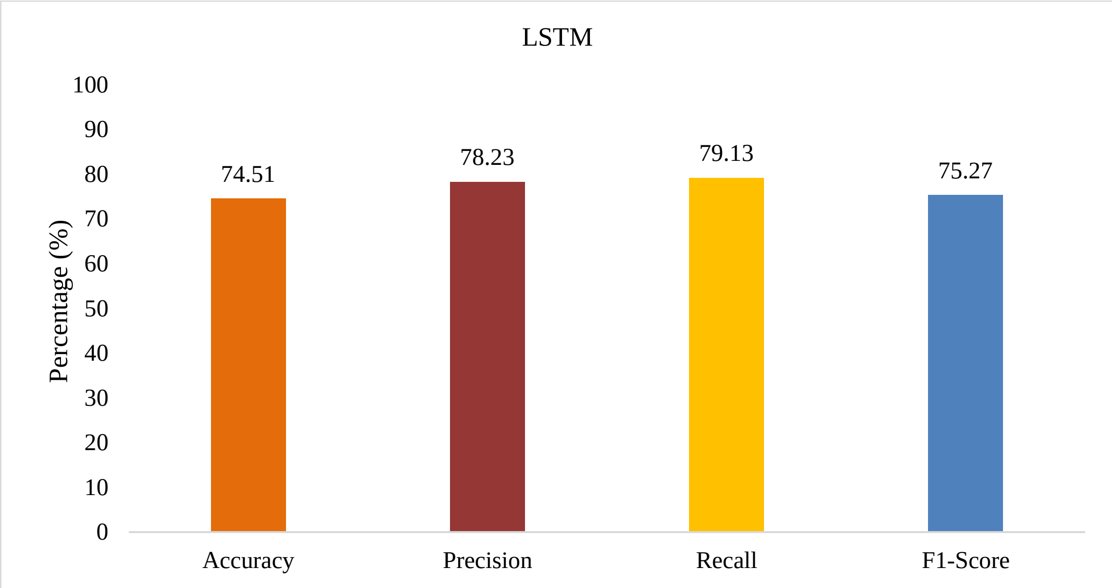

Figure 6: Performance of the LSTM model

Moreover, the recall score of 79.13% indicates the efficacy of LSTM in identifying genuine instances of IVF therapy, assuring minimal loss of true positive cases. The F1 score of 75.27% demonstrates a balance between precision and recall, indicating the model's ability to minimize false positives while effectively identifying pertinent cases.

- **Results based on Light GBM**

The LightGBM model illustrated outstanding efficacy in forecasting the requirement for IVF therapy, achieving an accuracy of 84.97%. This elevated degree of accuracy signifies that the model consistently recognizes instances for IVF intervention, which is vital in a medical context where precise predictions are imperative. The precision of 86.95% indicates that most patients identified as requiring IVF treatment were accurate, hence reducing false positives, as illustrated in Figure 7. This precision is essential in medical environments, as it ensures that patients are not exposed to excessive treatments, thus alleviating anxiety and mitigating any health hazards linked to unneeded operations.

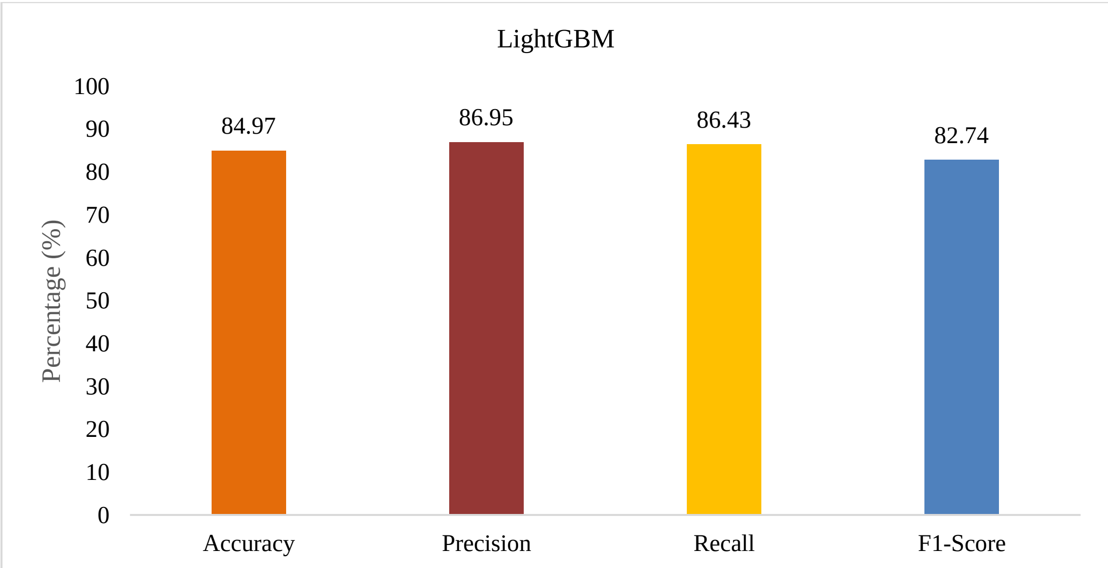

Figure 7: Performance of Light GBM Model

Furthermore, with an 86.43% recall, the model can reliably identify most positive cases, ensuring that only those who need IVF are identified. This strong recall helps patients by enabling timely therapies. Precision and recall are combined in the 82.74% F1 score, highlighting the balanced performance. In clinical applications, this balance shows the model's capacity to avoid false positives and negatives. The results show that LightGBM is a reliable IVF treatment prediction tool that aids clinical decision-making.

- **Results based on CNN**

The outcomes of the CNN model for forecasting IVF treatment needs are illustrated through essential metrics, demonstrating robust performance across all parameters. The model demonstrated an accuracy of 75.89%, suggesting that it accurately identified the need for IVF treatment in approximately 76% of cases. The accuracy of 77.41% indicates its capability to generate accurate positive predictions, signifying that a considerable percentage of the cases designated for IVF treatment were genuinely warranted, hence reducing false positives, as illustrated in Figure 8.

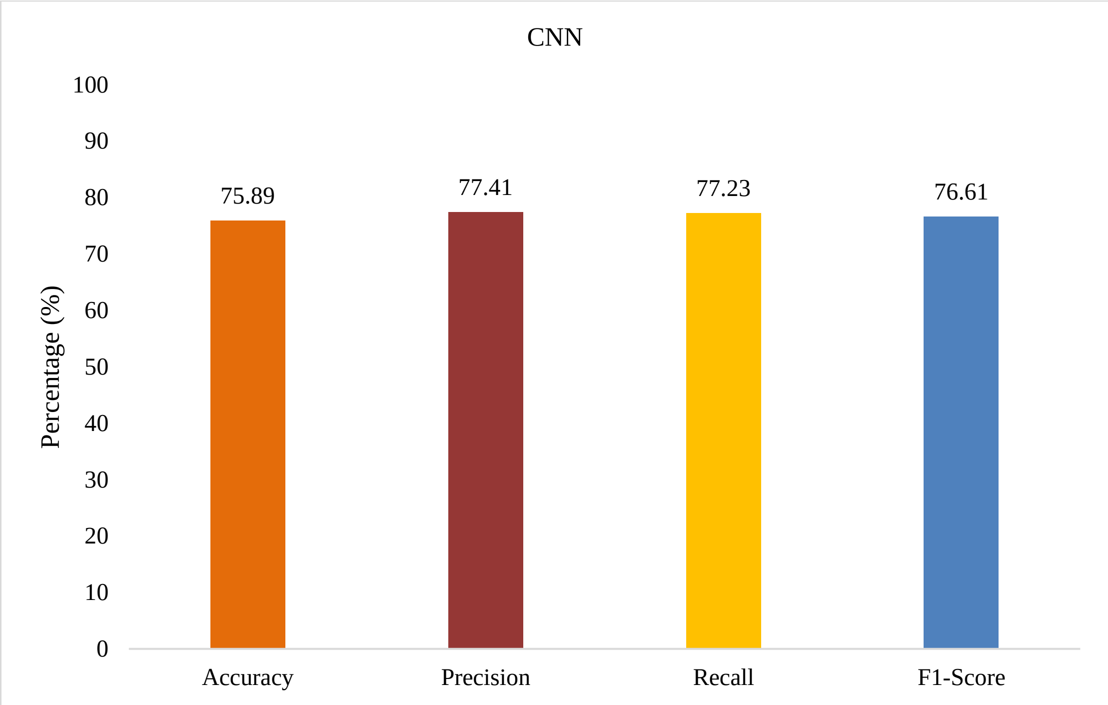

Figure 8: Performance of CNN model

CNN exhibits a recall score of 77.23%, indicating its ability to accurately identify the majority of genuine positive instances, hence ensuring that most persons in need of IVF treatment are correctly recognized. The F1-score of 76.61% highlighted the model's reliability in minimizing prediction mistakes while effectively identifying pertinent cases.

- **Results based on MLP**

The MLP model's results for predicting IVF treatment outcomes demonstrate consistent reliability across all assessed measures. The model attained an accuracy of 81.54%, as illustrated in Figure 9, indicating that it correctly identified the majority of instances, effectively forecasting the necessity of IVF therapy. The precision of 80.12% indicates that the model accurately identified IVF treatment requirements with a commendable degree of specificity, hence minimizing the incidence of false positives in treatment recommendations. The recall of 79.8% demonstrates the model's efficacy in identifying genuine positive instances, hence recognizing individuals who genuinely needed IVF treatment. This demonstrates the MLP's efficacy in identifying the most pertinent examples, however, there remains potential for enhancement in sensitivity.

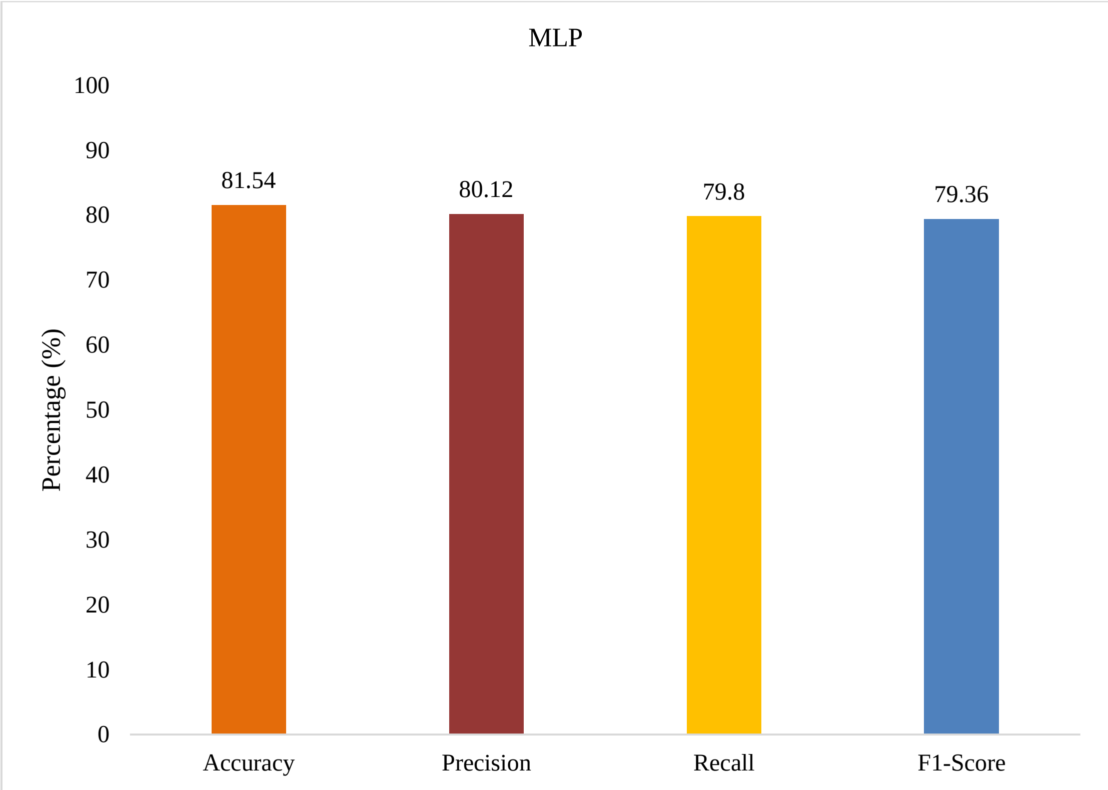

Figure 9: Performance of MLP Model

Additionally, the F1-score, integrating both precision and recall, stands at 79.36%. This demonstrates that the MLP model has successfully struck a noteworthy balance between reducing unnecessary recommendations and accurately pinpointing individuals in need of IVF therapy. The MLP model demonstrates dependable performance, effectively balancing accurate predictions and error reduction, exhibiting somewhat superior accuracy relative to precision and recall.

- **Comparative Analysis**

The comparative analysis of the four models, LSTM, CNN, LightGBM, and MLP,identifies LightGBM as the superior performer, demonstrating excellence across all essential criteria for predicting IVF treatment results. LightGBM attains the best accuracy at 84.97%, precision at 86.95%, recall at 86.43%, and F1-score at 82.74%, indicating its exceptional capacity for accurate prediction, minimizing false positives, and maintaining a balance between precision and recall, so establishing it as the most dependable model. MLP demonstrates commendable performance, achieving an accuracy of 81.54%, precision of 80.12%, recall of 79.80%, and an F1-score of 79.36%, indicating it as a robust alternative with a commendable equilibrium between accuracy and true positive identification. Table 1 delineates the comparative efficacy of each procedure for IVF recommendations.

Table 1: Comparative performance of each model

Model	Recall	F1-Score	Precision	Accuracy
LSTM	79.13	75.27	78.23	74.51
CNN	77.23	76.61	77.41	75.89
LightGBM	***86.43***	***82.74***	***86.95***	***84.97***
MLP	79.8	79.36	80.12	81.54

CNN demonstrates moderate performance with an accuracy of 75.89%, precision of 77.41%, recall of 77.23%, and an F1-score of 76.61%. While it demonstrates proficiency in managing intricate data, it falls short of the efficacy exhibited by LightGBM or MLP, highlighting its constraints in precision and recall, as illustrated in Figure 10.

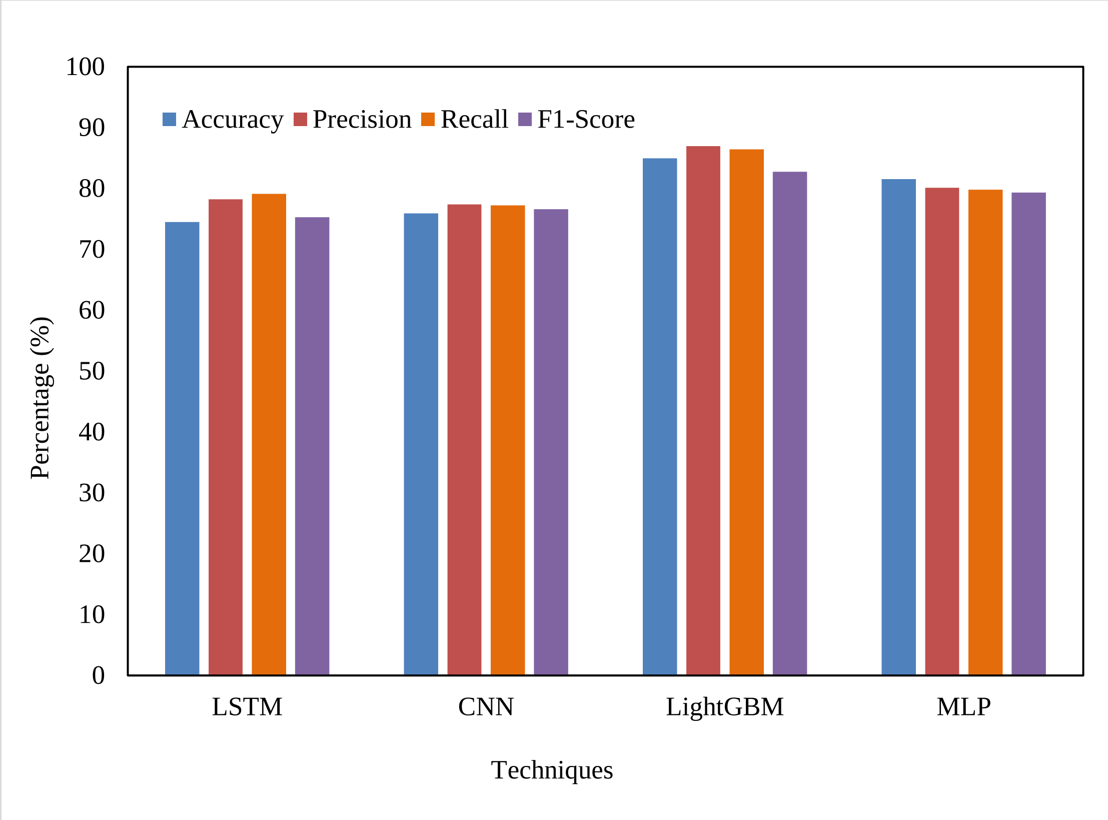

Figure 10: Comparative Analysis of Proposed Approaches

Conclusion and Future Scope

IVF is a crucial assisted reproductive technology intended for persons encountering difficulties with natural conception. The intricate nature of IVF necessitates individualized, data-driven strategies to improve treatment precision and success rates. This research aims to create a Machine Learning-driven Patient-Centric DSS that customizes IVF treatment recommendations according to each patient's distinct clinical and personal characteristics. To accomplish this, several sophisticated machine learning models are assessed, including LSTM, CNN, LightGBM, and MLP. The proposed model employs a systematic methodology that includes data collection, preprocessing, feature selection via PCA and RFE, model training, evaluation, and the formulation of therapy recommendations. Among the evaluated models, LightGBM has the greatest efficacy, with an accuracy of 84.97%, precision of 86.95%, and recall of 86.43%. Future study aims to improve the model's applicability among varied patient populations.

References

1. Xin, X., Wu, S., Xu, H., Ma, Y., Bao, N., Gao, M., ... & Tan, J. (2024). Non-invasive prediction of human embryonic ploidy using artificial intelligence: a systematic review and meta-analysis. *eClinicalMedicine*, *77*.
2. Abou Ghayda, R., Cannarella, R., Calogero, A. E., Shah, R., Rambhatla, A., Zohdy, W., ... & Forum, G. A. (2024). Artificial intelligence in andrology: from semen analysis to image diagnostics. *The World Journal of Men's Health*, *42*(1), 39.
3. Nadella, G. S., Satish, S., Meduri, K., & Meduri, S. S. (2023). A systematic literature review of advancements, challenges and future directions of AI and ML in healthcare. *International Journal of Machine Learning for Sustainable Development*, *5*(3), 115-130.
4. Yu, L., Lam, K., Ng, E., Yeung, W., Yu, L., Lee, Y. L., & Huang, Y. (2024). Deep learning-based embryo assessment of static images can reduce the time to live birth in in vitro fertilization. *medRxiv*, 2024-10.

5. UrcelayGanzabal, L. (2023). *Exploring the complexities of AI-Assisted Embryo Selection: a comprehensive review* (Master's thesis, UniversitatPolitècnica de Catalunya).

6. Bondarenko, D. (2024). *Digital marketplaces of modern business (based on the "COR-Medical" case)* (Doctoral dissertation, Private Higher Educational Establishment-Institute "Ukrainian-American Concordia University").

7. Nisal, A., Diwekar, U., & Hobeika, E. (2022). Personalized medicine for GnRH antagonist protocol in in vitro fertilization procedure using modeling and optimal control. *Computers & Chemical Engineering*, *156*, 107554.

8. Letterie, G., & Mac Donald, A. (2020). Artificial intelligence in in vitro fertilization: a computer decision support system for day-to-day management of ovarian stimulation during in vitro fertilization. *Fertility and Sterility*, *114*(5), 1026-1031.

9. Diwekar, U., Joag, S., Patel, N. H., Ghoghari, P. H. B. H. B., Vyas, K., Gupta, S. N., ... & Bhoi, N. R. (2023). IVF STIMULATION OPTIMIZED, PERSONALIZED, AND SIMPLIFIED USING AN ADVANCED DECISION-SUPPORT TOOL. *Fertility and Sterility*, *120*(4), e205-e206.

10. Aydin, B., Gudkova, D., Dorofeyeva, U., Yetim, I., &Vozniuk, V. (2024). DONOR OOCYTE SELECTION THROUGH ARTIFICIAL INTELLIGENCE: A NOVEL PREDICTIVE MODEL TO SUPPORT CLINICAL DECISION-MAKING AND IMPROVE IVF OUTCOMES. *Fertility and Sterility*, *122*(4), e355-e356.

11. Nisal, A., Diwekar, U., & Bhalerao, V. (2020). Personalized medicine for in vitro fertilization procedure using modeling and optimal control. *Journal of theoretical biology*, *487*, 110105.

12. Tammimy, Z., & Alizadeh, S. (2022). ICSI Protocol Advisor: A decision support system for infertility protocol suggestion. *Scientia Iranica*.

13. Villani, M. T., Morini, D., Spaggiari, G., Furini, C., Melli, B., Nicoli, A., ... & Santi, D. (2022). The (decision) tree of fertility: an innovative decision-making algorithm in assisted reproduction technique. *Journal of Assisted Reproduction and Genetics*, *39*(2), 395-408.

14. Patel, N., Diwekar, U., Patel, N., Patel, M., Bhadarka, H., Ghoghari, P., & Vyas, K. (2023). # 282: Maximizing IVF Success Rates: Optimized Simulation Using a Novel Decision-Support Tool. *Fertility & Reproduction*, *5*(04), 375-375.

15. Pérez-Padilla, N. A., Garcia-Sanchez, R., Avalos, O., Gálvez, J., Bian, M., Yu, L., ... &Yelian, F. D. (2024). Optimizing trigger timing in minimal ovarian stimulation for In Vitro fertilization using machine learning models with random search hyperparameter tuning. *Computers in Biology and Medicine*, *179*, 108856.

16. Liu, L., Liang, H., Yang, J., Shen, F., Chen, J., & Ao, L. (2024). Clinical data-based modeling of IVF live birth outcome and its application. *Reproductive Biology and Endocrinology*, *22*(1), 76.

17. Fu, K., Li, Y., Lv, H., Wu, W., Song, J., & Xu, J. (2022). Development of a model predicting the outcome of in vitro fertilization cycles by a robust decision tree method. *Frontiers in Endocrinology*, *13*, 877518.

18. Diwekar, U., Patel, N., Patel, N., Patel, M., Bhadarka, H., &Ghoghari, P. (2022). A non-randomized clinical trial of a decision support tool to optimize superovulation cycles in individual patients. *J Fertil In vitro IVF World w Reprod Med Genet Stem Cell Biol*, *10*(261).

19. Sadegh-Zadeh, S. A., Khanjani, S., Javanmardi, S., Bayat, B., Naderi, Z., &Hajiyavand, A. M. Catalysing IVF Outcome Prediction: Exploring Advanced Machine Learning Paradigms for Enhanced Success Rate Prognostication. *Frontiers in Artificial Intelligence*, *7*, 1392611.

20. Zhang, M., Ji, X., Hu, X., Zhu, Y., Ma, H., Xu, H., ... & Zhang, Q. (2024). Development and validation of a visualized prediction model for early miscarriage risk in patients undergoing IVF/ICSI procedures: a real-world multi-center study. *Frontiers in Endocrinology*, *14*, 1280145.

21. Yao, M. W., Nguyen, E. T., Retzloff, M. G., Gago, L. A., Copland, S., Nichols, J. E., ... &Walmer, D. K. (2024). Improving IVF Utilization with Patient-Centric Artificial Intelligence-Machine Learning (AI/ML): A Retrospective Multicenter Experience. *Journal of Clinical Medicine*, *13*(12), 3560.

22. Khan, F. M., Akhter, M. S., Khan, I. U., Haider, Z. A., & Khan, N. H. Clinical Prediction of Female Infertility Through Advanced Machine Learning Techniques.
23. Rathinaeaswari, S. P., and V. Santhi. "A New Efficient and Privacy-Preserving Hybrid Classification model for Patient-Centric Clinical Decision Support System." *Journal of Advanced Research in Applied Sciences and Engineering Technology* 33, no. 1 (2023): 299-316.
24. Niraula, D., Sun, W., Jin, J., Dinov, I. D., Cuneo, K., Jamaluddin, J., ... & Naqa, I. E. (2022). ARCliDS: A Clinical Decision Support System for AI-assisted Decision-Making in Response-Adaptive Radiotherapy. *medRxiv*, 2022-09.
25. Xi, Q., Yang, Q., Wang, M., Huang, B., Zhang, B., Li, Z., ... & Jin, L. (2021). Individualized embryo selection strategy developed by stacking machine learning model for better in vitro fertilization outcomes: an application study. *Reproductive biology and endocrinology*, *19*, 1-10.
26. Li, Fangyuan, Ruihui Lu, Cheng Zeng, Xin Li, and Qing Xue. "Development and validation of a clinical pregnancy failure prediction model for poor ovarian responders during IVF/ICSI." *Frontiers in Endocrinology* 12 (2021): 717288.
27. Hassan, M. R., Al-Insaif, S., Hossain, M. I., &Kamruzzaman, J. (2020). A machine learning approach for prediction of pregnancy outcome following IVF treatment. *Neural computing and applications*, *32*(7), 2283-2297.
28. Qiu, J., Li, P., Dong, M., Xin, X., & Tan, J. (2019). Personalized prediction of live birth prior to the first in vitro fertilization treatment: a machine learning method. *Journal of translational medicine*, *17*, 1-8.
29. Topolski, M. (2020). The Modified Principal Component Analysis Feature Extraction Method for the Task of Diagnosing Chronic Lymphocytic Leukemia Type B-CLL. *J. Univers. Comput. Sci.*, *26*(6), 734-746.
30. Levada, A. L. (2021). PCA-KL: a parametric dimensionality reduction approach for unsupervised metric learning. *Advances in Data Analysis and Classification*, *15*(4), 829-868.
31. Chavez-Badiola, A., Flores-Saiffe Farias, A., Mendizabal-Ruiz, G., Garcia-Sanchez, R., Drakeley, A. J., & Garcia-Sandoval, J. P. (2020). Predicting pregnancy test results after embryo transfer by image feature extraction and analysis using machine learning. *Scientific reports*, *10*(1), 4394.
32. Ali, U. M. E., Hossain, M. A., & Islam, M. R. (2019, December). Analysis of PCA based feature extraction methods for classification of hyperspectral image. In *2019 2nd international conference on innovation in engineering and technology (ICIET)* (pp. 1-6). IEEE.
33. *https://www.keboola.com/blog/pca-machine-learning*
34. Zebari, R., Abdulazeez, A., Zeebaree, D., Zebari, D., & Saeed, J. (2020). A comprehensive review of dimensionality reduction techniques for feature selection and feature extraction. *Journal of Applied Science and Technology Trends*, *1*(1), 56-70.
35. Tang, J., Alelyani, S., & Liu, H. (2014). Feature selection for classification: A review. *Data classification: Algorithms and applications*, 37.
36. Rumao, S. (2019). *Exploration of Variable Importance and Variable selection techniques in presence of correlated variables*. Rochester Institute of Technology.
37. Faysal, J. A., Mostafa, S. T., Tamanna, J. S., Mumenin, K. M., Arifin, M. M., Awal, M. A., ... & Mostafa, S. S. (2022, January). XGB-RF: A hybrid machine learning approach for IoT intrusion detection. In *Telecom* (Vol. 3, No. 1, pp. 52-69). MDPI.
38. Rinish Reddy, R., Sadhwika Rachamalla, Mohamed Sirajudeen Yoosuf, and G. R. Anil. "Convolutional Neural Network Based Intrusion Detection System and Predicting the DDoS Attack." In Data Intelligence and Cognitive Informatics: Proceedings of ICDICI 2022, pp. 81-94. Singapore: Springer Nature Singapore, 2022.
39. Zafar, Afia, Muhammad Aamir, Nazri Mohd Nawi, Ali Arshad, Saman Riaz, Abdulrahman Alruban, Ashit Kumar Dutta, and Sultan Almotairi. "A comparison of pooling methods for convolutional neural networks." Applied Sciences 12, no. 17 (2022): 8643.
40. Singhal, S., Kumar, H., &Passricha, V. (2018). Prediction of heart disease using CNN. *Am Int J Res Sci Technol Eng Math*, *23*(1), 257-261.

41. Rinish Reddy, R., Rachamalla, S., Yoosuf, M. S., & Anil, G. R. (2022). Convolutional neural network based intrusion detection system and predicting the DDoS attack. In *Data Intelligence and Cognitive Informatics: Proceedings of ICDICI 2022* (pp. 81-94). Singapore: Springer Nature Singapore.
42. Ye, X., Zeng, Q. T., Facelli, J. C., Brixner, D. I., Conway, M., & Bray, B. E. (2020). Predicting optimal hypertension treatment pathways using recurrent neural networks. *International journal of medical informatics*, *139*, 104122.
43. Kaji, D. A., Zech, J. R., Kim, J. S., Cho, S. K., Dangayach, N. S., Costa, A. B., & Oermann, E. K. (2019). An attention based deep learning model of clinical events in the intensive care unit. *PloS one*, *14*(2), e0211057.
44. Letterie, G. S., & MacDonald, A. (2019). A computerized decision–support system for day to day management of ovarian stimulation cycles during in vitro fertilization. *Fertility and Sterility*, *112*(3), e28.
45. Li, L., Cui, X., Yang, J., Wu, X., & Zhao, G. (2023). Using feature optimization and LightGBM algorithm to predict the clinical pregnancy outcomes after in vitro fertilization. *Frontiers in endocrinology*, *14*, 1305473.
46. Yuan, G., Lv, B., Du, X., Zhang, H., Zhao, M., Liu, Y., & Hao, C. (2023). Prediction model for missed abortion of patients treated with IVF-ET based on XGBoost: a retrospective study. *PeerJ*, *11*, e14762.
47. Ahn, B. C., So, J. W., Synn, C. B., Kim, T. H., Kim, J. H., Byeon, Y., ... & Kim, H. R. (2021). Clinical decision support algorithm based on machine learning to assess the clinical response to anti–programmed death-1 therapy in patients with non–small-cell lung cancer. *European Journal of Cancer*, *153*, 179-189.
48. Feli, E., Hosseini, R., & Yazdani, S. (2021). An Intelligent Model for Prediction of In-Vitro Fertilization Success using MLP Neural Network and GA Optimization. *Journal of AI and Data Mining*, *9*(4), 515-523.
49. Barnett-Itzhaki, Z., Elbaz, M., Butterman, R., Amar, D., Amitay, M., Racowsky, C., ... &Machtinger, R. (2020). Machine learning vs. classic statistics for the prediction of IVF outcomes. *Journal of assisted reproduction and genetics*, *37*, 2405-2412.
50. Babitha, M. (2019). A Survey on the Machine Learning Techniques used in IVF Treatment to Improve the Success Rate. *RTESIT*.

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