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Article

AI-Based Hybrid Decision Support Model for Patient-Centric Personalized IVF Treatment Recommendation and Outcome Optimization

Niku Brahmbhatt[1*], Tulsidas Nakrani[2]

[1,2]Department of Computer Application (MCA), Sankalchand Patel University, Visnagar, Gujarat, India. ORCID: 0009-0006-7134-9076. E-mail: niku.brahmbhatt@gmail.com

Abstract: In Vitro Fertilization (IVF) is one of the assisted reproductive techniques applied for couples with the inability to conceive naturally. As IVF has become rather complex, it has also become necessary for healthcare providers to provide patients with tailored recommendations with regard to every health profile. This study seeks to develop a hybrid Machine Learning (ML) based, patient-oriented Decision Support System (DSS) to enhance the treatment of patients undergoing IVF. Taking extensive data regarding patients' history, clinical factors, and lifestyle, this study employs advanced algorithms such as Long Short-Term Memory (LSTM), Convolutional neural Network (CNN), Light Gradient Boosting Machine (LightGBM), Multi-Layer Perceptron (MLP) and hybrid CNN-LightGBM with remarkable prediction accuracies. Among the evaluated models, the hybrid CNN-LightGBM demonstrates the highest accuracy of 90.34%, precision of 89.45%, and recall of 88.23%, thereby indicating the reliability of the model in recommending IVF treatment. The proposed model improves decision-making with economically varying models of IVF treatments and advocates for an individualized, evidentiary understanding of each IVF patient's requirements since it potentially enhances treatment outcomes. Future work includes increasing model robustness across heterogeneous populations.

Keywords: In Vitro Fertilization (IVF), Light Gradient Boosting Machine (LightGBM), Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), Recursive Feature Elimination (RFE).

1. Introduction

IVF is a significant process of assisted reproductive technology that is widely practiced among couples who cannot conceive naturally [1]. One of the most difficult forms of fertility treatment, the steps of an IVF cycle include ovarian stimulation, retrieval of oocytes, fertilization and transfer of the embryo. Each procedure in IVF treatment is carried out and done after a thorough evaluation of the clinical picture in order to improve the chances of a successful clinical pregnancy [2,3]. With the kind of physical, emotional, and monetary investment IVF demands, patient-focused approaches have become very important with the necessity to address individualized protocols tailored to each individual's needs [4,5]. Therefore, optimizing IVF treatment recommendations is important in improving success rates, but more importantly, it could provide a complete experience dedicated to the unique physiological and psychological profiles. It can improve outcomes and guide them through this arduous process of IVF journey [6]. Figure 1 details the step by step IVF, from consultation up to pregnancy testing.

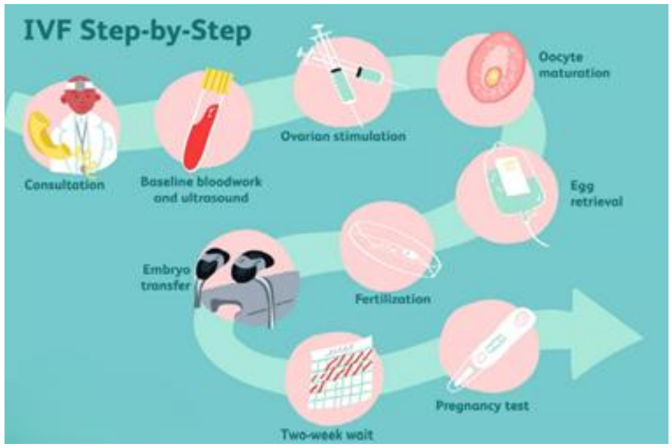

Figure 1. Stages of In vitro Fertilization procedure [7].

Emerging Machine Learning (ML) in healthcare is leading to groundbreaking potential and imaginative solution opportunities in improving clinical decision-making and personalized care, particularly in the realm of fertility treatments [8]. With the ability to process vast amounts of patient data to identify complex patterns, ML algorithms now open up unprecedented opportunities to develop highly individualized treatment recommendations in IVF [9,10]. These models can unveil rather subtle correlations while making predictions on the responses of patients to treatment protocols by analyzing historical data, thus leading to more informed and accurate recommendations [11]. Advanced ML techniques such as deep learning and ensemble methods can dive into much greater detail than traditional statistical approaches and provide granular insights that might significantly improve IVF treatment personalization and the success rate [12].

However, most current IVF treatment recommendations depend mainly on subjective parameters and general clinical guidelines, not fully taking into account the differences in each patient's case [13]. The usual methods are often inconsistent with a wide variation in treatment decision making by practitioners mainly due to their individual experience and expertise [14]. The outcome tends to vary while not meeting the requirements of precision toward patient-centric medicine. Additionally, traditional approaches might overlook important elements that must be factored into the prediction of responses to IVF protocols, such as genetic factors, lifestyle patterns and hormonal influences [15,16].

Considering such limitations, an urgent need for advanced ML-driven patient-centric decision support models is emerging to facilitate the best possible IVF treatments among clinicians [17]. This might include various forms of patient data, including both clinical and genetic factors, lifestyle, and so forth, to give a profile for all such patients who are approaching treatment via IVF [18]. This utilizes data-driven insights by ML algorithms to empower clinicians to generate insights that lie beyond the conventional guidance toward more precise, consistent, and individualized IVF treatment approaches. In the long run, this model for decision support increases success rates in IVF but also addresses fertility care through a patient-centric, empathetic approach, thus providing better experience and outcomes for the patients [19,20].

This research aims to design and test an ML-based decision support model that optimizes the results of IVF treatment through customized, evidence-based treatment protocol recommendations.

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.

2. 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 linked to prognostic reports using ML through pre-treatment counseling. A retrospective cohort analysis was conducted on 24,238 patients from seven reproductive institutions in the United States and Ontario, Canada. The findings showed that the use of the Univfy report was associated with a higher direct IVF conversion, as demonstrated by the odds ratios of 3.13, 2.89, and 2.04 for the 180-day, 360-day, and Ever analyses, respectively. Conversion rates for IVF, irrespective of the history of previous Intra-Uterine Insemination (IUI), were reported with odds ratios of 3.41, 3.81, and 2.78, where all were significant at $p < 0.05$.

Khan et al., (2024) [22] utilized advanced ML techniques to develop a novel approach for female infertility prediction. Detailed analysis of a set of data with medical features pertaining to the female reproductive system was performed using logistic regression, Naive Bayes, and Support Vector Machine (SVM), as well as the Random Forest algorithms. The Random Forest algorithm showed an accurate rate of 93%. The study proved useful for the development of possible applications for early detection of causes of infertility and perhaps offering treatment modalities in the future.

Rathinaeaswar and Santhi (2023) [23] designed an Efficient and Privacy-Preserving Patient-centric Clinical Decision Support System (EPPCD), which enabled the clinician to make even patient-related illness risk predictions without violating any privacy issues. This technology was meant to address the privacy issues that have been a problem in the Clinical Decision Support System (CDSS). The constructed system kept the historical records of the previous patients in the cloud which could help in the construction of the hybrid Rotation Forest and AdaBoost classifier. The findings revealed that the proposed RandRotBoost attained a 95% F1 Score which was higher than other methods.

Niraula et al., (2022) [24] developed an AI-driven decision-making framework to aid oncologists with Decision-Theoretic Radiotherapy. The framework termed Adaptive Radiotherapy Clinical Decision Support (ARCliDS) consists of two modules: Artificial RT Environment (ARTE) and Optimal Decision Maker (ODM). The underlying structure of ARTE was based on a supervised-learning-based Markov decision process, and the correct unphysical dose-response trends were corrected by a dual Graph Neural Network (GNN) architecture. The framework resulted in increased clinical decisions of 36% and 50% favorable clinical outcomes for patients with NSCLC and HCC, respectively, and improved 74% and 30% of previously suboptimal decisions.

Xi et al., (2021) [25] customized embryo selection strategy and pregnancy prediction model were designed using a stacked approach. A hierarchical model built with eXtreme Gradient Boosting (XGBoost) assessed simultaneously the potential implantation of embryos and the concurrent effects of Double Embryo Transfer (DET). Multiple regression analysis of 19 selected features revealed differences in the significance of prediction features and their statistical associations with outcomes. At 30 completed experimental iterations, the model had an 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 clinical pregnancy failure in Poor Ovarian Responders (PORs) during IVF procedures. The patient data from the group of 281 POR patients, consisting of a training set (179 patients) and a validation set (102 patients), were used to identify multiple variables such as age above 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 logistic regression method was applied to develop a nomogram, which was constructed with a demonstrated accuracy of prediction with an AUC of 0.786 in the training group and 0.748 in the test group.

Hassan et al. (2020) [27] employed a hill-climbing approach to identify the most important features, which were further used in machine learning to upgrade IVF pregnancy prediction precision levels. The authors have used 25 attributes for the evaluation and compared the predictability of 5 ML algorithms which were MLP, SVM, C4.5, Classification and Regression Trees (CART), and Random Forest (RF). The significant attribute dimension was reduced by the use of feature selection techniques, which resulted in 19 for MLP, 16 for RF, 17 for SVM, 12 for C4.5 and 8 for CART. The findings suggest that hill climbing feature selection potentially combined with classifiers such as SVM, MLP or RF can improve prediction performance and provide valuable information for practitioners evaluating the outcome of IVF procedures.

Qiu et al. (2019) [28] derived the predictive model for live birth probability before starting the first IVF cycle with the help of ML methodologies. The research is a retrospectively derived clinical report of 7,188 women who underwent their first-ever IVF treatment. Nested cross-validation has been used to achieve an unbiased estimation of the efficacy of the adaption of ML algorithms. The XGBoost model attained an area of 0.73 of a Receiver Operating Characteristic (ROC) curve applied to the validation dataset set with calib better than other ML.

3. Research Methodology

This study offers a robust analysis of the employed strategy, detailing the dataset, methods, and the recommendation approach as follows:

3.1.Dataset description

The study uses a primary dataset of 850 responses organized in an Excel file. Each entry contains fundamental information for the development of an IVF treatment recommendation model and, therefore, includes age group under 35, 35-40, over 45, fertility, medical history, fertility attempts, reproductive issues, health metrics, and past conditions such as hypertension or diabetes. The dataset also comprises aspects about ovarian reserve, uterine health, interest in genetic analysis, embryo transfer history, and outcomes. This comprehensive dataset facilitates the development of accurate ML algorithms, ensuring that users can get personalized IVF recommendations based on diversified relevant data.

3.2.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 plays an important role in pattern recognition and analysis of data, focusing on selecting relevant features of the original data for reducing training time and simplifying space complexity, thus carrying out dimensionality reduction. It transforms the input data into a condensed feature set holding important information from the original dataset [29,30]. PCA is one of the powerful techniques for identifying patterns in high-dimensional data and extracting useful features from that data [31]. In PCA, components are ordered by variance, and the first few components capture most of the 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.

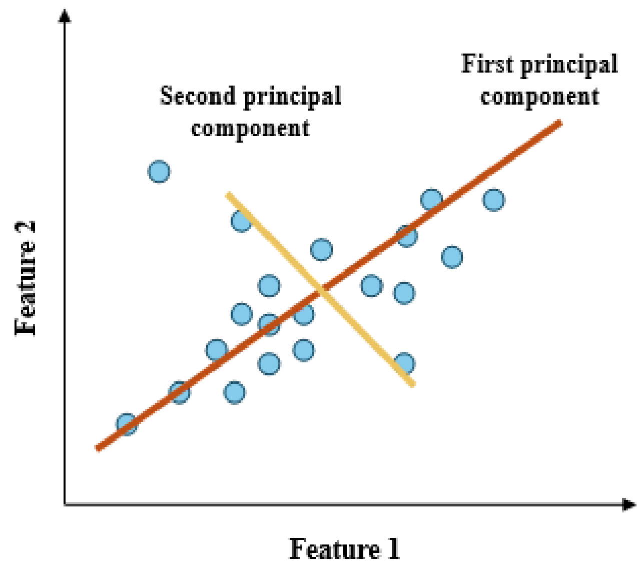

Figure 2. PCA [33]

- **Recursive Feature Elimination (RFE)**

Feature selection is critical for determining the relevant attributes of a given domain [34]. RFE is a popular method that provides optimal features based on learning the model and accuracy of classification. In large databases, irrelevant features impede efficiency and accuracy in classification [35]. RFE addresses this by iteratively ranking and removing less important features while holding onto those that are necessary for accurate prediction. This approach reduces dimensionality but retains key characteristics, improving both model performance and interpretability [36]. Using ML classifiers, RFE iteratively refines the feature set, training until an optimal subset is achieved. Figure 3 illustrates the RFE workflow. In this methodology, RFE is used to identify key features pertinent to the treatment recommendation models, which improved both accuracy and clarity within the suggestions.

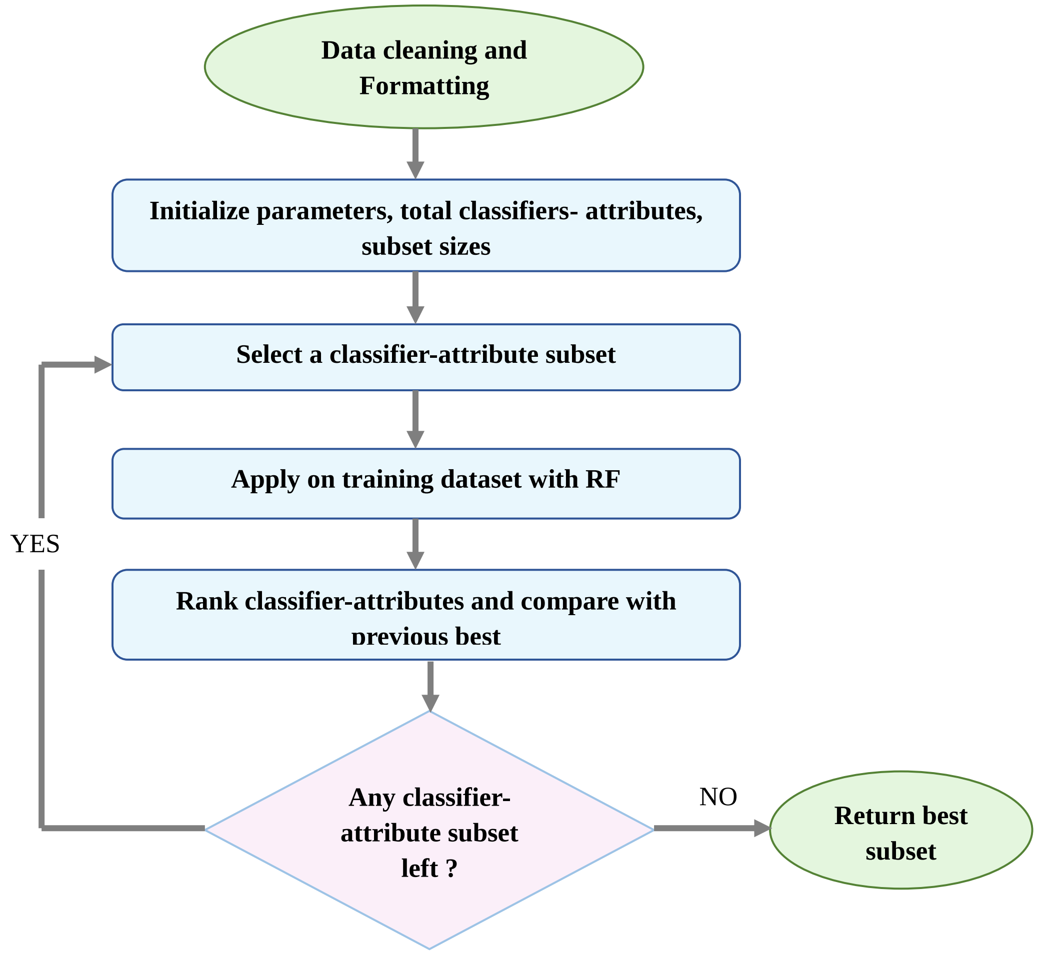

Figure 3. The working architecture of the RFE algorithm [37].

- **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 Figure 4, 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].

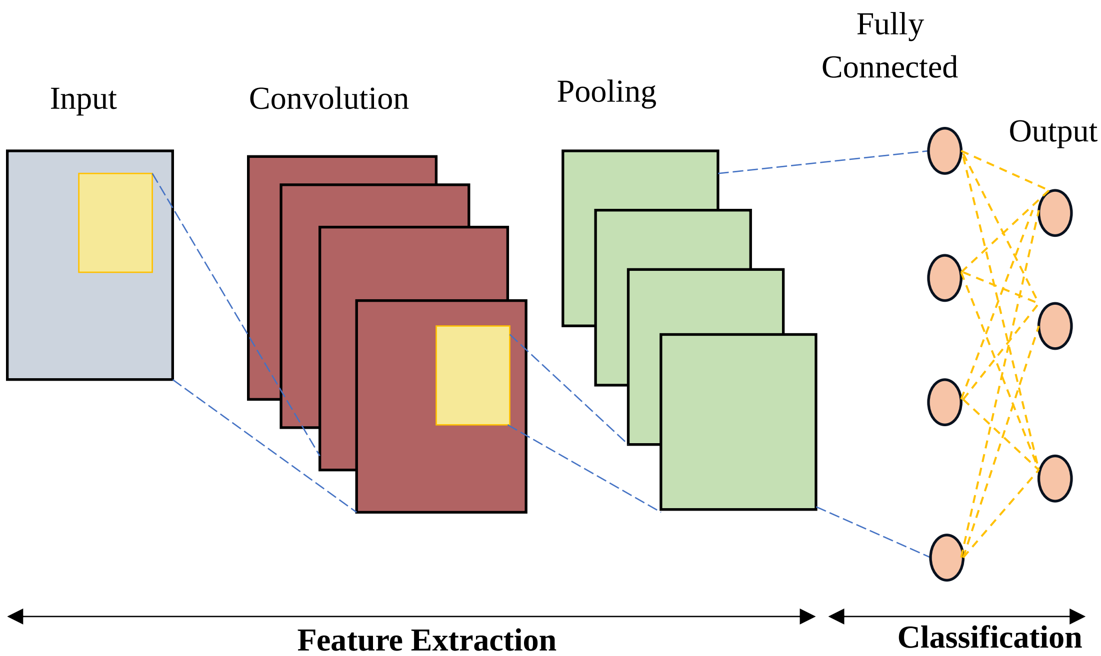

Figure 4. CNN [41].

- **LSTM**

The LSTM model is a very strong Recurrent Neural Network (RNN) designed for maintaining sequential data and, thus, applied also to patient-centric decision support in IVF treatment [42]. Keeping information across long sequences in a closed system captures essential patterns from patient histories related to previous treatment cycles and health metrics [43]. This allows for generating highly accurate, personalized recommendations founded on trends crucial for treatment success. This model can emphasize significant data points through advanced mechanisms like attention layers and lead to better accuracy in the forecasting of optimal IVF treatment paths, thereby improving success rates for each patient profile [44].

- **LightGBM**

LightGBM is a gradient-boosting framework that can effectively handle large-scale, high-dimensional data. This makes LightGBM suitable for patient-centric decision support in IVF treatment [45]. Using decision tree-based learning, LightGBM captures the complex interactions of patient health metrics, treatments, and outcomes. Its efficiency and speed at training allow for model tuning to be done within a very short period of time and ensure that the optimization of predictions for treatment recommendation is achieved [46]. LightGBM admits categorical and continuous features, thereby making its accuracy relevant to predict success rates in IVF by identifying key factors in data from patients. It finally ends up being an accurate and tailored IVF treatment pathway according to an individual's patient profile [47].

- **MLP**

The MLP model represents the implementation of a feed-forward neural network that is applied in designing an IVF patient-centric DSS for optimized recommendations [48]. It is effective in capturing complicated, non-linear relations among patient data when there is processing of multiple layers of nodes [49]. Here, it learns diverse patient metrics, including age, hormone levels, and history of treatment, so that it can predict rates of success and recommend personalized treatment paths. By applying backpropagation, an MLP optimizes its weight structures in order to make accurate recommendations using important features from patients that influence IVF treatment outcomes, thereby improving the decision toward treatment tailoring [50].

- **Hybrid CNN-LightGBM**

The integration of CNN and LightGBM in the decision support model for IVF treatment based on a patient perspective draws from the advantages of both methods. On the one hand, CNNs perform feature extraction from images and time series data in a very sophisticated manner [51]. On the other hand, LightGBM deals with structured information about the patient and makes such predictions based on the data available [52]. It is the hybrid scheme in which deep learning applies feature extraction and the gradient boosting effecter accurate decision making and hence making the recommendations on how to administer IVF treatment which is most appropriate to individual patients, and it decreases the chance for the doctors to be biased in preparing the treatment plan [53].

3.3.Proposed Methodology

The proposed methodology for developing a model to recommend IVF treatment involves several crucial components. Figure 5 outlines a step-by-step methodology in data management, model training, and validation that finally leads to accurate treatment recommendations. This method outlines a clear and definite approach to recommending IVF treatment. The following are the key stages illustrating the proposed methodology:

Step 1. Gathering Data

- Collect Patient Information: Start by gathering all the necessary details about patients. 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, MLP and hybrid CNN-LightGBM. 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 prediction.

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.

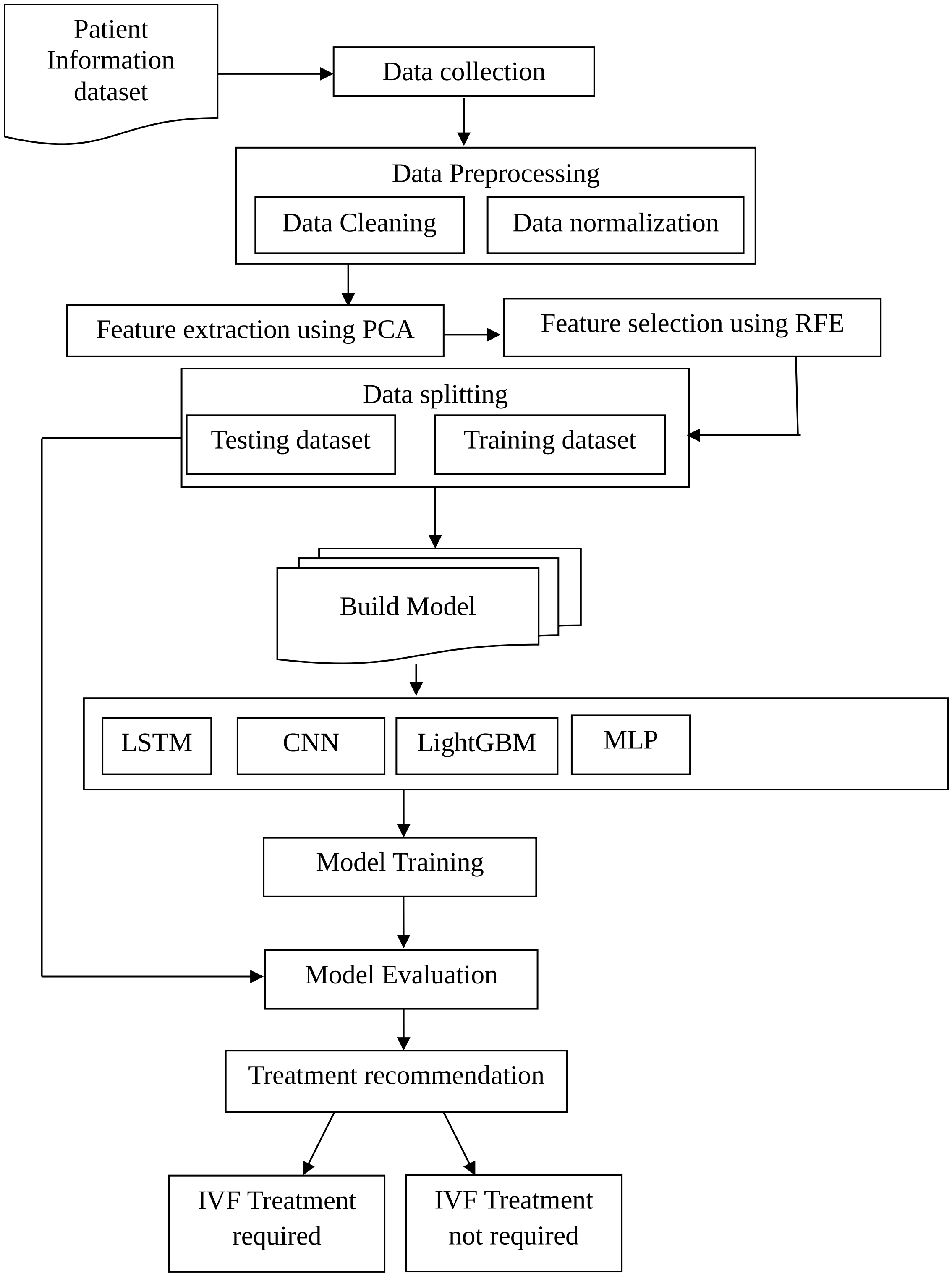

Figure 5. Proposed Methodology

3.4.Proposed Algorithm

Algorithm: Treatment recommendation model
Start
Step 1: Data Collection Collect the patient information dataset, denoted as D. **Step 2: Data Preprocessing** ***2.1 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** ***3.1 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 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: **5.1 *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 : $h_t = o_t \tanh c_t$

5.2 *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

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

Hybrid CNN-LightGBM

Mathematically, the hybrid model can be represented as:

$$Z = CNN(X)$$

Where Z represents the feature vector obtained from CNN, and X is the raw input data.

Next, the extracted features are passed to the LightGBM model for prediction:

$$\hat{y} = LightGBM(Z)$$

Where is the predicted output (e.g., whether IVF treatment is required or not) based on the features extracted by CNN.

Step 6: Model Training

Train each model using the training dataset.

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

Where L represents loss function, y represents true value, yˆ 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

4. Results and Discussion

This section examines the results of IVF treatment prediction models, including LSTM, CNN, LightGBM, MLP and hybrid CNN-LightGBM. 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.

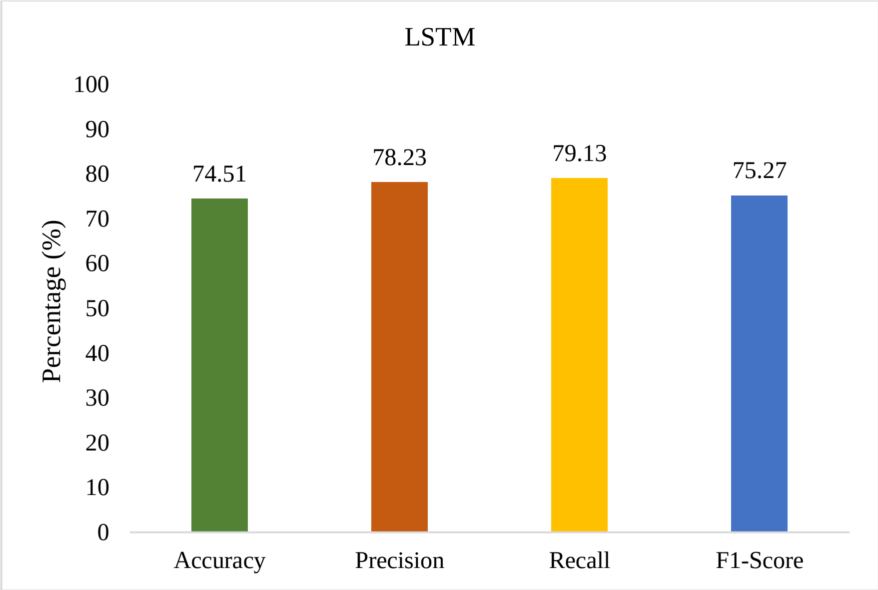

Figure 6: Performance of the LSTM model

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 LightGBM**

The LightGBM model illustrated outstanding efficacy in forecasting the requirement for IVF therapy, achieving an accuracy of 84.97%. This increased level of accuracy translates to the model's successful identification of instances for the input of IVF intervention, which is critical in medical practice where accurate predictions must occur. The precision of 86.95% means that most of the patients were identified to require IVF treatment, hence reducing the false positives depicted in Figure 7. Precision in a medical environment is important as it ensures that patients do not receive too many treatments, hence saving them from anxiety and the health risks of unnecessary operations.

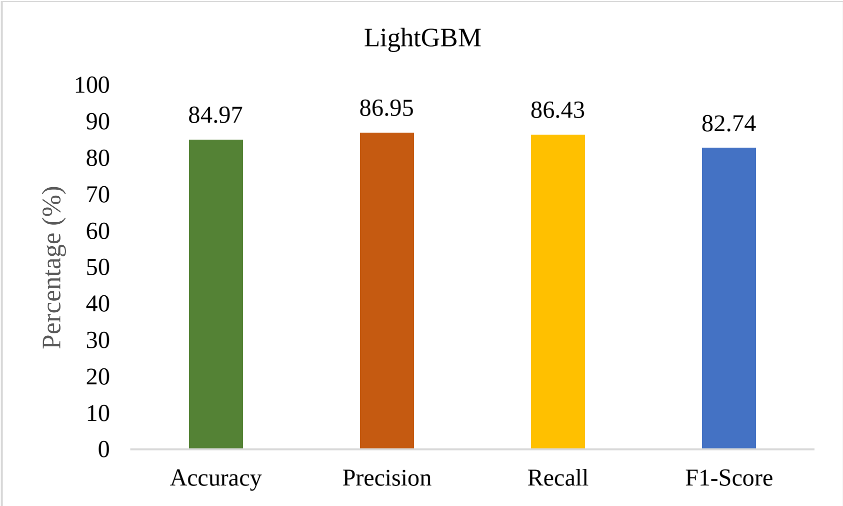

Figure 7: Performance of LightGBM model.

Furthermore, the model recalls 86.43%, meaning that it correctly identifies most of the positive cases so that only people requiring IVF can be identified. This strong recall benefits patients by allowing them to undergo timely therapies. The balanced performance is reflected through precision and recall by combining the 82.74% F1 score. In clinical applications, this balance explains the model's ability to refrain from false positives and negatives. Results show that LightGBM is a reliable IVF treatment prediction tool that might aid in clinical decision-making.

- **Results based on CNN**

The results of the CNN model for IVF treatment forecasting needs are represented using key metrics, with performance among all parameters showing strong performance. The model managed an accuracy of about 75.89%, indicating that in about 76% of the cases, the model correctly identified the need for IVF treatment. The precision of 77.41% indicates that it can clearly produce valid positive predictions, which means that a significant percentage of the cases identified for treatment through IVF were indeed justified, and therefore, false positives were diminished, as is evident from Figure 8.

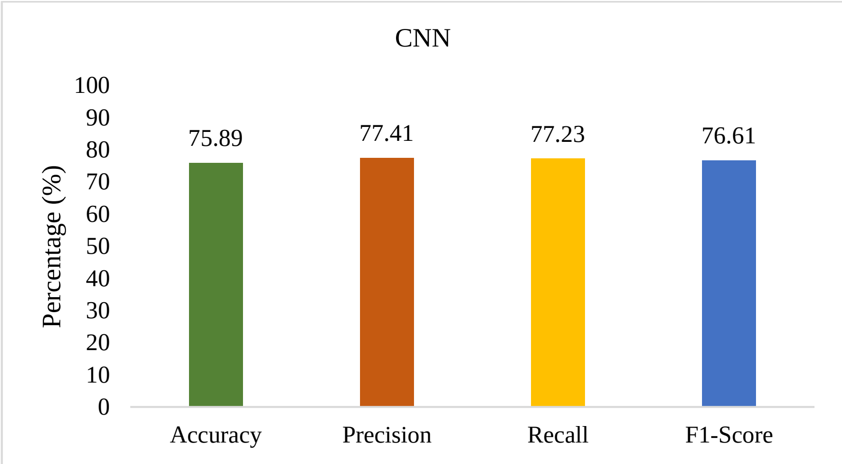

Figure 8: Performance of CNN model

CNN achieves a recall of 77.23%, meaning it correctly identifies most of the correct positive instances so that most people requiring IVF services are caught up in this system. An F1-score of 76.61% pointed to the robustness of the model in reducing prediction errors and picking the most relevant cases.

- **Results based on MLP**

The results of the MLP model for IVF treatment outcome prediction show reliable performance in all measures studied. As shown in Figure 9, the model achieved 81.54% accuracy, meaning the majority of instances were correctly classified as actually needing IVF therapy. The precision of 80.12% indicated that the model was able to classify with a commendable degree of specificity the requirements for IVF treatment and, thus, minimized the occurrence of false positives in treatment recommendations. The recall at 79.8% was a demonstration of the model's effectiveness at identifying real positive instances, that is, at recognizing persons who really needed IVF treatment. This shows MLP's ability to identify the most relevant examples, yet there is still scope for improvement in terms of sensitivity.

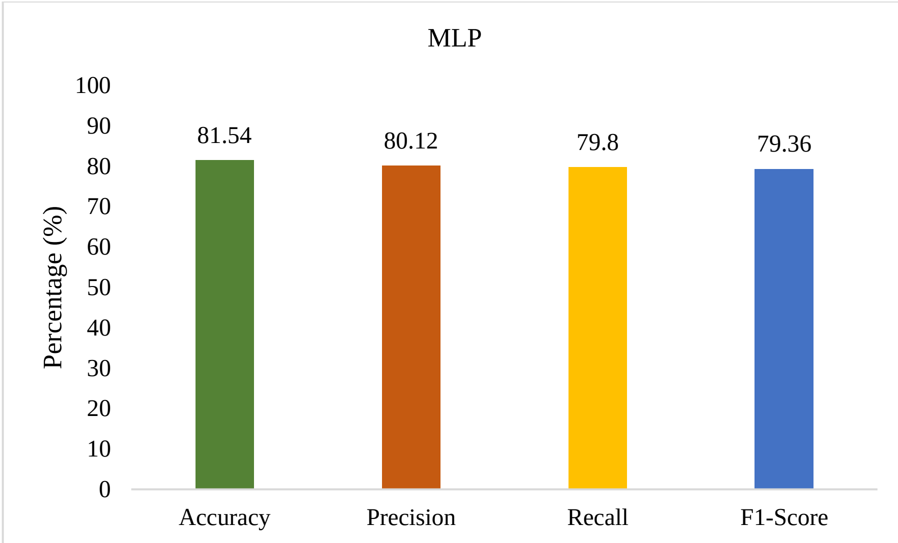

Figure 9. Performance of MLP model.

In addition, the F1-score, computing both precision and recall, is 79.36%. Thus, it follows that there was a good balance achieved by the MLP model on unnecessary recommendations with actual identification of individuals in need of IVF therapy. The MLP model performed well with dependable performance, balancing precise predictions and error reduction, a little more apt in terms of accuracy than precision or recall.

- **Results based on hybrid CNN-LightGBM model**

The hybrid CNN-LightGBM model for predicting the necessity of IVF treatment exhibits strong performance across key metrics. As shown in Figure 10, It achieves an accuracy of 90.34%, correctly classifying the majority of cases as needing or not needing IVF treatment. The precision of 89.45% reflects the model's ability to minimize false positives, while the recall of 88.23% indicates its effectiveness in identifying actual IVF cases with a low false negative rate. Additionally, the F1-Score of 85.65% highlights the balanced performance of the model, integrating precision and recall. These results suggest that the CNN-LightGBM model is a valuable tool for assisting healthcare providers in making informed IVF treatment recommendations.

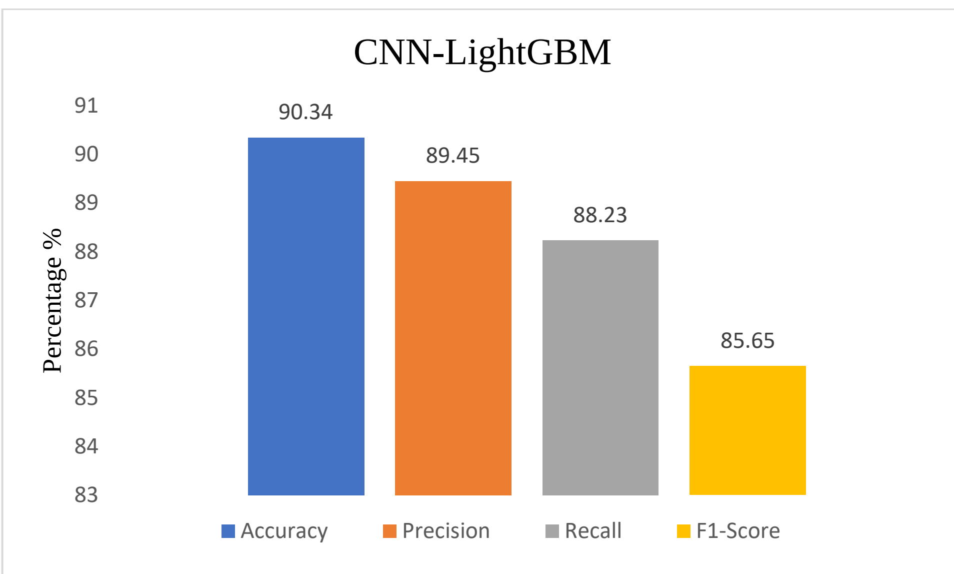

Figure 10: Performance of hybrid CNN-LightGBM model

4.1.Comparative Analysis

The comparative analysis of five models, LSTM, CNN, LightGBM, MLP and hybrid CNN-LightGBM, revealed CNN-LightGBM to be the top performer among these and on all of the most crucial metrics for predicting IVF treatment outcomes. CNN-LightGBM achieves the highest accuracy of 90.34%, precision of 89.45%, recall of 88.23%, and F1-score of 85.65%. This means it has exceptional ability in accurate prediction, fewer false positives, and proper balance between precision and recall, and therefore makes it the most reliable model. LightGBM exemplary shows an accuracy of 84.97%, precision of 86.95%, recall of 86.43%, and F1-score of 82.74%. MLP shows ideal performance with an accuracy of 81.54%, precision of 80.12%, recall of 79.80%, and an F1-score of 79.36%, which depicts it as a robust alternative with a commendable equilibrium between accuracy and true positive identification. Table 1 describes 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	79.80	79.36	80.12	81.54
Hybrid CNN-LightGBM	**88.23**	**85.65**	**89.45**	**90.34**

CNN performs moderately, with an accuracy of 75.89%, a precision of 77.41%, a recall of 77.23%, and an F1-score of 76.61%. While it proves to perform well in handling complex data, it fails to match the effectiveness shown by LightGBM or MLP, as can be seen from the restrictions in its precision and recall, illustrated in Figure 11.

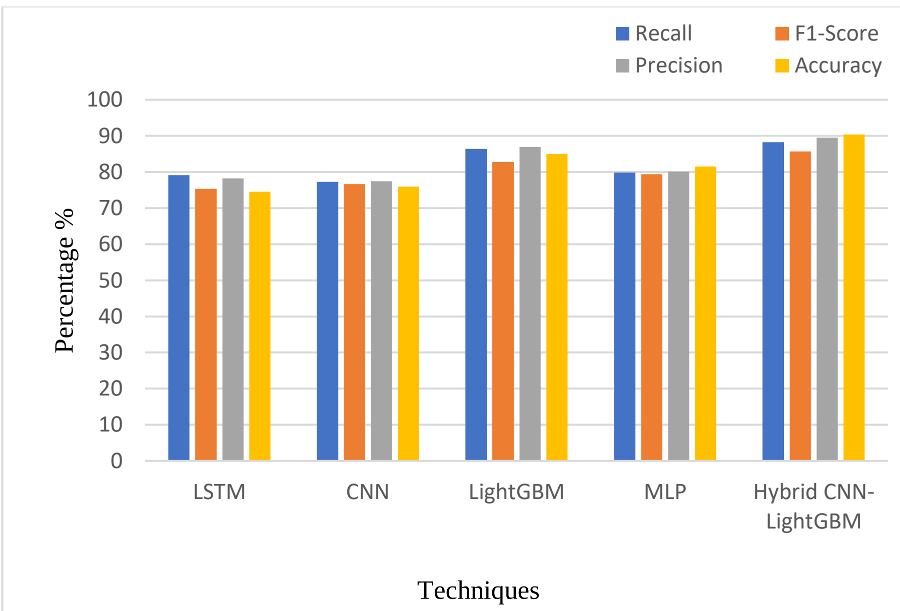

Figure 11: Comparative analysis of proposed approaches.

5. Conclusion and Future Scope

IVF is a critical assisted reproductive technology designed for individuals experiencing challenges with natural conception. The complexity of IVF requires tailoring, evidence-based interventions to enhance treatment accuracy and efficiency. This research aims to create a hybrid 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, MLP and hybrid CNN-LightGBM. 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, the hybrid CNN- LightGBM has the greatest efficacy, with an accuracy of 90.34%, precision of 89.45%, and recall of 88.23%. The proposed framework provides an AI-driven clinical decision support approach for IVF treatment recommendation. Future study aims to improve the model's applicability among varied patient populations.

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